Markus Brachner

Evaluating and Optimizing an Emergency Response System for Helicopter Transportation in the Arctic Region

Molde University College
Specialized University in Logistics

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A dissertation submitted to Molde University College -
Specialized University in Logistics
for the degree of Philosophiae Doctor

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Preface

This dissertation was prepared in Molde University College — Specialized University in Logistics in partial fulfilment of the requirements for acquiring the PhD degree in Logistics. The study was conducted during the period from September 2013 to August 2019 under the main supervision of Professor Lars Magnus Hvattum from Molde University College. Associate Professor Berit Helgheim from Molde University College has been co-supervisor.

This thesis consists of an introductory chapter and five articles, that show different aspects of planning emergency preparedness for helicopter ditching incidents from an operations research perspective. In particular, this research project deals with optimization and simulation models for helicopter ditching preparedness. We show that the integration of offshore operations with emergency preparedness would be a key success factor for future operations in the Arctic environment. Furthermore, algorithms and tools for planning and evaluating emergency preparedness systems are proposed.

Acknowledgments

It was my supervisor Professor Lars Magnus Hvattum, who taught me, that if I want to succeed in research, I have to stand on the shoulders of giants. I have tried to follow this advice, but failing miserably many times I have also realized, that it takes more than a few giants to write a thesis. While those will find themselves in the references, there are more people who supported me in many other ways to deliver this work. Whether one has to call them giants or simply great people is not up to me.

First and foremost, I would like to express my deepest gratitude to Professor Lars Magnus Hvattum. Over the years he guided me as my supervisor in my long quest of turning ideas into research, research into results, and results into a thesis. He did this with profound knowledge, unfailing patience, high accuracy, and constant encouragement. There were difficult moments, but he helped me to stay on my track and not to give up. This is also true for Associate Professor Berit Helgheim, who helped me particularly in the start and final phase of my work. Not only her in-depth domain experience, but also her moral support are greatly appreciated.

I would also like to thank Sigurd Robert Jacobsen from the Petroleum Safety Authority Norway. His work provided me with a great starting point, and the discussions with him were essential for me to develop the topic. Furthermore, thanks go to UiT The Arctic University in Tromsø, who, together with Troms county, financed a big part of my work, and to DNV GL, especially Rune Pedersen, who provided expert knowledge during the whole process.

Furthermore, I want to thank my parents Luise and Anton for encouraging me in difficult times. Finally, I wish to thank my wife Olga for her unconditional support, and my children Aleksander and Katherina, that have continually provided the requisite breaks from operations research and the motivation to finish my degree with expediency.

Oslo, Norway
March 2020

Markus Brachner

Contents

Introduction

Introduction

It is now 50 years since the Norwegian oil adventure began. In 1969, shortly before Christmas, the Norwegian government was informed about the discovery of the Ekofisk field, which transpired to be one of the largest offshore oil fields ever discovered. Over the following decades, offshore oil and gas exploration on the Norwegian continental shelf (NCS) played a vital role in the Norway's economy and in financing of the Norwegian welfare state.

As Ekofisk and other fields in the southern areas of the North Sea and Norwegian Sea are maturing, operators are increasingly focusing on the areas much further north, in the Arctic Circle. This area – which is the geographical focus of this thesis – is roughly delimited by the Russian border to the east and the Lofoten islands to the west, extending up to the latitude of the Bear Island to the north, as shown in Figure 1.

The focus of this thesis is on emergency logistics for personnel transportation to and from offshore platforms in the Arctic region. Transportation of personnel to offshore facilities on the NCS is nearly exclusively done by helicopter, which has become a safe means of transportation due to efforts in improving safety. Between 1999 and 2015, there was one accident and no fatalities in the Norwegian sector. However, in 2016, a helicopter crash at Turøy resulted in 13 fatalities. This event acted as a reminder, that accidents can still occur and need to be planned for, even when the figures suggest an effective system of accident prevention.

Operations in the Arctic area have very specific challenges. Harsh weather conditions, ice, and darkness may influence operations. Furthermore, the remoteness of potential installations is unprecedented. Distances to locations in blocks of recent licensing rounds are up to 300 nautical miles. In comparison, the Troll and Oseberg fields, which are supplied from the Mongstad base, are, on average, 65 nautical miles away from the supply base. The Haltenbanken installations are located, on average, 125 nautical miles from their bases. Even the most remote installations in the southernmost Ekofisk are only around 180 nautical miles away from the supply base in Stavanger (DNV 2015).

Finally, the lack of infrastructure in this area complicates the transportation of personnel to and from offshore facilities. Resources must be used in an effective and efficient way. This is particularly true for rescue resources, as including nearby traffic does not add considerable rescue capacity (Brachner 2016). Therefore, in this thesis, we investigate how the emergency system configuration – in terms of particular capacity requirements and resource locations – can be determined for a future emergency response system (ERS) in the Arctic region with the help of mathematical models.

1 Industrial emergency logistics

This thesis is concerned with the logistics of an ERS, to which we refer hereafter as *emergency logistics*, in line with Hammervoll and Helgheim (2015). Moreover, helicopter ditching while transporting offshore personnel is considered as a scenario within an industrial environment. This quite specific focus means that the ideas presented in this thesis mainly concern emergency management, but also incorporate concepts from human and industrial safety, risk management, and resilience engineering. In this section, we consolidate the relevant ideas into a framework that we use throughout this thesis.

1.1 Risk and the ALARP principle within the petroleum industry

We regard the *risk* of an accident as the combination of the probability of occurrence of harm and the impact of that harm. This definition conforms to the most prevalent interpretation, which the Norwegian

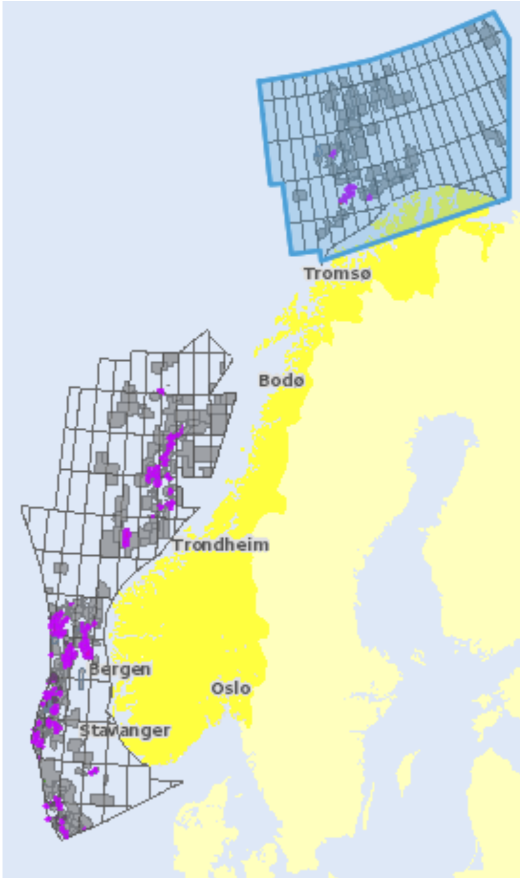

Figure 1: Arctic areas planned for offshore oil and gas exploration in Norway, framed in blue. (Source: Fact Maps of the Norwegian Petroleum Directorate, `https://www.npd.no`)

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petroleum industry also uses in its *Risk and Emergency Preparedness Assessment standard* (NORSOK 2010).

One of the leading principles in the Norwegian petroleum industry is the responsibility to reduce residual risk to a level that is *as low as reasonably practicable* (ALARP). The residual risk remains after an inherent risk has been reduced by certain risk control measures. There are various ways to do achieve this, the most common of which are *transfer, avoidance, mitigation, and acceptance*. A transfer is the shifting of risk to another party, usually through insurance. With regard to offshore-related accidents, emphasis is placed on avoidance; that is, one tries to minimize the probability of a hazard materializing by taking preventive action. For helicopter accidents, the efforts in Norway have proven to be effective in comparison to other actors in this industry; from 1990 to 2009, accidents involving offshore helicopter transportation in the UK occurred at a rate of 1.33 accidents per million person flight hours, compared to 0.38 in Norway (Herrera et al. 2010).

However, there is also a common understanding among both the industry and the authorities that not all accidents can be prevented, and precautions must be taken to reduce the consequences should one occur. Along with other mitigation measures, emergency response is one of the possible actions after an accident. Returning to our former definition of risk, accident prevention aims to reduce the probability of occurrence, while emergency preparedness and other mitigative measures reduce the impact of an incident.

The preventive and mitigative actions can be seen as barriers in a bow-tie diagram, as shown in Figure 2. This diagram is frequently used in risk analysis within the petroleum industry and combines a fault tree that describes the possible development toward an accident with an event tree that illustrates the sequence of events and resulting consequences after an accident.

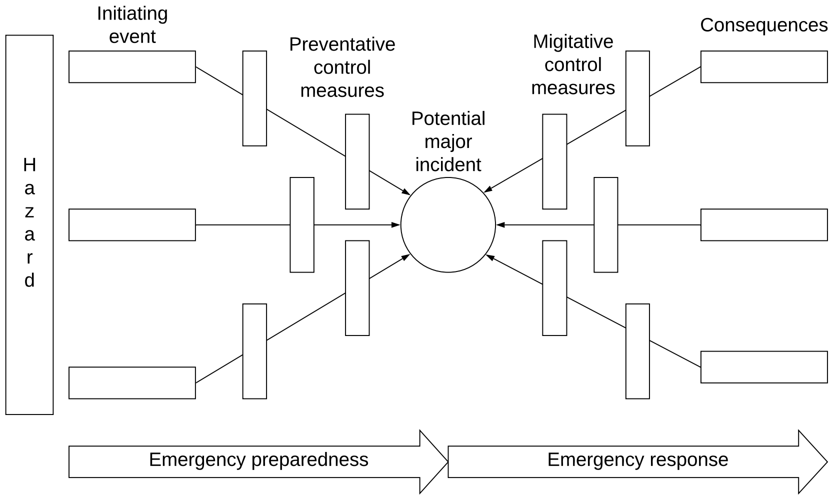

Figure 2: Bowtie. Adapted from: Cockshott (2005).

1.2 Emergencies

An emergency occurs when an accident hazard materializes. While emergencies can vary between small-scale accidents and global disasters, emergency management literature is mostly concerned with very large-scale emergencies, and with the management of the event itself. Haddow, Bullock, and Coppola (2011, p. xvii), for example, defined emergency management as the management of disasters. In contrast, we explore the management of an ERS that deals with smaller-scale types of accidents.

Emergencies can be of natural or technological origin (Haddow, Bullock, and Coppola 2011, pp. 29). In the traditional emergency management literature, the emphasis is more on mitigation than prevention. Haddow, Bullock, and Coppola (2011), for instance, completely omitted prevention as a separate strategy and instead included it as a part of mitigation. This may be due to the fact that traditional emergency management is driven by public services, which handle accidents as force majeure: an accident is either of natural origin or of technological origin and is beyond the control of the actor. This differs from the industrial domain, in which the actor controls the operations and is therefore accountable for accidents.

1.3 Operations and emergency systems

Haddow, Bullock, and Coppola (2011, p. 70) made a clear distinction between mitigation and response. This distinction is in line with our conceptual view throughout this thesis because we perceive two systems that are acting in parallel, as shown in Figure 3. We consider mitigation to be the effect of initially passive, static, and system-immanent features that are implemented in the pre-accident phase but exhibit their consequence-reducing effect during or after the incident. Crashworthy seats and seatbelts in a helicopter, as one example, will not have any positive effect in a nominal situation, while they will absorb a portion of the crash energy and reduce the effect of a high-energy impact. In contrast, emergency response involves an active and dynamic response to an event that is handled by a dedicated ERS.

The operations system conducts core operational duties. In our case, this would involve the transportation of offshore personnel from the shore to the offshore facilities and back. The emergency system exists in parallel. For both systems, the accident is a pivot point; in the nominal situation, preventive measures are built into the operations system as barriers, so that initiating events do not lead to a major incident. The emergency system focuses on preparedness, managing rescue resources to adapt to the current risk situation, and preparing for emergencies through exercises and training. However, as soon as an accident strikes, consequences start to unfold, but mitigative measures in the operations system reduce the consequences. In this phase the emergency system takes an active role to respond to the accident.

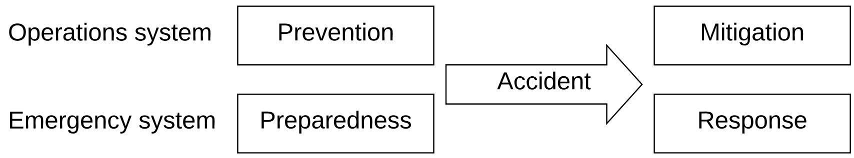

Figure 3: Operations and emergency systems are considered as two independent systems with separate objectives that change after the accident.

2 Research objectives

Jacobsen and Gudmestad (2013) introduced the idea of collaborative rescue schemes to ensure long-range rescue capacity in the Barents Sea. However, the rescue scheme was only a proof-of-concept for one offshore location, where a feasible solution could be determined easily. After a meeting with Jacobsen on 25 February 2014, we decided to formulate this idea into a mathematical model to make it easily solvable for more complex settings, and provide not only a rescue scheme for long-range capacity – that is, to cover not only a single transport route – but to cover a set of routes in the manner of an area-based emergency preparedness scheme, as described in Vinnem (2011). This was in line with the Norwegian Petroleum Safety Authority, who stated, that *“Resources available for emergency response in the Barents Sea are limited”*, and *“Going solo is out of question when moving into the new areas of the NCS”* (Petroleum Safety Authority 2014, p. 20). This lead to the primary objective of this thesis, formulated as follows:

Objective 1: Develop a decision support system for planning the optimal positioning of resources to ensure rescue capacity for helicopter transportation to and from multiple offshore locations within a large area, such as the Barents Sea.

This is achieved through the following secondary objectives:

Objective 2: Formulate models for cooperatively covering transport routes.

Objective 3: Research stochastic factors that influence the emergency system’s performance.

Objective 4: Investigate how rescue resources can be used more effectively.

Objective 5: Explore possible objectives and how different objectives can be combined.

Objective 6: Develop algorithms with reduced run-time to support sensitivity analysis.

3 Methodology

This thesis provides a framework for planning, evaluating, and improving an ERS. We employ operations research and mathematical modeling (in particular mathematical optimization and simulation) as the main methodologies. These methods are frequently used in emergency response research (Simpson and Hancock 2009).

As Simpson and Hancock (2009) stated, operations research has embraced emergency response and emergency services since its inception. According to these authors, Valinsky (1955), Hogg (1968), and Savas (1969) marked the beginning of a research stream in emergency-related topics. In their literature review the most significant focus in emergency response articles is on public services, such as firefighting, ambulance, or police services. Such services are characterized by a high number of cases, whereby uncertainty can be modeled from historical data. However, the incidents under consideration in this thesis have a much lower frequency. A much smaller part of the literature is dedicated to such kind of services (Simpson and Hancock 2009).

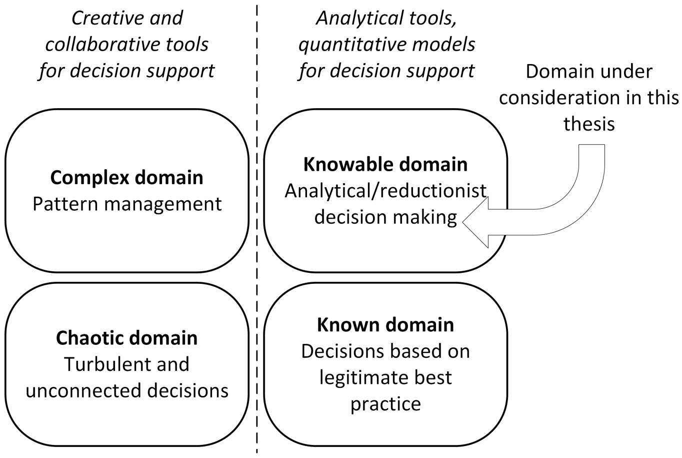

Figure 4: The scenarios in this thesis are in the knowable domain of the Cynefin framework. Adapted from: Snowden (2002) and French and Niculae (2005).

French and Niculae (2005) critically reflected on the use of mathematical models in decision support systems for emergency management. They used the Cynefin framework of Snowden (2002) to divide decision contexts into four categories:

- Within the *known* context, clear cause-and-effect relationships exist. Solutions for problems within this context are self-evident and undisputed (Snowden and Boone 2007). According to French and Niculae (2005), this is the domain in which decision-makers seek patterns to *categorize* situations and respond with actions that are well-rehearsed in emergency exercises.
- Within the *knowable* context, cause-and-effect relationships are still understood, but the solution can rarely be immediately identified, and different solutions may exist (Snowden and Boone 2007). In this domain, a decision-maker must analyze the situation to derive the correct actions (French and Niculae 2005).
- The *complex* context comprises too many cause-and-effect relationships to reliably predict system behavior.
- Finally, in *chaotic* space, no cause-and-effect relationships can be identified, and the system behavior is entirely unknown as events unfold beyond the actor's experience.

French and Niculae (2005) argued that models in the complex and chaotic space rather require creative and collaborative tools for decision support, while systems based on data analysis and quantitative modeling meet the needs of working in known and knowable space. We consider the scenarios that are under consideration in this thesis as knowable (see Figure 4). Cause-and-effect relationships have been well-studied and their processes have been clearly defined, as we are working with constructed operations and emergency systems (Johannson, Hollnagel, and Granlund 2002) within the industrial context.

The value of our models often lies much more in sensitivity analysis than in the crude output of one run. Therefore, we have striven to ensure responsiveness and short run times in the solution algorithms to provide an environment that encourages probing and what-if analysis, as presented in Brachner and Hvattum (2016). In Brachner, Stien, and Hvattum (2019), for instance, we proposed a workflow for a multi-objective planning process that can be interpreted as sensitivity analysis (French 2003). Furthermore, these models can be applied in discussions, using sensitivity analysis to elicit expert judgment to analyze or explore and achieve consensus on emergency system design issues (French 2003).

3.1 Mathematical optimization and facility location

Only resources that can reach an incident location within an acceptable timeframe are able to contribute to a rescue mission. Thus, the available resources have to be spatially distributed so that the area of potential incident locations can be sufficiently covered.

The optimal placement of facilities or resources according to defined criteria – such as minimal transport costs or maximum coverage of an area – is the subject of location problems, for which we provide a short overview in this introduction. A description of the state-of-the-art on this subject has been given by Farahani et al. (2012), while Laporte, Nickel, and Saldanha da Gama (2015) have provided a comprehensive summary of the field and its roots.

Facility location for emergency-related services has a long tradition in operations research. Its roots date back to the 1960s when the emergency medical services (EMS) in the USA underwent major changes. Until then, the responsibility for providing EMS had been up to the local level, and no coordination or nationwide standards were in place. Heart disease, cancer, and stroke were the major sources of concern, as it was expected that two-thirds of Americans would be affected or die due to one of these reasons. Furthermore, the rapidly increasing cost of traffic accidents had been recognized (Shah 2006). The government slowly realized that these problems could only be solved on a national level (Huntley 1970). Finally, this development culminated in the EMS Systems Act of 1973. This act set the requirement that 95% of request locations should be reached within 10 minutes, and in rural areas, incident locations should be reached within 30 minutes (X. Li et al. 2011). As such, it is unsurprising that many of the problems studied in this area are connected to emergency-related cases.

At this time, Hakimi (1964) described two problems in his seminal paper: one to locate switching centers in a communication network, and the other to place police stations on a highway system. Working with a weighted graph, he introduced two new concepts: the absolute center and the absolute median of the graph. A point, which can be located on any branch of the graph that may or may not be a vertex, is called the absolute center if the weighted maximum distance from this point to any other point is minimal. It is called the absolute median if the weighted sum of distances to the vertices is minimal. He showed that it is never sub-optimal to locate the median on a vertex, while the center can also lie on a path between vertices. The optimal location of a switching center for a communication network is an example of the median, as this point minimizes the total wire length. In contrast, the optimal location of a police station is the center of the graph, as this is the point at which the maximum distance to all vertices is minimal.

Hakimi (1965) extended this problem to not only locate one point, but a set of p points, so that they fulfilled the center and median criteria, calling them the *p-center* and *p-median*. The points of optimal *p-median* sets were still located on vertices, as it was with the special case of p equal to one. This was a very important property which made it easy to later formulate an integer programming model. Hakimi proposed a solution method for the *p-median* problem, which is the enumeration of all solutions, but this number grows rapidly as problem size increases. Thus, he was unable to recommend a definitive procedure for solving the *p-center* problem.

In the same paper, Hakimi presented a procedure for determining the minimum number of policemen to be located on the network to cover all demand points within a specified distance. He assigned Boolean variables to each vertex on the network to indicate whether a policeman was located on the vertex. For each vertex, the Boolean sum of adjacent vertices determined if it was covered by a policeman. These adjacent vertices can be considered as the ones that are within a defined maximum service distance. The Boolean product of these terms over all vertices is 1 if – and only if – all vertices are covered by a particular choice of variable assignments. The set of solutions that cover the graph with a minimum number of chosen vertices are then the alternative optimal solutions.

The approach of maximum service distance is fundamental to this problem, which is now commonly known as the location set covering problem (LSCP). However, Toregas et al. (1971) noted that Hakimi's solution method included the need to enumerate all feasible solutions, rendering the problem intractable with increasing size. They proposed a formulation as an integer programming problem, with one variable per vertex indicating whether it is to be chosen as the location of an emergency service. Adding a single cut constraint limited the fractional objective values to the next highest integer value and helped to achieve a solution in which all variables were binary.

Three years later, Charles ReVelle co-authored a paper describing a similar problem with his Ph.D. student, Richard Church (Church and ReVelle 1974). The maximum covering location problem (MCLP) sought not to minimize the number of facilities to locate but took this as a parameter. With a population assigned to each vertex, the objective was to maximize the covered population within a given distance from the facilities.

In the traditional models that have been discussed so far, a demand point is covered if the nearest facility is within a defined distance, assuming that the service for this demand point is to be provided by a single facility. The covered points may, for example, define the catchment area of a school, hospital, or supermarket. In this case, we refer to `individual coverage`, following the notion of Berman, Drezner, and Krass (2010b).

In contrast, services can also be provided collectively. The case that we investigate in this thesis has a well-defined objective for a successfully provided service, which is the requirement to rescue all persons involved in a helicopter ditching within a limited amount of time. This is a suitable example of an objective that can be achieved by the contribution of several actors that do not necessarily originate from the same location. Thus, we seek to distribute rescue resources so that they can form ad-hoc teams at any defined demand point to provide sufficient rescue capacity, an idea which was also proposed by Jacobsen and Gudmestad (2013).

The class of cooperative coverage problems has recently attracted increasing attention. Berman, Drezner, and Krass (2010b) introduced the idea of `cooperative coverage` and investigated the planar case (Berman, Drezner, and Krass 2010a), the discrete case (Berman, Drezner, and Krass 2011), and the network case (Berman, Drezner, and Krass 2013; Averbakh et al. 2014).

The basic idea in these models is a signal that is emitted by the facilities and decays over distance. A demand point is covered if the aggregation of the signals emitted by all facilities exceed a defined threshold. The signal can be, for example, of physical nature, like the sound of warning sirens, but it can also be non-physical, as in our case. Here, the rescue capacity of a resource decays over distance, as the travel time to the incident location reduces the remaining time of rescue until the two-hour limit is reached. We explain the underlying model for the rescue capacity in greater detail in Brachner and Hvattum (2017).

3.2 Simulation

The U.S. Department of Defense (2008) categorizes simulation into live, virtual, and constructive simulation according to the type of interaction between user and simulation. Live simulation involves real people operating real systems; virtual simulation involves real people operating simulated systems; and constructive simulation involves simulated people operating simulated systems.

In the form of exercises, simulation has always been a cornerstone of emergency management. According to Haddow, Bullock, and Coppola (2011, p. 112), FEMA defines an exercise as *"a controlled, scenario-driven, simulated experience designed to demonstrate and evaluate an organization's capability to execute one or more assigned or implicit operational tasks or procedures as outlined in its contingency plan."* Virtual and constructive simulations are preferable to real-life experimentation when such tests would be too costly, when real-life experiments would not be feasible due to missing capabilities yet to be developed, or when safety issues render such tests prohibitive (Loper 2015, p. 11).

When we refer to simulation later in this thesis, we consider it to be of the constructive type. For the planning of emergency systems, this type of simulation is often used to evaluate or refine candidate solutions. This method can also be used in combination with heuristic algorithms to provide near-optimal solutions (X. Li et al. 2011).

Within the offshore industry, most of developed models have concentrated on oil spill incidents. OSCAR (Reed, Aamo, and Daling 1995), for example, is a tool that is used to assess alternative oil spill strategies. It has already been in use for a long time and has been steadily improved since its first version. More recently, P. Li et al. (2014) combined a Monte Carlo simulation and optimization to provide decision support for device allocation and recovery operations during responses to offshore oil spills. Simulation models for search and rescue helicopter operations have been used by Nguyen and Ng (2000) and Karatas, Razi, and Gunal (2017).

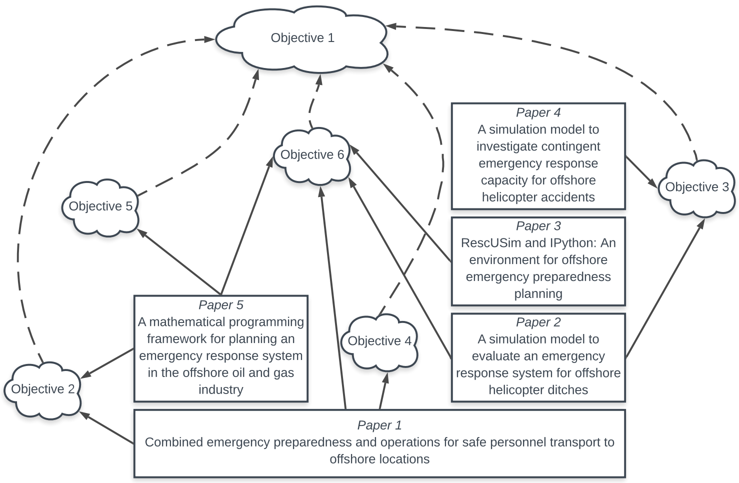

Figure 5: Relations between papers and how they contribute to the research objectives.

4 Summary of papers

This thesis consists of five papers that investigate different aspects of emergency preparedness for offshore helicopter transportation with tools from operations research. In the following section, a short summary of each paper together with its scientific contributions is presented. Furthermore, the contributions made by the candidate, co-authors, and other involved persons are enlisted. Figure 5 visualizes how the papers are related to each other and how they address the research objectives.

Paper 1 – Combined emergency preparedness and operations for safe personnel transport to offshore locations

The first paper suggests that the transportation system should be planned in a coordinated manner. That is, the transportation routes need to be planned in such a way that the emergency response resources are able to cover them. This involves two sub-problems: finding the best possible transportation routes and placing the rescue resources so that these routes can be sufficiently covered.

This paper formalizes the underlying concepts used in this thesis from a logistics perspective; it defines the components of a rescue response and the terms of rescue demand and capacity. It provides a decision support tool that gives decision-makers the freedom to balance the trade-off between the minimization of operational cost due to transport route distances and costs from emergency preparedness requirements. A mathematical model of the problem is presented that can be easily implemented using a Mixed Integer Programming solver, such as Gurobi or CPLEX. As the model becomes intractable for larger instances, a computational method that reduces the time to find a solution and allows decision-makers to solve real-life instances is presented. Computational experiments are conducted with the proposed model, based on prospective production sites in the Barents Sea.

The paper is co-authored by Lars Magnus Hvattum. The candidate developed the initial problem formulation, modeled the problem, developed the solution method, conducted the computational studies, and wrote the major part of the paper. Lars Magnus Hvattum contributed inputs that helped to formulate and model the problem and proposed ideas for developing the solution method. Furthermore, he provided feedback while writing the paper. The paper was published in Brachner and Hvattum (2017).

Paper 2 – A simulation model to evaluate an emergency response system for offshore helicopter ditches

The second paper accounts for the stochastic nature of emergency preparedness. Here, environmental data is used to simulate rescue helicopters' responses to helicopter ditching incidents under varying environmental conditions.

Based on models for travel and response time estimation, a trace-driven simulation model is developed. An algorithm is presented that improves the run-time of the computationally expensive part of the travel time simulation. In a case study, the simulation model is used to generate heat maps to show safe areas, that is, areas where the timely rescue of all persons on board the ditched helicopter is likely.

The candidate is the sole author of this paper, and all major work connected to the paper was conducted by the candidate. The paper was presented at the Winter Simulation Conference 2015 and published in Brachner (2015).

Paper 3 – RescUSim and IPython: An environment for offshore emergency preparedness planning

This paper presents a newly-developed simulation module that is still based on the model presented in paper 2. However, the simulation is implemented in C++ and provides bindings to Python. This simulation module integrates seamlessly into the workflow of data preparation, simulation, post-processing, and visualization that can be provided by the Python ecosystem.

We demonstrate how IPython can be used together with our custom simulation module to plan and evaluate emergency preparedness scenarios. We provide an overview of the simulator architecture and present the Python packages that have been used. Detailed examples are given for how to prepare the data, simulate scenarios, and visualize the results. We also discuss alternatives to the presented tools.

This paper was written by the candidate, with inputs from Lars Magnus Hvattum. The simulator and the workflow with the respective tools used have been entirely developed by the candidate. The paper was published in Brachner and Hvattum (2016).

Paper 4 – A simulation model to investigate contingent emergency response capacity for offshore helicopter accidents

This paper adds contingent capacity to the simulation model presented in paper 3. While the previous papers had predefined locations for emergency response units, this paper takes nearby fishing vessels into account. For oil spill response, this has been actively taken into account. For the rescue of people from the sea, this contingent backup capacity may not add much value.

