

# **POLICY RECOMMENDATIONS FOR AUTONOMOUS UNDERWATER VEHICLE OPERATIONS THROUGH HYBRID FUZZY SYSTEM DYNAMICS RISK ANALYSIS (*FuSDRA*)**

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## **ABSTRACT**

The advancement of science and technology has resulted in an emerging trend in the use of autonomous equipment in many maritime universities. One such example is the use of autonomous underwater vehicles (AUV) for marine research. However, a key challenge lies in preventing loss of the AUV during deployment. To better control this risk of loss, a new form of hybrid fuzzy system dynamics risk analysis (FuSDRA) is proposed. The three-step framework was demonstrated by a case study, analysing how reducing government support and increasing technological obsolescence can impact the long-term risk of AUV loss. Both results showed increase in risk of loss after 7 years into the AUV program and a synergistic combined effect when compared to a base scenario. A suite of risk control policy recommendations was proposed based on these results. Lastly, broader applications of the framework to other autonomous equipment is proposed.

## **1. INTRODUCTION**

The advancement of science and technology has resulted in an emerging trend in the use of autonomous equipment for research purposes in many maritime universities. With advantages such as the ability to reach inaccessible locations, reduce personnel dependence and improve safety, it comes as no surprise that a diverse range of research activities is now performed autonomously without human interference. One such example is the Autonomous Underwater Vehicle (AUV).

Autonomous Underwater Vehicles (AUVs) are self-powered robotic devices that operate underwater. Apart from the ability to operate autonomously, their versatility with customizable payloads allow AUVs to perform a wide range of research tasks <sup>(1)</sup>. However, the risk of losing a research AUV during deployment is ever present. Here, the term ‘risk of loss’ refers to the

likelihood that during a mission, an AUV vehicle will be rendered unusable for future missions. Not without precedent, two examples of loss are the Tadpole, an AUV operated by the Institute of Antarctic and Southern Ocean Studies, Australia,<sup>(2)</sup> and Autosub 2, an AUV developed and owned by the National Oceanography Centre, UK<sup>(3)</sup>. Like most autonomous equipment, the loss of an AUV can be financially costly due to higher resulting insurance premium, result in delay of research projects, damage reputation, loss of valuable research data and there is a possibility of contaminating the environment.

To reduce the risk of loss, a robust risk analysis approach is required to facilitate the formulation of effective risk control policies. Although different risk analysis approaches have been proposed in the literature<sup>(4)(5)(6)(7)</sup> there are still shortfalls to be addressed. First, these approaches tend to adopt a chain-of-event perspective, which views the loss of an AUV as the final unintended outcome. Such view promote a reductionist mentality, which often displaces more complex, and potentially fruitful accounts of multiple and interacting contributions. Second, these approaches mainly depended on the elicitation of expert's opinions for subjective probability quantification. However, experts may face difficulties to provide precise numerical figures due to the vagueness and ambiguity nature of risk<sup>(8)</sup>.

To address these shortfalls, a hybrid fuzzy system dynamics risk analysis (FuSDRA) approach is proposed; one which accounts for both the dynamic complexity of the system, as well as uncertainties about the interrelationships between risk variables. Despite being applied for the analysis of other problems<sup>(9)(10)</sup>, the use of fuzzy system dynamics remain rather uncommon. To our best knowledge, it has never been used for analyzing the operational risk of autonomous equipment.

## 2. METHODOLOGY

The FuSDRA approach follows a three step iterative framework comprising of the identification of risk variables, modelling and evaluation (Fig.1).

