Designing a Cased Based Reasoning Decision Support System for Ice Management Operations Using Expert Knowledge

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Abstract

Prevention of safety hazards plays an important role in the offshore and maritime industries, especially in offshore ice management operations as the safety of these operations depends on the judgment and decision making of experienced captains and their bridge teams. To address safety challenges that may arise in the context of ice management operations, this study focused on a human-centered approach to develop an early-stage decision support system (DSS) for offshore ice management operations by applying a case-based reasoning (CBR) method. The aim of this research is to (i) capture knowledge from expert seafarers to be used in the development of a DSS; and (ii) propose a DSS employing a CBR model to be used onboard ships in a real-time basis for ice management operations. To capture seafarers' experience, this study employed semi-structured interviews and bridge simulator exercises. The results of the knowledge capture exercises were translated into an ice management DSS using a CBR model. The case-based reasoning (CBR) model develops solutions to new problems by using similar problems in the past. The DSS employs a decision tree algorithm to retrieve a case to match observations from the current situation with an unknown outcome to a case base with known outcomes. This thesis describes the methods used in the development of the onboard DSS to provide tactical guidance for ice management operations. It also outlines the methods used to test the DSS software's suggested ice management strategies and adjustments during a series of simulator exercises.

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List of Abbreviations

DSS – Decision Support System

CBR – Case Based Reasoning

ICEHR – Interdisciplinary Committee on Ethics in Human Research

MUN – Memorial University of Newfoundland

ASPPR – Arctic Shipping Pollution Prevention Regulations

OSV – Offshore Supply Vessels

AHTS – Anchor Handling Tug Supply

VHF – Very High Frequency

FPSO – Floating Production Storage Offloading facility

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Chapter 1: Introduction

1.1. Overview

People deal with different decision-making problems every day. They have to decide how to overcome challenges that regularly arise in their lives, including personal choices or more complicated decisions regarding the economy, business management, or medicine. Assisting people with making the best decision regarding complicated situations has been an objective of researchers for years. A decision support system (DSS), which is a computer-based system, is one method that has been developed to fulfill this goal (Bohanec & Rajkovič, 1990).

Ice management is complex in nature and often takes place under challenging circumstances. Dynamic conditions in ice management operations cause some degree of uncertainty for making a safe and effective decision in a high-risk situation. This research proposes the development of a decision support system (DSS) to provide ad-hoc advisory services to the operators to make non-trivial decisions during an ice management operation. To address safety challenges that may arise in the context of ice management operations, this study focused on a human-centered approach to develop an early-stage decision support system (DSS) for offshore ice management operations by applying a case-based reasoning (CBR) method. The aim of this research is to (i) capture knowledge from expert seafarers to be used in the development of a DSS; and (ii) propose a DSS employing a CBR model to be used onboard ships in a real-time basis for ice management operations.

A DSS may have various definitions in different research areas. That means that a DSS's definition may vary based on its characteristics to solve different problems (Sprague, 1980). Although DSS can be described in several forms, Power (2002) provides three characteristics that decision support systems have in common (Power, 2002):

1. DSS facilitates the decision-making process,
2. DSS does not automate an action. It only helps decision-makers to make a decision,
3. DSS should help and respond quickly to the decision-makers' needs in changing situations.

Due to knowledge engineering growth, knowledge-based technologies are mostly used in advanced decision support systems to assist decision-makers (Babka & Whar, 1997). Among different reasoning methodologies that can be implemented in the knowledge-based DSS, Case-Based Reasoning (CBR) is a practical and effective method of solving complicated problems that cannot be managed using traditional reasoning models like model-based reasoning (Y. Liu, Yang, Yang, Lin, & Du, 2009).

Most people think that they can avoid repeating some mistakes that they have made before in a new similar situation. They think that their previous experiences help them to have a better performance in the similar situation. Although using the previous experience seems to be easy, it is difficult in practice. History shows that many unfortunate occurrences are repeated after some years (Virkki-Hatakka & Reniers, 2009). People are not like a computer to memorize every aspect and detail of an experience and they forget some points in the future. Consequently, similar accidents occur while they should be prevented using the previous experiences (Virkki-Hatakka & Reniers, 2009). Having a case base that keeps all experiences related to a specific problem may be effective to be used in similar situations to solve problems. Case-based Reasoning is a methodology that can be used to develop such a case base.

The CBR uses a ‘remember and compare’ cycle. Experiences stored in the CBR case base as cases are used to assist in new situations to make a recommendation. To bring out a suggestion, matching cases to the problem are retrieved and analyzed to prevent poor solutions. Once feedback is evaluated in CBR, cases are modified, and their outcomes are chosen to solve the problem. Finally, if the solution is valid, it will be added to the case base for future use (Leake & Plaza, 1997).

1.2. Offshore Ice Management Operations

Ice management operations are approaches that consider environmental, design, and operational elements to secure platforms and facilities in ice-covered waters. Activities off the coast of Newfoundland, like offshore oil operations, require ice management operations to maintain the oil platforms’ safety (Smith, Yazdanpanah, Thistle, Musharraf, & Veitch, 2020). Different activities are performed in ice management operations, such as (Keinonen, 2008)

1. observing and predicting ice conditions,
2. identifying and tracking icebergs and pack ice,
3. reporting ice conditions and,
4. avoiding, breaking, and deflecting ice threats.

Among the operations mentioned above, this thesis focuses on the operations that deflect or disperse encroaching pack ice from the area close to the oil platforms. Common techniques for moving the ice using the support vessels are linear, sector, circular, stationary/propeller wake, and pushing (Dunderdale & Wright, 2005). A combination of these techniques deflects and disperses the pack ice around the offshore platforms. Due to the changing environments during maritime operations (e.g., wind, current, response time), predicting the situations to manage the pack ice is a complicated task. Consequently, many strategies need to be adapted based on the current circumstances.

Basic and advanced training for ships operating in polar waters are required to be completed for ice management training. This regulation developed by IMO in collaboration with the Marine Institute's Centre for Marine Simulation and the professional organization Master Mariners of Canada (International Maritime Organization, 2017b, 2017a). In addition to these training, cadets with less experience rely on experienced operators in ice management operations and learn from seafarers once they are conducting these operations. On-the-job training lacks standardization and may cause some problems in practice. First, applying new rules and regulations is time-consuming. Second, many of the standard criteria for ice management training were established for the navigation of Arctic waters and may not be directly applicable for ice operations around offshore oil platforms.

To be an 'ice navigator', a master should spend 50 days serving at the vessel (30 days of this time should be in Arctic waters and performing ice advice or ice-breaking maneuvers) according to Canada's ASPPR (Arctic Shipping Pollution Prevention Regulations) (Canadian Coast Guard, 2012), and 90 days navigating in ice-covered water within 5 years (e.g., six trips with the duration of 15 days for each)(Transport Canada Joint Industry-Government Guidelines for the Control of Oil Tankers and Bulk Chemical Carriers in Ice Control Zones of Eastern Canada (JIGs) TP15163, 2015). As a result, to be an 'ice navigator' and consequently an advisor for offshore ice management vessels, many ice seasons are required for a seafarer to obtain enough expertise to be able to manage a situation in which a platform is surrounded by ice. On-the-job training may not be an entirely adequate means of knowledge exchange from experienced captains to new cadets.

Besides, transferring experience from captains to the cadets builds an inherited knowledge. That means that the cadet's ability to adapt ice management strategies strongly depends on the captain and their teams' experiences. This aspect of the on-the-job training causes variation in the domain of ice operations. Veitch et al.'s (2019) research results show this variation, where experienced seafarers performed emergency ice management scenarios in a bridge simulator (Veitch, Molyneux, Smith, & Veitch, 2018). According to the findings, a considerable difference in ice management effectiveness was observed once seafarers implemented scenarios.

1.3. Purpose

For several nations, operations in ice-covered waters are an ongoing need (Lehtola, Montewka, Goerlandt, Guinness, & Lensu, 2019). The decreasing ice amount and thickness in the Arctic has increased traffic and ship operations in the Arctic (Zhang, Zhang, Fu, Yan, & Goncharov, 2017). Increasing these operations requires some planning to ensure the safety of operations in ice-covered waters. For this purpose, two aspects that could be considered in maritime technologies are

1. reducing the hazards that threaten people's lives, and
2. using autonomous vessels to assist with decision-making (Lehtola et al., 2019).

Automation should be designed for the benefit of people instead of replacing them. This idea stems from the realization that completely automated services is impractical for certain tasks. The safety of offshore ice management operations depends on the decisions that experienced seafarers and bridge teams make. Also human error is one of the most important factors in maritime accidents (Y. Liu et al., 2009). Therefore, to increase the capabilities of seafarers and support them in their responsibilities, designing a human-centered system will be advantageous (Spath, Braun, & Bauer, 2009).

To implement ice management operations safely, seafarers need to have structured plans for ice management. To address this requirement, two fundamental knowledge gaps should be highlighted:

1. On-the-job training for cadets is a time-consuming process because seafarers are required to spend so many days in the ice. Due to the variable seasons of ice, it can be time-consuming to acquire the necessary experience to meet the regulatory requirement of on-the-job training for ice management.
2. There is not a unique strategy to conduct ice management operations securely, because ice management tactics from experienced seafarers may not be captured in the specific context of pack ice management.

Collecting expert knowledge and giving uniformity to ice management training is needed for addressing these two gaps. To do so, realizing how experienced seafarers approach ice clearing techniques and how they adapt their strategies in new situations is required (Smith et al., 2020).

Capturing safety knowledge should not rely solely on 'storytelling' and should include constructive procedures using training simulations. Simulation exercises can be conducted to capture the actions of participants and learn from them without any risk. It has been shown that using such a training simulation can be highly efficient (Virkki-Hatakka & Reniers, 2009). This research employs a simulator to collect expert knowledge on ice management scenarios. Using the data gathered from the simulation exercises, an expert-informed decision support system were developed to provide expert guidance to seafarers. Case-based reasoning stores this expert knowledge into its case base and then feeds them into the decision support system. CBR is an appropriate approach to store well-described and analyzed experiences (cases) and assist cadets and other seafarers using organized strategies.

The purpose of this research was as follow:

1. To capture expert knowledge from experienced seafarers
2. To transfer this knowledge into a case-based reasoning case base
3. To develop a decision support system for ice management operations

1.4. Research Questions

For this research, the hypotheses were:

1. How to integrate knowledge extracted from different data sources (questionnaires, audio files, etc.) to create one comprehensive case base containing consistent, accurate, and useful information?
2. What features do experienced seafarers pay attention to when performing ice management operations, and how can these features be captured and integrated into a decision support system to inform the guidance it provides?
3. Can the human decision-making process be imitated using CBR and ML methods that provide both accuracy and transparency?
4. Does the DSS's suggested strategies adequately reflect the experienced seafarers' heuristics/ decision-making strategies?

1.5. Hypothesis

For this research, the hypotheses were:

1. The bridge simulator used in this study would be a useful human laboratory for both knowledge capture and testing a decision support system.
2. Capturing expert knowledge would allow for the classification of ice management strategies, detection of important ice management factors, and identification of the relationships between them.
3. The CBR decision support system would be capable of recommending ice management strategies or offering adjustments during the implementation of a technique.

This thesis focuses on the development of a CBR decision support system. The remainder of this thesis is organized as follows. Chapter 2 presents an overview of different types of decision support systems and their applications, different reasoning methods especially case-based reasoning, case memory model, and methods for case retrieval such as decision trees. Chapter 3 describes the procedure used for capturing contextual knowledge from expert seafarers (e.g., data collection). Also, this chapter focuses on the methods used and the insights gained from translating interview data and expert performance from a bridge simulator into a case base that can be referenced by the CBR model. This includes indexing and matching data gathered from the simulator to cases in the case base, and developing the retrieval algorithm for the CBR model. Chapter 4 presents and discusses the results of the research and evaluation of the CBR decision support system in a simulator setting. Chapter 5 presents changes applied to the DSS after testing the DSS in the simulator setting, and in Chapter 6 limitations and future works is described.

Chapter 2: Literature Review

Decision support systems (DSS) are computer-based programs or algorithms used to guide people in making decisions and solving complicated problems. Researchers started to support people in solving complex problems and situations by developing a computer technology-based solution in the 1970s. In recent decades, technologies for developing such systems have grown rapidly (Felsberger, Oberegger, & Reiner, 2017). Today, DSSs are used in a variety of domains, such as business (Chan & Ip, 2011) and management (Asemi, Safari, & Asemi Zavareh, 2011), agricultural production (Rupnik et al., 2019), forecast management (Sayed, Gabbar, Fouad, & Ahmed, 2008), medical diagnosis (Ani, Jose, Wilson, & Deepa, 2018), ship navigation (Perera, Carvalho, & Guedes Soares, 2011; Perera, Rodrigues, Pascoal, & Soares, 2011), and offshore operations (Lee, Aydin, Choi, Lekhavat, & Irani, 2018).

While a DSS should provide decision-makers with some key factors to guarantee their success, it cannot suggest a good solution in all situations or for all users. The efficiency of a DSS is related to its compatibility with both the decision-maker and the nature of the decision. If the DSS is well matched to the task and the decision maker's capabilities, receiving benefits from the DSS can be expected. For this reason, the first step in matching the DSS technology with the intended application and user is knowing the benefits and the limitations of a DSS. Alexander (2002) in their literature review of decision support systems, highlight the benefits and limitations of these systems. The following list provides a summary of some of the benefits of a DSS outlined by (Alexander, 2002):

1. Improving the user's ability to process and understand information
2. Improving the user's ability to solve complicated problems and situations

3. Facilitating and accelerating the decision-making process
4. Making the outputs or results of a decision more reliable
5. Suggesting a new approach or strategy that the user may not have thought about before.

Alexander (2002) also provide a good summary of the limitations of decision support systems:

1. DSS suffer from the lack of some human characteristics in decision making such as imagination and creativity
2. The usefulness of the DSS can vary based on the computer system that a DSS is running, or the amount and validity of data it is using, and also the effectiveness of its design
3. DSS has some difficulties for using natural language processing while receiving the user's entries in the command interfaces
4. Generally, DSS has some difficulties generating multiple decision-making processes, and they are usually developed in a narrow range of frameworks (Alexander, 2002).

This section provides an overview of decision support systems theory and frameworks and describes the examples and methods used for each type of decision support system. Then, it is explained why a knowledge-based decision support system is suitable for this research purpose. In the following, among different reasoning models in the knowledge-based DSS, case-based reasoning and its role in ice management operations are defined. Then, two important parts of case-based reasoning, including the case memory model, and the case retrieval and similarity assessment are described in detail.

2.1.Decision Support Systems Definitions and Types

Decision Support Systems (DSS) are computer-based systems that can support complicated problems. Such a framework integrates and analyzes raw data to identify challenges and determine their solutions to assist decision-makers (Shim et al., 2002).

There are three types of problems to be solved. They include structured, unstructured, and semi-structured problems (Power, 2001). In structured problems, the decision is routine and the solution can be predicted in advance. Unstructured problems are the opposite of structured problems, and the procedures for solving the problem cannot be easily formulated in advance. Semi-structured problems are something between two other problems, which means that some procedures can be pre-defined.

DSS is not required for all three types of problems, for example, there is no need for structured problems to have a DSS because they tend to be straightforward and predictable. Most DSS applications support semi-structured problems, while a few assist decision-makers in unstructured challenges (Mashli Aina, 2015).

The literature categorized decision support systems based on three aspects and each will be briefly described:

1. the relationship with the user,
2. the scope, and
3. the mode of assistance it offers.

A DSS can be classified based on its relationship with users and can be passive, active, or cooperative (Aqel, Nakshabandi, & Adeniyi, 2019). A passive DSS helps and supports decision-makers but cannot suggest explicit solutions, while an active DSS provides decision guidelines. The cooperative DSS allows the decision-maker to modify or refine the suggested decision.

Based on the scope as the criterion, DSSs consist of Enterprise-wide DSS and the desktop DSS. An enterprise is linked to a large database, and many users can use it. In contrast, a desktop DSS is a small system that can serve an individual user (Felsberger et al., 2017; Jain, 2016).

Power (2002) distinguishes between DSSs based on the mode of assistance and has categorized the following modes: model-driven, data-driven, communication-driven, document-driven, or knowledge-driven DSS (Power, 2002). This is the most general categorization taxonomy (Nizetic, Fertalj, & Milasinovic, 2007) and will be discussed in detail in the DSS applications section.

2.2.DSS Models

2.2.1. Model-driven DSS

A model-driven DSS utilizes different models, such as statistical, financial, mathematical, analytical, or optimization models, to find solutions for problems and help users (Power & Sharda, 2007). According to the users' needs, this type of DSS uses either a single model to solve basic problems or a combination of models to deal with more complex situations. Some examples of a model-driven DSS are a spreadsheet with formulas, a statistical forecasting model, or an optimum routing model. Optimization and analytical methods (Afshin Mansouri, Gallear, & Askariazad, 2012) and operational research methods (quantitative methods) are some methods used in the literature to build a model-driven DSS (Nizetic et al., 2007).

2.2.2. Data-driven DSS

The most common type of DSS is data-driven DSS. A data-driven DSS analyzes the time-series of data and helps decision-makers by creating new information based on the evaluated data. A large amount of data is required for the analyzing process in a data-driven DSS. For example, some data-driven DSS applications include accessing the INTERPOL database for crime investigations and accessing the border patrol database for all incidents in a sector. Data warehouses and online analytical processing (OLAP) are common methods in data-driven DSSs (Power, 2008).

2.2.3. Communication-driven DSS

Communications-driven DSS helps decision-makers to come up with a new solution by providing a situation in which two or more people can communicate with each other and share important data and information. Some features of a communications-driven DSS are allowing communication between groups of people, facilitating knowledge or information sharing, supporting people's cooperation and teamwork, and supporting group decision making. Some examples of these system are video conferencing, audio conferencing, document sharing, electronic mail, computer-supported face-to-face meeting software, and interactive video. Network technologies are commonly used to develop a communication-driven DSS (Nizetic et al., 2007).

2.2.4. Document-driven DSS

A document-driven DSS retrieves documents using processing technologies to analyze them and suggest a decision. These documents may contain unstructured information in various electronic types such as images, sound, video, scanned documents, and hypertext documents. A document-driven DSS aims to find and retrieve an appropriate document based on specified keywords or defined terms. They are also able to convert documents into important data. A search engine is an example of a document-driven DSS that helps its users by searching web pages and retrieving desired documents (Felsberger et al., 2017).

2.2.5. Knowledge-driven DSS

A knowledge-driven DSS collects specific expert knowledge in a particular field and helps decision-makers solve specific problems. A knowledge-driven DSS uses different reasoning methods such as rule-based reasoning (Cesario & Esposito, 2012), case-based reasoning (Smith et al., 2020), narrative-based reasoning (Wang & Cheung, 2011), ontology-based reasoning, and genetic algorithms (Zaraté, Kersten, & Hernández, 2014) to assist decision-makers based on expert knowledge. Intelligent decision support methods, data mining (Lee et al., 2018), artificial intelligence methods, fuzzy logic (Perera, Carvalho, et al., 2011), knowledge discovery methods, and heuristic methods are other common methods for developing a knowledge-based DSS.

2.3.Reasoning Technologies in knowledge-driven DSS

The core component in the knowledge-driven DSS is the knowledge base (Nizetic et al., 2007). As this research aimed to gather knowledge in a specific domain, and its central part is knowledge captured from experienced seafarers in ice management operations, a knowledge-driven decision support system is most suited for this study.

Five reasoning or inference methods for knowledge-driven DSS include (S. Liu & Zaraté, 2014):

1. Rule-based reasoning (RBR): this reasoning method is used for reasoning that is based on a set of rules (Jiang, Qiu, Xu, & Li, 2017). In rule-based reasoning, expert knowledge is coded into some rules. These rules are presented as "if-then" sentences (Ribino, Augello, Lo Re, & Gaglio, 2011).
2. Case-based reasoning (CBR): case-based reasoning uses human experiences to solve a problem. It relies on the past and similar cases and reuses them to suggest a solution for a new problem.
3. Narrative-based reasoning (NBR): this approach deals with unstructured data. This reasoning method uses stories to assist the decision-making process by sharing what is learned from narratives (Wang & Cheung, 2011).
4. Ontology-based reasoning (OBR): using ontology some concepts are defined in a specific domain and then relationships between these concepts are represented (Riaño et al., 2012). Ontologies are used in applications that are required to process the content of information not just presenting data to humans (Valls, Gibert, Sánchez, & Batet, 2010).
5. Genetic algorithms (GA): The GAs are based on Darwinian evolution. GAs produce a population of chromosomes and each chromosome in the population can be considered as a solution. The chromosomes evolve using a fitness function and after several generations, the final chromosome would be the best solution to the problem (Aouadni & Rebai, 2017). The genetic algorithm is widely applied in different types of problems and provides appropriate solutions to those problems (Aouadni & Rebai, 2017).

In a knowledge-driven DSS, the decision-making process is conducted by an inference engine. Among reasoning technologies in knowledge-driven DSS, case-based reasoning theory utilizes past experiences to find solutions for new problems. It gives an automatic ranking to the previous cases and recommends the most suitable ones (Zaraté et al., 2014). Since experiences of seafarers in ice management operations were collected during this research for decision making, case-based reasoning is the most suitable reasoning method in the current thesis. More details of the case-based reasoning technique are described in the next section.

2.4.Case-Based Reasoning Theory

Case-based reasoning (CBR) is a problem solving methodology and is used in artificial intelligence applications. This type of reasoning is mostly used when the previous experiences are useful in solving a new problem. To solve the new problem, CBR methodology searches to find the solution from a similar problem that occurred in the past and then uses the same solution or adapts it for the new problem (Su, Yang, Liu, Hua, & Yao, 2019). Accordingly, most CBR applications follow a basic approach to solve a new problem. They search in a case base to capture a solution from past experiences and take it as an initial point to guide the discovery of the solution for the new problem. The case base is a collection of cases into which the previous experiences are stored. So, each case contains some information about the past solution of problems similar to the new problem. Sometimes the cases store fully or partially solved problems, and sometimes they record unsuccessful attempts (Kurbalija & Budimac, 2008).

Figure 1 illustrates a CBR lifecycle. As shown in Figure 1, there are four main steps (Aamodt & Plaza, 1994; Begum, Ahmed, Funk, Xiong, & Von Schéele, 2009):

1. Retrieve
2. Reuse
3. Revise

4. Retain

At the starting point, the new problem is considered as a new case. At the retrieve procedure, the most similar case to the new problem is retrieved. To find the matching case, features from all cases in the case base are compared to the new case, and their similarity metrics are computed. The case with the highest similarity metric is the closest experience to the new case (Hua Tan, Peng Lim, Platts, & Shen Koay, 2006). While the retrieved case may match the new problem perfectly, it may have some different aspects. The reuse procedure checks the reusable features and differences between the new case and the retrieved case. If the two cases are fully matched, a copy of the retrieved case is reused to solve the new problem. Otherwise, if they are partially matched, an adaptation is necessary before using the retrieved case in the new situation. In the revise procedure, the effectiveness of the suggested solution is examined. To evaluate the solution, the application can be tested in the simulator or in real life. Also, subject matter experts are another source to confirm or decline the solution. If the solution fails and needs to be fixed, it is repaired in the revise phase to prevent the same error in the future. Finally, in the retain phase, the learned case, which is the successful or repaired case, is indexed and stored in the case base.

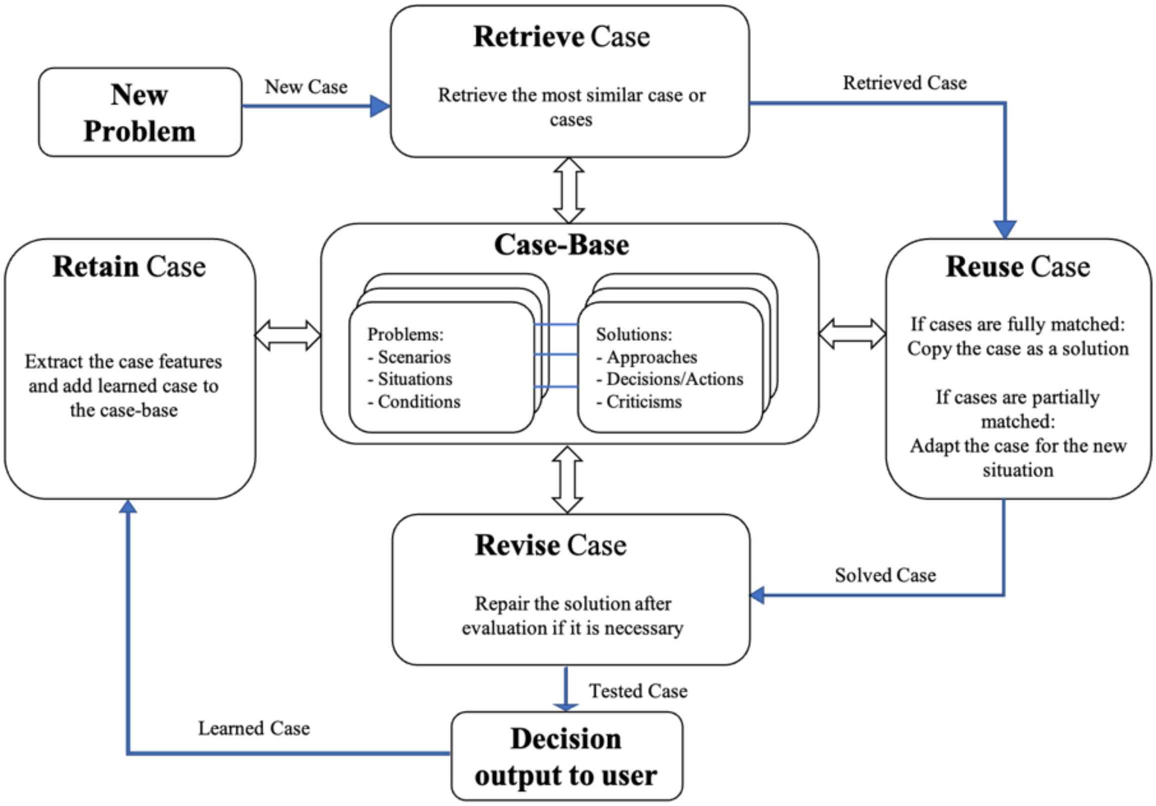


Figure 1 Case-based Reasoning Cycle (Aamodt & Plaza, 1994)

Case-based reasoning relies on expert and domain knowledge to improve the decision support applications using an intelligent way with less time, effort, and cost. Therefore, creating a case base with expert and domain knowledge, experience, and solutions is vital to develop a CBR model (Ali, Iqbal, & Hafeez, 2018; Kolodner et al., 2003). The specific domain knowledge in CBR is gathered from the experts' explanations about their domain and experiences in a specific situation. The specific domain knowledge is used to generate example solutions for the case base (Althoff & Bartsch-Spörl, 1996). The general domain knowledge is used to develop the reasoning structure of the CBR model. The general knowledge used within a CBR system guides the case feature matching, retrieval, and indexing by defining the similarities in the case-base network. It also helps to minimize the number of cases required to solve problems, enhance the reliability of possible solutions, increase the system's efficiency to manage the situations, and adapt to a new environment quickly (Aamodt & Plaza, 1994; Althoff & Bartsch-Spörl, 1996).

2.5.Case-Based Reasoning for Ice Management Decision Support

Developing an onboard DSS to support ship operation, in particular on decisions about ship handling in sea ice, will contribute to vessel safety (Perera, Rodrigues, et al., 2011). The CBR solves a new problem by remembering a past similar situation and reusing what was learned from that situation (Aamodt & Plaza, 1994). Therefore, it would be an appropriate reasoning method to implement an onboard decision support system to assist the seafarers. The way that CBR works for problem solving is by offering some advice based on the expert knowledge that is stored in its case base. This approach is similar to the training that seafarers provide on-the-job. That means that the CBR works similar to methods used by seafarers when they train others by transferring their experiences on-the-job, through storytelling. The following example is a good illustration of this similarity for solving a problem.

Consider a situation in which a captain is dealing with clearing pack ice around an offshore oil platform. This captain sees the situation as similar to their past trip working on the vessel in ice-covered waters. In the previous ice management maneuver, the captain used the pushing technique to clear medium and large ice floes from the drift line. In fact, they decided not to break the ice and instead push a large floe to remove the threat from the drift-line. Because they believed that if they break the ice up-drift, the broken pieces may still cause damage. But the captain did not forecast the change to the ice drift-line due to the unpredictable environmental conditions, and the situation became complicated and became a threat at a later time. Remembering the same operational situation and sudden change in weather conditions makes the captain avoid repeating the same mistake in the current situation.

The CBR model can be used to develop an onboard decision support system and assist a cadet in various maritime conditions similar to the way that a captain provides them with problem solving guidance based on their experiences. To inform the reasoning part of the CBR, providing the CBR with solved problems in its case base, and collecting experiences of a group of expert seafarers in ice management operations is needed (Smith et al., 2020).

2.6.Case Memory Model

The case base should be arranged in a manageable structure to support efficient case matching and retrieval techniques. The content of a case can be organized as a set of attribute-value pairs (Flat Memory Model), a part-subpart relationship (Hierarchy Memory Model), or as a network of attributes (Network-based Memory Model). These three types of organizations are illustrated in Figure 2.

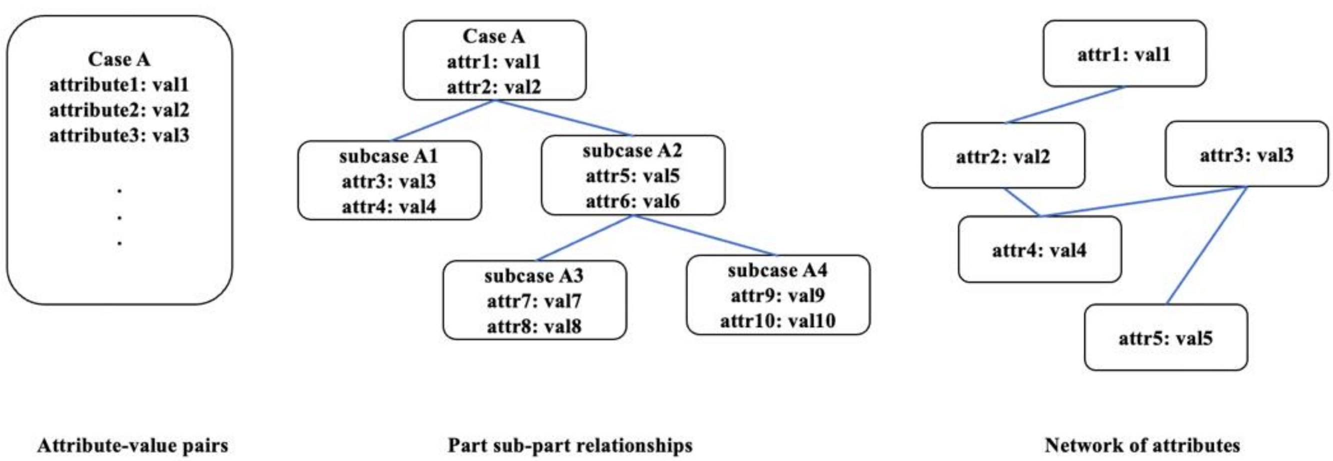


Figure 2 Organization of a Case in Case Memory (Maher, Balachandran, & Zhang, 1995)

Accordingly, several case memory models for organizing the case base include:

1. Flat Memory Model: all the cases in the flat memory are categorized at the same level. In this model, for each case retrieval, all cases in the case base should be compared with the new case. Therefore, the flat memory is not optimized for large data sets because the retrieval time would be very high. On the other hand, the high accuracy and easy retention are advantages of this memory model (Soltani & Martin, 2013).
2. Hierarchy Memory Model: in the hierarchy model, only a few cases are considered for the similarity matching based on a selective search in the hierarchy structure. Therefore, the similarity matching and retrieval time are efficient in this memory model, and it can be beneficial when the number of cases is very large. On the other hand, optimal cases may be neglected in the retrieval process if the wrong area of the hierarchical memory is selected for the search (Malek, 1995).
3. Network-based Memory Model: the network-based model represents cases with multiple attribute-value pairs at each node and shows additional types of relationships (Maher et al., 1995). Models of this category support complex attributes, but their construction is costly (Soltani, Martin, & Elgazzar, 2014).

Figure 3 illustrates different kinds of memory models. Some common memory models for the reasoning structure of the CBR are the flat memory model, the category-exemplar model (Porter, Bareiss, & Holte, 1990), and the case retrieval nets (CRN)(Lenz & Burkhard, 1996).

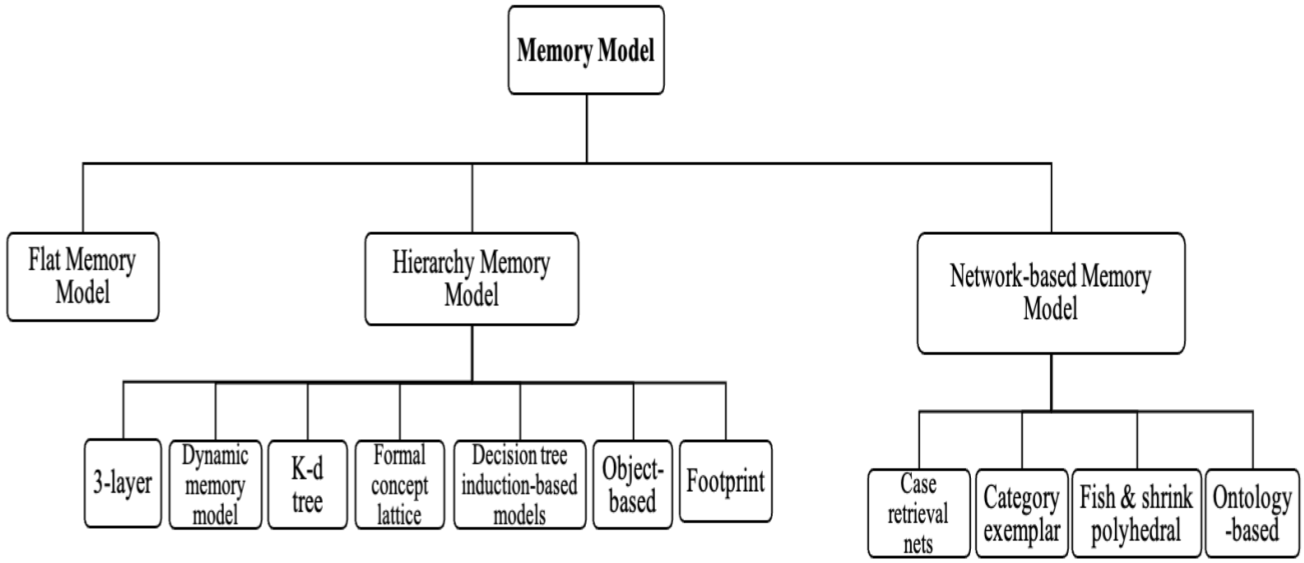


Figure 3 Hierarchy of Memory Models (Soltani & Martin, 2013)

Among memory models that are feasible for organizing the case base in this research, the flat memory best fits the case base. The flat organization is the simplest and most appropriate model to design and implement small case bases. Table 1 illustrates an example of cases organized using the flat memory model. This table consists of a list of attributes and different values for six cases. As is shown in the table, there are no relationships between the cases. That means that no one case has any relationship to another that needs to be represented, and the representation is complete.

Table 1 Flat Memory Model Example for Identifying Route Selection Strategies in Offshore Emergency Situations (Musharraf, Smith, Khan, & Veitch, 2020)

Attributes	**Case ID**					
	Case1	Case2	Case3	Case4	Case5	Case6
Scenario	LE2	LE3	TE1	TE3	LA2	LA3
Final destination	MS[1]	LB[2]	LB	MS	MS	LB
Lights	On	Off	On	Off	Off	On
Presence of hazard	No	No	No	No	No	No
Alarm	None	None	None	None	GPA[3]	PAPA[4]

Route direction in PA announcement	Primary	Secondary	None	None	None	None
Obstructed route	None	None	None	None	None	None
Previous Route taken	N/A	Primary	Secondary	Primary	Primary	Primary
Action	Primary	Secondary	Primary	Primary	Primary	Primary

[1] Muster Station
[2] Lifeboat Station
[3] General Platform Alarm
[4] Prepare to Abandon Platform Alarm

2.7.Case Retrieval and Similarity Assessment

The effectiveness of a case-based reasoning system depends on the retrieval of appropriate past cases to find the solution to a new case. To find the degree of similarity between the candidate cases and the new case, a similarity assessment is used. Figure 4 shows the similarity matching procedure. If the problem descriptor considers cases as a set of attribute-value pairs, the matching involves evaluating the similarity of the past cases' schema with the new case. This similarity can be evaluated using domain knowledge in the form of heuristics and domain-specific matching rules. To find the overall similarity (i.e., aggregation of attribute-value pairs), a matching function is utilized, and different methodologies like Tversky's matching function and Nearest-Neighbor (NN) have been proposed (Gupta & Montazemi, 1997).

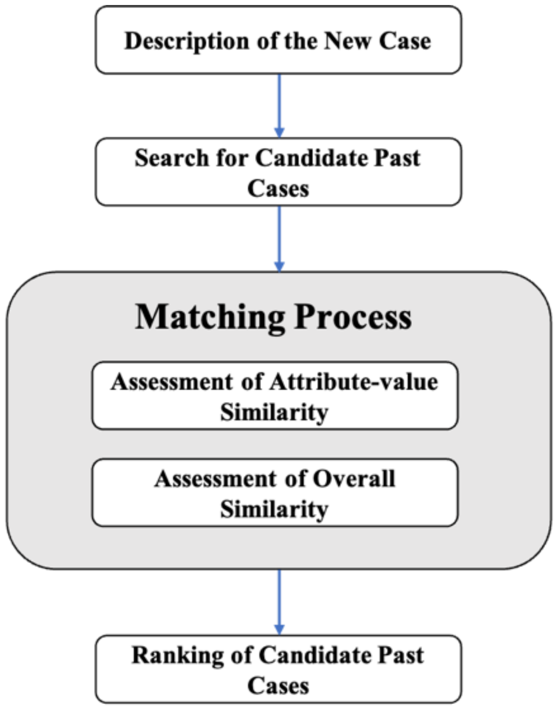


Figure 4 Process of CBR Retrieval (Gupta & Montazemi, 1997)

The literature categorizes different retrieval methods based on the similarity assessment. Some retrieval techniques are illustrated in Figure 5.

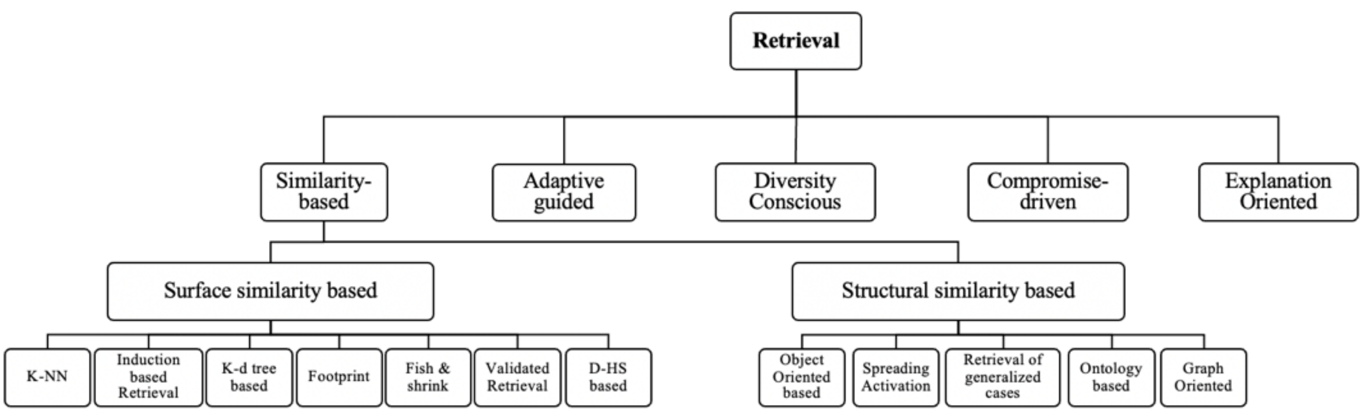


Figure 5 Hierarchy of Retrieval Methods (Soltani & Martin, 2013)

Among all retrieval techniques, the similarity-based methods use the similarity in the features or the structure of the cases to retrieve the most relevant case in the case base. The attributes used for comparison could be the surface attributes provided using the problem descriptor or derived attributes inferred from the domain knowledge (De Mantaras et al., 2005). This literature review focuses on the flat structure to organize the case base, and each case is described with attribute-value pairs. Hence, similarity-based algorithms are suitable for similarity matching. Among the various similarity-based methods, classification by similarity algorithms could be used for decision-making purposes (McKenzie & Forsyth, 1995; Trstenjak & Donko, 2016). Support vector machine method (SVM), logistic regression (LR), decision tree (DT), and random forest (RF) are some of these classification models (Al-hadhrami & Mohammed, 2021; Chao, Yu, Cheng, & Kuo, 2014).

1. SVM: this technique is a supervised machine learning (ML) algorithm that is utilized for decision making and data classification and regression problems. SVM uses a maximized margin to classify data into different groups. It can also handle non-linear problems by employing several support vectors.
2. LR: it is a statistical decision support tool that fits a model using a logistic function (sigmoid) to predict the probability of a class. LR makes a relationship between independent and dependent variables and could be considered as a multivariable method.
3. DT: with the growth of data mining, DT, which is a supervised learning technique, is getting lots of interest for classification and regression problems. It is a tree-like model that consists of different rules to divide independent features into variant zones.
4. RF: this method is a nonparametric technique that uses a large number of decision trees to build an accurate classification model. Each set of decision trees in this algorithm gives a vote to a class, and then the class that wins the most votes is chosen as the predicted result (Chao et al., 2014).

Although LR is easy to implement and effective to train, it tries to fit the best model on the training dataset that causes overfitting sometimes. Another disadvantage of logistic regression is that it makes a linear relationship between dependent and independent variables while a non-linear decision boundary is required. On the other hand, SVM is difficult to understand and interpret the final model and takes a long training time for a large database. Unlike LR, SVM generates more complicated decision boundaries and is appropriate for both linear and non-linear solutions. DT supports non-linearity and is popular due to its simplicity in interpreting the model. Although RF is more accurate than DT, a large number of trees makes the algorithm very slow. Therefore there would be a trade-off between time and accuracy specially when it comes to real-time predictions. Also, RF is more appropriate for large datasets. Since the scope of this research is limited to a small number of datasets and also suggesting a real-time solution is important for the DSS, DT would be an advantageous choice to have reasonable accuracy.

2.7.1. Decision Tree

A decision tree is a machine learning algorithm and builds a tree structure flowchart consisting of three items:

1. decision node: the internal node that represents the features or attributes of a case base
2. branch: that represents the decision rules, and
3. leaf node: that represents the decision or outcome.

The topmost node in a decision tree is known as the root node. The root uses recursive partitioning to partition the tree based on the attribute’s value. A decision tree is easy to understand and interpret and can visualize human-level thinking, so it can be useful in decision-making processes (Patel & Prajapati, 2018). Figure 6 illustrates a basic decision tree flowchart.

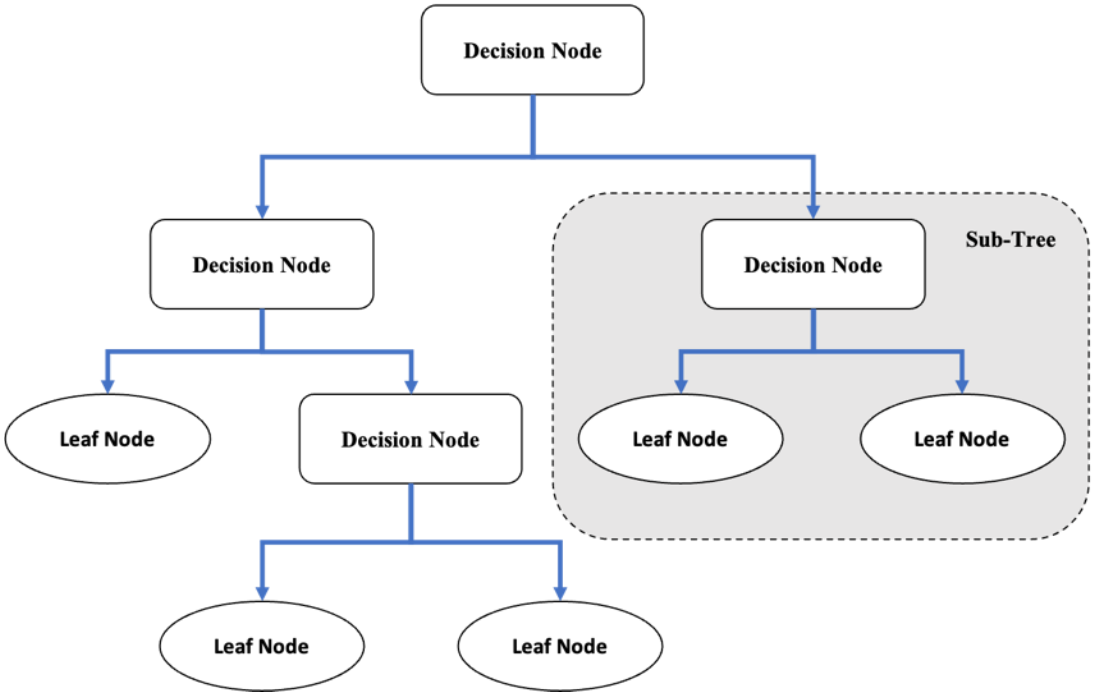


Figure 6 Basic Decision Tree Flowchart

According to Figure 7, a case base is divided into a training and test data set. Then the training data and attribute lists are given to the following algorithm to build a decision tree (Musharraf et al., 2020).

