



Master's degree thesis

LOG950 Logistics

**Optimization models for Emergency Preparedness in
the Arctic Region**

Fredrik Berg Stien

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Abstract

In order for oil & gas companies to operate in the Norwegian continental shelf, they have to show that they are operating in a safe manner. In difference from other areas on the Norwegian continental shelf, the Barents Sea stands out with sparse infrastructure, harsh weather and potentially longer distances to the offshore installations. Emergency preparedness, when transporting personnel back and forth to the offshore installations, is of huge importance.

This thesis presents multiple mathematical models that are developed in order to ensure safe helicopter transportation of personnel from onshore bases to offshore installations in the Barents Sea. The models seek to find the optimal locations of Rescue Units (RUs) to protect helicopter transportation routes of offshore personnel. The most frequently used performance measurements for emergency preparedness are related to distance of the helicopter route or to capacity standards for the industry. An essential part of this research has been to establish different types of performance measurements such as First Responder Time and Minimum Capacity which are reflected through the developed models. The research shows that only focusing on distance related measurements, has an undesirable effect on the proposed measurements, and that the emergency preparedness system will benefit from implementing the new measurements. Multiobjective models are introduced, being able to take into account all the new performance measurements, and shows a positive effect on the total performance of the emergency preparedness system. In order to obtain a solution to the problem in some instances where the exact methods come short, an improvement heuristic is proposed.

The models and methods provided in this paper are case specific, as it focuses specifically on emergency preparedness in the Barents Sea. However, it is reasonable to imagine that the models and methods can be applied in other areas in the Norwegian continental shelf and even in other international offshore environments. It is also reasonable to imagine that the ideas that are presented in this research are also transferable to other emergency preparedness environments, such as the police, the fire brigade and for the emergency medical services.

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1. Introduction

Since the first significant oil find on the Norwegian continental shelf in 1969, Ekofisk, the Norwegian oil & gas sector has become a highly developed industry and also the most important industry for Norway in terms of value creation and income. Areas like the Norwegian Sea and the North Sea are highly developed in terms of oil & gas installations and oil & gas related infrastructure. However, the Norwegian oil & gas area in the Barents Sea (Figure 1) is considered an immature area even though the search for oil and gas has been ongoing for almost thirty years. Until now, there are only two installations operating in the Barents Sea. Snøhvit, which is a gas subsea installation, has been producing since 2007 (Olje- og Energidepartementet 2014), while Goliat was put into production early 2016. The undiscovered oil & gas resources in the Barents sea is estimated to be approximately 1/3 of the total undiscovered oil & gas resources on the whole Norwegian continental shelf (Olje- og Energidepartementet 2014). With such a high amount of undiscovered resources, it is likely that this region will see an increase in oil & gas production in the future.

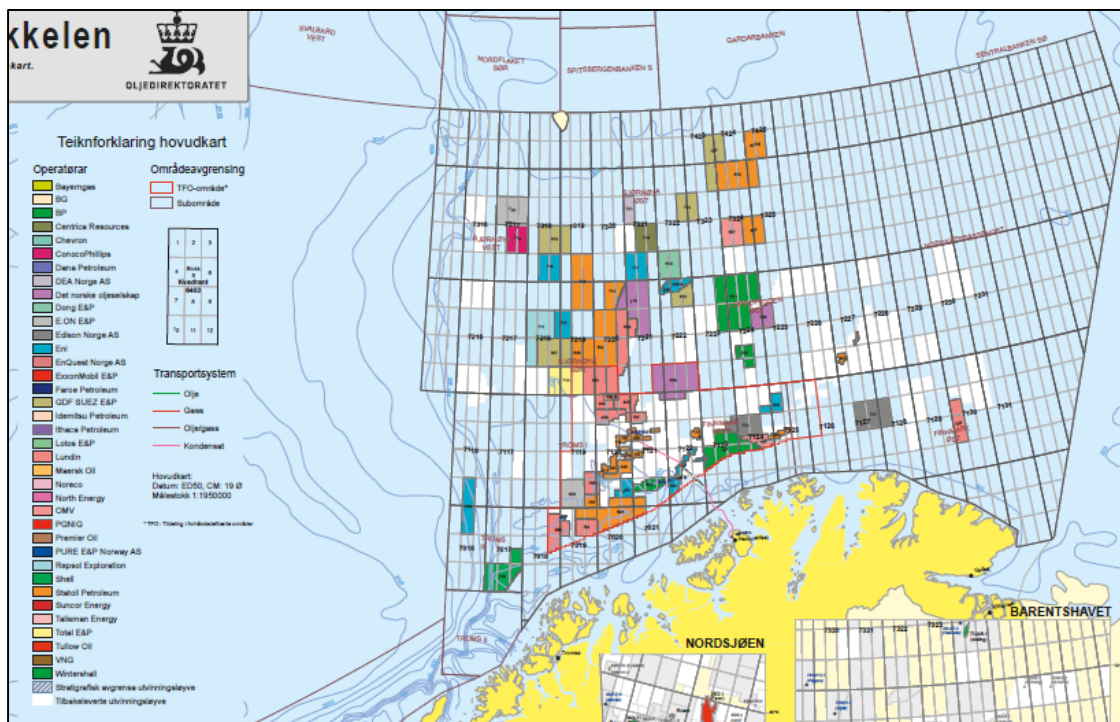


Figure 1 - Shelf map, the Barents Sea. Source: Norwegian Petroleum Directorate(2015)

The Barents Sea stands out from the other Norwegian oil & gas areas in terms of sparse infrastructure, harder weather conditions and potential longer distances from the land to the offshore installations. Among many requirements and guidelines that the offshore operators

have to follow, emergency preparedness is one of them. Companies wanting to operate in the Norwegian offshore sector have to show that they are operating safe and within certain requirements. Emergency preparedness is costly, and the importance of finding efficient and innovative solutions within this field can make a huge difference in terms of cost reduction for future companies wanting to operate in the Barents Sea. The main objective of this research will be to construct and compare mathematical models and methods for placing Rescue Units (RUs) in the Barents Sea giving rescue coverage for helicopter routes to offshore installations.

This paper is structured in the following way: Section 2 gives a description of the problem. It presents the terminology and the buildup of parameters such as response capacity and response time, which are important for the understanding of the problem. In addition to describing the problem, the research questions are also presented. Section 3 presents relevant literature for the research. It presents literature in association with the current guidelines and rescue performance in the Norwegian oil & gas sector. It also presents and review methods that can be applied for solving routing and coverage problems, as in the Barents Sea case. Section 4 describes the methodology that is used for solving the problem. It gives a description of the test instances that will be used for evaluating the model performances. Information about the buildup of the computation study is provided, explaining which models and instances are used for the research experiments. In Section 5, the mathematical structure of the exact models is presented among with a description of its objective and constraints. In addition, the section provides a description of a heuristic method that is used in situations where the exact methods comes short. The computational study with its result is presented and discussed in Section 6, followed up by concluding remarks and recommendations for future research in Section 7.

2. Problem description

In this section, a detailed description of the problem is presented. The section is divided into four subsections, each describing different sides of the problem. The first section gives some background information and motivation for the research as well as an interpretation of the main requirement for Emergency Preparedness in the Norwegian Oil & Gas sector. The second section gives a detailed description of the behavior of the parameters that are used in the research together with a description of different types of resource. The section also interprets and describes necessary assumptions. The third section provides a description of the objectives and performance indicators for the research, while the fourth and last section present the research questions.

2.1 Emergency Preparedness Requirements

Helicopter is by far the most used transportation method for moving personnel to offshore installations in the Norwegian offshore oil & gas industry. In 2014, approximately 690000 passengers were transported to Norwegian offshore installations (Avinor 2014). Helicopter transportation is considered as one of the most dangerous transportation methods. From year, 1990 to 2009 there has been recorded 5 accidents with 12 fatalities for passenger transportation in the Norwegian continental shelf, which corresponds to an accident rate of 0.9 fatalities per million person flight hours (Herrera et al. 2010). Health Safety and Environment is of high importance in the oil & gas sector, resulting in strict regulations and requirements for the operators. Among many requirements in the offshore oil & gas industry, Emergency Preparedness Requirements is one of them. In order for the companies to operate in the offshore industry, they have to show that they are able to operate safely. Regarding Emergency Preparedness and offshore personnel transport, the operators have to provide sufficient capacity to rescue people if a helicopter ditches, within a given amount of time.

The main objective of this paper is to provide solutions for creating Emergency Preparedness designs for offshore operators in the Barents Sea. To be more specific, the tasks will be to both decide the routes of the personnel transportation helicopters from the airports to the offshore installations and at the same time decide the positions of Rescue Units (RUs) that should be able to cover the helicopter routes with rescue capacity. Just like in the southern part of Norway, there exist rescue capacity in terms of National Preparedness in the Barents Sea. The Coast Guard and the Norwegian Sea Rescue (NSSR) both have rescue capacity in terms of navy vessels. In addition, it is stationed a Sea King helicopter in Banak airport in

Lakselv which is operated by the Royal Norwegian Air Force (Jacobsen and Gudmestad 2013). Even if there exist national rescue capacity in an oil & gas area, the offshore industry solely has to provide the rescue capacity themselves. The time of survival at sea is influenced by different factors, like sea temperature, sea state, quality of immersion equipment and physiology of the personnel (Golden and Tipton 2002). Due to the risk of both hypothermia and drowning if the personnel is forced to leave the helicopter in a ditching situation, the offshore industry has established a guideline which implies that a full helicopter of 21 persons should be picked up within a time of 120 minutes (Vinnem 2012). The 120-minute rule is set to be only within a 500-meter safety zone around the offshore installation. The risk associated with offshore personnel transportation is considered the highest at takeoff and landings, which supports the requirement of high emergency preparedness around the offshore installations. However, there are no reason for not applying this requirement for the whole transportation route (Jacobsen and Gudmestad 2013). Therefore, this research will use the assumption of the 120-minute rule applying from when the transportation helicopters leave the airport until they arrive on the offshore platforms.

In a real life situation, multiple helicopters might be performing transportation at the same time, resulting in a very low possibility of two or more incidents taking place simultaneously. However, it is assumed in this research that only one incident can happen at a time.

2.2 Rescue Units and Rescue Capacity

In situations where the potential transportation distances are long, just like in the Barents Sea, it might be necessary to use different types of RUs in order to carry out the rescue. Search And Rescue (SAR) helicopters are the most used RU in the Norwegian oil & gas sector. The SAR helicopters have limitations in travel distance due to fuel capacity and fuel usage. As a result of the travel limitations of the SAR helicopters, it is necessary to also use Emergency Rescue Vessels (ERV), which have to be positioned at sea at areas where the SAR helicopter cannot reach. Combining the response capacity of these two RUs, the personnel transportation routes should be fully covered with the rescue capacity of 21 people within 120 minutes.

In order to understand the problem and the forthcoming models, it is necessary to get an overview of the performance of the RUs, the time components of sea rescue and most im-

importantly the relationship between them. SAR helicopters and ERV boats have different characteristics and performance. For example, a SAR helicopter has a higher speed than an ERV boat, and is therefore able to do rescue at longer distances. On the other hand, a boat is able to carry more people than a SAR helicopter. In general, the SAR helicopters are restricted to be located at airports on land or at offshore platforms, but can also be located at special types of boats on sea, whereas ERV boats are restricted only to be located at sea. These RU performances will influence both the response time and response capacity along the route. Figure 2, which is inspired by the paper by Brachner and Hvattum (2016), gives an illustration about the time components that together defines the response time of the rescue. Some parameters define the performance of both the rescue and the RUs. The rescue process is divided into three main time periods, which is illustrated at the lower part of the figure. These periods are defined by different instances taking place along the time horizon, which is shown at the upper part of the figure. What is a central part of the rescue situation is to protect the transportation route with sufficient capacity. The rescue capacity is defined with the parameter c . As initiated earlier, the offshore guidelines describes the minimum capacity to be no less than 21 people, which is defined as c^{min} . The minimum capacity, c^{min} , is strongly related to the maximum time horizon of the rescue which is set to be 120 minutes, hereby referred to as t^{max} .

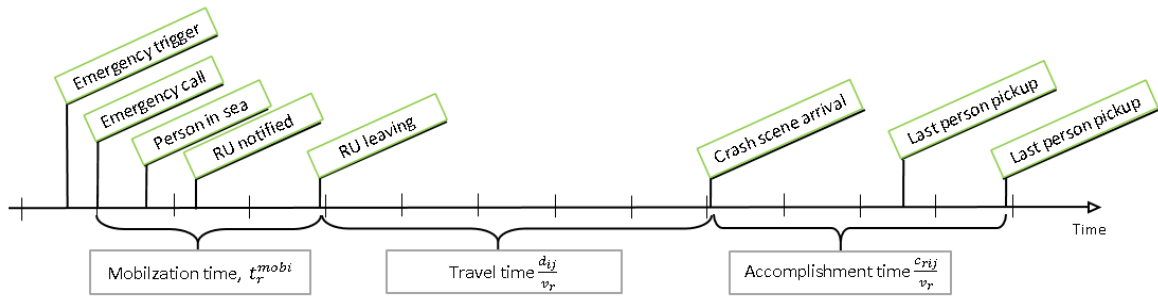


Figure 2 - Time components of emergency response and personnel rescue at sea

The emergency trigger is the basis for the rescue operation. For example, an emergency trigger can be a failure in the helicopter engine, resulting either in a ditch or in crash. An emergency call is normally sent from the helicopter to the emergency center. In some cases it is likely to imagine that the notification to the emergency center happening after the ditch, but in this research, we assume this happening before the helicopter ditches. After the emergency center has received the emergency notification, the RUs are notified about the situation. The relevant RUs will prepare for departure with destination to the crash scene. The

time it takes from when the emergency center is notified about the emergency until the RU departs its base, is referred to as the mobilization time, t_r^{mobi} . The mobilization time is resource dependent, meaning that one resource might have a faster mobilization time than another. In general, the ERV does not carry out the rescue by itself, but has a Fast Rescue Daughter Craft (FRDC), which is more mobile than the ERV itself and will be launched from the ERV in a rescue situation. A SAR helicopter typically needs to warm up the engine to a higher extent than an ERV before starting the transportation to the crash scene. Therefore, t_r^{mobi} , refers to the mobilization time of resource r , and will vary from resource to resource.

The travel time is also resource dependent. A SAR helicopter has a significantly higher speed than an ERV boat and its FRDC. The speed parameter is described as v_r . Not only is the travel time dependent on the speed of the RU, but also on the distance from the RUs position i , to the ditching position j , which is described with the parameter d_{ij} in Neutical Miles (nmi).

After the RU arrival at the ditching scene, the pickup of personnel at sea will start immediately. The RUs has different ability of picking up people. Therefore, the pickup rate p_r of personnel will differ between SAR helicopters and ERVs. The difference of the time between when the pickup is finished until the 120-minute time limit has been reached, can be interpreted as an over-capacity in terms of time and personnel. The accomplishment time is dependent on the capacity of the RU, r , at the ditching site and its pickup rate p_r . If the number of people in sea at the site is higher than the total capacity, there will not be sufficient resources and capacity to save all the personnel. The capacity, c_{rij} , of a RU doing rescue at a ditching site is dependent on the time it takes from its original position to the site. In other words, c_{rij} is dependent on the distance from its original position i to the ditching position j , and the speed v_r of RU r doing rescue. The rescue capacity if a RU at a ditching can be expressed as shown in function (1)

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

When deciding upon parameter values for the performance of RUs, it is necessary to do this based on assumptions. Parameters like pickup rate and speed of the RUs is by nature affected by conditions like weather and visibility, and will influence the performance of the response capacity. For example, the pickup rate of a boat will drop if the waves are high and especially if there is low visibility. There has been developed methods for also taking into consideration these stochastic parameters (Brachner 2015). However, these type of methods often includes simulations, which is not the scope of this research. Table 1, indicates the RU parameter values which are used for this research. The values are used based on recommendation from the articles by Jacobsen and Gudmestad (2013), and Vinnem (2012). The recommendations of RU performance parameters provided in these papers are done with a conservative approach. For example, an FRDC boat, which is referred to as an ERV boat in Table 1, is able to operate at a speed of 45 knots in calm sea with two people on board. However, with a conservative approach which is based on the fact that the sea not often is calm, it is reasonable to readjust the ERVs speed to be lower than what is actually possible.

<i>Parameter</i>	<i>SAR</i>	<i>ERV</i>
t_r^{mobi} (Minutes)	15 min	5 min
v_r (Knots)	140 kt	30 kt
	2 1/3 nmi / min	1/2 nmi / min
c_r^{max} (Persons)	21	24
p_r (Person / minute)	1/3	1/5

Table 1 -Rescue Unit performance -

As a way of understanding the capacity function (1), it might be valuable to give a small example. Imagine a situation where the distance from a potential crash point on a helicopter route to the position of the SAR helicopter is 175 nmi, which corresponds to a distance of approximately 324 kilometers. From the calculations in Figure 3, it is possible to see the logic of the capacity function. The mobilization time t_r^{mobi} , pickup rate p_r , and the speed v_r are the only parameters which are resource dependent, and will be constant based on the RU choice. The only parameter influencing the physical capacity, other than the RU properties, is the distance d_{ij} . From Figure 4, it is clear how the capacity decreases in pace with the distance needed to travel by the RU. The capacity of an ERV has a steeper decline over distance compared to the SAR due to its lower speed. The maximum distance by which the

SAR helicopters and ERV boats ability to save personnel is limited to respectively 238 and 55 nmi. This limit is restricted by the fact that there will not be sufficient time to save one person within 120 minutes for the RU. Another aspect of the rescue which is visual from Figure 4, is the meaning of the physical capacity c_r^{\max} of a RU. If not considering the physical capacity, the SAR helicopter would be able to save more than 21 people. For example, with a traveling distance of 20 nmi for a SAR helicopter, it should be able to save 32 people. However, due to the physical capacity of the SAR helicopter, it would only be able to save 21 people. In case of the capacity of the ERV, it will never be able to pick up its maximum capacity of 25 people. If the ERV is located at the same place as the incident scene, that is a distance of 0, it will only be able to save 23 people due to the mobilization time and pickup-time.

$$\begin{aligned}
 c_{rij} &= \left\lfloor \max \left\{ 0, \min \left\{ 21, \left(120 - 15 - \frac{175}{2^{1/3}} \right) 1/3 \right\} \right\} \right\rfloor \\
 &= \left\lfloor \max \left\{ 0, \min \left\{ 21, (120 - 15 - 75) 1/3 \right\} \right\} \right\rfloor \\
 &= \left\lfloor \max \left\{ 0, \min \left\{ 21, 10 \right\} \right\} \right\rfloor \\
 &= 10
 \end{aligned}$$

Figure 3 - Capacity calculation, an example

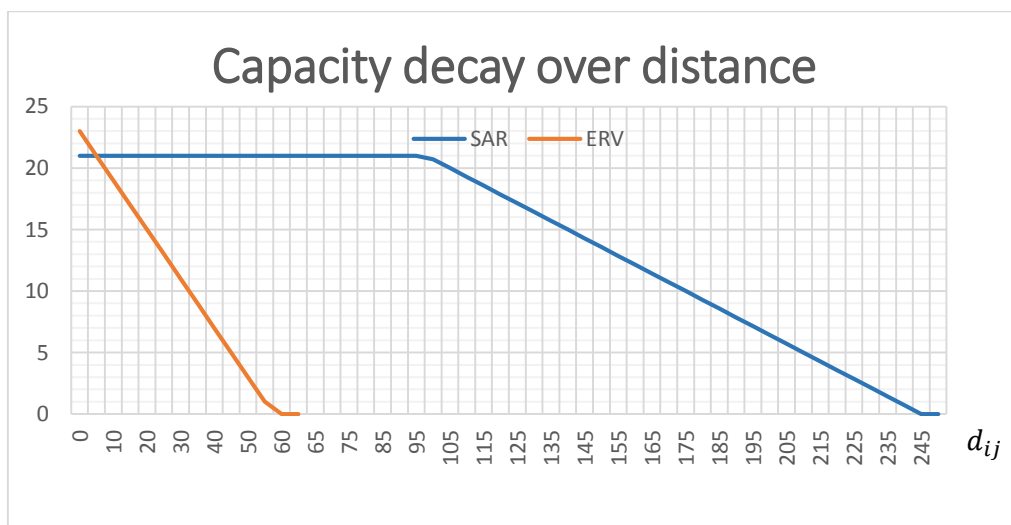


Figure 4 - Capacity over distance

An important aspect of the capacity usage is the fact that the RUs can collaborate on the capacity along the route. Consider a point of the helicopter route where a helicopter is able to reach with a capacity of 11 people and a boat is able to reach with 15 people. In total, this point is covered with a capacity of 26 people, which is well within the capacity requirement. The fact that the RUs can collaborate on covering the transportation route has a huge impact on the emergency preparedness design. If an ERV does not have backup coverage from another RU, it will only be able to save 21 people within a radius of 5 nmi (9.26 km) in 120 minutes. Considering the capacity function (1) again, the reason for flooring (rounding down) the capacity of each RU seems more logical when two or more RUs can collaborate. For example, if two ERVs are collaborating on picking up 21 people, both with a capacity of 10.5 people, it is hard to imagine how they will collaborate on picking up the last person. Flooring the capacity might be a conservative approach, but can be supported by the fact that it is reasonable to do so when working with emergency and safety.

Figure 5 and Figure 6 illustrates a possible scenario of an emergency preparedness design with helicopter routes and corresponding RU positions. From Figure 5, the blue areas represents the part of the route that is covered with rescue capacity. The yellow lines will have to be positioned in the blue parts of the map in order to have a valid emergency preparedness system. Figure 6, also gives an indication of which areas that are within the capacity requirements or not, but does also give an indication of the level of capacity within for each area of the polygon. It is clear that the blue areas from Figure 5 actually has quite large differences in terms of capacity when comparing them with their corresponding areas in Figure 6. The pure grey areas in Figure 6 have a capacity of 21 people, which is the maximum capacity of the SAR helicopter. It is possible to see from the figure, that the SAR helicopter seems to cover the capacity requirements alone in a quite big surrounding from its position, due to the relatively small covering radius of the ERVs. The closest surrounding areas of the ERVs, typically have a higher capacity. The two westernmost positioned ERVs both have overcapacity, which is a result of the SAR helicopter being able to support the areas. However, by considering the northeastern ERV, which is located at the same position as the oil & gas installation, it is not surrounded with overcapacity because the ERV does not have backup capacity from other RUs. The two ERVs that are located closely to each other, gives a good illustration of the effect of RU collaboration. Since the SAR helicopter is able to do rescue at the surrounding areas around the two ERVs, it is at most three RUs able to provide rescue/capacity, which is illustrated by the relatively big and dark area around them. The two

figures clearly shows that the positioning of the RUs heavily influences the capacity along the route.