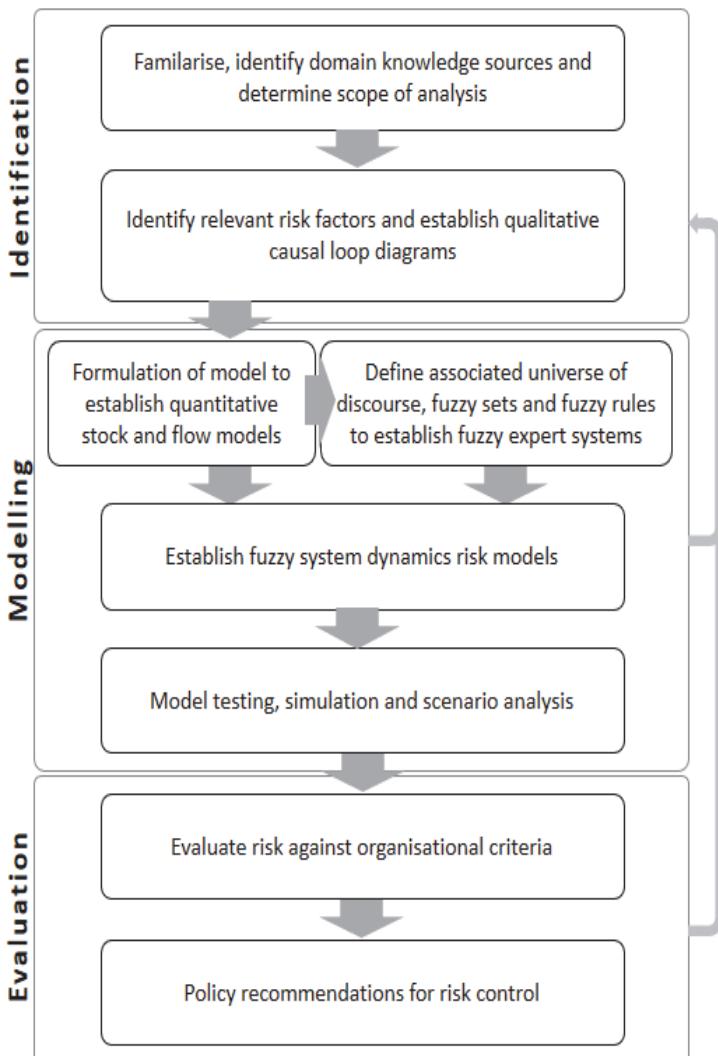


Fig 1: An overview of the FuSDRA framework

fuzzy expert systems are subsequently incorporated back into the stock and flow models to form the hybrid fuzzy system dynamics risk models. The models are tested and calibrated before simulation and scenario analysis.

In the final step of risk evaluation, insights are attained through simulation and scenario analysis, with the aim of identifying leverage points and leading indicators. Based on these insights, risk control policies can be derived and recommended to decision makers for implementation. To ensure effectiveness of the recommended policies, regular review of the risk models is necessary.

### 3. CASE STUDY

To demonstrate practicality of the FuSDRA framework, it was applied on an actual AUV named *nupiri muka*. Funded by the Australian government and managed by the University of Tasmania (UTAS), the AUV program aims to conduct research in the Antarctic and contribute to the research capabilities in Tasmania. With the AUV being relatively new, there are very limited historical data for probabilistic risk analysis. Therefore, the FuSDRA approach was applied to better understand the long-term risk of AUV loss.

In the identification step, the first task is to gain familiarity with the AUV program and identify domain knowledge sources, which very often comes from domain experts<sup>(11)</sup>. Tapping into these sources, the next task involves the identification of risk variables which may influence the long-term risk of AUV loss as well as the causal relationships between these risk variables.