1. Use Attribute Selection Measures (ASM) to choose the best attribute to branch the current node.
2. Consider that attribute as a decision node and break the dataset into smaller subsets
3. To construct a tree, repeat this procedure for each child until one of the following conditions match.
    a. All the attribute values belong to the same class.

b. No attributes are left for further classification.

c. No more instances are left.

After generating a decision tree, the generated model is evaluated using the test data, and performance measures are calculated.

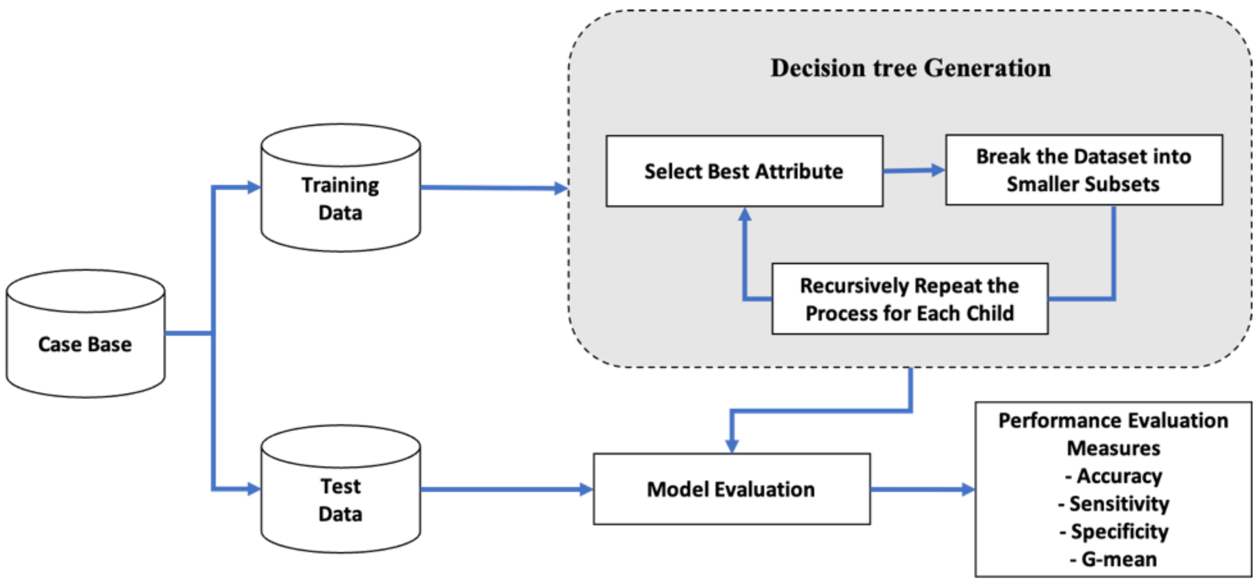


Figure 7 DT Algorithm Procedure

2.7.2. Attribute Selection Measures

Attribute selection is a critical step to develop a tree. An attribute selection measure (ASM) is used to partition the dataset by selecting the best splitting criterion. Different decision tree algorithms employ different types of ASM, such as information gain, gain ratio, and Gini index (Devi & Nirmala, 2018). All of these attribute selection methods can be used for building a decision tree because although the choice of the attribute selection measure affects the size of the tree, it does not change its accuracy. That means the classification accuracy of decision trees is not sensitive to the chosen feature selection method (Mingers, 1989; Tangirala, 2020).

2.7.2.1.Information Gain

Information gain uses entropy as the impurity measure and splits a node to build a tree. Consider node N represents or holds the tuple of partition D. To choose the splitting attribute at node N, the attribute with the highest information gain would be selected (Tangirala, 2020). Information gain is measured based on the following equations (Berrar & Dubitzky, 2013). First, the entropy is calculated to identify the class label of a tuple in D using Equation 1.

$$Info(D) = -\sum_{i=1}^{m} P_i log_2 P_i$$

Equation 1 Entropy

P_i is the probability of an element in D being classified for a distinct class (C_i) and is calculated using Equation 2.

$$|C_{i,D}|/|D|$$

Equation 2 Probability of an Element

Then the average entropy based on the partitioning by attribute A is calculated by Equation 3.

$$Info_A(D) = \sum_{j=1}^{V} \frac{|D_j|}{|D|} X\ Info(D_j)$$

Equation 3 Average Entropy

Finally, Information gain computes the difference between the entropy before the split and the average entropy after the split of the dataset based on given attribute values by Equation 4.

$$Gain(A) = Info(D) - Info_A(D)$$

Equation 4 Information Gain

2.7.2.2. Gain Ratio

The gain ratio is used to decrease the bias that information gain may cause (Shouman, Turner, & Stocker, 2010), and is measured using the following equations (Rizka, Efendi, & Sirait, 2018). Information gain prefers to select attributes that have a large number of values and consequently is biased. The gain ratio (Equation 6) handles this problem by splitting the information gain on split info (Equation 5).

$$SplitInfo_A(D) = -\sum_{j=1}^{V} \frac{|D_j|}{|D|} \times log_2\left(\frac{|D_j|}{|D|}\right)$$

Equation 5 Split Info

$$GainRatio(A) = \frac{Gain(A)}{SplitInfo_A(D)}$$

Equation 6 Gain Ratio

2.7.2.3. Gini Index

Gini index uses a binary split for each attribute and is calculated using the following equations ("Gini Index," 2008). It measures the impurity of each data partition or set of training tuples (D) using Equation 7.

$$Gini(D) = 1 - \sum_{i=1}^{m} P_i^2$$

Equation 7 Impurity

Pi is the probability of an element in D being classified for a distinct class (Ci) and is calculated using Equation 2.

Gini index computes a weighted sum of the impurity of each resulting partition. For example, if a partition is divided into two partition D1 and D2 the Gini index would be as follow (Equation 8).

$$Gini_A(D) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2)$$ **Equation 8 Gini Index**

An attribute with the least Gini index is preferred as the root node while making a decision tree (Devi & Nirmala, 2018).

2.7.3. Different Types of Decision Tree

Different algorithms are performed to construct decision-tree algorithms, including ID3, C4.5, and classification and regression trees (CART). ID3 is a very simple decision tree and is built in a top-down fashion. It builds the fastest and shortest tree and maybe over-fitted in a small data set. Also, it only handles the categorical attributes. C4.5 is the evolution of ID3 and uses a depth-first strategy to develop a tree. One of the advantages of C4.5 over ID3 is that it can handle both numerical and categorical attributes. Although C4.5 is tolerable for missing values, there are some empty or non-informative nodes in its tree, which makes it bigger and causes more complexity. CART constructs a binary tree and has the same characteristic as C4.5. Unlike C4.5, CART identifies the most relevant features and eliminates irrelevant ones, it also can easily handle outliers (Sonia Singh, 2014). Since the data set used in this research consisted of both numerical and categorical features, and there was a concern of missing data points, the CART algorithm was chosen to support these two criteria and to choose the best and most relevant features to build the tree model.

2.7.4. Distance Similarity

After applying the decision tree and finding a class that a new problem belonged to, a similarity metric could be used to detect which sample or case in the selected class was the best match to the new case (Cunningham, 2009; Feuillâtre et al., 2017; Richter, 2008). Measuring similarity between objects can be performed in several ways. Generally, similarity metrics can be divided into two categories:

1. Similarity-based metrics: similarity-based methods determine the most similar objects with the highest values indicating that they exist in the same neighborhood. Such algorithms are Pearson's correlation, Spearman's correlation, Kendall's Tau, Cosine similarity, and Jaccard similarity.
2. Distance-based metrics: distance-based methods prioritize objects with the lowest values to detect similarity amongst them. These methods include Euclidean distance and Manhattan distance.

Choosing an appropriate distance metric plays an important role in retrieval applications (Hoi, Liu, & Chang, 2010). Since distance-based metrics are like using a ruler to exactly measure a distance, they are more appropriate for numerical data, while similarity-based metrics are more suitable when the data set contains categorical attributes. Since the data set used in this research consisted of both numerical and textual features, similarity-based metrics were preferred to use in this research. Among similarity-based metrics, Cosine similarity is generally employed for measuring distance when the magnitude of the vectors is not a concern (Xia, Zhang, & Li, 2015). For example, Cosine can be used in document similarity and text data (Shirkhorshidi, Aghabozorgi, & Ying Wah, 2015; Tata & Patel, 2007). Cosine similarity is defined as follows (Equation 9).

$$Cosine(x, y) = \frac{\sum_{i=1}^{n} x_i y_i}{\|x\|_2 \|y\|_2}$$ **Equation 9 Cosine**

Where,

$$\|y\|_2 = \sqrt{y_1^2 + y_2^2 + \cdots + y_n^2}$$

Chapter 3: Methodology

This chapter contains the steps followed to develop a DSS for ice management operations. First, two experimental studies were conducted to gather expert knowledge to be integrated into the DSS. The collected data during the experiments was processed and converted to a CBR case base. The case base was stored in the form of a two-dimensional matrix and was divided into training and testing data sets. The training data set was used as input to the decision tree algorithm for case retrieval purposes. Section 3.1 describes the experimental design and data collection in detail. Section 3.2 discusses the data processing and creation of the CBR case base. Section 3.3 illustrates the development of the DSS and decision trees using the case base. Finally, to determine the stability of the DSS, the evaluation of the DSS in a simulator setting is discussed in section 3.4.

3.1.Experimental Design

This research aimed to address challenges in providing an assistant system in maritime operations related to the growing use of autonomous systems onboard maritime vessels. The study began with a pilot program intended to strengthen ice management operations by gaining a deeper understanding of how seafarers' strategies and emerging technologies impact these operations. The result was to develop an on-board decision support system (DSS) that provided tactical guidance for complex ice management operations. This research used experienced seafarers to capture expert knowledge to inform a DSS and improve the ice management performance when real-time decision support is offered. Two experiments were conducted to capture the expert knowledge:

1. Pre-pilot: Semi-Structured Interview

2. Pilot: Simulation exercises

As experienced vessel operators were needed to participate in this project, the potential number of available people that could be recruited was limited. Previously, two experiments were conducted to study the effects of experience (Veitch, 2018) and training (Thistle, 2019) on ice management performance (the results from these two studies were used to develop a DSS in this study). Based on these previous works, it was known that there exists a limited number of experienced vessel operators who could possibly be approached to participate.

Two groups of participants were used to benefit from their expert knowledge. The groups were: G1- experienced seafarers who shared their expertise through an interview, and G2- experienced seafarers who shared their knowledge by executing the ice management scenarios in the simulator. In total there were five participants, and they were free to choose one or both sessions. Three participants attended both sessions, while two participants completed just one session each. The knowledge captured from the two groups was fed to the DSS to help seafarers or cadets while implementing ice management scenarios.

The semi-structure interview included six parts (the session outline is provided in Appendix A: Interview Session Outline):

1. Briefing: the participant was given an explanation of the research and was asked to complete the Informed Consent Form (Appendix B: Informed Consent Form). Then, the information about the participant’s experience at sea was collected using the Experience Questionnaire (Appendix C: Experience Questionnaire).

2. Experience Interview: the researchers asked questions to expand the participant's responses to the Experience Questionnaire.
3. Ice Management Factor: the researchers asked questions related to factors the participant may consider during ice management.
4. Planned Approach Exercise: the participant was asked to explain their planned approach for ice management scenarios (leeway, pushing, and emergency scenarios).
5. Cadet Training Examples: the participant was shown examples of cadets managing ice in a bridge simulator (these examples came from the previous experiment (Thistle, 2019)). After each example, the participant was requested to give their opinions on the cadet's performance.
6. Feedback and Closing: before the completion of the session, the participant was asked to give feedback on the interview.

The interview was semi-structured. This meant some of the questions were pre-determined and others arose based on the participants' answers to previous questions.

Like the semi-structured interview, the simulation exercise started with a briefing and experience interview, and then the following steps were completed:

1. Simulator Sickness Questionnaire (SSQ): researchers asked the participant to fill out an SSQ (Appendix D: Simulator Sickness Questionnaires) to establish a baseline score. Researchers administered the SSQ to the participant throughout the tests to see if they were developing simulator sickness, which was indicated by a higher score.
2. Planning Exercise: this exercise consisted of an overhead diagram of the upcoming ice management scenario that the participant could use to draw and plan their movements.

3. Simulator Exercise: the participant was asked to enter the ice management simulator and perform the ice management scenarios (leeway, pushing, propwash, and emergency scenarios).
4. Debriefing: the participant was then shown a sped-up video replay of their current scenario, where researchers again asked them questions about their ice management techniques.

The interview and the simulator exercise were audio recorded and transcribed by the research team. A few weeks after the session, the researchers sent participants a copy of the results from the study and allowed them to add, change, or delete information as they saw fit.

After holding all sessions and gathering all required information, data collected from this study was used in the development of a case-based reasoning decision support system, and machine learning algorithms were used to develop autonomous systems onboard maritime vessels.

3.1.1. Experimental Overview

A pre-pilot study, a pilot study, and results from two previous experiments (Thistle, 2019; Veitch, 2018) were used in this research. All of these studies were approved by the Interdisciplinary Committee on Ethics in Human Research (ICEHR) at Memorial University of Newfoundland (MUN), and they followed an ethics protocol. The pre-pilot and pilot studies, which are the main focus of this research, were used to collect seafarers' experiences in managing pack ice offshore.

Experiment 1 studied the effects of experience on ice management performance and was conducted by Veitch (2018). The results were reported in (Veitch, 2018; Veitch, Molyneux, Smith, & Veitch, 2019). In that research, participants with a range of seafaring experience levels were asked to execute different ice management scenarios. Each participant's performance was recorded as a replayable video in Experiment 1 and used in the current study as a case to develop a case base for the case-based reasoning decision support system.

Experiment 2 studied the effects of training on ice management performance and was conducted by Thistle (2019). This experiment's results were reported in (Thistle, 2019) and used in the pre-pilot study of the current research to gather the participants' evaluations on the cadets' performance. In Experiment 2, one group of inexperienced cadets were trained through one training session, and another group was taught in two training sessions in the bridge simulator. After training, each participant was asked to complete two of the same ice management scenarios. As a result, on average, the cadets' performance improved with each training session, and a method for assessing the amount of training needed to meet an ideal performance was introduced (Thistle & Veitch, 2019).

The pre-pilot and pilot studies were performed from January to March 2020. The pre-pilot study was conducted in two different phases:

1. Using semi-structured interviews, participants were asked to describe how they would approach three different ice management scenarios. These scenarios were:
    a. The leeway scenario,
    b. The pushing scenario, and
    c. The emergency ice management scenario.

    Then experienced seafarers described what factors they would consider while performing the scenarios and explained why those would be important.

2. In phase two, six examples of the cadet's performance from Experiment 2 (two examples for each scenario) were shown to participants to collect their advice, recommendations, and feedback on the cadets' performance.

The pilot study was operated in two phases as well. The first part was conducted like the first part of the pre-pilot study, while an additional scenario was added. The pilot study phases were:

1. Asking participants to describe their approaches for four different ice management scenarios. These scenarios were:
    a. The leeway scenario,
    b. The pushing scenario,
    c. The prop-wash scenario, and
    d. The emergency ice management scenario.
2. Requesting participants to execute these suggested approaches in the bridge simulator to see their procedure in practice.

3.1.2. Description of Participants

Since experienced vessel operators were needed, researchers contacted potential participants directly to inform them about the study. If they expressed interest, a copy of the informed consent was sent to them for their review. After reviewing the form, the potential participant could get back in touch with the researcher and let them know they wanted to participate.

The only criterion to exclude participants from the pilot study was if they were prone to suffering from simulator sickness, and participants were asked to self-disclose if they felt any symptom. Also, participants were allowed to withdraw from the study at any time without reason.

At the beginning of each session, participants were given an experience questionnaire, which provided information about participant's years of experience and vessels they used in sea operations. The range of seafarers' experience operating at sea was between 10 to 30 years, while this range decreased in the presence of ice from 2 to 7 years. These participants had the experience of operating in different regions, such as coastal Newfoundland and Labrador, the Arctic/ North of 60, the Gulf of Saint Lawrence, and the Great Lakes. They also worked on various types of vessels including ice breakers, offshore supply vessels (OSVs), anchor handling tug supply (AHTS) vessels, tanker/ bulk/ cargo vessels, and coastal ferries. Among different operation types, three seafarers had experience conducting operations in the presence of ice, like watch keeping, ice management in open water and confined water, maneuvering a ship to escort another vessel, towing or emergency response, and maneuvering a ship while being escorted, whereas two other participants had experience watch keeping when passing through ice. In terms of the amount of training each participant had for operation in the ice, two participants had no formal training while three other seafarers had advanced training (Smith et al., 2020).

3.1.3. Description of Simulator

Figure 8 shows the ice management bridge simulator that was used in the simulation exercise (pilot study) for evaluating experienced seafarers' performances. This marine simulator's design consists of an instructor station and a debriefing station outside the simulator, and a 360-degree panoramic projection display surrounding a basic bridge console, which is located at the center of the simulator (Musharraf, Smith, Veitch, & Khan, 2019). The software for implementing physics in the simulator is called PhysX (Thistle, 2019).

For the pilot study, the anchor handling tug supply (AHTS) vessel was modeled in the simulation exercise. The reason why the AHTS was selected for this study was that these kinds of vessels are commonly used for offshore operations and supporting pack ice management in offshore Newfoundland. This virtual ship was 75 meters in length with ice-class ICE-C. Different features of the virtual ship are shown in Table 2. The ship consisted of two 5369 kilowatt engines and an 896 kilowatt tunnel thruster in both the fore and aft (Thistle, 2019).

Table 2 Virtual Vessel Elements (Thistle, 2019)

Parameter	**Value**
Length Overall	75 m
Length Between Perpendiculars	64 m
Moulded Breadth	18 m
Moulded Depth	8 m
Draft	6 m
Gross Tonnage	3157 tonnes

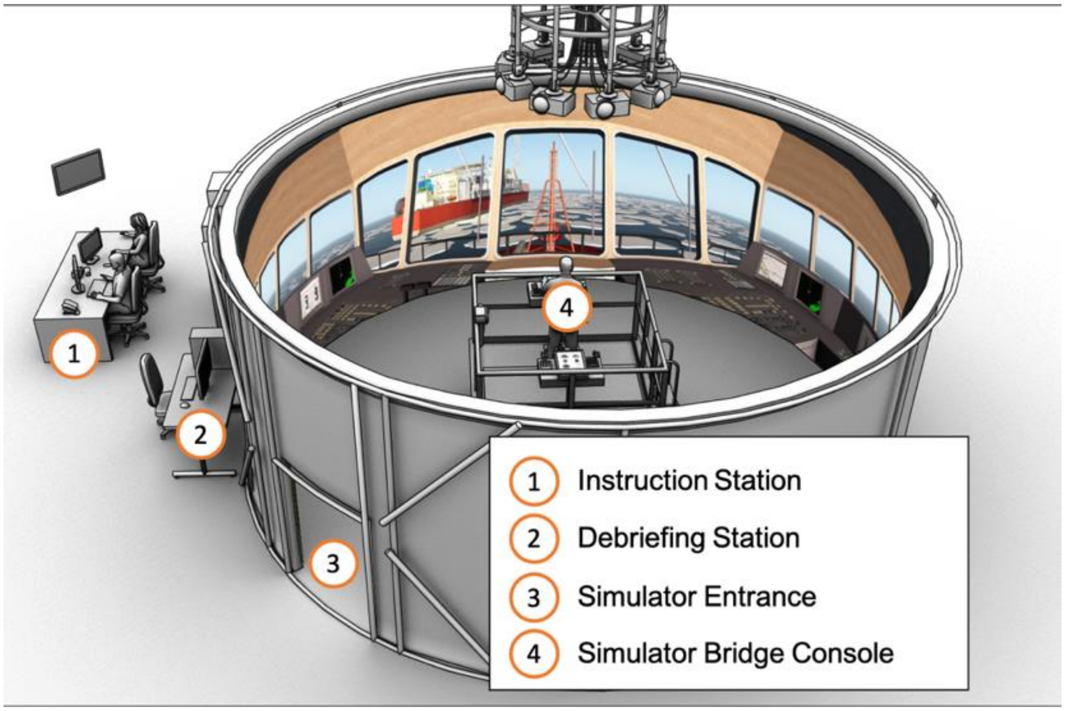


Figure 8 Ice Management Simulator

The simulator configuration that was used for the expert seafarers in pilot and pre-pilot experiments was the same configuration that was used for the cadets in the previous experiments. A simplified bridge console was built for the simulator to minimize task complexity and reduce some difficulties that may occur for cadets who are not very familiar with ships' controls and instructions. Although working with a more complicated simulator closer to the real ships' environment can result in a more realistic output, providing an easy-to-use interface for participants, especially non-experts, can have more benefits due to the lower cognitive load on them (Haji, 2015).

Figure 9 shows a bridge console with (2 m x 2 m) dimensions. Fore and aft consoles were embedded in the bridge console, so participants could switch between them any time they wanted. Different bridge simulation controls were:

a. two controls for the fore and aft tunnel thrusters,
b. two controls for the starboard and port engines, and
c. a steering wheel to control the angle of the two rudders.

The indicator screen embedded in the bridge simulator displayed different information to participants, such as the vessel’s speed over ground, heading, heading change, rudder angle, and engine and thruster power. As participants could not see their exact distances from the objects due to the lack of radar in the simulator, they could use the Very High Frequency (VFH) radio to communicate with the instructor station and ask their distance from other objects or vessels when they needed it.

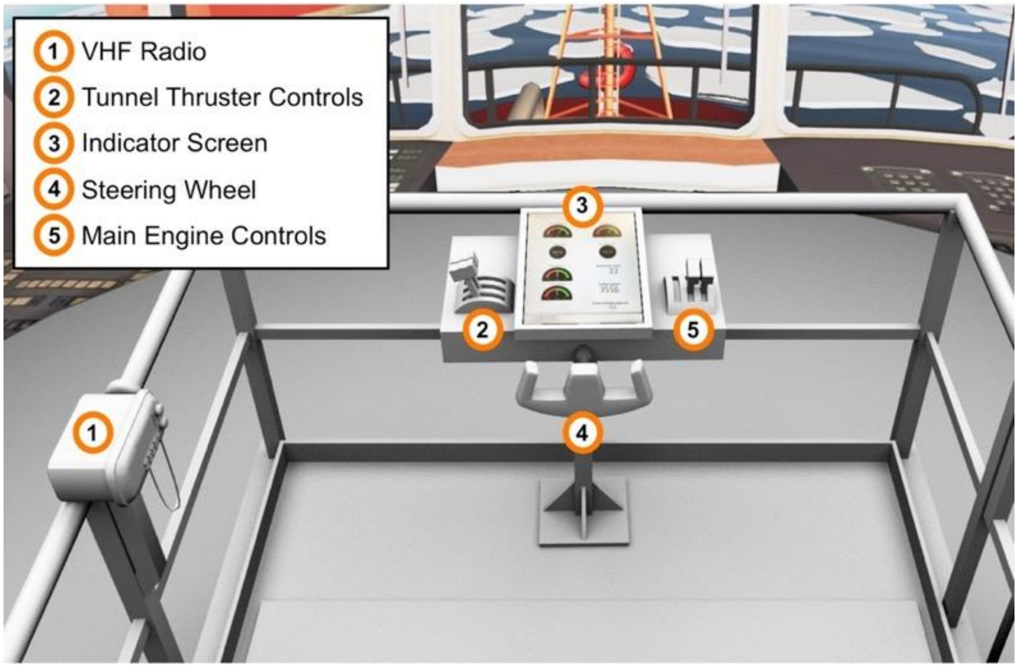


Figure 9: Simulator Bridge Console Design (Thistle, 2019)

3.1.4. Familiarization of the Simulator Through Habituation Scenarios

In the pilot study, the participants were asked to do the three habituation scenarios (shown in Appendix E: Habituation Scenario Instructions) before executing other main scenarios to familiarize themselves with the simulator and its bridge console. The purpose of the habituation scenarios was to decrease errors that could occur while performing scenarios due to participants' unfamiliarity with the simulator. During the implementation of these scenarios, participants could use the VHF radio to call the bridge officer and communicate with them. They could also make sense of how the controls and other parts of the virtual environment worked.

In Habituation 1, participants were asked to round the iceberg from the vessel's port side with a distance of 100 meters and then return to their starting location. This scenario was intended to take ten minutes, and if participants did not complete it within twenty minutes, the scenario was stopped. Participants also had the option of asking the bridge officer about the distance between the vessel and the iceberg.

In Habituation 2, seafarers were asked to make a parallel position with the port side of a Floating Production Storage Offloading facility (FPSO). The distance between the FPSO and the vessel was allowed to be 30 meters. The time allocated to this scenario, similar to the first scenario, was ten to twenty minutes. Practicing slow maneuvers and operating close enough to another vessel was the purpose of this scenario.

The last scenario was Habituation 3, in which participants used the propeller wash to clear small floes of ice from the aft of their vessel by pushing them away. At the starting point, the vessel's bow faced large pack ice, so for clearing the vessel's aft, participants were required to switch between the fore and aft console. The main goal of Habituation 3 was to teach seafarers how to switch between two consoles and how the prop wash could be implemented in the simulator. Approximately one to two minutes was enough to finish this scenario successfully.

Before seafarers' participation began in the simulator, they were asked to fill the simulator sickness questionnaires provided from Experiment 2 (Thistle, 2019). After performing each scenario, they filled out the questionnaires again to see if there were any severe simulator sickness symptoms. There were no signs of severe symptoms during any experiments; otherwise, they would have ended immediately. Whenever mild symptoms were identified, the experiment was stopped for a while until all symptoms went away.

3.1.5. Offshore Ice Management Scenarios

This research was designed to develop a DSS to improve ice management operations by providing expert advice to the bridge crew. For data acquisition, four scenarios were used in this study and designed to be similar to Newfoundland's offshore operations (Thistle, 2019). Appendix F: Scenario Instructions shows the instructions used to explain the scenarios to the participants.

All scenarios in the experiment were simply designed to avoid distracting factors for participants during execution. For simplicity, multi-year ice was not modeled in the scenarios, and the drift direction and the speed did not change during the scenario. First-year ice with 0.3 to 0.7 meter thickness was used in all scenarios. While the shape and size of the ice floes were randomized, they were kept the same in each scenario run.

Before explaining each scenario and technique, for making distinctions between them, Sc.1 is referred to the leeway scenario, Sc.2 is referred to the pushing scenario, Sc. 3 is referred to the emergency ice management scenario, and Sc.4 is referred to the prop-wash scenario. Techniques are mentioned as leeway, pushing, and prop-wash techniques.

In Sc.1, shown in Figure 10, a stationary tanker is located in five-tenths first-year ice with a 1 knot drift to the south. The stand-by vessel's support is required to clear the tanker's mid-ship port side from the ice to make the area suitable for launching a pilot ladder or reducing the damage risk for the equipment that the crew may want to launch. The time allocated for participants to perform their approaches in Sc.1 was fifteen minutes.

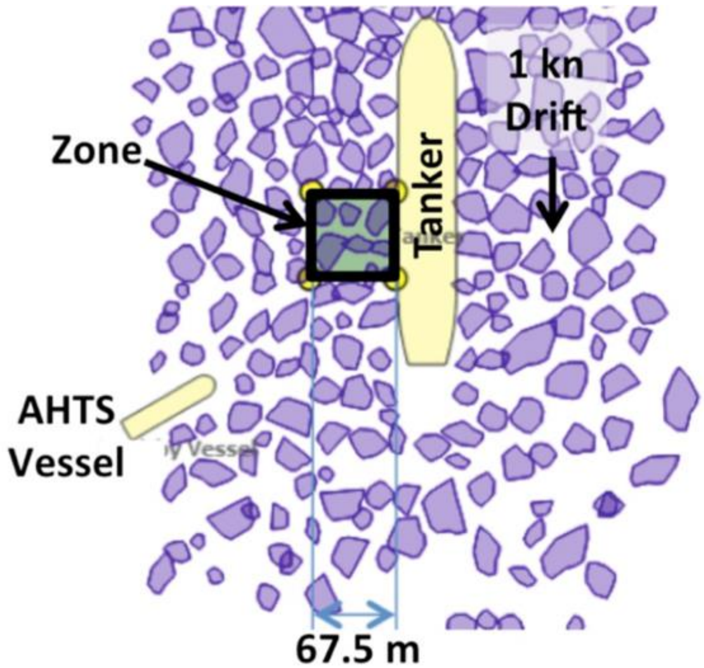


Figure 10 Leeway Scenario (Thistle, 2019)

Sc.2 is shown in Figure 11. In this scenario, participants were asked to clear the area around a stationary platform at a distance of 75 meters from each side using the pushing technique. As shown in the figure, the platform with 57 m x 57 m dimensions was located in the middle of the desired area that should be cleared. Therefore, in total, 207 meters on each side should be cleared of four-tenths of its first-year ice so that lifeboats can be launched in emergencies. In this scenario, the current is 0.4 knots drifting to the south, and fifteen minutes were given to each participant to do their best to decrease the ice load on the platform.

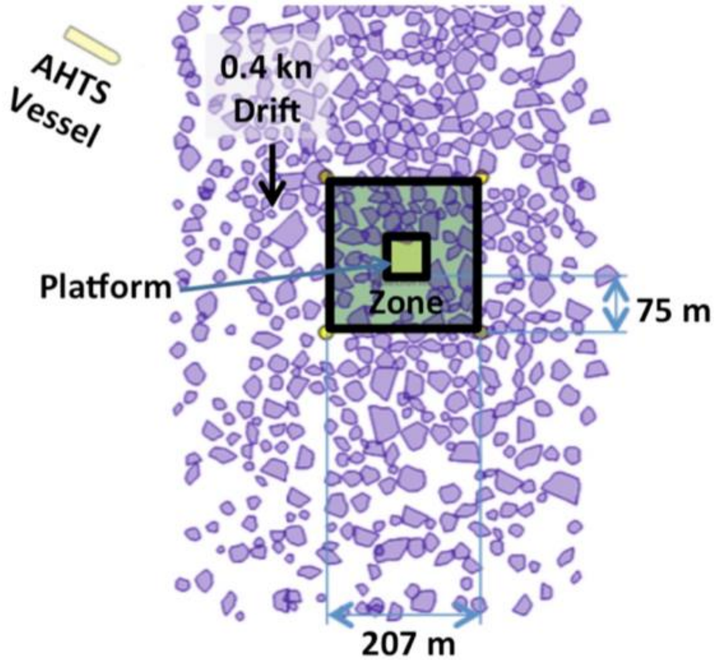


Figure 11 Pushing Scenario (Thistle, 2019)

Sc.3 is illustrated in Figure 12. In this scenario, a moored FPSO was turned to its starboard side, so that starboard side's lifeboat launch area was clear of ice to launch lifeboats. The participants' concentration should have been on the FPSO's port side lifeboat launch zone, indicated in grey, and they were allowed to utilize a single method or combination of any approaches or techniques they were comfortable with or thought were the most effective ones to make the target area free of ice. The ice concentration in Sc.3 was seven-tenths drifting from north to south at a speed of 0.5 knots, and it was first-year ice. This scenario was longer than the two other scenarios, and seafarers were given thirty minutes to show their expertise.

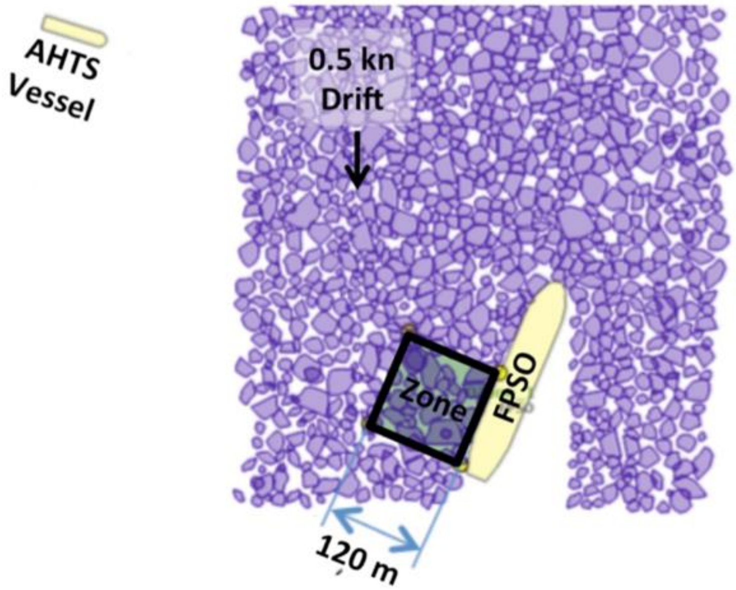


Figure 12 Emergency Ice Management Scenario (Thistle, 2019)

Sc.4 can be found in Figure 13. In this scenario, the starboard side of the stationary tanker was free of ice, while participants were required to clear the port side of the vessel for another ship to dock alongside the tanker. The purpose of clearing the pack ice was to reduce the risk of damage due to ice for the other vessel while docking. The tanker's port side is located in the seven-tenths first-year ice concentration, and there is no drift in the scenario. Using the propeller wake wash technique, participants were asked to clear 75 meters along the vessel's port side. This scenario took 15 minutes to complete.

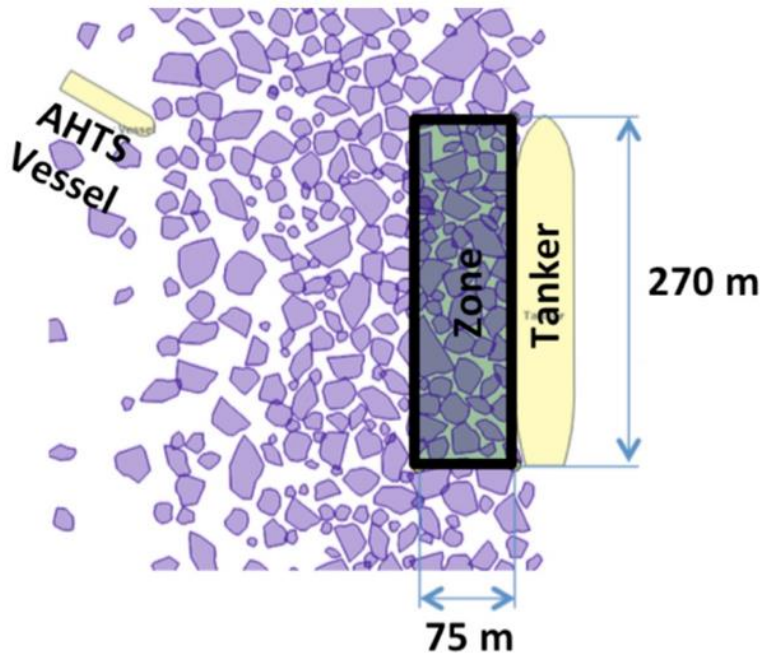


Figure 13 Prop-wash Scenario (Thistle, 2019)

3.1.6. Data Acquisition

In both interview and simulation exercise sessions, data gathered from seafarers was labelled randomly in an alphanumeric code, for example N12, to keep the participants' identities confidential.

Different types of data were recorded in both experiments. At the beginning of both sessions, participants were asked to fill out the experience questions in order to know the amount of their experience in the sea in the presence of ice. Also, the scenario diagram was given to the participants in both experiments to draw out their strategies for each scenario. The scenario diagrams are shown in Appendix G: Scenario Diagram Pages. The length of these sessions varied from person to person, but on average they took about three to four hours. Since the data gathered from the experiments was confidential and it should be protected from unauthorized access, researchers did not use any software for the transcription. Therefore, the researchers transcribed the audio files manually. Guidelines followed for transcribing are shown in Appendix H: Transcribing Guide.

In the pre-pilot sessions, the whole session was audio recorded and all parts including the participant's ice management approaches and comments on the cadet's replay videos were transcribed after each session.

In the pilot sessions, the participant's planned approach exercises and debriefing part were audio recorded for transcribing afterward. Also, in this experiment, data from the simulator was recorded for the main scenarios, while data related to the habituation scenarios were not recorded. Recorded data from the simulator had two forms:

1. a log file consists of information such as the vessel's speed over ground, course over ground, longitude, latitude, and heading at each time step and
2. a replay file that gives researchers, in the instructor station, the opportunity of reviewing the scenario at real speed when the scenario was completed. To calculate the ice concentration and make a sped-up replay video for each scenario's implementation, researchers could later capture screenshots of this replay file.

3.1.7. Experimental Procedure

Participants in this research were recruited based on a protocol that has been reviewed by the ICEHR at MUN and is in compliance with MUN's ethics policy. The recruitment process consisted of a call for subject recruitment email, which included information on contacting the researchers for those who were interested in participating in the experiment. The recruitment email was distributed to colleagues to recruit volunteers for the study by the research coordinators. Research coordinators were responsible for recruiting the potential participants and were the main point of contact for participants. They screened interested volunteers to ensure they are eligible to participate, ensure the potential participants were properly informed, and guided individuals through the informed consent process.

The experiment's informed consent form was sent to volunteers when they were contacted to set a participation schedule. After scheduling and assigning pre-pilot, pilot, or both sessions to the participants, they were randomly given an alphanumeric code.

3.1.7.1.Interview Session (Pre-pilot)

Figure 14 illustrates the procedure followed in Interview sessions. In these sessions, four people attended for holding the interview:

1. an interviewer,
2. two observers, and
3. a participant.

The pre-pilot sessions' outline was shown in Appendix A: Interview Session Outline.

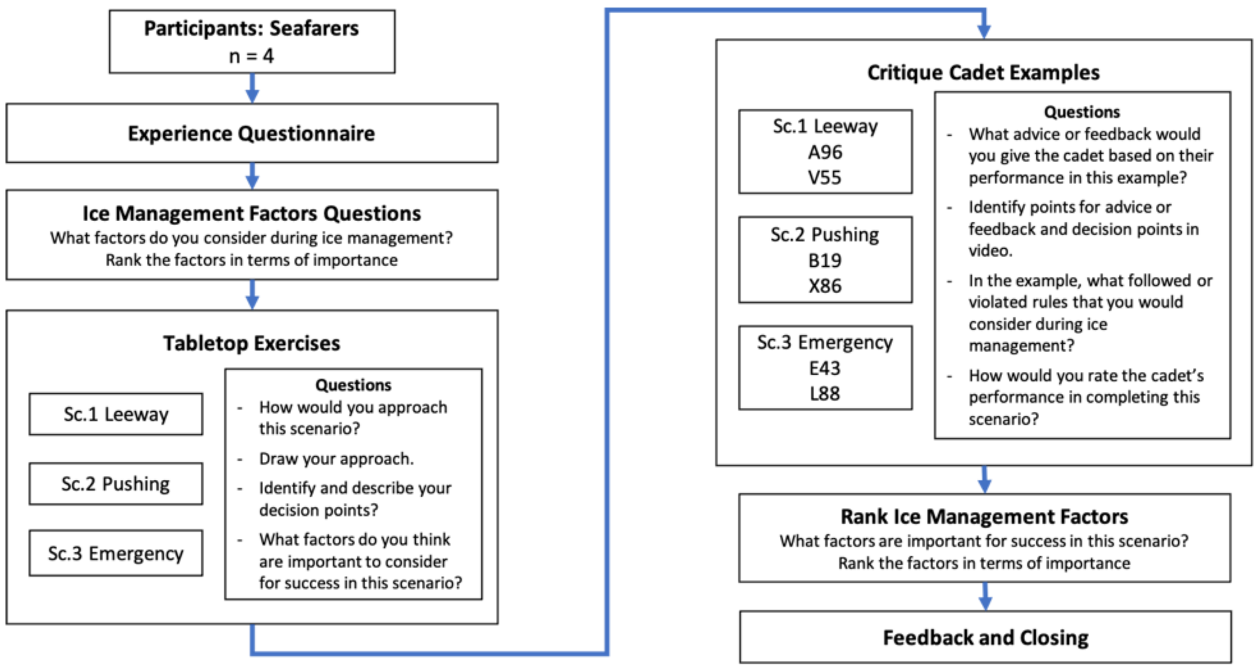


Figure 14 Experimental Procedure Flow Chart for Pre-pilot

At the beginning of the session, the informed consent form was reviewed by the interviewer to make sure that the participant was aware of every detail of this participation. After the agreement of the seafarer, both the participant and the interviewer signed the form. In the next step, the participant completed the experience questionnaire, and researchers asked them some questions if more details were required for clarification. During the interview, researchers used interviewer and observers' notes to take notes of the participant's comments and approaches. These forms are shown in Appendix I: Interviewer Notes and Appendix J: Observer Notes. The whole session was audio recorded.

Next, a list of important factors in ice management operations was provided for the participant, and they were asked to add any factor that they thought was missing from the list. For each of these factors, the researchers asked why these factors are important and why they should be considered during ice management operations in general. The list of provided factors is shown in

Appendix K: Factor Cards. After completing the list of factors and describing reasons for consideration, the participant was asked to rank them based on the overall importance. According to the Factor headings shown in Appendix L: Factor Headings, the participant gave a number between 1 to 5 to each factor, in which 1 was not important, and 5 was very important. This section aimed to understand what information is more valuable and has more priority in the participant's decision-making process.

There were three types of ice management scenarios that the participant was required to be familiar with. First, the interviewer explained the Sc.1 and asked the participant to describe how they approach this scenario. The scenario diagram was given to the participant, and they were requested to draw out a sketch of their approaches and explain every step of their decisions. The researchers asked the participant to use multiple colors in each decision point not to have difficulties while matching the audio recording with the drawn approaches. Decision points were any time in ice management plans that the participant went from one step to another. Figure 15 shows a sample of a participant's sketch of approach.

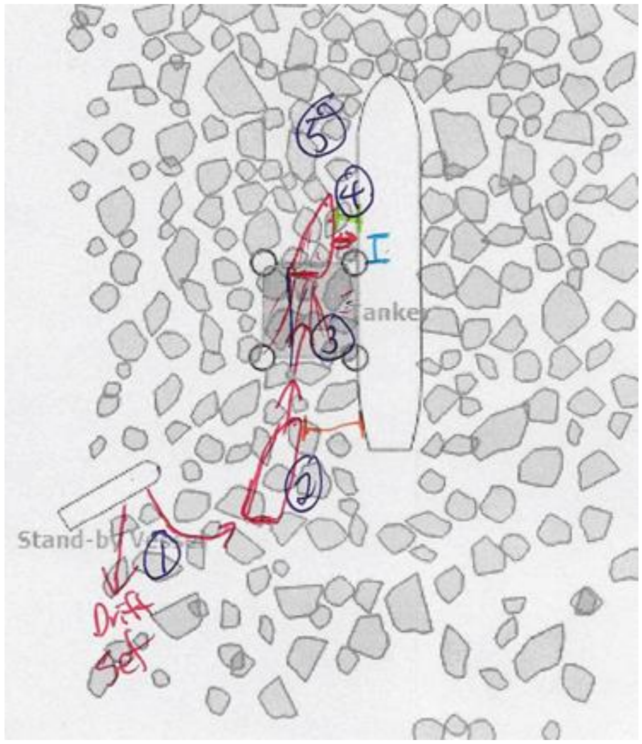


Figure 15 Sketch of Approach

After identifying all decision points and asking questions for clarifying all aspects of the drawn strategies, the participant was shown two pre-recorded examples of cadets' performance on the same scenario in the bridge simulation. This phase aimed to collect the seafarer's advice, recommendations, and feedback on the cadet's performance. The cadet examples came from Experiment 2 (Thistle, 2019). These examples were anonymized top-down replay videos, like what is shown in Figure 16, which were sped up to thirty-times real speed. The replay video represented an ice management operation using an offshore supply vessel, and the interviewer explained what the symbols in the replay video mean.

