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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 [22]. 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 [9], 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 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 [26]. In the UK, eight accidents in the past 30 years resulted in 110 fatalities [18]. Five accidents with 12 fatalities were recorded in Norway during the period of 1990–2009 [4].

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 Fig. 1, 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.

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0305-0483/

Fig. 1. A ditched helicopter near the Shetland Islands on 22 October 2012. *Source:* [1].

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 [12]. 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. [10] and, with a particular focus on emergency response, by Li et al. [14]. 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 et al. [23], 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 [5] 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 et al. [2] and Rennemo et al. [21] 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 et al. [6–8]. 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 et al. [6] 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. [16] developed a helicopter routing model that improved travel safety by reducing the number of offshore landings and the flight time. Qian et al. [20] 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 min [17]. While this requirement is enforced only within a security zone of 500 m around an offshore facility, we follow the argument in [12] 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 [24].

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.

Fig. 2 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

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

Fig. 3 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 $d_{ij} \le 98$, at which point the travel time is 42 min, leaving 63 min 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 [12]. 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, $\mathcal{R}$, at a collaborative pick-up rate of

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

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

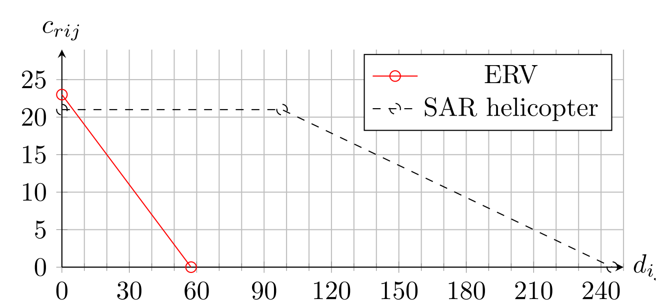

Fig. 3. Capacity function over distance.

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

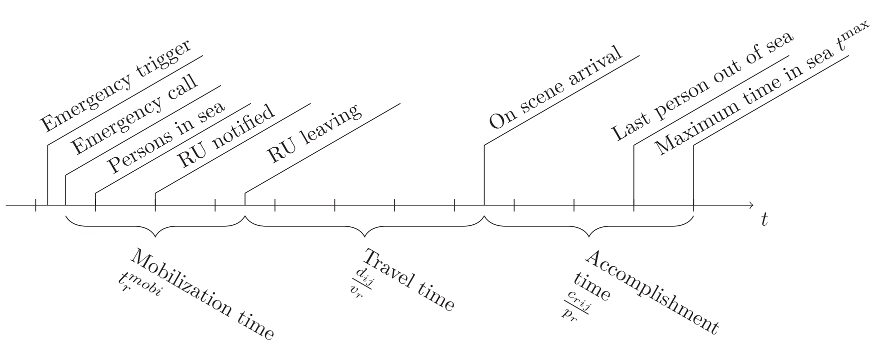

Fig. 2. Time components of a response, and their key drivers.

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As the travel time for each RU is different, the collaborative pick-up rate will vary over time. Fig. 4 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 Eq. (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 Fig. 5. In the case of Fig. 5a 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 Fig. 5b, 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 Fig. 5b, as areas with a rescue capacity below 21 are not shown. If the full capacity range is shown, as in Fig. 5c, 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 Fig. 5b, 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).