In the next modeling step, system dynamics stock and flow models<sup>(12)</sup> are constructed through parameters' estimation, formulation of causal relationships and establishing initial conditions. For causal relationships which are uncertain, a fuzzy expert system<sup>(13)</sup> is applied next. This involves determining the universe of discourse, fuzzy sets, membership functions and constructing fuzzy rules. The

In the identification step, two pressing issues were identified by the primary AUV operating team as having a long-term influence on the risk of AUV loss. First, a gradual reduction in government support to the AUV program. Apart from directly influencing the risk of AUV loss through budgetary pressure, several domain experts also expressed concerns on how such reduction can affect the continued renewal of employment contracts. Second, the availability of alternatives to AUVs for research data collection. Technological evolution can render existing AUV technologies less practical and competitive either against newer AUVs or other means of data collection. With more options available, scientists and other users will naturally choose the most effective and cost-efficient means of data collection, rendering the *nupiri muka* AUV obsolete. Risk variables with their causal relationships associated with the two issues were identified and presented as a causal loop diagram in Fig 2. Construction of the FuSDRA model was carried out next to quantify the risk of loss, with a simplified version shown in Fig 3.

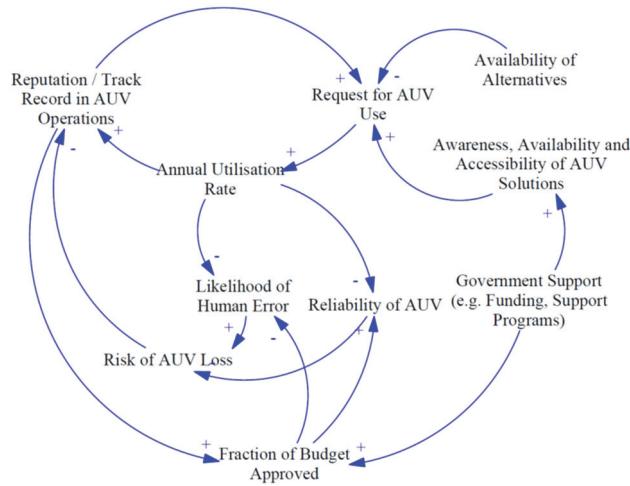


Fig 2: Causal loop diagram showing feedback loops and causal relationships between the identified risk variables.

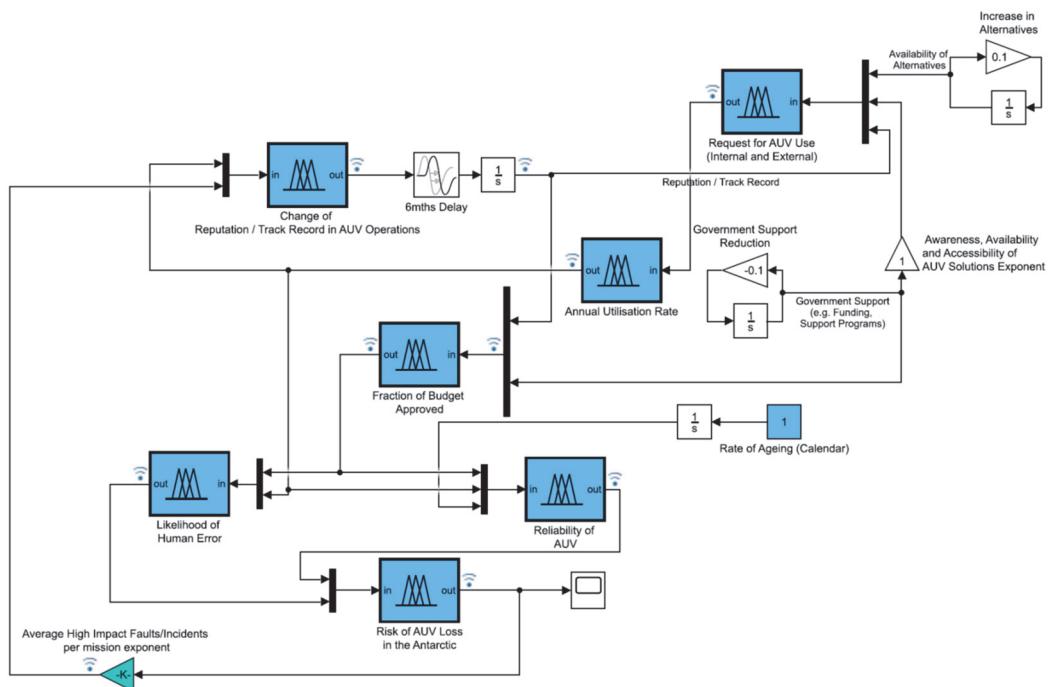


Fig 3: The resultant FuSDRA Model.