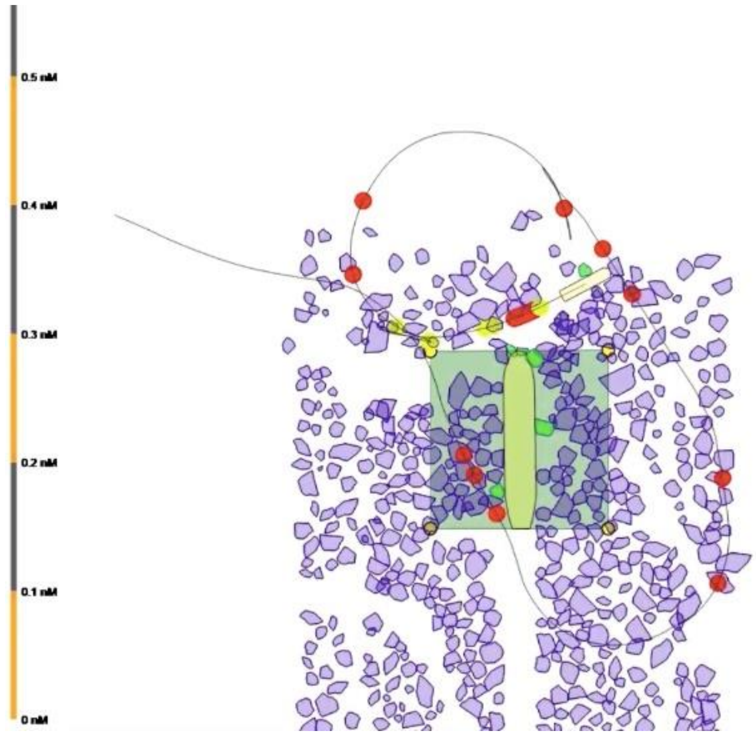


Figure 16 Replay Video Still Shot

The participant reviewed replay files once or more and mentioned their opinion about how effective the cadet performance was. They also gave some advice at critical stages where some changes were needed to have better performance (some changes in course, speed, technique, etc.). Then the seafarer was requested to identify any violation of rules in the cadets' performance. At the end of the cadet example section, the participant gave a rating between 1 to 5 to the cadet's performance.

In the last part of the scenario, the seafarer ranked the ice management factors again, according to the Sc.1. Using the factor ranking label, as shown in Appendix M: Factor Ranking Label, researchers categorized the factors' importance for the specific scenario.

Similarly, for Sc.2 and Sc.3, the participant drew their approaches, evaluated two cadet examples, and ranked factors for the two specific scenarios.

In total, the participant demonstrated their strategies for three scenarios and evaluated six cadet examples (two examples for each scenario) in the pre-pilot session. The order of scenarios and examples were determined in the scenario order sheet, as shown in Appendix N: Scenario Order Sheet. Each pre-pilot session took approximately three to four hours.

3.1.7.2.Simulation Exercise (Pilot)

The procedure followed in the pilot Experiment is demonstrated in Figure 17. In these experiments, four people attended the sessions:

1. an interviewer,
2. two observers, and
3. a participant.

The outline of the pilot sessions is shown in Appendix O: Simulation Session Outline. In addition to the steps mentioned in the procedure, one of the observers was responsible for loading and initiating scenarios in the simulator, screen capturing scenarios every three minutes, saving data collected from the scenarios, and communicating with seafarers during the simulation exercise via VFH radio.

Like the pre-pilot session, at the beginning, the informed consent form was reviewed by the interviewer, and both the participant and the interviewer signed the form. Then, the participant completed the experience questionnaire. In the next step, the interviewer gave a brief description of the simulator sickness questionnaire, and the participant was asked to fill it out to see if there was any symptom before implementing scenarios in the simulator. Once all forms were completed, the observer showed the simulator's environment and controls to the participant and explained different parts of the simulator's bridge console and the way they worked. The script related to the simulator's explanation can be seen in Appendix P: Introduction to Controls Script. These steps, which consisted of filling out the forms and introducing controls to the seafarer, lasted about fifteen minutes.

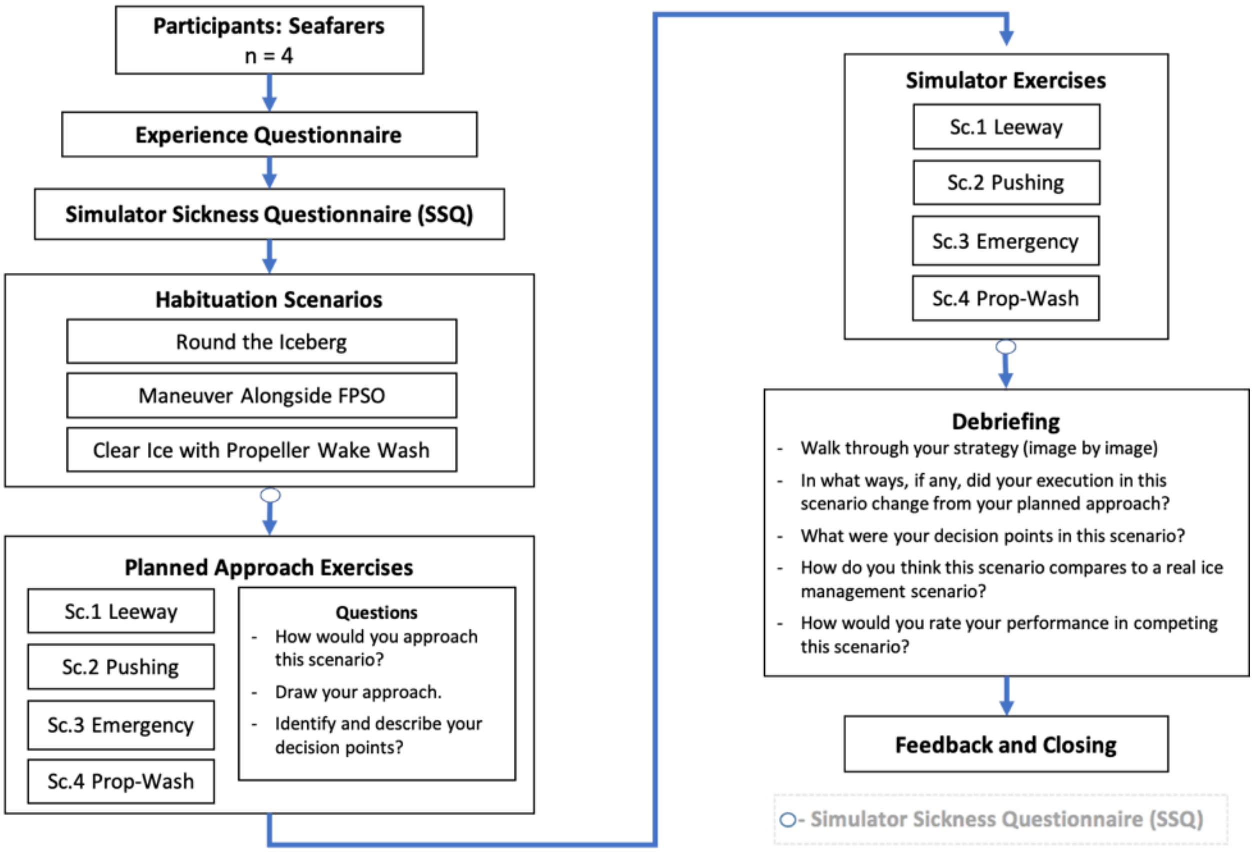


Figure 17 Experimental Procedure for Pilot Experiment

As shown in Figure 17, the next step was explaining the first habituation scenario in the training station and then asking the participant to execute it in the simulator. After completing the first attempt in the simulator by the participant, the observer introduced the second habituation scenario in the training station and again asked them to complete it in the simulator. The same procedure was repeated for the third habituation scenario as well. The habituation section took approximately

45 minutes to complete, and at the end of this section, the participant's sickness symptoms were checked by filling out the second simulator sickness questionnaire. Meanwhile, a break time was given to the seafarer if they needed any rest.

Next, similar to the tabletop exercise in the pre-pilot sessions, the first ice management scenario was described to the participant, and they were asked to draw a sketch of their strategies on the scenario diagram and explain their decision points. However, unlike pre-pilot sessions in which the participant was asked to complete three scenarios (Sc.1, Sc.2, and Sc.3), in the pilot sessions, the participant completed four scenarios (Sc.1, Sc.2, Sc.3, and Sc.4). All information provided from the participant in this step was audio recorded.

In the next step, the participant entered the simulator and completed the first scenario. The participant was allowed to perform their exact approaches described before or change the strategies if that was necessary. After completing the first scenario, the participant returned to the training station and filled out the simulator sickness questionnaire. Then, the debriefing section was performed.

In the debriefing section, researchers showed the screen captures of the scenario (captured by researchers during execution) to the participant and asked the seafarer to explain their strategies and any changes in their execution compared to their planned approach, if there were any. They were also requested to determine their decision points and compare the performed scenario to the real ice management scenarios. Debriefing was also audio recorded.

At the end of this phase, the participant rated their performance on a scale from 1 to 5, where one was not very successful, three was somewhat successful, and five was very successful. After completing each scenario, researchers asked if the participant wanted to have a break and help themselves with the available refreshments.

Similarly, all steps, including planned approached exercises, simulator exercises, and debriefing repeated for the other three scenarios. The pilot session lasted approximately four hours.

3.2.Data Processing and Developing the CBR Case Base

Developing a CBR case base for the DSS involved two main steps:

1. Knowledge capture - using the expert knowledge for building a case base to inform the DSS, and
2. Knowledge representation - organizing the information using the flat model.

All information gathered in the pre-pilot and pilot experiment, including the participant's ice management approaches, feedback on the cadets' examples, and strategies on the simulation exercises, was transcribed from the audio recording files. At the next step, these transcriptions were used to develop a case-based reasoning case base. Some parts of knowledge gathered from the participants, such as factor ranking and comments on ice management approaches, were used in similarity matching and the retrieval part of the DSS, while other information, such as the participants' verbal explanations of their ice management approaches and their feedback on the cadets' ice management performance, were used to build cases in the CBR case base. Next, for matching similar cases with the future scenarios' conditions, common features and characteristics of cases in the case base were categorized and indexed using the flat memory model. Finally, In order for the DSS to suggest a similar case, the DSS extracts common features from the simulation data and retrieves an expert solved case that matches the new situations using a similarity-based method.

This section describes every step of data processing for the DSS development in more detail.

3.2.1. Knowledge Capture—Gathering Cases to Populate the CBR Case Base

The transcribed data from the pre-pilot and pilot studies were used to develop cases to populate the CBR case base and develop the CBR reasoning structure. All transcriptions including verbal explanations of strategies and important factors were categorized using the Navicat Data Modeler software. Figure 18 illustrates the CBR knowledge representation that was developed using the transcriptions. As shown in the figure, the important factors were classified into different categories (e.g., 'task objectives', 'target vessel properties', 'weather conditions', etc.). Also, based on participants' comments during pre-pilot and pilot studies, additional factors were added to the list of factors and were assigned to different categories (e.g., separate categories for 'scenario attributes', 'target vessel properties' and splitting the 'operator characteristics and actions' category into two: operator characteristics and the operator's actions represented by the label 'ice management technique'). Important comments about each factor were also stored in the 'ice managements factor rank description' table for further use in DSS to show the decision-maker the reason of importance. Each case connected pre-programmed characteristics of the scenario (e.g., the scenario objective, the environmental conditions, and features of the ship), factor rankings and explanations of their importance, and the attributes of the participants' strategies to each other.

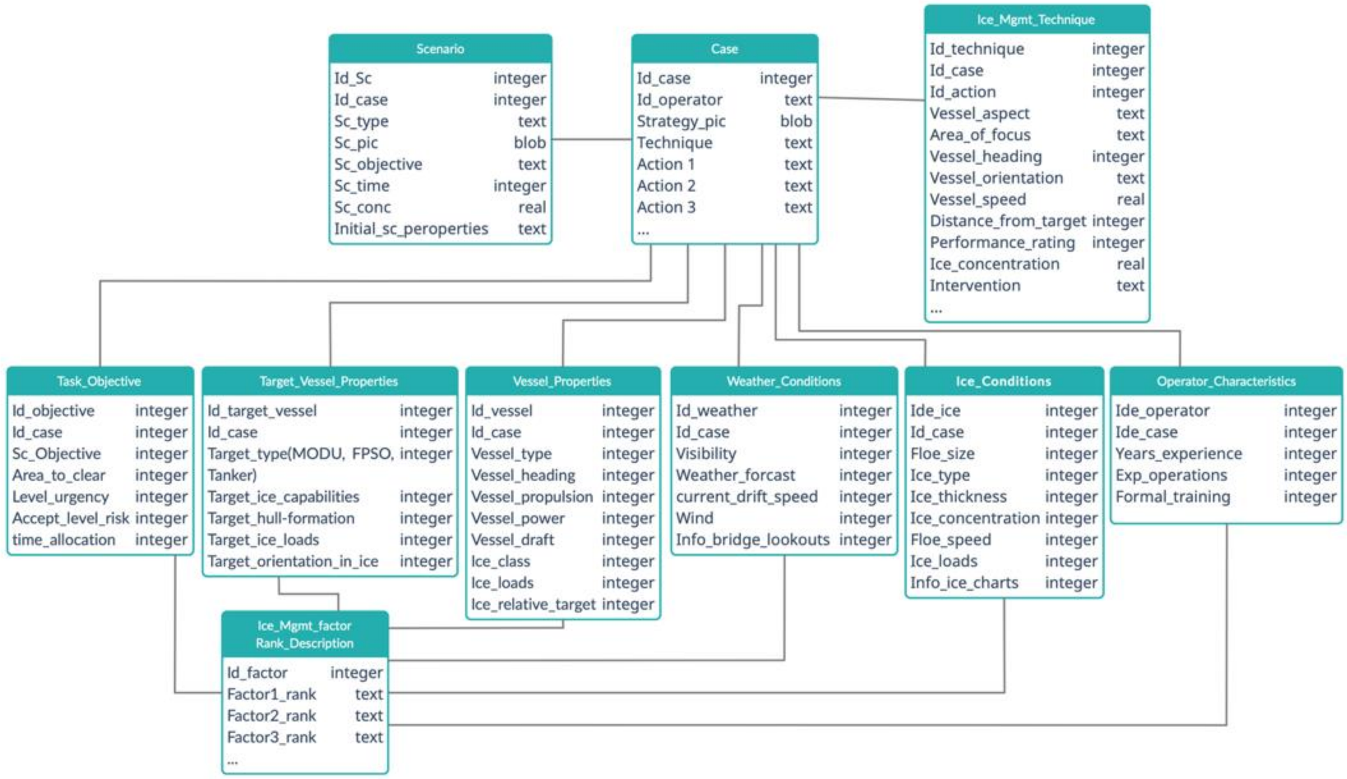


Figure 18 CBR Class Diagram for Ice Management Operations (Smith et al., 2020)

Based on the specific domain knowledge, a list of techniques (and corresponding features) were extracted for ice management scenarios. The specific knowledge included:

1. the participants' verbal explanations of their strategies and decision points,
2. the participants' observations and feedback on the cadets' performances, and
3. the participants' execution of scenarios in the simulator and their comments on their own performance.

These techniques are described in section 3.2.1.1.

Using the general domain knowledge captured from the participants, the reasoning structure of the CBR was developed. The reasoning part consists of the way the case-base data were indexed for similarity matching and case retrieval. The general domain knowledge was captured from three sources:

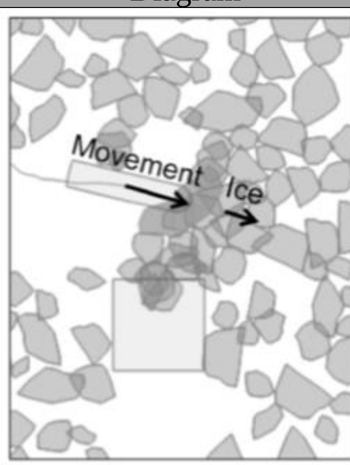
1. list of important ice management factors generated by participants and their rankings,
2. seafarers' comments about general ice management techniques, and
3. participants' comments about the rules that cadets followed or violated while performing scenarios.

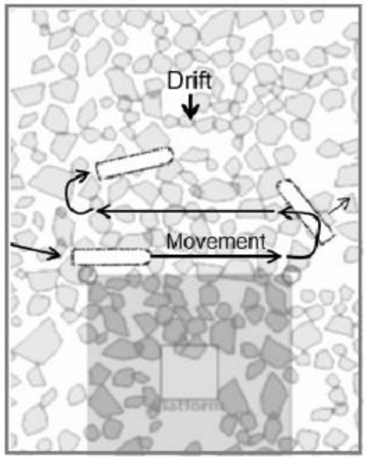
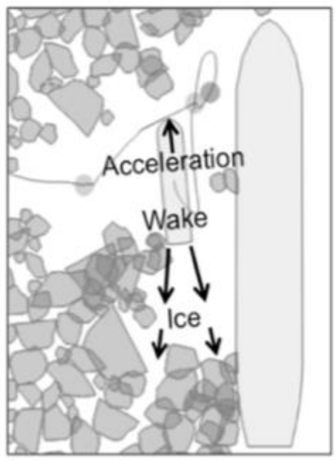
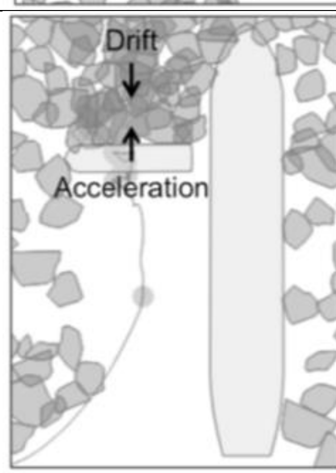
A list of factors and their rankings is illustrated in section 3.2.1.2.

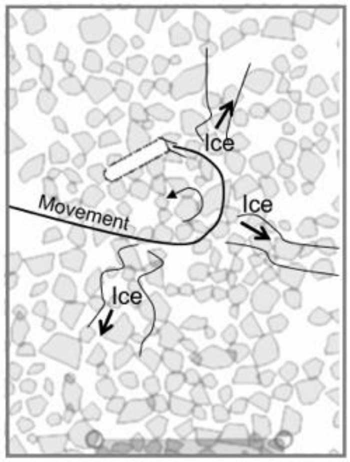
3.2.1.1.Ice Management Techniques Described by Participants

A list of techniques can be distinguished from the approaches that the participants used in the ice management scenarios. These techniques are shown in Table 3. A single technique or combination of these techniques was used by participants in each scenario in all experiments. For example, most participants in pilot and pre-pilot experiments preferred to use the combination of the leeway and prop-wash techniques in Sc.1 (leeway scenario).

Table 3 Ice Management Techniques Employed by Participants (Smith et al., 2020)

Technique	Diagram	Description
Pushing		Using the vessel's bow or broadside to clear ice around the indicated zone.

Sector		Using the vessel's bow or broadside and having a back and forth motion at the same time to clear the ice up-current from the zone.
Prop-wash		Maintaining a position above the zone and flushing the ice from the target using the vessel's propeller wake wash.
Leeway		Keeping the position above the target area and blocking the flowing ice using the vessel's broadside.

Circular		Using the combination of pushing and prop-wash techniques while having a circular motion above or around the target area.

3.2.1.2.Key Ice Management Factors and Rankings

As described in the method section, in the pre-pilot study, seafarers generated a list of important factors they consider during the ice management operations. They were also asked to explain the reason why those factors are important and rank them based on their priorities in different ice management scenarios. The list of some important factors and their ranks are shown in Table 4.

Table 4 Important Ice Management Factors and Their Ranks Based on Participants' Comments (Smith et al., 2020)

Category	Factors	Average Rankings			
		Initial	**Sc.1**	**Sc.2**	**Sc.3**
Task/ Objective	Area to be Cleared	4.0	4.0	4.0	4.5
	Level of Urgency	4.3	4.5	4.3	5.0
	Acceptable Level of Risk	3.8	3.8	4.0	4.0
Vessel Properties	Location Relative to Target Vessel	3.5	3.8	3.8	4.3
	Vessel Heading	2.8	4.0	4.3	4.5
	Vessel Speed	4.0	4.0	4.0	4.0
	Vessel Ice Class	4.0	4.0	4.0	4.0
Weather Conditions	Visibility and Weather Conditions	4.3	4.3	4.5	3.8
	Drift Speed (Current)	4.0	4.0	4.3	4.0
Ice Conditions	Floe Size	3.3	3.3	3.3	3.5
	Ice Type	3.5	3.5	3.5	3.5
	Ice Thickness	4.0	4.7	4.0	4.3
	Ice Loads	4.3	4.3	4.3	4.0

	Ice Concentration	4.3	4.8	4.3	4.0
Operator Characteristics and Actions	Experience	3.3	3.8	3.8	3.8
	Strategy	3.8	3.8	3.8	3.8

3.2.2. Knowledge Representation—Indexing Cases for Matching and Retrieval Using the Flat Memory Model

The flat memory model was used for the case memory knowledge representation. The purpose of indexing features and extracting common attributes that happened in the case base was to match similar cases with the attributes of future scenarios.

In total, five sources were used to build cases for the CBR case base. These sources include:

1. the participants' verbal explanations of their strategies and decision points from the pre-pilot and pilot experiments,
2. the participants' observations and feedback on the cadets' performances from the pre-pilot experiment,
3. the participants' execution of scenarios in the simulator and their comments on their own performance from the pilot experiment,
4. seafarers and inexperienced cadet's execution of scenarios in the simulator from Experiment 1, and
5. inexperienced cadets' execution of scenarios in the simulator from Experiment 2.

Among all these sources, number 4 and 5 contain the inexperienced cadets' execution. These sources were used because even if the cadets' performance is not as effective as experienced seafarers, a failed solution is an important piece of information. Using both successful and failed solutions could state what should be followed and what has to be avoided. Positive or successful experiences (cases) state ‘do it again’, and negative or failed experiences (cases) state ‘avoid this’ (Richter & Weber, 2013). The problems with inappropriate solutions (cases) were solved by adding a not recommended label to them and providing some tips to improve the approaches. These cases were explained in the result and discussion sections in more detail.

Considering all sources for building the case base of the DSS resulted in 180 cases. Table 5 shows the number of cases extracted, and the techniques used in each scenario and phase of experiments. As shown in this table, 30 cases from the pre-pilot study (24 cases from the interview and 6 cases from the evaluation and recommendations on the cadet examples), 10 cases from the pilot study, 18 cases from Experiment 1, and 122 cases from Experiment 2 were extracted.

Each case was an approach suggested by a participant or executed by them in the simulation to solve a specific scenario. For example, in the pre-pilot experiment, four participants attended and each of them suggested one or more approaches for Sc.1. As a result, in the pre-pilot study, 8 cases were extracted from four participants in Sc.1. Considering Sc.1, pre-pilot study, and interview approach section, the table shows that one approach appears to have consensus among the seafarers. The technique involved positioning the support vessel ahead of the tanker (or alongside ahead of the zone) using the vessel to create a leeway to block the pack ice from drifting into the zone and also using prop-wash to flush the pack ice (3 seafarers outlined 5 approaches using predominately this technique). Although all these five approaches have used a combination of leeway and prop wash techniques, they were considered as five different cases because these approaches are different in other attribute values (different values for aspect, area of focus, vessel heading, orientation, etc.). Three other approaches were suggested that followed conventional definitions of the techniques. One seafarer suggested the stationary/prop-wash technique, which involves maintaining a stationary position ahead of the tanker and using prop-wash to flush the pack ice (without any other techniques). Two other suggested approaches used the support vessel to block (lee) pack ice from drifting into the zone (without any other techniques).

All techniques that were used by participants in ice management scenarios were introduced before in Table 3.

Table 5 Summaries of Cases Collected from all Experiments

Phase		Technique	Total Case
Sc.1 Ice management alongside vessel to allow lowering of research equipment			
Pre-pilot	Interview Approach	Prop wash Leeway (x2) Leeway + Prop wash (x5)	8
	Cadet Example	Leeway + Prop wash Leeway	2
Pilot	Simulator Exercise	Prop wash Leeway Leeway + Prop wash	3
Experiment 2	Cadet Example	Prop wash (x2) Leeway (x33) Leeway + Prop wash (x8) Pushing + Prop wash (x6) Pushing (x4)	53
Sc.2 Ice management support for pack ice from around a platform			
Pre-pilot	Interview Approach	Pushing Prop wash Circular Sector Pushing + Prop wash (x3) Leeway + Prop wash	8
	Cadet Example	Circular Pushing	2
Pilot	Simulator Exercise	Pushing Prop wash Sector + Prop wash Leeway + Prop wash	4
Experiment 2	Cadet Example	Pushing + Prop wash (x7) Pushing (x20) Circular (x27)	54

Sc.3 Emergency Ice Management of FPSO create ice-free Lifeboat Launch zone			
Pre-pilot	Interview Approach	Pushing Leeway (x2) Prop wash Leeway + Pushing Leeway + Prop wash (x3)	8
	Cadet Example	Leeway + Prop wash Pushing + Leeway	2
Pilot	Simulator Exercise	Pushing Leeway + Prop wash (x2)	3
Experiment 1	Seafarer and Cadet Example	Pushing (x5) Leeway Leeway + Prop wash Pushing + Prop wash (x11)	18
Experiment 2	Cadet Example	Pushing (x4) Leeway (x3) Leeway + Prop wash Pushing + Leeway Pushing + Prop wash (x6)	15
		Total Cases	**180**

To design the real world situation, considering all aspects of a problem is not required, rather the aim is to find aspects that are relevant and helpful to find the problem's solution. Each experience as a case can be divided into two parts (Richter & Weber, 2013):

1. a problem part: describes a problem condition, and
2. a solution part: describes the way a person has reacted to solve the problem.

A solution can be described in various ways:

1. defining the solution in a narrow concept, or
2. defining the solution with additional detail, such as:
   a. comments, examples, and explanations,
   b. guidance on how to use the solution,
   c. mentioning effects of the solution used in the past, or

d. stating the strategies used to offer the solution.

The flat memory was used to represent a case using attribute-value (or feature-value) pairs. To present a case, a set of relevant attributes or features should be selected. For matching similar cases with the future scenarios' conditions, common features and characteristics of cases in the case base were categorized and indexed. Among all important factors collected from participants in pilot and pre-pilot experiments (Table 4 and Figure 18) The following features were extracted from the seafarer's verbal explanations in the interviews and their feedback on the cadets' examples:

- (F1) setting the aspect,
- (F2) area of focus for the ice clearing,
- (F3) approximate vessel heading,
- (F4) orientation of vessel to the target vessel,
- (F5) the specific vessel maneuvers for the technique,
- (F6) an estimate of the vessel speed
- (F7) an approximate distance from the platform,
- (F8) setting the vessel's controls (Rudder Angle, Engine, Thruster)
- (F9) the participant's priority ranking of the technique for the scenario and their rating of the cadets' performance in the examples.

Depending on the source of the data (i.e., interviews, simulation exercises, Experiment 1, or Experiment 2), details about the case features could vary. Some cases from the simulation exercises contained more information about features of a case than cases in the interviews. That means that participants in the interviews explained their strategies based on a static and ideal environment, while information from the simulator events is based on some parameters that cannot be considered in detail in interviews. Such features are

- (*F3) vessel heading,
- (*F5) vessel maneuvers,
- (*F6) vessel speed,
- (*F7) distance from target during clearing and the size of the clearing zone, and
- (*F8) setting the vessel’s controls.

Also, two other features were considered important to evaluate the result of each performance in the simulator. These features are

- (*F10) the change in ice concentration in the target zone and
- (*F11) estimate of the ice loads endured by the vessel.

There is no value available for the ice load feature in the cases. Also, the ice concentration feature was calculated based on the simulation exercise outcome when they were analyzed. Cases captured from the interview did not contain this feature. Therefore, these two features were not used for case retrieval purposes, but they could be used in the CBR retain procedure (Figure 1) when a case should be added to the case base as a positive or negative case.

To illustrate the indexing, two cases of the Sc.1 described by participants were illustrated in Figure 19.As shown in the figure, the approach that the participant defined in the interview (N12) represents the technique under static and ideal circumstances and provides an approximate value for some features like the vessel speed and heading. However, the simulator data (NR49) provides the exact amount of some features that cannot be explained in detail during the interview.

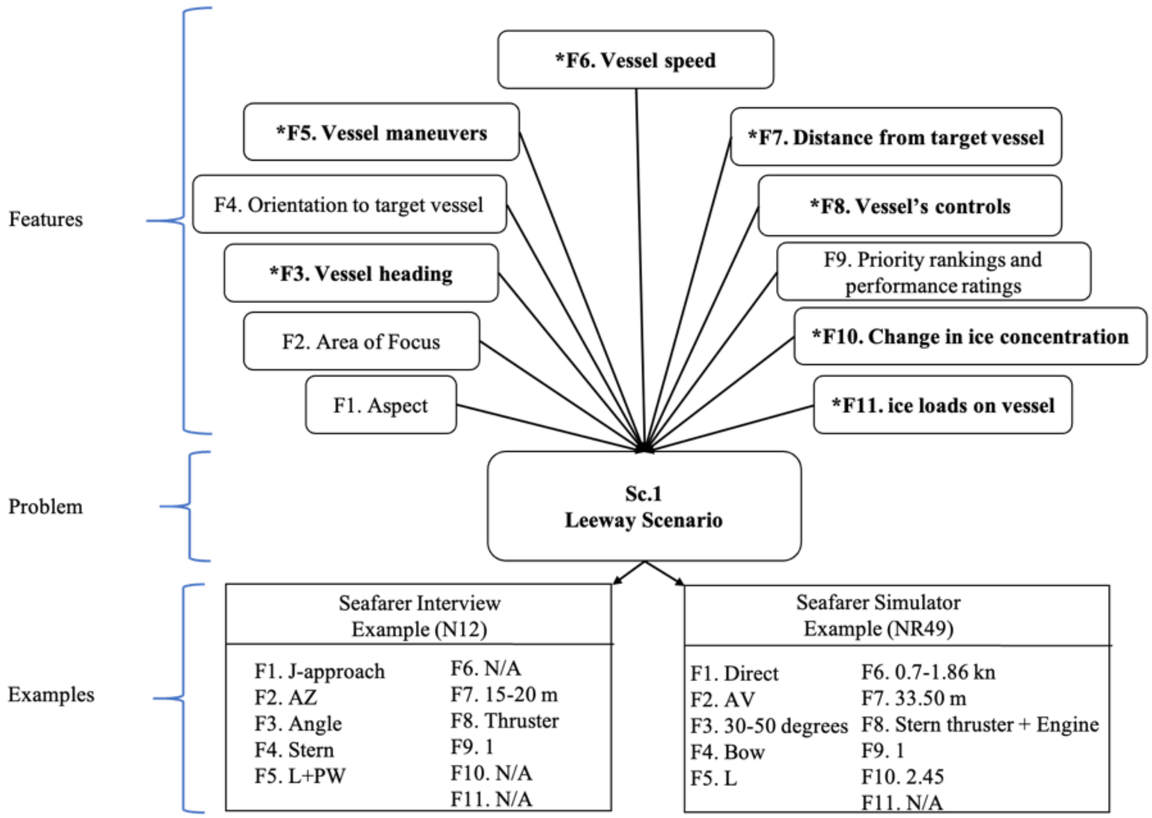


Figure 19 Case Indexing for the Leeway Scenario

The indexing process was repeated for all cases, and they were saved as a CSV file. After creating all cases, they were classified based on the important factor ranks (Table 4), participants' verbal explanation, and the technique used to approach a scenario. In fact, each case was divided into a problem part and a solution part. For each case, the technique was considered as the solution part, and the rest of the features were assigned to the problem part. Therefore, the vessel maneuvers or techniques were considered as the class labels, and samples were grouped for which participants used the same technique. For example in Sc.1, 'L+PW' (which was a vessel maneuver or technique and considered as a solution) was assigned to Class ID = 1, 'P+PW' was assigned to Class ID = 3, and so on. In total, 5 classes for Sc.1, 7 classes for Sc.2, and 6 classes for Sc.3 were detected. Table

6 illustrates an example of cases organized using the flat memory model. This table consists of a list of attributes of a problem and their values and solutions for six cases.

Table 6 Flat Model Representation of CBR Case Base

Attributes	**Sc.1**		**Sc.2**		**Sc.3**	
Participant/case ID	V05-12	A48-1	NM81-2	G69-22	Z11-3	Y93-3
Aspect	Direct	Direct	Upcurrent	Direct	J-approach	J-approach
Area of focus	AV	Z	AZ	Z	Z	Z
Vessel heading	Angle	Perpendicular	Angle	Angle	Angle	Stem
Orientation	Stern	Stern	Stern	Rotating	Bow	Bow
Vessel speed	Safe	0.74	Safe	1.44	1.16	0.78
Distance	30	34.56	112.5-150	29.8	59.13	36.97
Vessel's controls	Port engine + Rudder	Thruster	N/A	Engine + Rudder	N/A	Engine
Priority Ranking/ performance rating	2	N/A	3	N/A	N/A	N/A
Vessel maneuver (solution)	L+PW	P+PW	L+PW	C	P	P+PW
Class ID	1	3	3	6	1	4

3.3.DSS Development

The information gathered from expert knowledge was transformed into a case base to develop a decision support technology. This information was integrated into a decision support system to provide seafarers with onboard guidance in real-time. To provide real-time assistance to a participant while implementing a scenario in the training simulator, the DSS should extract common features (F1-F4, and F6-F8) from the simulation data to retrieve a similar case and suggest a solution. Also, after completion of the execution F10 and F11 should be analyzed for further evaluation (retain a case). Figure 20 provides a depiction of the procedural steps for the DSS. As shown in the figure, there are two important steps for retrieving similar cases to new problems. The key steps include

1. feature extraction, and
2. applying a retrieval method (similarity matching).

The following subsections will describe the development of DSS in more detail.

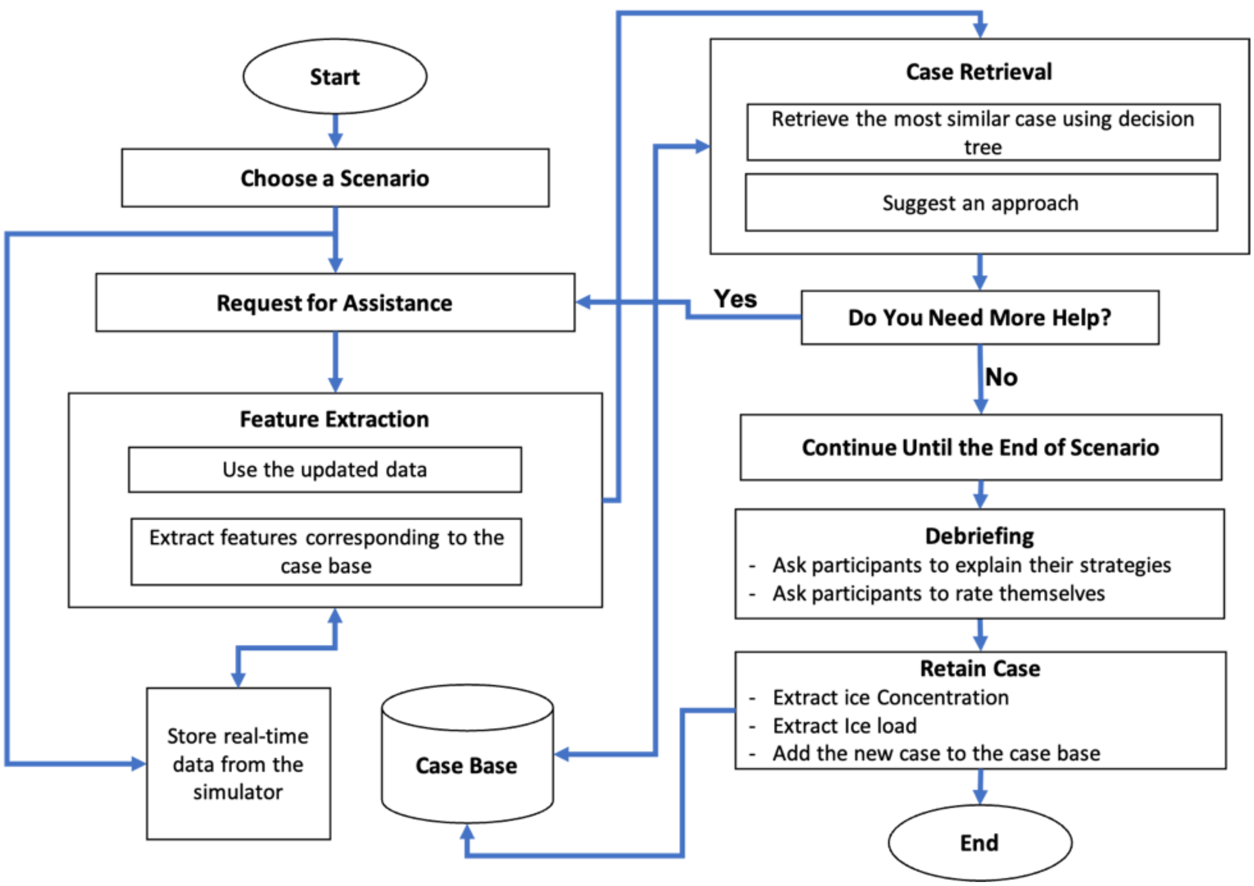


Figure 20 DSS Procedure

3.3.1. Feature Extraction

The DSS assists decision-makers by providing them with similar cases that have already been solved by experienced seafarers. In order for the DSS to suggest a similar case, the DSS extracts common features from the simulation data and retrieves an expert solved case that matches the conditions of the new situation.

The DSS requires real-time data from the simulator to extract or calculate the common features. So, As shown in Figure 20, the real-time data from the simulator will be stored to be used for feature extraction. The data collected from the simulator log file include the follow metrics:

- Scenario Time,
- Speed Over Ground (SOG),
- Longitude,
- Latitude,
- Heading,
- Coarse Over Ground (COG),
- Port and Starboard Rudder Angle,
- Port and Starboard Engine,
- Fore and Aft Thruster, and
- Ice Load.

As shown in Table 7, some of the parameters recorded in the simulator can be used directly by the DSS and others must be converted to features that the DSS can interpret. These features and how they were extracted from the real-time data were explained in detail in the following sections.

Table 7 Features to Extract from Simulator Log Files

Feature	Simulator output needed for calculation of a feature	Conversion
Features can be input directly from the simulator log files		
F3-Vessel Heading	Vessel Heading	Vessel heading in relation to target (Stem, Perpendicular, Angle, Rotating)
F6-Vessel Speed	Speed Over Ground (SOG)	Identify if seafarer is using safe speed (<3knots)
F8-Vessel's Controls	Control Outputs Fore/Aft Thruster Port/Star Engine Port/Star Rudder	Identify if seafarer is using thruster, engine, and/or rudder
F11-Ice Loads	Ice loads on 'Ownship'	Ice load
Features must be calculated from the simulator log files		
F1-Aspect	Latitude/ Longitude Vessel Heading	Vessel pathway in relation to target (J-approach, Direct, Upcurrent)
F2-Area of Focus	Latitude/ Longitude	Where seafarer is focusing most of the ice clearing time (AZ, AV, Z)
F4-Orientation of Vessel	Latitude/ Longitude Vessel Heading	Vessel orientation in relation to target (Bow, Stern, Parallel, Changing)
F7-Distance from Target	Latitude/ Longitude	Vessel distance from target vessel
F10-Ice concentration	Instructor Station View of Zone	Screen captures of zone before ice management and during ice management

3.3.1.1.Features from Simulator Log Files

The DSS can use four parameters from the simulator log files directly as features (Table 7). Features for the DSS that can be input directly from the log file include

- F3- Vessel Heading: Based on the cases in the case base that have already been solved by experienced seafarers, the vessel heading can have four different options:

    a. Stemming the condition (making headway against the current) (0 degrees)

b. Perpendicular to the target (90 degrees)

c. Angle (all other degrees but not changing during the execution)

d. Rotating (in the case of the circular technique, the heading changes constantly, so it was converted to the rotating option)

Since the vessel heading is accessible directly from the log file, the only needed processing is to convert the continuous heading values into categorical outputs. Figure 21 shows all headings options.

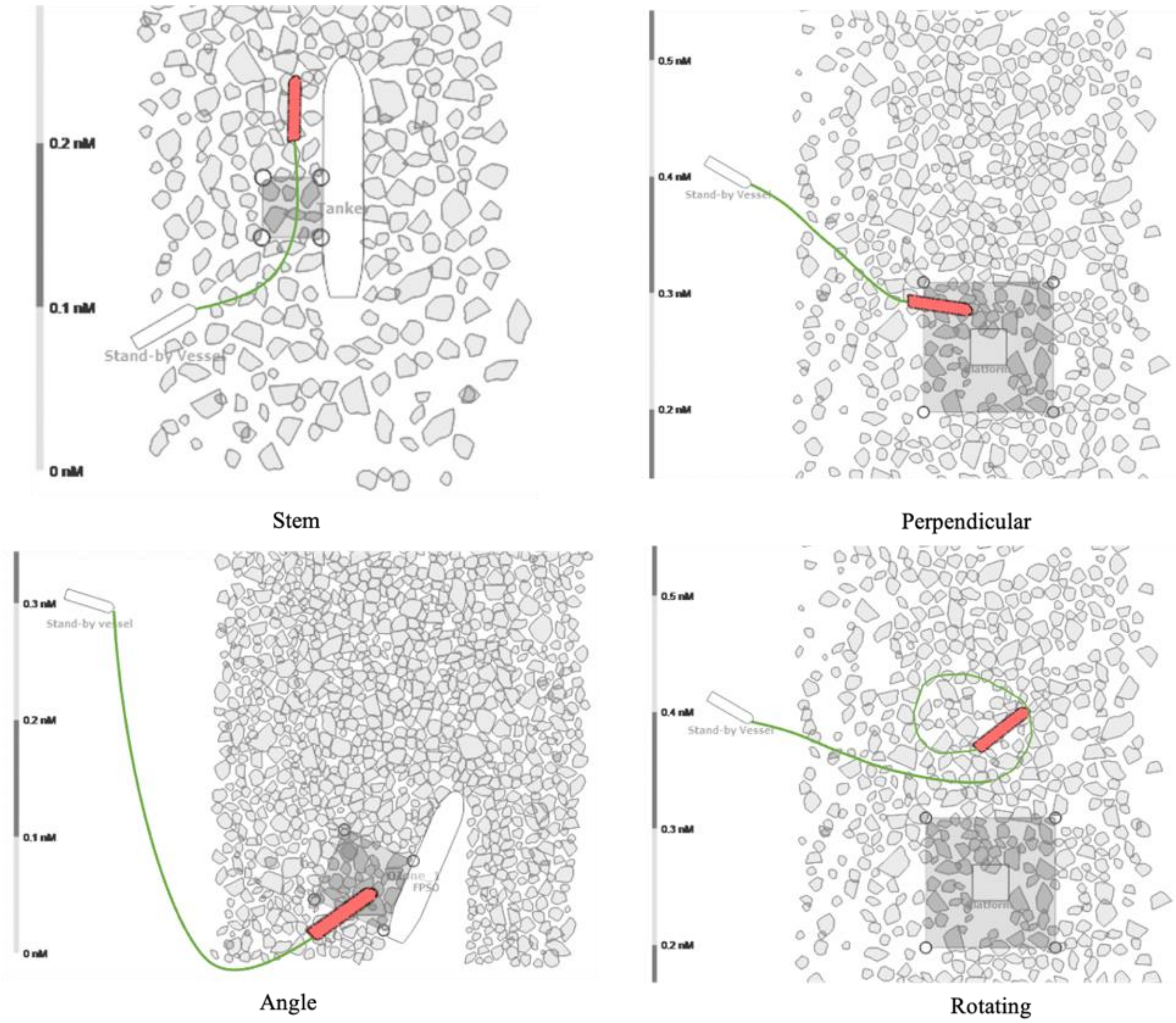


Figure 21 Heading Options

- F6- Vessel Speed: The only thing that should be considered about speed is identifying if seafarers are using a safe speed (<3 knots) because not all of the cases in the case base have a specific value for the speed feature. Consequently, the continuous value of the speed should be converted to the safe or dangerous speed.
- F8- Vessel's Controls: This feature could be used directly from the log file to see what vessel's properties are using for the vessel's maneuver. For example, rudders are used to turn the vessel to either side.