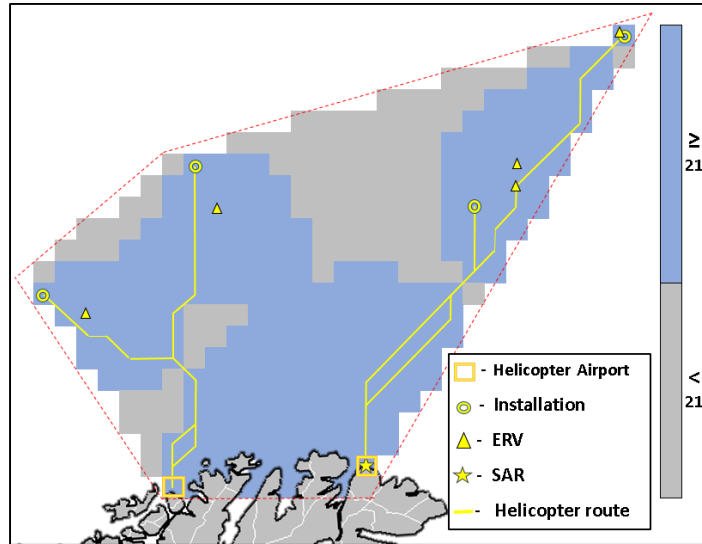


Figure 5 – Map over covered ares

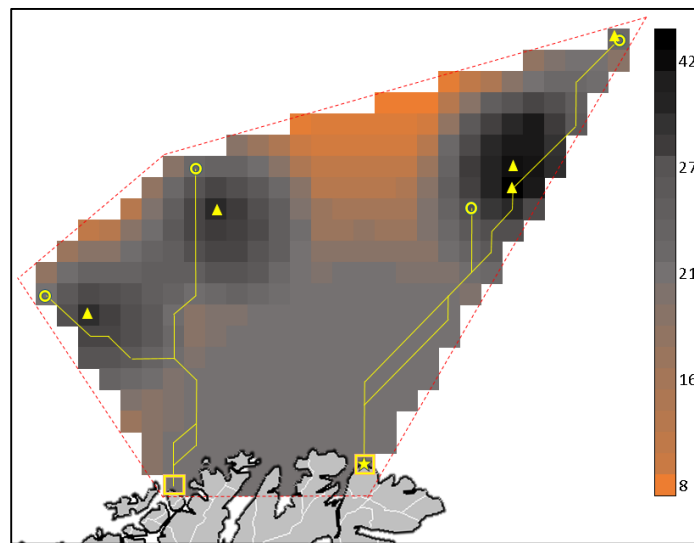


Figure 6 – Map over covered area with capacity illustration

2.3 Objectives and Performance Indicators

Many potential performance indicators can be used for creating and evaluating mathematical models for emergency preparedness designs. The objectives and performance indicators are important when using the models as decision support tools. As stated in the Section 2.1, the main objective when creating the emergency preparedness design is to both find a route for transporting personnel to offshore installations while at the same time determine positions for the RUs to contribute with rescue capacity. The article by Brachner and Hvattum (2016), which is wider explained in both Section 3.1 and Section 5.1, focuses on minimizing the distance of the personnel transportation route while at the same time being within the capacity restrictions. Except the 120-minute requirement, there is no other incentive for where to position the RUs, resulting in emergency response designs where there might exist alternative solutions in terms of the positioning of RUs. Therefore, as the title of the research indicates, the goal for this research will be to make alternative models for emergency preparedness which examines other objectives and performance indicators. The main objectives and performance indicators that will be included in this research is as listed underneath:

- Total transportation distance
- Lowest observed response capacity
- Average first responder time
- Highest observed first responder time

The total transportation distance is the standard measurement and objective in the model by Brachner and Hvattum (2016). This objective might be the most important objective for potential offshore operators in the Barents Sea, as a lower transportation distance will result in lower cost in terms of fuel. Not only will it keep the cost at a desirable level, but it will also reduce the risk associated with helicopter transportation for the offshore personnel. Based on a risk model in the book by Vinnem (2014), it is specified that the time spent in a helicopter is one of the main contributions to the total risk of helicopter transportation. Only takeoff and landings at offshore installations have a higher risk factor.

Capacity is an essential factor in the decision of where to set the helicopter routes and where to locate the RUs. Normally, the emergency preparedness system will be designed in a way so that the number of RUs needed to meet the response capacity requirement of 21 people is minimized. Minimizing the number of RUs to meet the requirements will in most cases

result in a minimum response capacity along the route of no less than 21 people. However, the 120-minute rule is not interpreted as a strict requirement, but rather as a guideline for the offshore operators. Therefore, it might be accepted to reduce the capacity requirement in special situations. For example, the summer periods in the Barents Sea is much calmer in terms of weather, which might facilitate a lower capacity requirement. This argument is also convenient in situations where there exist overcapacity and the offshore operators want to ensure/guarantee a minimum response capacity level.

From Figure 2, the Mobilization Time and Travel Time is presented as one of the main time elements in the rescue process. These two time elements together reflect the time it takes for a RU to reach an incident site. The two time elements describe what is hereof referred to as Response Time. Function (2) shows how the response time, t_{rij} , is calculated. The Response Time, just like the Mobilization Time and Travel Time, is RU dependent. ERV boats have a lower mobilization time than SAR helicopters, meaning that ERV boats have the advantage of leaving their base earlier than the SAR helicopters. However, the SAR helicopters have much higher cruising speed than the ERV boats, resulting in an advantage for the SAR for longer distances. The relationship between Response Time and distance is presented in Figure 7. For example, the distance of where the ERV boat and SAR helicopter will arrive at the incident scene at the same time is at 6.63 nmi. For distances smaller than 6.63 nmi, the ERV boats will arrive the earliest, whereas the SAR helicopter will arrive earliest for distances longer than 6.63 nmi.

$$t_{rij} = t_r^{mobi} + \frac{d_{ij}}{v_r} \quad (2)$$

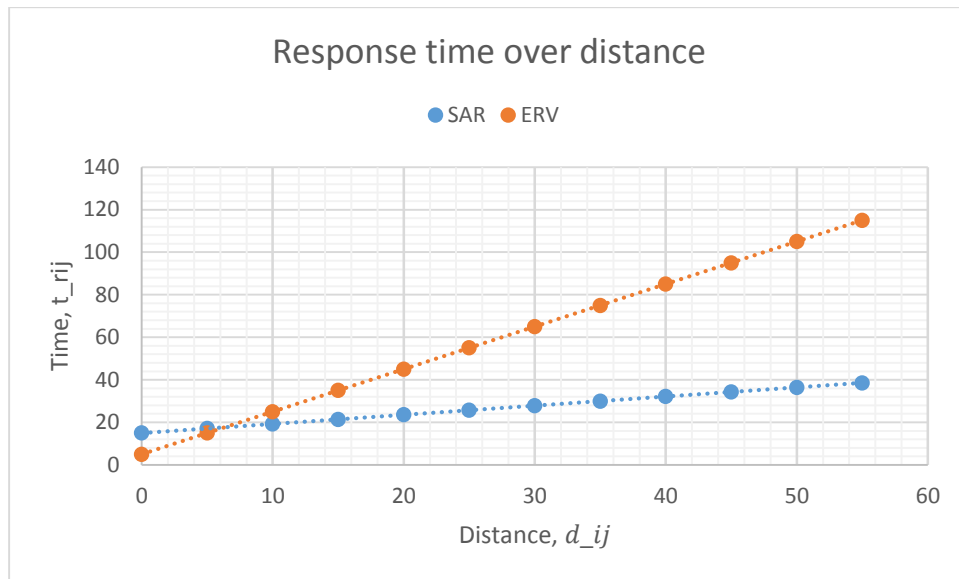


Figure 7 – Response time over distance

The Response Time will play an important role in the research, especially the First Responder Time. In situations where a helicopter has ditched or crashed, it is likely that some immersions suites might no longer be intact, allowing water to enter the suite. In cold sea temperatures and hard sea state like in the Barents Sea, the Response Time might be crucial of whether a person survives or not. With direct contact by the human skin and a water temperature of 5 °C, which is not unlikely during the winter period (Iden et al. 2012), the time until unconsciousness is estimated to be about 30 minutes (Golden and Tipton 2002). The First Responder Time, which is the time it takes for the first RU to arrive on an incident scene, will therefore be an important objective and performance measurement for the research. The First Responder Time is further split into two section, namely Average First Responder Time and Worst Case First Responder Time. The Average First Responder Time will measures the average time it takes for the first RU to arrive each potential incident scene along the route. The Worst Case First Responder Time on the other hand, will measure the maximum observed time it will take for the first RU to arrive a potential incident scene along the route. It is interesting to see the behavior of these two measurements when applying them as objectives the Emergency Preparedness Models.

2.4 Research Question

The purpose of this research is to examine different model designs and objectives for emergency preparedness in the Barents Sea. The performance of the models is therefore of great interest. The research question below will be helpful in the process of making conclusions of the model performance.

1. Under which circumstances will the solution provided when using different objectives actually differ from each other?
2. Which consequences would it have to choose one objective contra another?
3. Are there any disadvantages of applying some of the models / objectives?
4. Can some of the alternative models / objectives represent suitable alternatives to the existing model by Brachner and Hvattum?

3. Literature review

Both routing models and coverage models are well known within the optimization theory. However, the combination of both routing and coverage is a relatively immature field. This literature review will focus on different types of coverage and location models. It will also focus on relevant solution methods that will be used for solving and creating the models for emergency preparedness. Articles covering the performance of the RUs will be discussed, and the relevant guidelines for the offshore industry will be presented. Other relevant models that does not have a direct relationship with covering theory will also be reviewed.

3.1 Combined Routing and Coverage Problem

The most important literature for this research is the paper by Brachner and Hvattum (2016), which will be the base for this study. This article gives the assessment basis for the experiments in this specific research. Much of the same input data will be used in order to do a comparison. The paper by Brachner and Hvattum (2016) introduces a mathematical model which combines both routing and coverage (CRCP). The goal of this model is to find the optimal path for the helicopters from the helicopter bases to the offshore installations, and at the same time locate RU's so that they are able to cover the route within the response requirements. In order to handle the potentially large distances in the Barents Sea, the helicopters will not be able to cover the whole route, and ships will need to be placed at the sea to cover the parts of the route that the SAR helicopters cannot reach. The CRCP model is solvable for small instances (Brachner and Hvattum 2016), but is not solvable within reasonable time for big problems. In order to solve the model within reasonable time, it uses a 3-pass approach. This 3-phase model firstly simplifies the problem by decomposing the CRCP model, which results in a feasible solution in a relatively short time. This decomposed problem the user examine if it exists a feasible solution to the problem, which means that the number of RUs used in the model is sufficient so that the path can be fully covered. If it is feasible, the next step of the 3-pass model is to minimize the distances of the paths by fixing the RU positions from the first pass. The solution found in the second pass can generate a relatively good solution, but it is still possible to improve the solution. The last part unfixes the positions of the RUs and solves the CRCP model by starting with the solution found in the second pass.

A quite different article by Farahani et al. (2012) summarizes and reviews different type of location and coverage problems. The article covers both well-known models to more complicated and special models. It reviews and describes the notations, structure and the objective and constraints of the models. In general, most of the models consist of coverage problems and facility location problems. However, one model (Gendreau, Laporte, and Semet 1997) describes a problem which consist of both covering and routing. The Covering Tour Problem (CTP) minimizes the distance of a Hamiltonian cycle where some given nodes has to be visited. Each node, including the given visiting nodes, has a coverage radius. The Hamiltonian cycle has to be constructed in a way that the route covers certain vertexes in the graph.

3.2 Guidelines and rescue performance

The oil & gas industry has set a guideline for the offshore operators that states that 21 personnel in sea has to be saved within a time limit of 120 minutes. This guideline is described in a report by Vinnem (2012) that evaluates the emergency preparedness in the Norwegian oil & gas sector. Moreover, in theory this requirement does only apply within the 500-meter safety zone of an offshore installation. However, it is no logical reason why this requirement should not be applied during the whole personnel transportation that place over water (Jacobsen and Gudmestad 2013). Based on experience, it shows that to pick up 21 persons within 120 minutes is rather unproblematic. It must be said that these experiences are based on observations under good weather conditions. The ability to rescue personnel from the sea is influenced by factors like visibility, wind speed and wave heights. Even if the experience says that it is unproblematic to save personnel within 120 minutes, it is still important to have a conservative attitude toward personnel rescue rather than an opportunistic.

An important aspect when creating models for emergency preparedness is the properties and characteristics of the RUs. In addition to the 120-minute guideline, the report by Vinnem (2012) also analyzes the RU properties. SAR capacity, speed and pickup rate are input data needed when constructing the emergency preparedness models. Unlike SAR personnel capacity, the speed and pickup rate for the RU's are influenced by weather conditions like wind speed and wave heights. The report analyzes these factors under different weather conditions and provides recommendations for which parameter values to use for research purposes. As the report states, the recommendations are worked out based on earlier observations and with a conservative approach.

It is necessary to also find information about the performance of the ERV's and the FRDC which is launched from the ERV if an accident occur. Jacobsen and Gudmestad (2013), presents the performance of ERVs. This paper, like Vinnem's paper, provides information about the input values for both speed, capacity and pickup rate for these types of RU's. The report is carried out specific for the Barents Sea, which is beneficial for this research. Not only does the paper focus on the performance of the RU's, but it does also include other aspects like survival capability of humans under cold temperatures.

When transporting personnel to offshore locations, they are obliged to wear immersion suites. The purpose of these suites is to protect from hypothermia and drowning. In a situation where a helicopter crashes or ditches, one of the most important factors of survival is the body temperature of the personnel. The book "Essentials of Sea Survival" by Golden and Tipton (2002), evaluates different parameters influencing the survival time of personnel at sea. One of the most important issues addressed in the book is the comparison of survival time at sea and the sea temperature. The book analyses different types of approaches of comparison. For example, a retrospective analysis of recordings done by the U.S navy of ship sinking and aircraft crashes during the Second World War is presented. This analysis provides a way of calculating the survival time at sea given different sea temperatures.

3.3 Coverage and location models

Both routing problems and covering problems have been studied for many years. The first covering models was in fact developed for emergency medical services already in 1973. (Li et al. 2011). A lot of standard coverage models have been constructed since that time. Li et al. (2011) reviews a collection of different covering models with respect to emergency response facility location. These models has its origin in different papers, and can give good pointers when it comes to modeling techniques and solution methods for emergency preparedness.

A journal article by Verma, Gendreau, and Laporte (2012), studied where to locate oil spill facilities and what type of equipment were needed at the coast of Newfoundland. The researchers developed a model that focused on cost minimization, where the cost elements included set up cost of the facilities, equipment cost, equipment transportation cost, and environmental cost of a potential oil spill. The two-phase model uses stochastic programming in the second phase of the model in order to deal with the oil spill uncertainty.

Other types of research done in the routing and coverage field, is represented in an article by Asiedu and Rempel (2011). This research was done for the Canadian-wide volunteer aviation association that provides support to the SAR program in Canada. The goal of the research was to find the most efficient location of the SAR stations. The objective of the model was to maximize the rescue coverage and at the same time minimizing the number of stations.

3.4 Multiobjective Modelling

A central part of optimization theory is Multiobjective Optimization (MOO). In real life situations it might be necessary to not only consider one individual objective, but more objectives in a combined model. The article by Orumie and Ebong (2014) evaluates and examines current methods for solving Linear Goal Programming Models and informs about the main idea of Goal Programming (GP) as a tool for solving real life problems. As the article describes GP, the idea is to convert multiple objectives to a single goal. The most natural goal of GP is to minimize the deviation of each objective or all the objectives together from a desired goal/target. GP is considered one of the oldest methods of solving problems with more than one objective. As the article also states, the efficiency of GP is problem-, and user-dependent. When transforming a real life problem into a GP model it is necessary to weight the goal based on its importance. This process is considered as a crucial part of GP as setting wrong weight and non-reasonable targets might result in a non-efficient solution. The fact that the only limitation of GP is considered the error of its users, makes it a powerful tool for real life problems.

There exist many articles and literature regarding MOO theory. Ragsdale (2008), gives very good and practical examples of how to apply GP and Multi Objective Linear Programming (MOLP) to real life problems in his book. The idea and approach of GP is easily transferable to MOLP problems. Whereas traditional GP problems consist of soft constraints with preferable goals set by the users, the MOLP method provided in the paper of Ragsdale is based on individual optimal solutions from each individual problem. Even if the target values in MOLP problems are preferable goals, these target values have been proven optimal in closed and individual environments. As the number of goals applied in MOLP problems increases, it is also common that the sacrifice of the individual goals grows bigger. Therefore, it is the user's responsibility to establish the preferable weights in order to find an appropriate

tradeoff between the goals. The book points out two main methods for solving these types of problems. By establishing individual optimal solutions of each goal, the first method consists of minimizing the total percentage weighted deviation (sum of all individual weighted deviations) from the goals. This solution method will give a solution that will be positioned in an extreme point in the feasible region of the problem. However, to explore other non-extreme feasible solutions, this method will not work. The second method, which is referred to as the MINIMAX method, will allow the user to explore other points of the edge of a feasible region. The idea of this method is to minimize the maximum observed weighted deviation of all the established goals.

3.5 Related mathematical models

Past ten years, the focus on safe helicopter transportation in the offshore industry has increased. Due to the high risk of transporting people by helicopter to the installations, models have been constructed which minimize the risk of fatalities. The typical highest risk of helicopter transportation in the offshore industry is related to the take-off and landing at the offshore installations. In addition to the takeoff and landing, the time spent for transporting the personnel also implies risk. The routes that result in the lowest time spent in the helicopter, or in other words the shortest route, will be the optimal if only taking into consideration the traveling risk. Both articles by Gribkovskaia, Halskau, and Kovalyov (2015), and Menezes et al. (2010) studied these type of instances, and both were able to decrease the number of take-off and landings hence also reduce the total risk of offshore helicopter transportation. This article gives a good illustration of the risk elements in the offshore personnel transportation, and the fact that the risk associated with offshore helicopter transportation can be reduced if establishing good models and solution methods.

4. Methodology

This section describes the approach that is used in order to build the models and answer the research questions.

4.1 Problem analysis and data collection/generation

This research will focus on one particular emergency response situation, namely for the Norwegian oil and gas industry in the Barents Sea. The solution methods and models that are used in the research might be transferable to other types of emergency problems. However, the models and objectives for this research is case specific. This implies that the problem has to be analyzed and understood specifically for this case in order to develop solution methods for the problem. For this, the research by Brachner and Hvattum (2016), and Brachner (2015) are very helpful as they are focusing on the same specific case. In addition it will be necessary to collect and generate the necessary data for the Barents Sea case, such as distances, map positions of installations and properties of the RUs. This process is wider explained in Section 6.2.

4.2 Model development

A substantial part of this study is to construct mathematical models for solving emergency preparedness problems. There are many potential ways of doing so. Simulation modelling and heuristic approaches are both good methods to use. However, this research will mostly use exact methods as a way of generating solutions for the problem. The exact methods will have to be formulated mathematically in order to present the methods in a descriptive way. The mathematical models will be essential for evaluating the performance of the developed performance measurements. The objectives and parameters that are used for these models are described in Section 2.3. However a list of the models with a short description is presented below.

1. Minimization of the total distance of the helicopter transportation route (CRCP).
2. Maximization of minimum observed capacity.
3. Minimization of average first responder time.
4. Minimization of maximum observed first responder time.
5. Multiobjective model – Minimization of total weighted deviation.
6. Multiobjective model – Minimization of maximum observed weighted deviation.

4.3 Computational Experiments

In order to give an answer to the research questions, the research will use a computational study approach. Simple quantitative assessment methods are used as a way of doing the evaluation. Five computational experiments have been developed.

4.3.1 Evaluating objectives and models

The first experiment focuses on evaluating the new objectives and models against the already existing one. Model 1, which is mentioned in the numbered list in Section 4.2, is the base case model and will be used as a benchmark for the other models. The models that will be evaluated in this experiment are models 1 – 4. The idea of the experiment is to examine the behavior of the models under different conditions. These conditions, hereby denoted as cases, are not randomly chosen, but represents situations that might be relevant for real life instances. The cases are further described in Section 6.3, where the cases are presented among with the computational result. A list of the cases are shown below.

- Normal instance – based on one SAR helicopter and the minimum number of ERVs
- One extra SAR helicopter to a fixed location – leading to overcapacity
- One less offshore installation
- Reducing the minimum requirement, c^{min} , to 20 people – leading to overcapacity
- Reducing the minimum requirement, c^{min} , to 17 people – leading to overcapacity
- Fix the start of helicopter transportation route to only start from one position

In addition to the cases, the models will be examined under two different grid layouts. The grid layouts will double the number of instances for the experiments, as the grid layout is dependent for most of the parameters in the models. The two different grid layouts are 20 and 30 kilometer.

Models 1-4 will be examined by two different experiments. One of the experiment examines the models when the routing decision is fixed. An initial solution from Model 1, providing the shortest possible routes, is used as fixed routes when solving Models 2-4. The other experiment unfixes all variables, leaving both the routing decision and the decision of where to locate the RUs as free variables.

4.3.2 Multiobjective experimentation

The idea of creating multiobjective models is to show the purpose and value of gathering the individual objectives into one common objective. Models 5-6 will be used in this experiment. Multiobjective models are able to present a desirable solution to a problem where it exist more than one object. The purpose of the multiobjective experimentation is to present the effect of changing the weights of the individual goals. The individual objectives will change in pace with the setup of the weights, which will result in different solutions for the problem. The results provided by this experiment will be directly comparable with the results found in from the experiments in Section 4.3.1. This way it is possible to evaluate whether it is possible to increase the overall performance of the emergency preparedness design by using MOO.

4.3.3 Solution procedure for rescue time minimization

An addition for the research will be a presentation of a stepwise solution procedure for minimizing the rescue time in the emergency preparedness system without introducing a completely new model structure. By stepwise changing the t^{max} -parameter, which indicates the maximum allowed rescue time of all the personnel, it is possible to get an overview over the minimum threshold for the parameter before the model reaches infeasibility. The results provided from this experiment will also be comparable with the results from the other experiments.

4.3.4 Heuristic experimentation

In order to obtain solutions for all instances and models when both the routing variable and RU position variable are unfixed, a heuristic method has been developed. This heuristic method is meant to work as a complement where the exact methods come short. In order to get an indication of the performance of the heuristic, a small analysis examining the optimality gap is performed.

5. Models for Emergency Preparedness

This section presents the mathematical structure and description of the models that are constructed for the research. Section 5.1 presents the base model (CRCP) by Brachner and Hvattum (2016) which gives a more detailed explanation for some of the constraints that will also recur in the other models. Section 5.2 - 5.4 describes three type of models, where their objectives are later used as goals in two multiobjective models presented in Section 5.5 and 5.6. Each model is presents as if routing of for the personnel helicopters is a decision in the model. None of the models presented in this model, except the CRCP, will be solvable within reasonable time for realistic instances if including routing as a decision variable. Therefore, as an addition to the original description, there will also be presented the necessary adjustments for the model to deal with fixed routes. Section 5.7 describes the purpose and logic of the heuristic that is developed for the emergency preparedness case.

5.1 Base model - Combined Routing and Coverage Problem (Model 1)

The CRCP model constructed by Brachner and Hvattum (2016) is the basis for the development and analysis of the rest of the models for this research. The objective of the CRCP model is to minimize the total distances of the personnel transportation routes while at the same time keeping the response capacity within the requirement. The number of RU used for keeping the response capacity within the requirements should be as small as possible, meaning that the number of ERV boats and SAR helicopters should be minimized. The model does not facilitate to include the number of RUs to use as a variable to the model, but will have to be experimented with to find the minimum number of RUs to cover the routes. Originally, it is used a three-staged solution method for the CRCP model to solve problems. However, the mathematical model presented below, can be solved directly without a step-wise solution method for medium-sized instances.