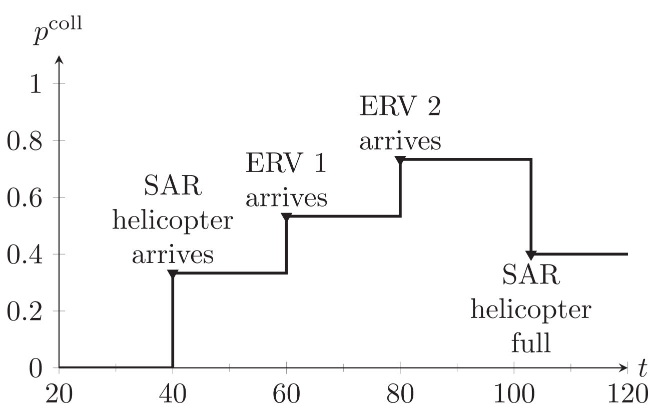
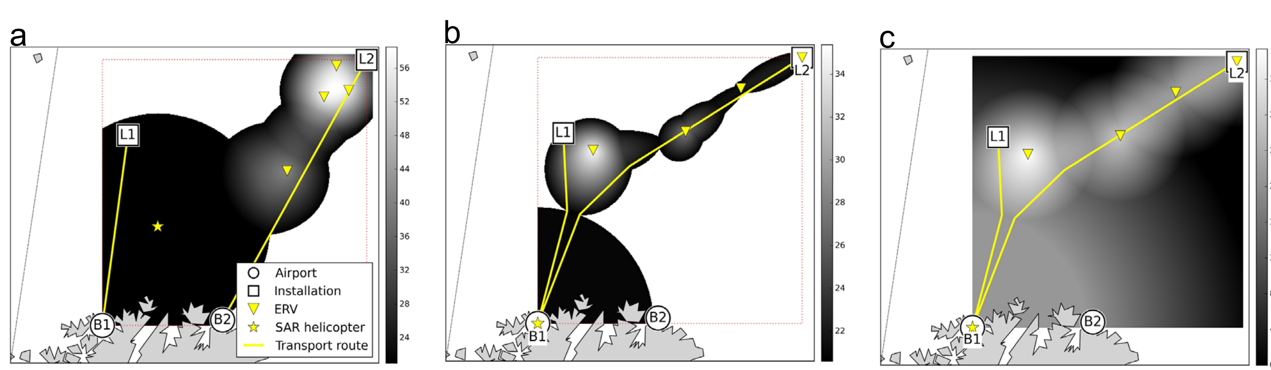


Fig. 4. Example of how the collaborative pick-up rate is changing during a rescue operation.

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 [19]. 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.



Freely placeable SAR helicopter. Offshore locations can be reached directly.

SAR helicopter fixed to $B1$. Routes need to be bundled in order to be within the corridor.

Full range of capacity.

Fig. 5. 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.

3.1. Basic model

Let $\mathcal{R}$ be a set of RUs, and $\mathcal{S}_r$ the set of nodes where a resource $r \in \mathcal{R}$ can be placed. Let $\mathcal{B}$ be a set of starting nodes such as onshore bases, and $\mathcal{L}$ a set of destination nodes such as offshore locations. Furthermore, let $\mathcal{N}$ be the set of nodes which can lie on paths that connect the starting and destination nodes. Let $\mathcal{K}$ 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 $(i,j) \in \mathcal{K}$. 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 $\mathcal{K}$ that provides end-to-end connections for each destination node, $l \in \mathcal{L}$, from a starting node, $b \in \mathcal{B}$. 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 Eq. (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 $(i,j) \in \mathcal{K}$ is selected for the path to $l \in \mathcal{L}$, and 0 otherwise. Finally, y_{ri} is a binary decision variable that equals 1 if resource $r \in \mathcal{R}$ is placed at node $i \in \mathcal{S}_r$, and 0 otherwise. The CRCP can be written as follows:

$$\min \sum_{(i,j) \in \mathcal{K}, l \in \mathcal{L}} d_{ij} x_{lij}, \tag{3}$$

$$\text{s.t.} \quad \sum_{i \in \mathcal{S}_r} y_{ri} = 1, \quad r \in \mathcal{R}, \tag{4}$$

$$\sum_{(b,j) \in \mathcal{K} \mid b \in \mathcal{B}} x_{lbj} = 1, \quad l \in \mathcal{L}, \tag{5}$$

$$\sum_{(i,j) \in \mathcal{K}} x_{lij} - \sum_{(j,k) \in \mathcal{K}} x_{ljk} = 0, \quad j \in \mathcal{N}, \ l \in \mathcal{L}, \tag{6}$$

$$\sum_{(i,l) \in \mathcal{K}} x_{lil} = 1, \quad l \in \mathcal{L}, \tag{7}$$

$$\sum_{(b,j) \in \mathcal{K}} \sum_{l \in \mathcal{L}} x_{lbj} \le w_b |\mathcal{L}|, \quad b \in \mathcal{B}, \tag{8}$$

$$\sum_{(i,j) \in \mathcal{K}} \sum_{l \in \mathcal{L}} x_{lij} \le w_j |\mathcal{L}|, \quad j \in \mathcal{N} \cup \mathcal{L}, \tag{9}$$

$$\sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{S}_r} y_{ri} c_{rij} \ge w_j c^{\min}, \quad j \in \mathcal{N} \cup \mathcal{L} \cup \mathcal{B}, \tag{10}$$

$$x_{lij} \in \{0,1\}, \quad l \in \mathcal{L}, (i,j) \in \mathcal{K}, \tag{11}$$

$$y_{ri} \in \{0,1\}, \quad r \in \mathcal{R}, \ i \in \mathcal{S}_r, \tag{12}$$

$$w_j \in \{0,1\}, \quad j \in \mathcal{N} \cup \mathcal{L} \cup \mathcal{B}. \tag{13}$$