After testing and calibration, the base scenario was simulated based on a set of assumptions on parameters, causal relationships and initial conditions. Three different scenarios were then simulated next and compared to the base scenario to analyse the impact on risk of AUV loss. First, a gradual reduction of government support at a rate of 10% annually was simulated. Second, the effect of increasing alternatives to the *nupiri muka* AUV, at a rate of 10% annually was simulated. Last, the combined impact of gradual reduction in government support (rate of 10% annually) and an increasing number of alternatives (rate of 10% annually) was simulated. The risk of loss, as presented in Fig 4, is dimensionless and intended to measure probability of occurrence between year 0 and year 10 of the AUV program.

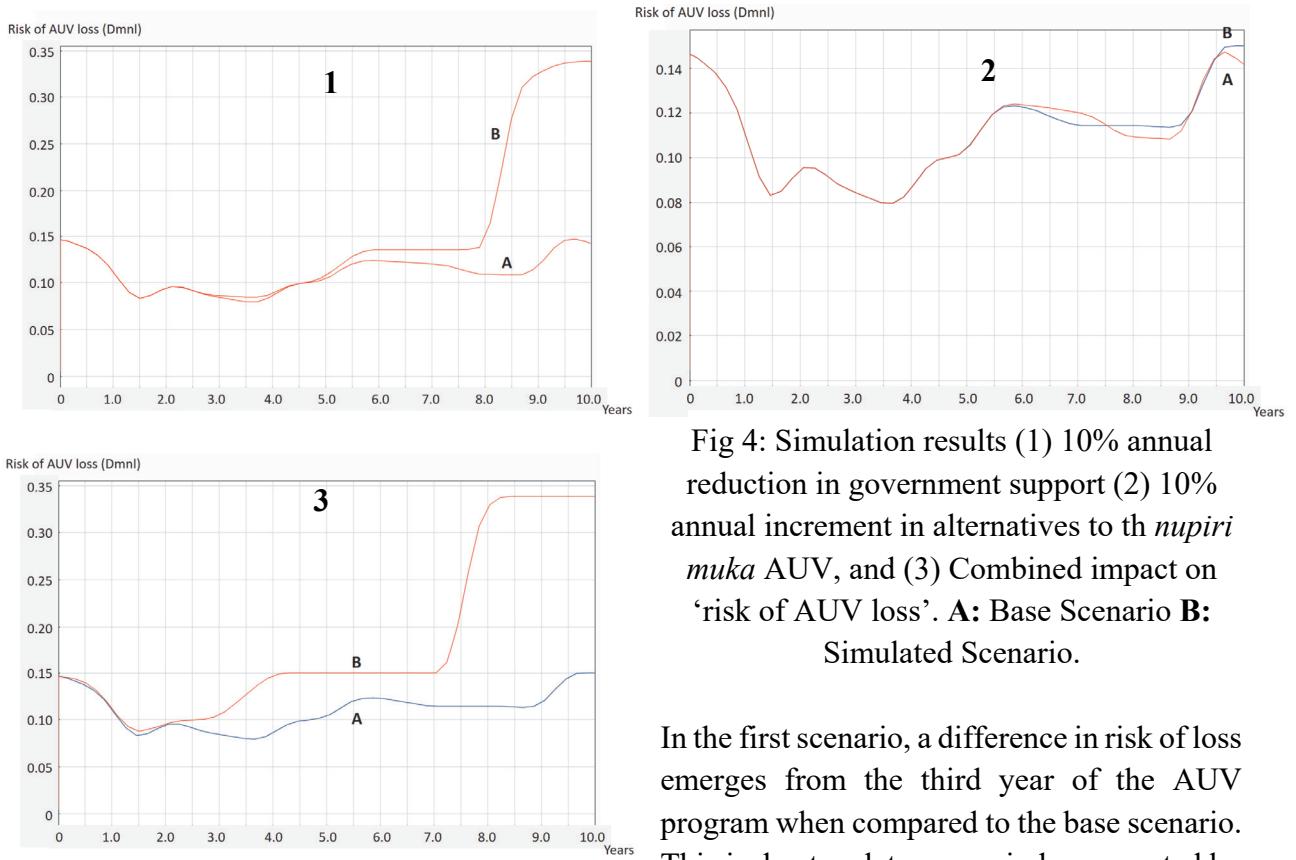


Fig 4: Simulation results (1) 10% annual reduction in government support (2) 10% annual increment in alternatives to the *nupiri muka* AUV, and (3) Combined impact on ‘risk of AUV loss’. A: Base Scenario B: Simulated Scenario.

In the first scenario, a difference in risk of loss emerges from the third year of the AUV program when compared to the base scenario. This is due to a latency period represented by

delays in the system. The risk of loss is also observed to increase sharply in the last 2 years of the simulation. This jump in risk can be attributed to the reduction of budget below a threshold level, where experienced personnel may leave the team and critical AUV components fall into disrepair. For the second scenario, the difference to risk of loss is only apparent in the last year of the AUV program, with the reason being twofold. First, the *nupiri muka* adopts newest AUV technologies and is considered state-of-the-art, manufactured by one of the leading company. Second, the use of AUV for Antarctic marine science research is a relatively new development with many potentials and advantages over existing means of data collection. Therefore, the obsolescence rate for the *nupiri muka* AUV is currently deemed to be very low, having an impact on the risk of loss only in the late stages of the AUV program. In the third scenario, the combination of reducing government support and increasing alternatives showed a synergistic effect on the risk of AUV loss, resulting in a greater increase in the risk of loss than the sum of their individual effects. Although the complex calculations and extensive fuzzy rules makes it