- F11- Ice Load: Ice load could be used directly from the log file. This feature was not used for retrieval purposes and did not need more processing. It will be considered as a threshold to identify if a case should be considered positive or negative in the retain procedure.

3.3.1.2.Converting Features

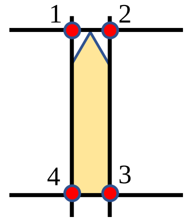
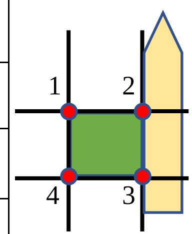
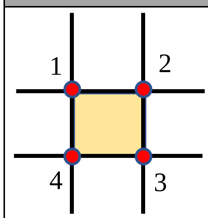
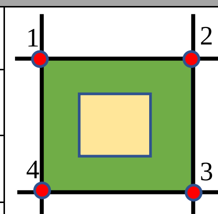
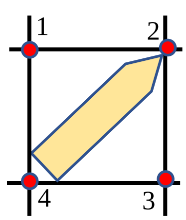
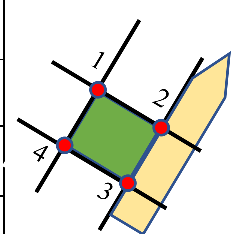
According to Table 7, some features needed to be calculated from the simulator log files (aspect, area of focus, orientation of vessel, vessel maneuver, distance from target, and ice concentration). Before extracting these features, two other features that were beneficial to compute were identified and are explained in sections 3.3.1.2.1 and 3.3.1.2.2. The two features are

1. ownship vessel's position, and
2. threshold for the heading.

3.3.1.2.1. Ownship Vessel's Position in Relation to the Target and the Zone

To calculate many of the DSS features the position of the 'Ownship' was required to be detected. Therefore, the position of the 'Ownship' vessel with respect to the target and the identified zone that needed to be clear was calculated using their latitude and longitude. Table 8 shows constant points extracted from the simulator to detect the 'Ownship' vessel's position. Using these points, different areas were detected for each scenario (Figure 22 and Figure 23). The 'Ownship' vessel's position then was used to calculate other common features more accurately.

Table 8 Simulator Points to Calculate the Ownship Vessel's Position

		Points for the Target			Points for the Zone	
		Latitude	Longitude		Latitude	Longitude
Sc.1						
	1	60.51039	146.35159		60.50914	146.35285
	2	60.51039	146.35074		60.50914	146.35162
	3	60.50790	146.35074		60.50853	146.35162
	4	60.50790	146.35159		60.50853	146.35285
Sc.2						
	1	60.51049	146.35544		60.51117	146.35678
	2	60.51049	146.35435		60.51117	146.35299
	3	60.50997	146.35435		60.50930	146.35299
	4	60.50997	146.35544		60.50930	146.35678
Sc.3						
	1	60.51833	146.35961		60.51773	146.36102
	2	60.51833	146.35749		60.51731	146.35900
	3	60.51614	146.35749		60.51624	146.35993
	4	60.51614	146.35961		60.51667	146.36194

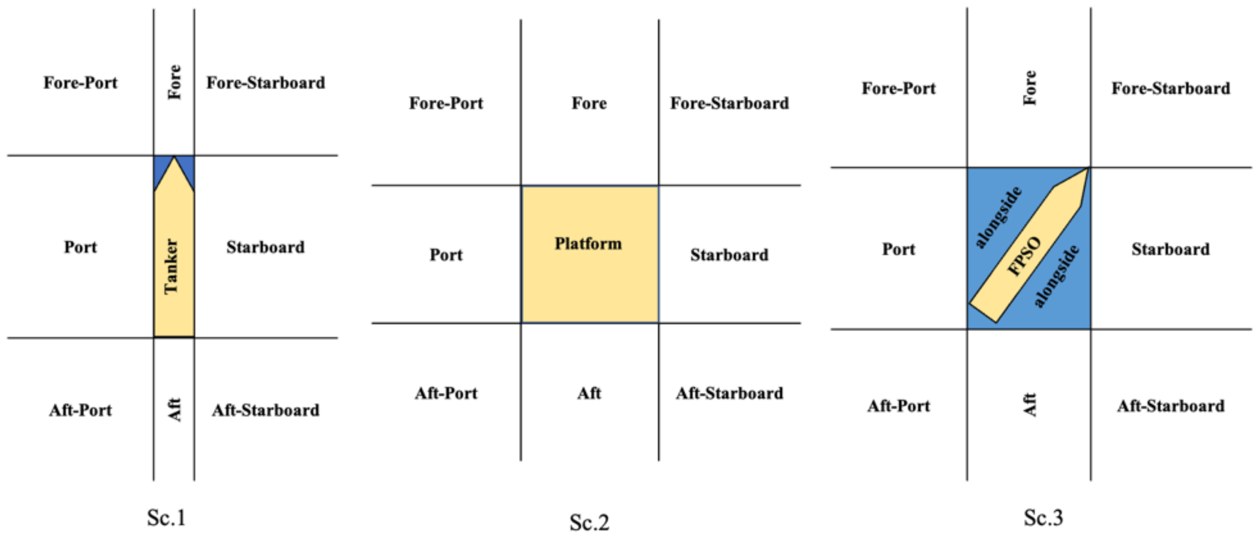


Figure 22 Determining the Ownship Vessel's Position Relative to the Target

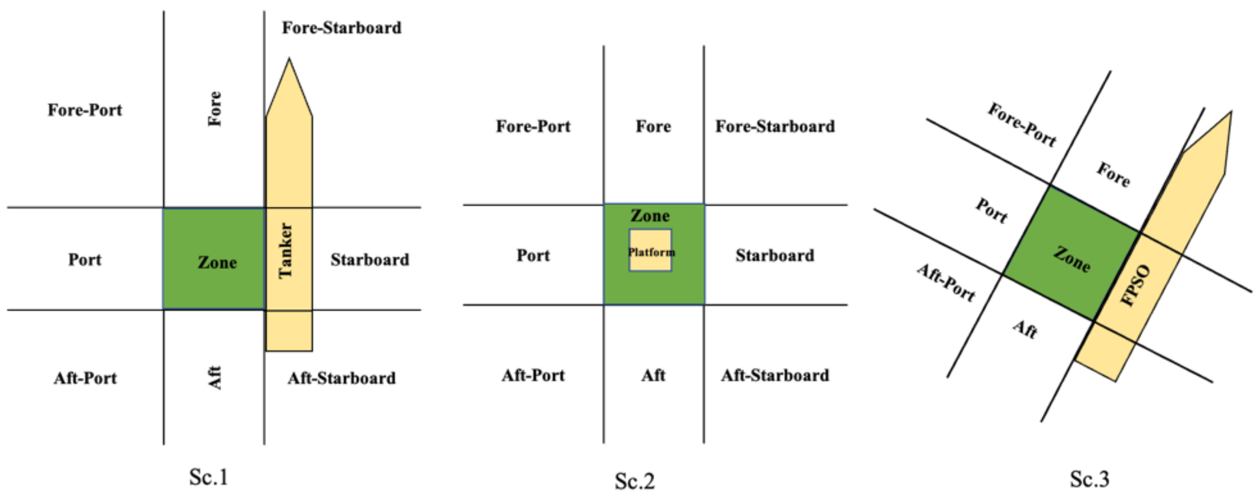


Figure 23 Determining the Ownship Vessel's Position Relative to the Zone

3.3.1.2.2. Threshold for the Heading

Some of the DSS features require a threshold to indicate if the heading of the 'Ownship' vessel is between the threshold. Figure 24 indicates down range and up range of the threshold. α is an angle between the own vessel and a point located on the top of the target according to the trigonometric circle, and θ is an angle between the own vessel and a point located on the bottom of the target according to the trigonometric circle. As shown in Table 9, different points of the target were considered to calculate α and θ according to the position of the ownship in relation to the target.

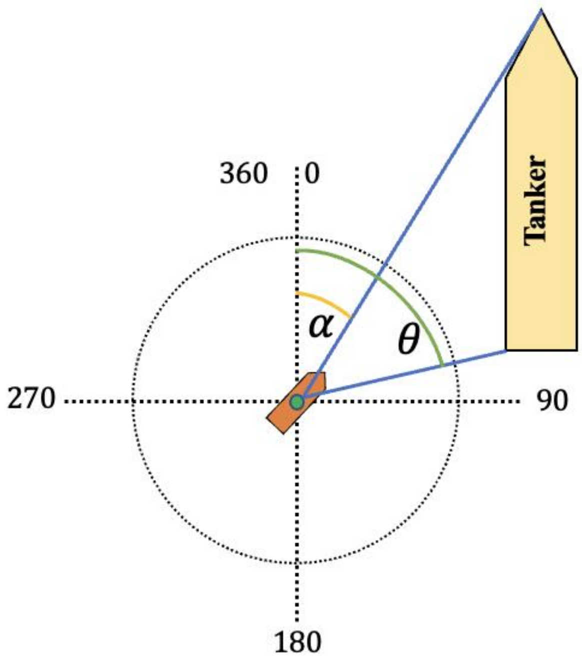
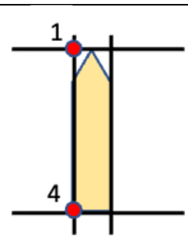
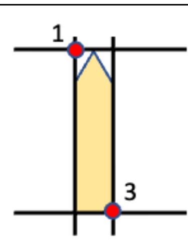
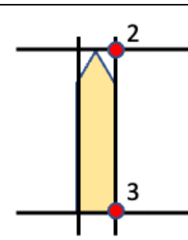
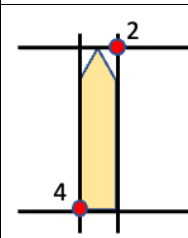
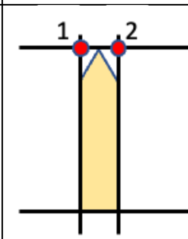
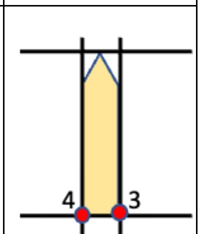
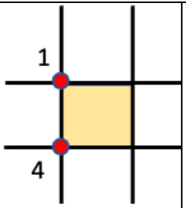
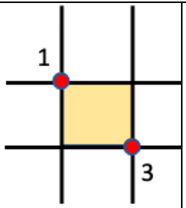
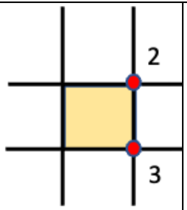
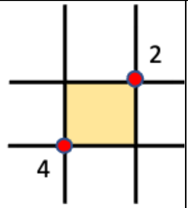
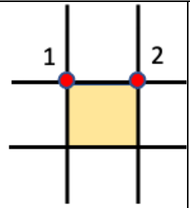
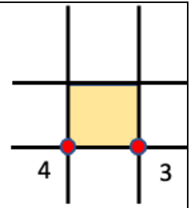
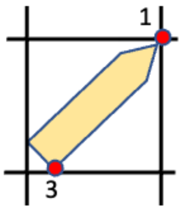
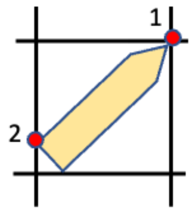
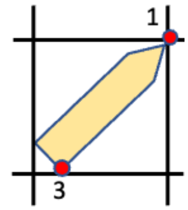


Figure 24 Heading Thresholds

Table 9 Different Points to Calculate Alpha and Betta

Sc.1						
position	Port Fore-Port	Aft-Port Fore- Starboard	Starboard	Aft- Starboard	Fore	Aft
points						
Sc.2						
position	Port	Aft-Port Fore- Starboard	Starboard	Aft- Starboard Fore-Port	Fore	Aft

points						
Sc.3						
position	Port Aft-Port		Fore-Port Fore Aft Alongside		Starboard Fore-Starboard Aft-Starboard	
points						

As shown in Figure 25, to calculate α and θ, Equation 10 and Equation 11 were used.

$$\beta = \tan^{-1}\frac{Y_b - Y_a}{X_b - X_a}, \alpha = 90 - \beta$$

Equation 10 Angle between the own vessel and a point located on the top of the target

$$\gamma = \tan^{-1}\frac{Y_d - Y_c}{X_d - X_c}, \theta = 90 - \gamma$$

Equation 11 Angle between the own vessel and a point located on the bottom of the target

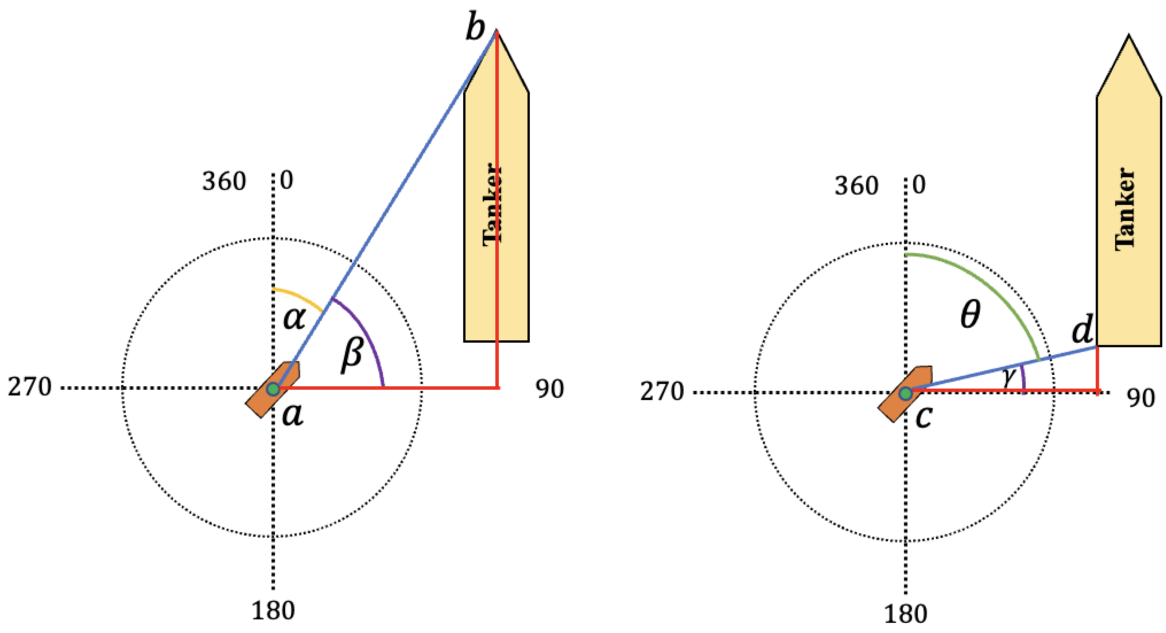


Figure 25 calculation of Angles

Different values for α and θ depending on the ownship's position in relation to the target are listed in Table 10. As shown in the table, once the ownship is located in the target's aft, θ is downrange, and α is up range.

Table 10 Different Ranges for $\boldsymbol{\alpha}$ and $\boldsymbol{\theta}$ to Calculate the Heading Threshold

Ownship's position in relation to the target	α	θ	Downrange	Up range
Sc.1 and Sc.2				
Port	$90-\beta$	$90+\gamma$	α	θ
Starboard	$270-\beta$	$270+\gamma$	α	θ
Fore	$90+\beta$	$270-\gamma$	α	θ
Aft	$270+\beta$	$90-\gamma$	θ	α
Fore-Port	$90+\beta$	$90+\gamma$	α	θ
Fore-Starboard	$270-\beta$	$270-\gamma$	α	θ
Aft-Port	$90-\beta$	$90-\gamma$	α	θ
Aft-Starboard	$270+\beta$	$9270+\gamma$	α	θ

Sc.3				
Alongside	$90 - \beta$	$270 - \gamma$	α	θ

α and θ in the simulator had different values than the amounts that were calculated by the equations. Equation 10 and Equation 11 required (x, y) coordinates of two points for calculating the angle, while the longitude and latitudes of the points were available in the simulator. Using longitude and latitudes of the points in the equation resulted in some differences in the angles. So the differences between angles calculated by the equation and the simulator was due to the different metric units. Table 11 illustrates the angle differences in the equations and the simulator. Using these angles, a cubic equation in Figure 26 was calculated for translation of angle differences. Based on Equation 12, the angles were converted to desired ones, and appropriate α and θ were computed. Then these thresholds were used to extract some common features.

Table 11 Difference Between Angles in Simulator and Equations

Angle in the simulator	Angle according to the equation
89.20	88.45
88.39	86.90
83.53	78.34
69.98	53.47
56.77	36.93
43.53	25.10
32.69	17.60
22.53	11.57
14.22	7.15
2.86	1.47
1.74	0.85
0.70	0.38

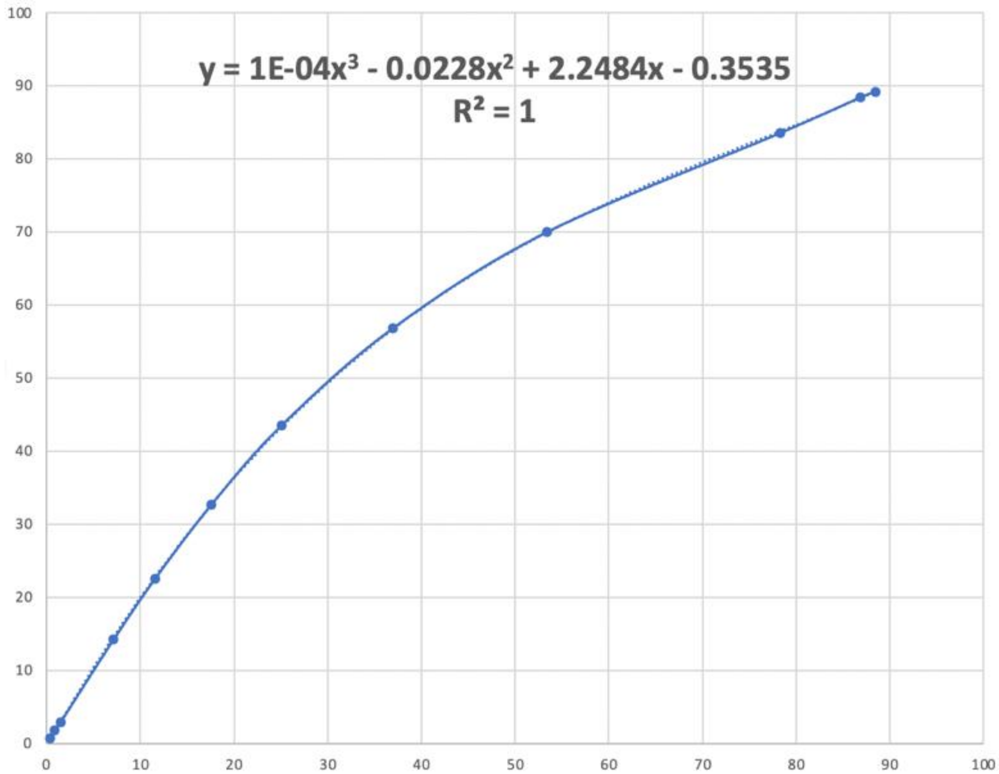


Figure 26 Cubic Equation Using Angles in Simulator and Equations

$$y = 10^{-4}x^3 - 0.0228x^2 + 2.2484x - 0.3535$$

Equation 12 Cubic Equation for Changing Angles

The DSS should convert some parameters from the simulator log files into features (Table 7). Features for the DSS that should be calculated from the log file include

- F1- Aspect: this feature shows the vessel pathway in relation to the target. Based on cases in the case base that were obtained from the participants' techniques in the interview or participants' action in the simulation exercises, three values were assigned to the aspect:

1. J-approach: getting close to the target from below the zone
2. Direct: getting close to the target directly

3. Up-current: getting close to the target from up-current of the target (Figure 27)

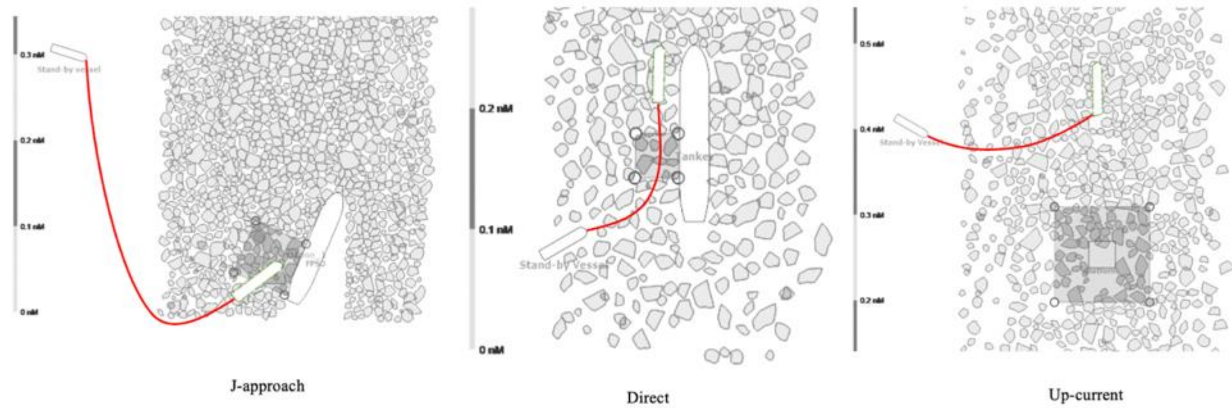


Figure 27 Aspect Options

To calculate this feature from the log files, the heading of the ownship vessel was compared to the thresholds (α and θ) that were calculated in section 3.3.1.2.2 using latitude and longitude of the vessels. Since the aspect shows how the ownship is moving toward the target, this feature will be calculated at the beginning of each participant's performance and does not change during the operation. Based on the starting position of the ownship vessel in each scenario, the aspect will be calculated in the first 3 minutes of each operation and will be used until the end of the scenario. Accordingly, If the heading of the ownship was more than the up range of the threshold (mostly θ and in some cases α), the aspect was considered as J-approach. If the heading of the ownship was between α and θ, the aspect was considered as Direct. Finally, if the heading of the ownship was less than the downrange of the threshold (mostly α and in some cases θ), the aspect was considered as Up-current.

- F2- Area of focus: this attribute was considered for identifying where the seafarers are spending most of their time clearing the ice. Based on cases in the case base, the values for this attribute can vary, including:

  1. above the zone (alongside the target),
  2. above the vessel or target, and
  3. in the zone (Figure 28).

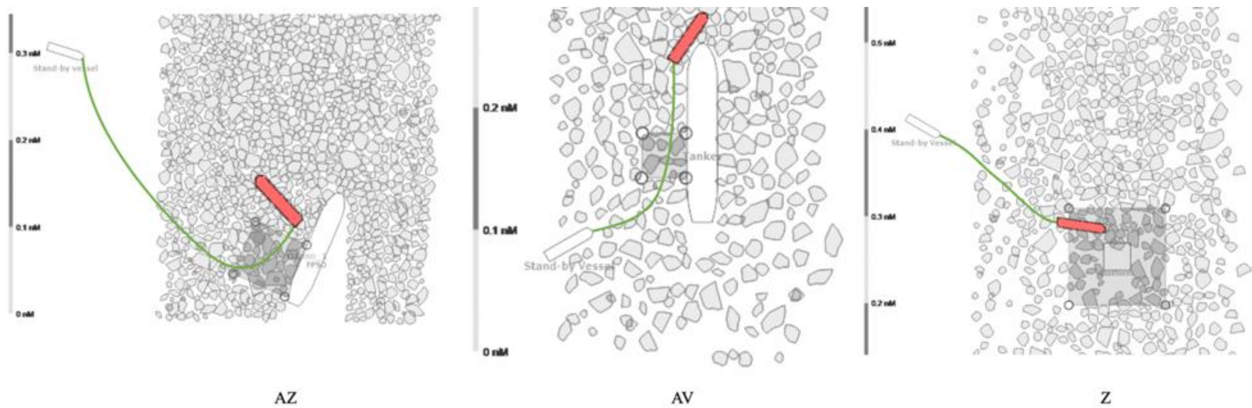


Figure 28 Area of Focus Options

The latitude and longitude of the ownship vessel were utilized to calculate this feature from the log file. First, based on the explanation in section 3.3.1.2.1, the ownship vessel's position with respect to the target and the zone was considered in each timestamp. Then, the position that occurred more than others during the operation was detected and assigned to above the zone (AZ), above the vessel (AV), or in the zone (Z).

- F4- Orientation to the target vessel: this feature determines the ownship vessel's orientation in relation to the target. Based on cases in the case base, this attribute has four options:

  1. ownship vessel's bow facing the target

2. ownship vessel’s stern facing the target
3. ownship is parallel with the target,
4. ownship’s orientation is constantly changing (this case occur when the circular technique is used) (Figure 29).

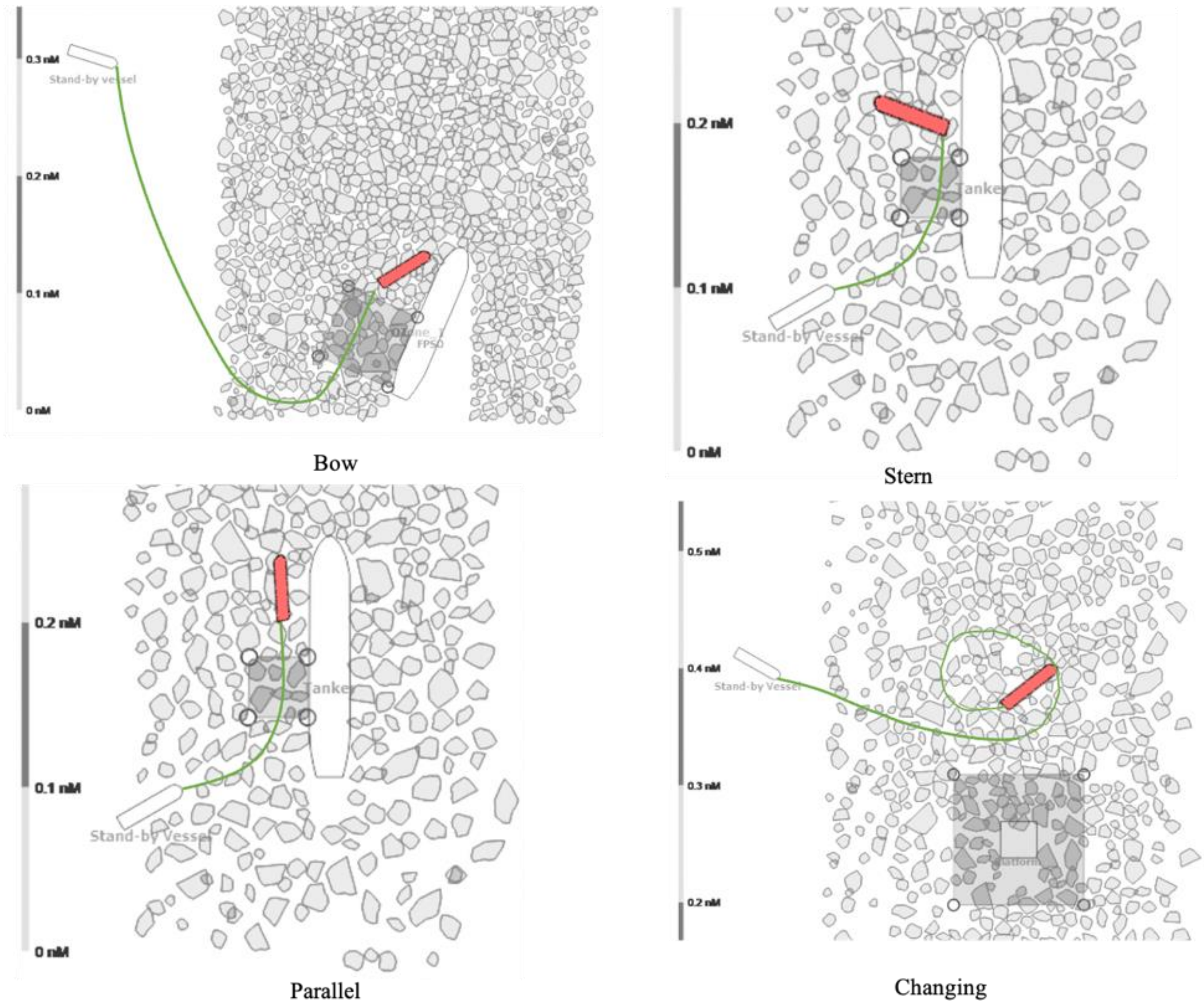


Figure 29 Orientation of Vessel’s Options

The heading, latitude, and longitude of the ownship vessel from the log file were utilized to calculate this feature. If the circular technique was used by the participant, the orientation was assigned to Changing. The parallel option was checked using the vessel heading, the scenario type, and the vessel's position. Finally, using the explanation in section 3.3.1.2.2, α and θ thresholds were calculated to create an interval. If the ownship vessel's heading is in between this interval, the ownship vessel's bow is facing the target. Otherwise, the vessel orientation will be assigned to Stern.

- F7- Distance from the vessel: this feature shows how far the ownship vessel is from the target. For calculating this feature, the latitude and longitude of the target and ownship vessel were used. Using the position of the ownship vessel in relation to the target several points were used to calculate the distance.

  For example, as shown in Figure 30, if the ownship vessel is near the top of the target, its distance from the top point is calculated. If it is in the middle of the target, its distance from the center point of the target is considered. Otherwise, if the ownship vessel is close to the bottom of the target, its distance from a bottom point on the target is used.

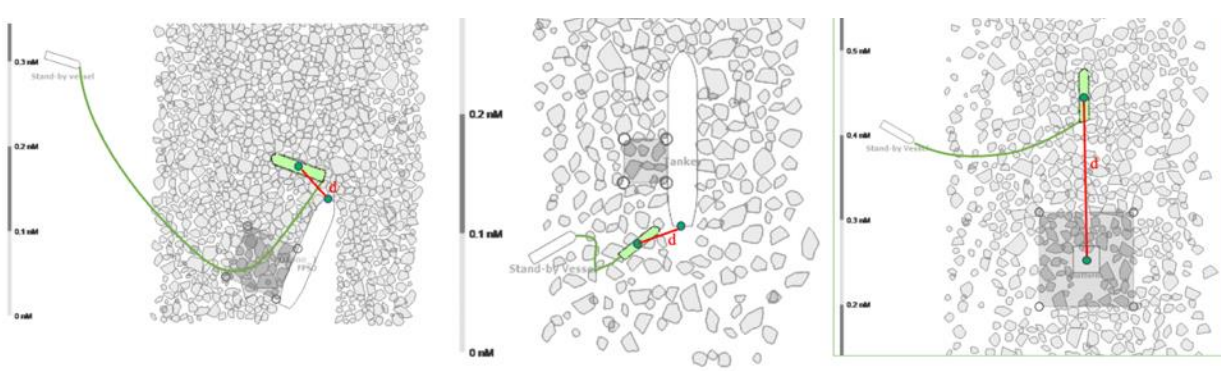


Figure 30 Distance from the Target Example

- F10- Ice Concentration: This feature was not used for retrieval purposes. It was considered as a threshold to identify whether a case should be considered positive or negative in the retain procedure. So, this step could be seen as a post-processing step for the retaining process in the CBR and was obtained using Experiment 2 scripts (Thistle, 2019). For computing this feature, screen captures of the zone before ice management and during ice management scenarios were taken. Using these images, the amount of ice that was removed from the indicated area was calculated automatically using the MATLAB scripts.

3.3.2. Decision tree development as a retrieval method used in the DSS

A decision tree generates a tree from the case base with defined classes characterized in terms of certain attributes (Musharraf et al., 2020). Given the case base shown in Table 6, for each case, the technique was considered as the solution part, and the rest of the features were assigned to the problem part. Therefore, the vessel maneuvers or techniques were considered as the class labels, and samples were grouped for which participants used the same technique.

The training case base was fed to the decision tree algorithm to fit a model. Considering these data as a set of attributes (A_1, A_2,…, A_n), values ([V_{11}, V_{12}, …, V_{1k}], [V_{21}, V_{22}, …, V_{2k}], …, [V_{n1}, V_{n1}, …, V_{nk}]), and classes (ID_1, ID_2, …, ID_m), the decision tree model could be shown in Figure 31.

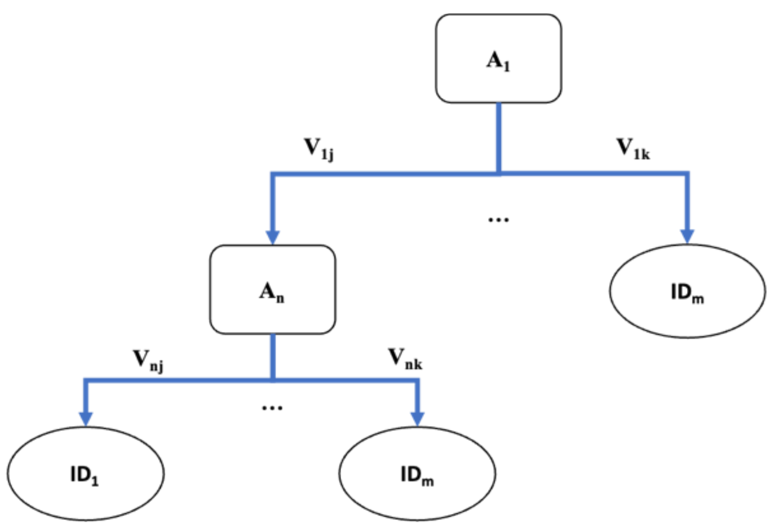


Figure 31 Classifying Cases Based on the Characteristic of Attributes (Musharraf et al., 2020)

This model could be used any time to retrieve the most similar class to a new case. To create such a model, the CART algorithm - a classification and regression tree - was utilized. As shown in Table 6, the case base consisted of numerical and categorical variables. The CART algorithm is capable of handling these two kinds of variables.

Once the generated model determined the class of the new case, it is time to specify which sample of the class is the most similar paired attribute-value to the new case using a similarity metric. Cosine similarity was used in this thesis among different similarity metrics, such as Euclidean and Manhattan. Since the magnitude of the new case vector does not matter in this study, Cosine similarity is an appropriate metric for measuring distance.

In the next chapter, more details about generating the decision tree using the training data set and prediction accuracy using the test data set are discussed.

3.4.Smoke testing

Smoke testing is a software testing process to evaluate software functionalities, and it involves a number of tests run to confirm the stability of the software. In fact, the purpose of smoke testing is to reveal if the software has functionality and works properly to be used for further works by the research team (Gerardi, 1984). To determine whether the designed DSS is stable or not, smoke testing was implemented in the ice management simulator.

The procedure followed for testing the DSS is demonstrated in Figure 32. The outline of this experiment is shown in Appendix Q: DSS Testing Session Outline.

In addition to the steps mentioned in the procedure, one of the researchers was responsible for loading and initiating scenarios in the simulator, screen capturing scenarios every three minutes, saving data collected from the scenarios, and communicating with seafarers during the simulation exercise via VFH radio.

The whole process of this test was somewhat similar to the pilot session, but the DSS was added to it. At the beginning, the participant completed the experience questionnaire (Appendix R: Experience Questionnaire) to collect information about the participant's experience at sea and/or sea ice. This data was used later to see whether the DSS causes a considerable difference in ice management effectiveness once participants have different amounts of experience. In the setup, the simulator's environment and controls were shown to the participant, and different parts of the simulator's bridge console were explained to them (Appendix P: Introduction to Controls Script). Then, the participant was shown the DSS user interface and how it works. A description of the user interface used in the experiment was explained in section 3.4.1. The setup lasted about twenty minutes.

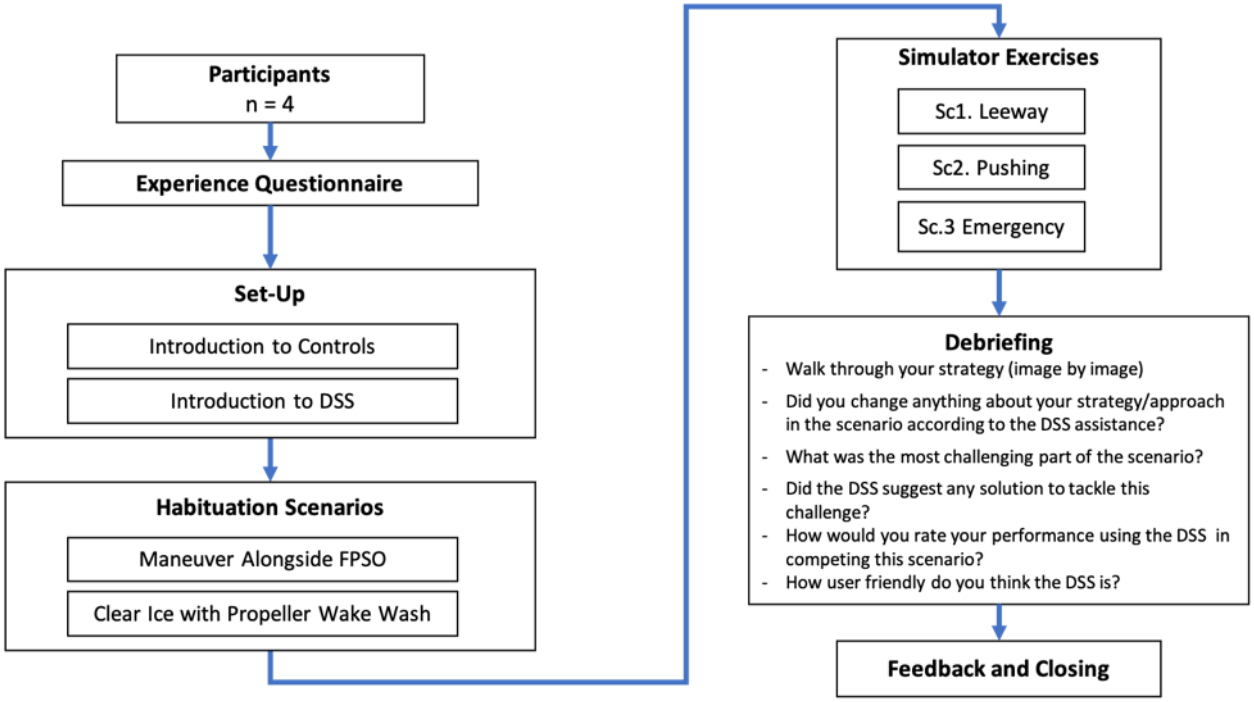


Figure 32 Experimental Procedure Flow Chart for the DSS Testing

As shown in Figure 32, the next step was explaining the habituation scenarios and asking the participant to conduct them in the simulator. The habituation scenarios took approximately 15 minutes to complete.

In the next step, the participant entered the simulator and completed the first exercise using the DSS. Anytime that the participant asked for assistance, the time of the request and the suggested cases were saved into the DSS for further analysis. After completing the first exercise, the participant returned to the debriefing station, and the debriefing was performed.

During the debriefing, researchers showed the screen captures of the scenario (captured by researchers while execution) to the participant and asked the seafarer to explain their strategies and any changes in their execution based on the DSS suggestion, if there were any. The debriefing questionnaire is provided in Appendix S: Debriefing Questionnaire for the DSS Testing.

At the end of this phase, the participant rated their performance using the DSS on a scale from 1 to 5, where one was not very successful, three was somewhat successful, and five was very successful.

Similarly, all steps, including simulator exercises, and debriefing were repeated for the other two scenarios. At the end of the session, the participant answered some closing questions about the user-friendliness of the DSS and how the system could be improved (Appendix T: Exit Interview for the DSS Testing). The whole session lasted approximately two hours.

3.4.1. DSS User Interface

The user interface of the DSS is shown in Figure 33. To operate the DSS, the participant was first asked to choose the scenario that they planned to complete. In the first frame of the DSS, the user is provided with some information about the available scenarios, such as a diagram of each scenario, each scenario's objectives, and the allocated time for executing each scenario.

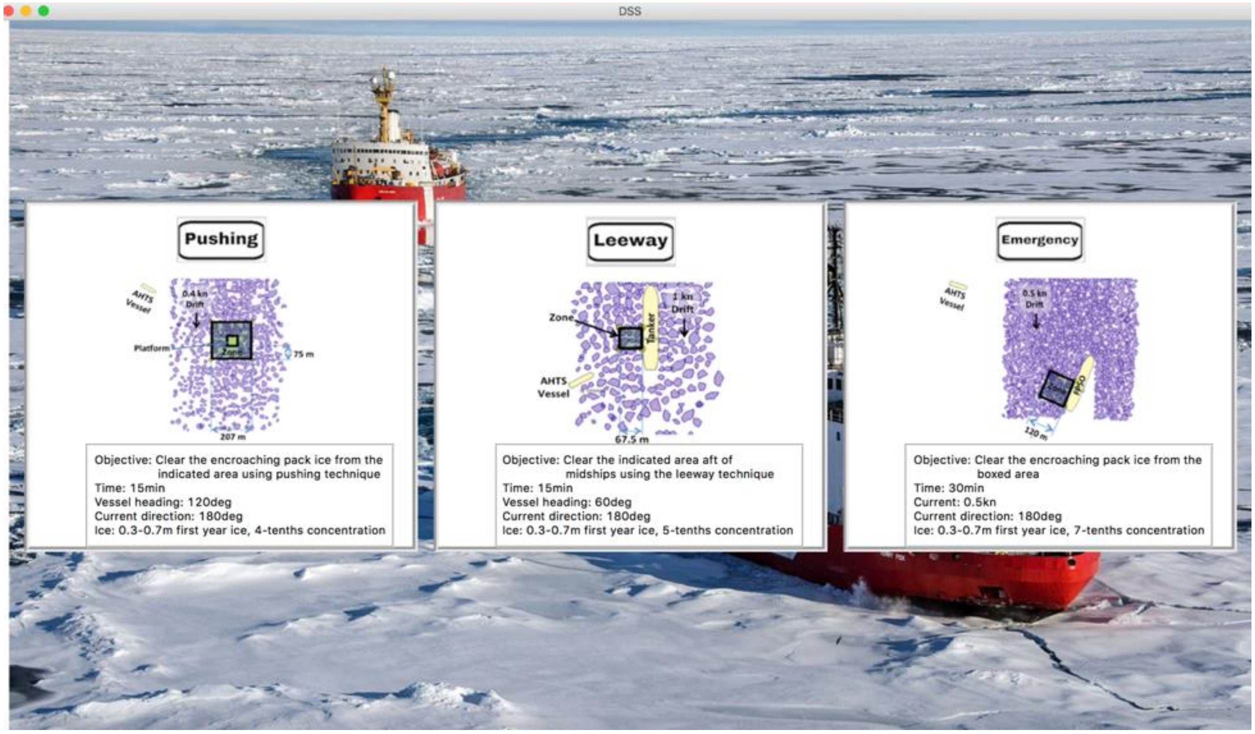


Figure 33 DSS User Interface

After choosing a scenario, the participant is shown a second frame, as illustrated in Figure 34. The following are the different components in the second frame:

- Back to Main Menu: this button lets the participant return to the first frame to choose a different scenario.
- Ownship Properties: in this section, the ownship vessel's features will be shown. These features are used to retrieve similar cases from the case base. At the beginning of the participation, some of the feature values are null, but they can be calculated during the scenario. As such, the values of these features will be updated after a few minutes of running the scenario.

- Assist button: this button activates the Suggested Solution and Suggested Approach frame, meaning that the features and the diagram of the most similar case will be shown on the screen.
- Suggested Solution: the features of the most similar case will be displayed.
- Suggested Approach: the suggested diagram of the retrieved case will be shown.
- More Info: this button provides a more detailed description of each solution and the suggested approach.