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 $\mathcal{S}_r$. Constraints (5) ensure that every path to a destination $l \in \mathcal{L}$ starts at exactly one starting node in $b \in \mathcal{B}$. 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 than 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 [20], 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 $(b,l) \in \mathcal{P}$ has to be formed that defines the legs of the tours, where $b \in \mathcal{B}$ is the starting node and $l \in \mathcal{L}$ 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 $\mathcal{P}$:

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

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 [13] 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:

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

$$\text{s.t.} \quad (4)\text{–}(9),$$

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

$$g_j \ge 0, \quad j \in \mathcal{N} \cup \mathcal{L} \cup \mathcal{B}. \tag{17}$$

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 $\sum_{j \in \mathcal{N} \cup \mathcal{L} \cup \mathcal{B}} g_j = 0$ 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 Fig. 6. 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.

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$^{\text{goal}}$, as follows: We define M as a constant that

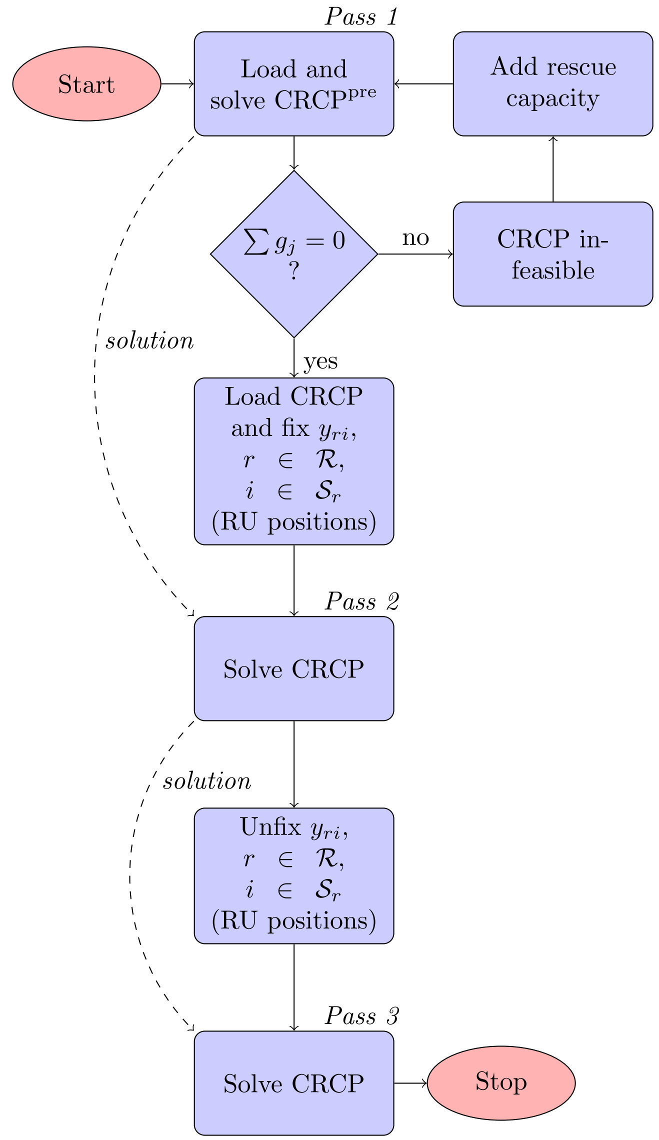


Fig. 6. Flow diagram of 3-pass method.

denotes the penalty for the coverage gap.

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

$$\text{s.t.} \quad (4)\text{–}(9), (11)\text{–}(13), (16), (17). \tag{18}$$

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

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2 virtual CPUs and 15 GB of memory [3]. Gurobi Optimizer in version 5.6.3 was used as the solver for the MIP model.