A case study is conducted that takes into account positional data of vessels in the Barents Sea to shows the influence of contingent capacity on the emergency rescue system. While the core regions may not profit significantly, contingent capacity could be a crucial factor in saving lives on the borders of the serviceable areas.

This paper was written entirely by the candidate. It was accepted and presented at the EurOMA 2016 conference in Trondheim.

Paper 5 – A mathematical programming framework for planning an emergency response system in the offshore oil and gas industry

This paper presents a detailed examination of the performance indicators for ERSs that are reflected in the model objectives. While response time is one of the most commonly used indicators, we discuss the importance of including response capacity as an additional aspect. Since we are evaluating these performance indicators for a whole service area, we also study different types of indicator aggregation.

With the help of mathematical models, we provide a case study in which we illustrate that ERS designs can differ substantially depending on the performance measures and their aggregation types that are optimized. We propose a multi-objective approach to combine these criteria. Furthermore, we present an algorithm that improves solution time and, for many instances, even allows users to solve instances that would not have been solvable directly by an MIP solver.

The candidate wrote this paper. The mathematical models were based on a master's thesis that was written under the co-supervision of the candidate. The algorithm was solely developed by the candidate.

A preliminary paper that presented the master's thesis was written by the candidate and accepted for presentation at the Preparedness and Emergency Response Logistics Conference 2016 in Oslo. The final paper was accepted and published in Brachner, Stien, and Hvattum (2019).

5 Concluding remarks and future research

The collaborative coverage models presented in this thesis can support the design of ERS by providing optimal configurations for a given scenario. However, when planning ERS systems, it is crucial to be clear about performance measures and aggregation types, because optimal ERS designs are dependent on them (Brachner, Stien, and Hvattum 2019).

Used together with our ERS simulation (RescUSim) and the working environment presented in Brachner (2015) and Brachner and Hvattum (2016), system designs can be evaluated and further refined. The improved solution algorithms that we have developed allow for the solution of real-life instances and decrease solution times so that several iterations can be performed efficiently to support, for instance, sensitivity analysis.

While the simulation model is based on well-grounded assumptions, the results require further validation. This is particularly difficult, as very few real incidents have occurred that could be taken as a reference (Vinnem 2011). However, face validity could be obtained by checking the outcome of simulated scenarios against expert opinions (Sargent 2013).

The integration of other stochastic factors can be considered. For instance, the mobilization time in our models is a constant that is the guaranteed mobilization time, and reflects, therefore, the worst-case scenario. Furthermore, there are constant parameters that could be replaced by functions. As an example, the maximum time in the sea is an agreed value between actors. However, survival in cold water is a well-studied subject (Wissler 2003) and the fixed rescue time limit currently assumed in our models could be replaced by a survival function, taking into account known environmental factors.

As mentioned above, simulation can be used to evaluate solutions of possible ERS configurations. This is not necessarily a manual process; the response simulation proposed in this thesis could be used for a simulation-optimization solver that would conduct a meta-heuristic search using the simulation of scenarios based on candidate solutions as the evaluation step.

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Paper 1

Combined emergency preparedness and operations for safe personnel transport to offshore locations

Combined emergency preparedness and operations for safe personnel transport to offshore locations

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Abstract

Long distances, sparse infrastructure, and adverse environmental conditions make the offshore emergency preparedness system in the High North a big and yet unsolved challenge. This applies in particular to the personnel transport between onshore bases and offshore facilities, which is usually conducted by helicopters. One of the issues to be solved is the sufficient coverage with emergency response units (RUs) in this sparse infrastructure environment. This paper proposes an answer to this issue by using sound logistical concepts, which involves connecting operations and preparedness. A mathematical model is introduced that combines a routing and a covering problem. On one hand, the shortest possible helicopter routes to offshore locations are sought, subject to being within the area covered by the deployed RUs. On the other hand, those RUs are placed so that a contingent helicopter ditching at any point on the chosen routes can be handled within given time limits. The combination of routing and covering forms a trade-off, which gives the decision maker the freedom to balance between the minimization of operational costs related to transport route distances and the long-term costs from response capacity requirements. A computational method that reduces the time to find a solution and allows decision makers to solve real life instances is presented. Computational experiments are conducted with the proposed model, based on prospective production sites in the Barents Sea.

1 Introduction

The Arctic region is estimated to contain 22% of the world's undiscovered oil and gas resources (U.S. Energy Information Administration 2009). This makes the northern regions attractive for the petroleum industry, and is one of the reasons why activity at sea in the northern areas of Norway is expected to see an above average increase.

There are considerable gaps in today's emergency preparedness system of this region. A report by SARiNOR, a project to define future preparedness solutions in Northern Norway (Det Norske Veritas 2014), points out that there is not enough private or public sector capacity to handle major accidents at sea that involve 20 or more persons in distress.

To get drilling licenses, operators have to show that they are able to operate safely, and in a self-reliant manner, i.e. they cannot rely on public preparedness services. Furthermore, their preparedness system

Figure 6: A ditched helicopter near the Shetland Islands on 22 October 2012. Source: AAIB (2014).

should be able to handle even large scale incidents. To have offshore preparedness in place can be understood as a ticket-to-trade for anyone who wants to operate in this area, and to date, this ticket comes at a high price. This is why the petroleum industry has to find innovative solutions that ensure safety while keeping costs at an economically feasible level.

One of the major issues of future operations in this area is the safe transportation of personnel. In Norway, air transport by helicopter is the main mode to bring personnel to offshore installations and back. However, this mode represents one of the major hazards for offshore personnel (Vinnem et al. 2006). In the UK, eight accidents in the past 30 years resulted in 110 fatalities (Oil & Gas UK 2011). Five accidents with 12 fatalities were recorded in Norway during the period of 1990–2009 (Herrera et al. 2010).

Future offshore locations in the Arctic region may be located as far as 350 km or more from the shore. While this represents a big challenge for logistical operations in general, it is in particular posing a problem to the transportation of personnel to these offshore locations. In case a helicopter needs to make an emergency landing on water as shown in Figure 6, which is commonly referred to as a *ditching*, measures have to be taken to be able to respond within a reasonable time. Thus, the transport routes need protection by rescue resources that are able to arrive at the scene quickly and can carry out the rescue within acceptable time limits.

In this paper we propose to plan the offshore personnel transportation system and the offshore preparedness system in the Arctic region in a coordinated manner. By planning transportation routes near to each other, rescue units (RUs) could be located more efficiently as they would be able to cover more routes or bigger parts of the routes. In a sparse infrastructure environment, operations and preparedness could therefore be combined to make safe personnel transportation possible. We present a mathematical model which combines covering and routing decisions to consider these aspects. In practice, this can be used as a decision support tool that takes both strategic and tactical decisions into account.

Some aspects of the presented problem have been covered in the existing scientific literature. Rescue operation in the Barents Sea was studied by Jacobsen and Gudmestad (2013). They developed the subject of collaboration between RUs and proposed a rescue scheme for a long-range flight to a distant offshore location.

Research on covering models for facility location has a long history. Extensive reviews of this class of problems were presented by Farahani et al. (2012) and, with a particular focus on emergency response, by Li et al. (2011). The latter highlighted the importance of the Emergency Medical Services Act of 1973, which defined a minimum response time requirement that has been the basis for most of the models studied afterwards. We take this one step further, as in the presented problem it is not sufficient to be on site within a defined timespan, but it is required to have the necessary capacity to rescue all *persons in sea* in time.

A better part of facility location and covering models related to the domain of offshore preparedness is dedicated to oil spill response. Verma, Gendreau, and Laporte (2013), for example, introduced a two-stage stochastic programming model with recourse for locating oil spill response facilities and deciding about what types of equipment to keep there.

Asiedu and Rempel (2011) presented a coverage-based model for civilian Search-and-Rescue (SAR). Their multi-objective model aims to maximize coverage, minimize the number of RUs, and maximize the backup coverage of SAR incidents.

Akgün, Gümüşbuğa, and Tansel (2015) and Rennemo et al. (2014) present models for facility location in emergency preparedness, taking into account distribution and routing. However, they mostly consider the disruption risk and the availability of infrastructure.

Covering models for facility location typically assume that coverage for a demand point is provided by a single facility. In our problem, several RUs are allowed to collaborate, that is, to conduct the operation together in order to rescue the *persons in sea* faster. In that respect this is a practical application of cooperative covering as introduced and studied by Berman, Drezner, and Krass (2010a, 2010b, 2011). In this class of problems each facility sends a signal that decays over distance. The demand is covered if the aggregated signal exceeds a given threshold.

Berman, Drezner, and Krass (2010a) provide cooperative versions of the classical location problems with a covering objective. Our problem differs from these in that we combine a cooperative cover location problem with a routing problem, with the objective to minimize the total route distance. While the demand points in the classical problems are given, the chosen routes determine the demand in our problem. Furthermore, our problem involves a set of different resources with varying properties.

Reducing the risk to personnel involves establishing measures to prevent accidents, as well as being prepared to act in the case of an incident. The operations research literature contains models related to helicopter routing that aim at reducing risk during operations. Menezes et al. (2010) developed a helicopter routing model that improved travel safety by reducing the number of offshore landings and the flight time. Qian et al. (2012) proposed a helicopter routing model with the objective to minimize the expected number of fatalities.

The rest of this paper is organized as follows: Section 2 describes the terminology used, including explanations of the response, its phases, and how our understanding of rescue capacity builds upon that. Section 3 presents a basic *combined routing and covering* model, as well as an extension for serving the installations on round trips. The real world application of the models is impractical, as the computational times are too long. Therefore, we develop a solution method that is described in Section 4. Section 5 presents a series of computational experiments, and our concluding remarks follow in Section 6.

2 Problem formulation

We consider the following problem: Personnel has to be transported to and from a number of offshore locations by helicopters. There are one or more onshore bases which can be used as points of departure. A full transport helicopter generally contains 2 pilots and up to 19 passengers.

In case of a helicopter ditching on the way, the crew and passengers may have to enter the sea. Due to the environmental conditions, particularly the low sea temperature, the human body can sustain this immersion only for a limited time. Dependent on the person's physiology, body protection equipment, and the sea state, this time limit may vary, but the Norwegian petroleum industry has adopted a requirement that a *person in sea* should be rescued within 120 minutes (Norsk olje og gass 2015). While this requirement is enforced only within a security zone of 500 meters around an offshore facility, we follow the argument of Jacobsen and Gudmestad (2013) that the consequences for a *person in sea* do not depend on whether he or she is within or outside of this security zone. We therefore assume this limit to be valid for the whole route, starting from the onshore base to the offshore location. Measures have to be taken so that the whole crew can be rescued within this time limit in the case of a ditching.

Transports can be conducted on several routes at any time and in parallel, and all routes have to be covered by sufficient rescue capacity. It is, however, assumed that only one incident at a time can happen, which is a common assumption in risk analysis for the petroleum industry that is backed by its low accident rate (Vinnem 2011).

For rescue operations, SAR helicopters and Emergency Rescue Vessels (ERVs) are used as RUs. An ERV does not carry out a rescue by itself, but is equipped with a Fast Rescue Daughter Craft (FRDC), which is launched from the ERV, proceeds to the incident site, and conducts the operation. Henceforth, the ERV/FRDC combination will solely be referred to as an ERV for the sake of convenience.

Each RU has specific performance characteristics that influence its rescue capability. The location of RUs can generally be freely decided, but some restrictions may apply. SAR helicopters are typically restricted to onshore bases, but sometimes they also may be stationed on offshore installations or ERVs.

It would be natural to use, for every offshore location, the direct route from the nearest onshore base, because this would minimize the distances traveled. However, in the case of a limited number of rescue resources, the only feasible option may be to bundle routes by choosing a common onshore base, or by using routes that are close to each other. In this way, RUs can be used more efficiently by covering several routes at the same time.

There are two interdependent parts of the problem: The first is to decide, for each offshore location, which onshore base to use as a starting point, and which route to follow for personnel transportation. The second is to decide locations for RUs such that the routes for personnel transportation are sufficiently covered by rescue capacity. Routes and RU locations should be chosen such that the sum of route distances is minimized.

A central part of this problem is the quantification of the capability to protect the transport routes sufficiently. For this purpose we define the rescue capacity, c, as the number of people which can be picked up from sea within a given time limit $t^{\max}$, requiring the rescue capacity to be not less than a minimum level $c^{\min}$ on any point of a route.

Figure 7 shows the components of an emergency response from the viewpoint of one RU and how they relate to its rescue capacity. The labels above the time line represent the events taking place, and the lower part shows the time components of the response as used in our model. The emergency trigger is the root cause for the need of an emergency response. This can be, for example, an engine or gearbox failure that forces the pilots to ditch the helicopter. As soon as the distress condition happens, an emergency call will be dispatched. The rescue coordination center receiving this call notifies the RU, which will instantly prepare for departure and start moving to the incident site. As soon as the RU arrives on scene, it can start to pick up people until the last person is out of the sea. We define the pick-up rate, p_r, as the number of people picked up per time unit. In the context of a manufacturing environment this would correspond to the unit production rate. The last person should be out of sea before the maximum time in sea, $t^{\max}$, is reached.

The emergency call is commonly the event from which time related indicators are counted: The mobilization time is measured from the moment of the emergency call to the departure of the RU. The travel time is calculated from the moment an RU leaves its origin until it arrives at the scene. Finally, the accomplishment time is the time from arriving at the incident location until the maximum time in sea is reached.

For an RU, r, the available time, $t^{\max}$, is reduced by the mobilization time of the RU, t_r^{mobi}, and the travel time to the accident scene. The remainder is the accomplishment time, in which it can pick up people at a rate p_r, until the time limit $t^{\max}$ or its physical capacity – the maximum number of persons on board of the RU – denoted as $c_r^{\max}$ is reached. The rescue capacity, c_{rij}, of an RU r placed at location i with respect to a potential ditching location j at a distance d_{ij} and an RU velocity v_r can therefore be expressed as

$$c_{rij} = \max\{0, \min\{c_r^{\max}, (t^{\max} - t_r^{\text{mobi}} - \frac{d_{ij}}{v_r})p_r\}\}. \tag{1}$$

Figure 8 shows the capacity function for an increasing d_{ij} for two types of RUs. Their parameters are given in Table 1. The SAR helicopter is able to pick up a full helicopter crew, that is, it has a physical capacity of $c_{\text{SAR}}^{\max} = 21$. The rescue capacity is limited by the physical capacity as long as $d_{ij} \leq 98$, at

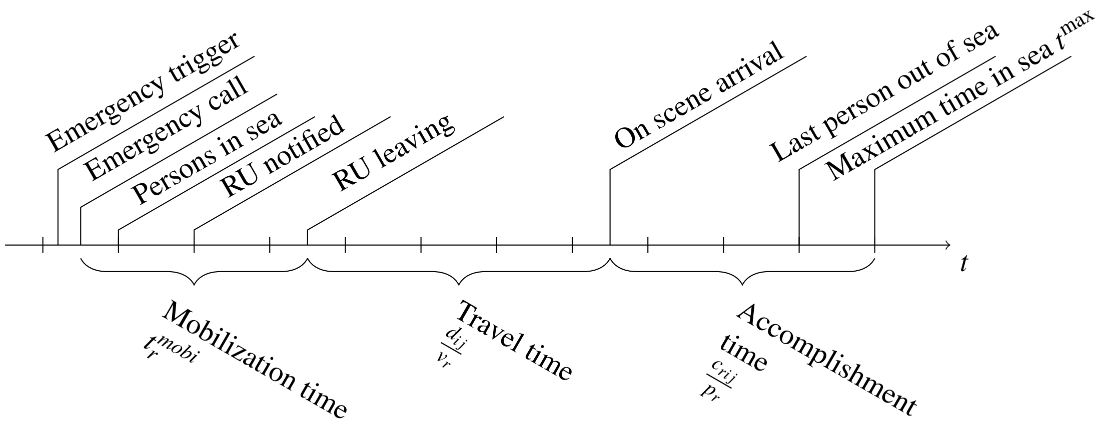


Figure 7: Time components of a response, and their key drivers.

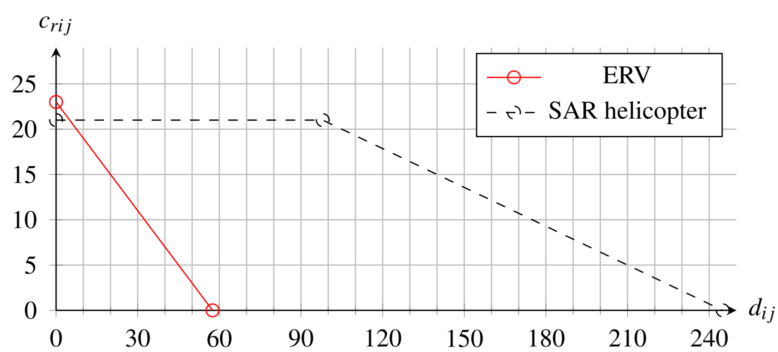


Figure 8: Capacity function over distance.

Table 1: Assumed parameters for calculating the rescue capacity of SAR helicopter and ERV.

	SAR helicopter	*ERV*
c^{max} (persons)	21	24
t_r^{mobi} (minutes)	15	5
v_r (knots)	140	30
p_r (persons per minute)	1/3	1/5

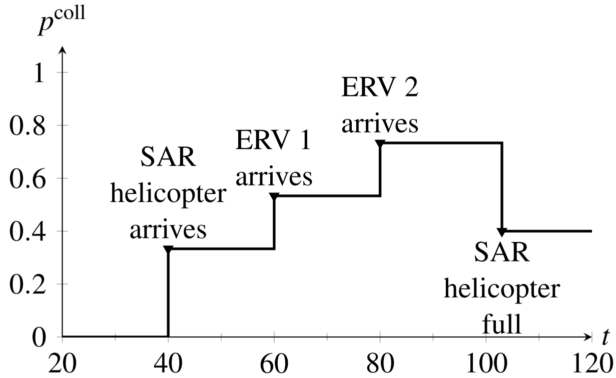


Figure 9: Example of how the collaborative pick-up rate is changing during a rescue operation.

which point the travel time is 42 minutes, leaving 63 minutes of accomplishment time during which 21 people can be rescued. For longer distances, the rescue capacity is limited by the accomplishment time, and the capacity decreases with increasing distance until reaching 0 at $d_{ij} = 245$. The ERV is able to pick up 23 persons at $d_{ij} = 0$. As the physical capacity of the ERV is higher and the speed is lower, the rescue capacity decreases immediately from the origin with increasing d_{ij}.

The required rescue capacity does not necessarily need to be fulfilled by a single resource, and RUs can collaborate following the idea of Jacobsen and Gudmestad (2013). In this case, each RU at the incident site is able to pick up people at its individual pick-up rate. That is, at the incident site people will be picked up by a set of RUs, $\mathscr{R}$, at a collaborative pick-up rate of

$$p^{\text{coll}} = \sum_{r \in \mathscr{R}} p_r. \tag{2}$$

This is assumed to be valid when only a few RUs are collaborating, such that no interference effects occur.

As the travel time for each RU is different, the collaborative pick-up rate will vary over time. Figure 9 shows an example where two ERVs and one SAR helicopter collaborate to rescue 21 persons. From the arrival of the SAR helicopter at $t = 40$ the pick-up rate is $1/3$ persons per minute. ERV 1 arrives at $t = 60$. From this moment, both the SAR helicopter and ERV 1 are operating on site, and people are picked up at a rate of $p^{\text{coll}} = 1/3 + 1/5$ persons per minute. As ERV 2 arrives at $t = 80$, the three RUs are picking up people at a combined rate of $p^{\text{coll}} = 1/3 + 2/5$. At $t = 103$ the physical capacity limit of the SAR helicopter is reached and it has to cease picking up people. Thus, the collaborative pick-up rate decreases to $p^{\text{coll}} = 2/5$ persons per minute, as only the ERVs are in operation.

In Equation (1) the rescue capacity is already adjusted for the individual mobilization and travel times of the RUs as well as their physical capacity limits. The capacity of collaborating RUs can therefore be calculated by simply adding up their individual rescue capacities.

If the required rescue capacity is fulfilled at every point within an area, the area is considered to be safe. A corridor is, in this paper, defined as a contiguous safe area through which one or more transport routes can pass. This is illustrated in Figure 10. In the case of Figure 10a there is plenty of rescue capacity available, particularly because the SAR helicopter can be freely placed. A very broad corridor makes it possible to serve each installation from its nearest onshore base using direct routes, that is, the helicopter can travel in a straight line from the onshore base to the offshore location. If the position of the SAR helicopter location is restricted to onshore base *B1*, as in Figure 10b, then the remaining freely placeable ERVs can barely create a corridor that includes both installations and *B1*. Hence, bundling the transport routes is the only option available given the limited rescue capacity. The route to installation *L2* has to start from *B1* as well, since the limited resources cannot cover both *B1* and *B2*. Neither *L1* nor *L2* can be reached by a direct route anymore.

The actual range of influence for each RU is bigger than the corridors indicated in Figure 10b, as areas with a rescue capacity below 21 are not shown. If the full capacity range is shown, as in Figure 10c, it can be seen that the rescue capacity of the SAR helicopter has a range that extends well beyond the area where it is able to rescue all people by itself. Even if its capacity does not suffice to rescue 21 people anymore, it still can contribute to locations further away to reach the capacity collaboratively. Thus, for example, safe areas around the ERVs do have a different size in Figure 10b, as some of them are still within the area of influence of the SAR helicopter.

Understanding the capacity decline over distance and the aggregation of response capacity by collaboration enables us to establish corridors which are protected in a sufficient way. Moreover, if the requirement of establishing transport routes a priori is given up, the definition of such corridors can be left to a model which positions response resources and decides about transport routes at the same time. This is advantageous as, with limited response resources, routes can be bundled into corridors such that one corridor can serve different routes simultaneously. The RUs may then be placed in a more effective way. This idea leads us to the formulation of the *combined routing and covering problem* (CRCP).

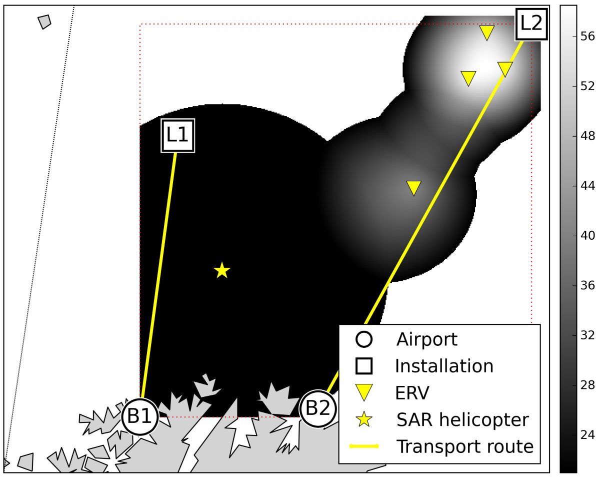
3 Mathematical model

This section describes a mathematical model of the CRCP. In the basic model we assume that outbound and inbound flights follow the same paths, implying that all installations are served directly. In terms of expected fatalities this would always be the best solution (Qian, Gribkovskaia, and Halskau 2011). Instead of direct flights to and from offshore locations, helicopters can fly round-trips to several offshore locations, hence in- and outbound paths may differ from each other. This situation is handled by a model extension, which we present in Section 3.2.

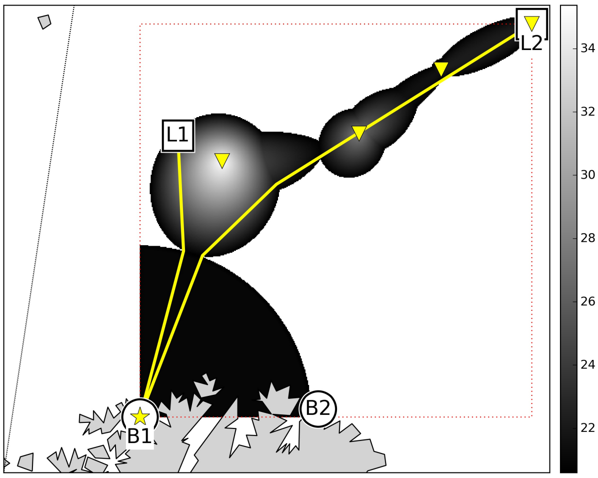
3.1 Basic model

Let $\mathscr{R}$ be a set of RUs, and $\mathscr{S}_r$ the set of nodes where a resource $r \in \mathscr{R}$ can be placed. Let $\mathscr{B}$ be a set of starting nodes such as onshore bases, and $\mathscr{L}$ a set of destination nodes such as offshore locations. Furthermore, let $\mathscr{N}$ be the set of nodes which can lie on paths that connect the starting and destination nodes. Let $\mathscr{K}$ be the set of arcs that represent the possible options to go from one node to another, and d_{ij} the distance between node i and node j for all arcs $(i, j) \in \mathscr{K}$. For each destination node, a path from an arbitrary starting node must be created. A valid set of paths is any subset of arcs from $\mathscr{K}$ that provides end-to-end connections for each destination node, $l \in \mathscr{L}$, from a starting node, $b \in \mathscr{B}$. Every node on the path has to be covered by a given minimum rescue capacity, $c^{\min}$. Let c_{rij} be the capacity of resource r placed at node i to conduct the rescue at node j. This capacity is calculated in a pre-processing step using Equation (1).

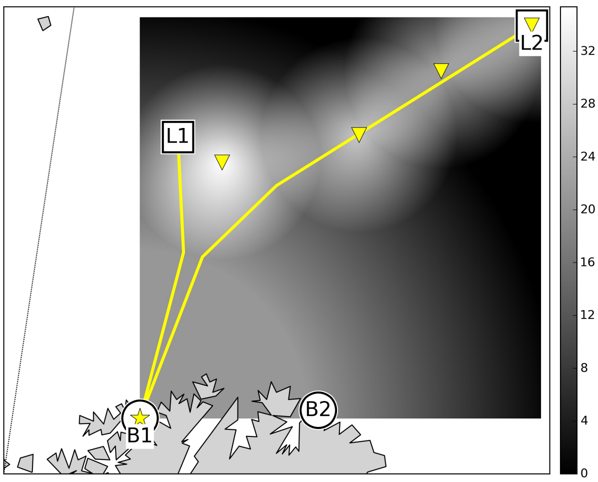
The binary variable w_j is 1 if node j needs to be covered, and 0 otherwise. Furthermore, the binary decision variable x_{lij} equals 1 if the arc $(i, j) \in \mathscr{K}$ is selected for the path to $l \in \mathscr{L}$, and 0 otherwise. Finally, y_{ri} is a binary decision variable that equals 1 if resource $r \in \mathscr{R}$ is placed at node $i \in \mathscr{S}_r$, and 0 otherwise. The CRCP can be written as follows:



(a) Freely placeable SAR helicopter. Offshore locations can be reached directly.



(b) SAR helicopter fixed to *B1*. Routes need to be bundled in order to be within the corridor.



(c) Full range of capacity.

Figure 10: Illustration of example solutions showing the routes to two offshore locations, with the requirement to rescue 21 people at any point of these routes. The shaded areas show the cumulative capacity at each point according to the attached color bars, with black showing the minimum capacity, and increasing capacity as the shading gets lighter.

$$
\begin{aligned}
\min \quad & \sum_{(i,j)\in\mathscr{K},l\in\mathscr{L}} d_{ij}x_{lij}, && && (3)\\
\text{s.t.} \quad & \sum_{i\in\mathscr{S}_r} y_{ri} = 1, && r\in\mathscr{R}, && (4)\\
& \sum_{(b,j)\in\mathscr{K}|b\in\mathscr{B}} x_{lbj} = 1, && l\in\mathscr{L}, && (5)\\
& \sum_{(i,j)\in\mathscr{K}} x_{lij} - \sum_{(j,k)\in\mathscr{K}} x_{ljk} = 0, && j\in\mathscr{N}, l\in\mathscr{L}, && (6)\\
& \sum_{(i,l)\in\mathscr{K}} x_{lil} = 1, && l\in\mathscr{L}, && (7)\\
& \sum_{(b,j)\in\mathscr{K}} \sum_{l\in\mathscr{L}} x_{lbj} \le w_b|\mathscr{L}|, && b\in\mathscr{B}, && (8)\\
& \sum_{(i,j)\in\mathscr{K}} \sum_{l\in\mathscr{L}} x_{lij} \le w_j|\mathscr{L}|, && j\in\mathscr{N}\cup\mathscr{L}, && (9)\\
& \sum_{r\in\mathscr{R}} \sum_{i\in\mathscr{S}_r} y_{ri}c_{rij} \ge w_j c^{\min}, && j\in\mathscr{N}\cup\mathscr{L}\cup\mathscr{B}, && (10)\\
& x_{lij} \in \{0,1\}, && l\in\mathscr{L}, (i,j)\in\mathscr{K}, && (11)\\
& y_{ri} \in \{0,1\}, && r\in\mathscr{R}, i\in\mathscr{S}_r, && (12)\\
& w_j \in \{0,1\}, && j\in\mathscr{N}\cup\mathscr{L}\cup\mathscr{B}. && (13)
\end{aligned}
$$

The objective (3) is to minimize the total length of the paths selected to reach the offshore locations. Constraints (4) restrict every resource to be positioned at exactly one node in $\mathscr{S}_r$. Constraints (5) ensure that every path to a destination $l \in \mathscr{L}$ starts at exactly one starting node in $b \in \mathscr{B}$. The balance constraints (6) enforce that, for every node and path, the number of ingoing arcs is equal to the number of outgoing arcs. Constraints (7) state that each destination node should have exactly one incoming arc.

