Decision Support for Planning Maritime Search and Rescue Operations in Canada

Irène Abi-Zeid, Michael Morin and Oscar Nilo
Operations and Decision Systems, Université Laval, Québec, Canada

Keywords: Search and Rescue, Decision Support System, Search Theory, Design Science Research, Optimal Search Planning.

Abstract: In this project we constructed and evaluated research artifacts to support Search and Rescue (SAR) mission coordinators in planning searches for missing persons or objects at sea. An iterative heuristic based optimization model was formulated and implemented in a prototype that is integrated in a Decision Support System. Using representative examples, we show that the new planning method can help coordinators with the complex task of allocating search resources to search areas in a way that maximizes the chances of finding survivors quickly. Although developed for the Canadian Coast Guard, our method can be used in other countries. We followed Design Science Research guidelines and our design process was according to the Design Science Research Methodology. The research entry point was client and context initiated and beta testing with users is planned in the spring of 2019. It is expected that our innovative artifacts will contribute to improving the SAR system and saving more lives.

1 INTRODUCTION

Search and Rescue (SAR) comprises "the search for, and provision of aid to, persons who are, or who are feared to be, in distress" (Canadian Coast Guard, 2014). The Canadian government is responsible for providing SAR in an area covering over 18 million square kilometers of land and water and the Canadian Coast Guard is involved in an average of 6000 incidents per year (Quadrennial SAR review, 2013). Maritime SAR operations are under the control of three joint rescue coordination centres and two marine rescue sub-centres where SAR mission coordinators (SMC) are responsible for planning, coordinating, controlling and directing the response to incidents. They are decision-makers who must make timely decisions in situations where lives are at risk. Search planning is a complex task where time is a crucial factor for survivors who must be found quickly. SAR operations are among the most critical responsibilities of the Canadian Coast Guard and can be difficult to carry out. Each situation is unique: Particular constraints limit the choice of the search resources and their deployment, difficult climatic and weather conditions may be present and operations are often carried out in remote and unfamiliar areas. It is therefore of the utmost importance to plan searches that ensure the best use of available search resources in order to maximize the chances of finding survivors.

The Canadian Coast Guard (CCG) is currently working on developing the Advanced Search Planning Tool (ASPT), the next generation decision support system (DSS) to replace CANSARP (Canadian Coast Guard, 1998), its current SAR planning system. During the requirements specification phase, the need for an intelligent search planning module, that can recommend search plans designed to ensure the optimal use of available search resources, was identified and confirmed. This led our research team to formulate the following research question:

RQ: How can optimal or near-optimal search operations be planned in reasonable time and decision support provided to assist maritime search mission coordinators?

The research presented in the paper was conducted within the Design Science Research (DSR) paradigm defined by Hevner and Chatterjee (2010), as *"a research paradigm in which a designer answers questions relevant to human problems via the creation of innovative artifacts, thereby contributing new knowledge to the body of scientific evidence. The designed artifacts are both useful and fundamental in understanding that problem*."

Abi-Zeid, I., Morin, M. and Nilo, O.
Decision Support for Planning Maritime Search and Rescue Operations in Canada.
DOI: 10.5220/0007730303280339
In *Proceedings of the 21st International Conference on Enterprise Information Systems (ICEIS 2019)*, pages 328-339
ISBN: 978-989-758-372-8

In order to answer the research question relevant to the human problem of searching for and quickly finding missing persons or objects at sea, we created a method consisting of innovative artifacts as follows: we first formulated a search planning model involving simulation and optimization based on search theory (Stone, 2004). Search theory can be seen as the application of Bayesian statistics to the question of where to search for a missing object. We refer the reader interested in learning about search theory to the seminal work of L. D. Stone (Stone, 2004).

Our model was then translated into an algorithm and further implemented in Search Planner, a prototype that provides optimal or *satisficing* (Simon, 1956) feasible search plans to the SMC. The figures of merit, probability of success, associated with the resulting search plans are obtained via simulation of moving search objects and available search and rescue units. Although a standalone application, Search Planner has been integrated within the ASPT DSS and beta testing with the users is planned in the spring of 2019. The work presented here was carried out over a span of three years, from 2016 to 2018.

The rest of this paper is structured as follows: In Section 2, we address the research background along with related work and research design. In Section 3, we describe and explain our search planning model, algorithm and present the implemented prototype. Using representative application examples in Section 4, we show some results. In Section 5 we provide a discussion as well as limitations. Finally, we conclude in Section 6.

2 BACKGROUND

Following the receipt of an alert pertaining to a maritime incident, SAR mission coordinator must gather information in order to establish whether a search is to be conducted, in which case he/she must begin the search planning process by verifying the search resources available, choosing the resources, determining the area to be searched and developing a search plan. A search plan is a distribution of the search resources over a search area, also called effort allocation. Optimal search planning may be defined as the allocation of the available search resources in such a way to maximize the chances of locating and rescuing survivors, subject to operational constraints.

Over the years, manual methods and procedures have been devised to develop search plans. However, these methods do not in general take advantage of today’s computer power and advances in search theory and simulation, and may not be specifically tailored to the search equipment on hand, which may result in plans that do not have the highest success probabilities.

Nonetheless, it has been known since the Second World War that search theory-based planning can result in significant gains in search effectiveness. It is now recognized that the use of search theory and organized planning results in higher success rates and a significant increase in the number of lives preserved (Frost and Stone, 2001; Abi-Zeid and Frost, 2005; Ferguson, 2008; Abi-Zeid et al., 2011). Furthermore, Stone et al. (2016) give examples of some high profile cases including the response to the submarine threat in the Atlantic, the search for a lost H-bomb in the Mediterranean, the search for the US nuclear submarine Scorpion, the clearing of unexploded ordnance in the Suez Canal, the search for the sunken treasure ship, the SS Central America, and more recently the locating of the wreckage of AF 447. The authors further identify two unsuccessful searches that might have benefited from better planning. In more recent years, search theory has also been applied in the area of autonomous searching by robots in structured environments, and by unmanned air vehicles for outdoor searching of large areas (Ablavsky and Snorrason, 2000; Lau et al., 2008; Sato and Royset, 2010; Kriheli et al., 2016; Venkatesan, 2016; Bernardini et al., 2017).