Sets

R	-	Set of RUs. SAR and ERV
S_r	-	Set of nodes where $r \in R$ can be placed
B	-	Set of starting nodes,
L	-	Set of destination nodes,
N	-	Set of grid points / nodes in the polygon
K	-	Set of all possible connections to travel from one node to another

Variables

- x_{lij} - 1 if arc $(i, j) \in K$ is selected for traveling to destination $l \in L$, 0 otherwise
 w_j - 1 if node $j \in N$ needs to be covered with rescue capacity, 0 otherwise
 y_{ri} - 1 if RU $r \in R$ is placed to do rescue from node $i \in S_r$, 0 otherwise

Parameters

- d_{ij} - Time for RU $r \in R$ to travel from node $i \in S_r$ to node $j \in N$
 c_{rij} - Capacity of RU $r \in R$ placed at node $i \in S_r$ to do rescue at node $j \in N$
 c^{min} - Minimum capacity. Number of people to be rescued within the time limit

Formulation:

$$\text{Minimize } \sum_{l \in L} \sum_{(i,j) \in K} d_{ij} x_{lij} \quad (3)$$

S.t.

$$\sum_{i \in S_r} y_{ri} = 1 \quad \forall r \in R \quad (4)$$

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

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

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

$$\sum_{(b,j) \in K} \sum_{l \in L} x_{lbj} \leq w_j |L| \quad \forall b \in B \quad (8)$$

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

$$\sum_{r \in R} \sum_{i \in S_r} y_{ri} c_{rij} \geq w_j c^{min} \quad \forall j \in N \cup L \cup B \quad (10)$$

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

$$y_{ri} \in \{0,1\} \quad \forall \quad r \in R, i \in S_r \quad (12)$$

$$w_j \in \{0,1\} \quad \forall \quad j \in N \cup B \cup L \quad (13)$$

The objective function (3) minimizes the total distance of the routes from the onshore facilities to the offshore platforms. Constraint (4) makes sure that each resource $r \in R$ is placed at exactly one node $i \in S_r$. Constraint (5) ensures that every path that ends at a destination node $l \in L$, begins at a starting node $b \in B$. The balance constraint (6) ensures that for every ingoing arc to a node, there is also an outgoing arc. Constraint (7) states that there must be one incoming arc for at each ending node $l \in L$. Constraints (8) and (9) ensures that each node that is a part of the helicopter route, will need to be covered. As an illustration for constraint (9), if there is an ingoing arc to node $j \in N$, that is the Left Hand Side (LHS) equals to one, the Right Hand Side (RHS) will need to be equal or greater. This means that the variable indicating weather a node needs to be covered or not, w_j , will have to take a value of one as well. The cardinality of the set of ending nodes $l \in L$, $|L|$, has the purpose of letting the potential incoming and outgoing arcs of a node to be the same number as there exist destination nodes. Constraint (10) enforce the total response capacity at each node that needs to be covered to be no less than the minimum required capacity. In addition, there are restrictions, (11) – (13), stating the attribute of the variables.

5.2 Maximization of the Minimum Capacity (Model 2)

The capacity of the emergency preparedness system is of high importance. As previously stated the minimum capacity of which each point has to be covered by is 21 people within 120 minutes. However, as discussed in section 2.3 there might be instances where it is accepted to have a lower response capacity or even a higher response capacity than what is the guideline. The complexity of the problem is considerably higher if using routing as a decision variable in the model. When applying fixed routes, the problem is drastically reduced, which will allow a more fine grained grid layout.

Additional Variables

σ - Lowest observed response capacity along the route

Additional Parameters

M - Big value, $M \geq \max\{\sum_{r \in R, (i,j) \in K} c_{rij}\}$

Formulation:

$$\text{Maximize } \sigma \tag{14}$$

S.t

$$(4) - (9), (11) - (13).$$

$$\sum_{r \in R} \sum_{i \in S_r} c_{rij} y_{ri} \geq \sigma - (1 - w_j)M \quad \forall j \in N \tag{15}$$

$$\sigma \geq 0 \tag{16}$$

The objective function (14) maximizes the smallest observed response capacity along the routes. Constraint (15) enforces the observed response capacity, σ , to take a value no bigger than the total capacity provided by the resources at each point of the routes. The big M ensures that when a grid point is not used in the helicopter route, that is w_j equals zero, the minimum observed capacity σ is forced to take a value no greater than the LHS. This applies if M is no lower than the maximum possible response capacity in the emergency preparedness design. The M-value value can be set to the total response capacity at a node where all resources are located together. That way it is never possible that the LHS will be smaller than the RHS. Constraint (16) states the attribute of the new introduced variable. Constraints (4) – (9) and (11) – (13) are also used in the model. See section 5.1 for a more detailed description of these constraints. If not routing is included as a decision in the model, constraints (5) – (9) and (11) would not be necessary to use. In addition, constraint (15) could be replaced by (17), and w_j would become a parameter, due to the routes being fixed, indicating whether a node lies on the path or not.

$$\sum_{r \in R} \sum_{i \in S_r} c_{rij} y_{ri} \geq w_j \sigma \quad \forall j \in N \quad (17)$$

5.3 Minimization of Average First Responder Time (Model 3)

First responder time is the time for which the first RU arrives an incident scene. Each point of the transportation route will have a first responder time, which is influenced by the position of the point of the route and its distance to the first responder RU.

Additional Variables

z_{rij} - 1 if RU $r \in R$ is placed at node $i \in S_r$ to do rescue as first responder RU at node $j \in N$, 0 otherwise

Additional Parameters

t_{rij} - Time for RU $r \in R$ to travel from node $i \in S_r$ to node $j \in N$
(First Responder Time)

Formulation:

$$\text{Minimize } \sum_{r \in R} \sum_{i \in S_r} \sum_{j \in N} t_{rij} z_{rij} \quad (18)$$

S.t

(4) - (13)

$$\sum_{r \in R} \sum_{i \in S_r} z_{rij} = w_j \quad \forall j \in N \cup B \cup L \quad (19)$$

$$z_{rij} \leq y_{ri} \quad \forall r \in R, i \in S_r, j \in N \quad (20)$$

$$z_{rij} \in \{0,1\} \quad \forall r \in R, i \in S_r, j \in N \quad (21)$$

The objective function (18) minimizes the total first responder time from the RUs to the route. In order to find the average response time, it is necessary to divide the objective by the number of grid points included in the transportation route. Constraint (19) makes sure there is only provided one First Responder RU for each point at the route. Constraint (20) ensures that there is only assigned RUs as First Responder Resources that has an origin from a point $i \in S_r$ where there is actually located a RU. Constraint (21) defines the domain of the new variable. The model also makes use of the all the constraints (4) – (13) which are described in the CRCP model in Section 5.1. If not having routing as a decision to the model, the necessary changes to the model will be to remove constraints (5) - (9) and (11), and at the same time change w_j from a variable to a fixed parameter indicating which points are included in the routes.

5.4 Minimization of Worst Case First Responder Time (Model 4)

By minimizing the highest observed First Responder time, it is possible to present an emergency preparedness design that is able to guarantee a minimum response time for each point at the transportation route.

Additional Variables

τ - Highest observed first responder time

Additional Parameters

M - Big-M, $M = \max \{t_{rij}\}$

Formulation:

$$\text{Minimize } \tau \tag{22}$$

S.t

$$(4) - (13), (19) - (21)$$

$$\tau \geq t_{rij}z_{rij} - M(1 - w_j) \quad \forall \quad r \in R, i \in S_r, j \in N \tag{23}$$

$$\tau \geq 0 \tag{24}$$

The objective function (22) minimizes the highest observed first responder time along the points on the transportation route. Constraint (23) makes sure that the highest observed first responder time will not be smaller than what is actually possible at each point of the route. The constraint takes into use the “big-M” method. By using a big-M value, with a value equal to the maximum possible response time t_{rij} , the RHS will take a zero or negative value if a node is not included in the path. This makes the RHS binding if a node is used ($w_j = 1$). Constraints (4) – (13), (19) - (20) and (21) are also used in thos model and are all described in section 5.1 and 5.3. If considering fixed routes, constraints (5) – (9) and (11) will be redundant. The variable indicating whether a node needs cover, w_j , will need to be a parameter indicating whether a node lies on the path or not. Constraint (23) can be changed to no longer include the big-M method by replace it with constraint (25) displayed bellow.

$$\tau \geq t_{rij}z_{rij}w_j \quad \forall \quad r \in R, i \in S_r, j \in N \quad (25)$$

5.5 Multiobjective Model – Minimization of Total Weighted Deviation (Model 5)

The models presented in section 5.1 - 5.4 gives the basis for creating Multiobjective Models. By using their objective as goals in MOLP models, it is possible to find desirable solutions including all the four objectives together. The MOLP model presented underneath uses routing as a decision variable, which implies that all the target values also have to be based on routing. The model when considering fixed route will be much smaller, both in terms of number of restrictions and problem size.

Additional Parameters

M_1	-	Big M. $M = \max \{t_{rij}\}$	
M_2	-	Big M. $M = \max \{\sum_{r \in R, (i,j) \in K} c_{rij}\}$	
g_1	-	Average first responder time (Model 3)	- Goal
e_1	-	Average first responder time (Model 3)	- Weight / importance
g_2	-	Worst case first responder time (Model 4)	- Goal
e_2	-	Worst case first responder time (Model 4)	- Weight / importance
g_3	-	Minimum observed capacity (Model 2)	- Goal
e_3	-	Minimum observed capacity (Model 2)	- Weight / importance
g_4	-	Total transportation distance (Model 1)	- Goal

e_4 - Total transportation distance (Model 1) - Weight / importance

Formulation:

$$\begin{aligned} \text{Minimize} \quad & e_1 \left(\frac{(\sum_{r \in R, i \in S_r, j \in N} t_{rij} z_{rij}) - g_1}{g_1} \right) + e_2 \left(\frac{(\tau) - g_2}{g_2} \right) \\ & + e_3 \left(\frac{-(\sigma) + g_3}{g_3} \right) + e_4 \left(\frac{(\sum_{r \in R} \sum_{i \in S_r} \sum_{j \in N} d_{ij} x_{lij}) - g_4}{g_4} \right) \end{aligned} \quad (26)$$

S.t

$$(4) - (10), (11) - (13), (15), (16), (19) - (20), (21), (23), (24)$$

The objective function (26) minimizes the total weighted percentage deviation from all the goals. In general, all the constraints used in the previous models that includes routing are used in the MOLP models. This is necessary, due to the fact that the MOLP model include the goal from each individual model. However, as previously stated, the size of the problem will be reduced when applying fixed route. By applying fixed routes, the model will have the structure as shown underneath (27), where w_j is no longer a binary variable, but a binary parameter indicating whether a node is included in the helicopter route or not.

$$\begin{aligned} \text{Minimize} \quad & e_1 \left(\frac{(\sum_{r \in R, i \in S_r, j \in N} t_{rij} z_{rij}) - g_1}{g_1} \right) + e_2 \left(\frac{(\tau) - g_2}{g_2} \right) \\ & + e_3 \left(\frac{-(\sigma) + g_3}{g_3} \right) \end{aligned} \quad (27)$$

S.t

$$(4), (10), (12) - (13), (16), (17), (19) - (20), (21), (24), (25)$$

5.6 Multiobjective Model – Minimization of Maximum Weighted Deviation (Model 6)

In order to examine other points on the edge of the feasible region, it is necessary to run a MINIMAX model. The structure of the MINIMAX model is quite similar to the previous described MOLP model in section 5.5.

Additional Variables

q - Highest observed weighted percentage deviation between individual goal and objective

Formulation:

$$\text{Minimize } q \tag{28}$$

S.t

$$(4) - (10), (11) - (13), (15), (16), (19) - (20), (21), (23), (24)$$

$$e_1 \left(\frac{(\sum_{r \in R, i \in S_r, j \in N} t_{rij} z_{rij}) - g_1}{g_1} \right) \leq q \tag{29}$$

$$e_2 \left(\frac{(\tau) - g_2}{g_2} \right) \leq q \tag{30}$$

$$e_3 \left(\frac{-(\sigma) + g_3}{g_3} \right) \leq q \tag{31}$$

$$e_4 \left(\frac{(\sum_{r \in R} \sum_{i \in S_r} \sum_{j \in N} d_{ij} x_{lij}) - g_4}{g_4} \right) \leq q \tag{32}$$

$$q \geq 0 \tag{33}$$

The objective function (28) minimizes the highest observed weighted percentage deviation from all the individual goals. Constraints (29) – (32) ensures that no individual object exceeds the highest observed weighted percentage deviation. In other words, each individual objective needs to be bigger or equal to the highest observed weighted percentage deviation. Constraint (33) states the attribute of the new included variable. As for the MOLP model in section 5.5, the previous constraints that includes routing is also used in this model. If applying fixed routes to the model, the objective function would stay the same while constraint

(32) would be excess. In addition all the constraints including routing would have to be removed, and for those constraints that take takes usage of Big-M techniques can be changed due to the variable w_j no longer being a variable, but a binary parameter indicating whether a node lies on the helicopter route.

5.7 Heuristic method – Fix-and-Optimize

In situations where exact methods adraw short, heuristics can be applied in order to obtain a solution to the problem. Heuristics has the advantage of often providing solutions within a relatively short time. However, the major drawback of heuristics, is the fact that they cannot guarantee an optimal solution to the problem. Even though optimal solutions cannot be guaranteed, it does not mean that heuristics cannot obtain good solutions. This research will take use of improvement heuristics in order to find solutions to some spesific situations. The main idea that will be used in this research is a heuristic named Fix-and-Optimize (F&O). F&O is an improvement heuristic that divides the binary variables of a problem into two separate sets. The operation of the F&O firstly fixes the variables of one of the divided sets while keeping the other set non-fixed (Pisinger and Ropke 2007). By feeding the heuristic with an initial solution, and stepwise improve the solution by alternating with fixing and unfixing the two sets, the procedure continues until a stopping criterion is met.

There exist examples of situations where the F&O has shown a good performance to real life problems. Helber and Sahling (2010) used a F&O approach for the multi-level capacitated lot sizing problem. This implies finding lot sizes for multiple product types, with changeover time and capacities at the available resources. They were able to create an algorithm that was flexible, accurate and fast. Another quite similar research by Lang and Shen (2011) which uses the F&O approach for the capacitated lot sized problem, showd that their method was able to provide a good and stable solutions for the problem. Their algorithm provided an average optimality gap of 5.56%.

Figure 8, illustrates the sequential steps of the F&O heuristic applied to the emergency preparedness case. The routing variable x_{lij} and the RU position variable y_{ri} constitutes the two seperate variable sets. The heuristic will be possible to apply for all Models 2-6. The first step of the heuristic is to apply an initial solution to the problem. The routes found from Model 1 (CRCP) is used as initial solution. By fixing the routes from Model 1, the first solve operation optimizes the emergency preparedness system by changin the position of the RUs based on which objective is used (Model 2-6). This operation is similar as if we were to optimize Models 2-4 with fixed routes. After the first solve operation, the looping over the F&O operations starts. Firstly, the positions of the RUs are fixed, while the currently fixed routes are unfixed. This way, the routes have the oppurtunity to change to new positions given the fixed RU positions. An additional constraint (34) is introduced to the model. This

constraint reduces the neighborhood search for the routes. The constraint ensures that the number of moves (arcs) in the new route does not exceed the limit G , which is set by the user. x_{lij}^{new} , represents the binary routing variable in the new solution, and x_{lij}^{old} represents the binary routing variable in the old solution.

$$\sum_{l \in L} \sum_{(i,j) \in K} x_{lij}^{new} - \sum_{l \in L} \sum_{(i,j) \in K} x_{lij}^{old} \leq G \quad (34)$$

After solving the problem with with fixed RU positions and unfixed routing variables, the fixation of the variables is reversed. This implies that the RU positions are unfixed while the routes are fixed. This procedure continues as a loop until the stopping criterion is met, which in this case is a time limit. As long as the current solve time of the system A is smaller than the time limit B , the loop continues. It is possible to apply different stopping criterias to the heuristic. An example would be to stop as soon as no improvements is observed. Since the purpose of this heuristic is to aobtain a feasible solution and not necessary solve the problem as fast as possible, a time limit stopping criterion is suffiecient.

The combination of the F&O approach and constraint (34), which reduces the search, makes sure that we are able to obtain a result in situations where the exact methods cannot.

Fix-and-Optimize Heuristic

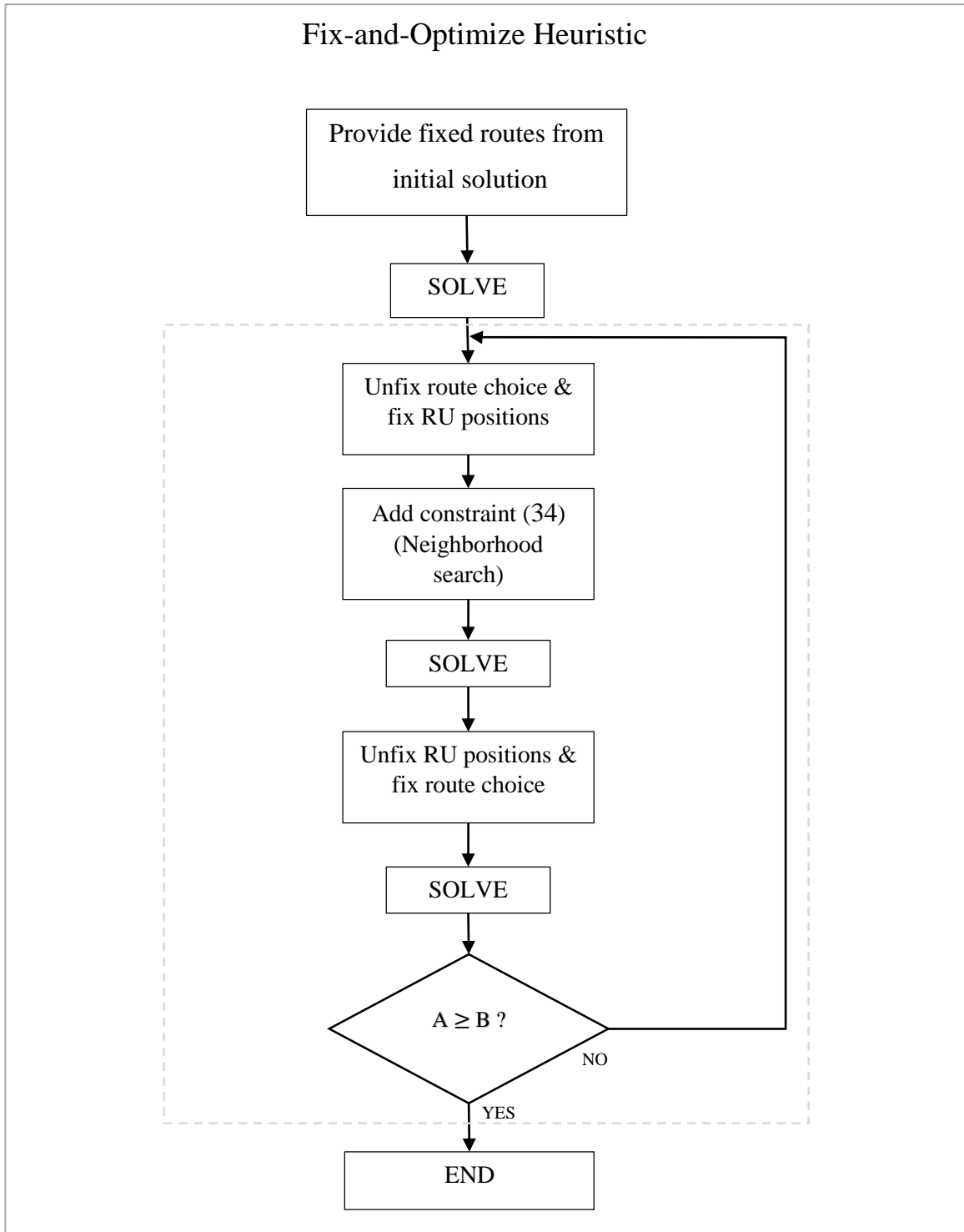


Figure 8 -Fix-and-Optimize algorithm for the emergency preparedness case

6. Computational study

This section gives a continued description of some of the parameters that are used for the research. A detailed description of the instances that are used in the different experiment is provided. In sections 6.4 - 6.8, a complimentary description of experiments is presented along with its main results.

6.1 Implementation

All the models in this research has been run on the NEOS-server (NEOS-server 2016a). The NEOS-server is a free internet-based service for optimization problems, and provides a wide range of solvers that can handle different types of problems. The NEOS-server project is a collaboration by different people and organizations within the optimization community, and is hosted by the Wisconsin Institute for Discovery at the University of Wisconsin in Madison. The models for this research have been formulated and programmed in AMPL, which is an algebraic modelling language for mathematical programming (Fourer, Gay, and Kernighan 2003). Furthermore, Gurobi 6.5.0 was used as solver. The NEOS-server provide high performance hardware through multiple available computers. When uploading the jobs to the server, it is not given which computer is solving the problem. The different computers provided by the NEOS-server each have its own hardware spec (NEOS-server 2016b). However, all jobs submitted to the server will have a limitation of 3 GB RAM and a maximum runtime of 8 hours. If a job has not been proven optimal within the maximum runtime or before the maximum memory usage is reached, NEOS does not return any solution.

6.2 Construction of sets and parameters

In this section, visual illustrations of the sets N , B , L and K will be provided. The polygon that is presented in Figure 9, limits the movement of helicopters and boats to a specific area in the Barents Sea. Set N , constitutes the nodes inside the polygon, and represents the potential points that can lie on a path between the helicopter bases and offshore installations. The orange circles are meant to illustrate set B , which represents the potential starting nodes for the helicopter route. The green squares, represents the offshore installations. These installations are the end nodes for the model, and is described through set L . All these sets are presented in Figure 9a. Another set which is visualized in Figure 9a is the set K , which represents the possible connection to travel from one point to the other. Obviously, not all the possible connections are presented in this figure. However, the possible ways of moving from one node to another are illustrated. The set K is constructed with the Moore neighborhood. The Moore neighborhood restricts the neighborhood of a cell to count only for those

cells in a Chebyshev distance of 1 (Ninh 2013). In other words, the eight red surrounding cells from the blue center-cell. The movement from a node for the personnel transportation helicopter is restricted to count only for movement neighborhood nodes as illustrated in the colored area in Figure 9a. However, the RUs, which also have to do a physical movement, are not restricted to move according to the Moore neighborhood. The RUs can move within an Euclidian distance from their position to the crash scene as long as the distance is within their reach. The Euclidian movement of the RUs is illustrated in Figure 9b, where a random helicopter route is generated along with random positioning of three ERVs. The Euclidian distances for each RU doing rescue at node j from position i is generated in order to describe the time parameter t_{rij} .

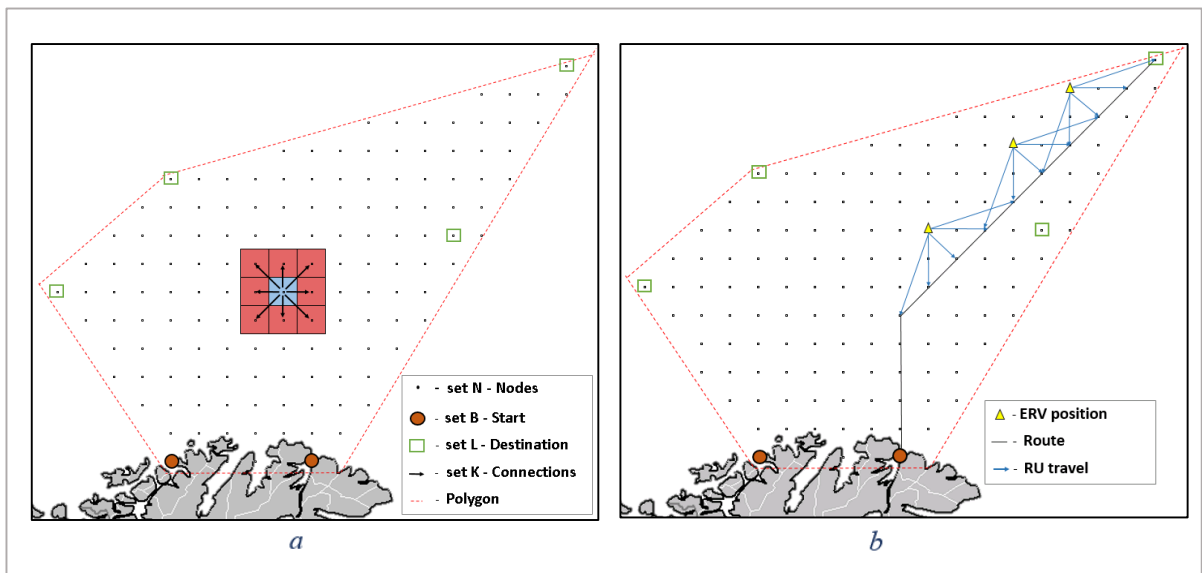


Figure 9 - Illustration of the existing sets

The research by Brachner and Hvattum (2016) experiments with eight different locations for offshore installations. However, four of these locations are the most frequently used throughout their paper. These four locations will also be the basis for this research. Two potential airports are used as basis for starting points of the helicopter routes. Table 2 and Figure 10 both describe and visualize these positions. As previously mentioned, there are only two offshore installations operating in the Barents Sea, namely, Snøhvit and Goliat. These installations are not included in the test instances. Snøhvit is a subsea installation located at the seabed, and will therefore not require personnel transportation. Goliat is located quite close to the coastline and will not be of interest for the emergency preparedness models. P1 represent the Johan Castberg field. By 2014, the Johan Castberg field, contributed with 51% of the total found oil & gas resources in the Barents Sea, and is considered as one of the most

important areas for the future (Oljedirektoratet 2014). P2, which is called the Wisting Central field, is one of the norther most areas in the Norwegian continental shelf where oil resources has been found. P3 is a randomly placed position. P4 is considered an extreme point, as it represents the north-eastern most possible positioning of oil & gas installations. At this point, the demarcation line between Norway and Russia, and the outer border of the shelf meets. H1 and H2, represents Hammerfest and Berlevåg airport respectively, and are existing airports in the region.