According to constraints (8) and (9), every node that lies on a path must be covered by RUs. These are the essential constraints that connect the operational aspect to the emergency preparedness. If the left hand side (LHS) is 0, that is, node j is not used by any path, w_j may take the value 0, indicating that the node does not need to be covered. However, if the node is used by at least one path, that is, the LHS is greater than 0, w_j needs to take a value greater than 0 as well. The LHS can be at a maximum of $|L|$, which happens if node j is part of every path. As w_j is a binary variable, it needs to be multiplied with $|L|$, such that the right hand side can be greater or equal to the LHS. Variables x_{lij} are to be defined for each route, while w_j are not. Any node that needs coverage because of one route is therefore also covered for all other routes that use this node. Furthermore, nearby nodes can be covered by the same RUs if they are within range. Because of this feature it is beneficial to bundle routes as described, if sufficient rescue capacity is an issue.

As for the capacity part, constraints (10) define a minimum required capacity for every node that needs coverage. This capacity can be fulfilled by the sum of the capacities of RUs covering this node. Constraints (9) and (10) together ensure that any path runs within a corridor. Constraints (11)–(13) define the domains of the variables.

3.2 Extension for round trips

The presented model can be modified to account for round-trips when serving the installations. This requires that the assignment of offshore locations to the tours, the onshore bases used, and the sequence of offshore locations visited are specified manually. A model such as the one presented in Qian et al. (2012), which finds tours that minimize the pilot and passenger risk, could support these decisions.

Round-trips can be modeled by duplicating offshore locations as starting nodes and onshore bases as destination nodes for each tour. Then a set of tuples $(b,l) \in \mathscr{P}$ has to be formed that defines the legs of the tours, where $b \in \mathscr{B}$ is the starting node and $l \in \mathscr{L}$ the destination node. By adding the following constraints to the model, the starting node for each destination can be restricted to the one specified in $\mathscr{P}$:

$$\sum_{(b,j)\in\mathscr{K}} x_{lbj} = 1, \qquad (b,l) \in \mathscr{P}. \tag{14}$$

4 Solution methods

While the described mathematical model can be implemented directly, this is not efficient enough for practical use. An optimal – or even feasible – solution can often not be found within reasonable time for realistic instances. Furthermore, with the introduced formulation of the CRCP it is hard to detect infeasibility with a given number of resources, or to find out how many RUs are needed to achieve feasibility.

Therefore we developed an alternative solution method, presented in Section 4.1, which makes real life instances solvable by decomposing the problem. As a second alternative we formulate a goal programming model, presented in Section 4.2. While the goal programming model may provide solutions that are not feasible for the original problem, it could be used for cases where full coverage is not required.

4.1 Three-pass method

We now present a 3-pass method, which starts with a modified version of the model, CRCP$^{\text{pre}}$, to obtain a feasible solution to the original problem. This approach follows the advice of Klotz and Newman (2013) to obtain an initial solution by solving an auxiliary problem. This may provide a better starting point than the solver heuristics and improve the cutoff value faster. The modified model always has feasible solutions and maximizes the degree of coverage for all paths used. We introduce the variables g_j, which denote the coverage gap at node j, and define the model as follows:

$$\min \sum_{j\in\mathscr{N}\cup\mathscr{L}\cup\mathscr{B}} g_j, \tag{15}$$

$$\text{s.t.} \qquad (4)-(9)\ ,$$

$$\sum_{r\in\mathscr{R}} \sum_{i\in\mathscr{S}_r} y_{ri} c_{rij} + g_j \geq w_j c^{\min}, \qquad j \in \mathscr{N} \cup \mathscr{L} \cup \mathscr{B}, \tag{16}$$

$$g_j \geq 0, \qquad j \in \mathscr{N} \cup \mathscr{L} \cup \mathscr{B}. \tag{17}$$

The new objective (15) minimizes the coverage gap over all nodes instead of total distance. Constraints (4)-(9) can be adopted without change from the CRCP formulation. Constraints (16) replace constraints (10), allowing a gap g_j in the capacity requirement, and constraints (17) restrict g_j to the non-negative domain.

Even if in this model distance is not minimized, it cannot grow infinitely, because any path must be within the covered area in order to keep the value of the objective function low. However, the paths within these areas can be quite long and intricate. Furthermore, they can contain superfluous sub-cycles within the covered area. This model will seek a configuration where all paths between starting and destination nodes can be fully covered. While for rich coverage capacity scenarios (i.e. scenarios with much more capacity available than needed) many such solutions can exist, in cases of sparse capacity, the feasible space will be small.

A solution where $\sum_{j\in\mathscr{N}\cup\mathscr{L}\cup\mathscr{B}} g_j = 0$ is also a feasible solution to the CRCP. This fact can be used to achieve speed improvements for the CRCP model. Our solution method is depicted in Figure 11. The stages are defined as follows:

Pass 1: The CRCP$^{\text{pre}}$ is solved to optimality. If the objective function value of this solution is 0, then the paths between starting and destination nodes can be fully covered. If the problem cannot be solved to an objective function value of 0, then the CRCP is infeasible. In this case more rescue capacity needs to be introduced either by adding more RUs or by adjusting the parameters of existing RUs.

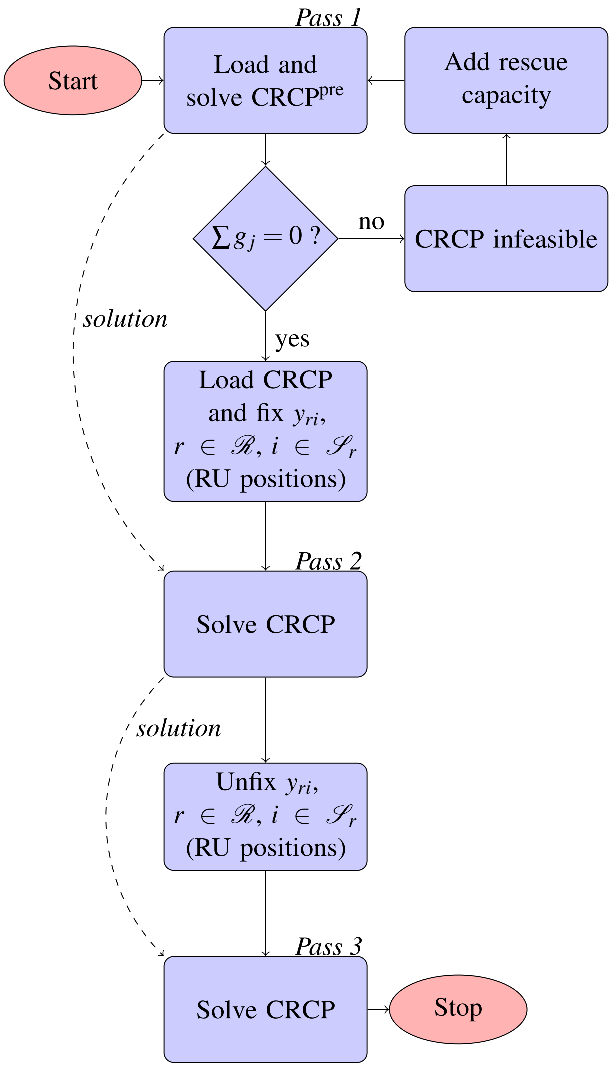


Figure 11: Flow diagram of 3-pass method.

Pass 2: The RU positions of Pass 1 are fed into the CRCP, fixed, and the model is solved. This minimizes the sum of path distances, eliminates sub-cycles, and is a heuristic solution to the CRCP which is particularly good for sparse capacity scenarios.

Pass 3: The original model is solved, with no fixed variables, starting with the solution to Pass 2. This can further improve the solution to the CRCP or solve the problem to optimality.

A comparison of computational times during the three passes can be found in Table 3 for three different instances. The advantage of this 3-pass method is that it keeps computational time low for both rich and sparse coverage capacity scenarios, while providing optimal to good solutions in all cases: If there is a lot of capacity, Pass 1 and 2 may not generate a good solution considering the CRCP objective of minimizing overall path distances. However, these two stages are solved quickly and Pass 3 will still have the freedom to find an improved or optimal solution to the problem. As capacity decreases, Pass 1 will find one of the feasible solutions of the CRCP, but as the feasible space is smaller, the chance of having a good solution to the CRCP increases. Furthermore, the solution can be still improved in Pass 3.

4.2 Goal programming model

In order to test the computational performance of our 3-pass method we also consider a goal programming formulation of the problem, CRCP^{goal}, as follows: We define M as a constant that denotes the penalty for the coverage gap.

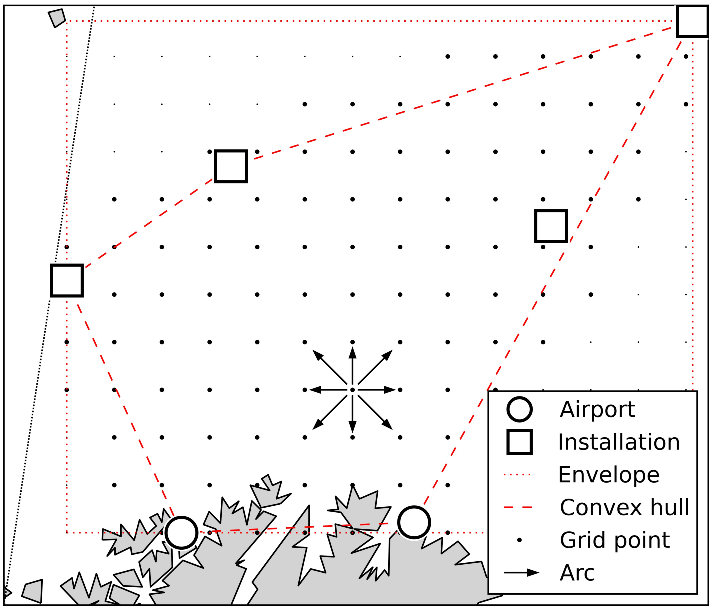


Figure 12: Illustration of the area discretization, grid point reduction, and generation of arcs to Moore neighbourhood.

$$\min \quad \sum_{(i,j)\in\mathscr{K},l\in\mathscr{L}} d_{ij}x_{lij} + M \sum_{j\in\mathscr{N}\cup\mathscr{L}\cup\mathscr{B}} g_j, \tag{18}$$

$$\text{s.t.} \quad (4)-(9),(11)-(13),(16),(17).$$

The objective (18) is to minimize the sum of route distances and the incurred penalty by insufficiently covered nodes.

While this model will always have feasible solutions, the resulting optimal solution may be infeasible for the original problem. This is because g_j is a real number that can be arbitrarily small. No matter how big M is chosen, it may be possible in this model to accept a certain penalty to obtain a smaller sum of route lengths. However, for problems where a lack of coverage is acceptable, this model would be a helpful alternative.

5 Computational experiments

In order to illustrate the features and characteristics of the model, we present a range of computational experiments. These were conducted on an Amazon Elastic Cloud Compute instance of type r3.large, which features an Intel Xeon E5-2670 v2 (Ivy Bridge) Processor with 2 virtual CPUs and 15 GB of memory (Amazon 2015). Gurobi Optimizer in version 5.6.3 was used as the solver for the MIP model.

Sets $\mathscr{R}$, $\mathscr{B}$ and $\mathscr{L}$ are the RUs, onshore bases, and offshore installations respectively. The sets $\mathscr{N}$, $\mathscr{S}_r$, and $\mathscr{K}$ are built as illustrated in Figure 12: First, $\mathscr{N}$ is obtained by discretizing the area in which the transport helicopter can move. This area is defined as the envelope of all bases and offshore locations. The bounds are used to generate a grid of equidistant points with a spacing of s^{grid}. The number of points in this grid can then be reduced by considering the following: With sufficient rescue capacity at each point, the best solution would be the shortest direct paths between a base and an offshore location. These paths lie either directly on one line segment of the convex hull polygon, or within the convex hull. If an RU is removed, given that for all RUs capacity is non-increasing over distance and there is still a feasible solution to the problem, paths need to be placed closer to each other in order to provide sufficient coverage with the remaining RUs. In an optimal solution RUs and paths must therefore lie on or within

Table 2: Coordinates of airports and installations used in the test instances. Latitude and longitude are given in decimal degrees.

Name	*Latitude*	*Longitude*	*Comment*
B1	70.701319	23.768302	Hammerfest
B2	70.854502	29.090389	Berlevåg
L1	73.491134	24.232358	Wisting central
L2	74.500000	37.000000	Extreme remote
L3	72.494341	20.347568	Johan Castberg
L4	73.059785	32.654140	Random placement
L5	73.125947	23.496317	Random placement
L6	71.584579	25.442689	Random placement
L7	72.922906	23.044665	Random placement
L8	73.721696	34.261504	Random placement

the convex hull. Grid points that lie outside of the convex hull, including a buffer of s^{grid} to account for the discretization, are therefore discarded. The set $\mathscr{S}_r$ is the union of $\mathscr{B}$, $\mathscr{L}$, and $\mathscr{N}$ for ERVs and equal to $\mathscr{B}$ for SAR helicopters.

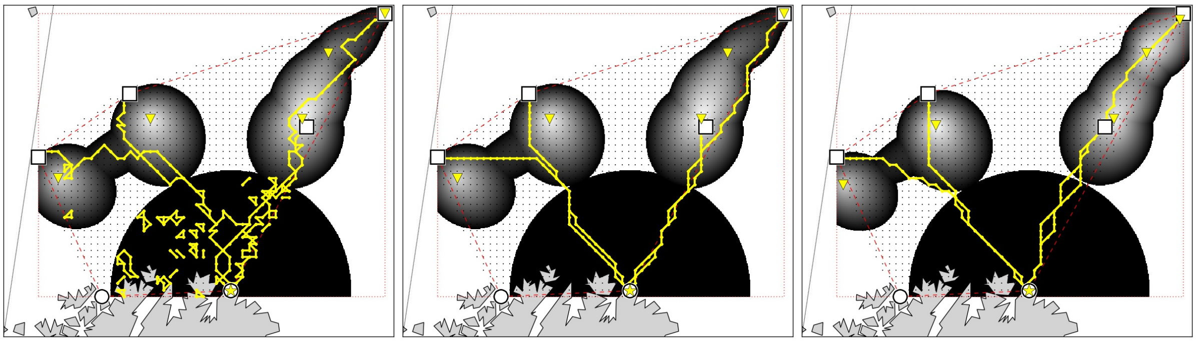
The set $\mathscr{K}$ is formed by generating arcs to nodes in the Moore neighbourhood (all nodes within a Chebyshev distance of the grid spacing) for each node in $\mathscr{B} \cup \mathscr{L} \cup N$. As a consequence, the arcs on the paths can only follow eight directions. This has implications on the minimum distance that can be achieved, as paths cannot follow a direct trail from one node to another non-neighbouring node. Increasing the neighbourhood to a Chebyshev distance of multiples of the grid spacing will increase the freedom in shaping paths. However, it will also relax the capacity requirements, since nodes in the grid could be skipped. We argue that it is more important to have a more fine-grained capacity requirement on the path and chose therefore to stay at a Chebyshev distance of s^{grid}. Our understanding of the model is that the routing part opens up the opportunity to adapt paths in such a way as to conform to the emergency capacity requirement and believe that eight directions are sufficient for this task.

5.1 Test instances

At the time of writing there is only one petroleum related production facility in place in the Norwegian part of the Barents Sea where offshore personnel is required: Goliat commenced operations in autumn 2015 and produces both oil and gas. However, this field is placed only 40 nautical miles from the shore. A second field, Snøhvit, is producing gas. This is a subsea installation, which is placed at the bottom of the seabed. The extracted gas is transported to the shore via a pipeline and thus does not require offshore personnel.

No other concrete projects have been initiated yet. We therefore created instances with remotely located, potential production sites as shown in Table 2. Helicopter base *B1* and *B2* are existing airports in this area. Installation *L1* is placed within the Wisting Central field, which is the northernmost oil discovery on the Norwegian continental shelf. Installation *L2* marks the north-easternmost location which could come into consideration in a possible future licensing round. Installation *L3* is located in the Johan Castberg field, where considerable oil and gas resources have been found. These sites delimit the area where the remaining installations *L4–L8* are randomly placed.

For the computational experiments we created three instances that differ from each other in the number of installations: Instance 1 contains installations L1–L3, Instance 2 contains L1–L4, and Instance 3 contains L1–L8. We use five ERVs and one SAR helicopter as RUs and set the minimum capacity requirement, $c^{\min}$, to 21 unless otherwise stated. The RUs characteristics are chosen as specified in Table 1. The assumptions for the pick-up rate and mobilization time are taken from Vinnem (2012). Speed assumptions are based on the technical specifications of a Super Puma EC 225 SAR helicopter, and a Norsafe Munin 1200 Daughter Craft, which is assumed to be the FRDC with which the ERV is equipped.



(a) Pass 1 (b) Pass 2 (c) Pass 3

Figure 13: Illustrations of solutions to Instance 2 after each pass of the 3-pass method.

Wind and wave conditions can influence the named parameters. Therefore, we chose the values for this deterministic model conservatively. The SAR helicopter can be located only at onshore bases. B1, B2, and L1–L3 define the convex hull of all these instances. In most of the tests we used a grid spacing s^{grid} of 10 km which results in 1315 grid points within the convex hull.

5.2 Computational performance

Figure 13 illustrates solutions using the 3-pass method for Instance 2. After the first pass (13a) the RU locations are part of a feasible solution to the CRCP, as the objective value is 0. However, the paths clearly show that the solution is non-optimal for the final CRCP, featuring sub-cycles and unnecessary detours. After Pass 2, the CRCP with fixed RU locations from Pass 1 is solved to optimality (13b). This solution is further improved in Pass 3 (13c).

We compared the runtime of the direct solution method to CRCP$^{\text{goal}}$ and the 3-pass method. We let the solver run until either a time limit of 5 hours is reached or the optimality gap becomes less than 1%. The solver was started with 10 different random seeds, from 0 to 9, in order to obtain robust results that allow us to make conclusions about the computational performance of the three methods. For Gurobi this is possible by using the parameter `Seed` (Gurobi 2015). The runtime of the MIP solver shows a remarkable variability in computational time dependent on the chosen random seed, which can be observed frequently with MIP solvers (Lodi and Tramontani 2013). By default, the Gurobi MIP solver balances the goals of finding feasible solutions and proving optimality. However, it provides the parameter `MIPFocus` to control this behavior. For the direct method we tried to set this parameter to prioritize obtaining a feasible solution, as this method had often problems in finding one. We found that it is better to leave this parameter in the default setting. For the 3-pass method, however, it turned out beneficial for Pass 3 to focus on the best objective bound.

Table 3 shows the computational time required for each run of the three methods. The results indicate an advantage of the 3-pass method over the direct method and the goal model. The solver found for the goal model the same best values as obtained with the other two methods, except for the random seed $s = 4$ for Instance 1 and $s = 6$ for Instance 3, where the penalties for insufficiently covered nodes could not be reduced to 0. This method encountered sometimes difficulties with improving the lower bounds. This may be subject to the weaker model formulation due to elastic variables (Klotz and Newman 2013). For Instance 1 none of the methods performed to full satisfaction. Two out of ten times the direct method did not lead to a feasible solution. For the goal model the solver did not succeed in reducing the optimality gap below 14.1%. The 3-pass method always found a feasible solution, but could not reduce the optimality gap below 1% within the 5 hour limit.

At this time it is still difficult to estimate the size of a real life instance. However, the oil and gas industry has successfully established four areas on the Norwegian continental shelf where maritime and air rescue resources are shared in order to use the available capacity in a more effective way (Norsk olje og gass 2015; Vinnem 2012). Three of these areas contain 5 fields and one area contains 9 fields, which

Table 3: Speed comparison of direct method, goal programming model and 3-pass method. The random seed is denoted by s. The runtime in minutes to the first feasible solution is denoted by t^f. The runtime in minutes until the objective value is proven to be within 1% of optimality is denoted by t^*. The column *gap* shows the relative optimality gap in percent. NaN denotes runs where no feasible solution could be found within the time limit. The rows *Avg* and *Med* denote the arithmetic mean and the median respectively.

	Direct			Goal		3-pass		
s	t^f	t^*	*gap*	t^*	*gap*	t^f	t^*	*gap*
Instance 1 (Best value: 1273866.80)								
0	NaN	300	NaN	300	14.1	2	302	10.3
1	49	300	14.1	300	14.1	1	301	14.1
2	9	300	14.1	300	14.1	1	301	1.2
3	9	300	14.1	300	14.1	4	304	1.4
4	2	300	14.1	300	97.2	4	304	13.7
5	6	300	14.1	300	14.1	1	301	14.1
6	22	300	14.1	300	14.1	5	305	14.1
7	3	300	14.1	300	14.1	1	301	1.4
8	NaN	300	NaN	300	14.1	6	306	13.9
9	2	300	14.1	300	14.1	1	301	1.4
Avg	> 13	> 300		> 300		3	> 303	
Med	> 7	> 300		> 300		1	> 301	
Instance 2 (Best value: 1571662.67)								
0	3	8	0	207	1	4	16	0.7
1	14	15	0.6	8	1	7	45	0.9
2	2	175	0	300	1.1	1	23	1
3	4	8	0	47	1	5	12	1
4	8	10	1	95	0.9	2	10	0
5	8	112	1	152	1	2	7	1
6	201	201	0.9	300	1.1	1	230	1
7	8	300	1.1	9	0	1	22	1
8	157	157	0.1	300	11.3	33	46	1
9	56	300	11.4	143	0.9	1	19	0.8
Avg	46	> 129		> 156		6	43	
Med	8	> 134		> 148		2	20	
Instance 3 (Best value: 2784471.31)								
0	3	11	0.6	125	0.6	14	37	0.6
1	22	22	0	69	0.6	6	40	0.6
2	10	10	0	26	0.6	11	17	0
3	196	196	0.5	300	11.4	9	22	0.6
4	3	13	0.6	164	0.6	6	181	0.5
5	9	19	0.6	60	0.6	13	47	0.6
6	151	164	0.6	300	94.3	9	27	0.6
7	3	77	0.6	14	0.6	3	14	0.6
8	2	99	0.6	18	0.6	7	20	0.6
9	4	14	0.6	141	0.6	6	44	0
Avg	40	62		> 122		8	45	
Med	7	20		> 97		8	32	

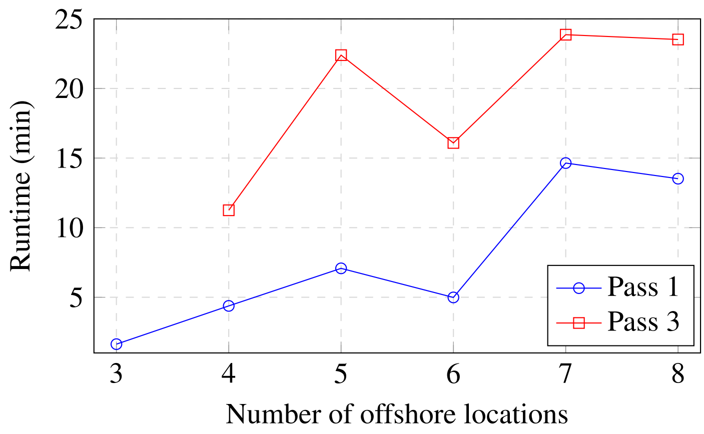


Figure 14: Number of offshore locations vs. runtime.

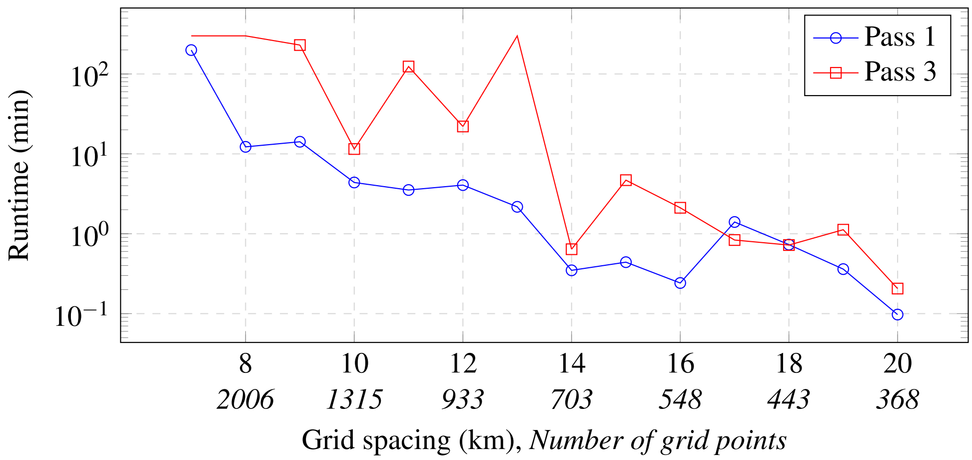


Figure 15: Grid spacing vs. runtime.

lets us assume that a real life instance may involve 5–10 destinations. The influence of the number of installations on the runtime for Pass 1 and Pass 3 is shown in Figure 14. Instance 1 was used as a baseline. The additional installations *L4–L8* were added one at a time, in such a sequence that 4 installations are equal to Instance 2 and 8 installations are equal to Instance 3. As they are located within the already existing safe area of the solution to Instance 1, no more resources are needed to cover them. This ensures comparability. The value for Pass 3 with 3 installations (Instance 1) is not shown as the solver terminated after 5 hours with an optimality gap of 10.3%.

The choice of the grid spacing has several implications for the model. With a bigger grid spacing, less points on the path need to be covered, which can make a solution too optimistic. On the other hand, the available capacity could be undervalued, as the possibilities to place RUs are more restricted using such a grid. The grid spacing also influences the problem size, as the number of variables and constraints increases with smaller grid spacing. Figure 15 shows the spacing on the x-axis and the resulting computational time for Pass 1 and Pass 3 of Instance 2 on the logarithmic y-axis. The plot for Pass 3 does not include the values for 6, 7 and 13 km as they terminated after 5 hours with an optimality gap of 1.56%, 1.26%, and 1.37% respectively.

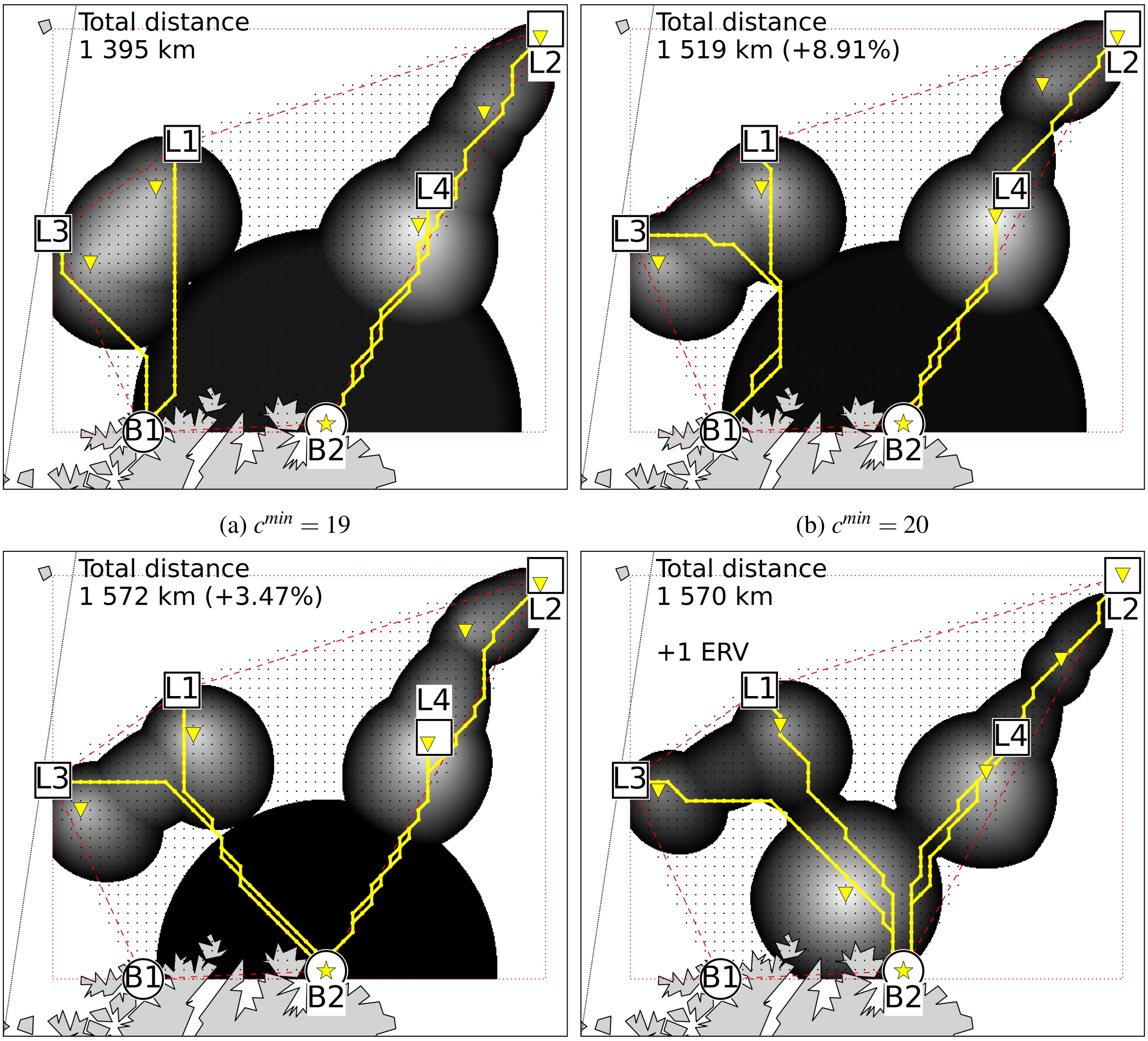


Figure 16: Transport routes dependent on minimum rescue capacity c^{min}. Total distance is the sum of paths from onshore base to offshore location. Percentage value denotes the total distance increase related to $c^{\min} - 1$.