The need for specific decision support systems that can assist a SMC has long been identified in the scientific literature (Abi-Zeid and Frost 2005; Hillier, 2008; Aronica et al., 2010; Kratzke et al., 2010; Stone et al., 2014; Małyszko and Wielgosz, 2016; Bellantuono et al., 2016). Various SAR information systems are currently available in various countries (Vidan et al., 2016), including the widely used SARIS (sold by BMT ships & Coastal Dynamics product), SARMAP (sold by RPS ASA), SAR (sold by TRANSAS), SARGIS (Guoxiang and Maofeng, 2010), and CANSARP (Canadian Coast Guard, 1998). However, at the present time, only SAROPS, a maritime SAR DSS developed for the US Coast Guard, provides capabilities for search theory-based search planning (Kratzke et al. 2010). Our research project was therefore created as an answer to an expressed requirement of the Canadian Coast Guard to fill an existing gap. Nonetheless, the knowledge created and our designed artifacts can benefit the whole international SAR community, since there is willingness on the part of the Canadian Coast Guard to share knowledge with other countries.

In the next subsection, we describe our research design and provide methodological context.

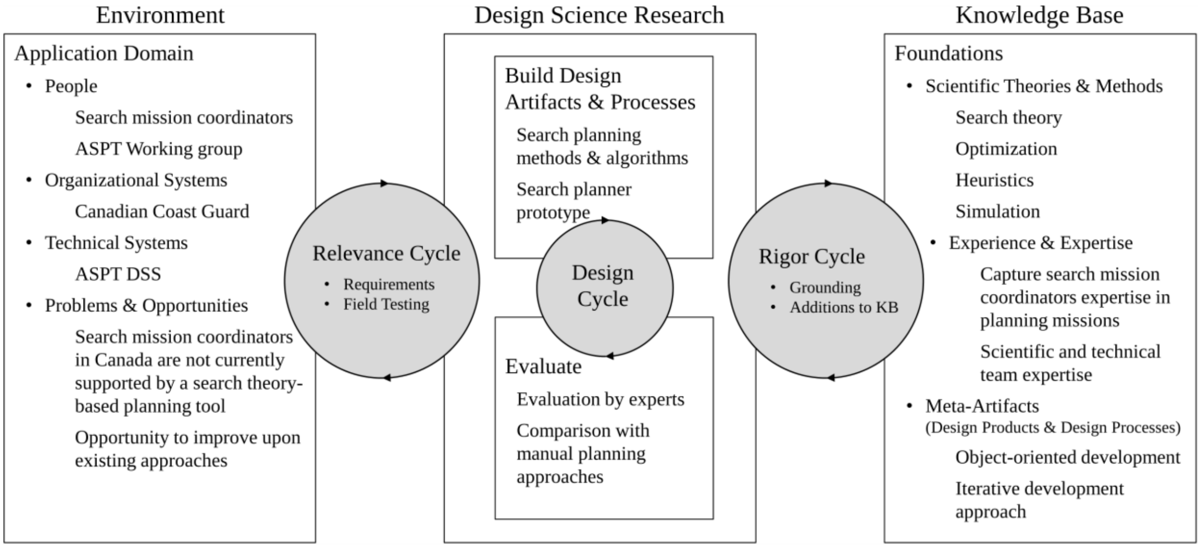

Figure 1: The three design research cycles (adapted from Hevner and Chatterjee, 2010, Fig. 2.2).

2.1 Research Design

Our project was conducted following recommendations from Hevner and Chatterjee (2010) who proposed three design research cycles, where the aim is to ensure that the research is both rigorous and relevant, and provided design science research guidelines. Figure 1 shows the three research cycle while providing additional context-specific information. Table 1 provides context-specific information to design science research guidelines.

Based on our research question, our objective and design requirement was to develop and implement methods and algorithms for optimal search planning that would provide results in reasonable time. Our artifacts are therefore, the search planning method, the algorithms and the resulting prototype. These are viable since they are compatible with existing technical systems, were transferred to an operational system in the organizational environment, and will be supported by training and technical teams.

The relevance of our research is established since the requirements were expressed by the organization responsible for search planning, namely the Canadian Coast Guard and by future users of our artifacts. Operations and management had identified problems with the current methods and foreseen opportunities to remedy this situation by taking advantage of advances in computing power and in simulation. As for rigor, our approach was based on search theory, a well-established theory for search and detection (Stone et al., 2016). We conducted a thorough literature review and had exchanges with other search theory experts. Furthermore, we have extensive experience with search theory for SAR, since two of the authors have been conducting research on this topic for over 20 years, and the third for over 10 years. In fact, we had previously developed SARPlan for overland search planning, a DSS that had won awards for innovative technology on the national level.

Our design process was iterative, as we defined and refined our artifacts. All along the project, there were regular meetings and exchanges with practitioners, technical staff and intended users and their representatives, who provided input, criticism, requests for modifications, constraints, etc. Five versions of the model and optimization algorithms were developed, compared and tested before adopting the current version. The aim of these iterations was to increase the solution's quality and reduce computation time. The acceptance of our artifacts was an ongoing process where we produced various documents, demonstrated the prototype, and had multiple meetings with the stakeholders. Furthermore, external scientific experts have been tasked to evaluate our methods and artifacts.

During the design process, we followed the Design Science Research Methodology as shown in Figure 2 (Peffers et al., 2007). Our research entry point was client/context centered. The problem identified was how to plan search operations for moving objects simulated using Monte Carlo based drift models. Our objective was to demonstrate a search planning method, which led us to design and develop search theory based artifacts that were implemented and demonstrated in a prototype. The client integrated the artifacts in their operational system. Evaluation and communication are on-going.

Table 1: Design research guidelines (adapted from Hevner and Chatterjee, 2010, Table 2.1).