challenging to pinpoint the reason behind this synergistic effect, the significant increase in risk clearly requires attention for tightened controls.

In the final risk evaluation step, policies are recommended based on the simulation results to dampen the effect of reducing government support and increasing obsolescence. As the gradual reduction in government support has a substantial effect on the risk of loss later in the program, the recommended measures should be implemented as early as possible. These include: (1) Having a robust system for monitoring budgets and forecast future additional funding requirements. (2) Actively seek diversity in funding base, such as commercial contracts and establish strong stakeholder relationships. (3) Establish a robust finance strategy, with regular review, which is aligned to the strategic plan, and. (4) Implement a process for reviewing and updating strategic or operational plans in response to changes in government support.

Recommended measures to better manage the risk of obsolescence in the later stages of the AUV program includes: (1) Ensuring a comprehensive repair and preventive maintenance program is in place. (2) Implementing a process for regular review of published literature and other information sources to spot emerging trends in both AUV technologies and alternatives to the AUV (3) Developing a strong partnership with the AUV manufacturer. The company should be well-aware of any impending obsolescence and have a migration or upgrade strategy. (4) Establishing a robust and clear long-range plan for the AUV program. This plan should assign a return of investment, state cost avoidance strategies, process optimization and best practices. In addition, the plan should position the AUV program as a multipurpose research program going beyond the AUV itself, such as battery capabilities or adaptive controls. This should lead to a strong underwater robotics research program at the University of Tasmania, exploring next generation alternatives to AUVs. Another Explorer AUV operated by Memorial University of Newfoundland, Canada is an example of an AUV program with robust and clear long-range plan.