5.3 Effect of rescue capacity requirements on transport routes

Figure 16 shows optimal solutions for Instance 2 with varying rescue capacity requirements. With a requirement of $c^{\min} = 19$ the offshore locations *L1*, *L2* and *L4* can be reached in a direct way from the nearest helicopter base, while the route from *B1* to *L3* needs a detour. This detour gets larger with $c^{\min} = 20$, but *B1* is still preferred as the onshore base. With $c^{\min} = 21$, all flights depart from *B2*. This is mostly because the SAR helicopter cannot cover the capacity requirement of routes departing from the other helicopter base any more, and there are not enough ERVs that can assist near the shore to fulfill the capacity requirement. If the requirement is increased to $c^{\min} = 22$, the physical capacity of the SAR helicopter is an issue. Big areas that have been safe with a lower requirement can no longer be covered by using only the helicopter. However, with one additional ERV, a corridor to all installations can be created, allowing routes with approximately the same total distance as for $c^{\min} = 21$.

The objective function value of the first pass gives an indication of how much of the path is uncovered. This is illustrated in Table 4, where the CRCP$^{\text{pre}}$ was solved iteratively using Instance 3, adding one more RU before each run. The maximum computational time was set to one hour. A solution where all routes

Table 4: Capacity gap as resources are added.

Added resource	*Capacity gap*	*Addidtionally covered capacity*
SAR Helicopter	542.29	-
ERV1	368.06	174.23
ERV2	169.46	198.60
ERV3	52.22	117.24
ERV4	13.02	39.20
ERV5	0.00	13.02

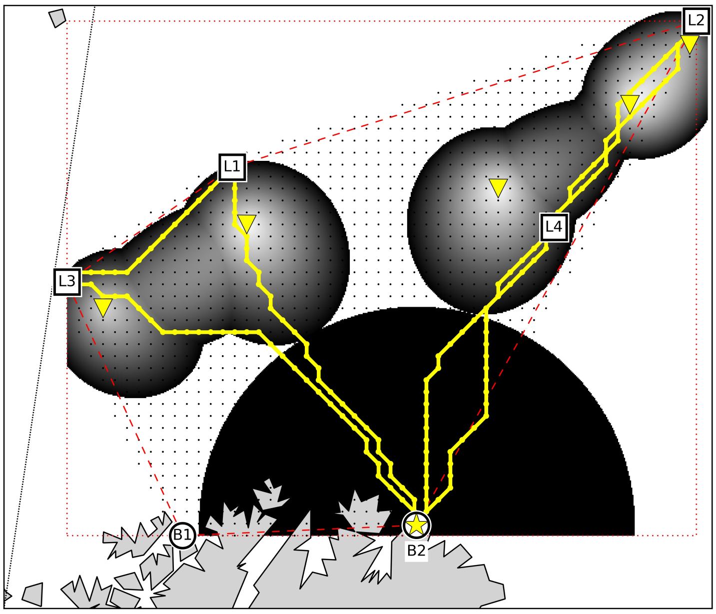


Figure 17: Illustration of a solution to Instance 2 where helicopters transporting personnel follow round trips to visit the offshore installations.

could be covered sufficiently was only found after adding six RUs (one helicopter and five ERVs) and for this case the computational time was 3 minutes. Due to the time limit, a feasible solution with less resources cannot be excluded.

5.4 Round trips

Section 3.2 presented an extension to the basic model that allowed the use of round trips. An example solution to Instance 2 with round trips is shown in Figure 17. The legs are in this case defined as follows: $\mathscr{P} = \{(B2^0, L1^0), (L1^1, L3^0), (L3^1, B2^1), (B2^0, L4^0), (L4^1, L2^0), (L2^1, B2^2)\}$, where the superscript n denotes the n-th copy of the node. Note also, that the onshore base only needs to be duplicated as a destination node, but not as a starting node. This method for round-trips works for the basic model described in Section 3, but also for the solution methods in Section 4, when the additional constraints are added.

6 Concluding remarks

Logistical concepts and terminologies find their way into emergency preparedness. For a long time preparedness planning was driven by response time. This paper shows how this measure can be extended into response capacity. We defined a problem related to safe personnel transport to offshore locations by helicopter and showed how available rescue capacity can be used efficiently by planning emergency preparedness and operations in a combined way.

We presented a mathematical model of this problem. As directly solving the model is inefficient, we developed a 3-pass method that shows an advantage over the direct approach and makes the problem solvable for real life instances.

Using the presented method, we conducted computational experiments. We showed a mutual interdependence between operations and preparedness. Planning both aspects jointly opens the opportunity to bundle demand. Consequently, resources can be used in a more efficient way. This is especially useful in environments with sparse infrastructure and long distances, as it allows establishing preparedness systems that would otherwise not be possible. However, the mutual interdependence between operations and preparedness leads to a trade-off, where a reduction in the preparedness resources leads to an increase of the total travel distance.

The *combined routing and covering problem*, together with the presented solution method, can be used in several ways. Among other things, it allows one to assess, how many and which types of RUs are needed, or what technical characteristics these RUs should have. Moreover, the model can be of help in assessing operational issues, such as the maximum number of personnel on board of the helicopter, which onshore bases to use for personnel transports, or how new offshore locations will affect the system.

We see several new directions to extend the work. Handling the time components of a response as probability distributions instead of expected values would be of interest. Furthermore, meteorological data may be considered, as wind and wave height influences the response. Finally, we see some potential to improve the solution method by iteratively solving the problem and adjusting the grid after each run to make it more fine grained around areas of interest.

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Paper 2

A simulation model to evaluate an emergency response system for offshore helicopter ditches

A simulation model to evaluate an emergency response system for offshore helicopter ditches

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Abstract

A simulation model that supports the planning of an offshore emergency response system is presented. This model is based on official guidelines for offshore preparedness and can be used to evaluate different designs of an emergency system in respect to quantity, performance and location of Search-and-Rescue helicopters by modeling the coverage of the area under consideration. The model is trace-driven by means of environmental data. It includes a number of stochastic parameters which show a complex system of location dependence and interdependency. As a result a heat-map to visualize the response capacity and its service level is generated. The petroleum industry in Norway is expected to move into new areas. One particular area of interest is the Barents Sea, which is characterized by long distances and challenging environmental conditions. A case study which shows possible designs of an emergency response system in this area using the simulation model is presented.

1 Introduction

The Norwegian oil and gas industry heavily relies upon helicopters as means of personnel transportation to offshore facilities. At the same time, helicopter transport is considered to be one of the major hazards for employees in this industry. This will be a particular challenge for the Arctic Region, which has received increased attention in respect to offshore oil and gas exploration, but has established neither necessary infrastructure for regular production nor an emergency response system (ERS) to react in case of incidents. There, long distances and averse environmental conditions will increase risks connected to offshore personnel transportation and will make emergency response more difficult than in any of the established areas. Polar lows, for example, can be short lived and difficult to detect, and are a hazard for operations in this latitude. Three months of permanent darkness during the winter are not only a psychological challenge, but can increase the time for rescue operations. Low sea temperatures are life threatening for persons in distress and limit the time to respond to an incident.

While the petroleum industry has seen emergency preparedness for a long time as an isolated issue for every installation, one of the most significant changes in offshore preparedness over the last 15 years is the introduction of an area preparedness concept. Thus, response planning would not be considered just on per-installation basis, but emergency resources are used to cover a certain area as far as minimum requirements can be fulfilled. The most important criterion for delimitation of preparedness areas for

Search-and-Rescue (SAR) operations is the requirement to be able to rescue 21 people in the sea within two hours (Vinnem 2011).

With particular attention to the Arctic region and its challenges a simulation model for evaluating the emergency preparedness was developed. This model involves a systems perspective, taking the environmental conditions and interplay of available resources with their technical specifications into account. The model can be used to evaluate variants of ERS designs and the robustness of the resulting coverage. This is particularly important as whole routes to the installations need to be covered. Thus feasible ERS designs should always allow routes between an onshore base and an offshore location that are entirely within safe ares. Heat-maps as one of the outputs of the simulation show the areas which can be covered with a required capacity at a minimum accepted probability on a map.

This paper is structured as follows. Similar problems in scientific literature are reviewed in Section 2. Then the problem and the underlying guidelines are described in Section 3. From this a mathematical formulation of the simulation model is derived in Section 4. After a short description of the technical realization in Section 5, results of a case study in the Barents Sea on the basis of the this model are presented in Section 6. The paper concludes with remarks and further opportunities for research in Section 7.

2 Literature review

The rescue capability for operations in the Barents Sea has been discussed by Jacobsen and Gudmestad (2013). A combination of a SAR helicopter and multipurpose emergency response vessels is proposed as a rescue scheme. A deterministic model for the capacity calculation is used, and the scheme is valid for a single route which runs as a straight line between an onshore base and an offshore location.

Simulation could be considered as a valuable tool in planning emergency preparedness systems for the offshore industry. Yet, most of developed models have concentrated on oil spill incidents. OSCAR (Reed, Aamo, and Daling 1995), for example, is a tool to assess alternative oil spill strategies. It has already been in use for a long time and has been steadily improved since its first version. More recently, P. Li et al. (2014) combined a Monte Carlo simulation and optimization to provide decision support for devices allocation and recovery operation during offshore oil spill responses.

When planning new installations in Norway and the UK, emergency preparedness has to be evaluated through a Probabilistic Risk Assessment studies. These are often not very detailed. Various approaches in scientific literature were developed that allow for more detailed analysis. Yun and Marsden (2010) present a methodology based on event trees and Monte Carlo simulation to evaluate the robustness of Escape, Evacuation, and Rescue strategies. Event tree analysis provides quantitative results and allows for interdependent variables. Vinnem (2011) points out that the cases where emergency preparedness solutions had to stand the test of reality rarely occur. Compared to other incidents, however, helicopter accidents and ditches still have been somewhat more frequent. He combines quantitative and qualitative data of different preparedness topics and consolidates the results to draw a picture of the overall preparedness status. This approach is rather an a posteriori evaluation of a preparedness system already in place. Norrington et al. (2008) model the reliability of Search-and-Rescue operations by identifying the primary variables and bringing them together in an Bayesian Belief Network (BBN). While the construction of the BBN resulted in a deeper understanding of the key factors, this did not result in a valid quantitative output. The closest approach to the one presented may be the software *Offshore Sea Rescue*, which simulates the rescue of people in distress at sea (Soma, Haugen, and Øygarden 2003). While the survival times are a function of sea temperature and clothing in this model, the user has to specify transit times and environmental conditions.

The presented model has features related to facility location and coverage problems, where a research stream can be found in the field of optimization (X. Li et al. 2011). Stochastic factors can be included into these models; e.g., Berman, Drezner, and Krass (2013) explore the maximum covering problem with travel time uncertainty in order to find the optimal location facilities for fire stations, such that fire trucks can be on the incident site within a certain amount of time. The authors mention, that the solution

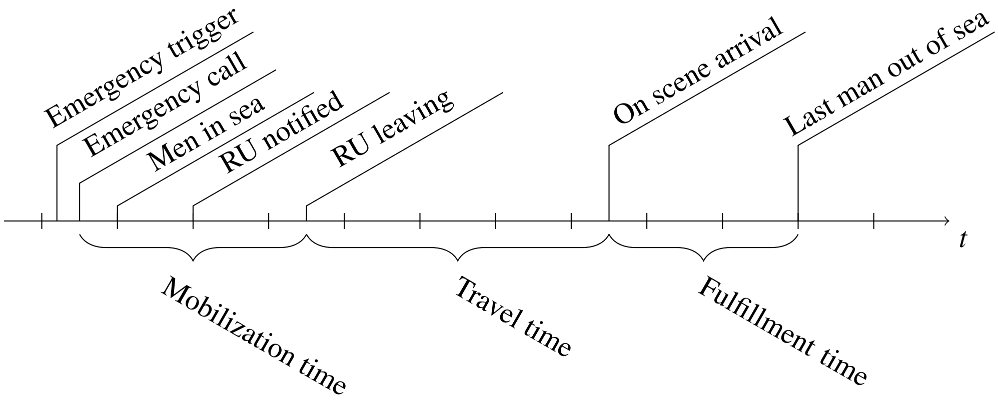


Figure 18: Time components of a response for one RU

quality of deterministic models can be very poor. Ingolfsson, Budge, and Erkut (2008) present a model to minimize the number of ambulances, that can fulfill a specified service level as the fraction of calls reached within a given time standard. Mobilization and travel time are modeled as stochastic variables.

The literature research did not reveal a similar personnel SAR model, that is able to evaluate the ERS performance of existing and new installations under stochastic capacity, which is a result of interdependent stochastic transit and pickup times.

3 Problem description

The presented model is based on the guidelines of the Norwegian Oil and Gas Association for establishing area preparedness (Norsk olje og gass 2015). These guidelines describe a set of defined hazards and accidents (DFU, as an acronym of the Norwegian term *Definerte Fare- og Ulykkessituasjoner*), which need to be considered for planning and dimensioning the preparedness system for offshore oil and gas facilities.

The model simulates particularly the DFU *Person in sea as a consequence of a helicopter accident*. A situation like this can arise, when personnel is transported by helicopter from or to an offshore platform, and the helicopter needs to ditch on the way. While it is possible for helicopters to float in sea conditions within certain limits, immediate capsizing has to be considered as the dimensioning scenario. Passengers and pilots do wear immersion suits, which protect them from hypothermia, however the effect is restricted over time.

According to the aforementioned guidelines, the available capacity has to be sufficient to rescue a full transport helicopter within 120 minutes. While this capacity can be provided by one response unit (RU), several RUs can cooperate to fulfill the requirement as well. RUs are usually SAR helicopters, in some cases specialized vessels are used in addition. The different time components of a response are shown in Figure 18. In case of an incident the Emergency Control Center is called and the necessary RUs are dispatched. A certain mobilization time elapses until they can leave. The mobilization time for SAR helicopters for offshore preparedness is usually agreed to be at a maximum of 15 minutes. The RUs will begin their travel to the incident site.

When the RUs arrive, the accomplishment phase starts by picking people in distress out of the sea. The pick-up time is considered to be dependent on the significant wave height H_s and visibility. As an addition to the above mentioned guideline, the Norwegian Oil and Gas industry published the underlying assumptions (Vinnem 2012). For the presented model, an adapted version of these values are used (see Table 5), because the pick-up time in the dark for $H_s > 6$ was found to be too conservative, changing this value to 4 minutes (Kråkenes et al. 2013).

Further on, we will refer to the rescue capacity for an incident site as the number of people that can be picked up from the sea within a given time limit. This rescue capacity is stochastic. While a multitude of

Table 5: Helicopter pickup times dependent on significant wave height (H_s) and light conditions

	Daylight	*Dark*
Waves < 6 m (H_s)	2 min	3 min
Waves > 6 m (H_s)	3 min	4 min

sources of stochasticity could be identified, the focus in this paper is on the environmental conditions as wind speed and direction, wave height, and daylight. Wind conditions influence the travel time of a RU, and the pickup time depends on the wave height at the incident site.

Moreover, additional RUs within the preparedness system increase the complexity. First, the cooperative aspect needs to be considered, as the capacity for several RUs on site is not simply additive. An overhead of coordination between RUs decreases the additional rescue capacity obtained by adding one resource. In the aforementioned guidelines this is accounted for by a reducing the pick-up rate of every additional RU by 50%. While the first RU on site has, e.g., a pick-up time of 3 minutes per person, any additional RU will only be able to pick up people every 6 minutes.

Second, the contributed rescue capacity of two RUs is expected to be not independent from each other, which makes it difficult to model it or its components as probability distributions. Several interdependencies can be observed. As explained earlier, the pick-up time is dependent on the on-site wave height and daylight conditions. Since every RU is exposed to the same environmental conditions on site, the interdependency is evident for this component.

Another interdependency, however, was expected between travel time of two different RUs. This can be understood by the scenario visualized in Figure 19. There are three RUs, positioned at the locations *Hammerfest*, *Alpha* and *Bjørnøya-B* respectively. For the exact locations see Figure 22. All of them have the same distance to an assumed incident site *Castberg*. Assuming wind as shown in the figure, the RU from *Hammerfest* will travel with head wind, which will slow it down, while the RU from *Bjørnøya-B* will experience a speed increase over ground. The RU positioned at *Alpha*, however, will mostly experience the same environmental conditions as the RU at *Hammerfest*. This leads to the assumption, that the travel times of the RUs from *Hammerfest* and *Bjørnøya* to the incident site could be negatively correlated, while travel times from *Hammerfest* and *Alpha* seem to be positively correlated.

One more inter-dependency should be mentioned. Wind and wave height are closely coupled to each other through the wind-wave mechanism (Komen et al. 1996, p. 60). Therefore, travel time and pickup time could show some degree of inter-dependency.

This complex interplay of stochasticity and interdependency lead us to the approach of a trace-driven simulation. This does, however, not necessarily mean, that real life data is used: The weather data, which is part of the input data, is already an output of a weather model.

4 Model description

The high number of points to calculate in order to generate a heat map require an efficient execution of the simulation model. Initially an approach using Discrete Event Simulation was considered. This, however, turned out to be too slow. Therefore, an alternative method was chosen, involving multiple stages of matrix operations: Ahead of execution the input data is prepared and preprocessed where possible and reasonable. During the execution the model goes through the phase of travel simulation for each RU, further on to the response simulation involving all available RUs, and finally the consolidation.

4.1 Input data

The model takes the environmental conditions for every point on the simulation grid at discrete, evenly distributed points in time t during a defined timespan T as an input. Waves are represented in terms of significant wave height H^{sig}, which is defined as the mean wave height of the highest one-third of waves observed (Holthuijsen 2007, p. 28) and commonly used to describe the sea state. H^{sig} for a point (x, y) at

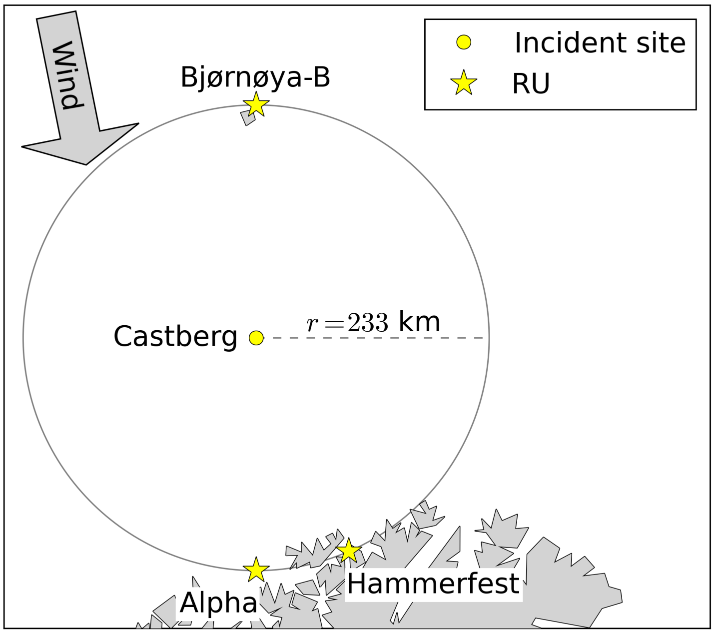


Figure 19: Scenario

a point in time t will be later on denoted as H_{txy}. Furthermore, binary values L_{txy} indicate the daylight at time t and point (x,y). 0 stands for darkness, 1 for light. Wind speed and direction are given and denoted as $\vec{W}_{txy}$.

Moreover, a set of RUs R with locations L_r, and the maximum true airspeed (TAS) S_r for every $r \in R$ is given. TAS is defined as the speed of the aircraft relative to the air mass. Finally, the mobilization time t^{mob} and the time limit for a person in sea $t^{\max}$ is given.

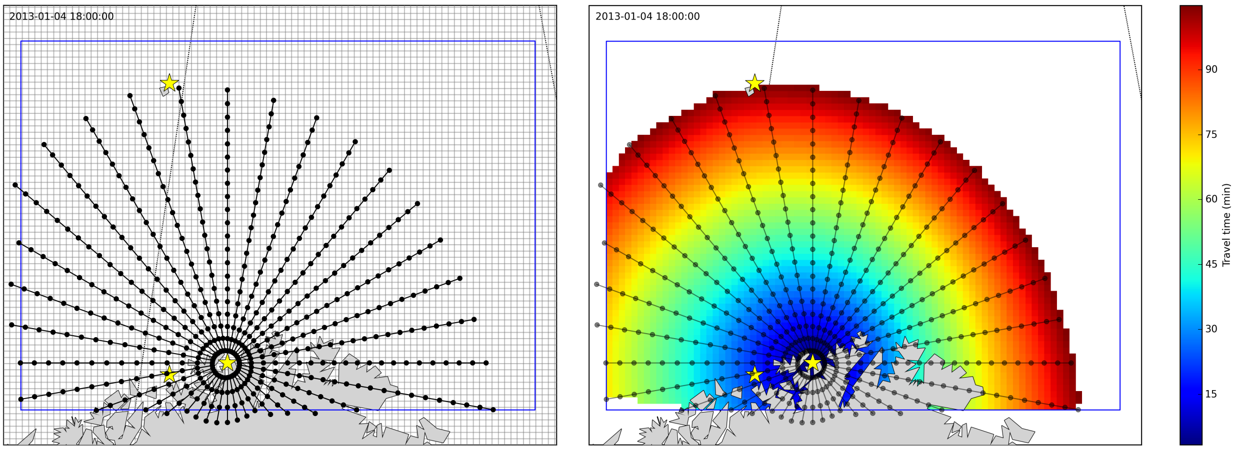
4.2 Travel simulation

The travel of an aircraft can be described as a relative movement to the airmass in which it is flying. As the helicopter is moving through the air as its medium, the air movement determines the helicopter speed related to the ground. Wind speed can be considerable and taking this factor into account when evaluating a preparedness system adds therefore an important perspective.

The travel simulation deserves particular attention, because it is the computationally most expensive operation in the simulation. A high number of repetitive operations are needed, and the speed of these operations can be decisive for the overall computational time.

In order to reduce this time, the travel of each RU is simulated from its initial position radially for a defined number of rays $n^{\max}$, maintaining a constant course $c(n) = \frac{360n}{n^{\max}}$ for the n^{th} ray, until the map bounds are reached or $t^{\max}$ is exceeded, such that the RU can not have an effect anymore in the fulfillment phase (Figure 20a). After this, the travel time to each point in the simulation grid is interpolated (Figure 20b).

The simulation follows a constant time step advance mechanism, i.e., the simulation clock is incremented step-wise, moving the RU by a calculated ground vector. For this, the nearest available weather and the daylight data of the current position and time is fetched from the preprocessed data. Based on the environmental data, the ground vector is determined by the wind triangle shown in Figure 21, where $\vec{V}_a$ describes the true air movement, $\vec{W}_{txy}$ designates the wind vector, and $\vec{V}_g$ is the vector over ground. While the direction of the ground vector is determined by the planned course of the aircraft $c(n)$, its length is a result of the known $\vec{W}_{txy}$ and $\vec{V}_a$. The length of $\vec{V}_a$ is known ($\left|\vec{V}_a\right| = S_r$), but the direction needs to be determined accordingly (see Federal Aviation Administration (2008, p. 15-12). The unit is moved by $\vec{V}_g$, and the time is incremented by a constant time step. The new position of the RU and the current time is



(a) Radial travel simulation from initial location (b) Interpolation of travel times

Figure 20: Transit time calculation

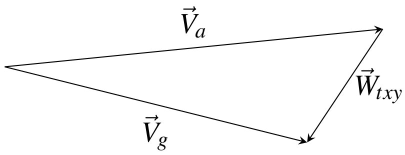


Figure 21: Wind triangle

recorded. The simulation continues by repeatedly advancing the RU until the end of the ray is reached under the aforementioned conditions. Then the RU is reset to its initial location and a new ray with a clockwise rotated course is calculated. This procedure repeats until a full revolution around the initial position has been done.

After simulating the radial travels, the grid points are interpolated by an inverse distance weighting interpolation (Shepard 1968) to the 4 nearest neighbors. The transit time for each resource $r \in R$ of time period $t \in T$ for each point x, y of the grid is written into the Matrix A_{rtxy}.

4.3 Response simulation

The response simulation consolidates the transit of different RUs to the incident site and the pick-up of the people in distress. As an output, the response capacity is obtained for each point in time on the grid. This results in a high number of operations needed. For example, the grid in use was 83 x 59, with 2,920 time periods for one year. This results in $2{,}920 * 83 * 59 = 14{,}299{,}240$ responses to be simulated. The response capacity increases as RUs arrive. This capacity is not increasing linearly, as any helicopter, that arrives after the first one, only contributes half of its capacity. This fact of interdependence makes it impossible to just add up the individual capacities of every single RU. This was solved by sorting the transit time matrix A along its resource dimension, resulting in the sorted matrix $A^{\star}$. As an example, if the arrival times at point $(50, 30)$ and time period 30 would be $24, 15, 36$, the ordered list $L = 15, 24, 36$ would represent the sequence, in which the RUs are approaching the incident site.

Given R the set of RUs, the matrix of significant wave heights H, the daylight matrix L. Then the pickup time matrix P is calculated for every time period t at the position (x, y) in the simulation grid as

$$P_{txy} = 2 + (1 - L_{txy}) + \frac{1}{6} H_{txy} \tag{19}$$

This is a result of a linear interpolation of the points given in Table 5.

Earlier it was mentioned, that additional rescue units arriving on site are not able to contribute their capacity to their full extent, as they will need to coordinate the operation with the other units. This is modeled with the effect matrix E, the proportional effect of the arrival of the r^{th} rescue unit.

$$1 \geq E_1 \geq \cdots \geq E_r \geq \cdots \geq E_{|R|} \geq 0 \tag{20}$$

Then, the capacity matrix C denotes the number of persons that can be picked up within $t^{\max}$ at an incident happening at a time t and point (x,y) and is the result of

$$C_{txy} = \sum_{r=1}^{|R|} \frac{(t^{\max} - t^{\text{mob}} - A^{*}_{rtxy})E_r}{P_{txy}} \tag{21}$$

4.4 Consolidation

The resulting capacity matrix can be used to calculate the fraction of time, when a point can be sufficiently covered by RUs. For this, a binary matrix B indicates whether the available resources can contribute the minimum capacity c^{req} at point (x,y) and time t:

$$B_{txy} = \begin{cases} 1 & \text{if } C_{txy} \geq c^{\text{req}} \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

The normalized sum over the time axis reflects the proportion, to which a point (x,y) could be covered sufficiently during a time period T.

$$M_{xy} = \frac{\sum_{t \in T} B_{txy}}{|T|} \tag{23}$$

Visualizing the points $(x,y)|M_{xy} \geq p$ on a map shows the safe areas, where the coverage is within an accepted threshold p.

5 Technical realization

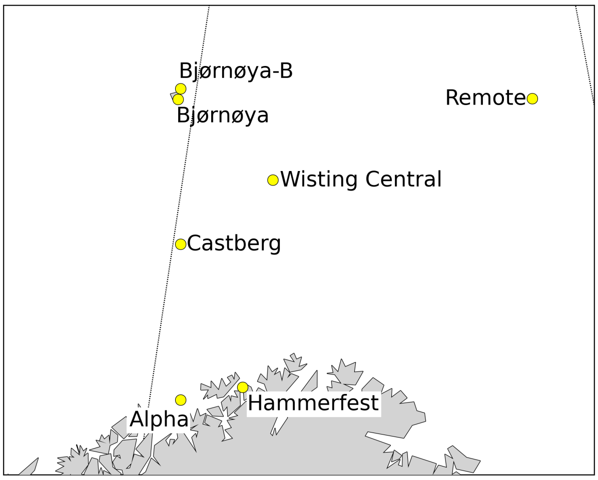
The simulation was programmed in Python. This environment presented itself as an efficient development platform for the model at hand with powerful abilities to process input data, and simulate and visualize spatial problems. Furthermore, the handling of multidimensional matrices in the form of arrays is very convenient. The computationally expensive parts of the simulation were still written in Python language, but compiled into native machine instructions using Numba (Continuum Analytics 2015).

6 Case study

The presented model was used to conduct experiments in an area of the Barents Sea region, which is delimited to the North and West by the small island Bjørnøya, to the East by the Russian border, and to the south by the city Hammerfest. Figure 22 shows the coordinates in decimal degrees for locations used in this case study. The maximum TAS of the SAR helicopters used as RUs are assumed to be 140 knots. Furthermore, the mobilization time t^{mob} is 15 minutes, and the maximum time of a man in sea $t^{\max}$ is 120 minutes.

6.1 Pre-Processing of environmental conditions

For the environmental conditions data from the Norwegian 10 km Reanalysis Archive (Reistad et al. 2011) for the year 2013 was used. This is hindcast data, providing significant wave height, wind speed and direction on a grid with a resolution of 10 km every 3 hours. The data is delivered on a rotated spherical grid and had to be regridded to fit the target grid used for the simulation. For the regridding one has to decide how to interpolate the data. For the wind, which is directional data, this can be particularly cumbersome. As Schaefer and Doswell (1979) point out, isolating the vertical and horizontal component



Name	*Lat*	*Lon*
Alpha	70.418539	21.240683
Bjørnøya	74.418419	19.170307
Bjørnøya-B	74.564738	19.214293
Castberg	72.494341	20.347568
Remote	74.500000	37.000000
Hammerfest	70.679720	23.668628
Wisting Central	73.491134	24.232358

Figure 22: Locations for case study

of the wind and applying common interpolation techniques on these components separately does not necessarily yield the same as interpolation of magnitude and orientation. Furthermore, interpolating the orientation is ambiguous, as the wind direction can change clockwise or counter-clockwise between two points. The data provided is already interpolated data on a regular grid without gaps. Additional interpolation, which does not take into account the underlying weather model would not improve the result. For this model regridding by using the nearest neighbor was therefore sufficient. There are, however, interpolation techniques for wind, which could be used in case of missing or too coarse wind data. Ye, Hong, and Wang (2015) provide a recent comparison of different methods. The significant wave height was interpolated by inverse distance weighting.