Name	Description	Latitude	Longitude
P1	Johan Castberg field	72.494341	20.347568
P2	Wisting Central field	73.491134	24.232358
P3	Random position	73.059784	32.654140
P4	North-eastern most point	74.500000	37.000000
H1	Hammerfest airport	70.701319	23.768302
H2	Berlevåg airport	70.854502	29.090389

Table 2 - Position of installations, decimal degrees

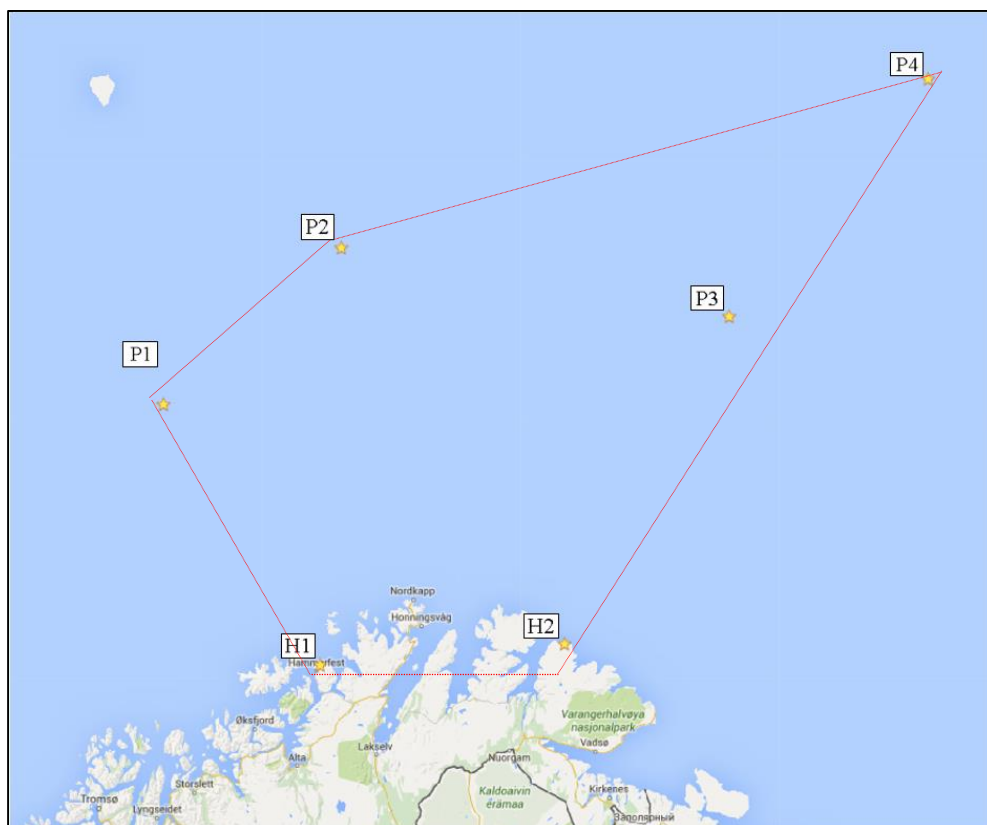


Figure 10 - Position of installations, Source: www.google.maps.no (Google 2016)

6.3 Test instances

In total, six models along with twelve instances are used for the experiments. The instances are built up on six different cases, whereas the two different grid layouts doubles the cases into twelve instances. Each experiment does not necessarily use all models and instances. In this section, the instances will be presented and discussed. The conditions of each case is as listen bellow. A summary of the cases is presented in Table 3.

- Case 1, is considered the base-case. The setup of installations, helicopter bases and number of RU's are built up in the way that it reflects the research by Brachner and Hvattum (2016) best possible. This implies using installation P1 – P4 as ending nodes and either H1 or H2 as starting nodes. The number of ERV boats needed to meet the capacity requirement is at the minimum level, which in this case is five boats, given that one SAR helicopter is used. The SAR helicopter can be freely placed at either H1 or H2. The minimum capacity requirement c^{min} is at the standard level of 21 people.
- Case 2, introduces overcapacity to the emergency preparedness system. The overcapacity is generated by fixing an extra SAR helicopter to the Wisting Central field P2, in addition to the SAR helicopter that is freely placed at H1 or H2. Other than the extra SAR helicopter, the setup of starting nodes and ending nodes are the same as Case 1. The number or ERVs available is fixed to five, which is the minimum required amount found in Case 1. It is interesting to examine the behavior of the models in overcapacity situations.
- Case 3, removes one offshore installation. Wisting central P2, is removed as an ending node. This way, the problem size is considered smaller due to the reduction of destination nodes. Other than the removal of one installation, Case 3 is similar to Case 1. The number of ERVs that are needed to carry out the rescue is set to four. If having less than four ERVs and one SAR, the problem would be infeasible. Therefore, overcapacity is not added to the emergency preparedness system.
- Case 4 and Case 5 have a minimum capacity c^{min} of respectively 20 and 17 people. Overcapacity is introduced to the models by reducing the capacity requirement and at the same time keeping one SAR helicopter and five ERV boats available. Other than the capacity requirement reduction, the set up of the other features is the same as in Case 1.

- Case 6 restricts the start of the helicopter route to H1, Hammerfest airport. In real life, it might not be an option to start the helicopter routes from two different airports. Five ERVs and one SAR helicopter are available. Having less resources will result in infeasibility. Other than fixing the start of the helicopter route, the other features stays the same as in Case 1.

<i>Case</i>	<i>Description</i>	<i>Offshore installations</i>	<i>Start position</i>	<i>SAR position</i>	c^{min}	<i># of SAR</i>	<i># of ERV</i>
1	Base-case	P1-P4	H1-H2	H1-H2	21	1	5
2	Extra SAR, fixed to P2	P1-P4	H1-H2	P2*, H1-H2	21	2	5
3	One less installation, remove P2	P1, P3-P4	H1-H2	H1-H2	21	1	4
4	$c^{min} = 20$	P1-P4	H1-H2	H1-H2	20	1	5
5	$c^{min} = 17$	P1-P4	H1-H2	H1-H2	17	1	5
6	Fix start of route to H1	P1-P4	H1	H1-H2	21	1	5

Table 3 – Summary of instances

The grid spacing for the models can also be varied. The grid space used when modelling the emergency preparedness system will influence the size of the problem. A fine grained grid layout will increase the number of nodes inside the polygon, hence increase the problem size. Whereas a coarse-grained grid layout will reduce the number of nodes. Some of the experiments will alternate between two grid layouts, 20 and 30 kilometer. Figure 11 illustrates the difference between these two layouts. Whereas the 30-kilometer grid layout consist of 145 nodes, the 20-kilometer grid layout consist of 325 nodes. The described six cases along with the 20, and 30 km grid layout, constitutes the twelve instances that will be used for examining the models, and is found in Table 4. If all models were to be examined under each instance, it would generate $6 \times 12 = 72$ unique setups.

Instances	
Grid layout	Case
20 km	1 - Base case
30 km	1 - Base case
20 km	2 - Extra SAR helicopter at P2
30 km	2 - Extra SAR helicopter at P2
20 km	3 - Remove installation P2
30 km	3 - Remove installation P2
20 km	4 - $c^{min} = 20$
30 km	4 - $c^{min} = 20$
20 km	5 - $c^{min} = 17$
30 km	5 - $c^{min} = 17$
20 km	6 - Fix start of helicopter route to Hammerfest
30 km	6 - Fix start of helicopter route to Hammerfest

Table 4 – Instances used for the research

Before describing the experiments and interpreting the results, it might be valuable to address potential disturbances that can affect the performance of the models. The capacity available at the route and its surrounding is of huge importance for the performance. A low overcapacity along the route and its surrounding will reduce the RUs ability to move from its current position to an improved position. The capacity along the route is influenced by different factors, like minimum capacity requirement, number of RUs and the physical location of offshore installations and airports. Therefore, in overcapacity situations, it is possible to observe significantly higher improvements from the base-case compared to situations where the overcapacity is smaller. This is something to be aware of when interpreting the results.

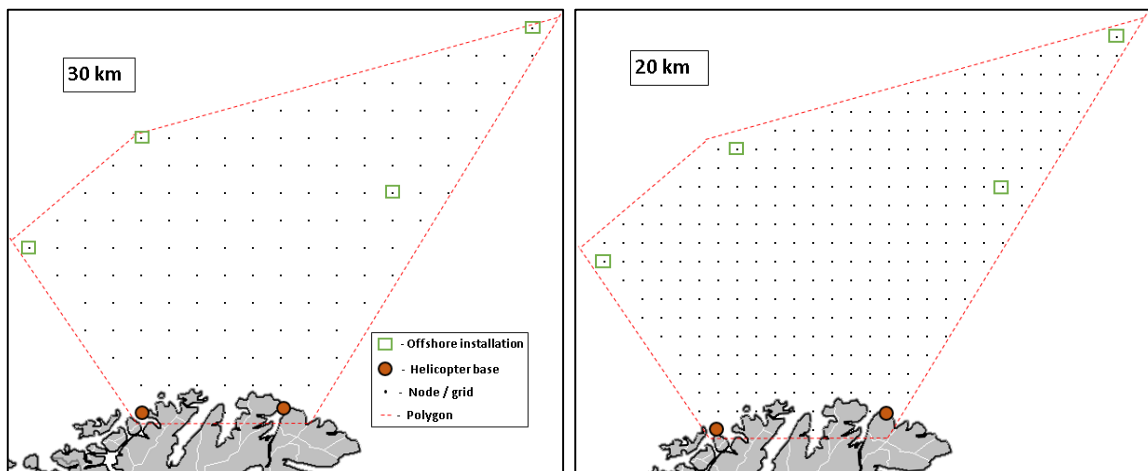


Figure 11 – 30-, and 20-kilometer grid space

6.4 Fixed route – model evaluation

In this section, the results from the fixed route models will be presented. Firstly, a complementary description of the experiment is provided, before the result is presented. In the end, a summary of the experiment is provided with general comments about the result.

6.4.1 Experiment construction

The first experiment will use models 1 – 4 and cases 1 – 6. In addition, both the 20 km and 30 km grid layout will be used. Table 5 illustrates all the unique setups generated when applying the combination of models and instances. 48 setups will be examined, where all have their own index. The reason for indexing the setups is to make it easier to refer to a certain situation when presenting the results. The indexing (35) is built up in the way that it describes sequentially the current model, case, grid layout that is used, and in addition whether the routes are fixed or not. For example, if wanting to refer to a situation that consist of Model 3, Case 2, 30 km grid layout, and fixed routes, the index would be “(M3).C2.30.F”.

$$Index = (Model) . Case . Grid Layout . Fixed/Unfixed route \quad (35)$$

An essential part for each case is initially to solve Model 1 before solving Models 2-4. By doing so, the upcoming models will have fixed routes to implement when solving them. The main idea for the experiment is to examine the behavior of the models under different instances. Some of the behavior is known in advance. For example, model 4 will always provide the best result it terms of worst case first responder time. Model 3 might provide the same worst case first responder time, but never a better one than model 4. The behavior that is known in advance is as follows:

- Model 1: Minimum total distance of the routes. Routes are later used in models 2-4.
- Model 2: The highest minimum observed capacity along the route.
- Model 3: The minimum average first responder time.
- Model 4: The lowest maximum observed first responder time.

Even though if parts of the behavior of the models are known in advance, it is still interesting to compare all the performance indicators under different models and instances. This way it is possible to get an overview of the effect of choosing one model layout contra another.

		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
20 km grid	Model 1	(M1).C1.20.F	(M1).C2.20.F	(M1).C3.20.F	(M1).C4.20.F	(M1).C5.20.F	(M1).C6.20.F
	Model 2	(M2).C1.20.F	(M2).C2.20.F	(M2).C3.20.F	(M2).C4.20.F	(M2).C5.20.F	(M2).C6.20.F
	Model 3	(M3).C1.20.F	(M3).C1.20.F	(M3).C3.20.F	(M3).C4.20.F	(M3).C5.20.F	(M3).C6.20.F
	Model 4	(M4).C1.20.F	(M4).C2.20.F	(M4).C3.20.F	(M4).C4.20.F	(M4).C5.20.F	(M4).C6.20.F
		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
30 km grid	Model 1	(M1).C1.30.F	(M1).C2.30.F	(M1).C3.30.F	(M1).C4.30.F	(M1).C5.30.F	(M1).C6.30.F
	Model 2	(M2).C1.30.F	(M2).C2.30.F	(M2).C3.30.F	(M2).C4.30.F	(M2).C5.30.F	(M2).C6.30.F
	Model 3	(M3).C1.30.F	(M3).C2.30.F	(M3).C3.30.F	(M3).C4.30.F	(M3).C5.30.F	(M3).C6.30.F
	Model 4	(M4).C1.30.F	(M4).C2.30.F	(M4).C3.30.F	(M4).C4.30.F	(M4).C5.30.F	(M4).C6.30.F

Table 5 – Unique setups for the fixed route experiment

6.4.2 Results

Applying fixed routes when solving the models has a positive impact on the computational time and solvability of the models under all instances. All four models under each instance have been solved to optimality. A detailed overview over the performance indicators for each scenario is available in Appendix A. Figure 12 however, is a summary of the behavior of the performance indicators for each model. It shows, for each model, the percentage improvement of each performance indicator from the base-case model. A detailed overview, showing the change per instance can be found in Appendix A.

If considering the first objective in the table, minimum observed capacity; it clearly shows that Model 2 contributes to a large improvement of the minimum capacity. The minimum observed capacity increases on average 19.44% from the base-case model. It must be said that only four observations are used a baseline for doing the comparison. Cases 2 and 5 are the only cases creating sufficient overcapacity, which is a necessity in order to see an improvement of the objective. In theory, case 4 can also have overcapacity, but the route generated in the first step (Model 1), does not facilitate an RU movement that increases the minimum observed capacity. Models 3 and 4 does not seem to have a positive effect on the minimum capacity, as the capacity is reduced with respectively -0.69% and -6.60% when applying those models.

The second objective, average first responder time, shows an average decrease from the base-case model to Model 3 by 12.12%. This is a quite good improvement. It also seems like both model 2 and 4 have a good impact on the average first responder time, as they contribute to an average decrease of 9.54% and 9.14% respectively. It is not given that Models 2 and 4 will have a positive effect on the average first responder, as it is not included in their objective. There are only two situations having a negative effect on the average first responder time. Situation “(M4).C1.30.F” and “(M4).C4.20.F” has an impact on the average first responder time of respectively -0.45% and -6.39%.

The average effect on the worst case first responder time of applying Model 4 is an 11.61% reduction from the base-case. This is a relatively good improvement. An average reduction of the worst case first responder time is also present when applying both Models 2 and 3. The reduction in worst case first responder time is 5.59% for Model 2 and 7.71% for Model 3. Out of all the instances and models, none has a negative effect on the worst case first responder time.

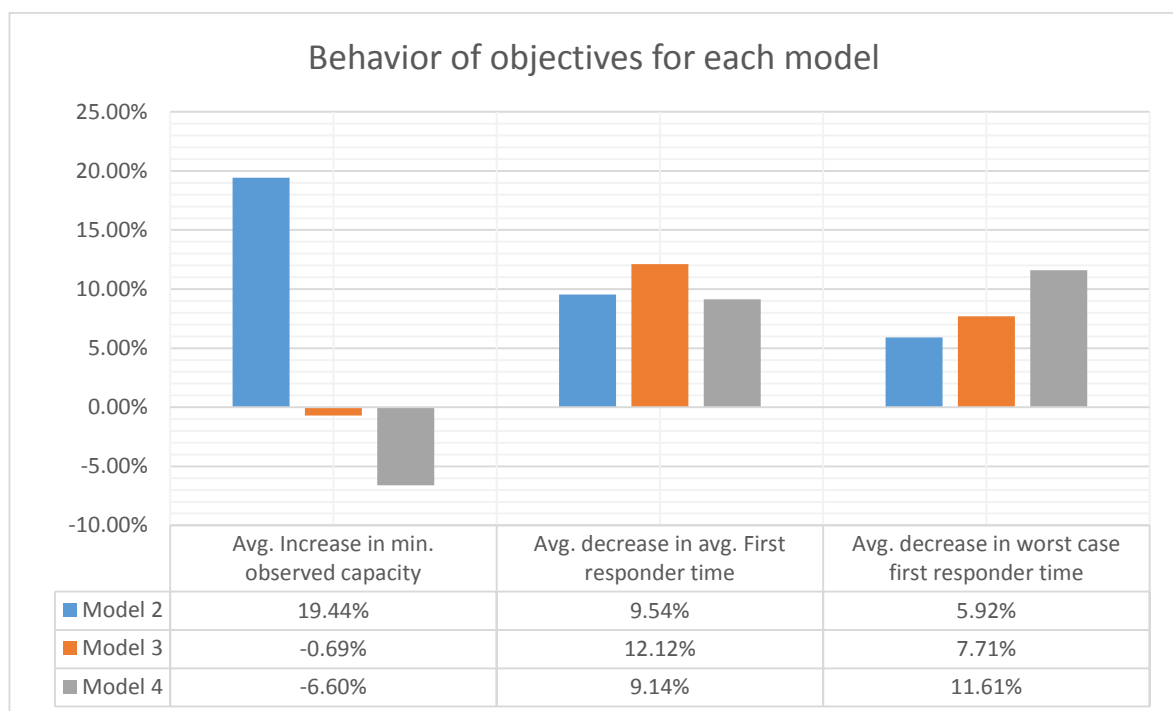


Figure 12 - Average behavior of each performance indicator for each model

It is a normal behavior to have overcapacity at part of the routes. Having a route covered with a response capacity of exactly 21 people at all parts is hardly possible. Even if the number of RUs is at a minimum level, it might be possible to have a situation where two

RUs are located at the same position in the map. Especially in overcapacity situations where there is an excess of RUs, a cluster of RUs might occur. Clustering of RUs has a negative effect on for example average first responder time, as it does not use the RUs ability to reach each point of the route in the fastest possible way. Another effect of RU clustering is clustering of the response capacity. Areas around an RU cluster will process a much higher response capacity than the rest of the route. Figure 13 shows the emergency preparedness design for Models 1-4 under case 2 with fixed routes and a 20 km grid layout. Case 2, which adds one extra SAR helicopter at the Wisting central P2, generates an excess of RUs. Setup (M1).C2.20.F is the benchmark for Models 2-4 for case 2 with the 20 km grid layout. By analyzing the emergency preparedness design for (M1).C2.20.F, it clearly shows a clustering of ERV boats at the northeastern part of the map. Four ERVs at the same position and one additional ERV at the neighboring position constitutes the RU-cluster. The dark areas of the cluster and its surrounding clearly shows a higher response capacity compared to the rest of the map.

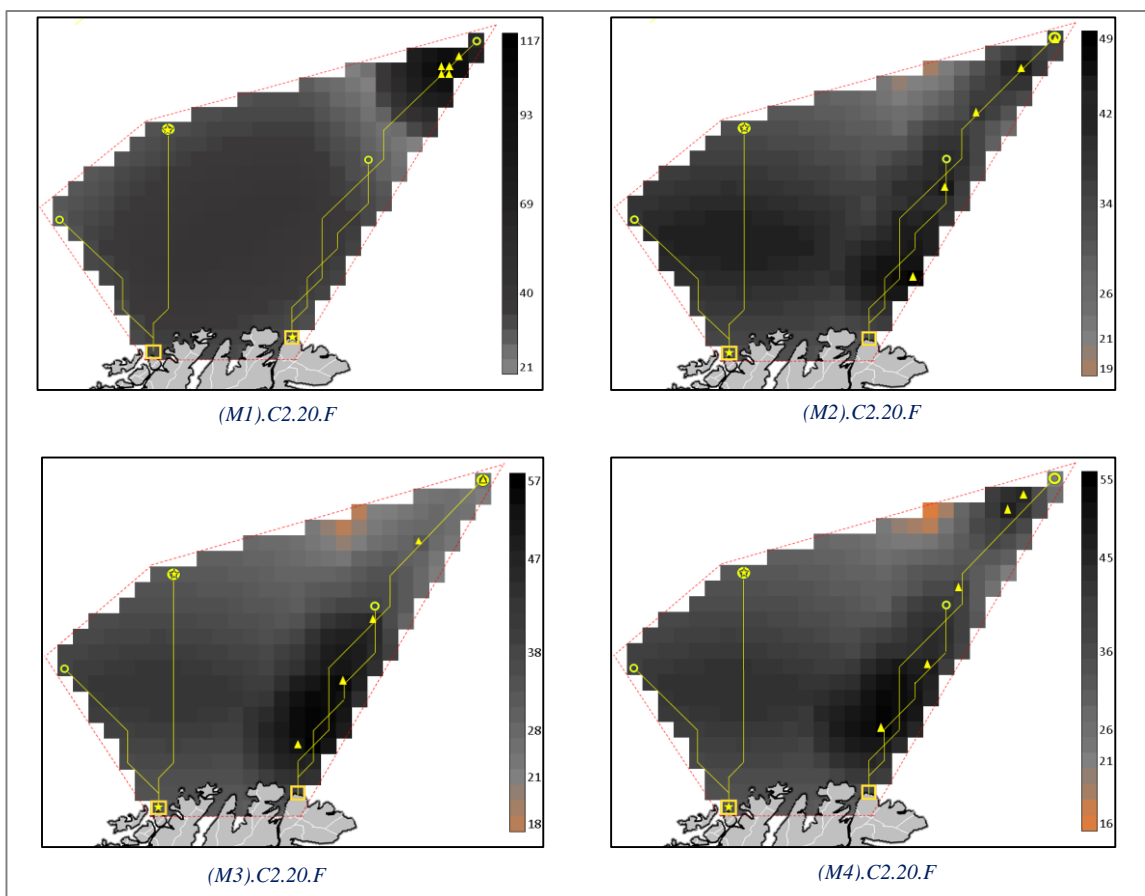


Figure 13 - Collection of result of Models 1-4 from Case 2, with 20 km grid layout and fixed routes

If comparing situation (M1).C2.20.F with the rest of the models for Case 2, it is obvious that Model 1 is doing a poor job of distributing the overcapacity. Model 2-4, all seems to have a positive effect of distributing the overcapacity compared to the base case. All three models have in common to move the “land-based” SAR helicopter from Berlevåg (H2) to Hammerfest (H1) when comparing them with the base-case. By doing so, the two SAR helicopters located at H1 and P2 solely are cooperating on the capacity on the two westernmost routes, while the ERV boats are cooperating and taking care of the two easternmost routes. If comparing the average capacity along the route, all three Models 2-4 show an increase from Model 1 of respectively 2.08%, 6.51% and 5.73%. The fact the average capacity along the route increases is a good sign in terms of having a better distributed overcapacity. Figure 14 and Figure 15 presents the capacity distribution of respectively (M1).C2.20.F and (M3).C2.20.F, and has to be seen in conjunction with Figure 16, which shows the fixed route of Case 2 under the 20 km grid layout. From the two tables, it is possible see how the overcapacity-cluster from Model 1 is removed and spread along the route in Model 3.