Guideline	Description (Hevner and Chatterjee, 2010)	Specific context
1. Design as an Artifact	Design science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.	Search planner prototype for ASPT
2. Problem relevance	The objective of design science research is to develop technology-based solutions to important and relevant business problems.	Relevant problem: maritime search and rescue operations planning
3. Design evaluation	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.	Comparison with search mission coordinators manual planning (forthcoming)
4. Research contributions	Effective design science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.	Proof of concept and prototype in response to search mission coordinators needs
5. Research rigor	Design science research relies upon the application of rigorous methods in both the construction and evaluation of design the artifact.	Agile development approach, implementation of search theory concepts, optimization approaches, search mission coordinators expertize
6. Design as a search process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.	Development of a prototype compatible with existing systems, algorithms and simulator short response time needed
7. Communication of research	Design science research must be presented effectively to both technology-oriented and management-oriented audiences.	Open source, professional and scientific publications

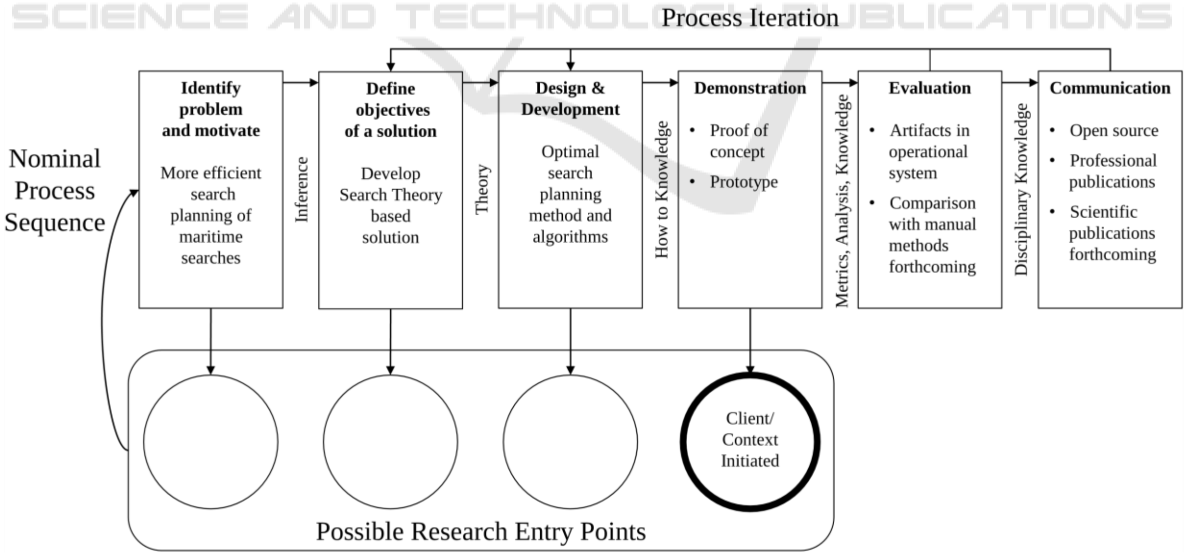

Figure 2: Our process iteration following the Design Science Research Methodology.

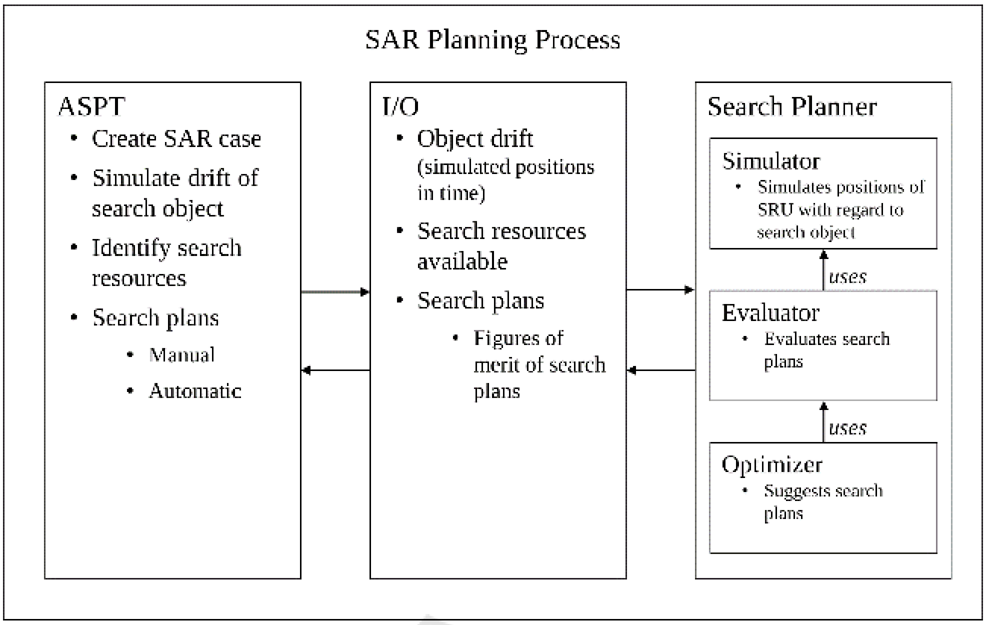

Figure 3: The SAR Planning process.

3 SEARCH PLANNER

When a SMC begins the process of planning a maritime search mission, he/she starts by creating a SAR case containing all the available information concerning the emergency, the characteristics of the vessel, the number of persons involved, the last known point, possible sightings, relevant communications, etc. The next step is to run, in ASPT, a Monte Carlo (MC) based stochastic drift simulation (particle filter) for computing probability distributions of the search object location. The first step in the simulation is to seed, in space, a certain number of particles (typically 5000), equally likely to be the search object, using a 2D Gaussian distribution with a standard deviation specified by the user. The locations where the particles are seeded in the simulation represent plausible last known positions of the search object. The particles are then moved, by simulation, in time and space, according to a drift model, as a function of surface currents and winds. The drift model calculates, over a simulation horizon, the positions of the particles at each time step. Each set of particle's positions in time represents a search object's likely trajectory (Breivik and Allen, 2008). The simulation's output, the MC drift file containing the particles' positions at each time step, is an input to Search Planner.

Subsequently, the SMC must identify available search resources that will be tasked to conduct the search operations. This is also an input to Search Planner. At this point, the SMC can either manually produce a search operation and send it to Search Planner for evaluation purposes, i.e. computing its probability of success, or request that Search Planner suggest a search operation in which case the Optimizer module is invoked. Planning a search operation (SO) consists of assigning search plans to the available search resources (SRU). A search plan (SP) is defined for a SRU by a search pattern over a search rectangle. A search area (SA) is a rectangular region where SRUs are tasked. It is defined over a drift simulation time horizon and is based on the simulated particles' positions.