Finally, daylight is included into the model. This is a computed binary matrix indicating if the sun is above or under the horizon for a given latitude, longitude, time and date. Rising and setting time are calculated using the method given by the U.S. Nautical Almanac Office (2014). It is pointed out, that this method can give somewhat inaccurate results at high latitudes near the dates when the sun remains above or below the horizon for more than 24 hours. The error of few minutes during two very short periods throughout the year is not assumed to influence the result significantly.

6.2 Experiments

For the experiments, the simulation was run for each environmental state given for the year 2013. As the time resolution was 3 hours, this resulted in a sample size of 2,920 for each experiment.

It is hypothesized, that not only the interdependence, but also the probability distribution is location dependent (Hypothesis 1). The histograms in Figure 23 show the simulated travel times during the year 2013. It is evident, that the two probability distributions differ significantly. Variance and median of the sample from *Bjørnøya-B* are considerably higher than the travel times from *Hammerfest*.

Hypothesis 2 states, that the travel times of two RUs to an incident site are interdependent, but the interdependency is defined by their location. To test this hypothesis, the scenario visualized earlier in Figure 19 was simulated. Figure 24a shows both RUs located opposite to each other, equidistant to the incident site Castberg. Both the scatterplot and pearson's correlation coefficient show the interdependency. However, the correlation is negative, in contrast to Figure 24b, where the two RUs are located near to each other.

These two facts have important implications, when it comes to the performance and robustness of the ERS. First, according to Hypothesis 1, some locations are favorable, because they have lower median travel times and/or the distribution of travel times is more stable over time. Second, as a consequence of Hypothesis 2, RUs can be located in such a way, that the travel time variation can be partially canceled out if they correlate negatively.

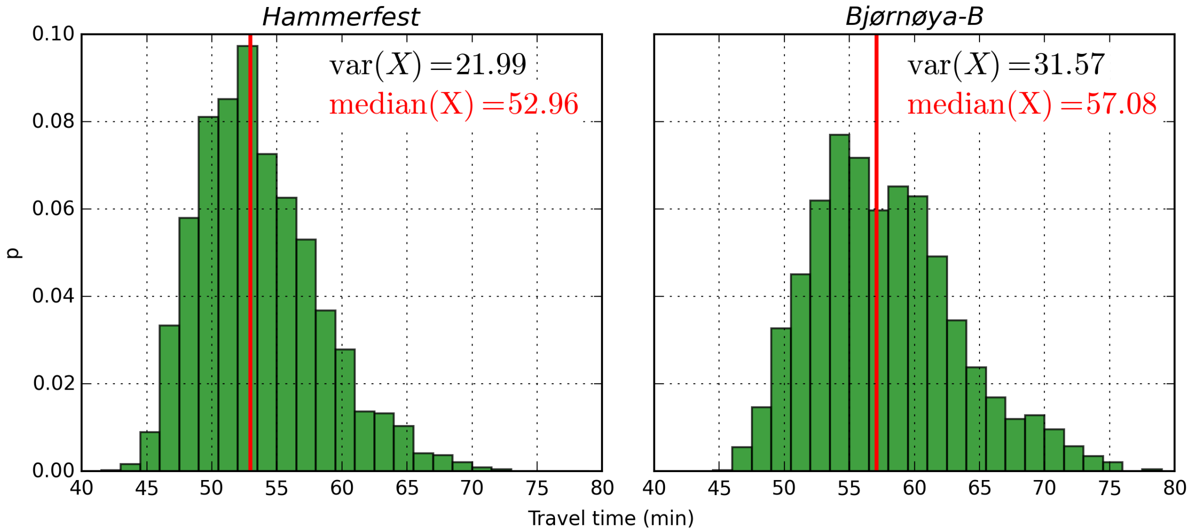
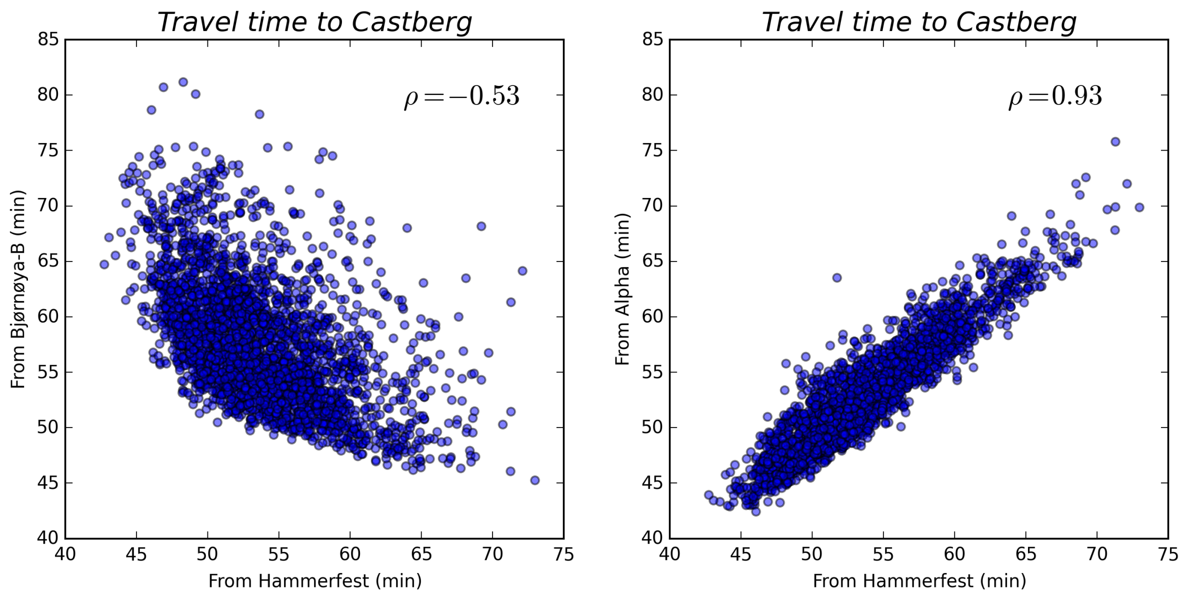


Figure 23: Histogram of simulated travel times from two equidistant locations to Castberg



(a)

(b)

Figure 24: Scatterplot of simulated travel times from two equidistant locations to Castberg

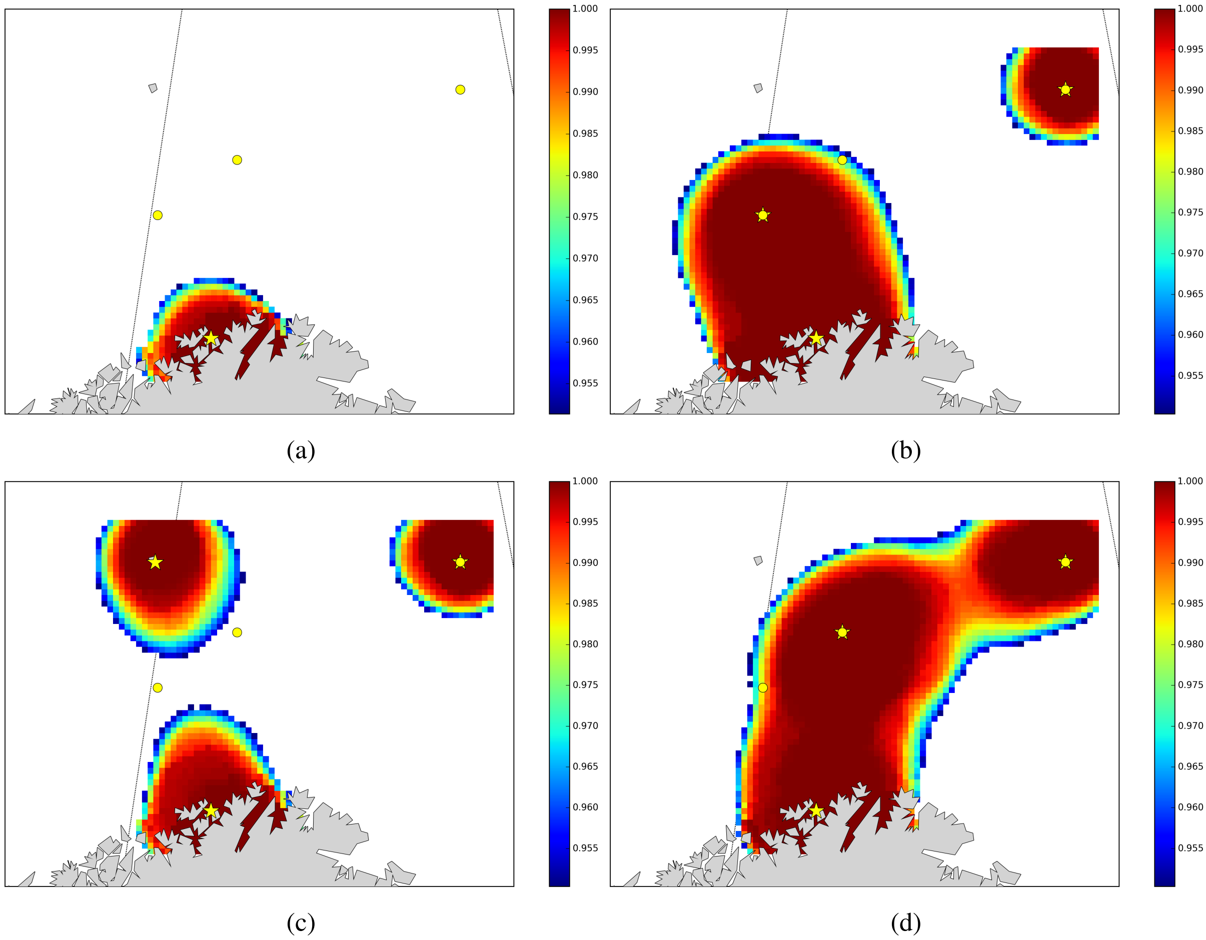


Figure 25: Safe areas for different scenarios at a threshold $p = 0.95$

These consequences make it even more important to consider emergency preparedness not isolated, but as a system. This system view is shown in Figure 25, where after the simulation run the results were consolidated with Equations 22 and 23, and heat-maps were generated, that show the fraction, at which it was possible to rescue the required number of people at a certain point in the area within 120 minutes throughout the year 2013. In Figure 25a only one RU was positioned at *Hammerfest*, marked by a star. It is quite striking how small the safe area is. The scenario in Figure 25b includes two more RUs at *Castberg* and *Remote*. Figure 25c involves locating a SAR helicopter at *Bjørnøya* – a variant, that has been frequently part of public discussion in Norway (Spitsbergen 2013). While there may be other reasons or assumptions, which support this variant (as, e.g., helicopters that can reach a higher TAS), in the given case this would not be a sound decision. The transports to neither of the three installations could be conducted within the safe area.

A favorable configuration is shown in Figure 25d, where the RU is positioned at a future installation in the *Wisting Central* area. In this case, a big area could be covered with the given requirements, and transport routes to all three installations would be safe.

The run times for the 4 scenarios are reported in Table 6. The interpolation part of the travel time simulation takes the bigger part of the resulting time. If needed there is definitely potential to decrease the run time by optimizing this part. The run times scale linearly with the number of RUs.

7 Concluding remarks

In this paper the importance of understanding preparedness from a systems perspective was shown. A simulation model for offshore emergency response that evaluates robustness and rescue capability in case

Table 6: Runtimes in seconds for the 4 presented scenarios

Scenario	Travel time simulation	Travel time interpolation	Response simulation and consolidation	Sum
(a)	1	45	1	47
(b)	3	131	4	138
(c)	3	121	4	128
(d)	3	146	4	153

of helicopter ditches was presented. This model can be developed in several directions. First, further validation is necessary. This is particularly difficult as very few real incidents have occurred so far that could be taken as a reference. Second, the integration of other stochastic factors, such as, for example mobilization time can be considered. That is also valid for the maximum time in sea which could be replaced by a survival function. Furthermore, nearby ships could be considered as RUs. As there is very low traffic in this area at this time, this will not significantly improve the accuracy. However, as ship traffic is increasing, these would become important rescue resources as well. Finally, applications for this model can be found in other industries as well. Fishing vessels, cargo and cruise ships do have similar issues in the Arctic Region, and the planning of an ERS, that can profit from economies of scale by joining efforts of private and public players like the petroleum industry, coast guard and military is believed to have potential.

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Paper 3

RescUSim and IPython: An environment for offshore emergency preparedness planning

RescUSim and IPython: An environment for offshore emergency preparedness planning

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Abstract

Emergency preparedness is crucial for oil and gas operators. While accidents in this industry are commonly connected to oil spill disasters, helicopter accidents are, in terms of incidence rates, a more grave concern in Norway. A recent helicopter accident near Bergen has brought this subject back into focus. We introduce RescUSim, a simulator for rescue missions after offshore helicopter accidents, which is implemented as an open source library with bindings for the Python language. We discuss the modules in the existing Python ecosystem that are used for data preparation and analysis. We show how RescUSim and the interactive computing environment IPython can join forces to provide a tool for planning rescue preparedness for oil and gas related offshore activities.

1 Introduction

On 29 June 2016, around noon, a Super Puma EC225 Helicopter with two pilots and eleven passengers lost its main rotor on the way inbound from the Gullfaks B platform and crashed on the small island Turøy near the coast. In this area, which features high offshore related activity, rescue resources were on site within short time, but to no avail: no one survived the crash. Helicopter transportation is one of the major hazards for employees on offshore installations (Vinnem et al. 2006). In the Barents Sea, an area under consideration for the future development of oil and gas exploration, long transport distances, sparse infrastructure, low maritime activity, and harsh environmental conditions will exacerbate the issue of transporting offshore personnel. There, relying on existing infrastructure will not be possible, and the Emergency Response System (ERS) needs to be planned from scratch in a robust but economically feasible way.

Planning and evaluating offshore emergency preparedness solutions is difficult, because of the – luckily – rare occurrence of incidents in the past. Besides running through real-life scenarios, computer simulation is one of the few possibilities to get estimates of the ERS capability (Vinnem 2011). Brachner (2015) presented a simulation model for offshore Search-and-Rescue (SAR) operations after a helicopter ditch. This simulation is – unlike Human-in-the-loop simulations like the one presented by Xiuwen, Fangbing, and Yicheng (2009) or VSTEP's RescueSim (`http://vstepsimulation.com/product/rescuesim/`, accessed Oct 18 2016) – not targeted at training SAR personnel, but at evaluating the capabilities of an ERS, that is, to check if the right amount and types of rescue units (RUs) are placed at the right locations to provide enough rescue capacity in case of an incident. We define rescue capacity as the number of

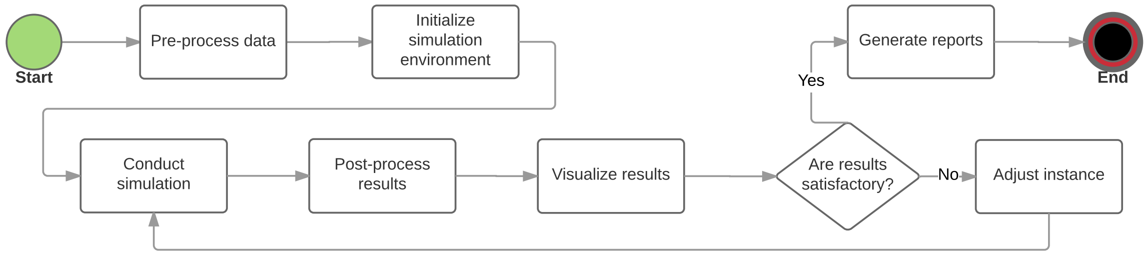


Figure 26: The intended work flow for offshore preparedness planning.

persons that can be rescued within a given time at a given incident location. This capacity can be obtained collaboratively by several RUs. That is, if several RUs are within range, all of them can contribute to the rescue operation. In the simulation the available RUs are mobilized, travel to the incident location, and conduct a rescue operation by picking up persons from the sea. Environmental conditions and other stochastic factors influence mobilization, travel, and pickup time. Many of the assumptions made when developing the simulation model are based on the report that was used as a basis for the Norwegian Oil and Gas guidelines for establishing area preparedness (Vinnem 2012) and on work done by SINTEF (Kråkenes et al. 2013).

The simulation based on this model, which was implemented in the Python programming language, provided the desired results, and the run time of up to several minutes was still adequate for single evaluations of ERS configurations (Brachner 2015). While Python allowed us to develop the model quickly, it became clear as new demands and requirements were emerging that the existing code base with no decent software architecture in mind could only serve as a close-ended prototype. In addition to the SAR helicopters originally modelled, we wanted also to include maritime RUs, that is, Emergency Rescue Vessels (ERVs). The simulator should be easily extendable with new RU types. The architecture should also allow for using the same data model with different simulator engines, as we wanted to experiment with alternative algorithms and a heterogeneous computing engine utilizing the Graphical Processing Unit. Furthermore, we wanted to utilize a good deal more weather data instead of the one year span used in the original model, to account for annual variations and climatic trends. Finally, the simulator run time should be drastically cut in order to allow for the evaluation of a big amount of scenarios within a short period of time in order to utilize the simulator in a simulation-optimization framework to support optimization of the ERS design.

For these reasons, the simulator was re-implemented from grounds up. Still, the Python ecosystem provides a rich set of libraries that are particularly useful for ERS planning. Very elegant solutions for working with spatial data, processing input data, and analyzing the output data are available in this environment. This made us transfer the computational intensive simulator core to an external C++ library with Python bindings, such that the best of both worlds could be utilized. While the main focus in Brachner (2015) was the model itself, in this paper we present the re-implemented and extended library together with third-party components that form our environment for ERS planning and evaluation.

The remainder of this paper is organized as follows: In Section 2 we describe the work flow that we intend for interacting with the simulator and derive the functionality that is required from the environment. In Section 3 we map this functionality to concrete third-party packages in the Python ecosystem where available. We give an overview over these packages and describe the RescUSimCpp library, which covers the simulation functionality that have been added. Following this, in Section 4 we give a concrete example of the usage and show how to set up and run a simulation, and we compare the run-times of the new implementation to the one we used earlier. We conclude the paper with Section 5, where we discuss alternatives to the presented environment and give some directions for future improvements.

2 Work flow and functional requirements

Figure 26 shows the intended work flow for using the simulator. The aim was to provide an environment that facilitates this process, but still is flexible enough to give the user the freedom to deviate from it. Below we describe the separate tasks and list the functions that are required to execute them.

The simulation uses historic weather data from the Norwegian meteorological institute (Reistad et al. 2011). In the pre-processing stage this weather data is prepared for further use. One feature of emergency preparedness is the operation in a wide area, where earth curvature needs to be taken into account. For the sake of efficient computation, we therefore work with projections into the Euclidean plane. Data sources, particularly the weather data, may come in one particular projection, but need to be re-projected into another one in order to work on one single projection; this operation is called *warping*. Thus, functions for conducting map projections and warping are needed.

To be able to handle large amounts of weather data, we need to compress the data by reducing the number of data points and cropping the data to the region under consideration. This requires the use of efficient in-memory as well as storage data structures combined with tools that allow efficient spatial queries for interpolating the values for the target grid nodes.

In this stage it is also possible to add data that are not collected, but pre-computed. In our model we use the daylight conditions as an input for the rescue operation. Those can be obtained by astronomical calculations; they involve computationally intensive operations, but the results can be used repeatedly. It is therefore better to put these in the pre-processing stage, rather than to include the computations in the simulation.

Finally, the pre-processed data need to be represented in a format that is easily store- and retrievable. Array slicing from permanent storage should be supported in order to retrieve spatial and temporal subsets of the weather data without the need to load the full data-set into working memory.

The stage of initialization involves instantiating the simulator, loading weather data, and providing the set of points where the simulation will measure the rescue capacity. Furthermore, at this stage the user decides about the amount, type, specification and location of RUs by instantiating them and setting their properties. Measuring points could be located along helicopter transport paths or within a defined area under consideration. As an increased number of measuring points also increases simulation time, spatial analysis including set-theoretic and constructive methods for calculating envelopes and convex hulls of given points, creating geometric figures and discretizing them, and performing operations on geometric sets are used for reducing the amount of measuring points to the minimum.

After the simulator is set up, the actual simulation is conducted, that is, the rescue operations to the specified incident locations are simulated, returning the number of people that could be rescued within a given time limit.

The task of post-processing involves the transformation of the raw simulator results into the target structure that should answer the questions to the simulation. This may require in-memory array slicing, aggregation operations over time or space, such as calculating the average or worst case rescue capacity at the measurement points, or filtering results to identify the time or location at which a minimum rescue capacity was undercut.

Furthermore, these results may be visualized. This not only requires basic functions like bar-charts, scatter-plots, or histograms, but also cartographic visualization, which is common to emergency management activities (Schafer et al. 2008). These maps could include heat-map overlays, geometric shapes, and annotations.

The simulation can be run with adjusted parameters until the results are satisfactory. A requirement may be, for example, that an area or transport path under consideration is sufficiently covered by RUs, that is, enough rescue capacity is provided for any point within this area or path. Since we see the work-flow as an iterative process, it is of advantage to reuse results from former runs of the simulation such that only components that are adjusted need to be recomputed. In this way the computational time can be further reduced.

As a final step, the execution process and the obtained results should be documented such that they are reproducible. The environment should provide functionality to do this in an easy way. Moreover, results –

particularly graphical visualizations – should be exportable for creating reports.

3 Python packages

In this section we discuss the central Python modules that are used to support the described work flow. We use *Anaconda* (`https://continuum.io`, accessed 18 Aug 2016), a Python distribution that is specifically intended for scientific computing. It already contains a big part of the needed packages and makes it easy to add the ones which do not come as a part of the distribution. All of the described packages are licensed under open source – most of them BSD-like – licenses, which allows use and redistribution with minimal requirements.

3.1 RescUSimCpp library

The RescUSimCpp library is the simulation core that was programmed in C++ to reduce the required computational time. It provides bindings to Python using pybind11 (`https://github.com/pybind/pybind11`, accessed 17 Aug 2016), a library that exposes C++ types in Python and vice versa. The source of the library is available at `https://github.com/mbrachner/RescUSim`.

This library simulates rescue missions at given incident locations and returns the rescue capacity. For each RU, the mobilization, transit, and pickup phases are simulated and the resulting individual rescue capacity is consolidated by accounting for possible interference effects between RUs. The mobilization time can be specified by a constant value or a probability distribution. The transit time to the incident location is calculated by iterative dead-reckoning, that is, by advancing the RU step-wise from origin to destination, summing up the individual times that a RU needs for completing the steps considering the local weather conditions. For the transit of SAR helicopters the wind conditions are taken into account in the way described by Brachner (2015). When simulating the transit of ERVs the wave height is influencing the travel time (Jacobsen and Gudmestad 2013). The pickup of persons from the sea is modeled after estimates by Kråkenes et al. 2013.

Figure 27 shows the basic architecture of the simulator library. The *Simulator* class is the central part and is the superclass of specific simulator implementations. At the moment, two simulators are implemented. The first one is *SimulatorCPU*, which simulates the ERS using the CPU. As many demand points have to be evaluated in one run, the simulation allows a high degree of parallelism which is exploited by using the OpenMP API (`http://openmp.org/`, accessed 16 Aug 2016). In this way it is possible to use all available cores on the CPU. The other implementation *SimulatorOpenCL* uses the GPU to conduct the simulation. A Simulator is associated to an instance of a Weather class, which is used to load the weather data from persistent storage into memory and retrieve the weather data for a given point.

Each RescueUnit entity is specified by a data holding object that represents its performance parameters. Its behavior, that is, which computations to perform on its performance parameters, are separated. As a consequence, for the CPU implementation the *ERV* and *Helicopter* data objects are associated to *ERVCPU* and *HelicopterCPU* objects. For the OpenCL implementation the behavior is part of the SimulatorOpenCL class. This is mainly because OpenCL provides a programming language that is based on a standard C language specification (C99) and thus does not provide object orientation. One more reason is the interaction between host and GPU, which makes very different programming approaches necessary. For the user, who only interacts with data objects, the separation of data and behavior is transparent. As soon as a data object is added to a simulator instance, it is handled in the simulator-specific way, that is, it is either wrapped by the appropriate behavioral classes or directly linked to the simulator instance.

The separation of data and behavior adds one more advantage: The data holding objects can be also used as entities for optimization problems like the one presented by Brachner (2016) or Razi, Karatas, and Gunal (2016), linking optimization and simulation of ERS.

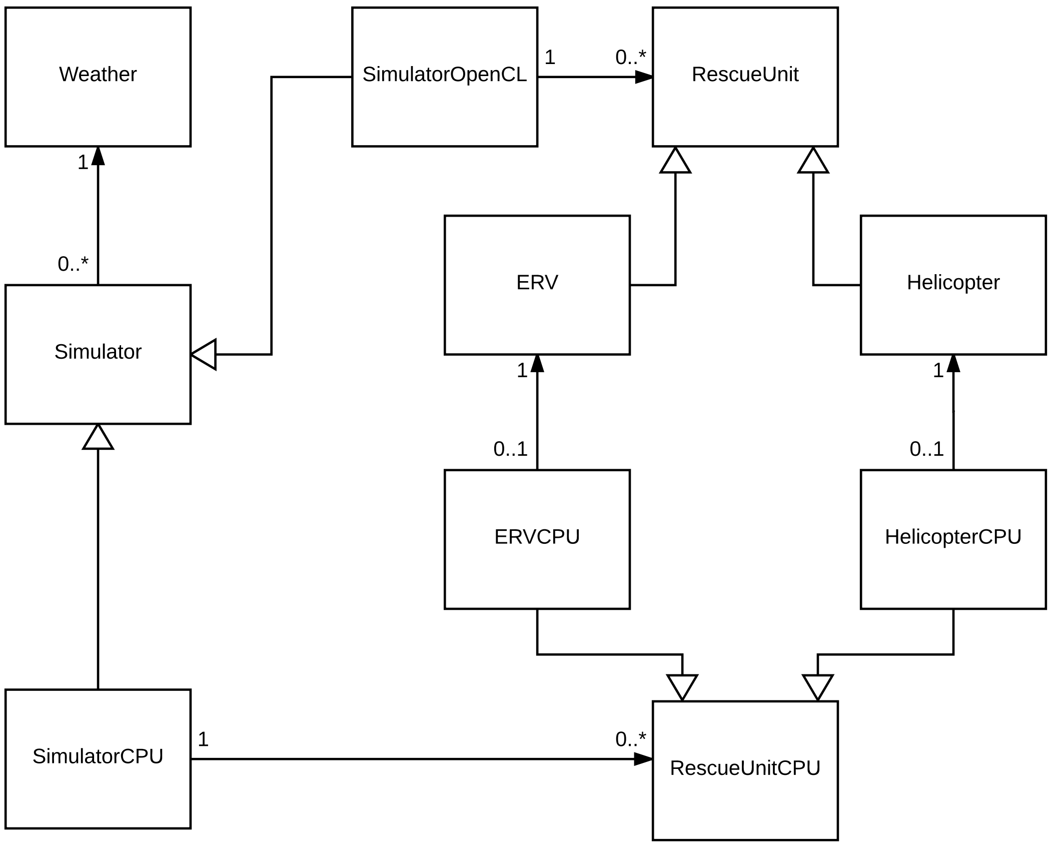


Figure 27: UML class diagram showing the core classes of the simulator.

3.2 Third party provided packages and projects

IPython together with *Jupyter* (`https://ipython.org/`, accessed 25 Aug 2016) are the fundamental components for interacting with RescUSim. IPython is built upon Python, adding interactive features such as tab-completion, object introspection, and a help system. A central feature is the Jupyter Notebook which very recently was spinned off as a separate project to support additional languages. This is a web application that allows to create and share notebook-like documents that unify executable code snippets and documentation by inline visualizations, explanatory text, and equations. While this provides the interactivity and flexibility needed to work with the simulator, it streamlines the process of documenting the work and presenting the results practically alongside the process to ensure reproducibility.

NumPy (Walt, Colbert, and Varoquaux 2011) provides a data structure for efficient manipulation and processing of multi-dimensional arrays. We use it for working with weather data, and the simulation returns its results as a NumPy array, which makes it easy to aggregate and filter the results during post-processing. This in-memory data structure plays very well together with *HDF5* and a package that provides Python bindings via *h5py* (http://www.h5py.org/, accessed 25 Aug 2016), which allow to store, manipulate, and retrieve a big amount of array-structured data.

The simulation results are analyzed and visualized using *Matplotlib* (Hunter 2007). This package includes also the *Basemap* toolkit for plotting data on maps, along with the *proj.4* library to project geographic coordinates into the plane. In addition, the functionality of this projection library is exposed such that arbitrary geographic data can be projected without visualizing it. This streamlines working with geographic data: once a map is created, converting geographic to planar data and data visualization happens through this object using the same projection.

Once the geographic coordinates have been projected onto the plane, *Shapely* (`http://toblerity.org/shapely/`, accessed 25 Aug 2016) facilitates manipulation and analysis of geometric objects. This package defines points, curves, and surfaces as fundamental geometric types and allows to conduct a wide range of set-theoretic, construction, transformation, and merging operations on these objects. As an example, the measurement points for the simulation as shown in Figure 28 can be constructed intuitively and with only few lines of code.