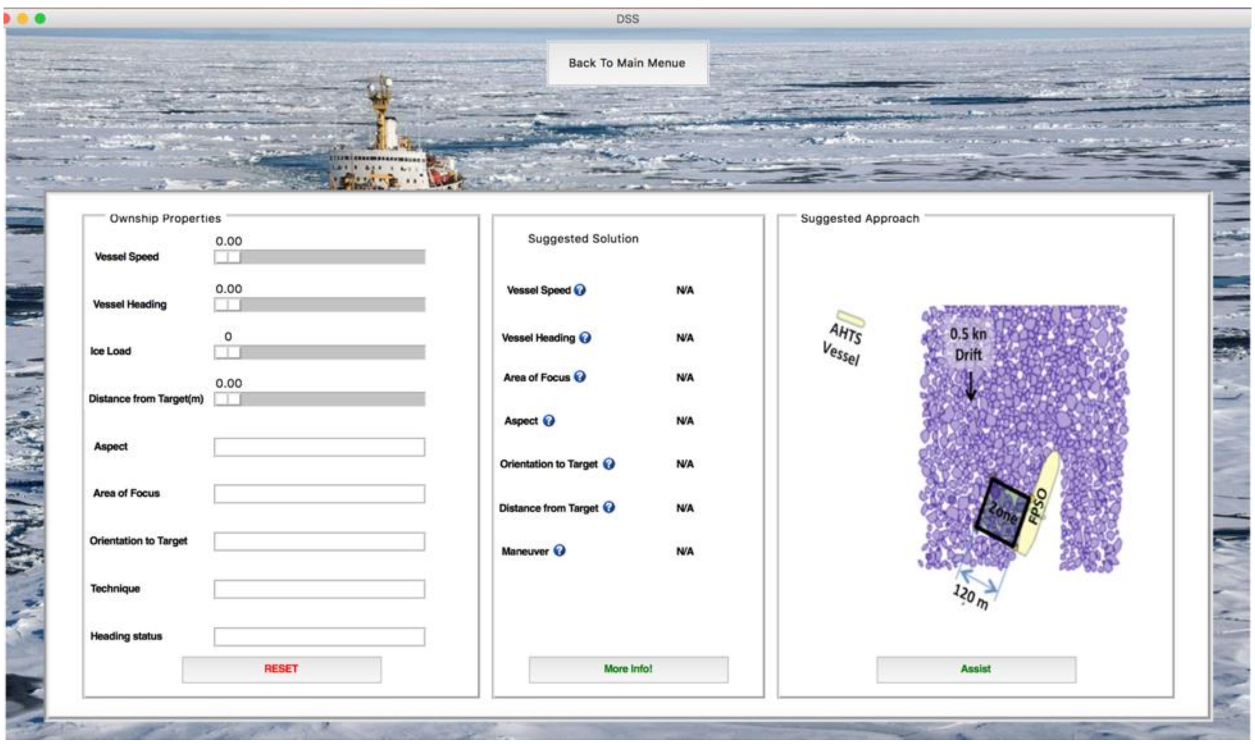


Figure 34 DSS User Interface After Choosing a Scenario

Each feature has a question mark icon displayed next to it. As shown in Figure 35, whenever the cursor hovers over the icon, the description of that feature is provided.

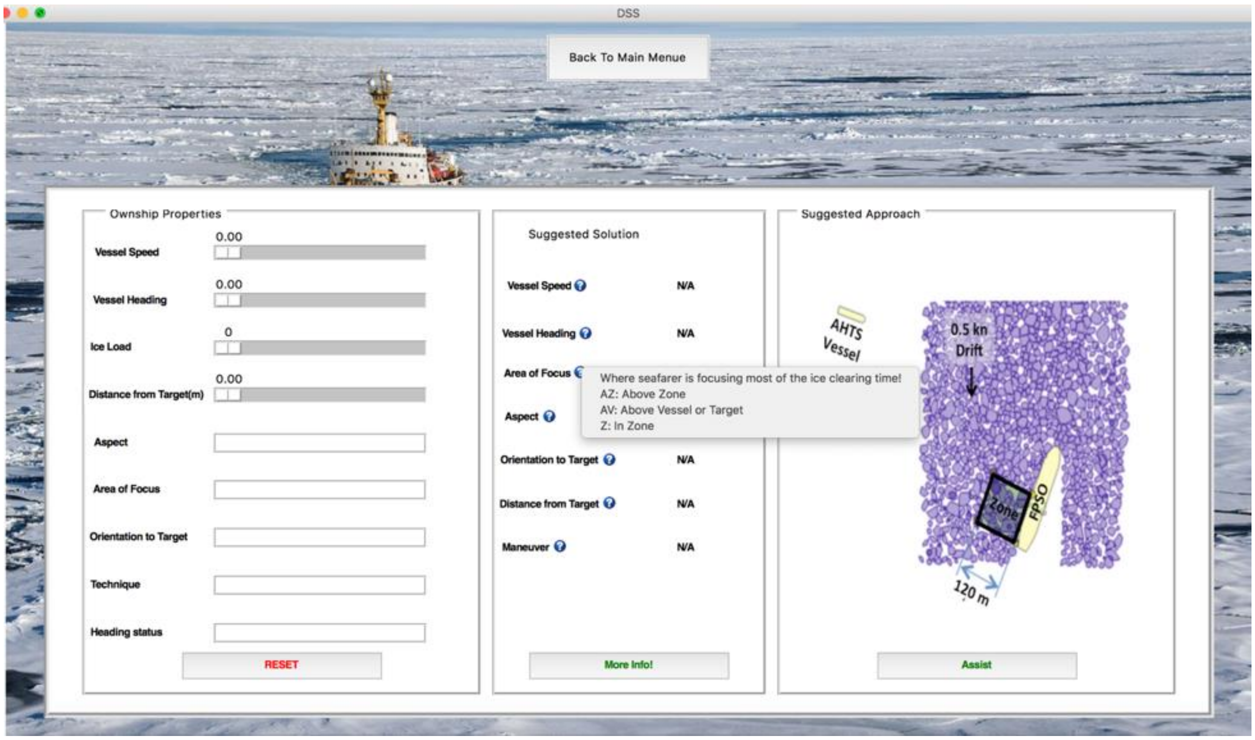


Figure 35 Description of features in DSS User Interface

Figure 36 and Figure 37 illustrate the information the DSS provides a participant when they seek assistance for the selected emergency scenario. As an example, using the retrieval method, the DSS searched for a solution to the new situation (case Z25-3 in this example), and case Y21-3 was predicted as the most similar case to Z25-3. As shown in Figure 36, all information about Z25-3 and Y21-3 was illustrated in Ownship Properties and Suggested Solution boxes, respectively. The suggested diagram for Y21-3 was shown in the Suggested Approach box for more clarification as well. By clicking on the More Info bottom, all tips about implementing the solution could be retrieved (Figure 37).

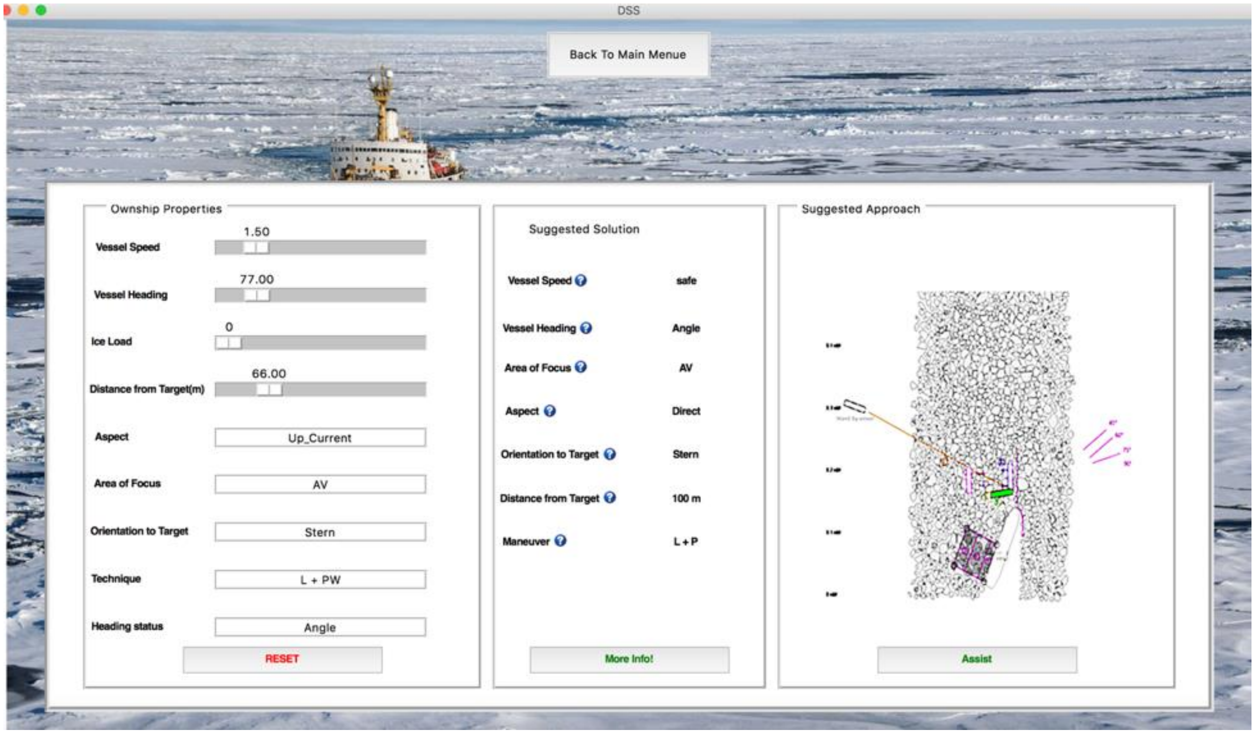


Figure 36 Example of the Case Retrieval in the DSS

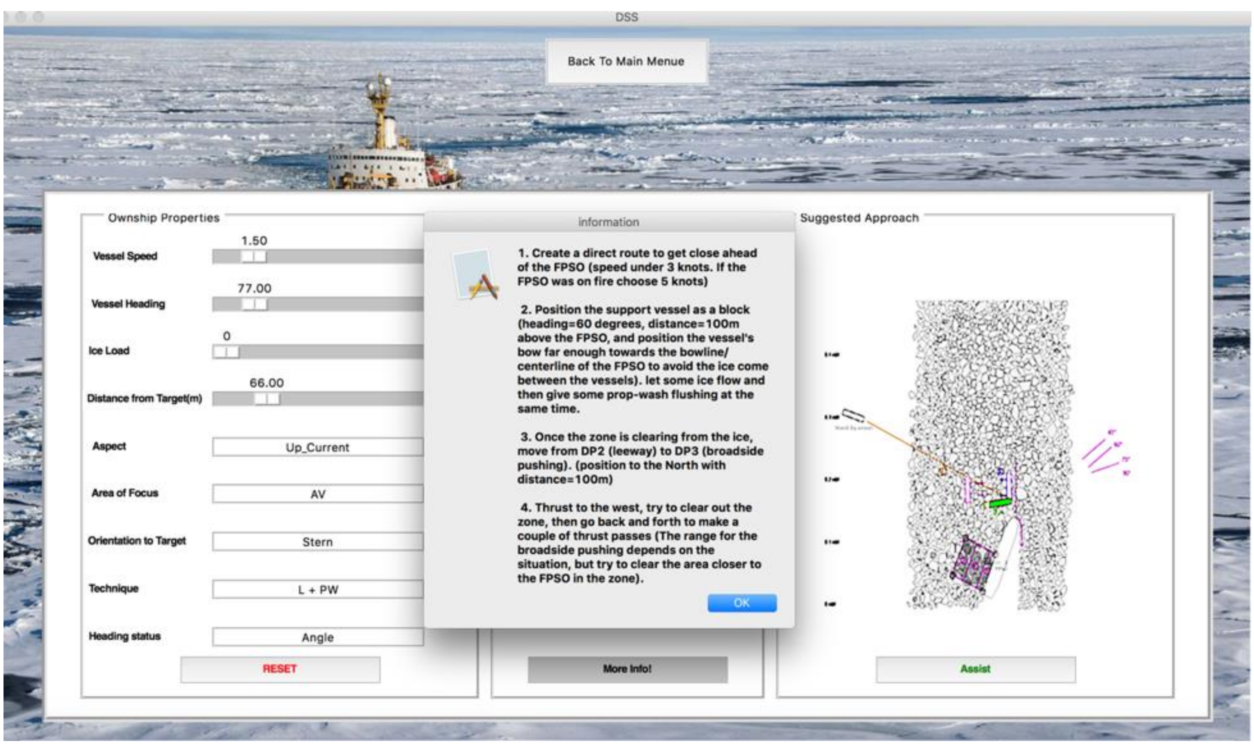


Figure 37 An Example of a Suggested Solution Details

Chapter 4: Results

This section provides a description of the analysis used to select the similarity matching algorithm, describes the decision tree method used, and finally explains the smoke testing used to evaluate the DSS functionality.

4.1. Analysis of results

After gathering all the common features from the simulator log file, the DSS can retrieve the most similar case. Among the various similarity-based methods, classification by similarity algorithms were performed in this study for retrieval purposes. The cross-validation algorithm was used to evaluate machine learning models on the case base. Using the same data for training and testing a model causes overfitting and would fail to suggest the useful prediction of yet-unseen data. To have a better performance, cross-validation was used to divide data into training and testing data sets.

K-fold cross-validation randomly splits data into K approximately equal-sized subgroups (Berrar, 2018). It uses K-1 parts to fit the model and the remaining parts for testing the performance of the generated model. This process is repeated K times, and in each iteration, a different group or fold is considered as the test data. Finally, using Equation 13, the average performance would be calculated. In this equation, K represents the number of folds, and P represents the performance of the test data using a given fold (Delen, Topuz, & Eryarsoy, 2020).

$$AP = \frac{1}{K}\sum_{i=1}^{k} P_i$$

Equation 13 Cross-validation's Average Performance

As an example, Figure 38 shows a schematic display of 5-fold cross-validation by Berrar (2018). In this figure, n observations (1, 2, 3,…, n) were randomly split into five groups. In each fold, the group shown in beige was considered the testing data and the remaining parts shown in blue were considered training sets.

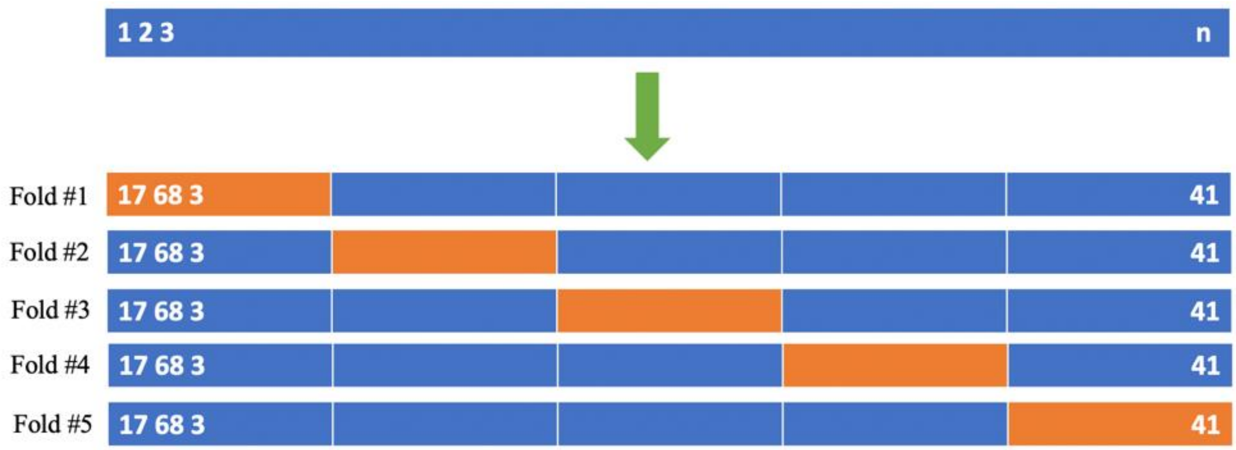


Figure 38 5-fold Cross-Validation (Berrar, 2018)

In the optimal selection of K, both training and test datasets would properly contain a complete description of conditions. Also, the best value of K would depend on a number of attributes of the dataset (Marcot & Hanea, 2020). To evaluate the generalizability and stability of the machine learning models, the k-fold cross-validation with different sizes of training and test sets was examined in this research. The ratios of 67:33% (k=3), 80:20% (k=5), and 90:10% (k=10) were tested as the size of the training and test data set. The value of K=5 resulted in better precision. Therefore, to evaluate the similarity-matching performance of the DSS a 5-fold cross validation was used.

Table 12 shows the total number of samples in each class for different scenarios in the case baes. Based on different solutions or vessel maneuvers, class IDs were assigned to each scenario. Overall, 5 solutions for Sc.1, 7 solutions for Sc.2, and 6 solutions for Sc.3 resulted in 5, 7, and 6 class IDs for each scenario, respectively. As it is illustrated in Table 12, the data is imbalanced and the classes are not represented equally. That means that some classes have only one sample, whereas some others have more.

Table 12 Number of Samples in Each Class for Scenarios

Class ID	**Sc.1**		Sc.2		Sc.3	
	Solutions/vessel maneuver	Number of samples	Solutions/vessel maneuver	Number of samples	Solutions/vessel maneuver	Number of samples
1	L+PW	15	S	1	P	11
2	L	37	P+PW	10	PW	1
3	P+PW	6	L+PW	2	L+PW	8
4	P	4	S+PW	1	P+PW	17
5	PW	4	PW	2	L	6
6	-	-	C	29	L+P	3
7	-	-	P	23	-	-

Selecting an inappropriate measurement metric for imbalanced data can be dangerous. To prevent obtaining an incorrect conclusion, applying a proper metric is vital (Shilaskar, Ghatol, & Chatur, 2017). For example, for the imbalanced data, considering solely the prediction accuracy results in a bias toward the majority class (Haixiang et al., 2017). Therefore, to estimate classification effectiveness, other performance evaluation metrics should be applied that consider class distributions, such as sensitivity (recall), specificity, and the geometric mean (Elamrani Abou Elassad, Mousannif, & Al Moatassime, 2020). These performance evaluation metrics were presented in this thesis.

To provide a comprehensive performance picture, four comparison categories were used.

1. the rate of correctly labeled examples (accuracy)
2. the capability to detect how well a test can identify true positive (sensitivity)
3. the capability to detect how well a test can identify true negatives (specificity), and

4. the geometric mean (G-mean), which is a measure of the balance between the sensitivity and specificity metrics.

These metrics were calculated by employing the confusion matrix, which is a summary of predicted outcomes on a classification task.

A confusion matrix consists of four values (Ting, 2017):

1. True positives (TP): the number of accurately predicted positive cases,
2. True Negatives (TN): the number of accurately predicted negative cases,
3. False Positives (FP): the number of negative cases that are incorrectly predicted as positive, and
4. False Negatives (FN): the number of positive cases that are incorrectly predicted as negative.

Equation 14, Equation 15, Equation 16, and Equation 17 (Pristyanto, Pratama, & Nugraha, 2018) are the performance metrics that were calculated based on the confusion matrix.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$ **Equation 14 Accuracy**

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$ **Equation 15 Sensitivity**

$$\text{Specificity} = \frac{TN}{TN + FP}$$ **Equation 16 Specificity**

$$\text{G-mean} = \sqrt{\frac{TP}{TP + FN} \cdot \frac{TN}{TN + FP}} \qquad \textbf{Equation 17 G-mean}$$

To evaluate the classification performance of the DSS, four machine learning methods were performed under the same conditions: random forest (RF), logistic regression (LR), support vector machine method (SVM), and decision tree (DT). Using the 5-fold cross-validation, a model was fitted with these four algorithms on the training dataset. Then, to evaluate the performance of each model, they were tested by the test dataset.

During the 5-fold cross-validation, one confusion matrix was generated for each fold and resulted in 5 different confusion matrices for each run. Figure 39 shows a sample of confusion matrices for Sc.3. These confusion matrices were captured from fold number 3 while evaluating RF, LR, SVM, and DT methods. Since there were 46 cases in Sc.3, using the 5-fold cross-validation, 37 cases were assigned to the training data set and 9 cases were considered as the test data. As shown in Figure 39, the confusion matrix contains two labels including the actual labels and predicted labels. The actual label represents the actual class ID of the test data's samples. The predicted label represents the class ID that was predicted based on the model. The values in the confusion matrix show the number of correct (on the diagonal) and incorrect (not on the diagonal) predictions, and they are broken down by each class. Also, the confusion matrix uses a color map for boxes, and different colors are assigned to different values. In the presented confusion matrices, the lighter colors show the higher values. In Figure 39 the actual class ID and the predicted class ID are as follows:

- actual= [1,2,3,3,3,4,5,5,6]
- predicted by RF=[1,5,3,4,4,4,1,1,4]

- Predicted by LR=[1,5,3,5,5,4,1,1,4]
- Predicted by SVM=[1,5,4,5,6,4,1,1,4]
- Predicted by DT=[1,5,3,3,3,4,1,5,6]

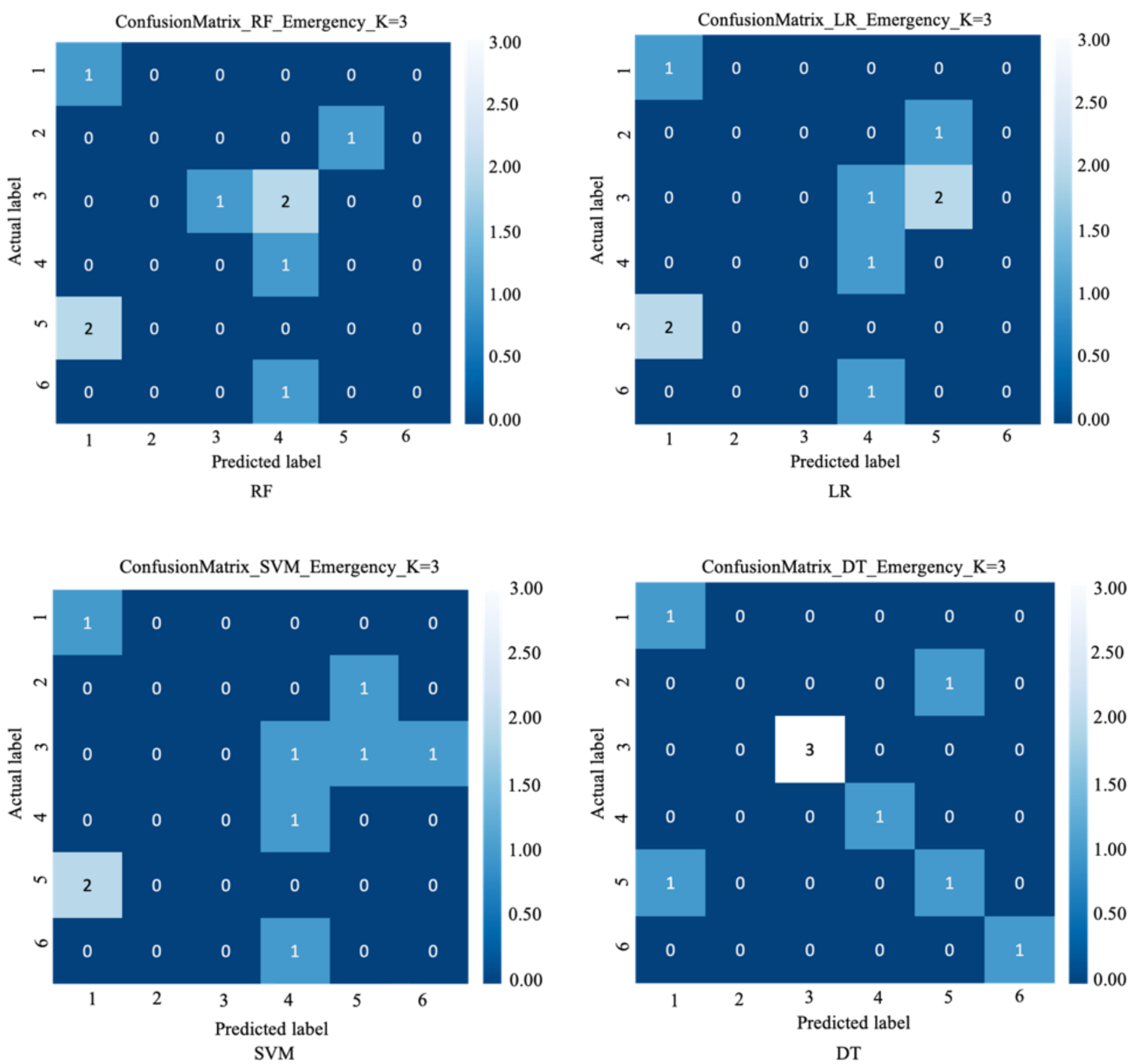


Figure 39 Example of Confusion Matrix for Emergency Scenario in Fold 3 of Cross-Validation

To have one confusion matrix for each method, 5 confusion matrices generated from each fold of cross-validation were summed to represents a model's performance for all of the data. Figure 40,

Figure 41, and Figure 42 show the final confusion matrix diagrams captured for the Sc.1, Sc.2, and Sc.3 respectively.

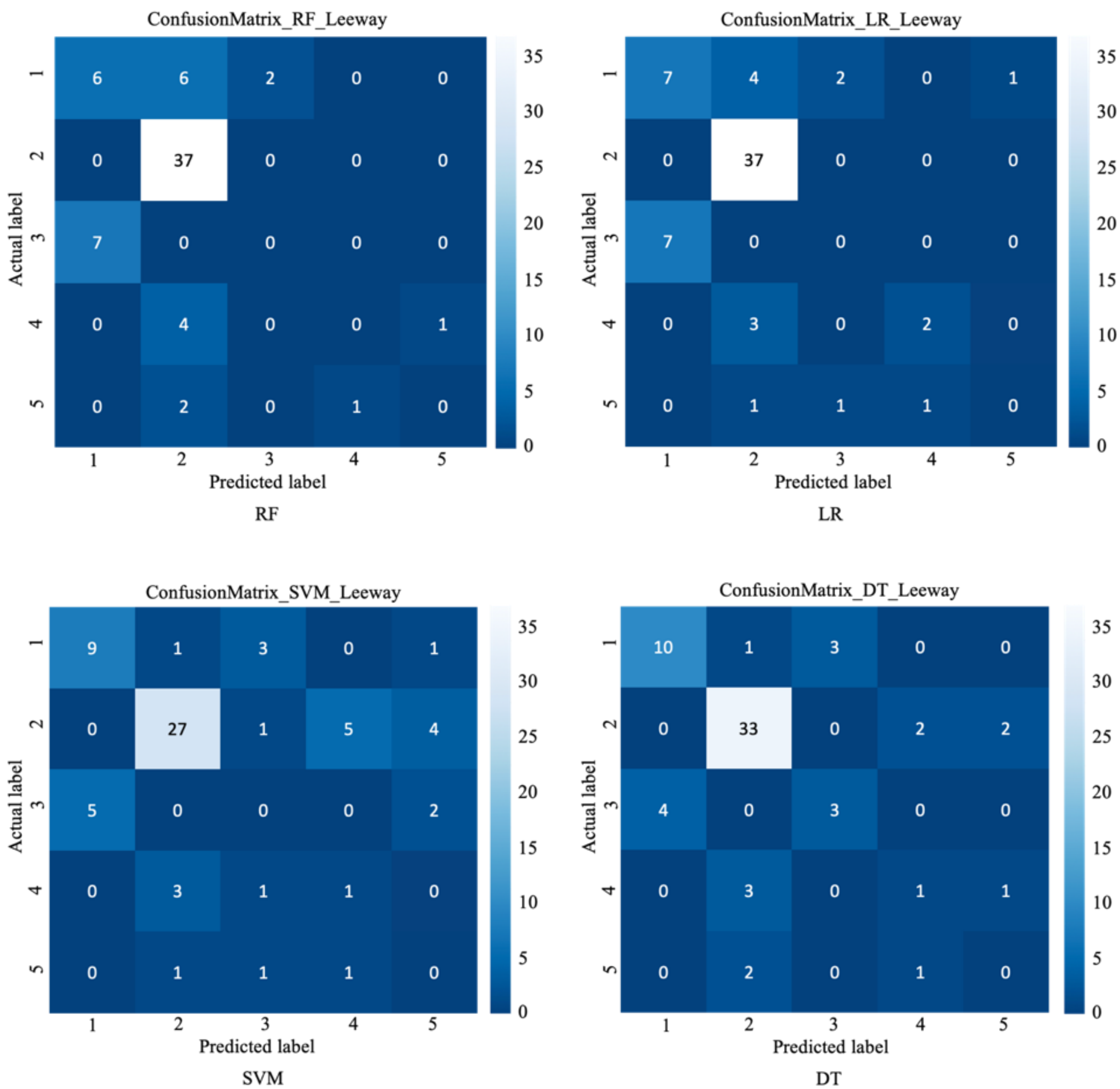


Figure 40 Confusion Matrix for Sc.1

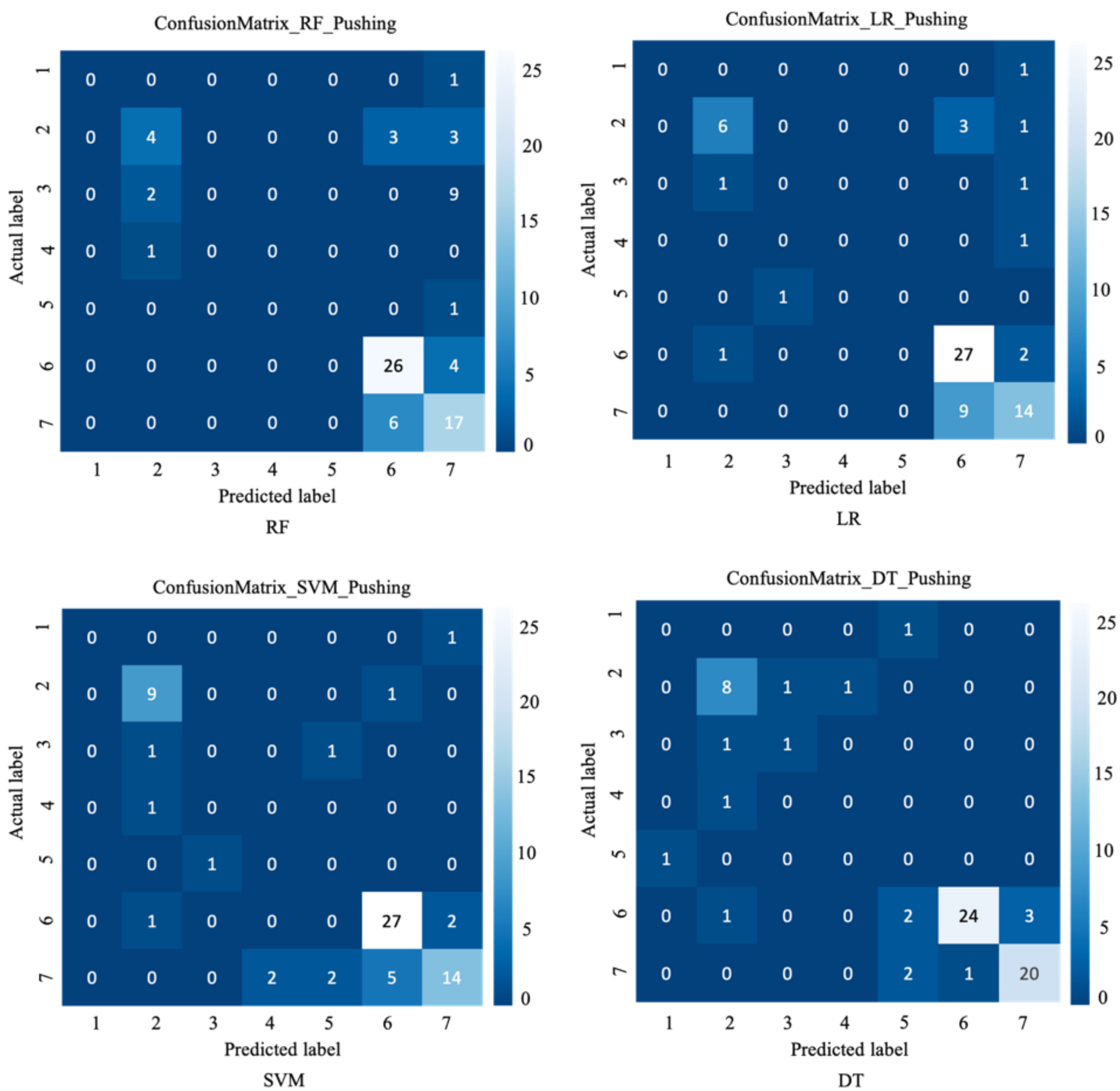


Figure 41 Confusion Matrix for Sc.2

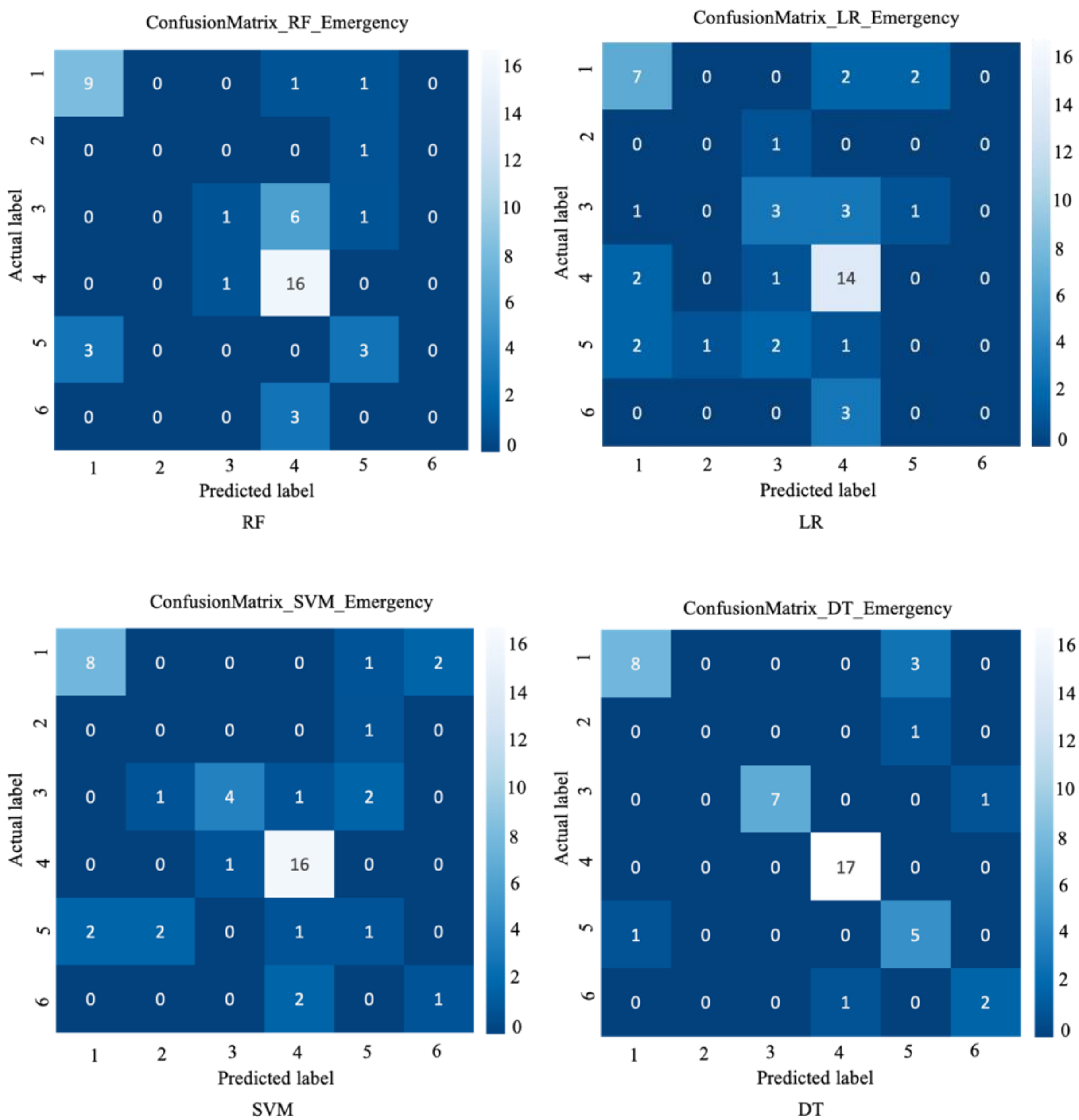


Figure 42 Confusion Matrix for Sc.3

Performance metrics received by each algorithm are shown in Figure 43, Figure 44, and Figure 45 for Sc.1, Sc.2, and Sc.3 respectively.

Class Statistics:

Classes	1	2	3	4	5
Population	66	66	66	66	66
P: Condition positive	14	37	7	5	3
N: Condition negative	52	29	59	61	63
Test outcome positive	13	49	2	1	1
Test outcome negative	53	17	64	65	65
TP: True Positive	6	37	0	0	0
TN: True Negative	45	17	57	60	62
FP: False Positive	7	12	2	1	1
FN: False Negative	8	0	7	5	3
TPR: (Sensitivity, hit rate, recall)	0.428571	1	0	0	0
TNR=SPC: (Specificity)	0.865385	0.586207	0.966102	0.983607	0.984127
ACC: Accuracy	0.772727	0.818182	0.863636	0.909091	0.939394

RF

Class Statistics:

Classes	1	2	3	4	5
Population	66	66	66	66	66
P: Condition positive	14	37	7	5	3
N: Condition negative	52	29	59	61	63
Test outcome positive	14	45	3	3	1
Test outcome negative	52	21	63	63	65
TP: True Positive	7	37	0	2	0
TN: True Negative	45	21	56	60	62
FP: False Positive	7	8	3	1	1
FN: False Negative	7	0	7	3	3
TPR: (Sensitivity, hit rate, recall)	0.5	1	0	0.4	0
TNR=SPC: (Specificity)	0.865385	0.724138	0.949153	0.983607	0.984127
ACC: Accuracy	0.787879	0.878788	0.848485	0.939394	0.939394

LR

Class Statistics:

Classes	1	2	3	4	5
Population	66	66	66	66	66
P: Condition positive	14	37	7	5	3
N: Condition negative	52	29	59	61	63
Test outcome positive	14	32	6	7	7
Test outcome negative	52	34	60	59	59
TP: True Positive	9	27	0	1	0
TN: True Negative	47	24	53	55	56
FP: False Positive	5	5	6	6	7
FN: False Negative	5	10	7	4	3
TPR: (Sensitivity, hit rate, recall)	0.642857	0.72973	0	0.2	0
TNR=SPC: (Specificity)	0.903846	0.827586	0.898305	0.901639	0.888889
ACC: Accuracy	0.848485	0.772727	0.80303	0.848485	0.848485

SVM

Class Statistics:

Classes	1	2	3	4	5
Population	66	66	66	66	66
P: Condition positive	14	37	7	5	3
N: Condition negative	52	29	59	61	63
Test outcome positive	14	39	6	4	3
Test outcome negative	52	27	60	62	63
TP: True Positive	10	33	3	1	0
TN: True Negative	48	23	56	58	60
FP: False Positive	4	6	3	3	3
FN: False Negative	4	4	4	4	3
TPR: (Sensitivity, hit rate, recall)	0.714286	0.891892	0.428571	0.2	0
TNR=SPC: (Specificity)	0.923077	0.793103	0.949153	0.95082	0.952381
ACC: Accuracy	0.878788	0.848485	0.893939	0.893939	0.909091

DT

Figure 43 Classification Performance Metrics for Sc.1

Class Statistics:

Classes	1	2	3	4	5	6	7
Population	68	68	68	68	68	68	68
P: Condition positive	1	10	2	1	1	30	23
N: Condition negative	67	58	66	67	67	38	45
Test outcome positive	0	7	0	0	0	35	26
Test outcome negative	68	61	68	68	68	33	42
TP: True Positive	0	4	0	0	0	26	17
TN: True Negative	67	55	66	67	67	29	36
FP: False Positive	0	3	0	0	0	9	9
FN: False Negative	1	6	2	1	1	4	6
TPR: (Sensitivity, hit rate, recall)	0	0.4	0	0	0	0.866667	0.73913
TNR=SPC: (Specificity)	1	0.948276	1	1	1	0.763158	0.8
ACC: Accuracy	0.985294	0.867647	0.970588	0.985294	0.985294	0.808824	0.779412

RF

Class Statistics:

Classes	1	2	3	4	5	6	7
Population	68	68	68	68	68	68	68
P: Condition positive	1	10	2	1	1	30	23
N: Condition negative	67	58	66	67	67	38	45
Test outcome positive	0	8	1	0	0	39	20
Test outcome negative	68	60	67	68	68	29	48
TP: True Positive	0	6	0	0	0	27	14
TN: True Negative	67	56	65	67	67	26	39
FP: False Positive	0	2	1	0	0	12	6
FN: False Negative	1	4	2	1	1	3	9
TPR: (Sensitivity, hit rate, recall)	0	0.6	0	0	0	0.9	0.608696
TNR=SPC: (Specificity)	1	0.965517	0.984848	1	1	0.684211	0.866667
ACC: Accuracy	0.985294	0.911765	0.955882	0.985294	0.985294	0.779412	0.779412

LR

Class Statistics:

Classes	1	2	3	4	5	6	7
Population	68	68	68	68	68	68	68
P: Condition positive	1	10	2	1	1	30	23
N: Condition negative	67	58	66	67	67	38	45
Test outcome positive	0	12	1	2	3	33	17
Test outcome negative	68	56	67	66	65	35	51
TP: True Positive	0	9	0	0	0	27	14
TN: True Negative	67	55	65	65	64	32	42
FP: False Positive	0	3	1	2	3	6	3
FN: False Negative	1	1	2	1	1	3	9
TPR: (Sensitivity, hit rate, recall)	0	0.9	0	0	0	0.9	0.608696
TNR=SPC: (Specificity)	1	0.948276	0.984848	0.970149	0.955224	0.842105	0.933333
PPV: Pos Pred Value (Precision)	NaN	0.75	0	0	0	0.818182	0.823529
ACC: Accuracy	0.985294	0.941176	0.955882	0.955882	0.941176	0.867647	0.823529

SVM

Class Statistics:

Classes	1	2	3	4	5	6	7
Population	68	68	68	68	68	68	68
P: Condition positive	1	10	2	1	1	30	23
N: Condition negative	67	58	66	67	67	38	45
Test outcome positive	1	11	2	1	5	25	23
Test outcome negative	67	57	66	67	63	43	45
TP: True Positive	0	8	1	0	0	24	20
TN: True Negative	66	55	65	66	62	37	42
FP: False Positive	1	3	1	1	5	1	3
FN: False Negative	1	2	1	1	1	6	3
TPR: (Sensitivity, hit rate, recall)	0	0.8	0.5	0	0	0.8	0.869565
TNR=SPC: (Specificity)	0.985075	0.948276	0.984848	0.985075	0.925373	0.973684	0.933333
PPV: Pos Pred Value (Precision)	0	0.727273	0.5	0	0	0.96	0.869565
ACC: Accuracy	0.970588	0.926471	0.970588	0.970588	0.911765	0.897059	0.911765

DT

Figure 44 Classification Performance Metrics for Sc.2

Class Statistics:

Classes	1	2	3	4	5	6
Population	46	46	46	46	46	46
P: Condition positive	11	1	8	17	6	3
N: Condition negative	35	45	38	29	40	43
Test outcome positive	12	0	2	26	6	0
Test outcome negative	34	46	44	20	40	46
TP: True Positive	9	0	1	16	3	0
TN: True Negative	32	45	37	19	37	43
FP: False Positive	3	0	1	10	3	0
FN: False Negative	2	1	7	1	3	3
TPR: (Sensitivity, hit rate, recall)	0.818182	0	0.125	0.941176	0.5	0
TNR=SPC: (Specificity)	0.914286	1	0.973684	0.655172	0.925	1
ACC: Accuracy	0.891304	0.978261	0.826087	0.76087	0.869565	0.934783

RF

Class Statistics:

Classes	1	2	3	4	5	6
Population	46	46	46	46	46	46
P: Condition positive	11	1	8	17	6	3
N: Condition negative	35	45	38	29	40	43
Test outcome positive	12	1	7	23	3	0
Test outcome negative	34	45	39	23	43	46
TP: True Positive	7	0	3	14	0	0
TN: True Negative	30	44	34	20	37	43
FP: False Positive	5	1	4	9	3	0
FN: False Negative	4	1	5	3	6	3
TPR: (Sensitivity, hit rate, recall)	0.636364	0	0.375	0.823529	0	0
TNR=SPC: (Specificity)	0.857143	0.977778	0.894737	0.689655	0.925	1
ACC: Accuracy	0.804348	0.956522	0.804348	0.73913	0.804348	0.934783

LR

Class Statistics:

Classes	1	2	3	4	5	6
Population	46	46	46	46	46	46
P: Condition positive	11	1	8	17	6	3
N: Condition negative	35	45	38	29	40	43
Test outcome positive	10	3	5	20	5	3
Test outcome negative	36	43	41	26	41	43
TP: True Positive	8	0	4	16	1	1
TN: True Negative	33	42	37	25	36	41
FP: False Positive	2	3	1	4	4	2
FN: False Negative	3	1	4	1	5	2
TPR: (Sensitivity, hit rate, recall)	0.727273	0	0.5	0.941176	0.166667	0.333333
TNR=SPC: (Specificity)	0.942857	0.933333	0.973684	0.862069	0.9	0.953488
ACC: Accuracy	0.891304	0.913043	0.891304	0.891304	0.804348	0.913043

SVM

Class Statistics:

Classes	1	2	3	4	5	6
Population	46	46	46	46	46	46
P: Condition positive	11	1	8	17	6	3
N: Condition negative	35	45	38	29	40	43
Test outcome positive	9	0	7	18	9	3
Test outcome negative	37	46	39	28	37	43
TP: True Positive	8	0	7	17	5	2
TN: True Negative	34	45	38	28	36	42
FP: False Positive	1	0	0	1	4	1
FN: False Negative	3	1	1	0	1	1
TPR: (Sensitivity, hit rate, recall)	0.727273	0	0.875	1	0.833333	0.666667
TNR=SPC: (Specificity)	0.971429	1	1	0.965517	0.9	0.976744
ACC: Accuracy	0.913043	0.978261	0.978261	0.978261	0.891304	0.956522

DT

Figure 45 Classification Performance Metrics for Sc.3

The summary of achieved performances from the four algorithms is shown in Table 13. As shown in the table, there is a large difference in sensitivity and specificity values due to the inherent bias towards bigger class. Also, considering solely the prediction accuracy results in a bias toward the majority class for the imbalanced data. Therefore, another performance evaluation metric like G-mean should be considered to evaluate the classification effectiveness. As shown in Table 13, the decision tree has the best performance among all algorithms (shown in bold).