Our prototype Search Planner contains three submodules, a Simulator (to simulate the positions of the SRU), an Evaluator, and an Optimizer. The Optimizer uses the Evaluator that in turns uses the SRU Simulator. The maritime SAR planning process using ASPT along with Search Planner is presented in Figure 3.

Our objective in designing and implementing the Optimizer is to provide a tool that recommends feasible search operations with the highest probability of success (POS). A POS is a figure of merit, associated with a search operation, loosely defined as the probability of finding the search object.

In order to illustrate the concepts used, Figure 4 presents an example of a search area containing a 12-hour simulated drift.

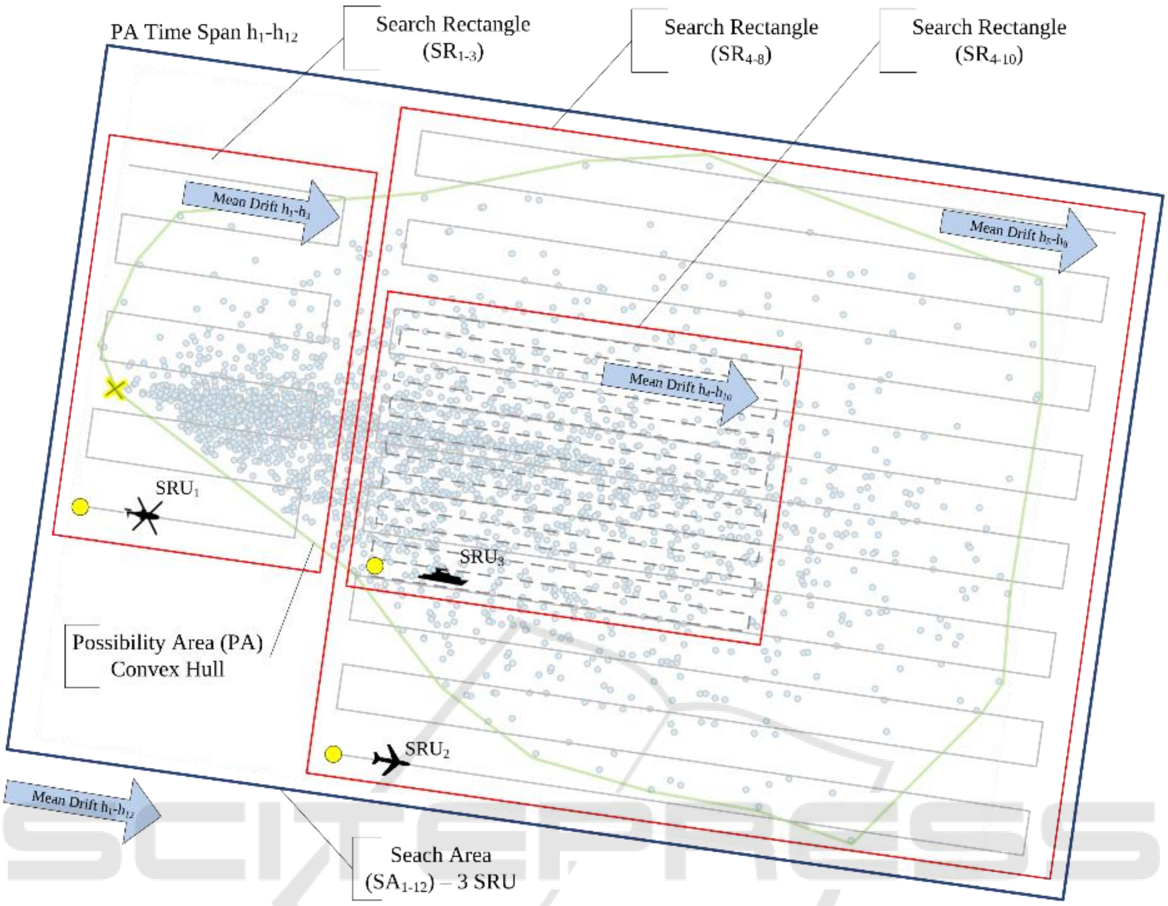

Figure 4: An example of a Search Operation.

The points are positions of drifting particles in time. The green polygon is the possibility area, a convex hull containing all search particles positions over the 12-hour period. The Search operation is composed of three SRUs each having their own search pattern over their search rectangle. A helicopter (SRU_1) is present on-scene between hours 1 and 3 of the simulation. A fixed wing aircraft (SRU_2) is present between hours 4 and 8 and a vessel (SRU_3) is present between hours 4 and 10. The patterns shown are parallel search patterns. Our artifacts are designed to recommend the search plans of a search operation, namely identify the best combination of search rectangles (in red) and the enclosed patterns.

We describe below the algorithm, based on search theory, implemented in the Optimizer module.

3.1 The Optimizer

We developed a heuristic based optimization algorithm that provides feasible optimal or near-optimal search plans, given appropriate input parameters, operational constraints and data. It takes into account the various characteristics of the SRUs namely their endurance, speed, altitude, and detection capability as a function of the environment and of the search object type. The activity diagram depicting the Search Planner process for suggesting a search operation is presented in Figure 5.

Given a SAR case, the optimal search planning problem or SRU allocation problem can be viewed in terms of the global problem of identifying a search area, and then locally defining a search plan for each SRU by assigning it to its optimal or satisfactory feasible search rectangle, yielding a feasible optimal or near-optimal search operation. This division of the optimization task is similar to the approach used by the SMCs. They tend to define the general SA first and then position the search patterns of various SRUs inside that large SA. The optimization procedure we propose uses a simulation-based evaluation of the POS of the candidate SO at each iteration.

3.1.1 Evaluating a Search Operation

Optimizing search operations requires that we find the best combination of search plans for the available SRUs. The figure of merit used to compare candidate search operations is the probability of success associated with the SRUs and a search object (Kratzke et al., 2010). This is the probability of detecting the object It is obtained via the Simulator and the Evaluator.