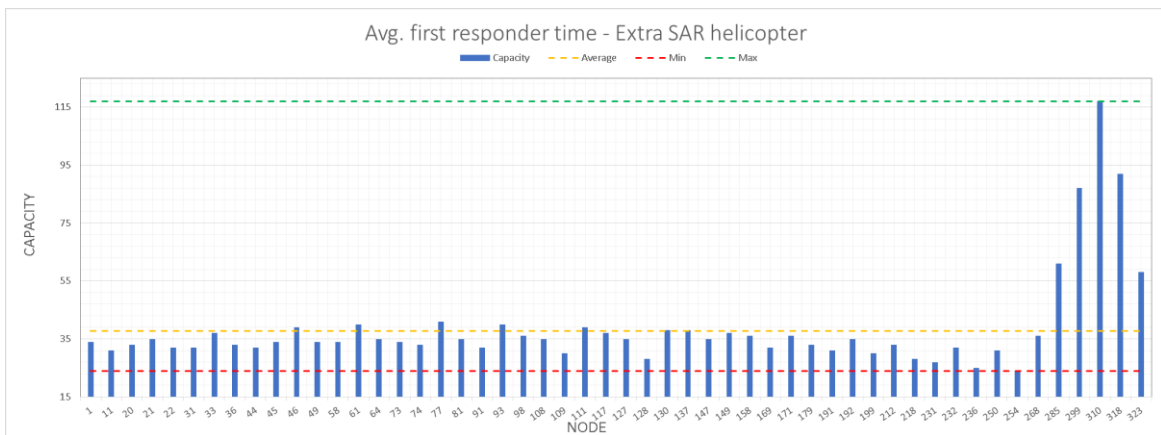


Figure 14 - Capacity distribution (M1).C2.20.F

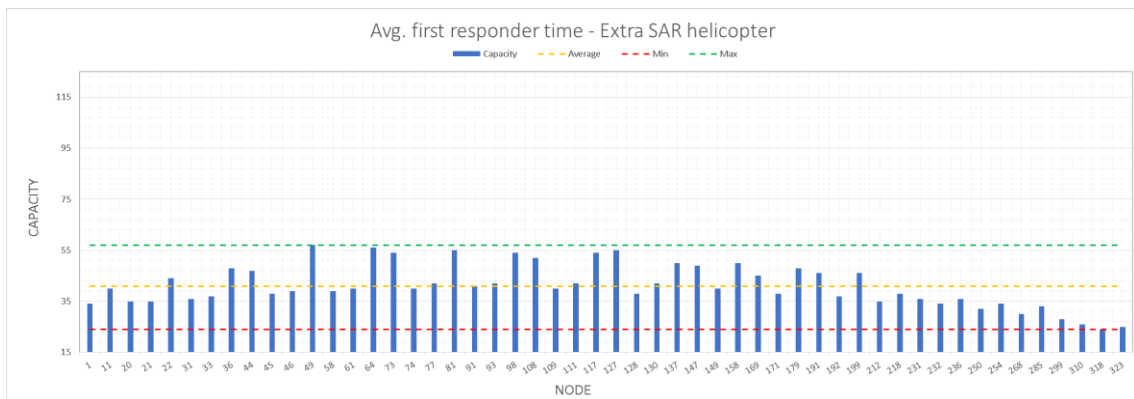


Figure 15 - Capacity distribution (M3).C2.20.F

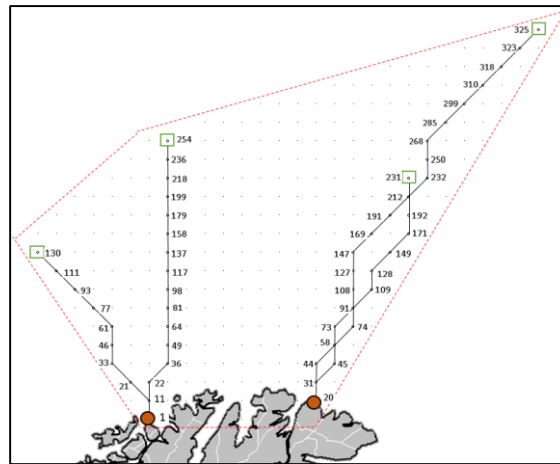


Figure 16 – Routes (with node number) that are used in Case 2 with 20 km grid layout

The major advantage of applying the 30 km grid layout to the models is the short computational time. However, as discussed in an earlier stage, the 30 km grid layout reduces the RUs ability to move to other positions. As the number of nodes inside the polygon is reduced, the options for the RUs to move becomes smaller. There are indicators supporting this statement when examining the behavior of the results for the 30 km grid layout. For example, all models for Case 3 under the 30 km grid layout and fixed route, give the exact same emergency preparedness design. Comparing the results for the same case only with the 20 km grid layout, all the models provide a different emergency preparedness design. It also exist different examples of this behavior, where models under the same case and 30 km grid layout provide the same emergency preparedness design. However, if considering all the four models under each case for the 20 km grid layout, all models provides an unequal emergency preparedness design. Based on these observations, it is reasonable to recommend using the 20 km grid space as far as practicable.

6.4.3 Summary

This experiments has shown that implementing Models 2 – 4 overall has a positive effect on the emergency preparedness system. Not only does the models have a positive effect each individual objective, but in general they also have a positive effect on all objectives when applying one of the three models. Implementing Model 2 (maximization of minimum capacity), will have a positive effect on all the three objectives. That is, an increase in lowest observed capacity, a decrease in average first responder time, and a decrease in worst case first responder time. Implementing Model 3 (average first responder time) and 4 (worst case first responder time) will have a positive effect on both the average first responder time and

the worst case first responder time, but a slight negative effect on the minimum observed capacity. It also seems like all the three models have a positive effect on the distribution of the capacity along the route, especially in situations with a high overcapacity. All the three models facilitate a more logical positioning of the RUs, as the RUs get other incentives to position themselves in comparison to Model 1.

6.5 Unfixed route - model evaluation

This section describes the experiment when using routes as a variable in the models. It describes both the experiment and its result. In the end, a summary is provided with comments about the result together with some general recommendations.

6.5.1 Experiment construction

The same instances as in Section 6.4 are used for evaluating the models that includes routing as a decision variable. 48 unique setups are examined, all presented in Table 6. Index (35) is also used for naming the setups in this section. Therefore, as an example, if wanting to refer to Model 3 under Case 4 with 30 km grid layout, the index would be “(M3).C4.30.U”, where the “U” represents the situation “Unfixed route”. When applying routing to the models, it implies that the routes are not fixed after initially solving Model 1 like in section 6.4. What it also implies is an increase in problem size compared to the fixed route models. The fact that the problem size increases, will bring some implications in terms of the solvability of some of the models under different instances.

		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
20 km grid	Model 1	(M1).C1.20.U	(M1).C2.20.U	(M1).C3.20.U	(M1).C4.20.U	(M1).C5.20.U	(M1).C6.20.U
	Model 2	(M2).C1.20.U	(M2).C2.20.U	(M2).C3.20.U	(M2).C4.20.U	(M2).C5.20.U	(M2).C6.20.U
	Model 3	(M3).C1.20.U	(M3).C2.20.U	(M3).C3.20.U	(M3).C4.20.U	(M3).C5.20.U	(M3).C6.20.U
	Model 4	(M4).C1.20.U	(M4).C2.20.U	(M4).C3.20.U	(M4).C4.20.U	(M4).C5.20.U	(M4).C6.20.U
		Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
30 km grid	Model 1	(M1).C1.30.U	(M1).C2.30.U	(M1).C3.30.U	(M1).C4.30.U	(M1).C5.30.U	(M1).C6.30.U
	Model 2	(M2).C1.30.U	(M2).C2.30.U	(M2).C3.30.U	(M2).C4.30.U	(M2).C5.30.U	(M2).C6.30.U
	Model 3	(M3).C1.30.U	(M3).C2.30.U	(M3).C3.30.U	(M3).C4.30.U	(M3).C5.30.U	(M3).C6.30.U
	Model 4	(M4).C1.30.U	(M4).C2.30.U	(M4).C3.30.U	(M4).C4.30.U	(M4).C5.30.U	(M4).C6.30.U

Table 6 - Setups for unfixed routes

6.5.2 Results

The grid layout represents a substantial impact whether or not a solution is provided by the NEOS-server in this experiment. Appendix B presents a detailed overview over the result from each unique setup. From this overview, it is possible to observe the relatively huge amount of non-returned solutions. Out of all the 48 unique setups, 16 are not solvable. Out of the 16 non-solvable setups, 12 are represented with the 20 km grid layout and 4 with the 30 km grid layout. The main reason for why no solution is presented for these setups is the limitation of 3GB memory at the NEOS-server. When the memory usage exceeds 3 GB, NEOS does not return any answer.

By analyzing the models and their result, it is possible to get a general clue regarding the solvability of each model. Model 1 is solvable for all instances. Model 2, which maximizes the minimum observed capacity, is relatively small in size and provides a solution for all instances. Model 3 however, seems to be too big for most of the instances and grid layouts. Only two setups, namely (M3).C2.30.U and (M3).C3.30.U, provide a solution for the model. Possible reasons why these setups are solvable is the overcapacity in Case 2 and the reduced number of installations in Case3. The overcapacity reduces the required memory needed to find the optimal positions of routes and RU positions. Also, by removing one offshore installations, the problem becomes smaller. When interpreting the solvability of model 4, it is clear that none of the setups for the 20 km grid layout are returning any solution. On the other side, all the cases for Model 4 with 30 km grid layout do.

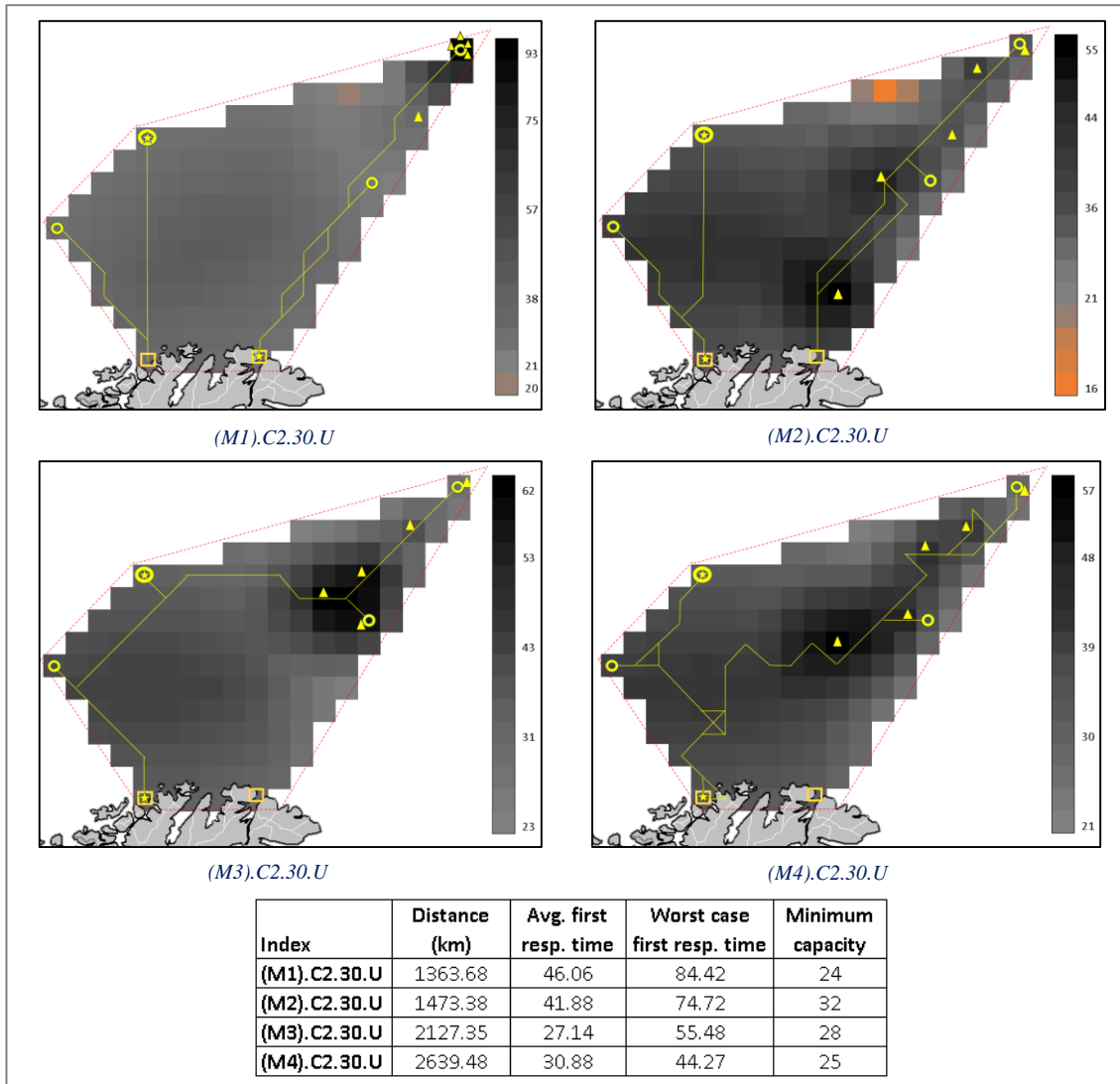


Figure 17 - Emergency preparedness design, Model 1 – 4, Case 2, 30 km grid layout, unfixed routes

The results from instance 2, with the 30 km grid layout enables a comparison of the behavior of each model with unfixed routes. These instances provides a coherent result for all four models, in difference with most of the other instances. Figure 17 presents the emergency preparedness design for Models 1-4 under Case2 with the 30 km grid layout. General observations of each model is presented in the bullet list below.

- Due to the overcapacity in Case 2 in terms of one extra SAR helicopter, Model 1 ((M1).C2.30.U) positions four ERV boats at installation P4 and an additional ERV not far away. This non-logical behavior was discussed in section 6.4, and seems occur when the RUs do not have any other incentive to position themselves other than keeping within the capacity requirement.
- Model 2 ((M2).C2.30.U)) clearly behave according to its objective as it increases the minimum observed capacity along the route from 24 to 32 people. In difference from

other instances for Model 2, the specific setup (M2).C2.30.U seems to provide an acceptable set of routes. However, there are examples of routes generated by Model 2 being quite irrational. As long as the capacity along the routes never exceeds the maximum observed capacity, the route can move wherever it want as long as it starts at an airport and eventually ends at an offshore installation. (M4).C2.30.U is a good illustration of such a behavior although it represents the emergency preparedness design for Model 4.

- Model 3 ((M3).C2.30.U) provides a quite different routing setup than the other models. Since Model 3 uses average first responder time as objective, each point of the route will have a saying for the objective value. In difference from the other models, Model 3 generates interconnected routes. Using Figure 17 as an illustration, it is clear that all the routes to the four destinations follows the same path from the departure node P1. By doing so, the response time is reduced from 46.06 minutes to 27.14 minutes from Model 1, which corresponds to a reduction of 41.08%.
- The results from Model 4 has much of the same characteristics as in Model 2. The routes provided by Model 4 can potentially create unnecessary detours, which is also the case for (M4).C2.30.U. If the first responder time at each part of the route never exceeds the maximum observed first responder time, the routes can potentially create detours as long as the route starts at an airport and ends at an offshore installation.

When applying routing to the models, it is reasonable to expect an improvement in the objectives if comparing the results from the fixed / unfixed models under the same instances. At least the models that include routing, when using exact methods, cannot perform worse than the models with fixed routes. Table 7, Table 8 and Table 9 presents the change in the main objective from the fixed route results to the routing result for respectively Model 2, Model 3 and Model 4. The improvement when applying unfixed routes is calculated as in (36), the average improvement is calculated based on the improvement of each instance.

$$Improvement = \frac{(Objective\ unfixed\ routes - Objective\ fixed\ routes)}{Objective\ fixed\ routes} \times 100\% \quad (36)$$

Bold numbers represents improved objectives

Model 2 comparison					
Input		Fixed routes		Unfixed routes	
Case	Grid (km)	Index	Capacity	Index	Capacity
1	20	(M2).C1.20.F	21	(M2).C1.20.U	21
	30	(M2).C1.30.F	21	(M2).C1.30.U	21
2	20	(M2).C2.20.F	32	(M2).C2.20.U	32
	30	(M2).C2.30.F	32	(M2).C2.30.U	32
3	20	(M2).C3.20.F	21	(M2).C3.20.U	21
	30	(M2).C3.30.F	21	(M2).C3.30.U	21
4	20	(M2).C4.20.F	20	(M2).C4.20.U	21
	30	(M2).C4.30.F	20	(M2).C4.30.U	21
5	20	(M2).C5.20.F	19	(M2).C5.20.U	21
	30	(M2).C5.30.F	19	(M2).C5.30.U	21
6	20	(M2).C6.20.F	21	(M2).C6.20.U	21
	30	(M2).C6.30.F	21	(M2).C6.30.U	21

Table 7 - Comparison for minimum observed capacity of fixed/unfixed routes

Model 2 is solvable for all instances both with fixed and unfixed routes, which in principle gives a good basis for comparison. Out of the twelve instances for Model 2, four are facilitating an improvement of the minimum observed capacity. Case 4 and 5, under both the 20 and 30 km grid layout increases the minimum capacity. An increase of the minimum capacity to at least 21 people is expected since this value has been obtained with the same number of RUs at an earlier stage. By observing the minimum capacity objective for each instance, it shows that it is not possible to increase the minimum capacity to above 21 people with one SAR helicopter and five ERVs with the current setup of airports and offshore installations. Case2 under both the 20 and 30 km grid layout is the only one able to provide a minimum capacity higher than 21. If adding excess capacity in terms of extra RUs, just like in Case 2, it is more likely to see an increase in the minimum capacity. If considering all instances for Model 2, the average increase in the minimum capacity when applying fixed routes is 2.59%. However, this increase has to be interpreted by the fact that some of the instances does not facilitate a capacity increase due to the specific combination of number of RUs and airports / offshore installations.

NS = Not Solvable, memory needed > 3 GB, Bold numbers represents improved objectives

Model 3 comparison					
Input		Fixed routes		Unfixed routes	
Case	Grid (km)	Index	Avg. first resp. time (min)	Index	Avg. first resp. time (min)
1	20	(M3).C1.20.F	41.68	(M3).C1.20.U	NS
	30	(M3).C1.30.F	41.75	(M3).C1.30.U	NS
2	20	(M3).C2.20.F	34.59	(M3).C2.20.U	NS
	30	(M3).C2.30.F	34.70	(M3).C2.30.U	27.14
3	20	(M3).C3.20.F	41.57	(M3).C3.20.U	NS
	30	(M3).C3.30.F	39.30	(M3).C3.30.U	36.94
4	20	(M3).C4.20.F	42.81	(M3).C4.20.U	NS
	30	(M3).C4.30.F	42.39	(M3).C4.30.U	NS
5	20	(M3).C5.20.F	40.10	(M3).C5.20.U	NS
	30	(M3).C5.30.F	40.09	(M3).C5.30.U	NS
6	20	(M3).C6.20.F	45.00	(M3).C6.20.U	NS
	30	(M3).C6.30.F	40.12	(M3).C6.30.U	NS

Table 8 - Comparison of average first responder time for fixed/unfixed routes

Since most of the instances for Model 3 are non-solvable, there is not a good basis for comparison of the average first responder time between the fixed / unfixed routes. As previously stated, (M3).C2.30.U and (M3).C3.30.U are the only situations providing a solution. If comparing the average first responder time for these two cases from fixed to unfixed routes, they contribute with an average reduction of 13.9%. However, such a reduction might not be representative for the other instances.

Table 9 presents the change in the worst case first responder time between the fixed / unfixed routes for Model 4. For the unfixed routes, none of the instances with the 20 km grid layout are solvable for model 4, so the comparative basis is done with the instances from the results with 30 km grid layout. It appears from the results that 65.06 minutes is the lowest possible worst case first responder time when having five ERVs and one SAR helicopter available with the current setup of airports and offshore installations. The minimum value of 65.06 minutes is never achieved when solving Model 4 with fixed route. Only two observations with the unfixed routes leads to a worst case first responder time lower than 65.06. (M4).C2.30.U, which has an overcapacity in terms of one excess SAR helicopter at P2 is able to have a worst case first responder time of 44.27 minutes. (M4).C3.30.U, which has one less offshore installation, provides a worst case first responder time of 64.57 minutes. Based on the six observation that facilitate a comparison between the fixed / unfixed routes,

the average decrease in the worst case first responder time is 8.67% when applying unfixed routes.

NS = Not Solvable, memory needed > 3 GB, Bold numbers represents improved objectives

Model 4 comparison					
<i>Input</i>		<i>Fixed routes</i>		<i>Unfixed routes</i>	
Case	Grid (km)	Index	Max. first resp. time (min)	Index	Max. first resp. time (min)
1	20	(M4).C1.20.F	69.79	(M4).C1.20.U	NS
	30	(M4).C1.30.F	69.79	(M4).C1.30.U	65.06
2	20	(M4).C2.20.F	57.67	(M4).C2.20.U	NS
	30	(M4).C2.30.F	55.48	(M4).C2.30.U	44.27
3	20	(M4).C3.20.F	66.74	(M4).C3.20.U	NS
	30	(M4).C3.30.F	65.06	(M4).C3.30.U	64.57
4	20	(M4).C4.20.F	69.79	(M4).C4.20.U	NS
	30	(M4).C4.30.F	69.79	(M4).C4.30.U	65.06
5	20	(M4).C5.20.F	66.09	(M4).C5.20.U	NS
	30	(M4).C5.30.F	66.09	(M4).C5.30.U	65.06
6	20	(M4).C6.20.F	70.73	(M4).C6.20.U	NS
	30	(M4).C6.30.F	77.44	(M4).C6.30.U	65.06

Table 9 - Comparison of worst case first responder time for fixed/unfixed routes

6.5.3 Summary

In general the comparability of the models with fixed / unfixed routes is reduced due to the relatively low number of solvable instances for some of the models. Model 2 provides a solution for all instances. However, there are only a few instances facilitating an improvement in the minimum observed capacity. Model 3, average first responder time, only has two observations that allows a comparison between the fixed / unfixed routes, which might not be representative for the other instances if they were solvable. Model 4 provides more comparable observations than Model 2 and 3. Therefore, the results provided by Model 4 might be the most trustworthy. It shows that on average, the worst case first responder time is improved by 8.67% when applying unfixed routes. In general the performance indicators other than the main objective of a model, might end up with a poor performance when applying unfixed routes. A good illustration of this is presented in the table in Figure 17. For example Model 4, which minimizes the first responder time does a very poor job in terms of the minimum observed capacity (25 people) if compared to Model 2 (32 people). Another example is the detours that potentially can occur when applying Models 2 and 4. Therefore, as a recommendation, the results provided by the models that include routing, would best fit in situations where the objectives later can be used as goals in multiobjective models.

6.6 Multiobjective evaluation

This section presents an experiment with the two multiobjective models. Initially, the construction of the experiment is presented, followed by the result of the experiments and in the end a summary.

6.6.1 Experiment construction

In this experiment, Model 5 and 6 under Case 5 with the 20 km grid layout and fixed routes are used in order to illustrate how multiobjective modelling can be used in an emergency preparedness situation. The routes that are used are the ones found in (M1).C5.20.F. Due to the routes being fixed, the three objectives: average first responder time, worst case first responder time and minimum observed capacity will be included in the MOLP models. Their respective goals are the objective values found from Model 2, 3 and 4 under Case 5 with the 20 km grid layout and fixed routes in Section 6.4. The goal of each objective is:

- Goal 1 - Average first responder time: **40.1 minutes**
- Goal 2 - Worst case first responder time: **66.1 minutes**
- Goal 3 - Minimum observed capacity: **19 people**

Both Model 5 and 6 will be examined under eleven different weight setups as presented in Table 10. The weights of each objective are evenly spread so that each objective is represented at all parts of the weight scale. This way we are able to produce as many unique solutions as possible.