Table 13 Summary of Classification Metrics for Four algorithms

Scenario	Sc.1				Sc.2				Sc.3			
Method	RF	LR	SVM	DT	RF	LR	SVM	DT	RF	LR	SVM	DT
Accuracy	86.00	88.00	82.40	88.40	91.42	91.42	92.57	93.71	87.67	83.83	88.17	95.00
Sensitivity	28.60	38.00	31.40	44.60	28.70	30.14	34.42	42.43	39.83	30.66	44.50	68.50
Specificity	87.40	90.00	88.40	91.20	93.00	92.85	94.71	96.29	74.50	89.17	92.50	97.00
G-mean	49.99	58.48	52.68	**63.77**	51.66	52.90	57.09	**63.92**	54.47	52.29	64.15	**81.51**

4.2. Decision Tree for the Scenarios

To create a final model, an algorithm would be fitted to the entire dataset (Berrar, 2018). Therefore, after selecting the decision tree as a chosen machine learning algorithm, the final tree model was built using the entire case base for making predictions on new data. Figure 46, Figure 47, and Figure 48 show the decision tree model created for Sc.1, Sc.2, and Sc.3. These trees were built based on the CART algorithm using Scikit learn library in Python (Pedregosa et al., 2011). In the CART tree, the information gain is used as an attribute selection measure and entropy computed to split the nodes. As shown in the figures, leaf nodes (pure nodes) are considered as a class ID and show the number of samples in each class. Therefore, a total of 5, 7, and 6 class IDs are predictable in the tree for Sc.1, Sc.2, and Sc.3, respectively. Whenever the search ended at leaf nodes, their class ID would be the predicted result.

For more clarity, in Figure 46, the green leaf with class=2 shows the class ID=2 with 39 samples in the case base.

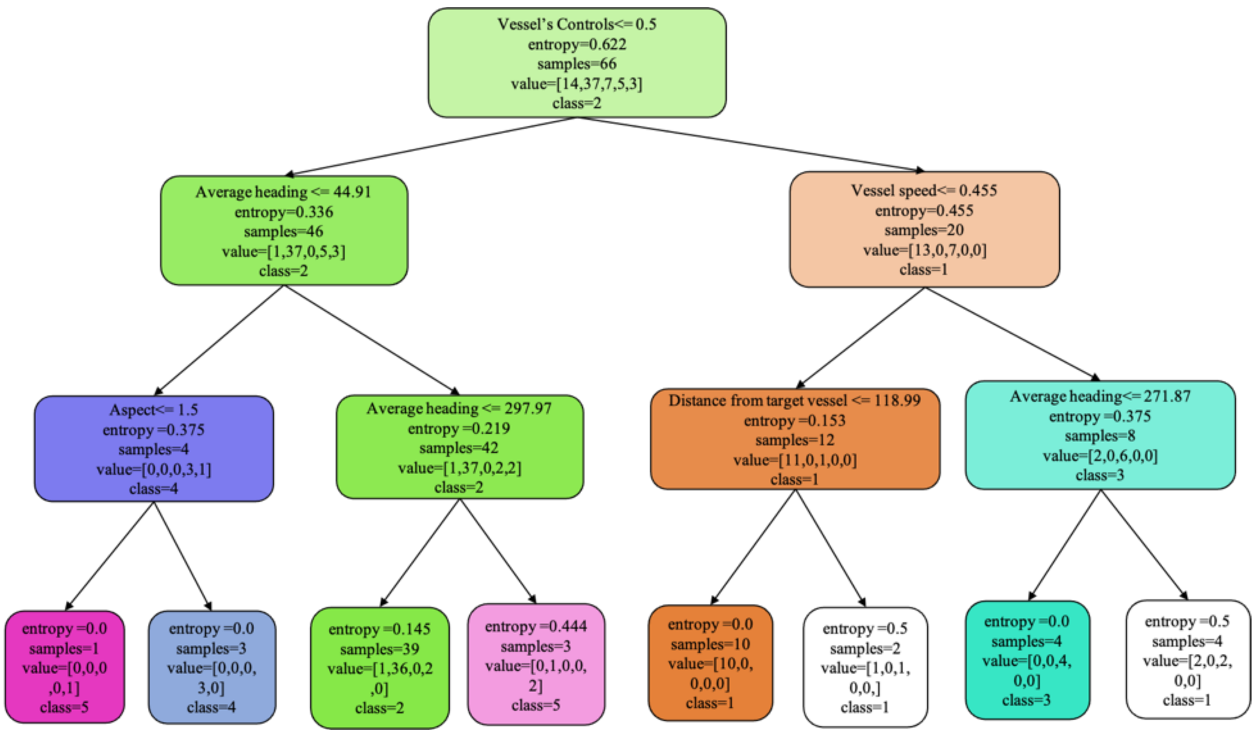


Figure 46 Decision Tree Model for Sc.1

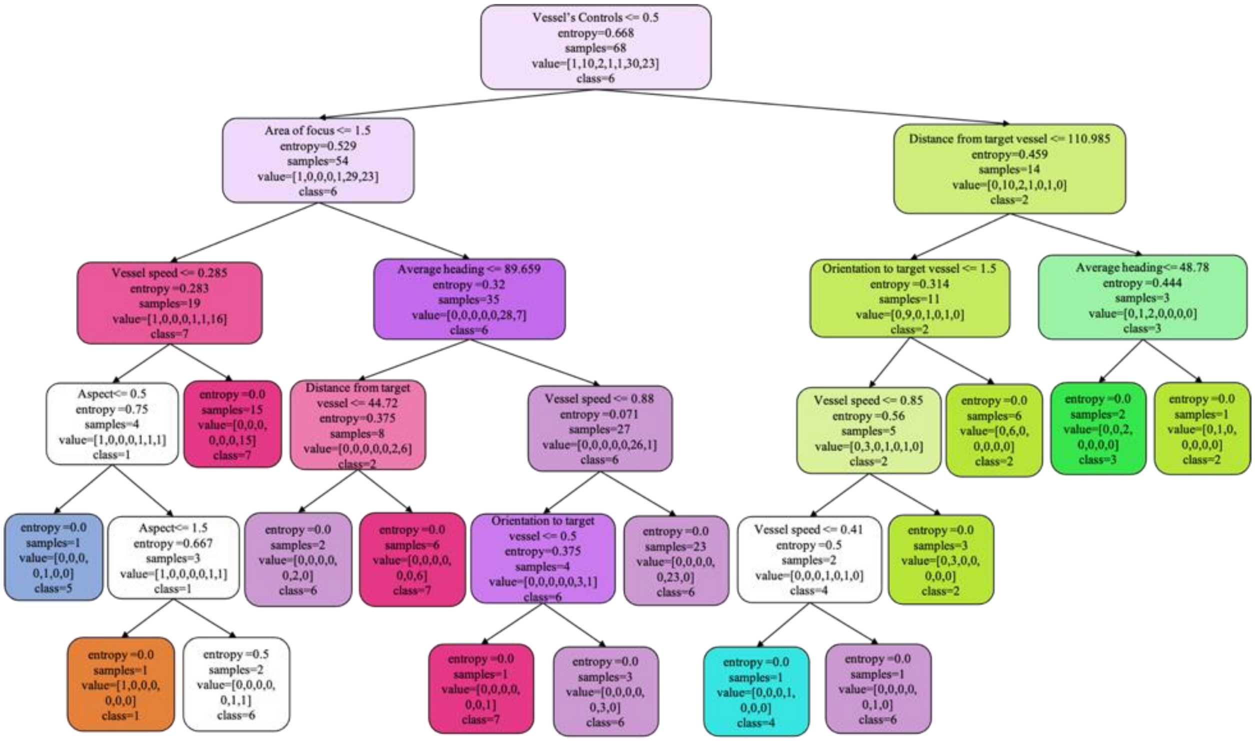


Figure 47 Decision Tree Model for Sc.2

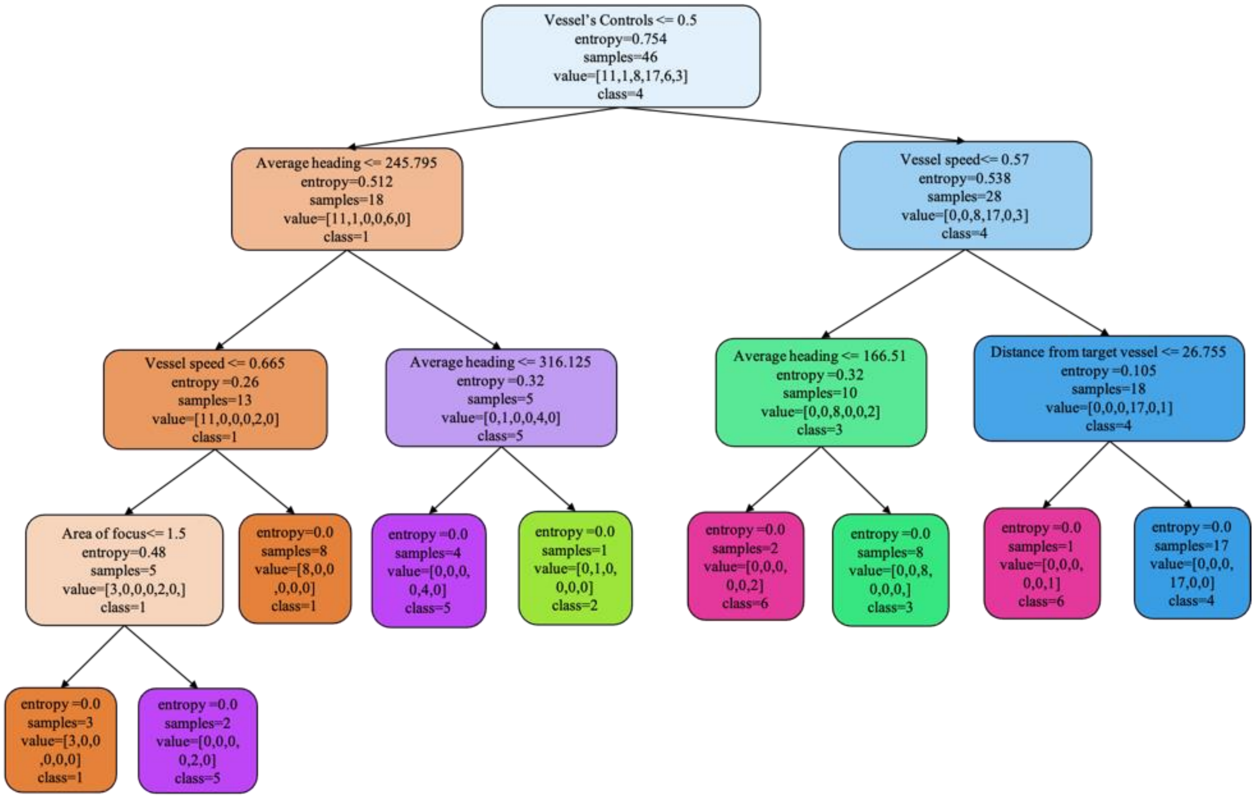


Figure 48 Decision Tree Model for Sc.3

Figure 49 shows a searched route for a new case in the tree model for Sc.3 (Figure 48). As shown in Figure 49, the new case is similar to a case with class ID=3 consisting of 8 samples in the emergency case base.

Once the new case class is predicted using the decision tree, the DSS searches to retrieve the most similar sample of the corresponding class. This step is done using the Cosine distance metrics. Using the Cosine similarity metric, the most similar case to the new case among 8 samples of class 3 is retrieved.

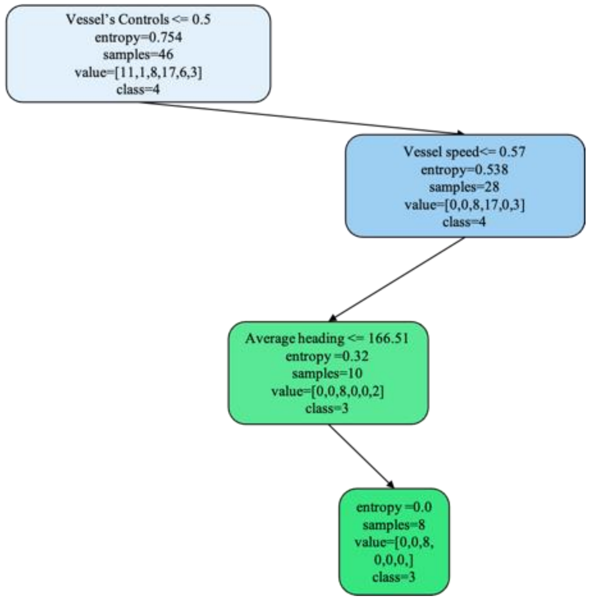


Figure 49 An Example of Selected Route for a New Case

4.3. Smoke Testing Result

Smoke testing of the DSS functionality was performed using four participants in the ice management simulator. However, after one of the sessions (participant R20), it was revealed that the DSS did not receive real-time data from the simulator and did not generate solutions based on the vessel's situation. Therefore, the result from this participant was not included in the thesis. The performance of the three remaining participants is described for the three different scenarios.

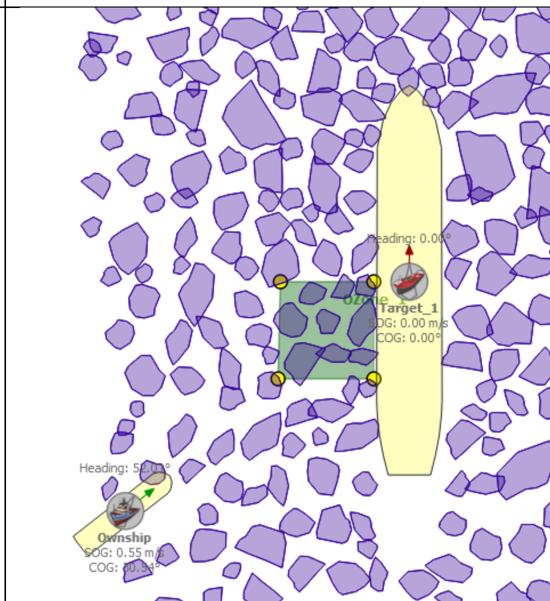
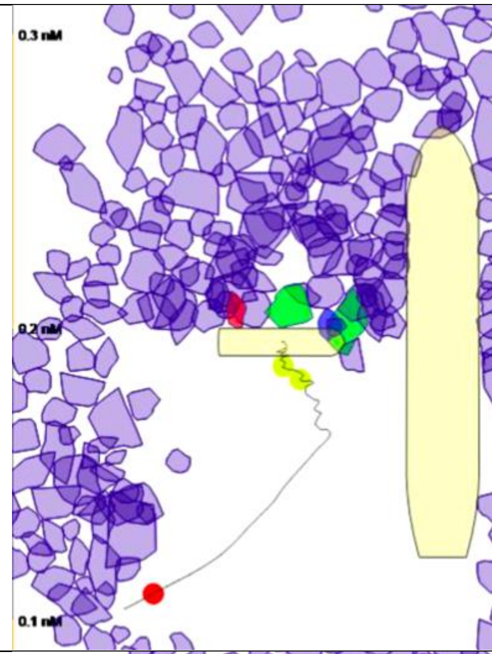
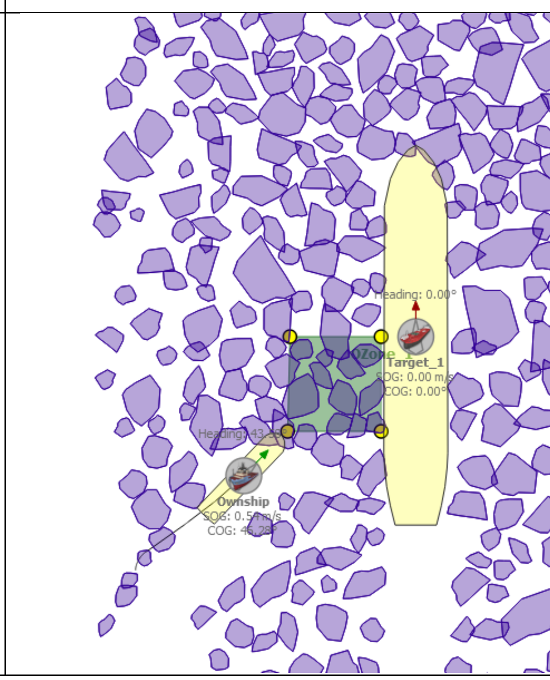
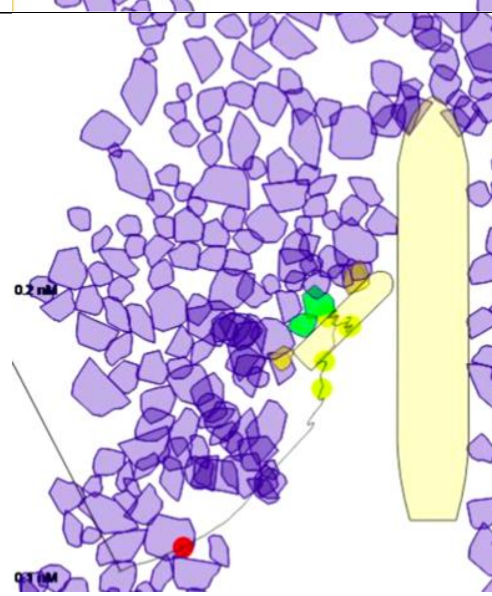
Table 14, Table 15, and Table 16 illustrate examples of executing Sc.1, Sc.2, and Sc.3 by the three participants using the DSS. These tables include timestamps in which participants asked for assistance, screen captures of their situation while they requested help, and DSS suggested solutions diagrams.

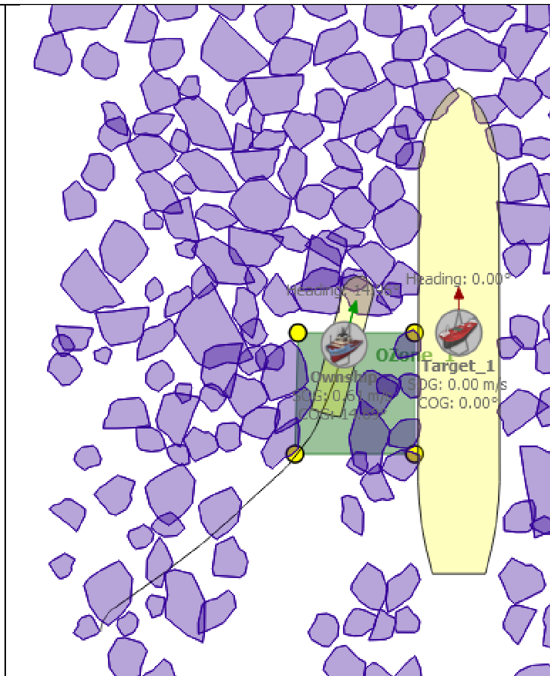
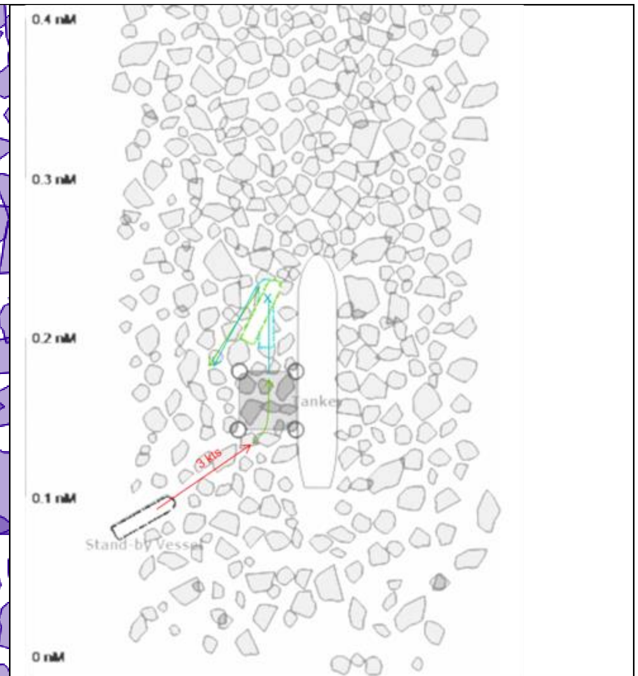
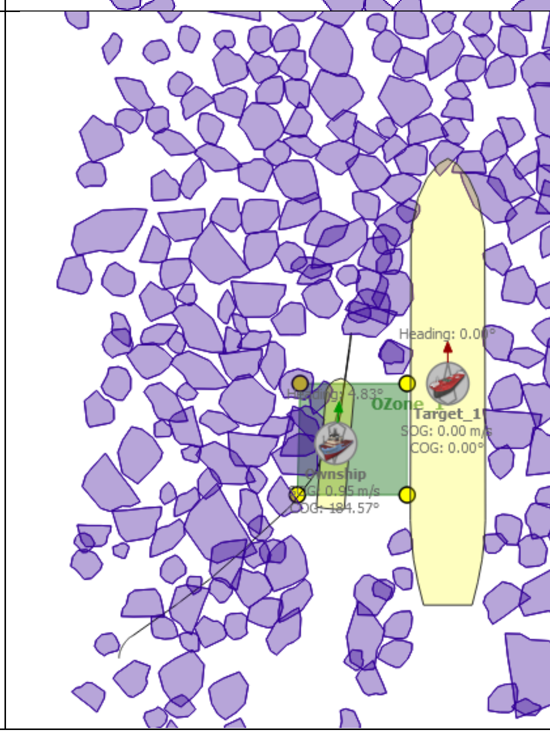
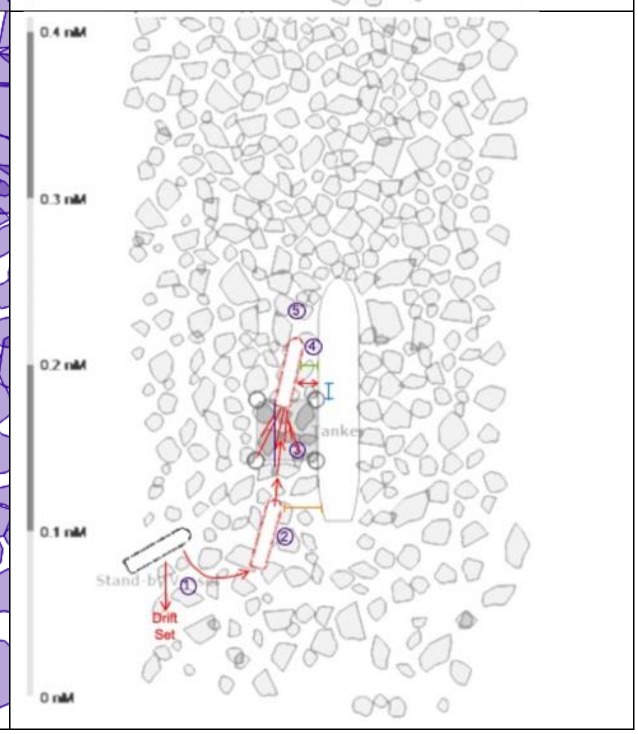
Prior to the participants' implementation, some information was given to the participants:

1. The DSS recommends not asking for help at the onset of the scenario because the system needs time to receive real-time data from the simulator and to calculate features for retrieving the most similar case.
2. The DSS may provide the same solution for a period of time because the solution depends on the vessel's situation, and if it does not change, there would not be any update for the solution.
3. In addition to the suggested approach diagram, some features of the most similar case were given to the participants. Also, more detailed information was provided for some solutions (not all), and participants had the option to review the additional guidance for more clarity.
4. Following the DSS's suggested approach is optional, and the participant could ignore the suggestion and implement their own approach. Thus, the final performance could result from DSS suggestions, participant experience, and their own strategies.

Three examples are used to demonstrate the DSS smoke testing performance in the three scenarios, leeway, pushing and emergency scenarios. First, Table 14 illustrates executing Sc.1 by participant K13. As shown in the table, although the participant asked for assistance at the beginning of the scenario, it seems that the DSS provided an appropriate approach for the user. The participant also asked for assistance a couple of times between 2 and 4 minutes, however the DSS provided the same solution as the vessel's situation did not change a lot. For this example, the DSS suggested a total of four solutions that depended on the vessel's situation. Overall, based on the smoke testing, it seems that the DSS provided appropriate solutions for Sc.1. The participant's final performance can be seen in Figure 50.

Table 14 Execution of Leeway Scenario Using the DSS

<table>
<tr><th>Time</th><th>K13 – Sc.1. Screen captures</th><th>DSS Solution</th></tr>
<tr><td>0</td><td>
</td><td>
</td></tr>
<tr><td>2-4</td><td>
</td><td>
</td></tr>
</table>

<table>
<tr><td>5-6</td><td>
</td><td>
</td></tr>
<tr><td>9</td><td>
</td><td>
</td></tr>
</table>

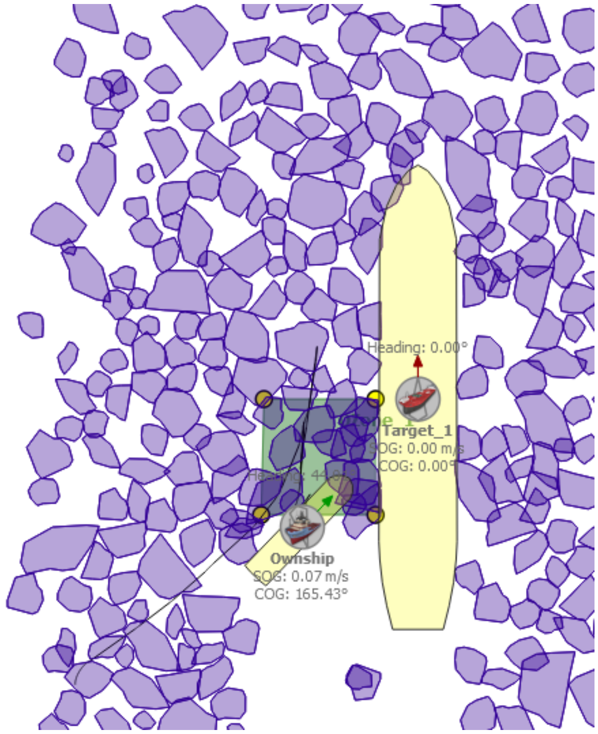


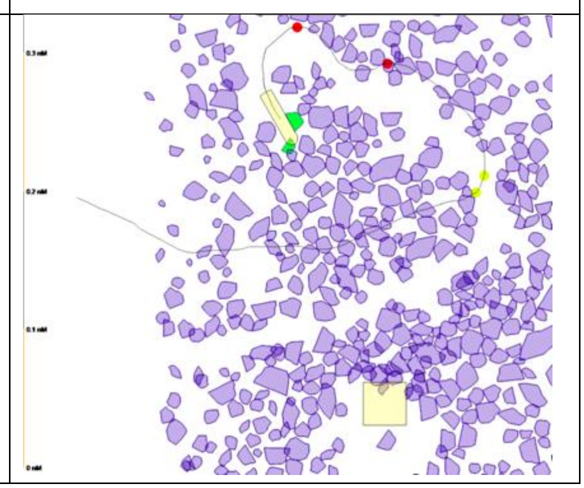
Figure 50 The Final Performance of Participant K13 in Sc.1

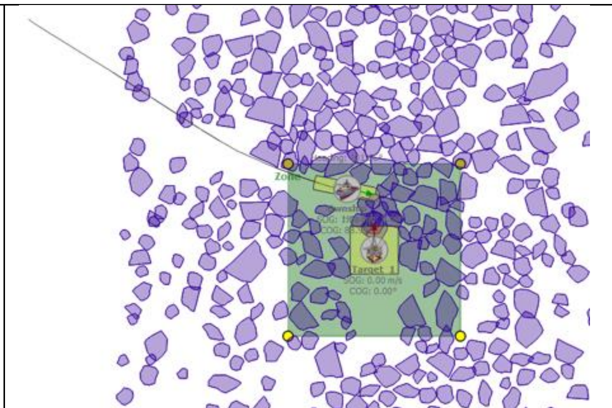
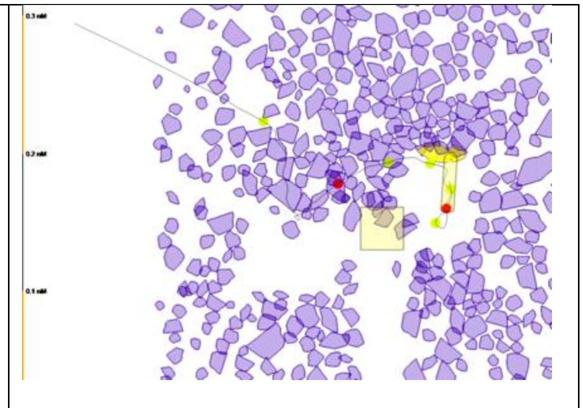
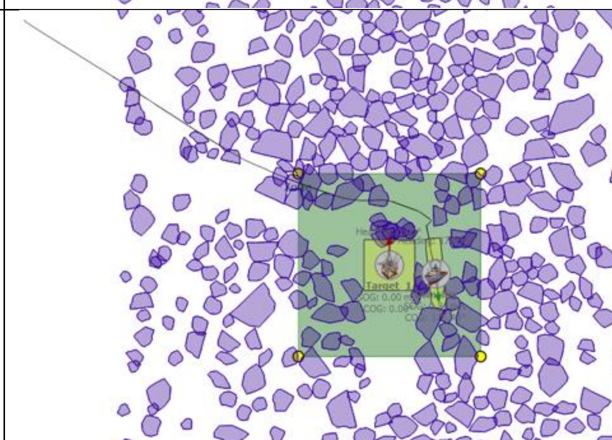
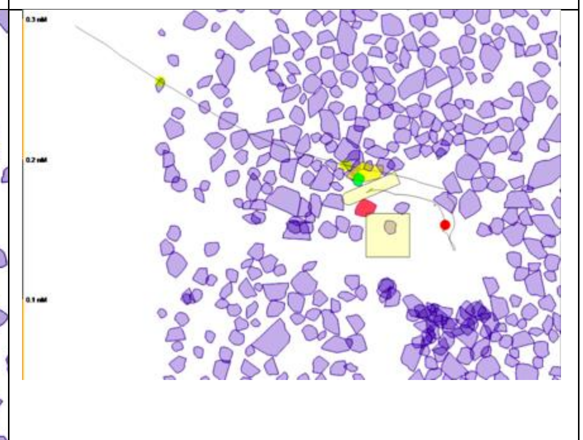
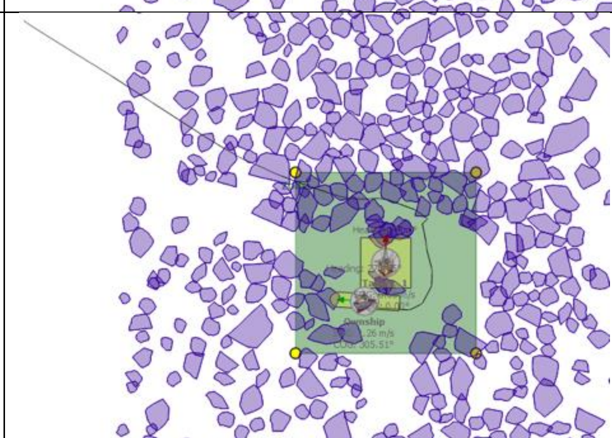
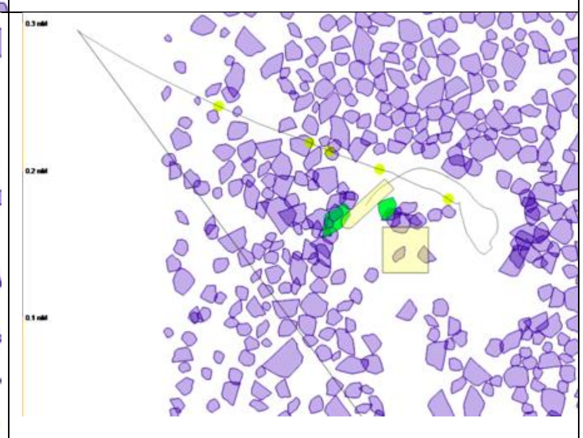
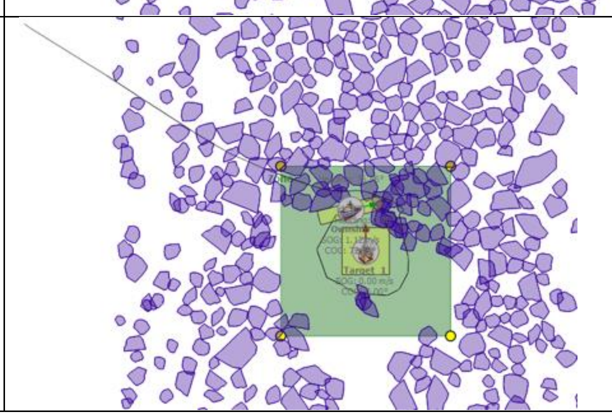
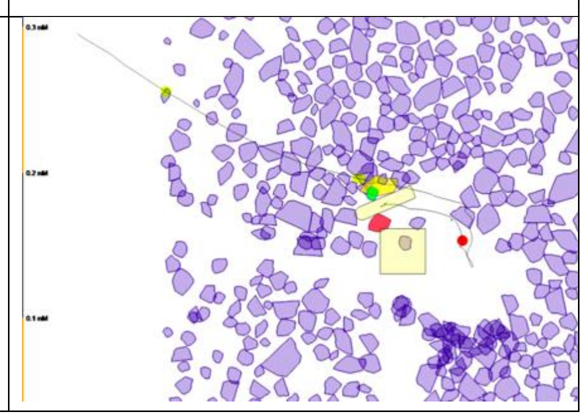
The second comparison for the smoke test was for the pushing scenario. Table 15 shows Sc.2 implemented by participant F09. At the beginning of the scenario, the participant asked for assistance, and the DSS suggested a circular approach above the platform. This approach seems not an appropriate strategy because of the vessel's distance from the platform and the mount of ice load on it. Therefore, the participant decided not to follow it. Then, at 4 minutes, the participant asked again for help, and the DSS suggested another strategy that involved using a leeway strategy above the platform. In fact, the new solution at timestamp 4 minutes meant to instruct the participant to ignore the ice under the platform and focus on clearing the ice above the platform because the drift would clear the ice under the platform. Unfortunately, this explanation was not provided in the DSS, so the participant could not understand the purpose behind this solution, and tried to follow their own approach, which was a circular approach around the platform.

The participant's choice to follow their own approach occurred with other proposed solutions from the DSS. It is possible this confusion resulted from a mismatch between the DSS suggested approach and the reasoning for the approach. Sometimes there was not enough explanation for the solutions and sometimes the participant forgot to click on the more info button to see a detailed explanation. The participant's final performance can be seen in Figure 51.

After completing the DSS testing experiment, the problems with inappropriate approaches were solved by adding a not recommended label to them and providing some tips to improve these approaches. Also, some explanations were added for more clarity to those approaches that did not contain a more detailed information. These changes will be explained in detail in Chapter 5: Discussion.

Table 15 Execution of Pushing Scenario Using the DSS

Time	F09 – Sc.2. Screen captures	DSS Solution
0		

4		
7		
9		
13		

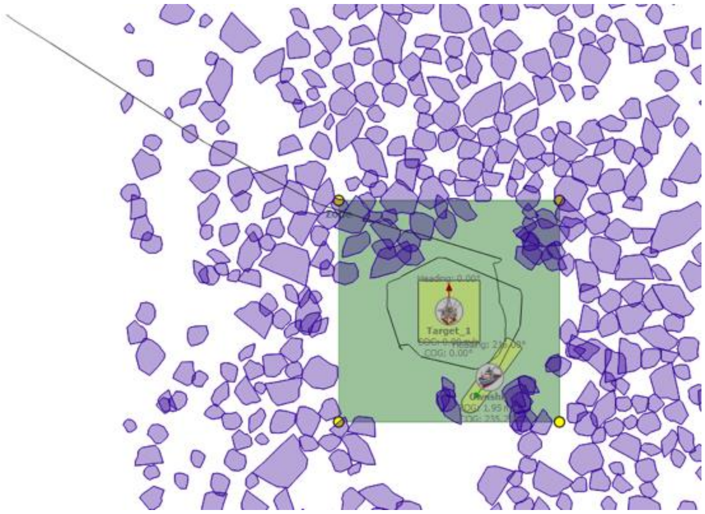
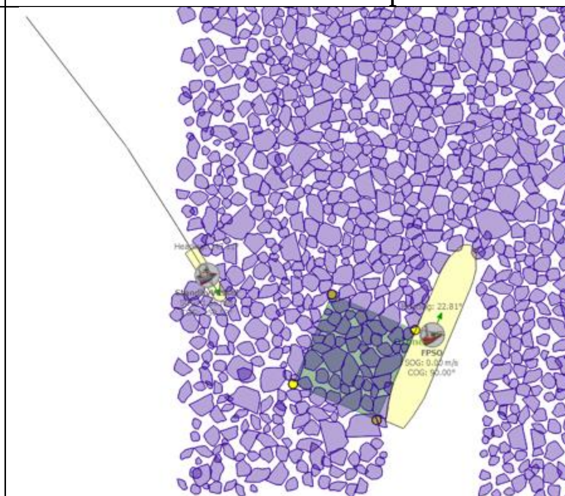
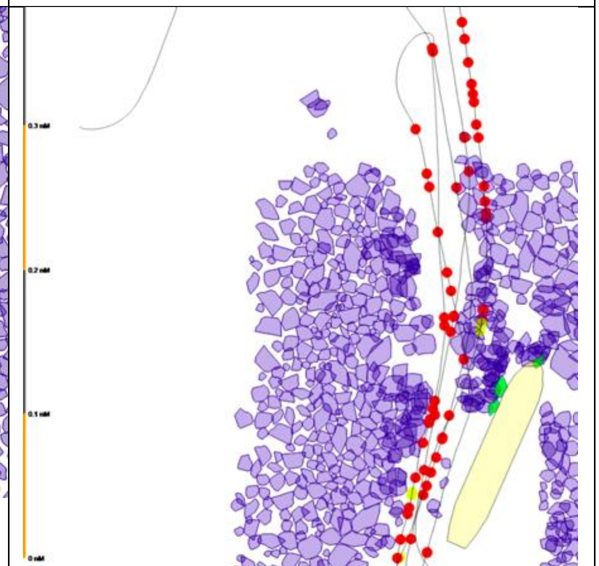
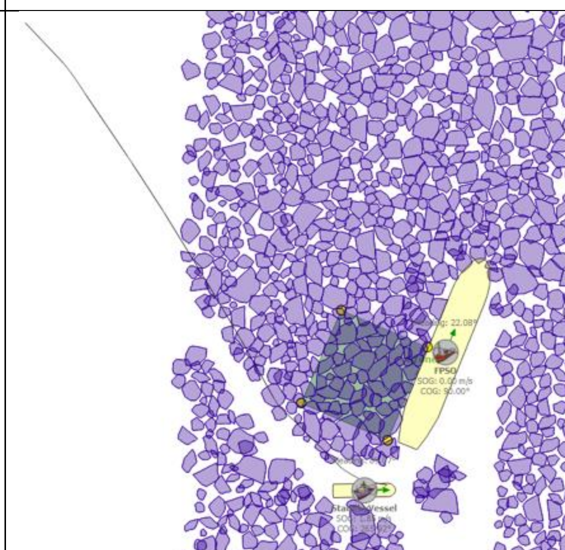
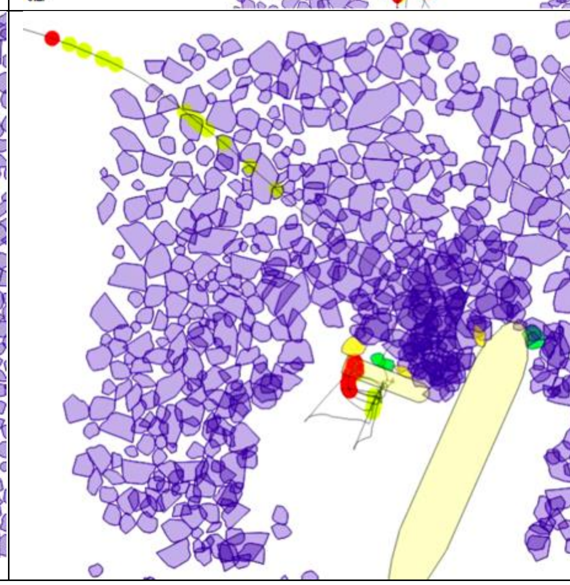


Figure 51 The Final Performance of Participant F09 in Sc.2

The final comparison for the smoke test was for the emergency scenario. Table 16 shows Sc.3 that was implemented by participant D51. In this scenario, the ownship vessel is located in the open water as a result most of the participants operated the vessel at higher speeds than when they operated the vessel in the ice. For this reason, if they asked for assistance before or while they were entering the ice, a case with a high speed in the case base was retrieved (the suggested case in time 4 minutes in Table 16). This case had a speed of more than 3 knots in its implementation that is not recommended as it exceeds the safe speed. To solve this problem after the experiment, the ‘speed’ feature’s priority was changed to a lower priority during the case retrieval. Inappropriate approaches were not removed from the data set because these cases are necessary for the learning process. Also, it is important to show inappropriate results caused by inappropriate strategies so that the participant can be aware of what will happen if they do not change their strategies in the remaining time of implementing a scenario. As shown in Table 16, except for the first suggestion, the DSS seems to retrieve the relevant cases to current situations. The participant’s final performance can be seen in Figure 52.