Suppose that we have P particles. Let $O(p)$ be the probability that particle p is the search object (prior to searching) and let $pfail(p)$ be the probability that particle p has not been detected. Before any search is conducted, this probability is 1. Consider a SRU u searching along K straight-line legs where d_k is the distance at the closest point of approach between the SRU u on leg k and the particle p. Let $f_u(d_k)$ be the probability that SRU u detects particle p when the distance, at the closest point of approach, between the particle and the SRU is d_k. This is computed from lateral range curves developed following extensive experiments under various weather and search conditions (Frost, 2002). It is a function of the search object and of the SRU. The probability the SRU u fails to detect the particle on the k^{th} leg is: $1-f_u(d_k)$. Detections are assumed to be independent along different search legs. The probability of SRU u not detecting particle p is therefore:

$$pfail(p, SRU_u) = \prod_{k=1}^{K}\left(1 - f_u(d_k)\right) \quad (1)$$

Suppose now that U SRUs are searching, then the probability of particle p not being detected is:

$$pfail(p) = \prod_{u=1}^{U}\left(1 - pfail(p, SRU_u)\right) \quad (2)$$

and the probability of a particle being detected is

$$POD(p) = \left(1 - pfail(p)\right) \quad (3)$$

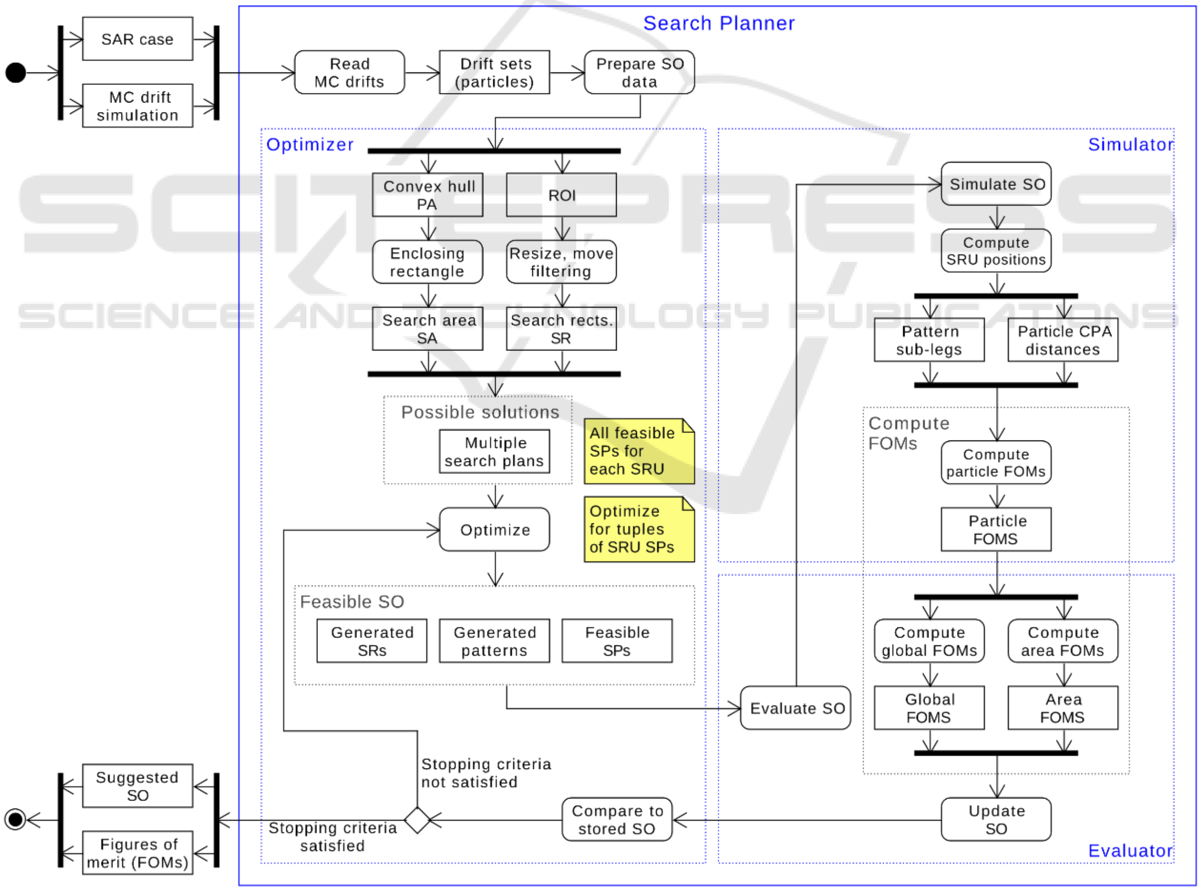

Figure 5: The Activity Diagram for optimization in Search Planner.

The probability of success of a search operation S is then defined as:

$$POS(S) = \sum_{p=1}^{P} O(p)\, POD(p) \tag{4}$$

After an unsuccessful search, the prior probability $O(p)$ is updated in a Bayesian fashion and the posterior probability (after the search) $O_a(p)$, used as an a priori probability for the subsequent search, is computed as follows:

$$O_a(p) = O(p) pfail(p) \tag{5}$$

3.1.2 The Optimization Algorithm

We begin by receiving, from ASPT, drift data containing the particle's position in space and time. Next, we create a convex hull (called a possibility area or PA) containing all the particles during the whole MC simulation. There are many algorithms to generate convex hulls from a set of 2D points. We use Andrew's monotone chain algorithm (Andrew, 1979) that has a O(n log n) complexity. We then compute a search area, a minimum spanning rectangle around the convex hull. The SA can be oriented according to the mean drift vector, or following the convex hull's longest side. Using the information about the available resources such as time on-scene, duration on-scene, detection capability as a function of the search object, operational constraints on track spacing in search patterns, etc., the next step is to generate, for each SRU, a region of interest (ROI), a rectangle enclosing the convex hull of particles present during a given time period, normally its on-scene duration. This uses the same procedure as computing a SA but with a subset of the particles. We then apply a sub-optimization filtering procedure: For each SRU, we modify its ROI by shrinking it or enlarging it and by moving its centre, within the operational constraints related to the SRU's capabilities. Each modified version of the ROI is a possible search plan (rectangle and search pattern). We only retain feasible search plans. We then evaluate all combinations of feasible search plans for all SRUs and we obtain a POS evaluation of the SO (Equation 4). The algorithm is iterative, we continue until we have evaluated all the combinations or until we reach a given stopping criterion such as a time limit or minimum global POS improvement. The pseudo-algorithm is summarized in Algorithm 1.