Weight Setup	Avg. first resp. time (g1)	Worst case first resp. time (g2)	Min. observed capacity (g3)
	e_1	e_2	e_3
WS-1	1/3	1/3	1/3
WS-2	0.3	0.3	0.4
WS-3	0.6	0.3	0.1
WS-4	0.9	0.05	0.05
WS-5	0.4	0.3	0.3
WS-6	0.1	0.6	0.3
WS-7	0.05	0.9	0.05
WS-8	0.3	0.4	0.3
WS-9	0.3	0.1	0.6
WS-10	0.05	0.05	0.9
WS-11	0.99	0.005	0.005

Table 10 - Weight setup

6.6.2 Results

If combining the results from Model 5 and 6 under all the different weight setups, it shows that there are only provided three different pareto optimal solutions among the 22 observations. A detailed overview over the performance indicators and weighted deviations by each model under the different weight setups can be found in Appendix C. Table 11 presents the three unique solutions among with the values of the performance indicators, and the corresponding weight setup that lead to each solution. It shows that among the three solutions, solution 2 is the most frequent. A possible reason for this is that the effect on the worst case first responder time of changing the positions of RUs is high. Changing one RU position might result in a great leap in the worst case first responder time, hence also a high deviation from its goal. The table also shows the purpose of MOLP, as the weight of each individual target value results in different solutions. For example, solution 1 is achieved by WS-11 for Model 5 and WS-4 and WS-11 for Model 6, which both have a high weight for the average first responder time. There are weight setups that are not present in the Maximum percentage weighted deviation since they are not contributing in a pareto optimal solution. WS-1 and WS-5 under the Maximum weighted deviation are both dominated by one of the three pareto optimal solutions in Table 11.

	Avg. first resp. Time	Worst case first resp. time	Minimum obs. capacity	Total percentage weighted deviation	Maximum percentage weighted deviation
Solution	40.1 (g1)	66.1 (g2)	19 (g3)	Weight Setups	
1	40.1	73.3	17	WS-11	WS-4, WS-11
2	40.4	66.1	18	WS-1, WS-3, WS-4, WS-5, WS-6, WS-7, WS-8,	WS-3, WS-6, WS-7, WS-8
3	41.6	69.8	19	WS-2, WS-9, WS-10	WS-2, WS-9, WS-10

Table 11 - Three unique solutions with their corresponding weight setup

Since the experiment uses Case 5 under the 20 km grid layout and the fixed route from Model 1, it is interesting to compare the results from the multiobjective models with the result from fixed route experiment in section 6.4. This way it is possible to see whether the multiobjective models are capable of improving the overall performance of the emergency preparedness system. Solution 1, which provides the lowest average first responder time is

comparable with Model 3, (M3).C5.20.F. Solution 2, providing the lowest worst case first responder time is comparable with Model4, (M4).C5.20.F, and solution 3 is comparable with Model 2, (M2).C5.20.F which brings the highest minimum observed capacity. Table 12 presents a comparison between the MOLP solution and the solution from Case 5. From the table, it is clear that the average first responder time is improved in solution 2 and solution 3. The average first responder time for model 2 and 3 is reduced by respectively 4.49% and 5.67 % from the solution in Case 5. Even though the other objectives does not improve, it may still be that they would if examining other cases with the multiobjective models.

Green cells represents improved performance measurement

	Avg. first resp. Time	Worst case first resp. Time	Minimum obs. capacity
Solution 1 (M3).C5.20.F	40.1	73.3	17
Solution 2 (M4).C5.20.F	40.4	66.1	18
Solution 3 (M2).C5.20.F	41.6	69.8	19
	44.1	69.8	19

Table 12 - Comparison of result from MOLP and Case 5 fixed routes

6.6.3 Summary

This experimentation has shown the purpose of multiobjective modelling and that it is applicable for emergency preparedness problems. It has shown that by changing weight for the preferable goals, the performance of the objectives changes along with the emergency preparedness design. The experiment also shows that by applying multiobjective modelling, it is possible to increase the overall performance of the emergency preparedness system. The average first responder time showed an improvement from the fixed route result from Model 2 and 4 with case 2 under the 20 km grid layout and fixed routes.

6.7 Minimization of rescue time

In this section, a stepwise solution procedure for minimizing the rescue time is presented. Initially, a description of the experiment is provided followed by a presentation of the results and a summary.

6.7.1 Experiment construction

In this experiment, Mode 1 under case 5 with a 20 km grid layout and unfixed routes ((M1).C5.20.U) is used to illustrate the procedure of stepwise reducing the t^{max} parameter in order to minimize the maximum rescue time. Even though routing is used in this experiment, fixed route would also be applicable. There are no obvious ways of minimizing the rescue time without changing the current model structure used in Models 1 – 4. Therefore, as an alternative method of minimizing the maximum rescue time, the stepwise solution procedure of reducing the t^{max} parameter is presented. From function (1) presented in section 2.2, the t^{max} parameter is represented as the maximum allowed time until the required amount of people should be rescued from sea. If getting a feasible solution when using a t^{max} value of 120 minutes, it is guaranteed that at each part of the route every people would be save within this time. However, it might be that it is possible to guarantee an even lower rescue time with the current setup of RUs. By stepwise reducing the t^{max} parameter until it the model reaches infeasibility, we will find the threshold for the rescue time. The t^{max} parameter will change the c_{rij} parameter. So for each change in the t^{max} parameter it will generate new values for the c_{rij} . (M1).C5.20.U, brings overcapacity to the model due to the c^{min} being reduced to 17 people and at the same time having five ERV boats and one SAR helicopter available. The initial t^{max} parameter was set to 120 minutes and then stepwise reduced by one minute until infeasibility was reached.

6.7.2 Results

Table 13 presents the performance indicators from the solutions provided by Model 1 under different t^{max} values. Infeasibility was reached at $t^{max} = 107$ minutes, which means that the maximum rescue time to save 17 people at each point of the route will not exceed 108 minutes. As a supplement to Table 13, there are figures giving a graphical illustration of the behavior of each performance indicator under each t^{max} value in Appendix D. Appendix D also provide a more detailed description for the output results.

NF = Not feasible, t-max not sufficiently large

t^{max}	Distance (Km)	Mimnimum obesverd capacity	Avg. First Responder Time (min)	Maximum First responder time (min)
120 min	1318.82	18	49.04	73.30
119 min	1318.82	17	49.04	73.30
118 min	1318.82	17	48.22	82.87
117 min	1318.82	17	48.61	82.87
116 min	1318.82	17	51.19	82.87
115 min	1318.82	17	47.52	73.30
114 min	1318.82	17	47.96	73.30
113 min	1330.54	17	46.93	75.17
112 min	1330.54	17	45.48	73.30
111 min	1495.39	17	45.99	70.73
110 min	1495.39	17	44.61	70.73
109 min	1495.39	17	44.41	70.73
108 min	1556.81	17	44.06	77.27
107 min	NF	-	-	-

Table 13 - Performance indicators for T-max experimentation

If observing how the performance indicators behave in tact with the t^{max} changes, it is possible to get an overview of the coherence between the t^{max} parameter and the performance indicators. If first considering the coherence between the t^{max} parameter and the total distance of the transportation routes, the distance seems to increase as the t^{max} decreases. Such a behavior seems logical as the potential places of putting the routes becomes smaller when reducing the capacity. The fact that minimization of the total transportation distance is the objective of Model 1, guarantees a minimum transportation distance. Figure 18, which shows the emergency designs for $t^{max} = 114, 112, 110$ and 108 minutes, is a good illustration of how the routes are forced to change due to the capacity becoming smaller. All t^{max} values including 114 minutes and higher, results in a total distance of 1318.12 km, which is the shortest possible route with the current setup of installations and airports. t^{max} values smaller than 140 forces a longer total transportation distance. At $t^{max} = 108$ minutes, all the four transportation routes starts from H2 (Berlevåg) as a result of the reduction in the capacity of the emergency preparedness system.

The minimum observed capacity seems to be more stable than the total distance. Since the capacity is not included in the objective function, it is not guaranteed that the capacity provided by different t^{max} is optimal. A minimum capacity of 18 people is the highest observed capacity, and is achieved when $t^{max} = 120$ minutes. However, as the t^{max} becomes smaller

and the capacity decreases, it is expected that the minimum observed capacity moves towards 17 people.

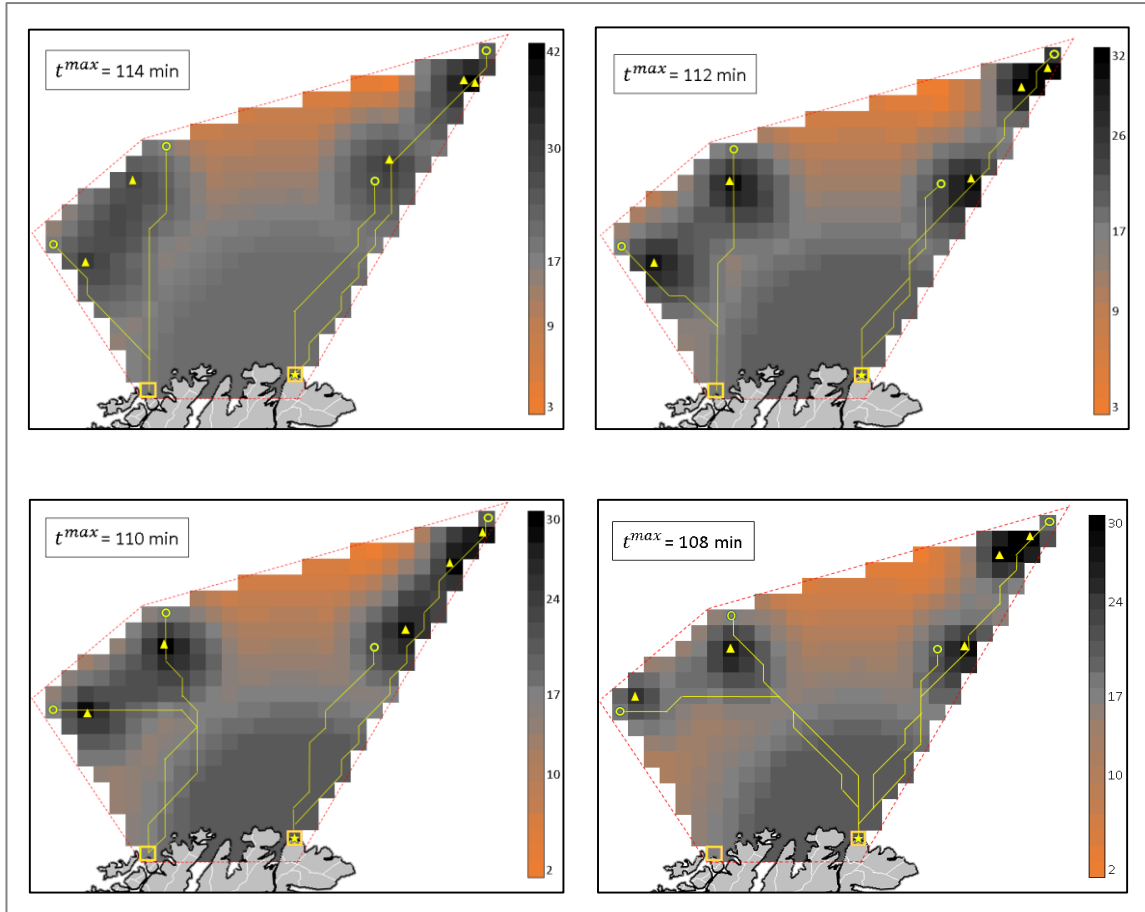


Figure 18 - Collection of emergency preparedness design with different rescue time restriction

The average first responder time shows a steady reduction as the t^{max} becomes smaller. A possible reason for this is that when the capacity becomes smaller, which is the case if t^{max} is reduced, the routes are more dependent on being close to an RU compared to an overcapacity situation. A result of a closer positioning between the RUs and the route is a reduced average first responder time. When it comes to the worst case first responder time, it does not seem to have clear coherence with the t^{max} .

6.7.3 Summary

This section has shown that it is possible to stepwise reduce the t^{max} parameter in order to create an emergency preparedness design that minimizes and guarantees a maximum rescue time along the transportation route. It has also shown that if reducing the capacity available

in the emergency preparedness system, the total transportation distance increases. In addition, the average first responder time benefits from a reduction in the t^{max} parameter.

6.8 Fix-and-Optimize Heuristic evaluation

In this section, a description of the experiment with the F&O heuristic is presented. The performance of the heuristic along with its results is presented, followed up by a summary.

6.8.1 Experiment construction

The purpose of including the heuristic is to be able to obtain a solution to the problem where the exact methods come short. Models 2-4 will be examined by applying the F&O heuristic. There exist situations where the heuristic solutions are directly comparable with the exact solutions. This way it is possible to get an indication on the general performance of the heuristic. The heuristic solutions is compared to the results found in Section 6.5 which presents the results of Models 1 – 4 when routing is included as a variable. Not all instances are necessary to compare. There exist situations where the solution found in Models 2 – 4 with fixed routes performs equally as for the unfixed route. In such situations, the heuristic is guaranteed to find the optimal solution already in the first step of the F&O algorithm, and will therefore not need to be compared. Appendix E provides detailed information of the Heuristic performance and also illustrates which setups that are not needed to compare.

For simplicity, the B parameter indicating the time limit for the algorithm, is set to 6 hours (21600 seconds). This value is set deliberately high so that each model and instance is guaranteed to reach a local optimum. The G parameter is set to a value of 50. By doing so we restrict the number of new arcs in the new routes to be no more than 50. Regardless of the type of model, case and grid layout, the G parameter stays the same for each situation. The same index (35) used in the previous experiments is also used for this experiment. If wanting to refer to a situation consisting of Model 4, Case 3 and with the 30 km grid layout, the index would be “(M4).C3.30.H”, where “H” represents “Heuristic”.

6.8.2 Results

All the models under each instance that was run with the F&O heuristic reached a solution where no more objective improvements occurred within the time limit of 6 hours.

The performance of the heuristic can be evaluated when comparing its result with the results from the exact methods. Table 14, presents the optimality gap of the observations that are comparable with each other. Since the F&O heuristic combines both routing and coverage, its result is compared to the unfixed route results. The grey areas in the table represents the values which has been compared with each other. In addition to the results from the heuristic and the unfixed routes, the results from the fixed routes are also present in the table. Since the results from the fixed routes represent the results from the first operation of the F&O heuristic, it will give an indication whether the heuristic has done improvement from the worst case solution. The optimality gap has been calculated as in (37).

$$Gap = \frac{(Heuristic\ objective - Unfixed\ route\ objective)}{Unfixed\ route\ objective} \times 100\% \quad (37)$$

	Index	Objective exact methods, fixed routes	Objective exact methods, unfixed routes	Objective heuristic method, unfixed route	Gap
Model 2	(M2).C4.20	20	21	20	4.76 %
	(M2).C4.30	20	21	20	4.76 %
	(M2).C5.20	19	21	21	0.00 %
	(M2).C5.30	19	21	21	0.00 %
Model 3	(M3).C2.30	34.70	27.14	27.16	0.07 %
	(M3).C3.30	39.30	36.94	36.94	0.00 %
Model 4	(M4).C1.30	69.79	65.06	66.79	2.66 %
	(M4).C2.30	55.48	44.27	54.27	22.59 %
	(M4).C3.30	65.06	64.57	64.57	0.00 %
	(M4).C4.30	69.79	65.06	69.79	7.27 %
	(M4).C5.30	66.09	65.06	66.09	1.58 %
	(M4).C6.30	77.44	65.06	69.79	7.27 %

Table 14 - Fixed route, unfixed route and heuristic performance. Optimality gap between unfixed route and heuristic

The optimality gap seems to vary among the three different objectives. Model 2 (Minimum observed capacity) and Model 4 (Worst case first responder time) both have an incremental objective function. A minimum capacity objective of for example 20 people can be obtained by many different combinations of routes and RU positions. Even though there are not that

many observations to do a comparison on, it seems like the F&O heuristic is not performing as good for Models 2 and 4 as for Model 3.

It might be that the probability of reaching a global optimum would be higher if the G -parameter would have been increased. However, it might also be in some situations that a global optimum would only be possible to obtain if the routing variable x_{lij} and RU position variable y_{ri} were unfixed at the same time. Model 3 seems to be able to improve its solution in a much better way than the two other models. Figure 19 illustrates the objective value (in this case the total first responder time) of Model 3, under Case 2 and 30 km grid layout when applying the F&O heuristic ((M3).C2.30H). The objective reaches a point where the objective value stabilizes at around 1200 seconds, which makes it unnecessary to show the evolution of the objective value for the whole time limit horizon.

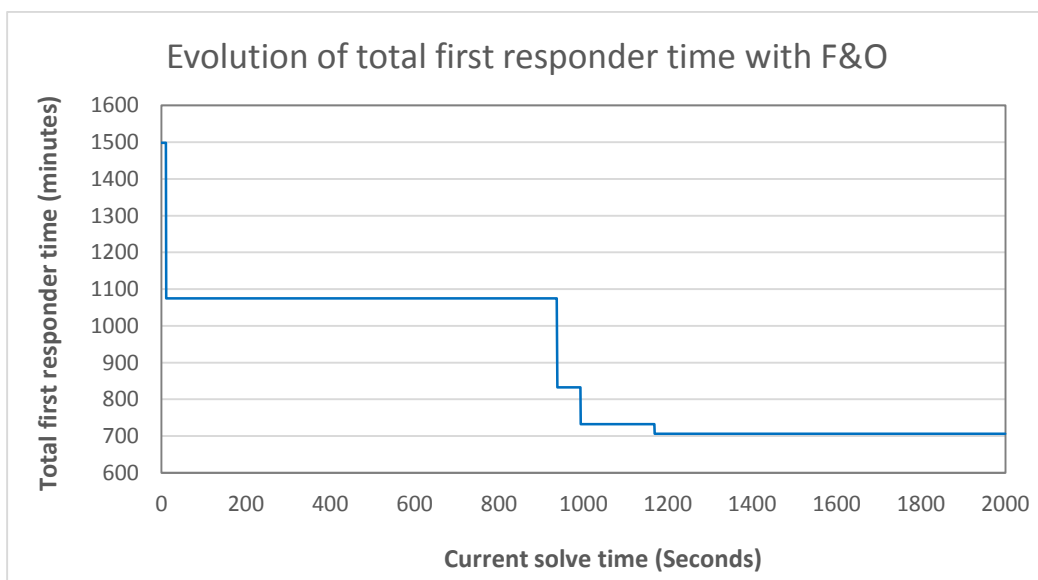


Figure 19 - Evolution of the total first responder time, over total solve time (M3).C2.30.H

The results provided by the unfixed routes showed an average improvement for all the three objectives in Models 2-4. However, the major weakness of the unfixed route results is the relatively high number of non-solvable instances, which is also the reason for the development of the F&O heuristic. The average improvements for each model of applying the heuristic compared to the fixed routes are discussed in the bullet list on the next page. The improvement has been calculated as in equation (38).

$$Improvement = \frac{(Objective\ heuristic - Objective\ fixed\ routes)}{Objective\ fixed\ routes} \times 100\% \quad (38)$$

- Model 2, minimum observed capacity, shows an average improvement of 1.75% when applying the F&O heuristic, which is appears from Table E 2. It must be said that, like for the unfixed route, some of the instances does not facilitate a capacity increase due to the specific combination of number of RUs and airports / offshore installations. The exact solutions when applying unfixed routes contributed to an improvement in the minimum capacity of 2.59%, which is higher than the average F&Q improvement. Out of the 4 instances that actually facilitate an improvement, only two of these show an improvement when applying the F&O heuristic compared to the fixed routes
- For Model 3, average first responder time, the F&O heuristic contributed to an average improvement of 8.93 % compared to the fixed route results (see Table E 3). If comparing the heuristic improvement with the improvement of the exact solution, it shows a slightly weaker performance, as the exact solutions contributed to an average improvement of 13.9%. Even though the results from the exact method shows a higher improvement than the heuristic result, it should be said that the exact method only provided two solvable instances, whereas the heuristic method provided 12 solvable instances. Under all instances, the F&O heuristic improves the average first responder time compared to the fixed routes.
- For Model 4, worst case first responder time, the F&O heuristic showed a 2.94% increase from the fixed routes (see Table E 4). The exact method showed a much higher improvement than the heuristic, namely an 8.67% improvement. It should be said that the exact solution method only provided a solution for six instances, whereas the F&O heuristic provided a solution for all twelve instances. Out of these twelve instances, 4 did not show an improvement if compared to the fixed route results.

Figure 20, illustrates the emergency preparedness system for Models 1-4 under Case 5 ($c^{min} = 17$) with the 20 km grid layout when applying the F&O heuristic. The emergency preparedness design shown much of the same characteristics as for the exact methods. The emergency preparedness design for Model 1 is obviously the same as for the fixed route case.

Model 2 creates detours, which is expected due to the routes having no other incentives be positioned other than keeping within the minimum observed capacity. The emergency preparedness design when applying Model 3 shows much of the same features as if we were to apply the exact model. The routes are interconnected and follows a similar path to the intersection point where they divide into individual paths. The emergency preparedness design created by Model 4 does not seem to have that many similarities with the exact model. The routes generated by Model 4 with the F&O heuristic seems to be quite similar to the ones created by Model 1. However, the two eastern routes now follow a similar path to installation P3, where they divide into two separate paths. In theory, Model 4, when applying both exact methods and the F&O heuristic has the potential of creating detours.