Sets $\mathcal{R}$, $\mathcal{B}$ and $\mathcal{L}$ are the RUs, onshore bases, and offshore installations respectively. The sets $\mathcal{N}$, $\mathcal{S}_r$, and $\mathcal{K}$ are built as illustrated in Fig. 7: First, $\mathcal{N}$ 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 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 $\mathcal{S}_r$ is the union of $\mathcal{B}$, $\mathcal{L}$, and $\mathcal{N}$ for ERVs and equal to $\mathcal{B}$ for SAR helicopters.

The set $\mathcal{K}$ is formed by generating arcs to nodes in the Moore neighborhood (all nodes within a Chebyshev distance of the grid spacing) for each node in $\mathcal{B} \cup \mathcal{L} \cup N$. 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-neighboring node. Increasing the neighborhood 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.

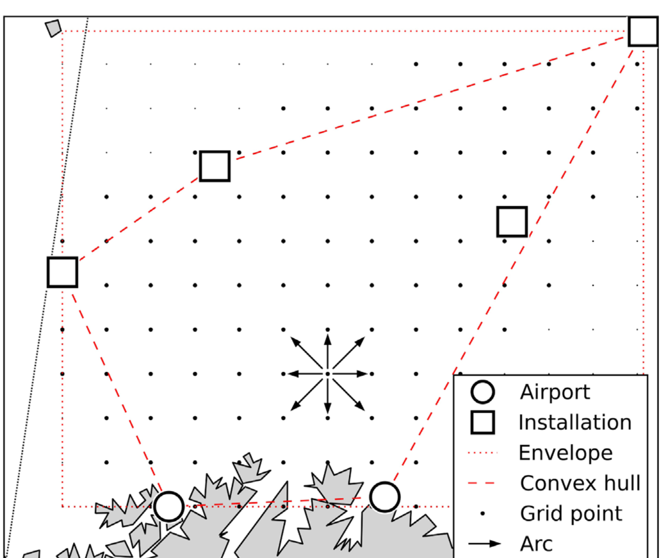

Fig. 7. Illustration of the area discretization, grid point reduction, and generation of arcs to Moore neighborhood.

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 *B*1 and *B*2 are existing airports in this area. Installation *L*1 is placed within the Wisting Central field, which is the northernmost oil discovery on the Norwegian continental shelf. Installation *L*2 marks the north-easternmost location which could come into consideration in a possible future licensing round. Installation *L*3 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 *L*4–*L*8 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 *L*1–*L*3, Instance 2 contains *L*1–*L*4, and Instance 3 contains *L*1–*L*8. 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 [25]. 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. 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. *B*1, *B*2, and *L*1–*L*3 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

Fig. 8 illustrates solutions using the 3-pass method for Instance 2. After the first pass (Fig. 8a) 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 (Fig. 8b). This solution is further improved in Pass 3 (Fig. 8c).

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 h 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

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

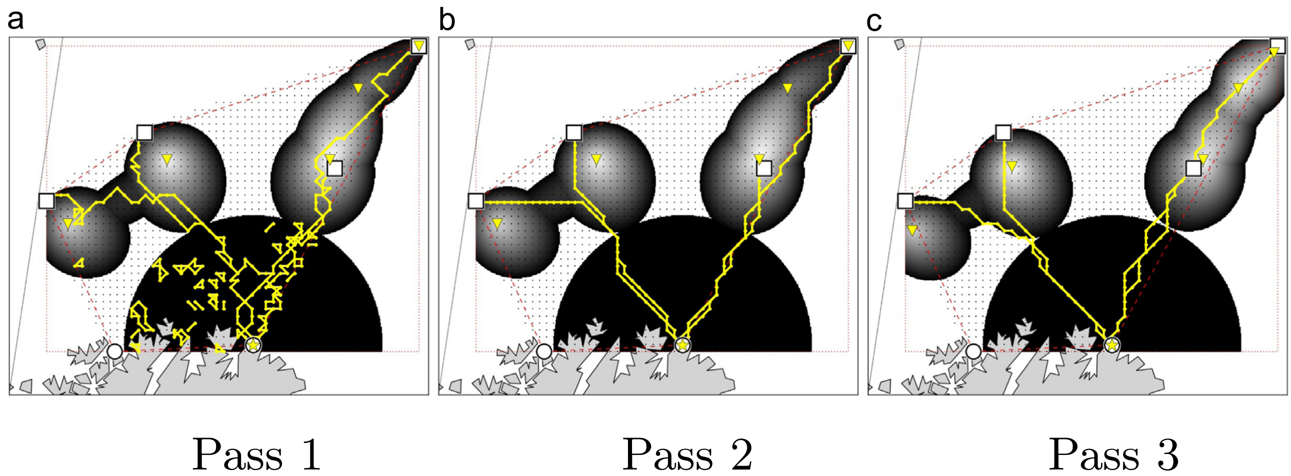

Fig. 8. Illustrations of solutions to Instance 2 after each pass of the 3-pass method.