Algorithm 1: The optimization pseudo-algorithm.

```
Input:
   U SRUs, search object, the
   drifted particles positions in
   time
Output:
   A best POS Search Operation
   containing a search rectangle
   and pattern for each of the U
   SRUs
Steps:
1 - Let z(u) be the total amount of
    available search effort for SRU
    u (hours)
2 - For each SRU u = 1 to U:
      i.  Construct the convex hull
          containing the particles
          during the on-scene
          period of the SRU u
      ii. Construct its ROI: A(u)
      iii.  Run the sub-optimization
          procedure to generate
          SR(u), a set of feasible
          search rectangles. This
          set is constructed by
          varying the location, the
          size and the orientation
          of A(u).
3 - Add the sets SR(u) to a
    candidate SO
4 - Simulate (Simulator) and
    evaluate (Evaluator) to obtain
    the SO's POS
5 - Let S be the POS value of the
    current candidate SO. Let S* be
    the POS value of the best so
    far incumbent SO. If S is
    strictly better than S* then
    the candidate SO becomes the
    best so far incumbent SO and S*
    is updated
6 - If the stopping criteria are
    not met, return to step 4.
    Otherwise recommend the best so
    far incumbent SO.
```

Search operations are successive in time (Alpha, Bravo, Charlie, etc.) and are planned as a function of the previous search operations. Consider for example an Alpha search that was conducted over N hours starting at time T. If it is unsuccessful, a subsequent search operation Bravo, must be planned over M hours, starting at time T+N. This is done by redrifting the particles starting at simulation time T for a duration of M+N hours and by re-evaluating the Alpha search as a function of the real environmental conditions observed between T and T+N. Re-evaluating the Alpha search produces more realistic figures of merit to update the probability that a given search particle is the actual search object, depending on whether it came within detection range of a SRU during the Alpha search. The optimized Bravo search is then obtained by maximizing Equation 4, between T+N and T+N+M, where O (p) are replaced by the updated particles probabilities, $O_a(p)$. Particles with lower $O_a(p)$, ones that came within detection range, are less likely to be the search object and their importance in planning subsequent searches are thereby reduced. Furthermore, the cumulative probability of success is computed for successive search operations. This information is very useful for the search reduction process. At some point, the commander will have to decide to reduce and stop the search. This happens when he/she is reasonably convinced that the chances of finding survivors are practically nil, reflected by many hours of unsuccessful search operations that had a very high theoretical cumulative POS. The rationale is, if survivors were to be found, they would have been found by the end of these well-planned searches. Other factors to take into account in the reduction decision include the average survival times of persons in water under the given environmental conditions.

4 APPLICATION EXAMPLES

In order to illustrate the applicability of our method, we present two representative examples of realistic maritime SAR cases. The first incident, described in Section 4.1, pertains to a person in water (PIW) and the second one, in Section 4.2, to a fishing vessel (FV). The drift model in ASPT is used to estimate the particles positions at time steps of 15 minutes. Currents and winds and last known points are entered in the MC module of ASPT. A total of 5000 particles are seeded. The corresponding lateral range curves for computing detection probabilities are used. The results are presented using the geographic information system QGIS (QGIS development team, 2019). It is important to note that both the search object and the SRUs are moving. Detection opportunities depend on both positions being synchronized. The heat maps presented correspond to the position of all particles during the whole search. They do not necessarily convey a good idea of the movement of the particles. The ability of our search planning method to take into account the particles' movements is one of its main advantages over the current manual planning method using deterministic drift. In fact, a person manually developing a plan will be tempted to position the search pattern over the heat map. Although a good starting heuristic, it does not automatically produce the best probabilities of success since it is not possible to synchronize in one's head the positions of the particles and of the SRU. This can only be done by simulation, as in our Simulator component. The white triangle shows the direction of the drift. The solution for both examples was obtained in under one minute. The area searched is much larger for the FV because its search duration is longer.

4.1 Case 1: Person in Water

A person has gone overboard in water and is assumed to have a survival suit. Two SRUs are available: One helicopter with endurance (time on-scene) of 2 hours and one fixed wing with endurance of 4 hours. The visibility is of 10 nautical miles (NM). The waves are 5 m high. The Search Planner results are presented in Figure 6 where we see the search rectangles and corresponding search patterns (expanding square in blue and parallel in purple) assigned to the two SRUs. The helicopter, flying at 50 knots at an altitude of 750 ft, has a recommended search rectangle of 6 by 9 (NM) (smaller rectangle). The fixed wing has a recommended search rectangle of 11 by 14 (NM) (larger rectangle). Its search speed is 100 knots and altitude is 1000 feet. The combined probability of success is 31%. This may seem not very high but the probability of detecting a person in water is very small because of the size of the person. The total area searched is 154 NM^2 and represents a 4 hour drift. Deconfliction between SRUs is based on altitudes.

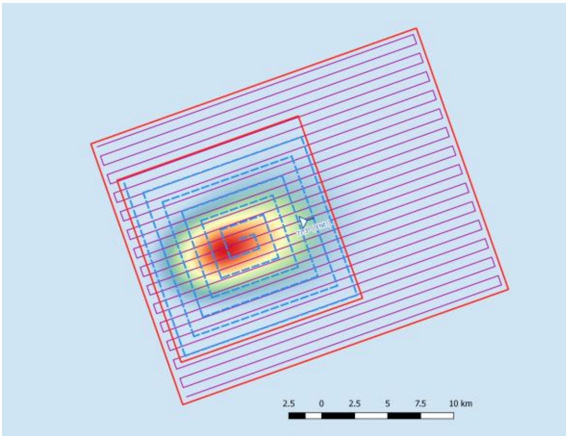

Figure 6: The proposed search operation for the PIW.

4.2 Case 2: Fishing Vessel

A fishing vessel is missing. Two SRUs are available: One helicopter with endurance (time on-scene) of 2 hours and one fixed wing with endurance (time on-scene) of 6 hours. The visibility is of 10 nautical miles (NM). The results are presented in Figure 7 where we see both search rectangles (in red) and corresponding search patterns (parallel patterns, dotted blue and purple lines). The helicopter, flying at 50 knots at an altitude of 100 ft, has a recommended search rectangle of 17 by 20 (NM). The fixed wing, flying at 120 knots and an altitude of 1500 feet, has a search rectangle of 38 by 45 (NM). All particles were covered (came within detection range). Under these conditions, the probability of success is very high: 99%. This can be explained by the fact that the object has high detectability. The total search area is 1710 NM^2 and represents a 6 hour drift. Deconfliction between SRUs is based on altitudes.