Table 16 Execution of Emergency Scenario Using the DSS

Time	D51 – Sc.3. Screen captures	DSS Solution
4		
8		

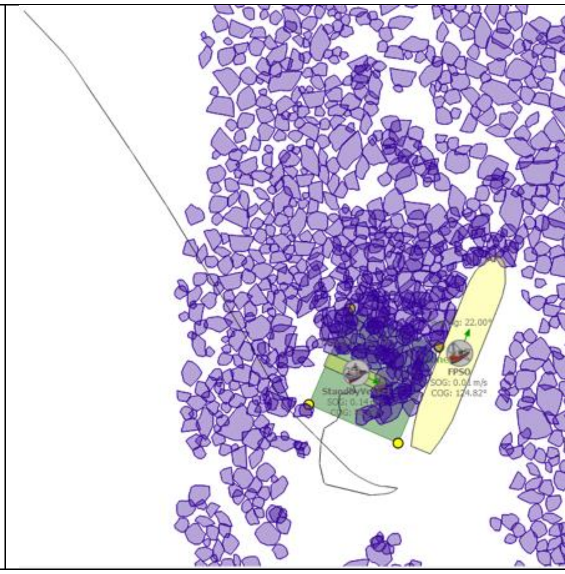
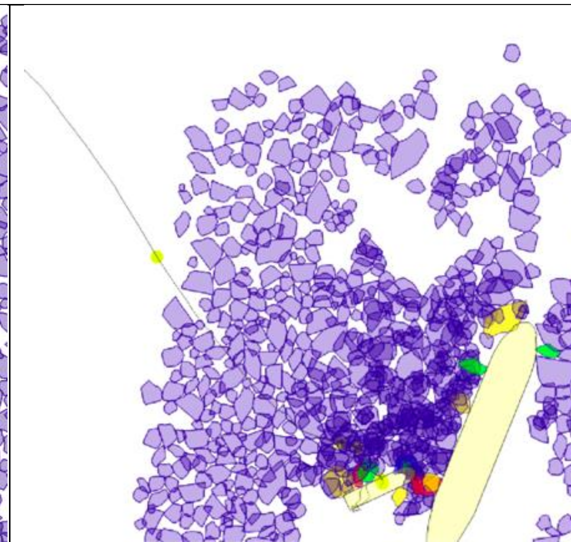
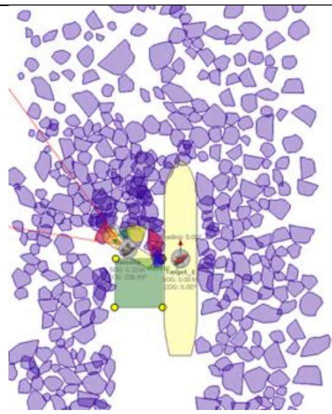
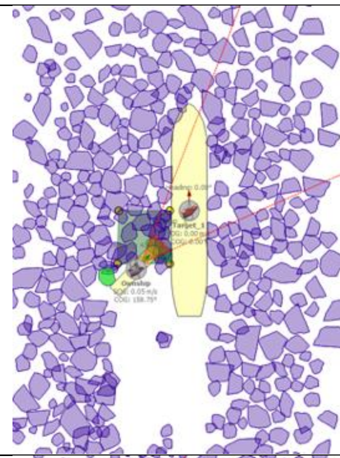
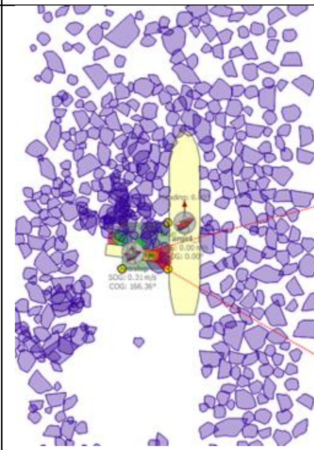
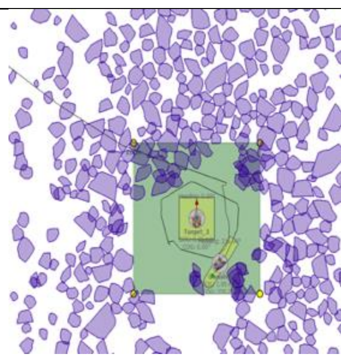
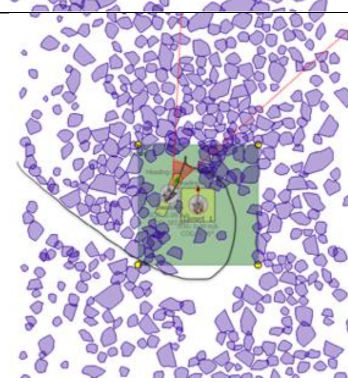
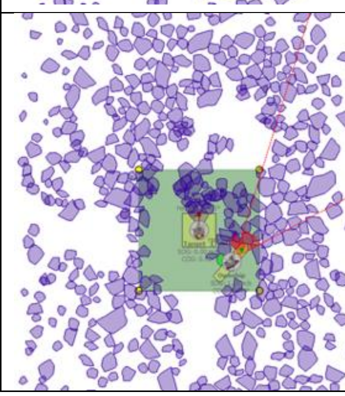
20		

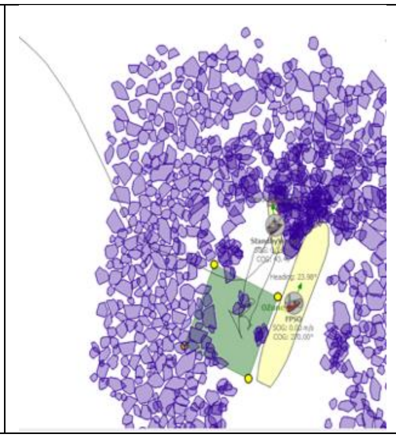
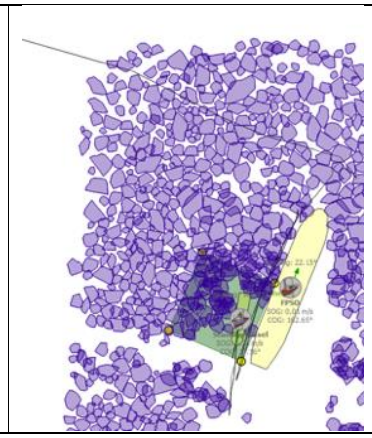
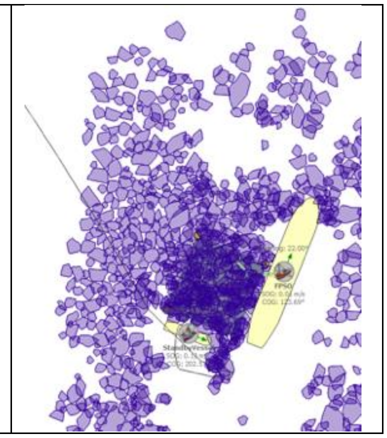
Figure 52 The Final Performance of Participant D51 in Sc.3

The final performance of the three participants in the three different scenarios is shown in Table 17. The performance by the participants can be a result of the DSS guidance and the participant's prior experience. However, based on the experience questionnaire, participant F09 had about three years of experience at sea and spent about 1 month in the presence of sea ice, while the two other participants had no experience.

Overall, the smoke testing of the DSS successfully tested the system in terms of hardware and software integration. Future works is required to evaluate the effectiveness of the DSS in providing adequate guidance in ice management operations.

Table 17 Comparing the Final Performance of Participants in Different Scenarios

	F09	K13	D51
Sc.1			
Sc.2			

Sc.3			

Chapter 5: Discussion

This thesis designed a Cased Based Reasoning Decision Support System (DSS) for marine operations using expert knowledge. A bridge simulator was used in this research as a useful human laboratory for both the knowledge capture and testing of the DSS. This section discusses the findings related to the hypothesis of this research. Specifically, (i) capturing expert knowledge to classify ice management strategies, detect important ice management factors, and find the relationship between them; (ii) developing a CBR decision support system; and (iii) testing the CBR decision support system's capability of recommending ice management strategies and offering adjustments during the implementation of a technique in the simulator. This section will discuss each.

5.1. Knowledge Capture

5.1.1. Ice Management Interviews to Construct the CBR Model and Generate Cases

To develop a preliminary decision support system using a CBR reasoning model, data were captured from the expert seafarers through interview sessions. Audio recorded from the interviews, including seafarers' strategies and their opinions about the cadet examples, was transcribed and converted into the cases. Although this process was time-consuming, the knowledge captured using this approach helped categorize ice management strategies and determine the key ice management factors and the relationship between any of these factors. Domain knowledge to construct the CBR structure and case feature indices were collected through this step.

In the interview sessions, the seafarers shared their approaches, such as their rule-of-thumb knowledge, and demonstrated the important aspects that should be considered during ice management operations. According to the participants, their ice management strategies were adaptable. They believed that there are different approaches and techniques to be used for performing ice management scenarios. That means that their plans to conduct these scenarios were not fixed, and in some cases, they were a trial-and-error process. When participants were explaining different steps of their strategies (different decision points), they expressed that they tend to place the ownship vessel in a way that they can easily change the ship's position securely if necessary. That means that if the situation changed and the chosen strategy was not working, the participants adapt their technique and test another approach.

In addition, the strategies that participants described in the interview were static strategies because they were considered in ideal situations. Therefore, the information provided in the interview session about the suggested strategies and their possible results was limited. The data collected from the cadet examples and simulator exercises aimed to address these limitations.

5.1.2. Determining the Scope of Ice Management Operations Using Cadet Examples

To define the scope of the ice management problem and provide advice about preventing or fixing problems, different successful and unsuccessful cases should be considered in the CBR model. Therefore, some examples of appropriate and inappropriate strategies implemented by cadets were shown to the seafarers, and they were asked to provide some advice and suggestions that could be used to inform the DSS. These comments and suggestions were used to improve the examples and then were added as a case to the case base. The interview session described the scenarios in ideal circumstances. As such, these examples could help participants remark on how an ice management approach may cause poor performance and which situation needs a higher level of expertise to implement a strategy more accurately. In addition, this information could be included in the DSS to assist users in understanding why the techniques should be executed in a specific way or under different conditions. Overall, the experienced seafarer's evaluation of cadet examples helped to add some advice and instructions for the cases in the DSS.

5.1.3. Improving the CBR Model and Adding Details to Cases Using Simulation Exercises

The CBR decision support system should have enough functionality to suggest ice management techniques and adjust the strategies during the implementation of the scenarios. The simulation exercise strengthened the CBR model by providing some details like the scenario outcome to the case base. For instance, due to the static situation in the interview, cases created from the interview did not show the level of the technique's success or failure. On the other hand, cases created from the simulation exercise contain the strategies' outcome and subjective measures like the participants' priority rankings of their approaches. Also, objective measures such as (1) ice concentration in the target zone (a measure of ice management effectiveness) and (2) ice loads, showing how well the ice management technique was executed.

In addition, the simulation exercises contained the dynamic aspects of ice management approaches. That means that these cases present continuous information for some features like speed and heading that could not be measured in the interview session.

5.2. DSS Development

5.2.1. Machine learning algorithms for the similarity matching aspect of the DSS

For the similarity matching aspect of the DSS, similarity-based algorithms are suitable. Similarity-based algorithms are practical learning frameworks for problems that can be solved based on the human similarity judgements. Therefore, different classification by similarity methods were compared for decision-making purposes including support vector machine method (SVM), logistic regression (LR), decision tree (DT), and random forest (RF).

In machine learning, model selection and model evaluation are key elements. To do that, using different performance metrics are necessary for evaluating the effectiveness of a classifier. Although, prediction accuracy is used as a common evaluation metric for classification, it may be inappropriate for imbalanced data, because accuracy results in a bias toward the majority class. Different performance metrics that are more appropriate for imbalanced data were used for model selection and evaluation including sensitivity, specificity, and G-mean. These metrics consider class distribution, so they are more reliable metrics measure for imbalanced data.

5.2.2. DSS Changes after Smoke Testing

Based on the results achieved by smoke testing, some changes were made in the DSS. These changes were as follow:

1. Modifying the DSS user interface
2. Adding general tips for each scenario
3. Adding specific instruction for all cases
4. Labeling inappropriate features and improving the approaches
5. Changing the priority of features for retrieving the similar cases

According to the participants' comments and suggestions, some changes were made to the DSS user interface. Figure 53 shows the new user interface. Comparing to the previous interface depicted in Figure 34, changes include:

1. Ownship Properties section was removed from the DSS for two reasons. First, there was no need to include some features like the ownship vessel's speed over ground and heading in the DSS because these features would be displayed to the participant using the indicator screen embedded in the bridge simulator. Based on the participants' comments, showing these features on both the bridge screen and in the DSS may cause confusion. Second, providing some information to the participants about other features like "distance from the target" and "area of focus" was removed. Because experiments that would be implemented using the DSS in the future are supposed to be compared with the previous experiments of the research team (Thistle, 2019; Veitch, 2018). In the previous experiments, the participants did not have any extra information about their vessel's position. They only could use the VHF radio to call the bridge officer and ask about their distances. Therefore, the same situational information was provided for the participants using the DSS. Otherwise, experiments would not be comparable.
2. Instead of the Ownship Properties section, an Instruction Section was added to the DSS, and the "More Info" button in the previous version was removed. Based on the smoke testing experience, sometimes participants forgot to click on the "More Info" button, and they inadvertently did not success detailed information about a suggested approach. Consequently, this button was removed from the DSS, and all information was displayed in the mainframe in the instruction section. This section was divided into general and specific instructions. In the general part, some tips that were common in each scenario were

shown to the participant. In the specific instruction, all instruction for a specific strategy and all notes for improving a strategy was presented.

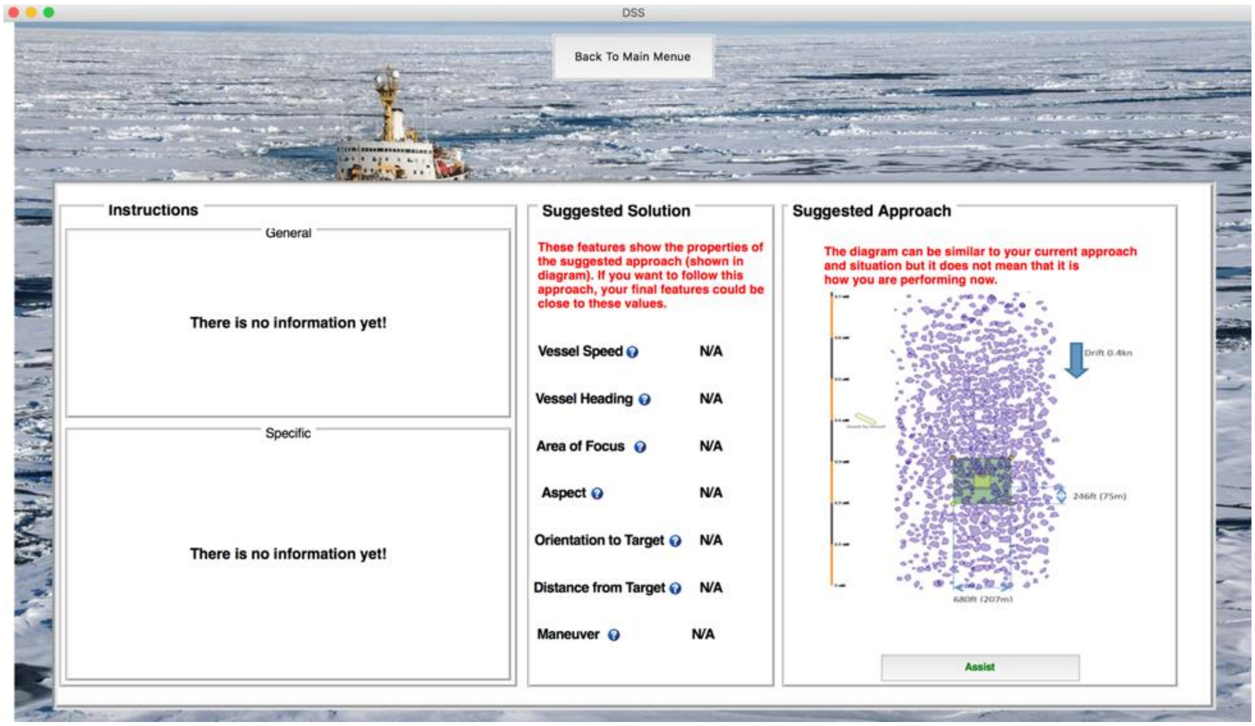


Figure 53 New Version of the DSS

As shown in Figure 54, the DSS asks the participant's name the first time that they request assistance. The name will be generated randomly before starting the session for confidentiality purposes. Using this name, all information related to the participant will be added to a log file for further analysis. This information includes the timestamps that the participant asked for help and retrieved cases by the DSS.

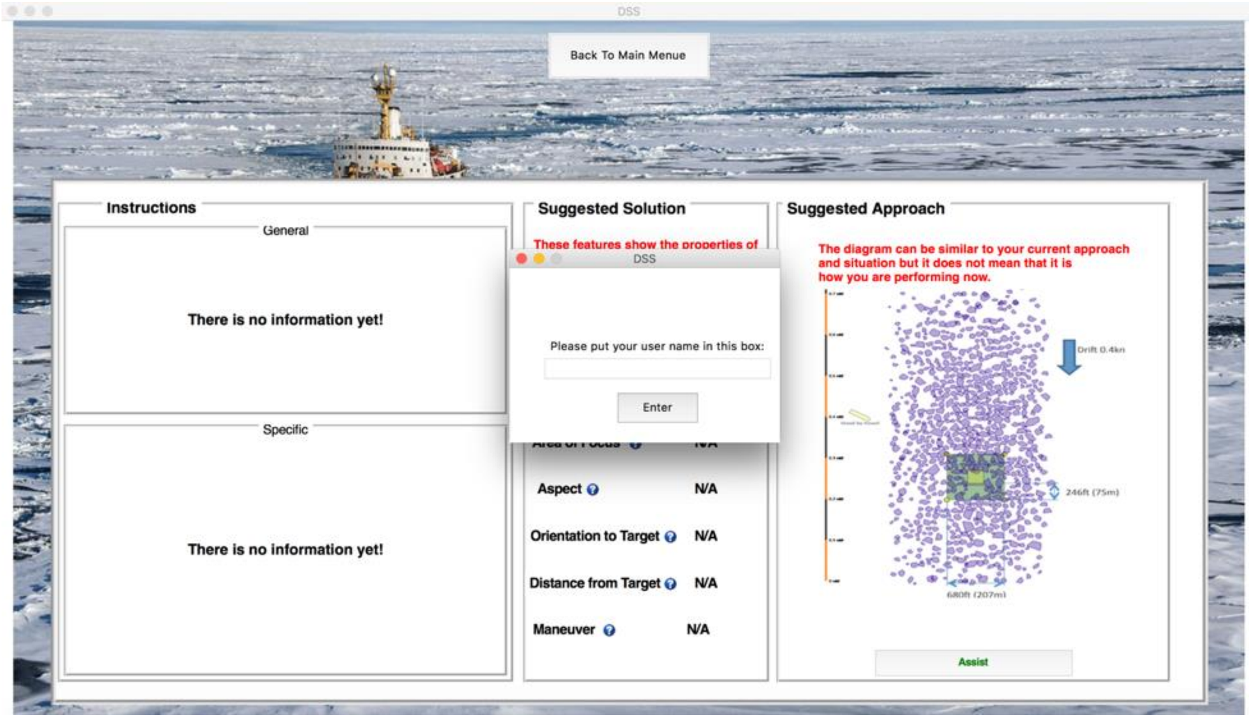


Figure 54 Saving Result in a Log File with participants' name

Figure 55 shows the new configuration of the DSS interface after all the changes from the smoke testing were implemented. In this example, the suggested approach from the DSS is similar to the user's current situation, but the suggested approach is not an appropriate strategy on its own. Therefore, the participant is first shown a "caution" warning in red and then the DSS guides them in the specific instruction on how to have a better performance.

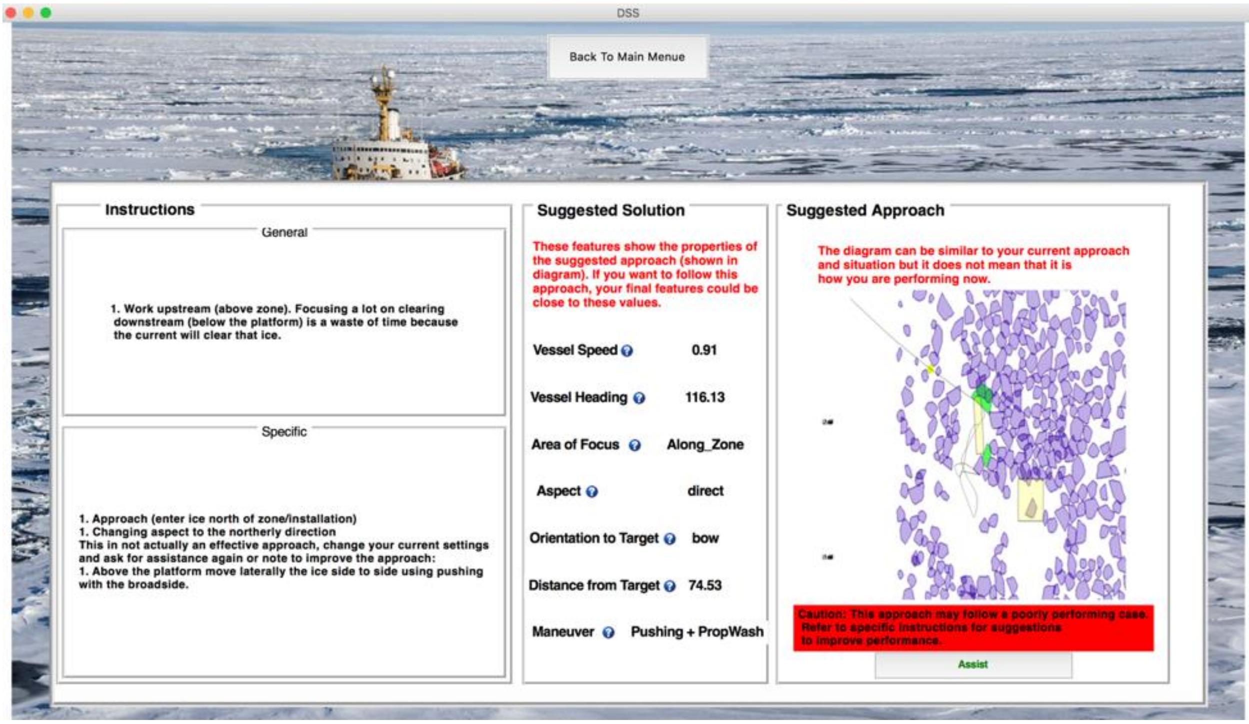


Figure 55 Suggested Solution by the DSS

Chapter 6: Conclusions

Prevention of safety hazards plays an important role in the offshore and maritime industries. This study focused on a human-centered approach to develop an early-stage decision support system (DSS) for offshore ice management operations by applying the case-based reasoning (CBR) method. The DSS can tackle conventional on-the-job training weaknesses and can assist in the knowledge exchange between seafarers. Knowledge capture from experienced seafarers was used to inform the development of an onboard decision support system for ice management operations.

At the knowledge capture phase, three different methods were used for gathering ice management information from the experienced seafarers, including (1) semi-structured interviews on ice management approaches, (2) reviewing cadet examples, and (3) performing simulation exercises. The data gathered from these methods was employed to develop a CBR model and resulted in 34 cases in the case base. CBR is under the assumption of similar problems have similar solutions, and new problem can be solved by retrieving similar problems or adapting retrieved solutions. Thus, a rich CBR case base is needed before it can match user's condition. Although 34 cases were used to develop the CBR case base at the starting point, adding more cases to the case base was essential to enhance the solution generation and developing an effective DSS. To do so, 140 cases were generated from the previous simulation experiments (Thistle, 2019; Veitch, 2018).

The aim of this research was the development of an onboard DSS using a CBR case base. Several machine learning methods has been implemented in the DSS development. In order to verify the efficiency and the accuracy of each model, four algorithms were selected to compare their effectiveness, which are the support vector machine method (SVM), logistic regression (LR), decision tree (DT), and random forest (RF). By observing the experimental results, the decision tree gave the best result in comparison to other machine learning methods that were used during the evaluation. This study is certainly a great starting point for further development with various types of classification. Future testing of different machine learning algorithms will indicate the aspects that will need to be modified, with the main purpose to obtain better outcomes.

To test the CBR decision support system's functionality in a simulated environment and evaluate the way it generates solution by matching similar cases, the DSS has been set up and installed on the ice management simulator. The system collected time series data from the simulator during the implementation of scenarios and provided targeted solutions according to values of different attributes in each case. The DSS has been successfully tested in terms of hardware and software integration.

Some limitations in this research should be noted. First, this research mainly focused on the processes of case retrieval and case reuse and the other two processes, case revision and case retention are not explained in detail. Moreover, in terms of CBR, similar problems have similar solutions and new problems can be solved by retrieving similar problems. Therefore, a large case base is needed to match the user's conditions.

The number of cases in this study was small and my weaken the reliability of the proposed CBR-based model in the DSS. Despite the small number of cases, the methodology used for capturing data is an important aspect of this thesis. In addition, the data collection methods used in the pilot study required post-processing and interpretation before they were added into the CBR model as cases. Automating the data could be considered in the future work by parsing and indexing the case in the existing simulation technology to create more informative and practical DSS.

Future work will focus on validating the DSS by using the DSS in a simulator setting to support cadets and seafarers in effectively managing ice during a series of safety critical operations. Validation of the DSS in a simulated environment would verify the decision support system's capabilities of offering onboard guidance on pack ice management techniques. The purpose of this work would be to determine if participants supported by a DSS would perform better in the ice management bridge simulator. This research could also analyze the variability amongst participants' performances to see if variability would be lower due to the uniformity that the DSS will give to ice management strategies.

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Appendices

Appendix A: Interview Session Outline

Session Outline

1. **Briefing**
    - Overview of project
    - Informed Consent Form
2. **Experience Interview**
    - Experience Questionnaire
    - Questions about your seafaring experience
3. **Ice Management Factors**
    - ***Q1**: What factors do you consider for success in ice management?*
        - Rank factors in terms of importance
4. **Cadet Training Examples**
    - **Scenario x3 scenarios**
        - Introduce scenario
        - ***Q2**: How would you execute this scenario?*
            - Sketch approach and identify decision points on diagram.
        - **Example x2 examples for each scenario**
            - Watch cadet example
            - Advice, Recommendations, Feedback, and Decision Points
                - **Q3:** *What advice, recommendations, or feedback would you give the cadet based on their performance in this example?*
                - **Q4:** *What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.*
                    - Identify points for advice, recommendations, or feedback and decision points in video
            - **Q5a:** *What in this example violated rules that you would consider during ice management?*
            - **Q5b:** *What in this example followed rules that you would consider during ice management?*
            - ***Q6**: How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?*
        - ***Q7**: What factors would you consider for success in this scenario?*
            - Rank factors in terms of importance
5. **Feedback and Closing**
    - Your feedback for us about the session

Appendix B: Informed Consent Form

Informed Consent Form

Title: Knowledge Capture of Decision Making Processes Using Experienced Personnel in a Simulator Environment

Researchers: Memorial University:

Dr. Brian Veitch, Professor of Ocean and Naval Architectural Engineering, Faculty of Engineering and Applied Science, Memorial University, (709) 864-8970, bveitch@mun.ca

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National Research Council of Canada:

Dr. Jonathan Power, Research Council Officer, National Research Council of Canada / Government of Canada, (709) 772-8430, jonathan.power@nrc.ca

Benjamin Colbourne, Research Council Officer, National Research Council Canada – Ocean, Coastal, and River Engineering (NRC-OCRE), (709) 772-6001, Benjamin.Colbourne@nrc-cnrc.gc.ca

Jeffery Brown, Graduate Student and Research Council Officer, National Research Council of Canada / Government of Canada, (709) 772-4339, Jeffrey.Brown@nrc-cnrc.gc.ca

You are invited to take part in a research project entitled *"Knowledge Capture of Decision Making Processes Using Experienced Personnel in a Simulator Environment."*

This form is part of the process of informed consent. It should give you the basic idea of what the research is about and what your participation will involve. It also describes your right to withdraw from the study. In order to decide whether you wish to participate in this research study, you should understand enough about its risks and benefits to be able to make an informed decision. This is the informed consent process. Take time to read this carefully and to understand the information given to you. Please contact the researcher coordinators, *Jonathan Power* or *Jennifer Smith*, if you have any questions about the study or would like more information before you consent.
It is entirely up to you to decide whether to take part in this research. If you choose not to take part in this research or if you decide to withdraw from the research once it has started, there will be no negative consequences for you, now or in the future.

Introduction:
This project is being funded by both the National Research Council of Canada and Memorial University's Safety at Sea Project which is funded by Natural Sciences and Engineering Research Council (NSERC), Husky Energy, and InnovateNL.

Advancements in software engineering in recent years has led to the development of vehicles that do not require people to drive or pilot them. It is believed that these autonomous machines will be used in the near future, possibly replacing the need to have people behind the wheel.

In order to make sure that these autonomous machines are operating as safely as possible, we would like them to operate in the same way an experienced person would if they were driving. For the autonomous machines to be able to do this, we need to be able to tell them what information is important, and how they should make a decision based on it. For example: if there were an obstacle in front of a car/ship, the autonomous machine needs to not only to go around it, but to know if it should go to the left or right, or speed up or slow down.

To provide the autonomous machine with this kind of informed decision-making we will be performing a study to see if different technologies and methods can capture information experienced people, like yourself, use to make a decision. We are hoping to be able to determine if these technologies and methods provide good insight into how decisions are made, and then use them for future studies other than this one.

Purpose of Study:
You are being asked to be a participant on a study designed to evaluate methodologies and technologies for capturing what knowledge is used by experienced people to inform their decision-making in ice management operations.

What You Will Do in this Study:
If you choose to participate in this study, you will be asked to complete a number of ice management trials in an ice management simulator.

You will work with a member of the research team to schedule times that are convenient for you to participate in this study. It is expected that the study will take two separate sessions to complete.

Each session will take place at the Safety at Sea project's Simulation Lab (EN1035) in the Engineering and Applied Sciences (SJ Carew) building on Memorial University's St. John's campus.

You will arrive at the ice management simulator at the scheduled time where you will meet a member(s) of the research team.

The sessions will be split into four parts: (1) Briefing, (2) Familiarization Trial, (3) Ice Management Scenarios, and (4) Feedback and Closing. With your consent, portions of the Ice Management Scenarios (i.e. the planning exercise and post-trial debrief) will be audio recorded and transcribed by the research team.

Note: You do not need to complete all trials during one visit to the ice management simulator. If at any point you wish to stop for the day, and return at a later date to complete the remaining trials, we can arrange a follow up time for you to return.

Refreshments (water and snacks) will be on hand for you during the trials. We will have time for you to take multiple breaks throughout the sessions to allow you to have some refreshments, move around outside of the simulator, or use the washroom.

1. *Briefing:*

We will explain the research and an opportunity to ask questions or express concerns. If satisfied, you will indicate your free and informed consent by completing this Informed Consent Form.

Before you start any trials, we will ask you to complete an experience questionnaire. We will also ask you to fill out a simulator sickness questionnaire (SSQ) in order for us to establish a baseline score for you. We will administer the SSQ to you throughout the trials to see if you are developing simulator sickness, which will be indicated by a higher score.

After you have completed the SSQ for the first time, you will be fitted with a set of eye glasses that will record what direction you are looking in, and record where your eyes are focusing. These glasses are worn like a pair of sunglasses (with no tint) and are connected to a battery pack, which will clip on to your belt. Once the glasses are in place and working, we will escort you into the console of the ice management simulator.

2. *Familiarization Trial:*

Once in position on the console, you will be asked to perform the 3-familiarization trials. These trials are designed to allow you to get familiar with the ice management simulator, and how the ship handles in the simulation. The trials are expected to take approximately 5-10 minutes for a total of 15-30 minutes.

After the familiarization trials are completed, we will move on to the ice management scenarios.

3. *Ice Management Scenarios:*

The ice management scenarios consist of a planning exercise, simulator scenario, and a post-trial debrief. There will be five ice management scenarios to complete in total. Each scenario takes approximately 15-30 minutes, for a total of 75-150 minutes.

Prior to starting each ice management scenario, you fill out a SSQ and go through a planning exercise with us. The planning exercise will consist of a diagram of the upcoming ice management scenario that you can use to draw on, and plan your movements. We will be asking you interview style questions during this planning session (e.g. Why are you choosing to go this way with the ship as opposed to that way?). Your responses in the planning exercise will be audio recorded.

Upon finishing the planning session, you will re-enter the ice management simulator and perform the ice management scenario.

When the scenario has been completed, you will be escorted off the ice management simulator and fill out another SSQ to determine if you are experiencing any symptoms of simulator sickness. You will then be shown a sped up video replay of your current scenario, where we will ask you interview style questions about your ice management techniques. We will ask you a series of questions to get your opinion on your performance and what factors you considered during ice management. Your responses in the post-trial debrief will be audio recorded.

4. *Feedback and Closing:*

You will be asked to give feedback on the planning exercises, scenarios, and post-trial questions. After this, the session will be completed.

Length of Time:
You will be asked to attend 1-2 session(s). The length of this session may vary from person to person but is expected to be between 4-6 hours.

Withdrawal from the Study:
You can withdraw from this study at any point during your participation without giving any reason, and all data collected up until that point will be destroyed. There are no consequences to you for withdrawal from the study. If you choose to withdraw from the study after your participation, your data can be removed from the study up to two weeks after your participation. To withdraw from the study just inform the research coordinators, Jonathan Power or Jennifer Smith.

Compensation and Travel Expenses Reimbursement:
You will be given a $200 CAD honorarium for participating in this study. Any travel expenses incurred in order to attend this study at MUN will be reimbursed. We will abide by the most recent Schedule of Reimbursable Expenses listed by the Financial and Administrative Services at MUN for on travel expense claims. Note that the honorarium and travel claim do not oblige you to participate; regardless of whether you are paid to travel, you are free to withdraw from the study and your participation status will remain anonymous.

Possible Benefits:
There will be no direct benefit to you for participating in this study.
Data collected from this study will benefit in the development of machine learning algorithms for autonomous ships.

Possible Risks:
A risk associated with participating in this study is the potential development of simulator-induced sickness. Simulator-induced sickness is very similar to motion sickness and can occur when people use equipment such as virtual reality headsets or simulators. Symptoms can include fatigue, headache, eye strain, difficulty focusing, increased salivation, sweating, nausea, stomach awareness, blurred

vision, dizziness, vertigo, and burping. The symptoms can sometimes occur during, immediately after or several hours after exposure to the simulator.

We will be monitoring you for simulator sickness throughout the ice management scenarios by asking you complete the simulator sickness questionnaire (SSQ). If you self-report any of the above symptoms as "moderate" or "severe", we will pause the trials and you will be provided with a rest period until your symptoms have subsided. You can decide whether you would like to resume the trials after the rest period. If the symptoms subside, and you choose to do so, we can continue with the trials. If you choose to not continue with the trials, we will stop the trials and you will exit the simulator.

If after the session ends the symptoms of simulator sickness persist for more than 20 minutes, we will arrange for you to get home safely.

Your performance in the simulator will be recorded throughout the study. For some individuals, this may cause performance anxiety or stress. This anxiety or stress may be caused by poor performance in the scenarios, by the difficulty or novelty of the task, or by repeated trials. To reduce the likelihood of anxiety and stress, where possible, we will guide you through the scenarios of the study. You will receive a break between scenarios to rest and you will be instructed not to worry or dwell on the previous scenarios.

You will be reminded that if you are not comfortable with any aspect of the trials, then you have the right to withdraw from the study at any point. To reduce the likelihood of embarrassment, you will perform the task individually and you will be reminded that your performance in the simulator will be anonymous. That is, your data is not linked to your identity and that your performance or withdrawal will not be reported to anyone.

If at any time you experience symptoms or discomfort, which prevent you from continuing in this study you retain the right to withdraw from the study.

As discussed in the *Anonymity* section of this form, the researchers cannot guarantee your complete anonymity in this research. While your name will not be reported, you may be identifiable to other people based on other information you provide. This means there is a risk of being identified based on your participation in this study. To reduce the likelihood of you being identified the researchers will avoid reporting any identifiable information such as specific vessels you have worked on.

There is a risk of embarrassment in this study if you feel you cannot answer the researchers' questions adequately. To reduce the likelihood of embarrassment you will be reminded that you are not being tested by these simulator trials.

Confidentiality:
The ethical duty of confidentiality includes safeguarding participants' identities, personal information, and data from unauthorized access, use, or disclosure. Protecting your privacy and maintaining confidentiality is important to the research team. The information gathered in this study will be used

solely for research purposes. Only researchers involved in this study will have access to the data. The research coordinator, Jennifer Smith, will be the data custodian for this study. All other researchers at MUN and NRC will have access to anonymized data.

Anonymity:
Anonymity refers to protecting participants' identifying characteristics, such as name or description of physical appearance.

Protecting your privacy is an important goal for the research team and this means ensuring all personal data recorded during yout participation remains anonymous. You will not be directly identified in publications. The study will use a number to identify you, not your name. For example, researchers will use an alphanumerical participant code (e.g. AB001) to identify you in all reports of your data including when direct quotations are used. Identifying information such as your name and the names of any companies or vessels you reference will not be reported. However, information such as the types of vessels you have worked on and the positions you have held (e.g. Caption, Deck Officer, etc.) may be reported and it is possible that you will be identifiable to other people on this basis. Additionally, since the participants for this research project have been selected from a small group of people, who are likely known to each other, it is possible that in reports of this study you may be identifiable to other people based on what you have said. This means the research team cannot guarantee your complete anonymity in this research.

Recording of Data:
As part of this study, we will be collecting the following data from you:

- Name and contact information.
- Experiences managing ice operations.
- Simulator sickness questionnaire scores.
- Eye tracking data (from the eye tracking glasses)
- Ice management scenario performance (from the simulator)
- Hand drawn plans created during planning sessions.
- Audio from planning sessions.
- Audio from post-trial debriefs.

Use, Access, Ownership, and Storage of Data:
The research team will collect and use only the information they need for this research study. Your name and contact information will be kept in a locked office on a password protected computer by the research team at MUN (specifically the research coordinator, Jennifer Smith). It will not be shared with others without your permission. You will receive a randomized alphanumeric participant code (e.g. AB001). All information collected from you will be recorded with the participant code. Your name will not appear in any report or article published as a result of this study.
Information collected, anonymized, and used by the research team will be stored by the research coordinators, Jonathan Power and Jennifer Smith, and they are the people responsible for keeping it secure. A hardcopy of your transcribed audio recordings and question responses will be kept in a

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filing cabinet in a locked office accessible only by the research team and will be kept separate from your signed informed consent form. Electronic files (e.g. simulator log files, eye tracking records, and audio-recordings) from this study will be kept in a password-protected file on a hard drive accessible only by the research team. Data will be kept for a minimum of five years, as required by Memorial University's policy on Integrity in Scholarly Research. After five years, all electronic records of your participation will be permanently deleted and all paper files will be destroyed.

Data collected in this study will be documented in an Ocean Engineering Research Center (OERC) report. This will make the data accessible to other researchers. This report will not include your name.

Reporting of Results:
The research team intends to publish the findings of this study in peer-reviewed journals and academic conferences. Formal reports will be made available to the research project partners (the National Research Council, Husky Energy, and Virtual Marine). The data will be reported in a descriptive form and may also include direct quotations and/or summarized question responses. Your name will not be reported in any form.

Sharing of Results with Participants:
When data analysis is completed, a report will be prepared and participants who wish to be informed of the results will have the opportunity to receive a copy of this report.

Questions:
You are welcome to ask questions before, during, or after your participation in this research. If you would like more information about this study, please contact:
Jonathan Power (jonathan.power@nrc.ca) or Jennifer Smith (jennifersmith@mun.ca).

ICEHR Approval Statement:
The proposal for this research has been reviewed by the Interdisciplinary Committee on Ethics in Human Research and found to be in compliance with Memorial University's ethics policy. If you have ethical concerns about the research, such as the way you have been treated or your rights as a participant, you may contact the Chairperson of the ICEHR at icehr@mun.ca or by telephone at 709-864-2861.

NRC Research Ethics Board Statement:
This study has also been approved by the NRC Research Ethics Board (NRC-REB) under protocol number 2019-119. REB review seeks to ensure that research projects involving humans as participants meet Canadian standards of ethics. Any questions or concerns about the ethics of this study may be directed to the NRC-REB Secretariat, NRC-REB@nrc-cnrc.gc.ca, (613) 949-8681.

Consent:
Your signature on this form means that:

- You have read the information about the research.

- You have been able to ask questions about this study.
- You are satisfied with the answers to all your questions.
- You understand what the study is about and what you will be doing.
- You understand that you are free to withdraw participation in the study without having to give a reason, and that doing so will not affect you now or in the future.
- You understand that if you choose to end participation during data collection, any data collected from you up to that point will be retained by the researcher, unless you indicate otherwise.
- You understand that if you choose to withdraw after data collection has ended, your data can be removed from the study up to two weeks after your participation.

I agree to be audio-recorded	☐ Yes ☐ No
I agree to the use of direct quotations	☐ Yes ☐ No
I allow data collected from me to be archived in an Ocean Engineering Research Center Report	☐ Yes ☐ No

By signing this form, you do not give up your legal rights and do not release the researchers from their professional responsibilities.

Your Signature Confirms:

☐ I have read what this study is about and understood the risks and benefits. I have had adequate time to think about this and had the opportunity to ask questions and my questions have been answered.

☐ I agree to participate in the research project understanding the risks and contributions of my participation, that my participation is voluntary, and that I may end my participation.

☐ A copy of this Informed Consent Form has been given to me for my records.

______________________________ ______________________________

Signature of Participant Date

Researcher's Signature:
I have explained this study to the best of my ability. I invited questions and gave answers. I believe that the participant fully understands what is involved in being in the study, any potential risks of the study and that they have freely chosen to be in the study.

______________________________ ______________________________

Signature of Principal Investigator Date

Appendix C: Experience Questionnaire

Participant Number: _______________
Date: _______________

Appendix C: Experience Questionnaire

Please review and answer the questions as you see fit. You are free to omit any questions that you do not wish to answer. If something is unclear, ask the experiment coordinator. Your answers are confidential.

Question	Answer
1. Approximately how many years experience do you have at sea?	________________________
2. On what types of vessels have you operated? (Select all that apply)	☐ OSV / AHTS ☐ Icebreaker ☐ Tanker / Bulk / Cargo ☐ Ferry / Coastal ☐ I have not spent time at sea
3. Have you ever operated in sea ice?	☐ Yes ☐ No
4. What types of operations did you perform while in ice? (Select all that apply)	☐ Watchkeeping during transit ☐ Maneuvering ship while being escorted ☐ Maneuvering ship to escort another vessel ☐ Ice management (open water) ☐ Ice management (confined water) ☐ Towing or emergency response ☐ I have only observed operations in ice ☐ I have not operated in ice
5. Where have you obtained your experience in operating in ice? (Select all that apply)	☐ Great lakes ☐ Gulf of St. Lawrence ☐ Coastal Newfoundland and Labrador ☐ Arctic (north of 60) ☐ Baltic Sea ☐ Caspian Sea ☐ Sea of Okhotsk ☐ Antarctic ☐ I have not operated in ice
6. Approximately how many years have you spent in the presence of sea ice?	________________________

Participant Number: _______________

7. What types of shore based training have you taken for operating in ice? (Select all that apply)	☐ Basic training in ice operations ☐ Advanced training in ice operations ☐ Attendance at professional seminars discussing techniques and procedures relevant to ice operations ☐ I have never received training related to ice operations
8. Do you have any experience using a marine simulator? (Select all that apply)	☐ Training for navigation in open water ☐ Training for navigation in ice ☐ Research study ☐ I have no experience using a marine simulator

Appendix D: Simulator Sickness Questionnaires

Simulator Sickness Questionnaire[1]

Please place an X in the box for each symptom you are experiencing at this current moment.

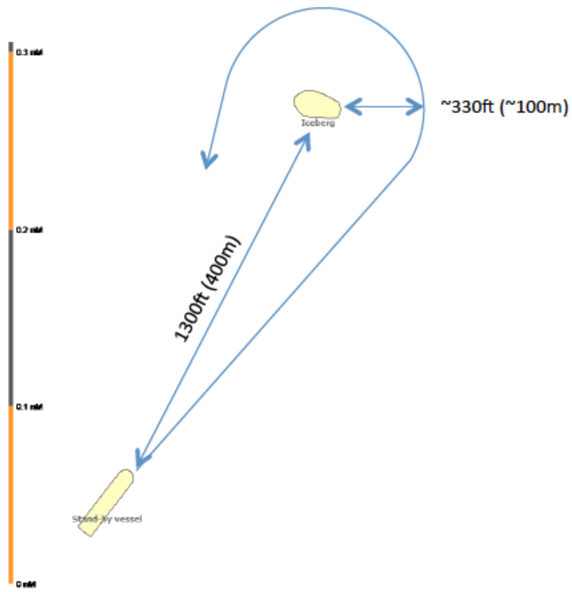
Date: ___________ **Trial:** ____________

Symptom	None	Mild	Moderate	Severe
General discomfort				
Fatigue				
Headache				
Eyestrain				
Difficulty focusing				
Increased salivation				
Sweating				
Nausea				
Difficulty concentrating				
Fullness of head				
Blurred vision				
Dizziness (with eyes open)				
Dizziness (with eyes closed)				
Vertigo				
Stomach awareness				
Burping				

[1] Derived from: Kennedy, R., Lane, N., Berbaum, K., and Lilienthal, M. (1993). *Simulator Sickness Questionnaire: An Enhanced Method for Quantifying Simulator Sickness.* The International Journal of Aviation Psychology, 3:3, p.203-220.