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.

s	Direct			Goal		3-pass		
	t^f	t^*	*gap*	t^*	*gap*	t^f	t^*	*gap*
Instance 1 (Best value: 1,273,866.80)								
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: 1,571,662.67)								
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: 2,784,471.31)								
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	

methods. For Gurobi this is possible by using the parameter `Seed` [11]. 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 [15]. 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 [13]. 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 h 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 [17,25]. Three of these areas contain 5 fields and one area contains 9 fields, which 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 Fig. 9. 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 h 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. Fig. 10 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 h with an optimality gap of 1.56%, 1.26%, and 1.37% respectively.

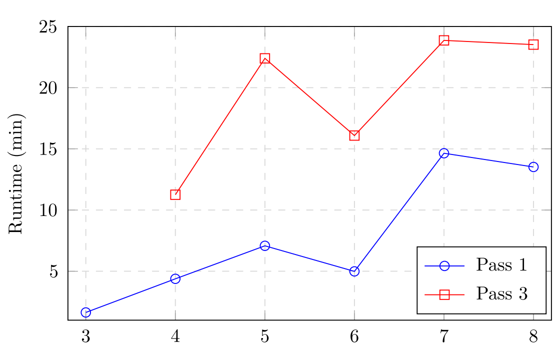

Fig. 9. Number of offshore locations vs. runtime.

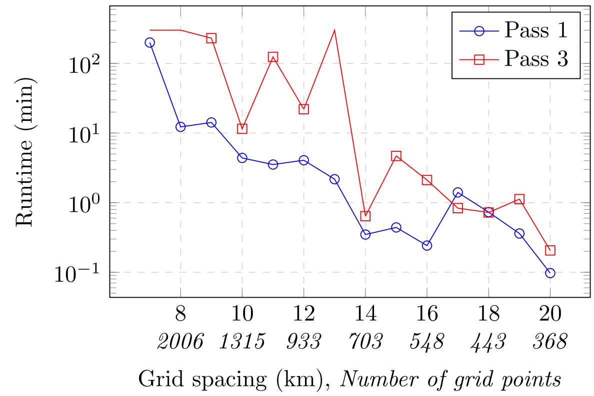

Fig. 10. Grid spacing vs. runtime.

5.3. Effect of rescue capacity requirements on transport routes

Fig. 11 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^{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 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 min. 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 Fig. 12. The legs are in this case defined as follows: $\mathcal{P}=\{(B2^0,L1^0),(L1^1,L3^0),(L3^1,B2^1),(B2^0,L4^0),(L4^1,L2^0),(L2^1,B2^2)\}$, where the superscript n denotes the nth 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