4 Usage

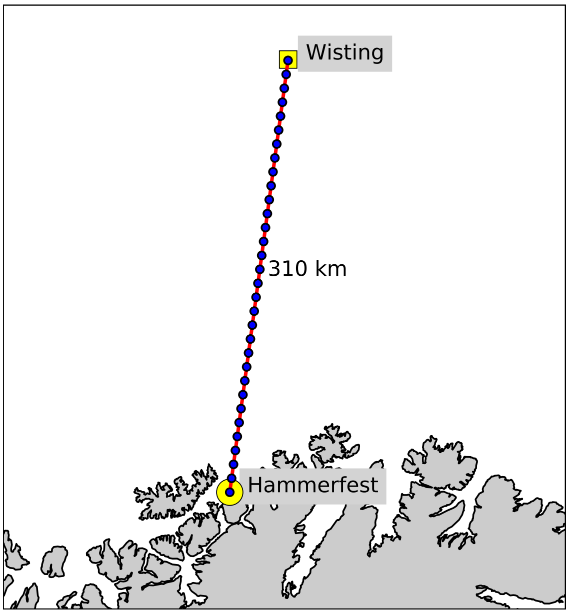
Listing 1 shows the full process of setting up and running a simulation. Figure 29a presents the exemplary analysis of the simulation results that could assist in planning decisions. For instance, rescue capacity could be better distributed along a transport path, given that the number of persons to rescue is not varying along the route. Alternatively, analyzing a whole area as shown in Figure 29b would allow for adapting the transport paths to avoid regions that do not provide sufficient coverage, similar to what is described by Brachner (2016) in a deterministic variant. These two figures highlight also, that arbitrary criteria – in the presented case average rescue capacity, and required fraction of successful rescue missions – can be applied to decide which incident locations can be considered to be sufficiently covered. By decoupling instance preparation, simulation, and analysis and conducting the first and the last step in IPython the presented environment provides the freedom to adapt the process to the specific questions that need to be answered.

Table 7 shows the run time for the instances as specified by Brachner (2015). The results of the former implementation have been obtained by re-running these instances with the simulation model described in the referred paper with more recent hardware, which is a dual-core Intel Core i5-4210U CPU with 8GB of working memory. The results show that we achieved a speed-up of approximately factor three. As the new library is also able to utilize multiple processor cores, we report the run-times of the library with OpenMP disabled in order to show the effect of parallel computing. The computation scales well. Moreover, as the comparison between running the simulation with two and four threads shows, the simulation can also take advantage of the hyper-threading feature of the dual-core processor.

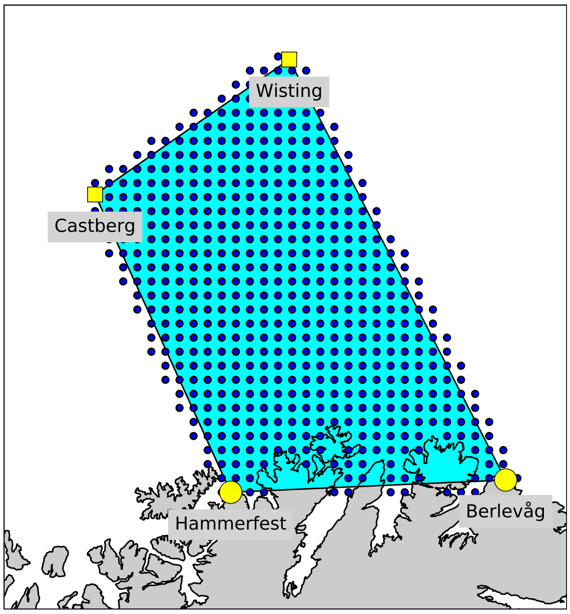
We provide also the results of re-running the simulation after re-locating a rescue unit to a new position:

Listing 1: Full example for initializing and running the simulation.

```
# Imports
import numpy as np
import RescUSimCpp
from mpl_toolkits.basemap import Basemap
from shapely.geometry import LineString, MultiPoint, Point
from shapely.ops import cascaded_union

# Initialize a dictionary with off- and onshore facilities
poi = {name :          {’coords’:c,            ’type’:s} for name,c,s in [
      [’Hammerfest’,   (23.768302, 70.701319), ’helibase’ ],
      [’Berlevaag’,    (29.090389, 70.854502), ’helibase’ ],
      [’Wisting’,      (24.232358, 73.491134), ’platform’ ],
      [’Castberg’,     (20.347568, 72.494341), ’platform’ ],
]}

# Initialize map. This map is not only used for visualization, but also for projecting geographic coordinates into the euclidean plane.
bmap = Basemap(projection=’aeqd’, lat_0=72, lon_0=29, resolution=’l’,
                  llcrnrlon=15, llcrnrlat=69,
                  urcrnrlon=41, urcrnrlat=75.6, area_thresh=100)

# Create a transport path from Hammerfest to the Wisting facility
path = LineString([   bmap(*poi[’Hammerfest’][’coords’]),
                      bmap(*poi[’Wisting’][’coords’])])

# Discretize path into measuring points 20 km apart from each other
measure_points = MultiPoint([path.interpolate(d)
   for d in np.arange(0,path.length,20000)])

weather = RescUSimCpp.Weather("c:\\tmp\\data_idw.h5") # Load weather
sim = RescUSimCpp.SimulatorCPU(weather) #Initialize simulator

sim.addStationaryRU( # Add stationary rescue units:
   RescUSimCpp.Helicopter("Heli1",weather) # One SAR Helicopter
      .setPos(*bmap(*poi[’Hammerfest’][’coords’]))) # ... at Hammerfest,
sim.addStationaryRU(RescUSimCpp.ERV("ERV",weather) # ... and one ERV
   .setPos(393174,350706)) # ... inbetween Hammerfest and Wisting.

# Create for each point a sample of 1000 incidents at different times
incidentArray=np.array([[(p.x,p.y,r) for p in measure_points_path
  for r in np.random.random_sample(1000)*(weather.getNumScenarios()-2)])
sim.addIncidents(incidentArray); # Pass the incidents to the simulator

# Conduct simulation
res=sim.simulateResponseSample()
```

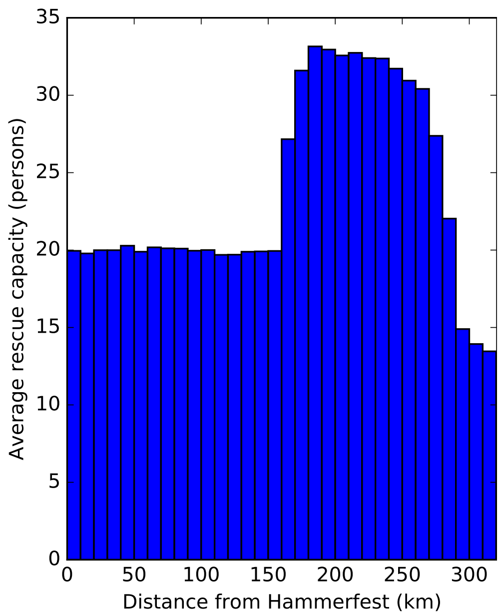


(a) Discretization of a transport path.

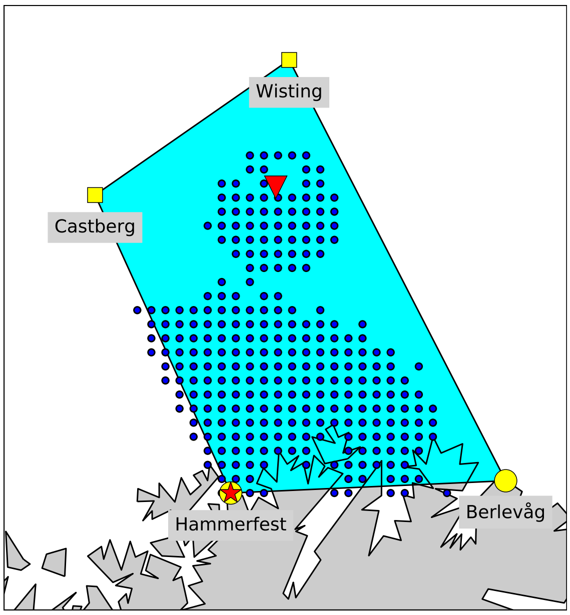


(b) Discretization of an area defined by the convex hull of a set of given facilities including a buffer, excluding points on the landmass.

Figure 28: The Shapely library facilitates the discretization of measurement points. Even complex geometrical operations are conducted by few lines of code.



(a) Average rescue capacity along a transport path



(b) Incident locations, where 95% of the rescue missions were successful

Figure 29: Results of the simulation experiments

Table 7: Run times for executing the simulation on the instances specified by Brachner (2015) in seconds. The reported values show the best out of three runs, respectively.

Scenario	Former implementation	RescUSim full run without OpenMP	RescUSim full run with OpenMP 2 threads	RescUSim full run with OpenMP 4 threads	RescUSim recalculation with OpenMP 4 threads
(a)	39	27	16	12	7
(b)	107	81	48	35	8
(c)	104	88	50	37	8
(d)	110	75	46	33	8

The new simulation library features the caching of intermediate results. Consequently, simulations that are re-run will only simulate the response of RUs that changed in any of its parameters, for example its position, or its maximum speed. Thus, computational time is considerably reduced when searching for the optimum of a single decision variable, for instance, the best position of a RU, assuming the other RU positions to be fixed.

Some comments have to be made when comparing the new library with the former solution. In the earlier implementation we approximated the travel times by simulating several radial travels starting from the RU origin and then interpolating the resulting travel times to the measuring points. This results in less accurate travel times the further the measurement points are located from the origin, because of the increasing distance between two radials. In RescUSimCpp the travel to each single measurement point is simulated, which increases accuracy. Furthermore, in the former implementation, the weather data was taken from the nearest point on a 10x10 km grid. However, in the new simulation the 50-fold amount of weather data does not allow for such a fine-grained grid. Thus, the grid spacing is increased to 20x20 km, but the weather data on a certain point is now determined by bi-linear interpolation from the four surrounding grid nodes.

We also performed tests using a GPU-implementation on an NVIDIA GeForce 840M GPU. This implementation was straight-forward and not particularly optimized for GPU, with one thread per measurement point. The run time turned out to be sometimes on par, but mostly worse than for the CPU implementation. However, simulating a series of incidents that have the same incident time, but vary by location, reduced run times by more than 80%, if the locations were close to each other. In our opinion, this points to a bottleneck at the GPU global memory: the reason for the speed-up with constant incident time seems to be the fairly large (1 MB) L2 memory cache of the GPU, where data locality can be exploited with incident locations that are near to each other.

5 Concluding remarks

In this paper we presented an environment, which we believe to be a useful tool to support planning and evaluation of ERSs for offshore helicopter ditching. However, there exists other options to achieve the desired results.

For the similar purpose of evaluating an ERS, Jakobsen (2015) used MATLAB and Simulink with the SimEvents discrete event simulator. These products are tightly integrated with each other, as they are developed by the same software provider. Though we have not done a full implementation, we are convinced that the required functionality for data processing and visualization is fully available in MATLAB. However, some prefer Python in terms of clarity and functionality (Fangohr 2004). Moreover, using a discrete event simulator like SimEvents for the rescue operation involves unnecessary overhead due to the relatively simple process with little interaction between the simulated entities. Last, but not least MATLAB, Simulink, and SimEvent are commercial closed-source products that cause considerable cost even for academic licenses, while Python is free and open-source.

ArcGIS is a Geographic Information System, that would cover well the aspects of spatial processing and map visualization. It is also a commercial closed-source product. The use of scripting languages, out of which Python is the most popular, is well supported. However, we would have needed too little of the functionality of this feature-rich solution to justify the cost. Nevertheless, our environment does not exclude ArcGIS, which can rather be seen as an add-on option.

Finally, an alternative would have been to implement the full functionality in C++. There are several reasons that speak against this approach. While compiled C++ code runs considerably faster than interpreted code, this generally involves longer development times and requires more verbose code compared to scripting languages (Prechelt 2003). Moreover, it distracts the user from the actual problem-solving process, with an increased need to deal with implementation issues (Fangohr 2004). Finally, in a pure C++ implementation we would have missed the possibility of interaction such as adjusting parameters, repositioning or adding RUs, or analyzing various aspects of the results without recompiling and rerunning. While we did not want a full-blown graphical user interface, it was important to target an easy and agile way of interaction. Any user interface in a C++ only solution would have needed to be built additionally to the simulation core. In contrast, with IPython and Jupiter the Python ecosystem provides interactivity for free, so to speak.

The RescUSim environment will be developed further. We intend to combine the simulation with meta-heuristic optimization in order to find robust ERS configurations that can cover flight paths under varying environmental conditions. We also see a potential to extend the simulator to other domains, for instance land based missions. This would require to include new types of RUs. Furthermore, a more advanced visualization of the results, for example an interactive, 3-dimensional visualization using CesiumJS (`https://cesiumjs.org/`, accessed Oct 18 2016) would improve human-computer interaction. Finally, there has been some research to model the reliability of SAR operations in more detail (Norrington et al. 2008), which may be taken into consideration in our simulator.

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Paper 4

A simulation model to investigate contingent emergency response capacity for offshore helicopter accidents

A simulation model to investigate contingent emergency response capacity for offshore helicopter accidents

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Abstract

It has been argued that one of the challenges in establishing a reliable emergency response system (ERS) for offshore operations in the High North is the lack of maritime activity. The petroleum industry must provide sufficient rescue capacity to respond to a incidents, but contingent rescue resources, such as nearby vessels, should supplement the ERS in case of deviations in response capacity. This paper presents a model that simulates an ERS for offshore helicopter accidents. A computational study shows the effect of contingent response capacity on the ERS service level.

Keywords: simulation, offshore, emergency

1 Introduction

The petroleum industry in Norway is expected to move into new areas, with one particular area of interest being the Barents Sea. One of the major issues of future operations in this region is the safe transportation of personnel. In Norway, air transport by helicopter is the main mode to bring personnel to offshore installations and back. This mode, however, represents one of the major hazards for offshore personnel (Vinnem et al. 2006).

There is no established ERS in place that could respond to helicopter accidents when transporting offshore personnel in the Barents Sea. Support decision tools are therefore needed to assist in planning and establishing an efficient and reliable ERS for this area to address this type of incident. For this purpose, Brachner and Hvattum (2017) presented an exact optimization model. This model helps decision makers to plan the required rescue resources that need to be provided by the operating companies. This is a deterministic model and is unable to take stochastic processes into account.

For a reliable ERS, however, we should consider the case in which a planned ERS does not work as expected. In this case, contingent capacity should be able to take over and fill the required gap. In the described context, this contingent capacity can most probably be delivered by nearby vessels that are performing other duties and can be called by the rescue coordination center to assist in the rescue operation. DNV (2015) has stated that due to the limited maritime activity in the Barents Sea this contingent capacity might not be sufficient to make the ERS reliable. Therefore, backup capacity must be taken into account when planning a reliable ERS. That this factor of serendipity has in fact already saved lives in search-and-rescue (SAR) operations is also supported by real-world examples, as in two recent incidents in the Mediterranean sea in which oil tankers received urgent distress calls from the Italian coast guard and succeeded in saving 222 and 300 refugees, respectively (TORM 2014, 2015).

For the Barents Sea region, initiatives have been started to actively involve local fishermen in the ERS for oil spill response (Knol and Arbo 2014). Cooperation between petroleum and fishing industry in order to take advantage of this contingent capacity would therefore also improve the robustness of an established SAR ERS.

However, the question arises as to how to evaluate whether (and to what extent) capacity that is dedicated to serving duties other than emergency response can contribute to the ERS. In order to answer this question, two issues need to be addressed: Firstly, which approach should be chosen to evaluate the ERS. Secondly, how to include unplanned, contingent capacity into this evaluation.

Various approaches to evaluating offshore preparedness can be found in the literature. Yun and Marsden (2010) presented a methodology based on event trees and Monte Carlo simulation to evaluate the robustness of rescue strategies in the Arctic, but the input data had to be based on subjective estimates. Vinnem (2011) combined quantitative and qualitative data of different preparedness topics and consolidated the results to provide an overview of the overall preparedness status. This approach is, however, an a posteriori evaluation of a preparedness system that is already in place and cannot be used for a future ERS. Norrington et al. (2008) modeled the reliability of SAR operations by identifying the primary variables and bringing them together in a Bayesian belief network (BBN). Among other factors, weather conditions, wind strength, sea state, visibility level, daylight, distance, and passing ships were identified as primary variables that contribute to an effective SAR operation. To evaluate the reliability of an ERS these factors should be taken into account. However, while the construction of the BBN resulted in a deeper understanding of the key factors, this did not result in a valid quantitative output.

The aforementioned approaches used risk management techniques. In this paper, a view from the logistical perspective is taken; the focus lies on the availability, forwarding, and collaboration of resources that result in rescue capacity. As a consequence of stochastic processes, this rescue capacity underlies variations that may not be guaranteed under all circumstances at a reasonable cost. Therefore, Hammervoll and Helgheim (2015) suggested *service level* as relevant performance indicator.

In order to evaluate the ERS, a system modeling approach was chosen. A closed-form analytic solution for this system is too complex; the travel times and pick-up times of individual rescue units (RUs) are interdependent, and the capacity of individual RUs does not simply add up, as a higher number of RUs leads to an increased coordination overhead (Brachner 2015). Thus, a computer simulation approach was chosen to model this system. Soma, Haugen, and Øygarden (2003) simulated the rescue of people in distress at sea. In that simulation model, however, the user had to specify transit times and environmental conditions manually.

Brachner (2015) simulated rescue operations related to helicopter ditching based on real environmental data in the area under consideration. The presented model extends this simulation model by adding contingent capacity. The category to which this simulation could be related is not immediately evident. From the modeling perspective, it could be described as an agent-based model (ABM), with the individual RUs interacting with the environment (Macal and North 2010). The agents in this system are, however, quite simple and do not make decisions. Furthermore, their interaction is limited to the on-site rescue process. Realizing the model with ABM tools was therefore not deemed to be appropriate, as the involved overhead would unnecessarily inhibit performance.

Performance is an important factor due to the nature of the resulting output, namely heat maps that show the resulting service level in its spatial context spanning the whole area under consideration. Thus, from a realization perspective, it would be perhaps better to describe this simulation as a combination of trace-driven and Monte Carlo simulation elements.

The remainder of this paper is organized as follows: First, an overview of the used terminology and concepts is provided, after which the simulation model is presented. Using this simulation model, a computational study is then conducted. The paper concludes with remarks on applicability and further research.

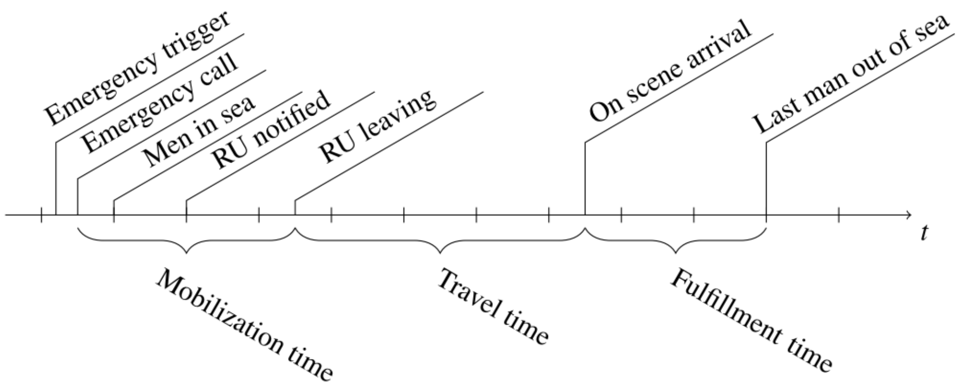


Figure 30: Emergency response after helicopter ditching from an RU perspective.

2 Capacity and service level

In this paper, the rescue capacity is understood as the number of people who can be rescued within a given amount of time $t^{\max}$. Within this time frame the RU needs to be mobilized, travel to the incident site, and pick up people until the last man is out of the sea, as illustrated in Figure 30. An RU has a physical capacity limit. If this limit is reached, the RU cannot pick up more people and other RUs must finish the operation.

Due to the travel time component, the capacity is dependent on the distance between the initial RU position and the incident location. That is, the capacity declines over distance until it is zero at the point where the sum of mobilization time and travel time is greater than or equal to $t^{\max}$.

Several RUs can cooperate and, as a consequence, their individual capacities accumulate. This is, however, not necessarily the sum of the individual capacities. Several RUs onsite may incur a coordination overhead. In the present model this happens if two SAR helicopters are on-site. In this case the pick-up time for the second helicopter is doubled. This conforms to the Norwegian Oil and Gas guidelines for area preparedness (Norsk olje og gass 2015).

Both the travel time and the pick-up time are dependent on wind, waves, and visibility. The capacity is therefore influenced by environmental conditions. A required rescue capacity may or may not be fully served in the case of an incident, according to the current conditions. In order to determine the reliability of an ERS, we therefore introduce the service level, which denotes the number of accidents that are fully served as a percentage of the total number of accidents that requested the emergency response service in question (Hammervoll and Helgheim 2015). In this context, this would be the percentage of accidents in which a given number of people could be rescued within the time limit.

3 Model description

This model simulates an ERS that responds to helicopter ditching incidents at a given location. Available RUs will proceed to incident sites and conduct rescue operations, given their individual properties. The basic idea of the simulation model is to reconstruct trace-driven scenarios based on empirical data from various data sources and to simulate incidents for each scenario, as illustrated in Figure 31. The output should be a heat map that shows the areas where the required service level can be fulfilled. For this reason, the area under consideration is tiled into a grid with 10 x 10 km wide squares, and for each square, an incident location is assumed. For the presented model, data from the year 2013 has been used.

3.1 Response scheme

The simulation of each individual RU response adheres to the following scheme. At the moment at which an incident occurs, a certain mobilization time elapses to start the operation. This includes communication

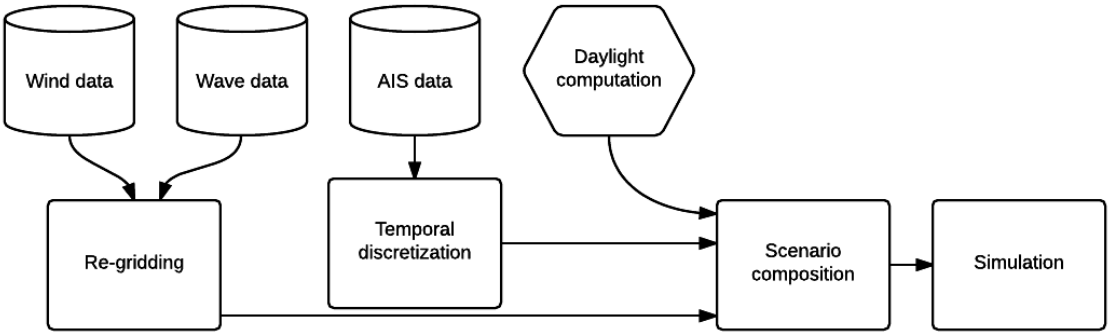


Figure 31: Process of data preparation and simulation.

of the incident and pre-travel procedures, such as launching the rescue boat from the mother ship or pre-flight checks and the rotor spin up time of the helicopter. The RU then leaves the point of origin and proceeds to the incident site. As soon as the RU arrives at the incident site, the rescue operation starts by picking up people from the sea at an individual pick-up rate. For both helicopters and vessels, the pick-up rate is dependent on the wave height; that is, the pick-up rate decreases with worsening conditions.

3.2 Travel simulation

Depending on the RU type, the travel time is influenced by the weather conditions en route to the incident location. The RU travel is simulated by iteratively applying the following procedure:

Given an initial RU location $\vec{p}^{init}$, an incident site $\vec{p}^{incident}$, and a step distance s^{step},

1. Set RU position $\vec{p}^{current} = \vec{p}^{init}$.
2. Determine step vector $\vec{d}^{step} = \dfrac{\vec{p}^{incident} - \vec{p}^{init}}{||\vec{p}^{incident} - \vec{p}^{init}||}$.
3. Set travel time $t^{travel} = 0$.
4. Repeat the following until $\vec{p}^{incident}$ is reached:
   a) Determine the environmental conditions of $\vec{p}^{current}$.
   b) $s^{actual} = \min(s^{step}, ||\vec{p}^{incident} - \vec{p}^{current}||)$.
   c) Adjust RU travel speed according to environmental conditions and calculate the time to travel the distance s^{actual}, t^{actual}.
   d) $\vec{t}^{current} = \vec{p}^{current} + \vec{d}^{step} s^{actual}$.
   e) $t^{travel} = t^{travel} + t^{actual}$.

Helicopters' travel time is influenced by the wind conditions as described in Brachner (2015). The travel times of vessels may also vary according to wave height. In this model, however, the vessels that will act as contingent capacity could have very different properties regarding the dependency of speed and wave height, therefore, worst-case values are employed.

3.3 RU classes

Two different classes of RUs can be found in this model: *Static RUs* are pre-defined RUs placed at static locations that are solely intended to conduct the rescue duty. In this model, SAR helicopters are used as static RUs. The simulation of the SAR helicopter response is explained in detail in Brachner (2015). The class of dynamic RUs consists of traffic that is moving around in the area of question and is providing contingent rescue capacity. Such vessels can be, for example, fishing or cargo vessels. The dynamic traffic

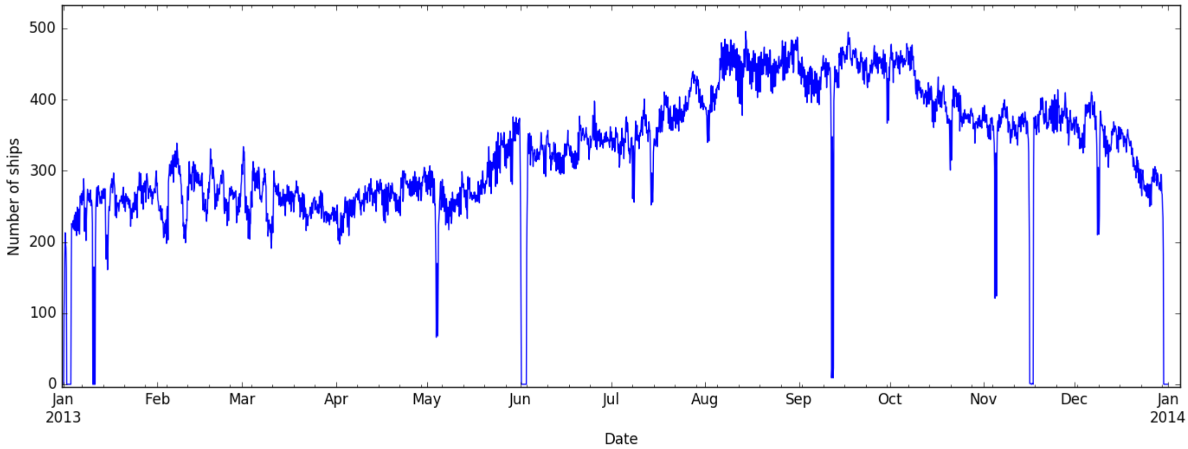


Figure 32: Traffic in the Barents Sea over the year 2013. The dips are missing data sets which have been filtered out in the simulation runs.

is generated from automatic identification system (AIS) data obtained from the Norwegian Coast Guard. Figure 32 shows the development of the traffic over the year 2013. An increase in traffic can be observed from the beginning of August to mid-October. This may be due to the increased exploration drilling activity conducted during this period. It should also be noted that there are gaps in the available AIS data. These periods were marked during data analysis and filtered out when conducting the simulation.

The process of reconstructing the vessel positions from an AIS dataset requires special attention for several reasons. Firstly, the vessel positions for the time-discrete scenarios are not exactly known. This is because AIS messages are sent by individual vessels at regular intervals, and the update intervals vary between two seconds for fast-moving and maneuvering vessels and three minutes for vessels at anchor (Tetreault 2005). It is therefore unlikely that the time at which a vessel is sending its position and the scenario time coincide. Secondly, and with much more severe consequences, the incompleteness of the available data set must be assumed. The AIS was initially designed as a short-range system with a line-of-sight range of 15–20 nautical miles. With terrestrial receivers, only near-shore data can be collected. Recently, low-orbiting satellite receivers have been used to increase coverage, particularly in regions that could not have been covered otherwise. Messages can, therefore, be lost during transmission due to interference, and satellite data is only available for vessels that are within the coverage of an orbiting satellite. The network of AIS-receiving satellites does not fully cover the region under question at all times. As a consequence, it is typical for AIS data to have gaps between two successive position reports varying from seconds to days (Peters and Hammond, 2011). In order to construct the vessel position $\vec{p}(t)$ at a given time t, the following algorithm is applied, with w being a defined time window:

1. Determine the set of vessels V^{pre} for which a positional report was received within the time span $[t-\frac{w}{2},t]$ and the set of vessels V^{post} for which a positional report was received within the time span $[t,t+\frac{w}{2}]$.

2. $V = V^{pre} \cap V^{post}$.

3. For each vessel $v \in V$, determine the last positional report within the time span $[t-w/2,t]$ with t_v^{pre} and $\vec{p}_v(t_v^{pre})$ being the time and the position vector at this time, and the first positional report within the time span $[t,t+w/2]$, with t_v^{post} and $\vec{p}_v(t_v^{post})$ being the time and the position vectors at this time, respectively.

4. For each vessel $v \in V$, interpolate the vessel's path between those two positional reports: $\vec{p}_v(t) = \vec{p}_v(t_v^{pre}) + \frac{t-t_v^{pre}}{t_v^{post}-t_v^{pre}}(\vec{p}_v(t_v^{post}) - \vec{p}_v(t_v^{pre}))$.

Figure 33 shows the resulting system state at two different times during the year.