Appendix E: Habituation Scenario Instructions

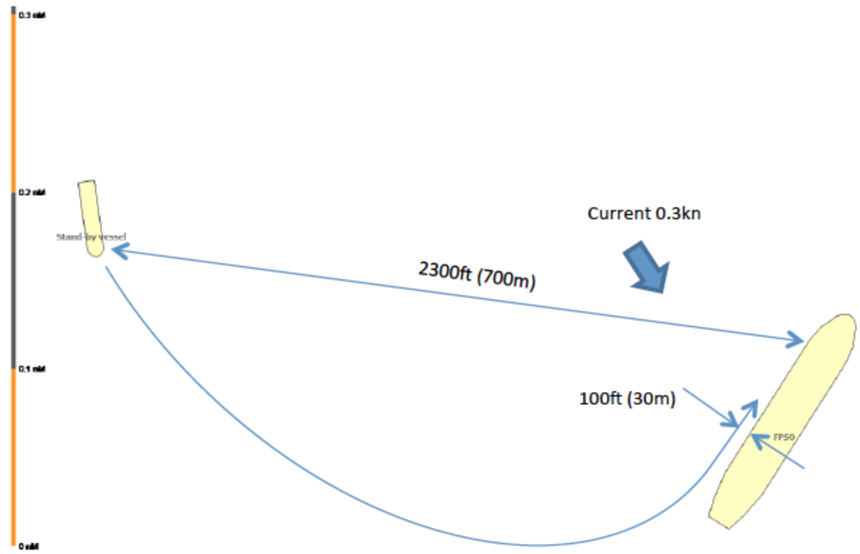
Habituation 1: Rounding the Iceberg



Objective: Round the iceberg, passing it to your port, and return
Time: ~10min (20min cut-off)

- This will give you the opportunity to:
  - Get used to the virtual environment
  - Get a feel for the controls and the bridge layout
  - Get used to calling the bridge officer in the wing console
- There is a bridge officer in your wing console. Radio them to ask for the distance between the iceberg and your vessel
  - Vessel heading: 33.5deg
  - Current: 0kn
  - Current direction: N/a
  - Wind: Light

Habituation 2: Maneuver alongside FPSO



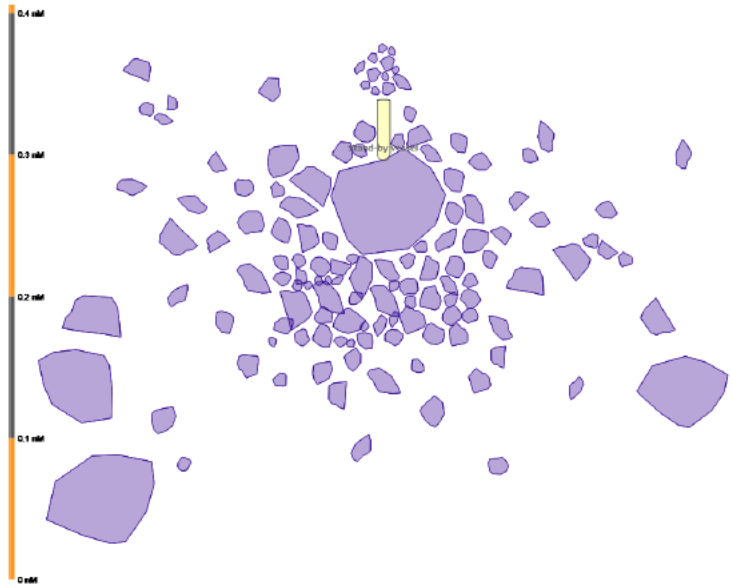
Objective: Stop 30m (100ft) abeam of FPSO port side

Time: ~10min (20min cut-off)

- This will give you the opportunity to:
  - Get used to slow maneuvers
  - Get used to radioing your wing console bridge officer for distance

- There is a bridge officer in your wing console. Radio them to ask for the distance between the iceberg and your vessel
  - Vessel heading: 172deg
  - Target heading: 32.5deg
  - Current: 0.3kn
  - Current direction: 327deg (NNW)
  - Wind: Light

Habituation 3: Clear ice using propeller wake wash



Objective: Use your propeller wash to push away the small floes directly aft of your vessel

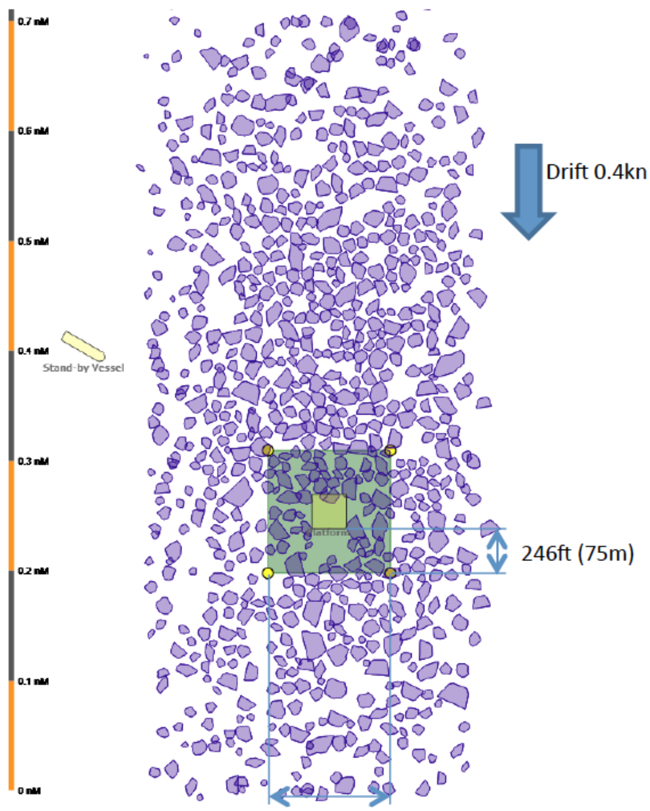
Time: ~1min (or until complete)

- This will give you the opportunity to:
  - Get used to prop wash as a way to clear ice

  - Vessel heading: 180dg
  - Current : 0kn
  - Current direction: N/a
  - Wind: Light
  - Ice: 0.3-0.7m first year ice

Appendix F: Scenario Instructions

Training: Pushing



Objective: Clear the encroaching pack ice from the indicated area using the pushing technique

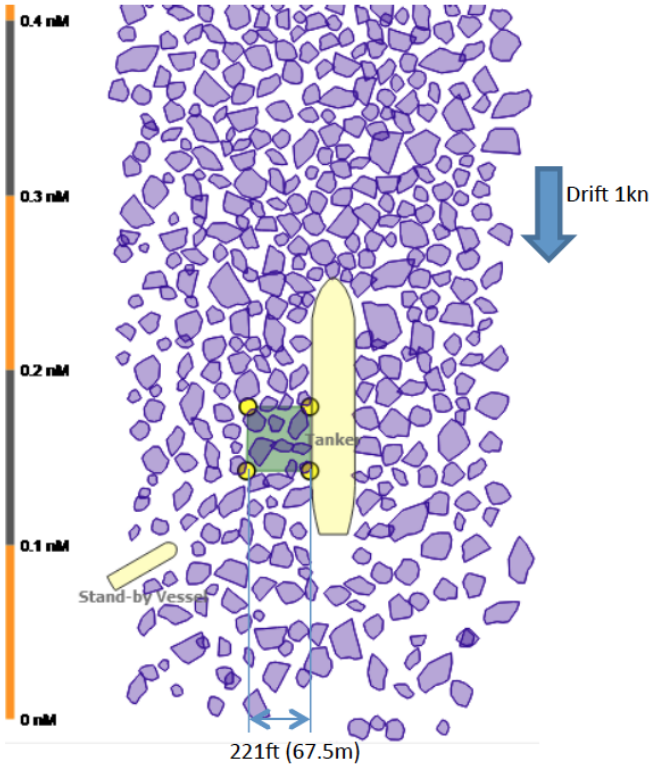
Time: 15min

- Stand-by vessel support is required to clear the ice around the platform
- Ice clearing reduces the risks due to ice pressure on the platform and damage to the facility from ice

- Maintain a safe speed of 3kn
- The Atlantic Hawk has unprotected rudders while reversing; reverse in ice with caution

- Vessel heading: 120deg
- Current: 0.4kn
- Current direction: 180deg S
- Wind: Light
- Ice: 0.3-0.7m first year ice, 4-tenths concentration

Training: Leeway



Objective: Clear the indicated area aft of midships using the leeway technique

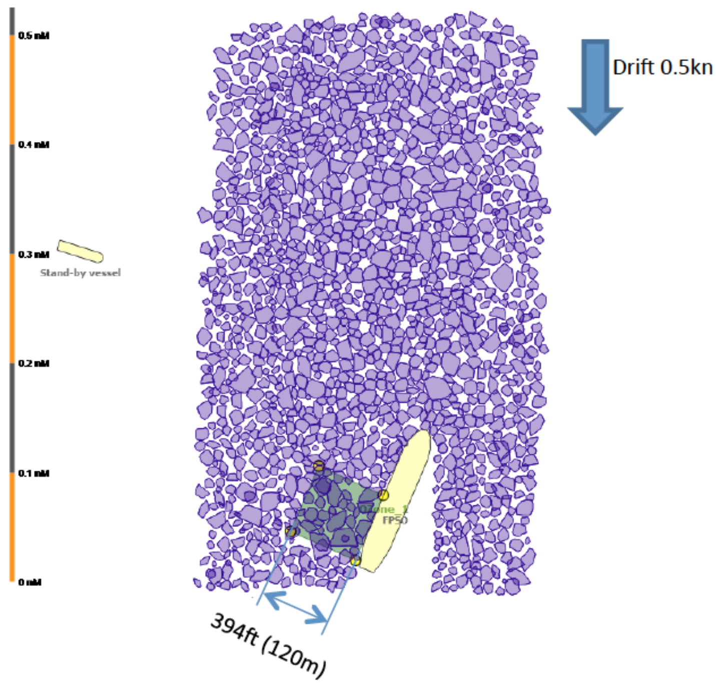
Time: 15min

- Stand-by vessel support is required to clear the indicated area so that research equipment can be launched
- Ice clearing reduces the risks of damage to the research equipment from ice

- Maintain a safe speed of 3kn
- The Atlantic Hawk has unprotected rudders while reversing; reverse in ice with caution

- Vessel heading: 60deg
- Target heading: 0deg
- Current: 1kn
- Current direction: 180deg S
- Wind: Light
- Ice: 0.3-0.7m first year ice, 5-tenths concentration

Scenario B: Emergency ice management (7tenths concentration)



Objective: Clear encroaching pack ice from the boxed area shown
Time: 30min

- Stand-by vessel support is required to clear the ice under port lifeboat launch zone
- FPSO's starboard side is already clear due to ice drift direction

- Maintain a safe speed of 3kn
- The Atlantic Hawk has unprotected rudders while reversing; reverse in ice with caution

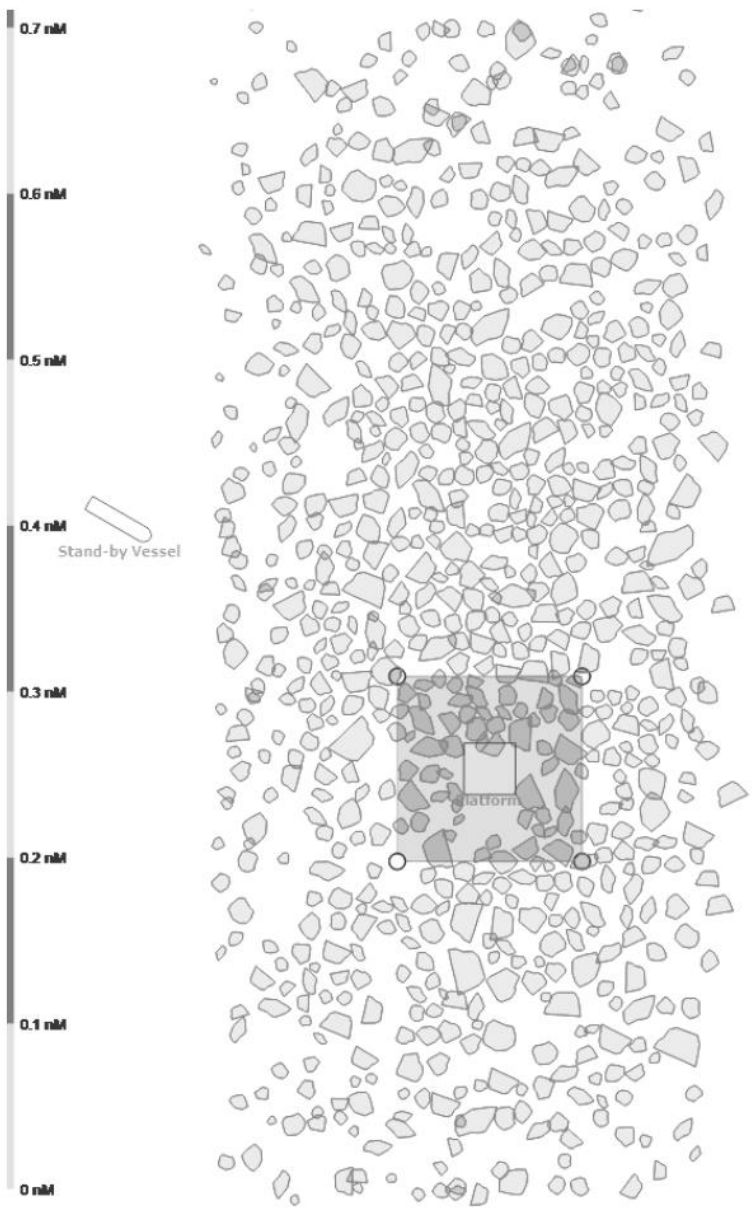
- Current: 0.5kn
- Current direction: 180deg S
- Wind: Light
- Ice: 0.3-0.7m first year ice

Appendix G: Scenario Diagram Pages

Participant Code: _______________ Date: _______________

Approach Number: _______________ Time: _______________

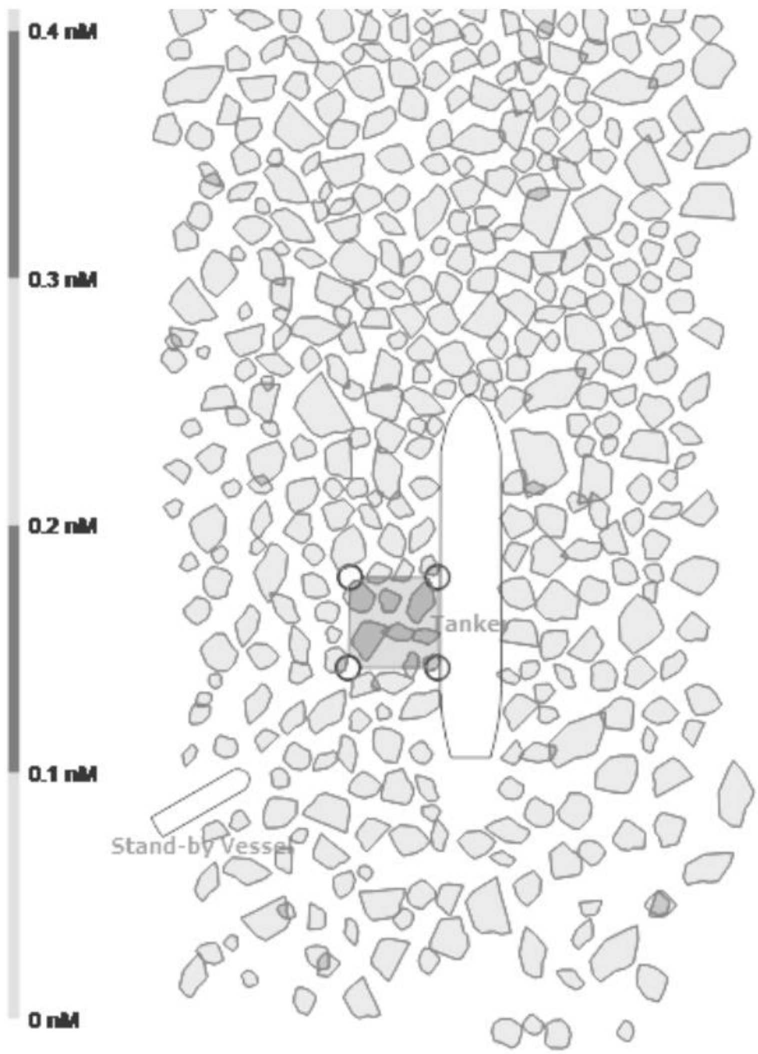
Pushing Scenario



Participant Code: _______________ Date: _______________

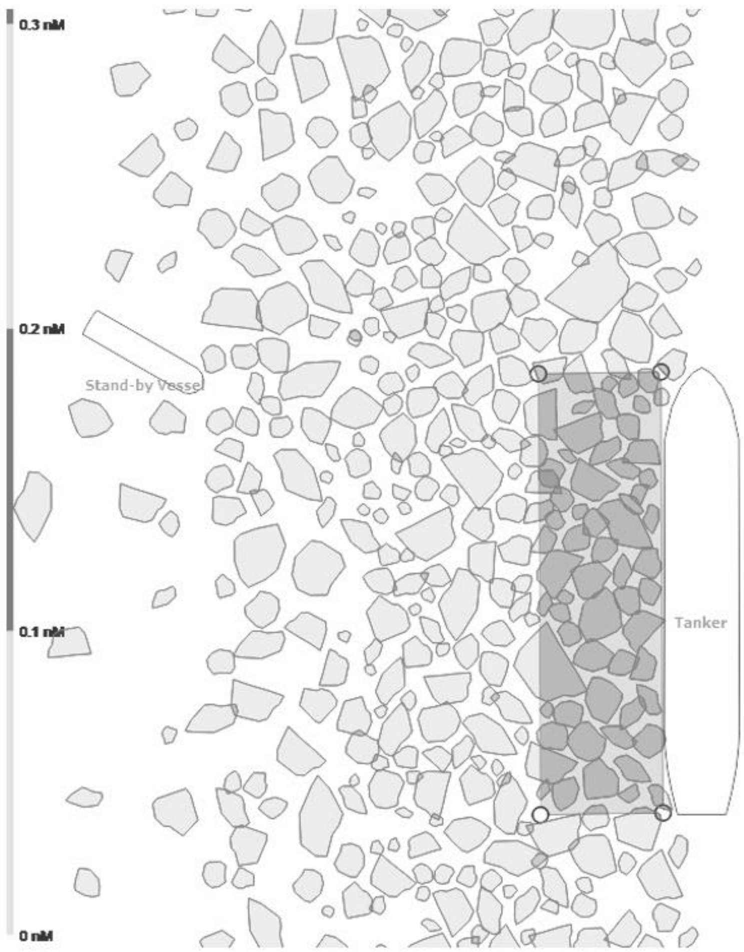
Approach Number: _______________ Time: _______________

Leeway Scenario



Participant Code: _______________ Date: _______________

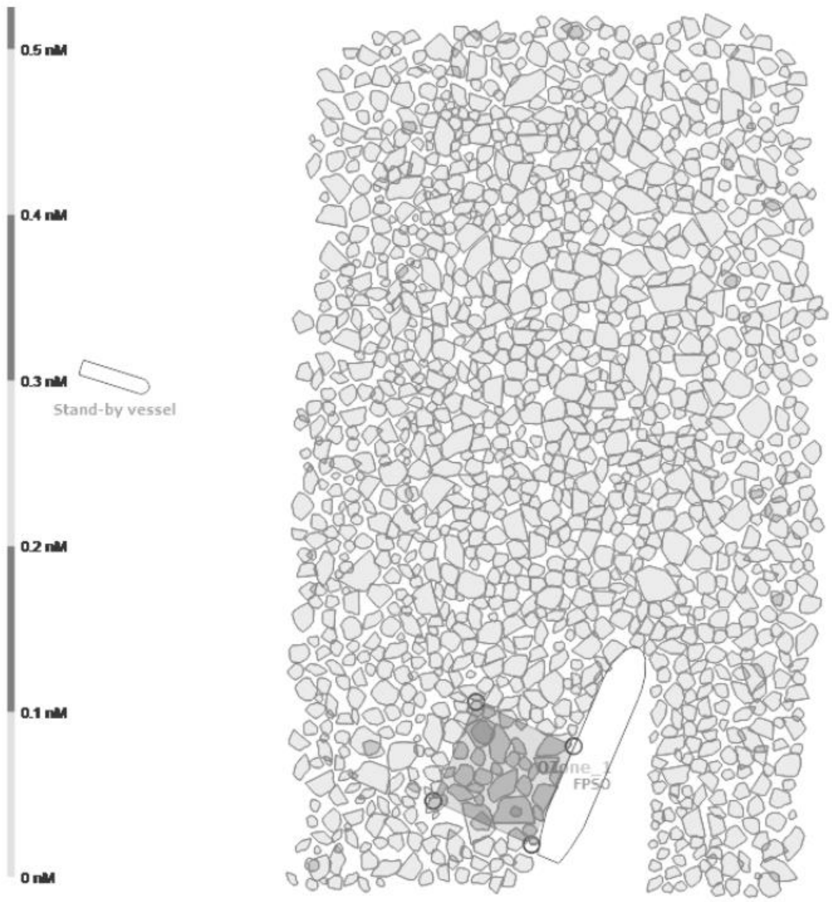
Prop Wash Scenario



Participant Code: _______________ Date: _______________

Approach Number: _______________ Time: _______________

Emergency Ice Management Scenario – 7 tenths



Appendix H: Transcribing Guide

Transcribing Guide

- Before each section have a heading with the following format:

Section: *Audio file name – start time* to *end time*
Transcribed by: *Transcriber*   Checked by: *Checker*

For example:

Section: Recording Part 2 – 20:55 to 21:24
Transcribed by: FY   Checked by: RT

- Everything in between the start and end time listed should be transcribed.

- Stuff at the beginning of sections where the topic is being explained and the participant doesn't say anything relevant doesn't need to be transcribed (i.e. start the transcription section after that).

- Format for transcription:

T00: Who's speaking then tabbed. Text in plain size 12 Arial font single spaced. Left aligned.

RT: Line between. Then, who's speaking. Then, tabbed.
Second line also tabbed. (Tables use the same format)

For example:

RT: Okay. Yeah.

T00: Yeah, I think that's it.

RT: Alright.

- For tables follow the format in 'T00- Interview Experiment Data – R2'

- If something in the audio is un-clear write *in audible* in italics and highlight it. The checker will go back to that part and if it's unclear to them it will be left as *in audible* un-highlighted.

- If there is anything in the transcription you are not sure about just highlight for the checker to review.

- To clarify something (e.g. define what is meant by here or this) put in brackets and italics, e.g. [*words in italics*]. If you think you know what is being referred to but are not sure but a question mark after e.g. [*Decision Point 1?*].

- We don't need to transcribe vocal fillers (e.g. 'ums', 'ahs', etc.). I have also been removing 'so' unless it's relevant to the context. (e.g. being used as therefore).

- We don't need to use stylistic forms of words (e.g. because instead of writing 'cause).

- I've been using contractions where appropriate (e.g. weren't, it'd, it's). I guess we will continue that unless someone says otherwise. If it would be clearer not to use contractions we can use the full words (e.g. were not, it would, it is).

- When someone starts to use the wrong word and then corrects themselves no need to add the wrong word part (e.g. starboard instead of writing por…starboard). If they use two words and it's unclear which they actually mean just put both in as they're said. The same goes for when someone restarts a sentence.

- Format for when someone is interrupted and continues what they're saying:

T00: First part…

RT: Interruption

T00: …second part.

- An ellipsis can also be used when a sentence trails off and isn't completed.

- Some words have multiple acceptable spellings. We should use the same spellings for consistency:
  - Okay.
  - Yeah.
  - Doughnut.
  - Colour.
  - Maneuver.
  - Um-hum.

- Use camas to separate side thoughts in the middle of a sentence. (e.g. How do you balance the risk of colliding with the vessel or the platform, in this case it's a tanker, with blocking the ice from the zone.) Dashes or brackets could also be used but to stay consistent use camas.

- When starting a transcription section in a table just put everything in the table rather than splitting up the table with a section of text in the middle.

- Transcribe in the order things were said. It can be rearranged latter for actually using it but it’s easier to follow if it’s in order.

- Participant codes are capital letters (e.g. X86)

Appendix I: Interviewer Notes

Participant Code: _______________ Date: _______________

Interviewer Notes

Experience Interview

What factors do you consider for success in ice management?

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 1:

How would you execute this scenario?

Decision Points (*Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.)*

Alternative Approaches

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 1: **Example 1 Code:**

What advice, recommendations, or feedback would you give the cadet based on their performance in this example?

____

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What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.

____

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____

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____

How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?

1 2 3 4 5

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 1: **Example 2 Code:**

What advice, recommendations, or feedback would you give the cadet based on their performance in this example?

What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.

How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?

1 2 3 4 5 (Cadet's Performance Compared to Other Example)

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 1:

Are there any rules from documented regulations or recommendations that you would consider when executing this scenario?

Are there any rules based on common practice that you would consider when executing this scenario?

Are there any rules that you have learned from experience that you would consider when executing this scenario?

What factors would you consider for success in this scenario?

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 2:

How would you execute this scenario?

____

____

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____

Decision Points (*Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.)*

____

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Alternative Approaches

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____

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 2: **Example 1 Code:**

What advice, recommendations, or feedback would you give the cadet based on their performance in this example?

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____

What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.

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____

How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?

1 2 3 4 5

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 2: **Example 2 Code:**

What advice, recommendations, or feedback would you give the cadet based on their performance in this example?

____

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____

What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.

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How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?

1 **2** **3** **4** **5** (Cadet's Performance Compared to Other Example)

Participant Code: _______________ Date: _______________

Interviewer Notes

Training Scenario 2:

Are there any rules from documented regulations or recommendations that you would consider when executing this scenario?

Are there any rules based on common practice that you would consider when executing this scenario?

Are there any rules that you have learned from experience that you would consider when executing this scenario?

What factors would you consider for success in this scenario?

Participant Code: _______________ Date: _______________

Interviewer Notes

Emergency Ice Management Scenario – 7 tenths

How would you execute this scenario?

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Decision Points (*Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.)*

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Alternative Approaches

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Participant Code: _______________ Date: _______________

Interviewer Notes

Emergency Ice Management Scenario – 7 tenths Example 1 Code:

What advice, recommendations, or feedback would you give the cadet based on their performance in this example?

What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.

How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?

1 2 3 4 5

Participant Code: _______________ Date: _______________

Interviewer Notes

Emergency Ice Management Scenario – 7 tenths Example 2 Code:

What advice, recommendations, or feedback would you give the cadet based on their performance in this example?

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What do you view as the decision points in this example? Decision points are points where the cadet made a decision to change action. This could include deviation from the previous ice management approach or moving from one step of their ice management plan to another.

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How would you rate the cadet's performance in completing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?

1 2 3 4 5 (Cadet's Performance Compared to Other Example)

Participant Code: ______________ Date: ______________

Interviewer Notes

Emergency Ice Management Scenario – 7 tenths

Are there any rules from documented regulations or recommendations that you would consider when executing this scenario?

____

____

Are there any rules based on common practice that you would consider when executing this scenario?

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Are there any rules that you have learned from experience that you would consider when executing this scenario?

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What factors would you consider for success in this scenario?

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Appendix J: Observer Notes

Participant Code: _______________ Date: _______________

Observer Notes

Briefing

Experience Interview

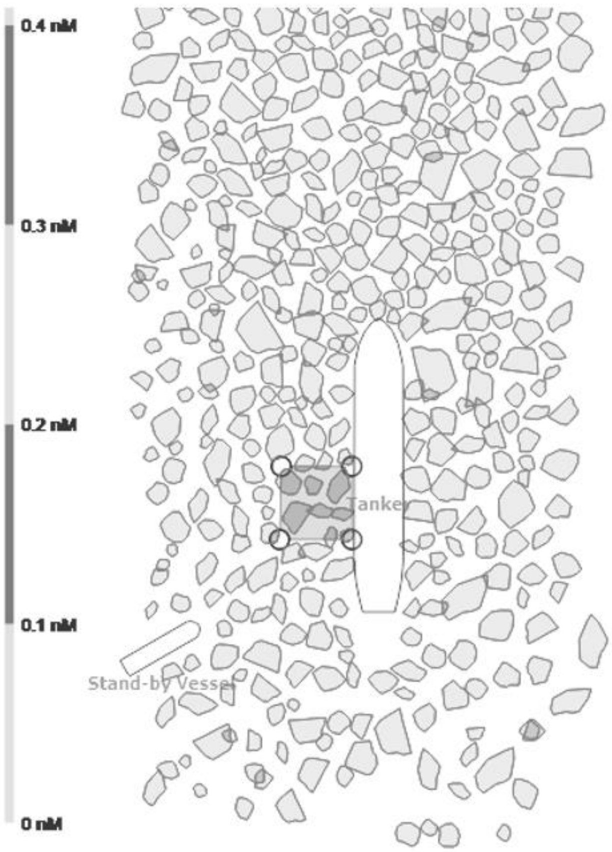
Initial Ice Management Factors

Participant Code: _______________ Date: _______________

Observer Notes

Leeway Scenario - Sketch of Approach and Decision Points

Approach Number:



Participant Code: _______________ Date: _______________

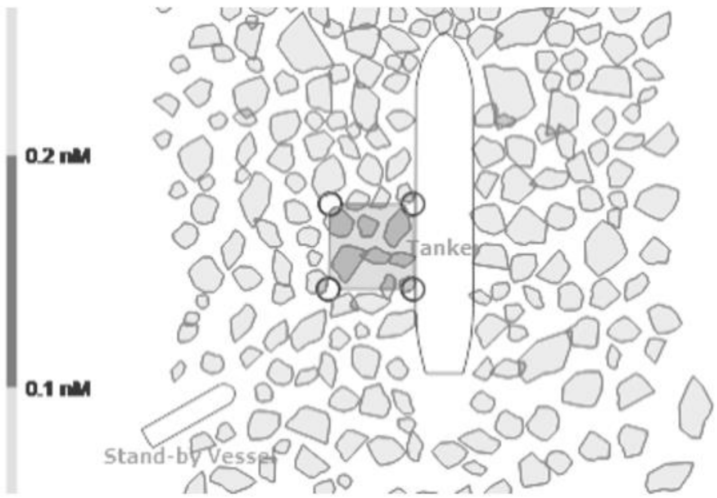
Observer Notes

Leeway Scenario – Advice, Recommendations, or Feedback - Example Code:

____

____

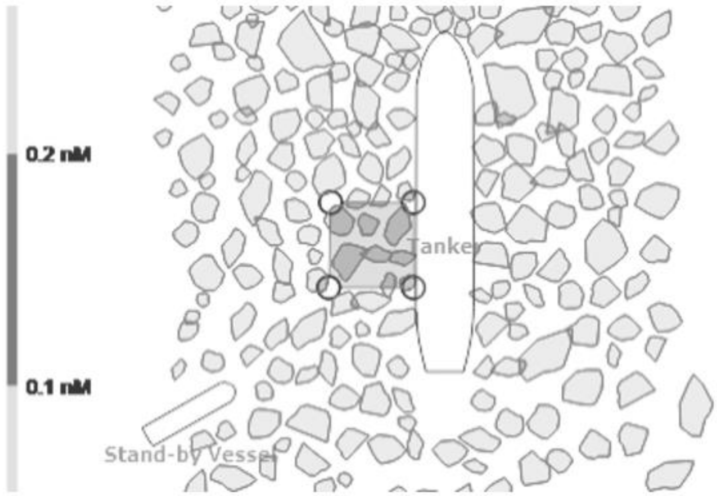
____



Participant Code: _______________ Date: _______________

Observer Notes

Leeway Scenario – Decision Points - Example Code:



Rate Cadet's Performance

Not Successful 1 2 3 4 5 Very Successful

Participant Code: _______________ Date: _______________

Observer Notes

Leeway Scenario

Rules from documented regulations or recommendations

Rules based on common practice

Rules from experience

Ice Management Factors

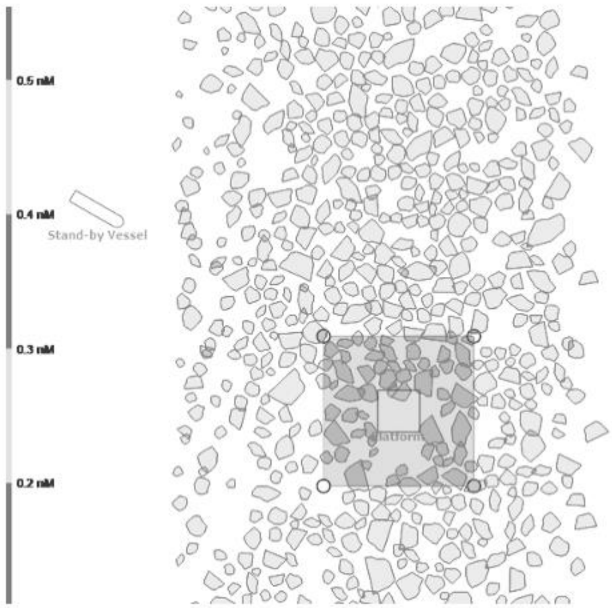
Other Comments

Participant Code: _______________ Date: _______________

Observer Notes

Pushing Scenario - Sketch of Approach and Decision Points

Approach Number:



Participant Code: _______________ Date: _______________

Observer Notes

Pushing Scenario – Advice, Recommendations, or Feedback - Example Code:

Participant Code: _______________ Date: _______________

Observer Notes

Pushing Scenario – Decision Points - Example Code:

Rate Cadet's Performance

Not Successful 1 2 3 4 5 Very Successful

Participant Code: _______________ Date: _______________

Observer Notes

Pushing Scenario

Rules from documented regulations or recommendations

Rules based on common practice

Rules from experience

Ice Management Factors

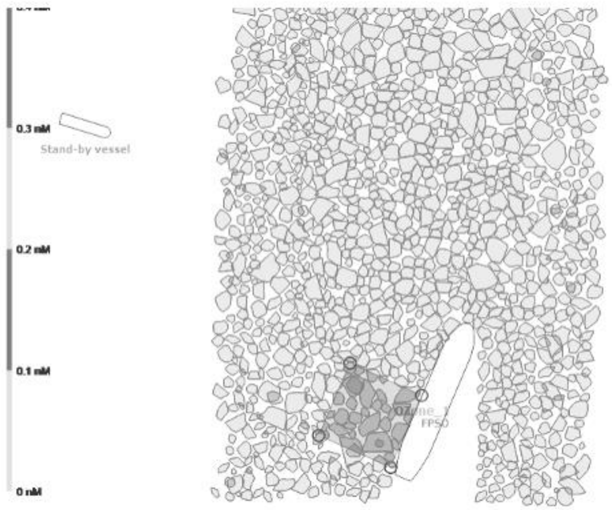
Other Comments

Participant Code: _______________ Date: _______________

Observer Notes

Emergency Ice Management Scenario - Sketch of Approach and Decision Points

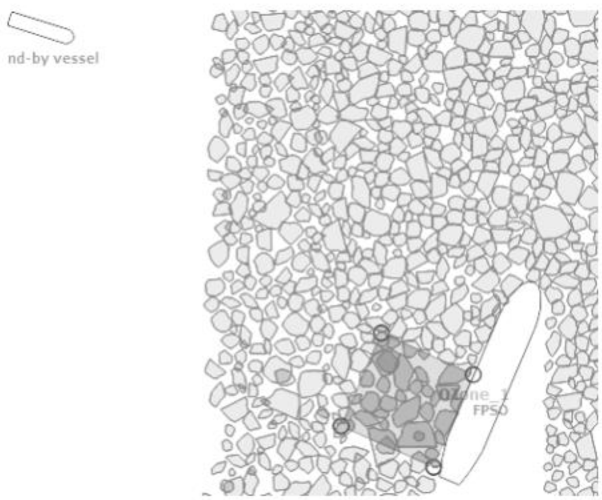
Approach Number:



Participant Code: _______________ Date: _______________

Observer Notes

Emergency Ice Management Scenario – Advice, Recommendations, or Feedback - Example Code:



Participant Code: _______________ Date: _______________

Observer Notes

Emergency Ice Management Scenario – Decision Points - Example Code:

Rate Cadet's Performance

Not Successful 1 2 3 4 5 Very Successful

Participant Code: _______________ Date: _______________

Observer Notes

Emergency Ice Management Scenario

Rules from documented regulations or recommendations

Rules based on common practice

Rules from experience

Ice Management Factors

Other Comments

Participant Code: _______________ Date: _______________

Observer Notes

Feedback and Closing

Appendix K: Factor Cards

Level of Urgency	Acceptable Level of Risk	Ability of Ship Driver
Floe Size	Vessel Capability	Strategy
Vessel Heading	Ice Concentration	Ice Loads

Vessel Location Relative to Target Vessel	**Distance Traveled**	**Vessel Speed**
Area to be Cleared	**Drift Speed**	**Visibility and Weather Condtions**

Appendix L: Factor Headings

(1) – Not Important
(2)
(3) – Important
(4)
(5) – Very Important

Appendix M: Factor Ranking Label

Factor Ranking

Participant:

Date:

Time:

Circle Section of Ranking

Initial	After Pushing Scenario	After Leeway Scenario	After Emergency Scenario

Factor Ranking

Participant:

Date:

Time:

Circle Point of Ranking

Initial	After Pushing Scenario	After Leeway Scenario	After Emergency Scenario

Appendix N: Scenario Order Sheet

Participant Code: _______________

Date: _______________

Scenario Order

Training Scenario 1:

Example 1 Code:

Example 2 Code:

Training Scenario 2:

Example 1 Code:

Example 2 Code:

Emergency Ice Management Scenario – 7 tenths Ice Concentration:

Example 1 Code:

Example 2 Code:

Appendix O: Simulation Session Outline

NRC-MUN Pilot – Session Outline

1. **Briefing**
   - Overview of Project
   - Informed Consent Form
   - Experience Questionnaire
2. **Set-Up**
   - SSQ
   - Introduction to Controls
   - Eye Tracking Glasses Setup
3. **Habituation**
   - Habituation Scenario 1: Rounding the Iceberg
   - Habituation Scenario 2: Maneuver Alongside FPSO
   - Habituation Scenario 3: Clear Ice Using Propeller Wake Wash
   - SSQ
4. **Simulator Scenarios X4**
   - Introduce scenario
   - **Q1:** How would you approach this scenario?
     - Sketch approach
   - Complete scenario in the simulator
   - SSQ
   - Review of scenario performance
   - **Q2:** In what ways, if any, did what you did in this scenario change from your planed approach?
   - **Q3:** What were your decision points in this scenario? Decision points mean points where you made a choice to change action. This could include deviation from the previous ice management approach or moving from one-step of your ice management plan to another.
   - **Q4:** What factors did you consider while executing this scenario?
   - **Q5:** How would you rate your performance in competing this scenario on a scale of 1 to 5 where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?
   - **Q6:** How do you think this scenario compares to a real ice management scenario?
5. **Feedback and Closing**
   - Your feedback for us about the session

Appendix P: Introduction to Controls Script

Introduction

The bridge of the simulator is modeled after that of the Atlantic Hawk, a conventional diesel, twin screw, fixed pitch propeller Offshore Supply Vessel (OSV). The Atlantic Hawk is class 1C, meaning it is not an ice class vessel. Therefore, POLARIS guidelines for operations in icy water recommend a speed of no greater than 3kn when operating in ice. Exceeding this speed could damage the vessel. Please consider that the Atlantic Hawk has unprotected rudders, so be cautious when reversing as ice can damage the steering gear. The design speed of the Atlantic Hawk is 13kn so its limits in ice can easily be exceeded.

Control Consoles

The forward console display screen allows the operator visual feedback from the control gauges as well as the vessel speed, heading, and change of heading.

The steering wheel controls both the port and starboard rudders. The rudders may be locked by turning the steering wheel to lock and pressing the left-right slider button on the right hand of the steering wheel. To return controls of both rudders press the up-down slider button on the right hand of the steering wheel. The buttons on the left hand of the steering wheel do not control anything. Verify rudder position by checking the gages on the display screen. I suggest steering with the bottom of the wheel to avoid inadvertently locking a rudder.

The port and starboard throttles control the main engines and the fore and aft throttles control the fore and aft tunnel thrusters. For all controls operation is fairly intuitive, you push the controls in the direction you wish to go. Control inputs can be verified by checking the gages on the display screen. The black levers do not control anything.

Switching Controls

To switch between forward and aft controls, at the forward controls press the 3 transfer buttons below the port and starboard main throttle of the active controls, then at the aft console press the 3 transfer buttons corresponding on the opposite console to take control of the opposite console. Control may be verified by checking the gages on the aft display screen. The same process is reversed to return to the forward console. Press the 3 transfer buttons at the aft console, then press the corresponding buttons on the forward console and verify control has been switched by checking the forward display screen. All ice management scenarios will begin with forward controls.

Radio

The radio is used to communicate with me at the control center. To use it, depress and hold the large button and speak, then release the button and wait for a reply. You may use the radio for any questions you have while inside the simulator such as distance from your vessel to a target object, or heading of a target object, or time remaining in the simulation.

Habituations

To begin we will have you complete 3 habituation scenarios to become familiar with the simulator controls. In the first habituation you will round a bergy bit and return towards your starting position. This habituation is to help you become familiar with reading your gauges and using landmarks to navigate. We ask that you use your radio to request distances between your ship and the bergy bit. In the second habituation you will park your vessel alongside an FPSO practicing maneuvering at slow speeds using your tunnel thrusters. In the third habituation you will practice switching between forward and aft consoles and use propeller wake wash to clear the ice aft of the vessel.

Please ask me if you have any questions.

Appendix Q: DSS Testing Session Outline

Session Outline

1. **Briefing**
    - Overview of Project
2. **Questionnaires**
    - Experience Questionnaire - Questions about your seafaring experience
3. **Set-Up**
    - Introduction to Controls
    - Introduction to DSS Interface
4. **Habituation**
    - Habituation Scenario: Maneuver Alongside FPSO
    - Habituation Scenario: Clear Ice Using Propeller Wake Wash
5. **Simulator Scenarios (Leeway, Pushing, Emergency)**
    - Introduce scenario
    - Complete scenario in the simulator
    - Review of scenario performance
    - Debriefing Questionnaire
6. **Feedback and Closing**
    - Exit Interview - Your feedback for us about the session

Appendix R: Experience Questionnaire

Participant Number: _______________
Date: _______________

Experience Questionnaire

Please review and answer all questions as you see fit. You are free to omit any questions that you do not wish to answer. If something is unclear, ask the experiment coordinator. Your answers are confidential.

Question	Answer
Approximately how many years of experience do you have at sea?	________________________
On what types of vessels have you operated? (Select all that apply)	☐ OSV / AHTS ☐ Icebreaker ☐ Tanker / Bulk / Cargo ☐ Ferry / Coastal ☐ I have not spent time at sea
Have you ever operated in sea ice?	☐ Yes ☐ No
Approximately how many years have you spent in the presence of sea ice?	________________________
What types of operations did you perform while in ice? (Select all that apply)	☐ Watchkeeping during transit ☐ Maneuvering ship while being escorted ☐ Maneuvering ship to escort another vessel ☐ Ice management (open water) ☐ Ice management (confined water) ☐ Towing or emergency response ☐ I have only observed operations in ice ☐ I have not operated in ice
What types of shore based training have you taken for operating in ice? (Select all that apply)	☐ Basic training in ice operations ☐ Advanced training in ice operations ☐ Attendance at professional seminars discussing techniques and procedures relevant to ice operations ☐ I have never received training related to ice operations
Do you have any experience using a marine simulator? (Select all that apply)	☐ Training for navigation in open water ☐ Training for navigation in ice ☐ Research study ☐ I have no experience using a marine simulator

Appendix S: Debriefing Questionnaire for the DSS Testing

Participant Code:
Date:

Debriefing Questionnaire

1. **In your own words, describe what you did in this scenario?**

2. **Did you change anything about your strategy/approach in the scenario according to the DSS assistance?**

3. **What was the most challenging part of the scenario?**

4. **Did the DSS suggest any solution to tackle this challenge?**

5. **What were your decision points in this scenario? Did you make these decision points based on your own plan or because of the DSS suggestion?**
   (Decision points mean points where you made a choice to change action. This could include deviation from the previous ice management approach or moving from one-step of your ice management plan to another)

6. **How would you rate your planned strategy in completing this scenario on a scale of 1 to 5, where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?**

7. **How would you rate your performance using DSS in completing this scenario on a scale of 1 to 5, where 1 is not very successful, 3 is somewhat successful, and 5 is very successful?**

Appendix T: Exit Interview for the DSS Testing

Exit Interview

1. **What would you like to add to the DSS to better assist users for implementing scenarios?**

2. **How user friendly do you think the DSS is?**

3. **What is your feedback for us about the session?**