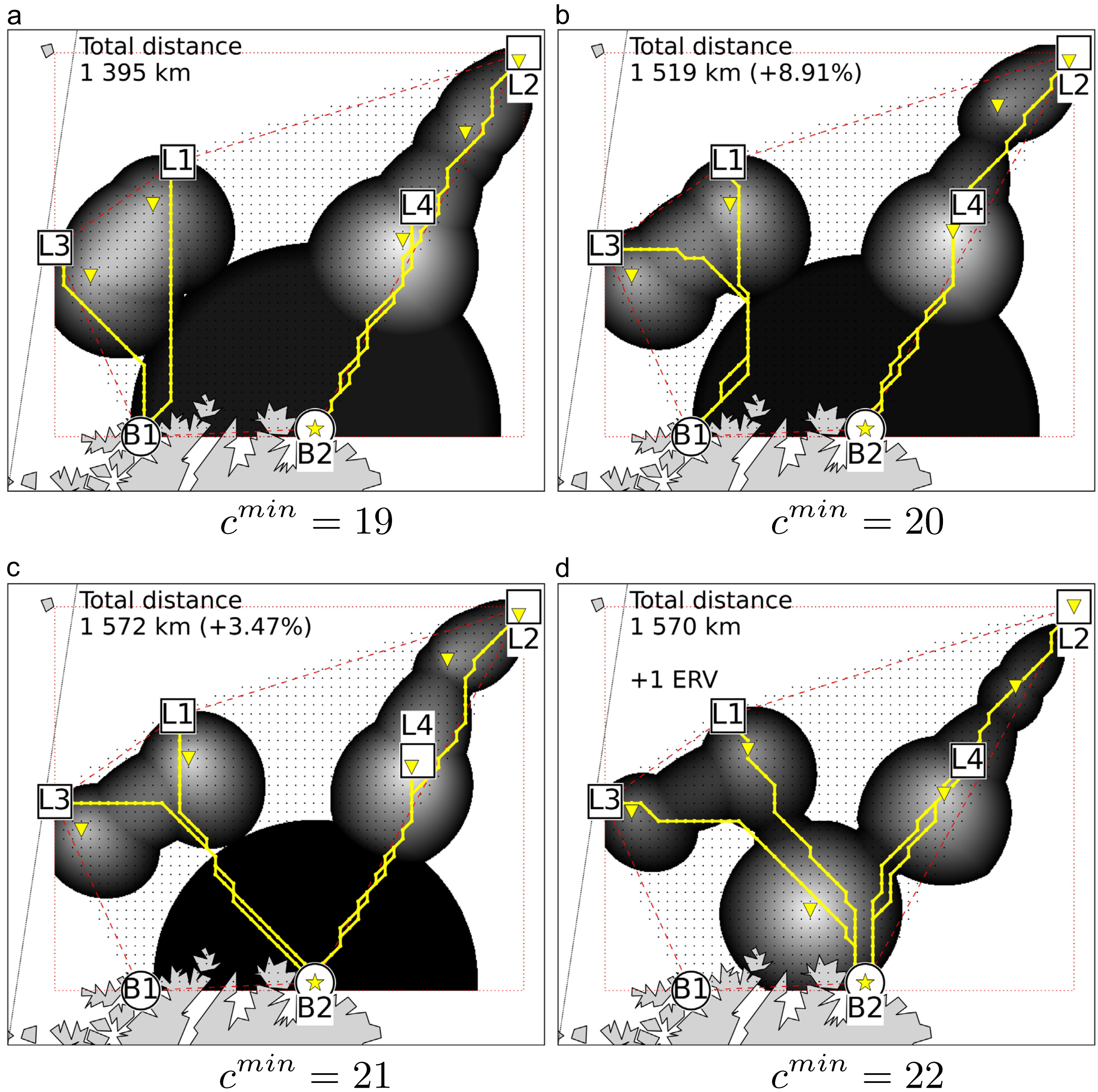

Fig. 11. Transport routes dependent on minimum rescue capacity c^{min}. Total distance is the sum of paths from onshore base to offshore location. Percentage value denotes the total distance increase related to $c^{min}-1$.

Table 4
Capacity gap as resources are added.

Added resource	*Capacity gap*	*Additionally 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

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

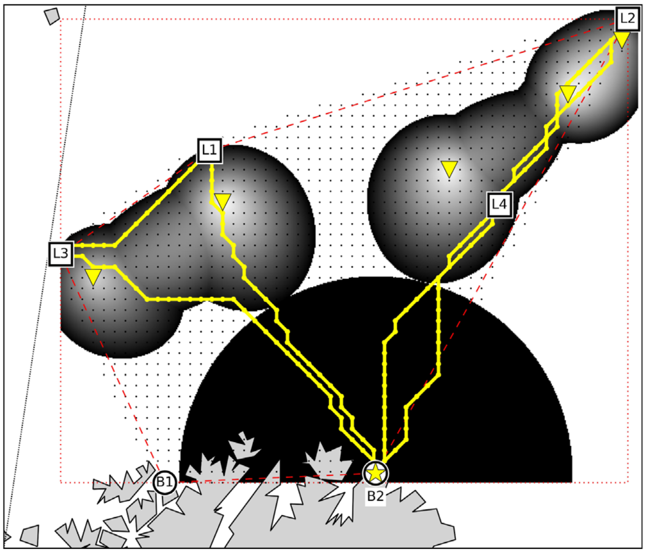

Fig. 12. Illustration of a solution to Instance 2 where helicopters transporting personnel follow round trips to visit the offshore installations.

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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