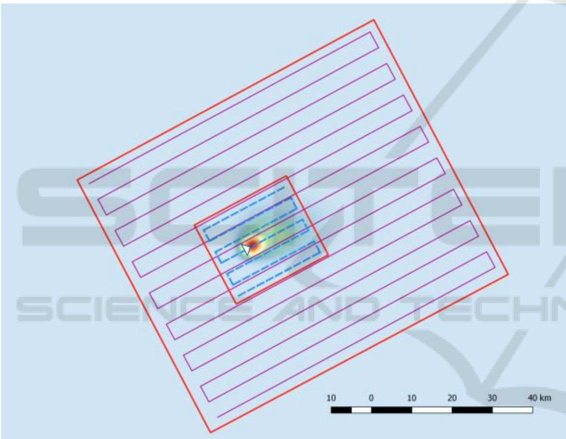

Figure 7: The proposed search operation for the FV.

5 DISCUSSION

The two examples presented above illustrate how, by designing Search Planner, we were able to answer our research question. Our new method, implemented in a prototype and integrated in a DSS, *can assist search mission coordinators in planning optimal or near-optimal search operations in reasonable time*. As required, Search Planner produces search plans for each available SRU that have the best combined POS within a limited computation time defined by the user.

The software has been verified in the sense that it meets the specifications of the designed method. Its validation, i.e. ensuring that the software meets the requirements of the users is planned in the spring of 2019. However, the evaluation of the results produced (search plans quality) is an ongoing process that requires some months, and is planned as follows: First, “beat the DSS” sessions where experienced SMCs are asked to provide manual plans will be conducted. The POS of the manually produced plans will be compared with the automatically produced plans. It is expected that the DSS will compete advantageously with the human operator. In all cases, this experiment will contribute to improving the algorithm’s heuristics based on practical human experience and knowledge. Second, past solved SAR incidents will be used to validate the artifacts. They will be defined as new cases, and the search plans produced by the DSS will be evaluated as a function of the locations where the search objects were actually found in the past incidents. DSS-produced search plans will be considered valid if they contain the locations of the found search objects. Third, to help validate their drift simulation module, experiments are planned by the Canadian Coast Guard where buoys will be released in water and tracked. Their actual physical trajectories will be compared to the simulated particles positions. Comparing the output of our DSS with existing similar systems could further validate our artifacts. However, at the current time, we do not have access to the only other DSS, developed in the US, that has similar optimal search planning functionalities (Kratzke et al., 2010).

Our search planning method has limitations. The main one is related to the model itself. Any model is a simplified assumption of reality based on underlying hypotheses. In our case, in order to use theoretical search theory and lateral range curves to compute probabilities of detection and of success, we make the assumption of independent detections along infinitely long parallel search tracks. This a reasonable assumption when the tracks are longer than the detection range. Furthermore, the lateral range curves, constructed and validated in experiments (US unpublished reports, 1998; 2005), are simplified detection models. However, both the underlying hypotheses and the lateral range curves are behind a DSS that has been operational and is successfully used for over 10 years in the US (Stone et al., 2016).

Another limitation is related to scaling up. Drift simulation may imply the use of thousands of particles that drift for many hours. Their positions can be computed at various time steps ranging from 1 minute to 30 minutes. This has great implications on the size of the problem. Computing, using step by step search pattern simulation, probabilities of detections of millions of particles, in order to evaluate a possible search operation, can be very time consuming. Alternatives including particle random sampling and evaluating a subset of particles can reduce computation time. Working with larger simulation time steps is another option. Intensive sensitivity analyses are necessary to arrive to a compromise in terms of solution quality and computation time.

One of the challenges we face is the acceptance of the DSS by the users as this implies a new way of working and a new way of thinking. Furthermore, this will imply extensive training (already planned) before we can be confident that the tool is used to its full capability. Moreover, the real ability of the proposed method to increase the number of lives saved can be assessed only after it has been in operation for a few years when it is established that the average number of lives saved has actually increased. Finally, search operations with very high success probabilities do not guarantee that the search objects will be found. There have been many examples of SRUs flying over a missing object and not seeing it. Although the POS is accepted as a figure of merit for a search plan, it remains only a probability.

6 CONCLUSION

We have designed research artifacts to support SAR mission coordinators in planning searches for missing persons or objects at sea. An iterative heuristic based optimization model was formulated and implemented in a prototype that is integrated in a DSS. Following the identified limitations in the discussion section, further research is needed to improve the quality and performance of the heuristic optimization algorithm, and to measure the real gains obtained in an operational setting. For example, in order to try to reduce computation time related to evaluating the POS of each candidate search rectangle by simulation, we are currently exploring machine-learning techniques from Artificial Intelligence to automatically “learn” then estimate, without having to simulate the whole search pattern, the POS of a search rectangle from a set of previously evaluated similar rectangles in a similar area. This could result in a significant decrease in computation time.

Future planned research includes the development and evaluation of clustering algorithms that divide the drifted particles set in clusters, which kernels can be used as a starting centre points for the candidate search rectangles. Another possible avenue is to explore the influence of the search pattern type and its starting point as a function of the drift’s direction. Further algorithm enhancements could also be achieved by adding some degrees of freedom in designing the search plans: the initial convex hull defining the possibility area could be constructed using the rotating callipers algorithm to obtain the most promising orientation of the search area (Toussaint, 1983). In addition, the candidate search rectangles could be rotated within the search area in an attempt to improve the POS. Most importantly, data on the DSS use in an operational context must be gathered to continuously improve its acceptability and performance over the next years.

In the future, as the users become more comfortable with the new DSS, it is expected that they will require additional functionalities, such as for example, simultaneous planning for multiple search objects, or planning with concurrent unequally likely scenarios related to what might have happened in the SAR incident and where.