#### **4. CONCLUSION**

The risk of losing autonomous equipment during deployment is a dynamic and complex problem. Data may not always be available, and the vagueness and ambiguous nature of risk makes the analysis of risk challenging. This paper presents a three-step hybrid FuSDRA framework to facilitate risk control policy recommendations.

The FuSDRA framework was applied in a case study to analyse two issues: a reduction in government support to the AUV program and increasing availability of alternatives to AUVs for research data collection. Both results showed increase in risk of loss in the later stages of the AUV program and a synergistic combined effect. A suite of risk control policy recommendations was proposed based on these results. These include implementing a system for budget monitoring and forecast, seek funding diversity, establish a finance strategy, prepare for changes, having a repair and preventive maintenance program, establish strong partnership and having a long-range plan for the AUV program.

Due to the generic nature of the approach, the FuSDRA framework can also be applied to other types of autonomous equipment. For example, in the field of autonomous cars, unmanned aerial vehicles and unmanned surface vessels. Therefore, the FuSDRA approach provides both contribution to knowledge, as well as a pragmatic tool for maritime universities for better analysis of risk.

## **5. ACKNOWLEDGEMENT**

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## **6. REFERENCES**

1. IMAS. New Antarctic Underwater Robot to Arrive in Tasmania in 2017 [Internet]. [cited 2017 Apr 1]. Available from: <http://www.imas.utas.edu.au/antarctic-gateway-partnership/news/news-items/new-antarctic-underwater-robot-to-arrive-in-tasmania-in-2017>
2. Michael K. ANARE's Tadpole that got away [Internet]. Ormerod R, editor. Antarctic. New Zealand: New Zealand Antarctic Society Inc; 1979. Available from: <https://antarciticsociety.org.nz/wp-content/uploads/2017/07/Antarctic.V13.4.1993.pdf>
3. Strutt JE. Report of the Inquiry into the Loss of Autosub2 under the Fimbulisen. Southampton. 2006;44(12):43.
4. Griffiths G, Brito M. Predicting Risk in Missions Under Sea Ice with Autonomous Underwater Vehicles. In: 2008 IEEE/OES Autonomous Underwater Vehicles, AUV 2008.
5. Griffiths G, Brito M. Risk management for autonomous underwater vehicles operating under ice. In: OTC Arctic Technology Conference. Houston, Texas; 2011.
6. Thieme CA, Schjølberg I. A risk management framework for unmanned underwater vehicles focusing on human and organizational factors. In: Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE 2015. 2015. p. 1–10.
7. Xu H, Li G, Liu J. Reliability Analysis of an Autonomous Underwater Vehicle using Fault Tree. 2013 IEEE International Conference on Information and Automation (ICIA). 2013;(August 2013):1165–70.
8. Helton JC, Johnson JD, Oberkampf WL, Sallaberry CJ. Representation of Analysis Results Involving Aleatory and Epistemic Uncertainty. International Journal of General Systems. 2010;39(6):605–46.
9. Khanzadi M, Nasirzadeh F, Alipour M. Integrating System Dynamics and Fuzzy Logic Modeling to Determine Concession Period in BOT Projects. In: Automation in Construction. 2012. p. 368–76.
10. Mutingi M, Mbohwa C. Fuzzy System Dynamics of Manpower Systems. In: Handbook of Research on Novel Soft Computing Intelligent Algorithms: Theory and Practical Applications. 2014. p. 913–30.
11. Kuhnert PM, Martin TG, Griffiths SP. A Guide to Eliciting and Using Expert Knowledge in Bayesian Ecological Models. Vol. 13, Ecology Letters. 2010. p.900–14.
12. Sterman JD. Business Dynamics: Systems Thinking and Modeling for a Complex World. 1st ed. McGraw-Hill Education; 2000. 982 p.
13. Mendel JM. Uncertain Rule-based Fuzzy Logic Systems: Introduction and New Directions. Vol. 2, IEEE Computational Intelligence Magazine. 2001. 555 p.