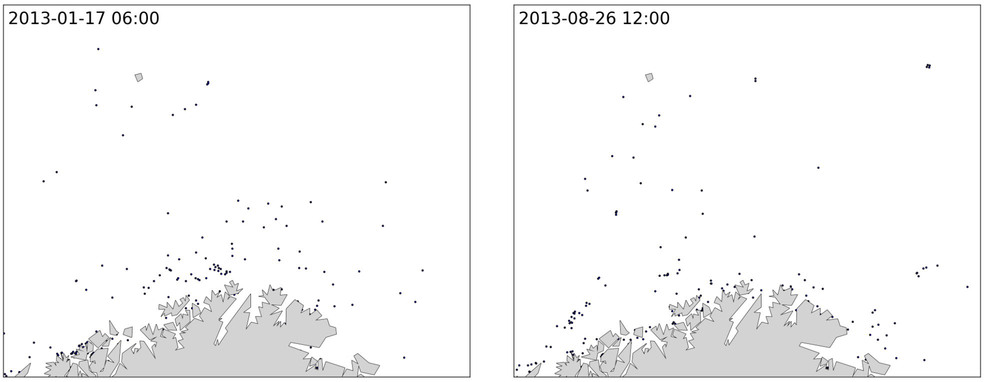


Figure 33: Interpolated traffic in the Barents Sea at two points in time, reconstructed from AIS data.

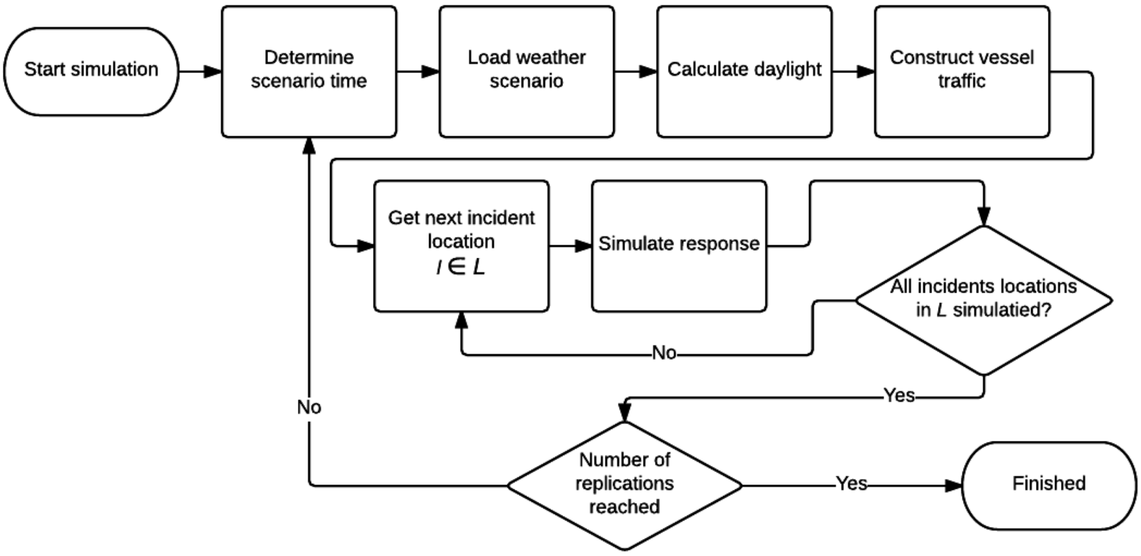


Figure 34: Schematic visualization of the simulation run.

3.4 Environmental data

Wind and wave data were obtained from the Norwegian meteorological institute. The daylight was computed according to the method given by the U.S. Nautical Almanac Office (2014). The meteorological data were available in three-hour intervals. The decision was therefore made to construct the simulation scenarios at the same discrete times; that is, the first scenario is the system state on 01.01.2013 at 00:00 UTC, the next scenario on the same day was at 03:00 UTC, and the last scenario was on 31.12.2013 at 21:00 UTC. The weather conditions were assumed to be static within the three-hour interval; in this case, no time-related interpolation of the weather data was needed.

4 Simulation run

The conceptual process of the simulation run is visualized in Figure 34. The output of the simulation run is a heat map visualization, as the simulation had to be conducted for multiple locations over the area in question. Therefore, the whole area in question was divided into equally spaced 10 x 10 km cells. A set L was formed to contain all cell centers, representing the assumed incident locations.

The simulation run starts by selecting the scenario time. This time determines which weather scenario (wind and waves) should be loaded from the database. The scenario time also determines the daylight conditions, which are calculated in the subsequent step. After this, the vessel traffic is generated according to the simulation time. For each location $l \in L$, the response is simulated. This simulation loop is run over a defined number of replications until it comes to an end.

5 Simulation output

With a given time limit, required rescue capacity, and location, the simulation returns the service level. In order to show the results dependent on the incident location, a heat map visualization was chosen. The color of a cell represents its service level; however, cells are colored only if they exceed a minimum service level. In this way, it is easy to see which areas can be considered as safe, that is, where the required capacity can be fulfilled with a certain probability.

5.1 Technical realization

While the Python programming language was used to conduct the pre-processing stage, the simulation was realized in C++. Alternative higher-level tools or programming languages transpired to be not suitable; discrete event simulation tools as used in Jakobsen (2015) were not a viable option due to performance reasons. In Jakobsen's model, only one RU was considered, while in the presented model, it is in the order of magnitude of hundreds. For the same reason, the use of the Python programming language as in Brachner (2015) was abandoned; however, the prototyping was still conducted in Python. The simulation takes advantage of multiple cores, and can, therefore, reduce the computational time, scaling nearly linearly with the number of cores.

6 Computational study

The simulation model is based on the following assumptions:

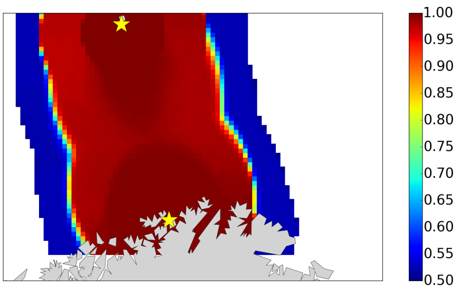
- The in-air speed of SAR helicopters is assumed to be 140 knots. Mobilization time is 15 minutes. The physical capacity is 21 people.
- Two SAR helicopters are positioned as static RUs: one at Hammerfest (latitude: 70.679720, longitude: 23.668628), and the second at Bjørnøya (latitude: 74.418419, longitude: 19.170307). Coordinates are given in decimal degrees.
- Nearby vessels are assumed to be able to approach the incident site at a speed of six knots, and the physical capacity is six people. This is the worst-case scenario, in which a nearby vessel launches a rescue boat that fulfills the minimum safety requirements according to the International Convention for the Safety of Life at Sea (SOLAS) of 1974. The mobilization time is assumed to be five minutes.
- It is assumed that nearby vessels that are called will participate in a rescue operation with a chance of 50%.

The pick-up times are chosen as given in Table 8. The maximum time for the rescue is set to two hours and the number of people to be rescued is 21, as given in OLF (2012).The results of the simulation run are shown in Figure 35, with the service level color-coded as specified in the figure. The first striking feature is that there are two rather homogeneous areas. This is mostly the effect of day and night times, where pick-up times vary accordingly. As a consequence, the blue area can only be serviced during daylight, while the red area is serviceable for the whole year.

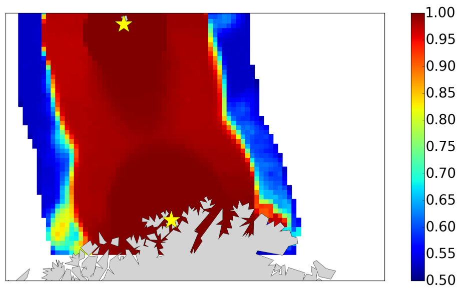
With regard to the influence of contingent capacity, the result shows that the effect on the areas where a high service level can be guaranteed is negligible. However, at the outer rim regions, where the service level falls to as low as 50%, contingent capacity helps to increase the service level notably. This applies particularly to the coastal region, where the maritime traffic is much denser than further north.

Table 8: Pick-up time by resource type (Source: personal communication, SINTEF).

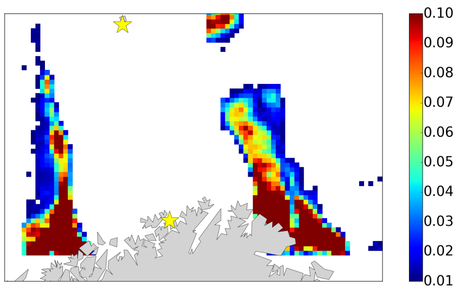
Rescue resource	*Weather conditions*	*Pick-up time [min/person]*	
		Daylight	*Dark*
Dynamic RU (nearby vessel)	Waves $< 2\,\text{m}\ H_s$	2	3
	Waves $2\,\text{m} - 4.5\,\text{m}\ H_s$	3	5
	Waves $4.5\,\text{m} - 6\,\text{m}\ H_s$	5	8
Static RU (SAR helicopter)	Waves $< 6\,\text{m}\ H_s$	2	3
	Waves $> 6\,\text{m}\ H_s$	3	4



(a) Service level without contingent capacity.



(b) Service level with contingent capacity.



(c) Difference between 35a and 35b.

Figure 35: Comparison of service level with and without contingent capacity.

7 Concluding remarks

This paper presented a simulation model that shows the influence of contingent capacity on an offshore oil and gas ERS. Advancing the argument that this industry must plan their ERS in a self-contained manner, it may be deemed inappropriate to take serendipity into account. Some may argue that by doing so, the actors and decision-makers would tend to more risk-seeking behavior. However, this proposition can also be viewed in the opposite way; the results of this simulation model show that with today's traffic, the core area for which the ERS should be planned may not profit from contingent capacity. In contrast, on the border regions of the serviceable area the presence of this contingent capacity could be a crucial component in saving lives. This also means that the ERS in the more northern areas should be planned even more conservatively, as in this region, this component is rarely available.

The presented model still runs with highly conservative assumptions, because the traffic is not differentiated and is run with worst-case parameters, reflecting the minimal rescue capability. In a further step, the traffic will be analyzed in more detail and rescue capabilities will be assigned according to the ship type, that is, fishing vessels will have different rescue capabilities to oil tankers or supply vessels. Furthermore, we intend to generate different types of random traffic that can be used to analyze the consequences of changeable conditions.

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Paper 5

A mathematical programming framework for planning an emergency response system in the offshore oil and gas industry

A mathematical programming framework for planning an emergency response system in the offshore oil and gas industry

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Abstract

While accidents in the petroleum industry are commonly connected to oil spill disasters, helicopter accidents are, in terms of incidence rates, a more grave concern in Norway. In this paper we present a range of mathematical programming models and a workflow that support decision makers in planning an emergency response system. For the models that are difficult to solve directly, we introduce a tailor-made solution method. With respect to the optimization objectives and constraints, we particularly focus on the performance metrics of response capacity and response time and show that the optimal solutions can differ remarkably, depending on which metric is in the optimization objective. Moreover, we present a multi-objective model that combines the optimization goals to achieve a balanced solution. A case study shows the concrete application of our framework.

1 Introduction

Recently, the Barents Sea has seen an unprecedented surge of interest in the exploration of hydrocarbon resources. Several major discoveries have been made in the past years. However, the sparse infrastructure in this area and the long distances to prospect sites (Berg et al. 2013), together with oil prices that have decreased considerably, hamper economic feasibility of these projects and call for new ways to design emergency response systems (ERSs).

In this paper we focus on the issue of emergency preparedness in this region, particularly on the response to a helicopter ditching during a personnel transport to or from offshore facilities. Helicopter accidents are one of the most frequent types of accidents on the Norwegian Continental Shelf (NCS) (Vinnem 2011). This is why helicopter ditchings are also relevant accident scenarios for offshore risk assessments, for which the operator has to demonstrate proper arrangements that make it possible to respond to such incidents in a timely manner (Brandsæter 2002).

One success factor that is often mentioned with respect to operations in the High North, also by the Petroleum Safety Authority (2014), is the cooperation between actors to create solutions bearing the whole system in mind. This is particularly valid for emergency preparedness where an area based approach can open a big potential to keep costs at a reasonable level without impairing quality: In the southern regions of the NCS, area based preparedness solutions have shown the same appraisal of positive development, if not better, compared to areas without existing cooperation (Vinnem 2011). These preparedness solutions typically involve sharing marine rescue resources, as, for example All Weather Search-and-Rescue (SAR) helicopters and high speed emergency rescue vessels (ERVs).

According to Vinnem (2011), the main limitation of area based preparedness is the extent of the covered region, which determines the feasibility of such a solution. In the Barents Sea, where distances are expected to be much larger than in the established areas, this could therefore constitute a significant problem. Combining different types of rescue resources that cooperate in a rescue mission could be one solution. For this purpose, Jacobsen and Gudmestad (2013) developed a rescue scheme compound by search-and-rescue (SAR) helicopters, as well as emergency rescue vessels (ERVs), and positioned it such that the rescue requirements could be met on the whole transport route from Berlevåg to a remote offshore location in the North East close to the Russian border.

We followed up on this idea, and investigated, how an optimal ERS configuration can be planned for multiple installations that constitute a more complex transport system. The resulting ERS should not only satisfy minimum requirements, but also use the available resources in an optimal way. This required also to contemplate the meaning of *optimality* in this particular sense, bringing up the issue of how ERS performance can be measured, and how different performance objectives can change the optimal solution.

In our considerations we use response time and response capacity as central metrics. *Response time* has always played a central role in planning, evaluating and improving ERSs (Li et al. 2011). Not only is the common reasoning that a faster treatment of casualties may increase the chances of survival, but particularly in a low infrastructure area as the Barents Sea it may be essential for establishing situational awareness to have a RU on site as fast as possible.

Furthermore, we employ *response capacity*, which we define as the number of persons that can be rescued within a given time limit. This is conceptually equal to the widely known *Golden Hour*, which suggests to provide medical care within the first hour after an incident, as mortality rises if no treatment is provided within this period (Lerner and Moscati 2001).

We have seen response time and response capacity used in a synonymous or inaccurate manner, and suggest to be particularly wary of the difference. The Golden Hour, for instance, is used as an argument for improved response time in the body of literature of many different fields (Peleg and Pliskin 2004; Helsloot and Ruitenberg 2004; Akella et al. 2003; Ramenofsky et al. 1983). However, it actually suggests to maximize the number of people that can be treated within an hour, not to minimize response time. In fact, our results show that a higher response capacity can even impair response time, and the ERS designs differ from each other dependent on the performance metric.

Under the condition of one incident at a time, we can safely assume, that the required response capacity in the presented problem does not exceed a certain value, because it cannot exceed the maximum amount of persons on board a helicopter. Instead of maximizing the response capacity, we therefore suggest to rededicate this surplus capacity to improve response time goals. Both worst case and average response time are important to consider. We show how these goals can be combined in one single model.

Rescue units (RUs) in a transport system for multiple installations can cover several routes. As a result, the simple analytical methods used by Jacobsen and Gudmestad (2013) are not sufficient due to the inter-dependencies between the different routes. Hence, more advanced methods have to come into place; we introduce models that are based on mathematical programming. Some of the introduced optimization models do have a long run-time or are not solvable within reasonable time when solved directly. We have therefore developed a simple algorithm that is easy to implement and makes real world instances solvable. With the presented tool set of models and solution methods at hand we introduce a framework that supports planning an ERS system, which we apply in a case study.

Using mathematical programming to support decision making and analysis of ERSs has become an important stream in operations research (Li et al. 2011; Fiedrich, Gehbauer, and Rickers 2000). The United States Emergency Medical Act of 1973 was the basis for one of the most widely known ERS models, the maximal covering location model. It was not only restricted to medical services but also applied to other emergency services. For example, soon after its first formulation, the model was used to locate fire stations, as the guidelines for fire protection turned out to be similar to the EMS regulations

(ReVelle et al. 1977). Collaborative forms have been developed recently by Berman, Drezner, and Krass (2011), and we have used this form to plan helicopter travel routes in case of a limited amount of rescue resources (Brachner and Hvattum 2017).

Advanced mathematical methods specifically for planning SAR or sea rescue systems have also been presented by other authors. Azofra et al. (2007), for example, present a methodology, where they group possible accident sites, and assign them to so-called *superaccidents*, which are single geographical locations determined by a gravitational model. They place resources, such that the distance to these superaccidents is minimized. They do not account for capacity issues, nor is this method appropriate to achieve full coverage of a whole area. Karatas, Razi, and Gunal (2017) present a integer linear program for optimally placing SAR helicopters such that the average response time to past incidents sites is minimized. Nguyen and Ng (2000) choose a two step approach for a helicopter location problem, assuming that they cannot cover all incidents with a given amount of helicopters. They maximize the number of incidents they can handle, and minimize the distance to those incidents in a second step. Assimizele, Oppen, and Bye (2013) employ a mixed integer mathematical program to allocate patrol tugs to oil tankers with the objective to minimize the distance of patrol tugs to the oil tankers. All of these papers use distance related measures as the main criteria for planning, with none of them considering the difference between response time and response capacity, or differentiating between average and minimum response time.

While the bigger part of ERS planning problems does not take forms of interaction between RUs into account, this is an important aspect in the presented problem. However, Azofra et al. (2007) consider different means of rescue resources for a rescue mission. Similarly, Karatas, Razi, and Gunal (2017) distinguish between different rescue functions, with the need to cooperate for certain incident types. Both of these problems are rather concerned with *cooperation*, where several different functions need to be fulfilled for the same mission goals in contrast to our case of *collaboration*, where different actors with different performance characteristics work together in the same function.

The remaining part of this paper is structured as follows: In Section 2 we define the relevant performance metrics and formulate the problem. We first present single objective mathematical models that optimize the individual metrics, and then a multi-objective model that integrates the individual goals. Furthermore, we introduce a solution method for the models that can not be solved with a direct formulation. Section 3 describes a workflow that can be used to plan an ERS. We conduct a case study based on this workflow in Section 4. Finally, we have some concluding remarks in Section 5, where future developments are also discussed.

2 Problem formulation and mathematical models

The Norwegian Oil and Gas Association has defined guidelines for dimensioning its area based emergency preparedness systems (Norsk olje og gass 2015). The guidelines comprise eight defined situations of hazards and accidents, and we focus on the event of persons in sea as a result of a helicopter accident. This situation can arise when transporting personnel between onshore bases and offshore platforms, which in Norway is exclusively done by helicopter. The guidelines require the rescue of all persons on board of a full helicopter, which corresponds to 19 passengers and 2 pilots, within 120 minutes. This applies only within the 500 meter safety zone around the offshore facility, but as clear standards en-route are not formulated elsewhere, we assume for our considerations the same requirement all along the routes, as also done by Jacobsen and Gudmestad (2013).

This guideline is the basis for our problem, which we later on refer to as the collaborative covering problem (CCP): A set of given RUs must be located such that this rescue requirement is met along a set of given transport paths. Figure 38 shows an example of a problem instance, with the on- and offshore locations, and transport paths that need to be covered.

We consider the minimum response capacity as a requirement that defines the feasible set of solutions, but from all possible solutions the optimal solution is to be chosen. Speaking of an optimal ERS, we need to specify the criterion of optimality, that is, which performance metric is to be optimized. As we are using mathematical programs for optimization, this criterion has to be expressed in a single scalar. Hence,

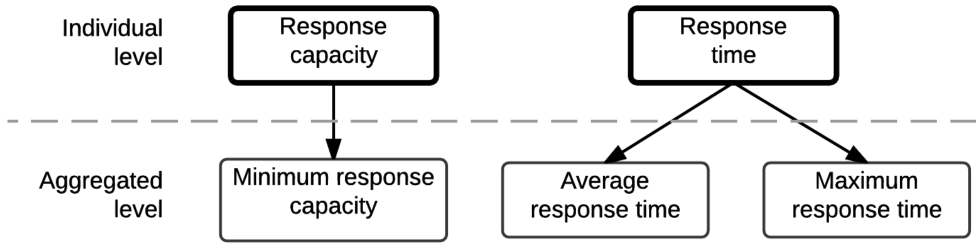


Figure 36: ERS performance metrics.

meaningful aggregations need to be defined, that can express the essence of individual observations. We have identified three important performance metrics that we use in our models as shown in Figure 36 and described as follows.

We use the minimum of the individual response capacities on all routes, because it reveals the bottleneck in the ERS system, which is at the same time the number of persons that can be safely rescued on any route. This implies the assumption of a system wide limit, that is, there are no individual limits per route; this is a valid supposition as long as it is a balanced transportation system without significant disparities in the transport demand per offshore facility. The first performance metric is therefore the *minimum response capacity*.

Furthermore, we express the ERS performance in terms of response time; as the presented problem involves a collaborative response where several RUs can be involved, it is necessary to specify that we consider response time as the time for the *first* RU to be on site. In two different ERS configurations with the same response capacity the one with an early arriving RU is preferable, because the first responder is able to triage at an earlier time such that help can provided to those that are most in need for treatment.

Two aggregation functions for the response times are of relevance: First, the average response time should measure the general timeliness of the response on any point of the route; however, locations where a quick response is possible can compensate for other locations where the response would take considerably longer. Therefore, we also employ the *maximum response time*, which expresses the worst case response time over all potential ditching locations.

In the following subsections we present mixed integer programming formulations for the CCP with three different objectives addressing each of these performance metrics.

2.1 Maximization of minimum capacity

We start with the collaborative covering problem that maximizes the minimum response capacity, $CCP^{MaxMinCap}$. Its optimal objective value reveals the number of persons that can be rescued in any case, regardless of where in the transport system the incident occurs. Consequently this model also answers whether the minimum capacity requirement can be met. If not satisfiable, the optimal solution gives an indication of how close one can get to the requirement. Let $\mathscr{R}$ be the set of RUs. Let $\mathscr{S}_r$ be the set of nodes where a RU $r \in \mathscr{R}$ can be placed. While the possible locations of SAR helicopters are usually restricted to certified heliports, ERVs could be freely located within an area. These areas are therefore approximated by a discrete set of equally spaced grid points. Let $\mathscr{D}$ be the set of demand nodes to be covered, which are obtained by discretizing the given flight routes of the transport helicopters. Let c_{rij} be the contribution to the response capacity at point $j \in D$, if RU r is placed on node $i \in \mathscr{S}_r$. Furthermore, the binary variable y_{ri} is 1 if RU $r \in \mathscr{R}$ is positioned at location $i \in D$. Variable σ represents the lowest observed response capacity along the flight route. The model is formulated as follows:

$$\max \quad \sigma, \tag{24}$$

$$\text{s.t.} \quad \sum_{i \in \mathscr{S}_r} y_{ri} = 1, \qquad r \in \mathscr{R}, \tag{25}$$

$$\sum_{r \in \mathscr{R}} \sum_{i \in \mathscr{S}_r} y_{ri} c_{rij} \geq \sigma, \qquad j \in \mathscr{D}, \tag{26}$$

$$y_{ri} \in \{0, 1\}, \qquad r \in \mathscr{R}, i \in \mathscr{S}_r. \tag{27}$$

The objective function (24) equals the smallest observed response capacity at the demand nodes. Constraints (25) ensure, that each RU is placed at exactly one node. The smallest observed capacity can take a value no bigger than the total response capacity at each demand point due to constraints (26). The placement variables are restricted to the binary domain (27).

2.2 Minimization of average response time

With the cooperative covering problem that minimizes the average response time, $CCP^{MinAvgRT}$, we introduce the notion of the *first responder*, that is, the RU that is the first to arrive at the incident location. In contrast to $CCP^{MaxMinCap}$, the minimum required capacity needs to be included as a hard constraint. The following parameters are added to those in $CCP^{MaxMinCap}$. Let t_{rij} be the time needed for RU r to travel from location i to demand point j, and c^{min} the required minimum response capacity. Furthermore, we add the binary variable z_{rij}, which is 1 if RU r positioned at i is the first responder for an incident at j.

$$\min \quad \sum_{r \in \mathscr{R}} \sum_{i \in \mathscr{S}_r} \sum_{j \in \mathscr{D}} t_{rij} z_{rij}, \tag{28}$$

$$\text{s.t.} \quad (25), (27),$$

$$z_{rij} \leq y_{ri}, \qquad r \in \mathscr{R}, i \in \mathscr{S}_r, j \in \mathscr{D}, \tag{29}$$

$$\sum_{r \in \mathscr{R}} \sum_{i \in \mathscr{S}_r} z_{rij} = 1, \qquad j \in \mathscr{D}, \tag{30}$$

$$\sum_{r \in \mathscr{R}} \sum_{i \in \mathscr{S}_r} y_{ri} c_{rij} \geq c^{min}, \qquad j \in \mathscr{D}, \tag{31}$$

$$z_{rij} \in \{0, 1\}, \qquad r \in \mathscr{R}, i \in \mathscr{S}_r, j \in \mathscr{D}. \tag{32}$$

The objective function (28) minimizes the sum of first responder times for each demand node, which also minimizes the average first responder time since the number of demand nodes is fixed. Constraints (29) link the placement variables to the first responder variables; only a properly placed RU can be a first responder. For each demand node there can be only one first responder, as ensured by constraints (30). Constraints (31) are the minimum capacity requirements for the demand points. Constraints (32) limit the first responder variables to the binary domain.

2.3 Minimization of worst case first responder time

While $CCP^{MinAvgRT}$ minimizes the average response time, individual response times can deviate in a pathological way. The following formulation, $CCP^{MinMaxRT}$, provides a guarantee that any individual first responder time is no worse than the model objective value. In addition to the variables of $CCP^{MinAvgRT}$ we add the continuous variable τ denoting the worst case first response time. The $CCP^{MinMaxRT}$ is formulated as follows:

$$\min \quad \tau, \tag{33}$$

$$\text{s.t.} \quad (25), (27), (29) - (32)$$

$$t_{rij} z_{rij} \leq \tau, \qquad r \in \mathscr{R}, i \in \mathscr{S}_r, j \in \mathscr{D}. \tag{34}$$

The objective function (33) equals the worst-case time that it takes the first responder to be on an incident site. Constraints (25), (27), and (29)–(32) are adopted from $CCP^{MaxMinCap}$ and $CCP^{MinAvgRT}$ without change. According to constraints (34) the worst case first responder time can be no less than the elapsed time at any demand location until the first RU arrives.

Solution method

For the $CCP^{MinMaxRT}$ we have not been able to solve the case study and similar instances with a direct implementation within a time limit of 24 hours. Compared to objectives that minimize a sum, as in $CCP^{MinAvgRT}$, standard branch and bound algorithms are much less amenable to minimizing a maximum, as in $CCP^{MinMaxRT}$, because pruning of nodes is much more difficult at the intermediate level of the search tree due to the lack of information on the value of the objective (França et al. 1995). Therefore we have developed an alternative solution technique based on a closely related problem, which we call CCP^{MinCRT}. In this problem we set lower and upper bounds of variable τ by adding constraints

$$\tau \geq \lfloor t \rfloor, \tag{35}$$
$$\tau \leq \lceil t \rceil \tag{36}$$

to $CCP^{MinMaxRT}$. For the relation between $CCP^{MinMaxRT}$ and CCP^{MinCRT}, the following propositions can be made:

Proposition 1. *Let z_*^{MinCRT} and $z_*^{MinMaxRT}$ denote the optimal value of the associated problems, respectively. Then $z_*^{MinCRT} = z_*^{MinMaxRT}$ if CCP^{MinCRT} is feasible and $z_*^{MinCRT} \neq \lfloor t \rfloor$.*

Proof. Excluding the case of $z_*^{MinMaxRT} = \lfloor t \rfloor$, we can differentiate between the following three cases: First, assume that $z_*^{MinMaxRT} < \lfloor t \rfloor$. Then CCP^{MinCRT} is feasible, and $z_*^{MinCRT} = \lfloor t \rfloor$ due to constraint (35). Second, assume that $z_*^{MinMaxRT} > \lceil t \rceil$. In this case CCP^{MinCRT} becomes infeasible, as constraint (36) can not be satisfied. Third, assume that $z_*^{CCPMinMaxRT} \in (\lfloor t \rfloor, \lceil t \rceil]$. In this case constraints (35) and (36) are non-binding, thus $z_*^{MinCRT} = z_*^{MinMaxRT}$. □

Proposition 2. *Assume that we solve $CCP^{MinMaxRT}$ with a reduced set of possible locations $\mathscr{S}_r' \subset \mathscr{S}_r, r \in \mathscr{R}$. Then the value of the optimal solution obtained through the reduced set is greater or equal to the one obtained through the original set.*

Proof. Reducing the set is equivalent to constraining variables $y_{ri}, i \in (\mathscr{S}_r \setminus \mathscr{S}_r')$ in the original problem to zero. With additional constraints the objective value can only be greater than or equal to that of the original problem. □

Algorithm 1 uses these two propositions, is easy to implement, and makes it possible to solve the CCP^{MinCRT} within reasonable time. It employs an downward search by iteratively solving CCP^{MinCRT} with decreasingly tighter limits on response time. The start value for the response time is obtained from other models that can deliver feasible solutions in regards to the minimum capacity requirements; we obtained solutions to the instance for the models $CCP^{MaxMinCap}$ and $CCP^{MinAvgRT}$, calculated the worst case response times for both solutions and used the lower one as initial value.

For vessel type RUs that can be positioned freely (approximated by a grid), the algorithm starts with a relatively coarse grid and switches to a finer grid whenever the optimal solution for the given grid size is found, until the solution for the target grid is obtained. A coarser grid can lead to infeasibility, thus the initial grid width has to be determined manually.