ACKNOWLEDGEMENTS

The authors wish to thank the ASPT Working group and the SMCs for their support during the project. Special thanks to the project manager and the technical team from the Canadian Coast Guard College in Sydney. This project was funded by the Canadian Government, contract number FP802-150046 to Neosoft Technologies. Research and any resulting information/theory gathered or compiled during employment of the author of this published work by the Government of Canada is licensed for publication by the Department of Fisheries and Oceans, and Canadian Coast Guard. No transfer of Intellectual Property (IP) is implied by the granting of said license.

REFERENCES

Abi-Zeid, I. and Frost, J.R., 2005. SARPlan: A decision support system for Canadian Search and Rescue Operations. European Journal of Operational Research, 162(3), pp.630-653.

Abi-Zeid, I., Nilo, O. and Lamontagne, L., 2011. A constraint optimization approach for the allocation of multiple search units in search and rescue operations. INFOR: Information Systems and Operational Research, 49(1), pp.15-30.

Ablavsky, V. and Snorrason, M., 2000, August. Optimal search for a moving target-A geometric approach. In AIAA Guidance, Navigation, and Control Conference and Exhibit (p. 4060).

Andrew, A.M., 1979. Another efficient algorithm for convex hulls in two dimensions. Information Processing Letters, 9(5), pp.216-219.

Aronica, S., Benvegna, F., Cossentino, M., Gaglio, S., Langiu, A., Lodato, C., Lopes, S., Maniscalco, U. and Sangiorgi, P., 2010. An Agent-based System for Maritime Search and Rescue Operations. In WOA.

Bellantuono, N., Camarda, P., Lisi, S., Caneva, P., Pontrandolfo, P., Romano, V., Striccoli, D., Scozzi, B., SpA, C. and Selex, E.S., 2016. Emergency management at sea: A decision support system for Search and Rescue operations. Journal of Software & Systems Development.

Bernardini, S., Fox, M. and Long, D., 2017. Combining temporal planning with probabilistic reasoning for autonomous surveillance missions. Autonomous Robots, 41(1), pp.181-203.

Breivik, Ø. and Allen, A.A., 2008. An operational search and rescue model for the Norwegian Sea and the North Sea. Journal of Marine Systems, 69(1-2), pp.99-113.

Canadian Coast Guard/Department of Fisheries and Oceans Canada, 2014. *Canadian Aeronautical and Maritime Search and Rescue Manual, Combined Edition* – Volumes I, II and III, B-GA-209-001/FP-001.

Canadian Coast Guard College, 1998. *A brief guide to CANSARP*, TP 11718E.

Ferguson, D., 2008, February. GIS for wilderness search and rescue. In Proceedings of ESRI Federal User Conference.

Frost, J.R. and Stone, L.D., 2001. Review of search theory: advances and applications to search and rescue decision support (No. CG-D-15-01). SOZA AND COMPANY LTD FAIRFAX VA.

Frost, J.R., 2002. Elements, Modules and Algorithms for Planning Optimal Searches - A High Level Overview. Prepared for. U. S. Coast Guard Office of Search and Rescue. Potomac Management group Inc. Alexandria, Virginia.

Hevner, A. and Chatterjee, S., 2010. Introduction to design science research. In Design Research in Information Systems (pp. 1-8). Springer, Boston, MA.

Hillier, L.E., 2008. Validating and improving the Canadian coast guard search and rescue planning program (CANSARP) ocean drift theory (Masters dissertation, Memorial University of Newfoundland).

Guoxiang, L. and Maofeng, L., 2010, May. Sargis: A gis-based decision-making support system for maritime search and rescue. In E-Business and E-Government (ICEE), 2010 International Conference on (pp. 1571-1574). IEEE.

Kratzke, T.M., Stone, L.D. and Frost, J.R., 2010, July. Search and rescue optimal planning system. In Information Fusion (FUSION), 2010 13th Conference on (pp. 1-8). IEEE.

Kriheli, B., Levner, E. and Spivak, A., 2016. Optimal search for hidden targets by unmanned aerial vehicles under imperfect inspections. American Journal of Operations Research, 6(02), p.153.

Lau, H., Huang, S. and Dissanayake, G., 2008. Discounted mean bound for the optimal searcher path problem with non-uniform travel times. European journal of operational research, 190(2), pp.383-397.

Małyszko, M. and Wielgosz, M., 2016. Decision support systems in search, rescue and salvage operations at sea. Zeszyty Naukowe/Akademia Morska w Szczecinie, (45 (117)), pp.191-195.

Peffers, K., Tuunanen, T., Rothenberger, M.A. and Chatterjee, S., 2007. A design science research methodology for information systems research. Journal of management information systems, 24(3), pp.45-77.

QGIS Development Team (2019). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org. Visited on 21/2/2019.

Quadrennial SAR Review, available at: https://www.publicsafety.gc.ca/cnt/rsrcs/pblctns/archive-nss-qdrnnl-rvw/index-en.aspx. Visited on 30/12/2018.

Simon, H.A., 1956. Rational choice and the structure of the environment. Psychological review, 63(2), p.129.

Sato, H. and Royset, J.O., 2010. Path optimization for the resource- constrained searcher. Naval Research Logistics (NRL), 57(5), pp.422-440.

Stone, L. D. ,2004.Theory of Optimal Search. Academic Press, New York, 2nd edition.

Stone, L.D., Keller, C.M., Kratzke, T.M. and Strumpfer, J.P., 2014. Search for the wreckage of Air France Flight AF 447. Statistical Science, pp.69-80.

Stone, L.D., Royset, J.O. and Washburn, A.R., 2016. Optimal Search for Moving Targets, International Series in Operations Research & Management Science. Reston and Monterey, CA. doi, 10, pp.978-3.

Toussaint, G.T., 1983, May. Solving geometric problems with the rotating calipers. In Proc. IEEE Melecon (Vol. 83, p. A10).

Venkatesan, S., 2016, November. AUV for Search & Rescue at sea-an innovative approach. In Autonomous Underwater Vehicles (AUV), 2016 IEEE/OES (pp. 1-9). IEEE.

Vidan, P., Hasanspahić, N. and Grbić, T., 2016. Comparative Analysis of Renowned Softwares for Search and Rescue Operations. NAŠE MORE: znanstveno-stručni časopis za more i pomorstvo, 63(2), pp.73-80.