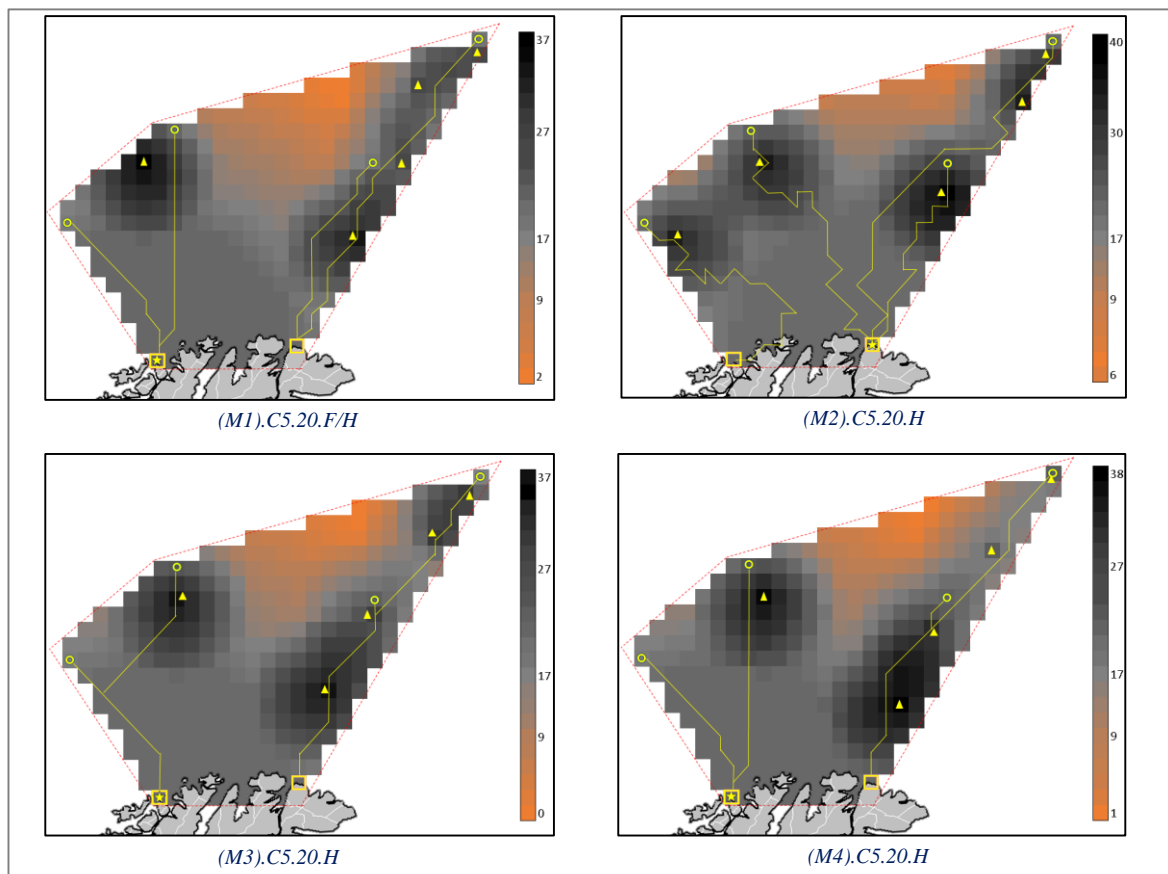


Figure 20 - Models 1-4, Case 4, with 20 km grid using the F&O heuristic

6.8.3 Summary

This experiment has shown that it is possible to apply an F&O heuristic to the Barents Sea case in situations where exact methods comes short. The F&Q heuristic showed a varying performance between Models 2-4, but were in many situations able to improve the worst

case solution. Applying the F&O heuristic to Model 3 seems to have the best impact on the objective. Model 2 and 4 both have an incremental objective function, resulting in a possibility to get stuck in a local optimum in an early stage of the algorithm. The optimality gap of each model when applying the F&Q heuristic could maybe have been reduced by increasing the G parameter in the neighborhood search constraint (34). However, it might also be that an optimal solution would only be possible to achieve by having the routing variable x_{ij} and RU position variable y_{ri} unfixed at the same time. An idea could be to allow some y_{ri} variables to change while at the same time having unfixed routes. That way, the probability of finding solutions that requires both of the variables to be unfixed at the same time, increases. As for the unfixed route example, the performance indicators other than the main objective of a model, might end up with a poor performance when applying F&O heuristic. A good example is the potential development of detours for both Model 2 and 4, which will not be appropriate to use in real life. A suggestion would therefore be to use the objectives found with the F&O heuristic as target values in MOO models. Since the target values found by the F&O heuristic cannot be proven optimal, the recommended approach would be to apply GP rather than MOLP.

7. Conclusion and further research

Several mathematical models, including a heuristic, has been developed in order to create and evaluate emergency preparedness designs for safe helicopter transportation of offshore personnel from onshore bases to offshore installations. Three new performance measurements was established, each with an associated mathematical model: Average First Responder Time, Worst Case first Responder Time, and Minimum Observed Capacity. These performance measurements with its associated models has been tested under different instances, with both fixed and unfixed helicopter routes.

The fixed routes that was used for evaluating the new performance measurements was generated by using distance related measurements, which is the standard for creating emergency preparedness designs. It showed, for each performance measurement, a clear improvement in the main objective when applying the models on the fixed routes. Not only did it show a positive effect on each individual objective, but in general it also showed a positive effect on all objectives when using one of the three models on the fixed routes. A stepwise solution procedure for minimizing the maximum Rescue Time was also presented. This procedure showed that it is possible to find a maximum Rescue Time by easily adjust the time parameters in the basic model. The Rescue Time minimization procedure also showed a positive effect on the First Responder Time.

Two MOLP models has also been developed in order to optimize and evaluate all the three objectives in one model. The MOLP models was implemented on fixed routes, but will also be applicable on unfixed routes. The experiment showed that applying multiobjective modelling has a positive effect on the total performance of the emergency preparedness system. It also showed the purpose of multiobjective modelling, as the emergency preparedness system changed based on the preferable weight of each target value.

Applying unfixed routes to the problem showed an improvement for all individual objectives compared to the fixed routes. However, due to an increase in the problem size when applying unfixed routes, the exact methods resulted in quite many non-solvable instances. Therefore, the F&O heuristic was developed in order to obtain solutions to all instances. In general the heuristic showed a reasonable optimality gap, but also a varying performance for each individual model. Both for the exact models and the F&O heuristic, the performance measure-

ments other than the main objective of a model, can potentially end up with a poor performance when applying unfixed routes. Therefore, a recommendation would be to only use the unfixed route and F&O results for multiobjective purposes.

From the different experiments that has been carried out in this research, it is clear that the capacity of the emergency preparedness system is decisive for the performance of each model. Situations with a high level of overcapacity, results in higher improvements in the objective. Like for the maximization of the minimum observed capacity, the overcapacity even is decisive whether or not an improvement takes place at all.

The F&O heuristic was developed in a relatively late stage of the research due to the non-solvability of some of the instances when applying the exact methods. In future research, it might be an idea to develop the heuristic to perform faster and more accurate. There are several ideas that could be tested for the F&O heuristic. An idea would be, while having the routing variable unfixed, also keeping a selection of the RU variables unfixed. That way the probability increases of finding solutions that require both the routing variable and the RU position variable to be unfixed at the same time while keeping the memory usage and computational time at an acceptable level. Applying other, higher level, heuristics might result in a better performance than the F&O improvement heuristic. Especially would it be interesting to combine the multiobjective models with heuristic methods, as the multiobjective models in this research only focused on fixed helicopter routes.

8. References

- Asiedu, Y., and M. Rempel. 2011. "A multiobjective coverage-based model for Civilian search and rescue." *Naval Research Logistics (NRL)* no. 58 (3):167-179. doi: 10.1002/nav.20387.
- Avinor. 2014. Trafikkstatistikk.
- Brachner, M. 2015. A simulation model to evaluate an emergency response system for offshore helicopter ditches. Paper read at Proceedings of the 2015 Winter Simulation Conference.
- Brachner, M., and L. M. Hvattum. 2016. "Combined emergency preparedness and operations for safe personnel transport to offshore locations." doi: <http://dx.doi.org/10.1016/j.omega.2016.03.006>.
- Farahani, R. Z., N. Asgari, N. Heidari, M. Hosseininia, and M. Goh. 2012. "Covering problems in facility location: A review." *Computers & Industrial Engineering* no. 62 (1):368-407. doi: <http://dx.doi.org/10.1016/j.cie.2011.08.020>.
- Fourer, R., D. M. Gay, and B. W. Kernighan. 2003. *AMPL : a modeling language for mathematical programming*. 2nd ed. ed. Pacific Grove, Calif: Thomson/Brooks/Cole.
- Gendreau, M., G. Laporte, and F. Semet. 1997. "The Covering Tour Problem." *Operations Research* no. 45 (4):568-576. doi: doi:10.1287/opre.45.4.568.
- Golden, F., and M. Tipton. 2002. *Essentials of Sea Survival*.
- Google. *Google maps. Barents Sea, Norway* 2016 [cited 03.04.2016. Available from <https://www.google.no>.
- Gribovskaia, I., O. Halskau, and M. Y. Kovalyov. 2015. "Minimizing takeoff and landing risk in helicopter pickup and delivery operations." *Omega* no. 55:73-80. doi: <http://dx.doi.org/10.1016/j.omega.2015.02.010>.
- Helber, S., and F. Sahling. 2010. "A fix-and-optimize approach for the multi-level capacitated lot sizing problem." *International Journal of Production Economics* no. 123 (2):247-256. doi: <http://dx.doi.org/10.1016/j.ijpe.2009.08.022>.
- Herrera, I. A., S. Håbrekke, T. Kråkenes, P. R. Hokstad, and U. Forseth. 2010. Helikopter Safety Study 3 (HSS-3) Main Report.
- Iden, K. A., M. Reistad, O. J. Aarnes, R. Gangstø, G. Noer, and N. E. Hughes. 2012. Kunnskap om vind, bølger, temperatur, isutbredelse, siktforhold mv. - "Barentshavet SØ". In *Bistand til OEDs åpningsprosesser for petroleumsvirksomhet i nord*.
- Jacobsen, S. R., and O. T. Gudmestad. 2013. Long-range rescue capability for operations in the Barents Sea. In *ASME 2013 International Conference on Ocean, Offshore and Arctic Engineering*. France, Nantes.
- Lang, J. C., and Z.-J. M. Shen. 2011. "Fix-and-optimize heuristics for capacitated lot-sizing with sequence-dependent setups and substitutions." *European Journal of Operational Research* no. 214 (3):595-605.
- Li, X., Z. Zhao, X. Zhu, and T. Wyatt. 2011. "Covering models and optimization techniques for emergency response facility location and planning: a review." *Mathematical Methods of Operations Research* no. 74 (3):281-310. doi: 10.1007/s00186-011-0363-4.
- Menezes, F., O. Porto, M. L. Reis, L. Moreno, M. P. d. Araújo, E. Uchoa, H. Abeledo, and N. C. d. Nascimento. 2010. "Optimizing Helicopter Transport of Oil Rig Crews at Petrobras." *Interfaces* no. 40 (5):408-416. doi: doi:10.1287/inte.1100.0517.
- NEOS-server. *Free internet-based service for solving optimization problems* 2016a [cited 31.03.2016. Available from <https://neos-server.org/neos/>.

- NEOS-server. *NEOS server FAQ* 2016b [cited 31.03.2016. Available from <http://neos-guide.org/content/FAQ>.
- Ninh, A. Q. 2013. "Two Discrete Stochastic Cellular Automata Models of Cancer Stem Cell Proliferation."
- Norwegian-Petroleum-Directorate. *Map of the Norwegian continental shelf*, 03.04.2016 2015. Available from <http://www.npd.no/en/Maps/Map-of-the-NCS/>.
- Olje- og Energidepartementet. 2014. *Fakta 2014*. Norsk Petroleumsverksnemnd Report 2014. Olje og Energidepartementet.
- Oljedirektoratet. 2014. *Petroleumsressursene på norsk kontinentalsokkel*. Resursrapport om felt of funn på norsk sokkel. Stavanger: Oljedirektoratet.
- Orumie, U. C., and D. Ebong. 2014. "A Glorious Literature on Linear Goal Programming Algorithms." *American Journal of Operations Research* no. Vol.04No.02:3. doi: 10.4236/ajor.2014.42007.
- Pisinger, D., and S. Ropke. 2007. "A general heuristic for vehicle routing problems." *Computers & Operations Research* no. 34 (8):2403-2435. doi: <http://dx.doi.org/10.1016/j.cor.2005.09.012>.
- Ragsdale, C. T. 2008. "Spreadsheet modeling & decision analysis : a practical introduction to management science." In, 298 - 338. Mason, OH: Thomson/South-Western.
- Verma, M., M. Gendreau, and G. Laporte. 2012. "Optimal location and capability of oil-spill response facilities for the south coast of Newfoundland." *Omega* no. 41 (5):856-867. doi: <http://dx.doi.org/10.1016/j.omega.2012.10.007>.
- Vinnem, J. E. 2012. "Retningslinjer for områdeberedskap - Underlagsrapport, forutsetninger og faglige vurderinger. In Norwegian."
- Vinnem, J. E. 2014. *Offshore Risk Assessment voll. 3* ed, *Springer Series in Reliability Engineering*: Springer-Verlag London.

9. Appendices

Appendix A: fixed route performance

Fixed route performance																
Input					Output											
Case	Fix / Un-fix route	Grid (Km)	Model	Index	Dist. (Km)	# of SAR	# of ERV	Avg. first resp. time	Min. first resp. Time	Max. first resp. Time	Min. obs. cap.	Avg. cap	Max. Obs. cap.	Solve time (Sec.)		
1	F	20	1	(M1).C1.20.F	1387.11	1	5	46.37	5	70.73	21	24.6	44	426.87		
			2	(M2).C1.20.F	1387.11	1	5	43.58	5	69.79	21	25.2	36	0.27		
			3	(M3).C1.20.F	1387.11	1	5	41.68	5	69.79	21	25.6	38	15.28		
			4	(M4).C1.20.F	1387.11	1	5	42.92	5	69.79	21	25.3	36	2096.63		
		30	1	(M1).C1.30.F	1363.68	1	5	41.75	5	77.44	21	24.7	37	0.13		
			2	(M2).C1.30.F	1363.68	1	5	41.75	5	77.44	21	24.7	37	0.01		
			3	(M3).C1.30.F	1363.68	1	5	41.75	5	77.44	21	24.7	37	0.15		
			4	(M4).C1.30.F	1363.68	1	5	41.93	5	69.79	21	24.2	36	109		
		2	F	20	1	(M1).C2.20.F	1318.82	2	5	48.62	5	84.58	24	38.4	117	0.19
					2	(M2).C2.20.F	1318.82	2	5	37.46	5	73.30	32	39.2	47	0.09
					3	(M3).C2.20.F	1318.82	2	5	34.59	5	66.09	24	40.9	57	7.69
					4	(M4).C2.20.F	1318.82	2	5	37.93	5	57.67	22	40.6	55	56.12
30	1			(M1).C2.30.F	1363.68	2	5	46.06	5	84.42	24	40.3	104	0.12		
	2			(M2).C2.30.F	1363.68	2	5	36.03	5	74.72	32	38.8	52	0.9		
	3			(M3).C2.30.F	1363.68	2	5	34.70	5	55.48	26	40.6	56	0.32		
	4			(M4).C2.30.F	1363.68	2	5	35.81	5	55.48	21	40.6	59	8.84		
3	F			20	1	(M1).C3.20.F	1062.25	1	4	43.90	5	69.79	21	24.5	34	15.76
					2	(M2).C3.20.F	1062.25	1	4	41.83	5	66.74	21	24.9	38	0.11
					3	(M3).C3.20.F	1062.25	1	4	41.57	5	66.74	21	25.1	39	6.57
					4	(M4).C3.20.F	1062.25	1	4	42.66	5	66.74	21	24.8	37	796.59
		30	1	(M1).C3.30.F	1063.68	1	4	39.30	5	65.06	21	24.0	36	0.01		
			2	(M2).C3.30.F	1063.68	1	4	39.30	5	65.06	21	24.5	36	0.04		
			3	(M3).C3.30.F	1063.68	1	4	39.30	5	65.06	21	24.5	36	0.08		
			4	(M4).C3.30.F	1063.68	1	4	39.30	5	65.06	21	24.5	36	135.18		
		4	F	20	1	(M1).C4.20.F	1330.54	1	5	44.41	5	82.87	20	25.9	39	21.58
					2	(M2).C4.20.F	1330.54	1	5	43.52	5	73.30	20	25.3	37	0.31
					3	(M3).C4.20.F	1330.54	1	5	42.81	5	73.30	20	25.5	39	17.68
					4	(M4).C4.20.F	1330.54	1	5	47.47	5	69.79	20	25.0	37	1458.2
30	1			(M1).C4.30.F	1363.68	1	5	49.09	5	77.09	20	23.7	39	1.39		
	2			(M2).C4.30.F	1363.68	1	5	42.39	5	69.79	20	24.5	36	0.14		
	3			(M3).C4.30.F	1363.68	1	5	42.39	5	69.79	20	24.5	36	2.33		
	4			(M4).C4.30.F	1363.68	1	5	42.39	5	69.79	20	24.5	36	238.41		
5	F			20	1	(M1).C5.20.F	1318.82	1	5	49.04	5	73.30	18	23.0	34	1.12
					2	(M2).C5.20.F	1318.82	1	5	44.13	5	69.79	19	24.5	42	0.37
					3	(M3).C5.20.F	1318.82	1	5	40.10	5	73.30	17	25.5	38	14.93
					4	(M4).C5.20.F	1318.82	1	5	42.33	5	66.09	18	25.1	37	3705.05
		30	1	(M1).C5.30.F	1363.68	1	5	48.80	5	74.72	18	22.5	30	0.13		
			2	(M2).C5.30.F	1363.68	1	5	42.17	5	69.79	19	24.9	39	0.09		
			3	(M3).C5.30.F	1363.68	1	5	40.09	5	73.30	17	25.4	38	1.59		
			4	(M4).C5.30.F	1363.68	1	5	41.31	5	66.09	17	25.0	35	127.16		
		6	F	20	1	(M1).C6.20.F	1587.94	1	5	50.37	5	79.46	21	23.7	30	510.1
					2	(M2).C6.20.F	1587.94	1	5	46.84	5	72.99	21	25.2	36	0.25
					3	(M3).C6.20.F	1587.94	1	5	45.00	5	73.30	21	25.3	37	35.43
					4	(M4).C6.20.F	1587.94	1	5	46.83	5	70.73	21	25.4	42	3014.47
30	1			(M1).C6.30.F	1523.09	1	5	45.97	5	77.44	21	24.5	38	1.73		
	2			(M2).C6.30.F	1523.09	1	5	40.12	5	77.44	21	24.5	38	0.17		
	3			(M3).C6.30.F	1523.09	1	5	40.12	5	77.44	21	24.5	38	10.32		
	4			(M4).C6.30.F	1523.09	1	5	40.12	5	77.44	21	24.5	38	61.85		

Table A 1 - Detailed performance information of fixed route results

		Min. observed capacity		
Grid	Case	Model 2	Model 3	Model 4
20 km	1	0	0	0
30 km		0	0	0
20 km	2	0.3333	0	-0.0833
30 km		0.3333	0.0833	-0.1250
20 km	3	0	0	0
30 km		0	0	0
20 km	4	0	0	0
30 km		0	0	0
20 km	5	0.0556	-0.0556	0
30 km		0.0556	-0.0556	-0.0556
20 km	6	0	0	0
30 km		0	0	0
Average	20 km	0.1944	-0.0278	-0.0417
Average	30 km	0.1944	0.0139	-0.0903
Average	Total	0.1944	-0.0069	-0.0660

Table A 2 - Proportion increase in minimum observed capacity along the routes compared with model 1

		Average first responder		
Grid	Case	Model 2	Model 3	Model 4
20 km	1	0.0602	0.1011	0.0744
30 km		0	0	-0.0045
20 km	2	0.2295	0.2885	0.2199
30 km		0.2179	0.2468	0.2226
20 km	3	0.0472	0.0532	0.0284
30 km		0	0	0
20 km	4	0.0200	0.0360	-0.0689
30 km		0.1366	0.1366	0.1366
20 km	5	0.1000	0.1793	0.1368
30 km		0.1358	0.1785	0.1535
20 km	6	0.0702	0.1066	0.0702
30 km		0.1274	0.1274	0.1274
Average	20 km	0.0878	0.1275	0.0768
Average	30 km	0.1029	0.1149	0.1059
Average	Total	0.0954	0.1212	0.0914

Table A 3 - Proportion decrease in average first responder time compared with model 1

		Worst case first responder		
Grid	Instance	Model 2	Model 3	Model 4
20 km	1	0.0132	0.0132	0.0132
30 km		0	0	0.0988
20 km	2	0.1333	0.2186	0.3181
30 km		0.1149	0.3428	0.3428
20 km	3	0.0437	0.0437	0.0437
30 km		0	0	0
20 km	4	0.1155	0.1155	0.1578
30 km		0.0947	0.0947	0.0947
20 km	5	0.0478	0	0.0984
30 km		0.0659	0.1155	0.0190
20 km	6	0.0814	0.1099	0.0776
30 km		0	0	0
Average	20 km	0.0725	0.0781	0.1235
Average	30 km	0.0459	0.0761	0.1086
Average	Total	0.0592	0.0771	0.1161

Table A 4 - Proportion decrease in worst case first responder time compared with model 1

Appendix B: Unfixed route performance

NS - Not solvable, Memory needed > 3 GB RAM

Routing performance																	
Input					Output												
Case	Fixed / Unfix	Grid (km)	Model	Index	Dist. (Km)	# of SAR	# of ERV	Avg. first resp. time	Min. first resp. Time	Max. first resp. Time	Min. obs. cap.	Avg. cap.	Max. Obs. cap.	Solve time (Sec.)			
1	U	20	1	(M1).C1.20.U	1387.11	1	5	46.37	5	70.73	21	24.6	44	426.87			
			2	(M2).C1.20.U	4471.86	1	5	48.59	5	94.05	21	23.6	36	92.24			
			3	(M3).C1.20.U	NS	1	5	-	-	-	-	-	-	-	-		
			4	(M4).C1.20.U	NS	1	5	-	-	-	-	-	-	-	-		
		30	1	(M1).C1.30.U	1363.68	1	5	41.75	5	77.44	21	24.7	37	0.13			
			2	(M2).C1.30.U	3158.89	1	5	40.66	5	69.79	21	23.9	36	3.61			
			3	(M3).C1.30.U	NS	1	5	-	-	-	-	-	-	-	-		
			4	(M4).C1.30.U	2519.48	1	5	39.23	5	65.06	21	24.8	37	3856.02			
		2	U	20	1	(M1).C2.20.U	1318.82	2	5	48.62	5	84.58	24	38.4	117	0.19	
					2	(M2).C2.20.U	2067.94	2	5	42.83	5	73.30	32	38.9	54	42.81	
					3	(M3).C2.20.U	NS	2	5	-	-	-	-	-	-	-	-
					4	(M4).C2.20.U	NS	2	5	-	-	-	-	-	-	-	-
30	1			(M1).C2.30.U	1363.68	2	5	46.06	5	84.42	24	40.3	104	0.12			
	2			(M2).C2.30.U	1473.38	2	5	41.88	5	74.72	32	38.8	52	3.58			
	3			(M3).C2.30.U	2127.35	2	5	27.14	5	55.48	28	39.9	62	-			
	4			(M4).C2.30.U	2639.48	2	5	30.88	5	44.27	25	39.6	53	-			
3	U			20	1	(M1).C3.20.U	1062.25	1	4	43.90	5	69.79	21	24.5	34	15.76	
					2	(M2).C3.20.U	3468.81	1	4	44.44	5	73.30	21	23.7	36	13.73	
					3	(M3).C3.20.U	NS	1	4	-	-	-	-	-	-	-	-
					4	(M4).C3.20.U	NS	1	4	-	-	-	-	-	-	-	-
		30	1	(M1).C3.30.U	1063.68	1	4	39.30	5	65.06	21	24.0	36	0.01			
			2	(M2).C3.30.U	1727.94	1	4	42.88	5	77.44	21	23.3	36	2.39			
			3	(M3).C3.30.U	1130.95	1	4	36.94	5	65.06	21	24.8	36	-			
			4	(M4).C3.30.U	1632.60	1	4	42.37	5	64.57	21	24.3	37	-			
		4	U	20	1	(M1).C4.20.U	1330.54	1	5	44.41	5	82.87	20	25.9	39	21.58	
					2	(M2).C4.20.U	2896.70	1	5	44.11	5	82.87	21	24.2	38	22.87	
					3	(M3).C4.20.U	NS	1	5	-	-	-	-	-	-	-	-
					4	(M4).C4.20.U	NS	1	5	-	-	-	-	-	-	-	-
30	1			(M1).C4.30.U	1363.68	1	5	49.09	5	77.09	20	23.7	39	1.39			
	2			(M2).C4.30.U	1768.23	1	5	43.78	5	77.44	21	24.1	36	4.46			
	3			(M3).C4.30.U	NF	1	5	-	-	-	-	-	-	-	-		
	4			(M4).C4.30.U	2277.35	1	5	40.67	5	65.06	20	24.1	37	312.82			
5	U			20	1	(M1).C5.20.U	1318.82	1	5	49.04	5	73.30	18	23.0	34	1.12	
					2	(M2).C5.20.U	2069.36	1	5	42.12	5	82.87	21	24.5	35	15.4	
					3	(M3).C5.20.U	NS	1	5	-	-	-	-	-	-	-	-
					4	(M4).C5.20.U	NS	1	5	-	-	-	-	-	-	-	-
		30	1	(M1).C5.30.U	1363.68	1	5	48.80	5	74.72	18	22.5	30	0.13			
			2	(M2).C5.30.U	2307.35	1	5	45.39	5	77.44	21	24.8	39	2.24			
			3	(M3).C5.30.U	NS	1	5	-	-	-	-	-	-	-	-		
			4	(M4).C5.30.U	2567.06	1	5	41.15	5	65.06	20	37.7	36	286.86			
		6	U	20	1	(M1).C6.20.U	1587.94	1	5	50.37	5	79.46	21	23.7	30	510.1	
					2	(M2).C6.20.U	6225.24	1	5	45.90	5	82.87	21	23.5	37	19.12	
					3	(M3).C6.20.U	NS	1	5	-	-	-	-	-	-	-	-
					4	(M4).C6.20.U	NS	1	5	-	-	-	-	-	-	-	-
30	1			(M1).C6.30.U	1523.09	1	5	45.97	5	77.44	21	24.5	38	1.73			
	2			(M2).C6.30.U	1547.94	1	5	45.42	5	77.44	21	24.8	38	1.37			
	3			(M3).C6.30.U	NS	1	5	-	-	-	-	-	-	-	-		
	4			(M4).C6.30.U	2399.48	1	5	38.74	5	65.06	21	24.8	38	301.26			