The basic idea of the downward search is similar to the one used by França et al. (1995) for the m-Traveling Salesman Problem with Minmax objective, but it differs in two main aspects: They do not use intervals for the maximum value and therefore always will try to solve an infeasible instance in the last iteration, often leading to a very large search tree. Furthermore, due to a different problem structure, they can not employ a simplified instance in the search, as we have done in our problem by using the reduced grid.

gridwidth $\leftarrow$ start value for grid width;
$t \leftarrow$ start value for upper bound of first responder time;
while *gridwidth* $\geq$ *targetGridWidth* **do**
  instance $\leftarrow$ create instance (*gridwidth*);
  repeat
    optVal $\leftarrow$ solve CCP^{MinCRT}(*instance*, $\lfloor t \rfloor$, $\lceil t \rceil$);
    $t \leftarrow t - 1$;
  until *optVal* $\neq \lfloor t+1 \rfloor$;
  gridwidth $\leftarrow$ *gridwidth* / 2;
end

Algorithm 1: Downward search with grid refinement

2.4 A multi-objective model to minimize maximum weighted deviation

As shown later in our case study, objectives that target only one aspect of distance or capacity related indicators can have undesirable effects on the indicators that are not included in the model. The multi-objective models presented in this section combine individual goals into one objective and seek to balance them, such that all of them contribute in identifying a good ERS configuration.

Both the individual goals and their respective weights as an importance measure have to be defined as input parameters. One way to obtain the goals is to use the objective values of the optimal solutions to each model presented in the previous section. Other sources, such as expert opinions or external regulations, are also valid. Furthermore, experts can define the relative weights of the goals. By systematically testing different weights and solving the model iteratively, different configurations can be obtained and presented to the decision makers.

Let g_1 and g_2 be the goal values for the average and worst case first responder time, respectively. Let e_1 and e_2 be the respective weights of the goals. The multi-objective model $CCP^{MinAvgWD}$minimizes the weighted average deviation from the target values and is formulated as follows:

$$\begin{aligned} \min \quad & e_1 \frac{\sum_{r\in\mathscr{R}} \sum_{i\in\mathscr{S}_r} \sum_{j\in\mathscr{D}} t_{rij} z_{rij} - g_1}{g_1} + e_2 \frac{\tau - g_2}{g_2}, && (37)\\ \text{s.t.} \quad & (25), (27), (29) - (32), (34). \end{aligned}$$

However, we found two drawbacks with this model: First, it can result in solutions where certain goals are fulfilled only to a marginal extent, because those can be compensated by other goals that are well fulfilled. Second, this model is intractable to solve for real life instances.

We employ therefore a model that minimizes the maximum deviation from each individual goal, $CCP^{MinMaxWD}$ that is formulated as follows. The variable q denotes the highest observed weighted percentage deviation from individual goal.

$$\begin{aligned} & \min q && (38)\\ \text{s.t.} \quad & (25), (27), (29) - (32), (34), \\ & e_1 \frac{\sum_{r\in\mathscr{R}} \sum_{i\in\mathscr{S}_r} \sum_{j\in\mathscr{D}} t_{rij} z_{rij} - g_1}{g_1} \leq q, && (39)\\ & e_2 \frac{\tau - g_2}{g_2} \leq q, && (40)\\ & q \geq 0. && (41) \end{aligned}$$

The objective function (38) minimizes the maximum weighted deviation from the individual goals. The constraints from $CCP^{MaxMinCap}$, $CCP^{MinAvgRT}$, and $CCP^{MinMaxRT}$can be adopted without change, with the exception of dropping the minimum capacity constraints (26). Additionally, constraints (39) and (40) limit the maximum deviation to be no less than the deviations from the weighted individual goals. $CCP^{MinMaxWD}$ may return dominated solutions, but solving the model iteratively by systematically sweeping the weight parameters can eliminate those solutions, producing a Pareto-efficient frontier.

Solution method

For this model we used a solution method that works analogous to the algorithm described in 2.3. We again start with a coarse grid and constrain variable q to an interval of predefined step size. In our experiments we set this interval size to 0.01, starting from the upper bound of

$$\max([e_1 * (t^{\max} * |\mathscr{D}|) - g_1)/g_1, e_2 * (t^{\max} - g_2)/g_2]), \tag{42}$$

due to the assertion that the response time is certainly lower than $t^{\max}$; otherwise, the model would be infeasible.

3 Workflow

Planning the ERS involves a series of design decisions that need to be made: Fleet size and composition, including individual RU performance characteristics, have to be defined. Possible locations for the RUs need to be determined. Even operational issues, as the set of offshore facilities to include into this system, or the transport routes used, have to be part of considerations in the planning process.

Figure 37 suggests a planning workflow that supports these decisions, making use of the presented models. It basically follows the logic that increasingly computationally expensive models have to be used to make decisions with increasing degrees of freedom. Thus, we have split the process such that the design parameters are decided at different stages: First the rescue fleet that is needed to cover the minimum response capacity is found. Then surplus capacity needs to be added by increasing the fleet or improving RU parameters. This surplus capacity is finally rededicated to improve the response time goals.

In the first step the instance is defined, that is, one or more onshore bases from which the personnel transports are conducted, offshore facilities, and a transport network that connects these facilities with the mainland have to be decided. Furthermore, possible locations for the RUs have to be contemplated. RUs can be positioned freely, as in the case of ERVs, or they can be subject to restrictions, as, for example, SAR helicopters, which are only able to be located at approved heliports.

Subsequently, this instance needs to be pre-processed to serve as an input for the optimization models. The flight paths of the transportation network have to be discretized into a set of points. The same applies to areas, in which certain RUs can be freely placed. Furthermore, the individual RU capacity and response time matrices have to be pre-calculated, as they serve as inputs for the subsequent steps.

As a next step, an initial fleet of RUs that can fulfill the basic capacity requirement has to be defined. The model $CCP^{MaxMinCap}$ supports in determining whether a given RU fleet can provide enough response capacity to cover all of the flight paths sufficiently. In case of insufficient capacity the objective value gives an indication of the extent to which the resulting worst case capacity undercuts the requirements. Response capacity has to be added or the composition of the rescue fleet has to be adjusted until the required capacity is achieved. In this stage a certain capacity surplus should be allowed for.

This surplus is sacrificed for improving the response time objectives in the next stage, where the optimal values for the average response time and the worst case response time can be determined using the models $CCP^{MinAvgRT}$ and $CCP^{MinMaxRT}$, respectively. The worst case response time that has been earlier obtained from $CCP^{MaxMinCap}$ can serve as an upper bound for the solution method that is employed for $CCP^{MinMaxRT}$. In this stage it should become clear if the intended response times are within reach. If, for example, the optimal solutions to both $CCP^{MinAvgRT}$ and $CCP^{MinMaxRT}$ exceed intended average response time and worst case response time, then additional response capacity needs to be added.

If either one or both response time goals are fulfilled, we can move to the next stage using the multi-objective model $CCP^{MinMaxWD}$. Through the weightings of average and worst case response time the model can be adjusted to set more or less focus on either goal.

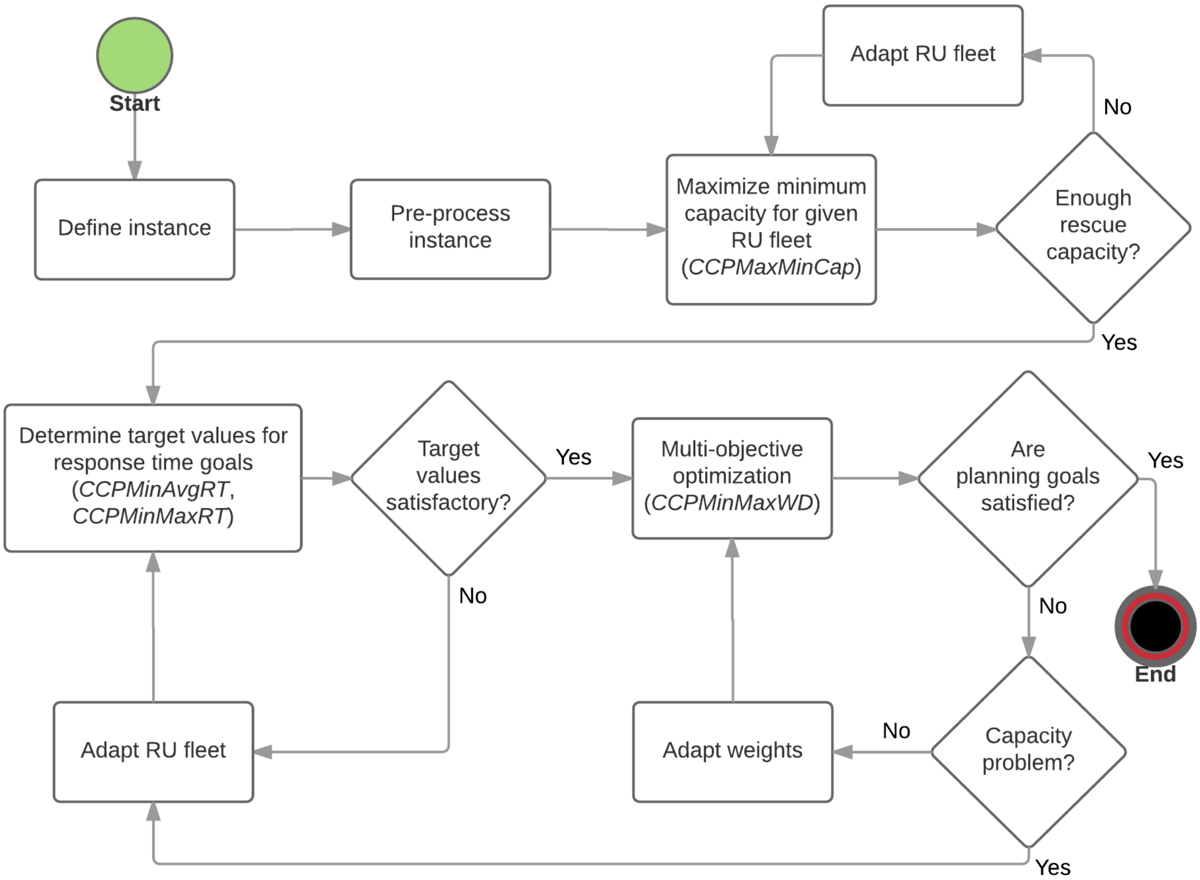


Figure 37: Workflow in the planning process.

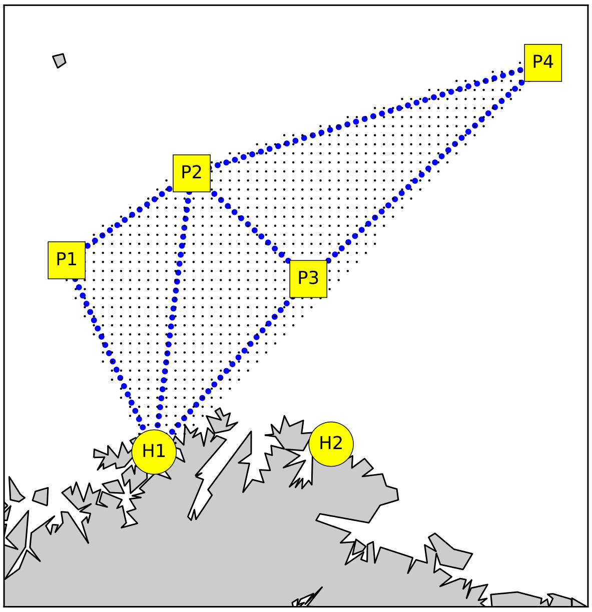


Figure 38: Visualization of case instance. Helicopter transport paths from onshore bases (circles) to offshore facilities (squares). The blue nodes define the set of demand points, the gray nodes are the possible locations for placing ERVs. A SAR helicopter can be placed either on H1 or H2.

Table 9: Facilities used in the test instance

Name	Description	Latitude	Longitude
P1	Johan Castberg field	72.49434	20.34757
P2	Wisting Central field	73.49113	24.23236
P3	Random position	73.05978	32.65414
P4	North-eastern most point	74.50000	37.00000
H1	Hammerfest onshore base	70.70132	23.76830
H2	Berlevåg onshore base	70.85450	29.09039

4 Case study

For the case study we assume a scenario in the Barents Sea using the facilities listed in Table 9. These facilities are connected to each other and to the shore through the transport routes shown in Figure 38. An ERS configuration is sought that covers these transport routes, such that in the case of a helicopter ditching, crew and passengers can be rescued within two hours.

The transport routes are discretized into nodes with a 10 km spacing. These nodes form the set of demand points D that need to be covered. Likewise, the areas for the ERVs are discretized into a set of nodes as required by the models. This set can be reduced by removing the nodes located outside of the convex hull of the on- and offshore facilities, as any placement outside of this area is clearly suboptimal.

Furthermore, we assumed the set of RUs $\mathscr{R}$ to consist of five ERVs and one SAR helicopter. Table 10 provides the performance data for these two RU types. While the physical capacity limit for ERVs does not have any influence on the results as long as the minimum requirement is lower, we set the physical limit of the SAR helicopter to 17, which assumes a capacity of 21 persons on board and a crew of 2 pilots, but also 2 rear crew: one winch operator and one winchman, who is lowered on the winch in the rescue operation.

Table 10: Performance data for RUs.

		SAR	ERV
Mobilization time (min)	t_r^{mobi}	15	5
Travel speed (knots)	v_r	140	30
Pickup rate (persons / min)	p_r	$1/2$	$1/3$
Physical capacity limit (persons)	c_r^{max}	17	30

For each resource we constructed a set of nodes $\mathscr{S}_r$ which represent its possible locations of placement. For the SAR helicopter this set contains the onshore bases H1 and H2. That is, the helicopter can only be placed at the onshore bases. For ERVs, a grid identical to the one shown in Figure 38 is used.

From the performance data, time matrices for each resource are calculated that hold the response times to get from a node i to node j for a resource r:

$$\forall r \in \mathscr{R}, i \in \mathscr{S}_r, j \in \mathscr{D} : t_{rij} = t_r^{mobi} + \frac{d_{ij}}{v_r}, \tag{43}$$

with d_{ij} denoting the distance between nodes i and j. The capacity matrices for each resource r contain the resulting contribution of response capacity at a node j if the resource is placed on i. With the parameter $t^{\max}$, the maximum available time, set to 120 minutes, the matrices are calculated as follows:

$$\forall r \in \mathscr{R}, i \in \mathscr{S}_r, j \in \mathscr{D} : c_{rij} = \max\{0, \min\{c_r^{max}, (t^{max} - t_{rij})p_r\}\}. \tag{44}$$

The experiments where conducted on a Intel Core i5-4210U CPU with a base frequency of 1.7 GHz and 8 GB of working memory. For the mathematical programs we used the solver *Gurobi*[1].

4.1 Response time versus response capacity

Response time is an important performance metric for an ERS. However, not taking into account the response capacity can lead to particularly bad solutions. Figure 39 compares the solution to $CCP^{MinAvgRT}$ with no capacity requirements to our requirement of 21 persons.

In fact, with no response capacity requirements in place it can take more than 4.5 hours to rescue 21 people. Admittedly, we have to remark here that such a pathological solution is mainly due to the physical capacity limit of the helicopter, but this limit has to be taken into account as well.

Moreover, we investigated the effect of an increasing response capacity requirement on the response time. We chose the grid for the ERV positions to have a resolution of 20 km, as the run time for a 10 km grid would have been too long. Solving model $CCP^{MinAvgRT}$ iteratively while increasing the minimum capacity requirement, we obtained the results visualized in Figure 40.

We mentioned earlier, that both response capacity and response time have to be taken under consideration. These results support this statement, because striving to improve one value negatively affect the other: The more persons that have to be rescued within the two hours time limit with the same rescue fleet, the later the first responder arrives in average. This is somewhat counterintuitive on first sight, but explainable by the tighter capacity constraints (31) that can only worsen, but never improve, the objective value.

4.2 Multi-objective ERS planning

In this section we plan a rescue fleet and locate the individual RUs by applying the workflow presented in Section 3. We start with $CCP^{MaxMinCap}$ to determine the composition of the rescue fleet. We use one SAR helicopter that can be placed either on *H1* or *H2*, and increase the number of available ERVs from 0 to 10. Table 11 shows the results of this run. The requirements can be fulfilled with at least one SAR helicopter

1 `http://www.gurobi.com`, accessed 05.05.2018

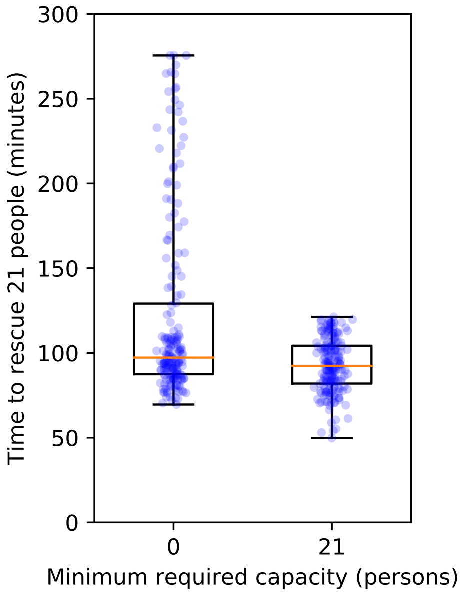


Figure 39: Distribution of response time over the transport network. The solution optimizing the average response times without taking into account capacity requirements can lead to pathological solutions.

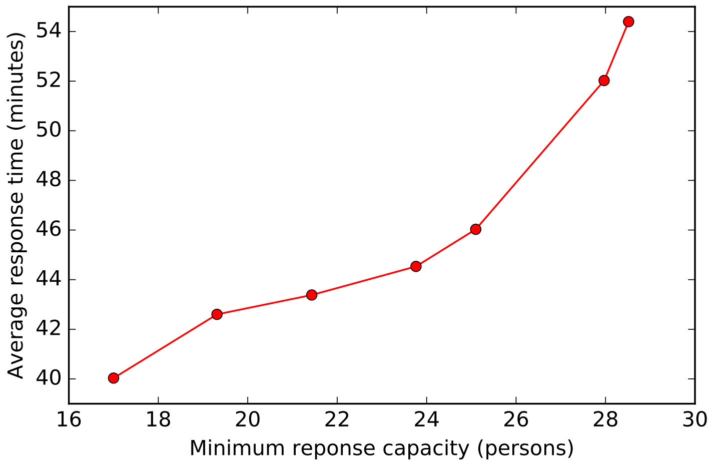


Figure 40: The average response time increases with increasing response capacity requirement.

and six ERVs. A fleet that would just fulfill the minimum requirements would not have any degrees of freedom to improve these goals significantly. Hence, we add surplus capacity by increasing the number of ERVs to seven, with the purpose of rededicating this capacity later on to improve the response time goals, leading to the solution visualized in Figure 41a.

Subsequently, we solve $CCP^{MinAvgRT}$ and $CCP^{MinMaxRT}$ to optimality. The parameter c^{min}, the minimum capacity requirement, is set to 21 persons. The solutions are visualized in Figure 41b and 41c, and the performance measures are shown in Table 12.

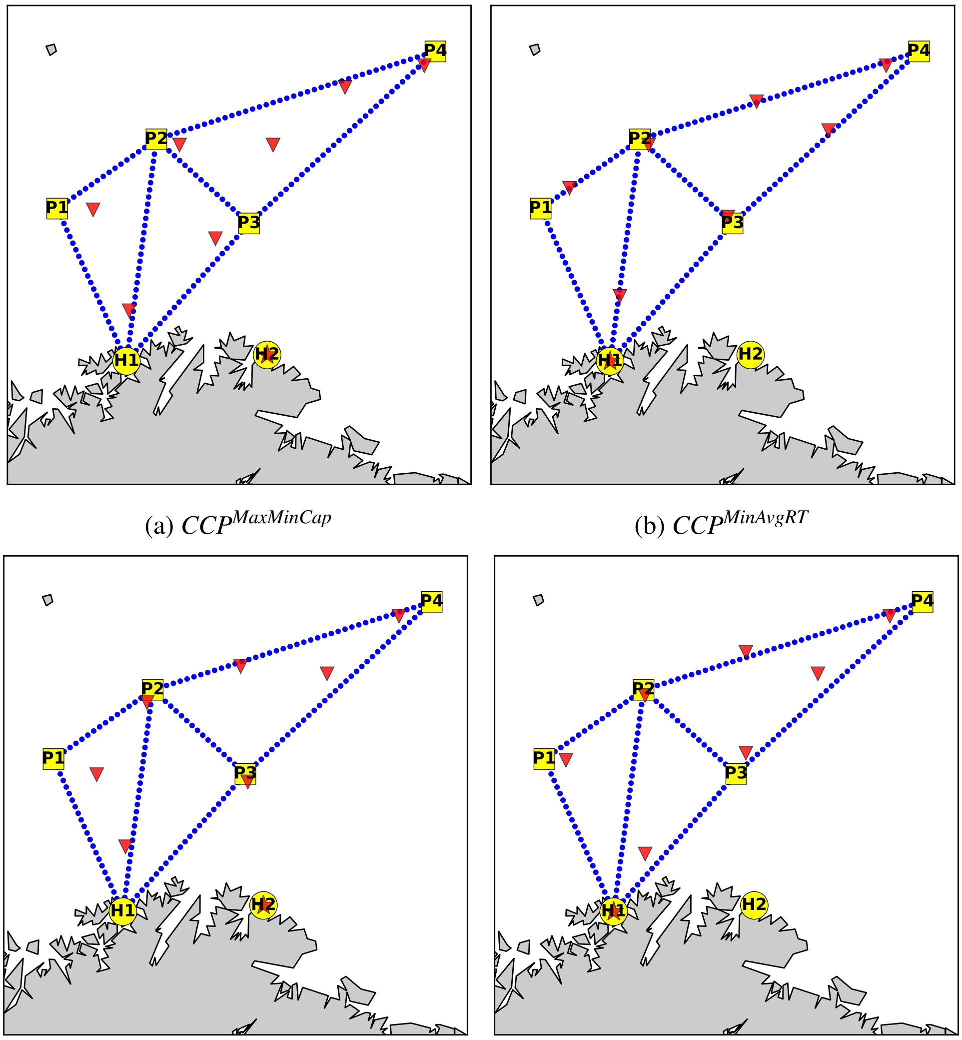
This table also includes the performance measures for $CCP^{MaxMinCap}$. Maximizing the minimum capacity would definitely lead to an undesirable solution: While the worst case capacity is much higher than needed, the average time of the first RU on site would be more than 10 minutes later than a solution that would be optimal in this respect. The same applies for the worst case response time of $CCP^{MaxMinCap}$ compared to $CCP^{MinMaxRT}$. Furthermore, comparing the optimal solutions of $CCP^{MinAvgRT}$ and $CCP^{MinMaxRT}$ show that the single objective of either average response time or worst case response time would be undesirable as well: The difference between these two solutions are more than

Table 11: Minimum capacity with one SAR helicopter that is freely placeable on H1 or H2 and an increasing number of ERVs.

Number of ERVs	*Worst case capacity (persons)*	*Run time (seconds)*
0	0	0
1	9.83	1
2	12.00	1
3	17.00	2
4	17.00	602
5	18.44	2515
6	24.67	103
7	**29.91**	**209**
8	32.81	6126
9	36.86	4843
10	40.88	4926

Table 12: Results for case instance.

	Optimization runtime (minutes)	Minimum capacity (persons)	Average response time (minutes)	Maximum response time (minutes)
$CCP^{MaxMinCap}$	1	**29.91**	53.89	87.08
$CCP^{MinAvgRT}$	35	21.20	**42.51**	97.29
$CCP^{MinMaxRT}$	8	21.20	50.6	**77.59**
$CCP^{MinMaxWD}(0.25, 0.75)$	358	21.20	45.13	79.70
$CCP^{MinMaxWD}(0.50, 0.50)$	410	21.20	44.68	81.84
$CCP^{MinMaxWD}(0.75, 0.25)$	230	21.20	43.68	82.79



(a) $CCP^{MaxMinCap}$ (b) $CCP^{MinAvgRT}$

(c) $CCP^{MinMaxRT}$ (d) $CCP^{MinMaxWD}(0.75, 0.25)$

Figure 41: Solutions to the case instance using the presented models. ERVs are depicted by triangles, while the star indicates the position of the SAR helicopter.

eight minutes for the average first responder time, and nearly 20 minutes in the worst case.

Thus, following the workflow, we set the target values to the best solutions for the average response time (42.51 minutes) and worst case response time (77.59) and solve $CCP^{MinMaxWD}$ with varying weights as shown in Table 12. None of these weight combinations can be regarded as the *right* one; however, the combination of 0.75 for the average response time goal and 0.25 for the worst case response time goal seems balanced, because the gap to the target values is only one minute for the average response time goal, and five minutes for the worst case.

Applying the presented workflow we have finally found the solution shown in Figure 41d, which employs one SAR helicopter and seven ERVs and allows rescuing 21 people within two hours at any point of the transport system, with the first RU being on site within 43.68 minutes in average and 82.79 minutes in the worst case.

Figure 42 shows how the solutions to the different models influence the distribution of capacities and response times over the whole network. The rescue capacities for $CCP^{MaxMinCap}$ are well over the required capacity over the whole network, giving away the opportunity for improved response times. Using the minimum capacity constraints in the other three models make sure that capacities are never undercut, but open the possibility to improve response times. Compared to the clearly suboptimal response times of $CCP^{MaxMinCap}$, $CCP^{MinMaxRT}$ does not improve the response times considerably, but it addresses the

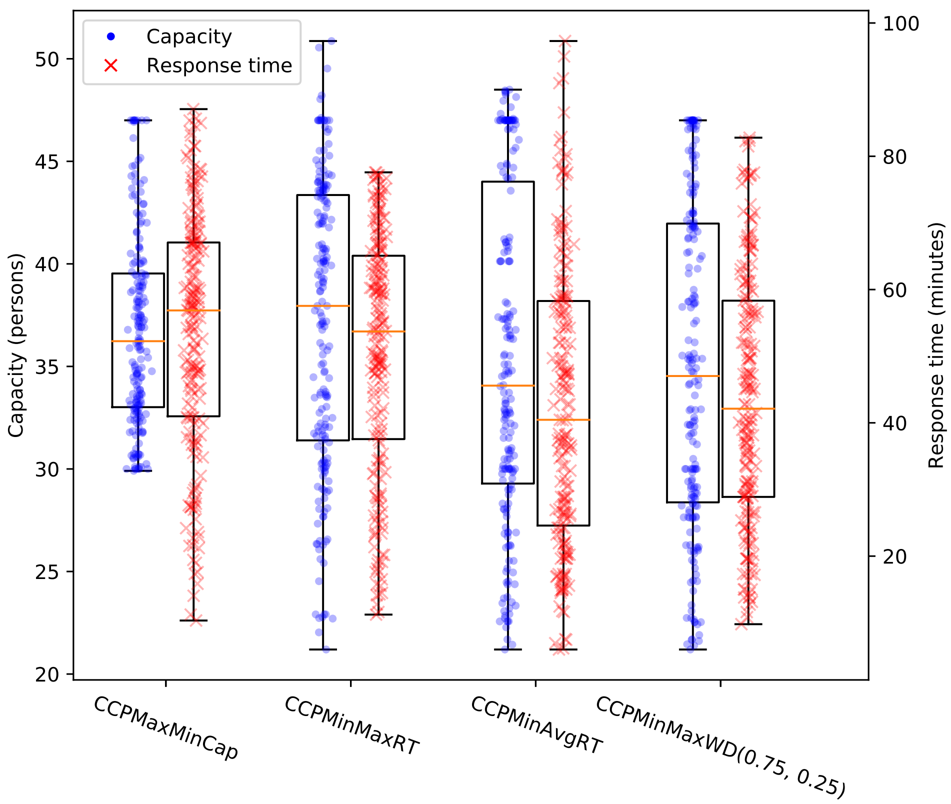


Figure 42: Comparison of the optimal solutions to the example instance using the presented models.

approximately 10% of the network that have very high response times. $CCP^{MinAvgRT}$ even worsens the problem of response times on the higher ends, while it provides very good performance on the rest of the network. Finally, $CCP^{MinMaxWD}(0.75, 0.25)$ provides indeed a performance close to $CCP^{MinAvgRT}$, while keeping the maximum response times still on a level not far off the results of $CCP^{MinMaxRT}$.

5 Concluding remarks

Based on our findings we suggest to consider both response time and response capacity as ERS performance metrics. Not only the average response time, but also the maximum response time is an important metric for ERS. Our multi-objective mathematical programming model allows to optimize both average and maximum response time, according to a defined weighting.

We see much potential in developing these models from a planning tool to an online decision support tool. Integrated operations will deliver a better risk picture and allow to dynamically adapt the ERS according to the needs, going from a re-active emergency management to a pro-active approach where rescue demand and capacity could be dynamically adapted and anticipated based on real-time information, as called for by Tveiten et al. (2012). One such possibility would be to fix the variables y_{ri} that correspond to the current locations of stationary RUs to 1, and solve only for one or few RUs, that can be relocated in order to improve the system capacity, the response times, or both. Another option would be to allow for minor relocations of RUs to increase RU effectiveness: The same variables y_{ri} could be fixed to zero for locations that are not within the desired relocation radius or that are not an option for relocation. Knowing which transport flights will happen in the near future, certain demand points could be excluded, and a readjusted system configuration with improved objective values could be proposed.

There are several paths for future research. First, the involved parameters as, for example, travel times or response capacity are subject to variation. While we have presented deterministic models, stochastic models could take this variability into account. The quality of the solutions of the presented deterministic models have to be evaluated in an stochastic environment, and the additional value of stochastic optimization models needs to be investigated. Moreover, we have considered this ERS to be static, that is, RUs are stationarily standing by for incidents. It would be interesting to see, if moving RUs that intercept helicopter transports would improve the effectiveness. Finally, we use response time and response capacity as central metrics in our models. Other metrics could further improve the solution quality. Takeoff and landing risk for helicopters, for example, is higher than the risk en-route (Qian et al. 2015), while we considered the risk equally distributed in our models. Thus, including the risk into the models may give better solutions, but to which extent still needs to be investigated.

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