Table B 1 - Detailed performance information of routing results

Appendix C: Multiobjective modelling

Total weighted percentage deviation										
Input	Output									
Weight setup	Distance (Km)	# Of SAR	# Of ERV	Avg. first resp. Time	Min. first resp.time	Max. first resp. time	Min. obe.d cap.	Avg cap.	Max cap	Solve time (Sec)
WS-1	1318.82	1	5	40.4	5	66.1	18	25.4	38	2208.46
WS-2	1318.82	1	5	41.6	5	69.8	19	25.0	39	92.58
WS-3	1318.82	1	5	40.4	5	66.1	18	25.4	38	677.4
WS-4	1318.82	1	5	40.4	5	66.1	18	25.4	38	32.16
WS-5	1318.82	1	5	40.4	5	66.1	18	25.4	38	2226.38
WS-6	1318.82	1	5	40.4	5	66.1	18	25.4	38	123.13
WS-7	1318.82	1	5	40.4	5	66.1	18	25.4	38	636.36
WS-8	1318.82	1	5	40.4	5	66.1	18	25.4	38	2949.02
WS-9	1318.82	1	5	41.6	5	69.8	19	25.2	39	56.24
WS-10	1318.82	1	5	41.6	5	69.8	19	25.2	39	827.51
WS-11	1318.82	1	5	40.1	5	73.3	17	25.4	38	26.24

Table C 1 - Detailed output result for total weighted deviation performance indicators

Total percentage deviation detailed overview deviation						
Weight setup	Target value	Average first responder time	Worst case first responder time	Minimum observed capacity	Objective	
		g1	g2	g3	Total weighted deviation	Max observed deviation
WS-1	Weight	1/3	1/3	1/3		
	Objective	40.4	66.1	18		
	Weight. Dev.	1.06 %	1.55 %	1.75 %	2.03%	1.75 %
WS-2	Weight	0.3	0.3	0.4		
	Objective	41.6	69.8	19		
	Weight. Dev.	1.12 %	1.68 %	0 %	2.80 %	1.68 %
WS-3	Weight	0.6	0.3	0,1		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.50 %	0 %	0.53 %	1.02 %	0.53 %
WS-4	Weight	0.9	0.05	0.05		
	Objective	40.4	66.1	18		
	Weight. Dev.	0 %	0.55 %	0.53 %	1.01%	0.74%
WS-5	Weight	0.4	0.3	0.3		
	Objective	40.4	66.1	18		
	Weight. Dev.	1.20 %	0 %	1.58 %	1.91%	1.58%
WS-6	Weight	0.1	0.6	0.3		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.08 %	0 %	1.58 %	1.66%	1.58%
WS-7	Weight	0.05	0.9	0.05		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.04 %	0 %	0.26 %	0.3%	0.26%
WS-8	Weight	0.3	0.4	0.3		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.25 %	0 %	1.58 %	1.83%	1.58%
WS-9	Weight	0.3	0.1	0.6		
	Objective	41.6	69.8	19		
	Weight. Dev.	1.12 %	0.56 %	0 %	1.68%	1.12%
WS-10	Weight	0.05	0.05	0,9		
	Objective	41.6	69.8	19		
	Weight. Dev.	0.19 %	0.28 %	0 %	0.47%	0.28%
WS-11	Weight	0.99	0.005	0,005		
	Objective	40.1	73.3	17		
	Weight. Dev.	0.00 %	0.05 %	0 %	0.11%	0.05%

Table C 2 - Total weighted deviation & maximum weighted deviation, total weighted deviation

MINIMAX

Input	Output									
Weight setup	Distance (Km)	# Of SAR	# Of ERV	Avg. first resp. Time	Min. first resp.time	Max. first resp. time	Min. obs. cap.	Avg cap.	Max cap	Solve time (Sec)
WS-1	1318.82	1	5	41.38	5	69.17	18	24.9	37	164.93
WS-2	1318.82	1	5	41.60	5	69.79	19	25.0	39	204.6
WS-3	1318.82	1	5	40.43	5	66.09	18	25.4	38	174.21
WS-4	1318.82	1	5	40.09	5	73.30	17	25.4	38	129.02
WS-5	1318.82	1	5	41.30	5	66.09	18	25.1	38	149.76
WS-6	1318.82	1	5	40.43	5	66.09	18	25.4	38	196.22
WS-7	1318.82	1	5	40.43	5	66.09	18	25.4	38	303.77
WS-8	1318.82	1	5	40.43	5	66.09	18	25.4	38	217.94
WS-9	1318.82	1	5	41.60	5	69.79	19	25.2	39	144.4
WS-10	1318.82	1	5	41.60	5	69.79	19	25.0	39	3105.22
WS-11	1318.82	1	5	40.09	5	73.30	17	25.4	38	769.47

Table C 3 - Detailed overview over MINIMAX performance indicators

MINIMAX detailed overview deviation

Weight setup	Target value	Average first responder time	Worst case first responder time	Minimum observed capacity	Objective	
		g1	g2	g3	Max observed deviation	Total weight deviation
		40.1	66,1	19		
WS-1	Weight	1/3	1/3	1/3		
	Objective	41.4	69.2	18		
	Weight. Dev.	1.06 %	1.55 %	1.75 %	1.75 %	4.37 %
WS-2	Weight	0.3	0.3	0,4		
	Objective	41.6	69.8	19		
	Weight. Dev.	1.12 %	1.68 %	0 %	1.68 %	2.80 %
WS-3	Weight	0.6	0.3	0,1		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.50 %	0 %	0.53 %	0.53 %	1.02 %
WS-4	Weight	0.9	0.05	0,05		
	Objective	40.1	73.3	17		
	Weight. Dev.	0 %	0.55 %	0.53 %	0.55 %	1.05 %
WS-5	Weight	0.4	0.3	0,3		
	Objective	41.3	66.1	18		
	Weight. Dev.	1.20 %	0 %	1.58 %	1.58 %	2.78 %
WS-6	Weight	0.1	0.6	0,3		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.08 %	0 %	1.58 %	1.58 %	1.66 %
WS-7	Weight	0.05	0.9	0,05		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.04 %	0 %	0.26 %	0.26 %	0.30 %
WS-8	Weight	0.3	0.4	0,3		
	Objective	40.4	66.1	18		
	Weight. Dev.	0.25 %	0 %	1.58 %	1.58 %	1.83 %
WS-9	Weight	0.3	0.1	0,6		
	Objective	41.6	69.8	19		
	Weight. Dev.	1.12 %	0.56 %	0 %	1.12 %	1.68 %
WS-10	Weight	0.05	0.05	0,9		
	Objective	41.6	69.8	19		
	Weight. Dev.	0.19 %	0.28 %	0 %	0.28 %	0.47 %
WS-11	Weight	0.99	0.005	0,005		
	Objective	40.1	73.3	17		
	Weight. Dev.	0.00 %	0.05 %	0 %	0.05 %	0.11 %

Table C 4 - Maximum weighted deviation & total weighted deviation, MINIMAX

Appendix D: Experimentation with t^{max}

Nf = Not feasible, t-max not sufficiently large

t^{max} Experimentation

Input	Output									
t-max	Dist. (Km)	# of SAR	# of ERV	Avg. first resp. time	Min. first resp. Time	Max. first resp. Time	Min. obs. cap.	Avg. cap	Max. Obs. cap.	Solve time (Sec)
120 min	1318.82	1	5	49.04	5	73.30	18	23.0	34	1.12
119 min	1318.82	1	5	49.04	5	73.30	17	22.7	33	0.05
118 min	1318.82	1	5	48.22	15	82.87	17	21.5	28	1.14
117 min	1318.82	1	5	48.61	5	82.87	17	22.5	36	0.8
116 min	1318.82	1	5	51.19	5	82.87	17	21.9	34	3.14
115 min	1318.82	1	5	47.52	5	73.30	17	22.4	31	1.27
114 min	1318.82	1	5	47.96	5	73.30	17	22.1	42	2.4
113 min	1330.54	1	5	46.93	5	75.17	17	22.0	35	35.71
112 min	1330.54	1	5	45.48	5	73.30	17	21.9	32	42.75
111 min	1495.39	1	5	45.99	5	70.73	17	20.8	32	477.84
110 min	1495.39	1	5	44.61	5	70.73	17	20.8	30	87.06
109 min	1495.39	1	5	44.41	5	70.73	17	20.3	29	106.86
108 min	1556.81	1	5	44.06	5	77.27	17	20.5	30	3282.86
107 min	Nf	1	5	-	-	-	-	-	-	-

Table D 1 - Experimenting with t-max, Model 1, Case 5, 20 km grid layout, unfixed routes



Figure D 1 - Distance over t^{max} ,

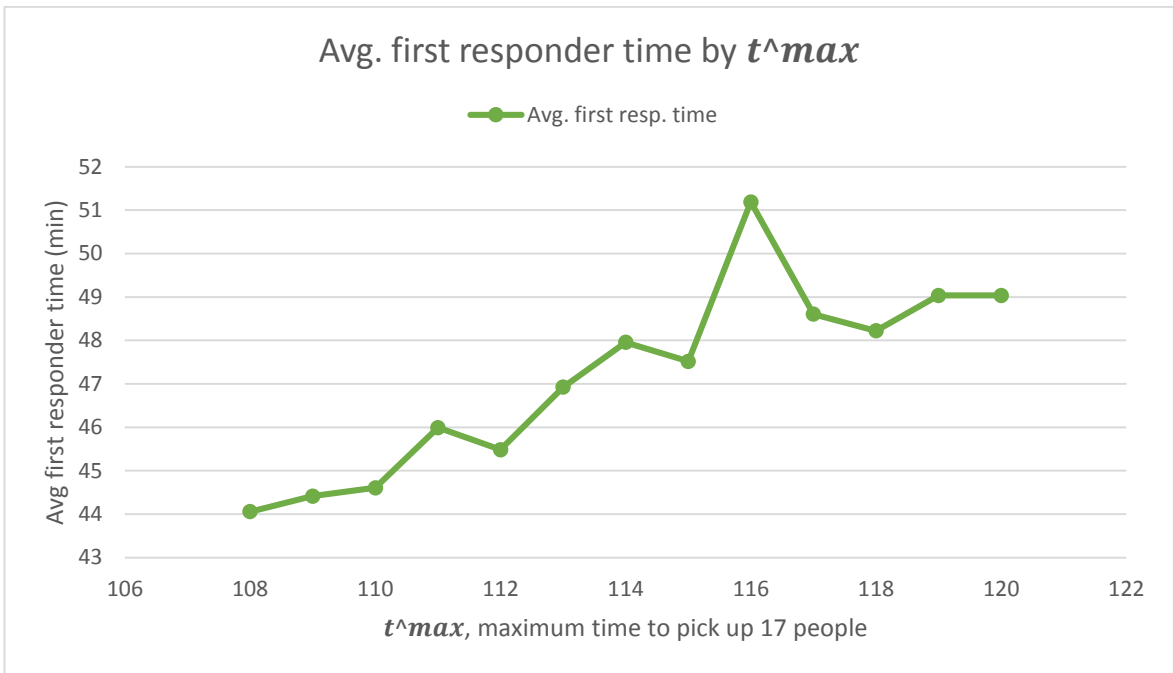


Figure D 2 - Avg. first responder over t^{max} ,

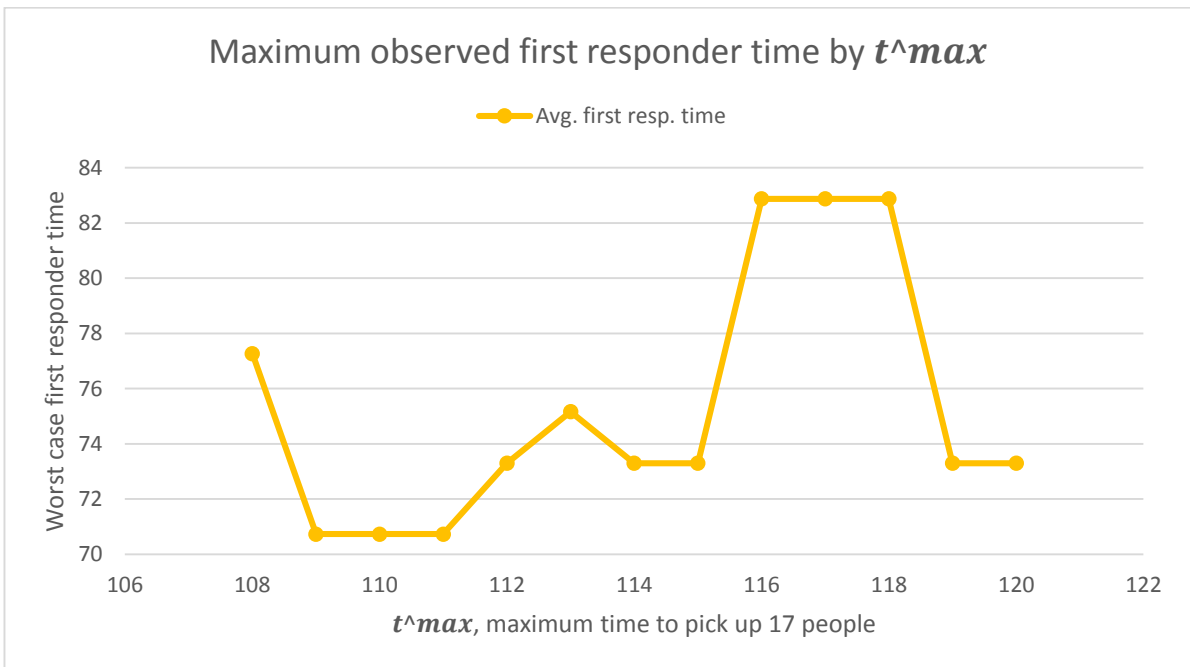


Figure D 3 - Max. obs. first responder over t^{max}

Appendix E: Fix & Fix and Optimize Heuristic

NN – Not needed

Heuristic performance																	
Input					Output												
Case	Fixed / Unfix	Grid (km)	Model	Index	Dist. (Km)	# of SAR	# of ERV	Avg. first resp. time	Min. first resp. Time	Max. first resp. Time	Min. obs. cap.	Avg. cap	Max. Obs. cap.	Solve time (Sec.)			
1	H	20	1	(M1).C1.20.H	NN	-	-	-	-	-	-	-	-	-			
			2	(M2).C1.20.H	NN	-	-	-	-	-	-	-	-	-	-		
			3	(M3).C1.20.H	1656.22	1	5	37.72	5	66.09	21	26.7	37	-	-		
			4	(M4).C1.20.H	1691.37	1	5	41.69	5	66.09	21	21.0	35	-	-		
		30	1	(M1).C1.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
			2	(M2).C1.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
			3	(M3).C1.30.H	2288.26	1	5	38.80	5	77.44	21	25.2	36	-	-		
			4	(M4).C1.30.H	1363.68	1	5	41.79	5	66.79	21	25	36	-	-		
		2	H	20	1	(M1).C2.20.H	NN	-	-	-	-	-	-	-	-	-	
					2	(M2).C2.20.H	NN	-	-	-	-	-	-	-	-	-	-
					3	(M3).C2.20.H	1429.95	2	5	33.19	5	66.09	21	40.8	55	-	-
					4	(M4).C2.20.H	1398.82	2	5	36.78	5	57.67	22	41.8	55	-	-
30	1			(M1).C2.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
	2			(M2).C2.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
	3			(M3).C2.30.H	2127.35	2	5	27.16	5	55.48	28	39.5	54	-	-		
	4			(M4).C2.30.H	1847.74	2	5	38.82	5	54.27	25	38.3	58	-	-		
3	H			20	1	(M1).C3.20.H	NN	-	-	-	-	-	-	-	-	-	
					2	(M2).C3.20.H	NN	-	-	-	-	-	-	-	-	-	-
					3	(M3).C3.20.H	1432.79	1	4	37.93	5	69.00	21	25.8	38	-	-
					4	(M4).C3.20.H	1078.82	1	4	42.19	5	66.09	21	24.8	37	-	-
		30	1	(M1).C3.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
			2	(M2).C3.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
			3	(M3).C3.30.H	1113.38	1	4	36.94	5	65.06	21	25.1	36	-	-		
			4	(M4).C3.30.H	1342.64	1	4	42.77	5	64.57	21	25.0	37	-	-		
		4	H	20	1	(M1).C4.20.H	NN	-	-	-	-	-	-	-	-	-	
					2	(M2).C4.20.H	1330.54	1	5	44.35	5	69.79	20	25.4	39	-	-
					3	(M3).C4.20.H	1627.94	1	5	37.30	5	66.09	21	26.1	37	-	-
					4	(M4).C4.20.H	1683.09	1	5	41.70	5	66.09	20	24.2	38	-	-
30	1			(M1).C4.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
	2			(M2).C4.30.H	1363.68	1	5	43.21	5	70.97	20	24.0	36	-	-		
	3			(M3).C4.30.H	1703.09	1	5	36.97	5	67.87	20	25.4	37	-	-		
	4			(M4).C4.30.H	1363.68	1	5	44.84	5	69.79	20	24	36	-	-		
5	H			20	1	(M1).C5.20.H	NN	-	-	-	-	-	-	-	-	-	
					2	(M2).C5.20.H	2153.23	1	5	43.76	5	82.87	21	24.7	40	-	-
					3	(M3).C5.20.H	1418.23	1	5	37.88	5	66.09	17	25.4	37	-	-
					4	(M4).C5.20.H	1343.54	1	5	41.45	5	66.09	17	23.8	35	-	-
		30	1	(M1).C5.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
			2	(M2).C5.30.H	1964.92	1	5	40.36	5	77.44	21	25.8	38	-	-		
			3	(M3).C5.30.H	2021.91	1	5	36.30	5	65.06	17	24.5	37	-	-		
			4	(M4).C5.30.H	1790.07	1	5	41.74	5	66.09	20	24.1	37	-	-		
		6	H	20	1	(M1).C6.20.H	NN	-	-	-	-	-	-	-	-	-	
					2	(M2).C6.20.H	NN	-	-	-	-	-	-	-	-	-	-
					3	(M3).C6.20.H	1946.76	1	5	41.05	5	66.09	21	26.1	38	-	-
					4	(M4).C6.20.H	2210.19	1	5	45.40	5	66.09	21	25.8	42	-	-
30	1			(M1).C6.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
	2			(M2).C6.30.H	NN	-	-	-	-	-	-	-	-	-	-	-	
	3			(M3).C6.30.H	1672.20	1	5	39.85	5	77.44	21	25.1	36	-	-		
	4			(M4).C6.30.H	1535.51	1	5	43.92	5	69.79	21	24.0	36	-	-		

Table E 1 - Detailed performance information for the F&O heuristic

Green areas represents the guaranteed optimal objectives

Model 2 comparison						
Input		Fixed routes		Heuristic		Improvement
Case	Grid (km)	Index	Capacity	Index	Capacity	
1	20	(M2).C1.20.F	21	(M2).C1.20.H	21	0.00%
	30	(M2).C1.30.F	21	(M2).C1.30.H	21	0.00%
2	20	(M2).C2.20.F	32	(M2).C2.20.H	32	0.00%
	30	(M2).C2.30.F	32	(M2).C2.30.H	32	0.00%
3	20	(M2).C3.20.F	21	(M2).C3.20.H	21	0.00%
	30	(M2).C3.30.F	21	(M2).C3.30.H	21	0.00%
4	20	(M2).C4.20.F	20	(M2).C4.20.H	20	0.00%
	30	(M2).C4.30.F	20	(M2).C4.30.H	20	0.00%
5	20	(M2).C5.20.F	19	(M2).C5.20.H	21	10.53%
	30	(M2).C5.30.F	19	(M2).C5.30.H	21	10.53%
6	20	(M2).C6.20.F	21	(M2).C6.20.H	21	0.00%
	30	(M2).C6.30.F	21	(M2).C6.30.H	21	0.00%
Average						1.75%

Table E 2 – Model 2 comparison of fixed route objective and heuristic objective

Grey areas represents the non-solvable setups for the unfixed routes

Model 3 comparison						
Input		Fixed routes		Heuristic		Improvement
Case	Grid (km)	Index	Avg. first resp. time (min)	Index	Avg. first resp. time (min)	
1	20	(M3).C1.20.F	41.68	(M3).C1.20.H	37.72	9.50%
	30	(M3).C1.30.F	41.75	(M3).C1.30.H	38.80	7.07%
2	20	(M3).C2.20.F	34.59	(M3).C2.20.H	33.19	4.05%
	30	(M3).C2.30.F	34.70	(M3).C2.30.H	27.16	21.73%
3	20	(M3).C3.20.F	41.57	(M3).C3.20.H	37.93	8.76%
	30	(M3).C3.30.F	39.30	(M3).C3.30.H	36.94	6.01%
4	20	(M3).C4.20.F	42.81	(M3).C4.20.H	37.30	12.87%
	30	(M3).C4.30.F	42.39	(M3).C4.30.H	36.97	12.79%
5	20	(M3).C5.20.F	40.10	(M3).C5.20.H	37.88	5.54%
	30	(M3).C5.30.F	40.09	(M3).C5.30.H	36.30	9.45%
6	20	(M3).C6.20.F	45.00	(M3).C6.20.H	41.05	8.78%
	30	(M3).C6.30.F	40.12	(M3).C6.30.H	39.85	0.67%
Average						8.93%

Table E 3 - Model 3 comparison of fixed route objective and heuristic objective

Grey areas represents the non-solvable setups for the unfixed routes

Model 4 comparison						
Input		Fixed routes		Heuristic		Improvement
Case	Grid (km)	Index	Max. first resp. time (min)	Index	Max. first resp. time (min)	
1	20	(M4).C1.20.F	69.79	(M4).C1.20.H	66.09	5.30%
	30	(M4).C1.30.F	69.79	(M4).C1.30.H	66.79	4.30%
2	20	(M4).C2.20.F	57.67	(M4).C2.20.H	57.67	0.00%
	30	(M4).C2.30.F	55.48	(M4).C2.30.H	54.27	2.18%
3	20	(M4).C3.20.F	66.74	(M4).C3.20.H	66.09	0.97%
	30	(M4).C3.30.F	65.06	(M4).C3.30.H	64.57	0.75%
4	20	(M4).C4.20.F	69.79	(M4).C4.20.H	66.09	5.30%
	30	(M4).C4.30.F	69.79	(M4).C4.30.H	69.79	0.00%
5	20	(M4).C5.20.F	66.09	(M4).C5.20.H	66.09	0.00%
	30	(M4).C5.30.F	66.09	(M4).C5.30.H	66.09	0.00%
6	20	(M4).C6.20.F	70.73	(M4).C6.20.H	66.09	6.56%
	30	(M4).C6.30.F	77.44	(M4).C6.30.H	69.79	9.88%
Average						2.94%

Table E 4 - Model 4 comparison of fixed route objective and heuristic objective