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Optimizing maritime preparedness under uncertainty – Locating tugboats along the Norwegian coast

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Abstract. We study the strategic problem of locating tugboats along the Norwegian coast to optimize maritime preparedness. The problem is formulated as a two-stage stochastic program. In the first stage, we locate the tugboats such that nominal coverage requirements are satisfied, whereas we deploy the located tugboats in the second stage in order to assist vessels in distress. The objective is to minimize the sum of the costs of publicly operated tugboats in the emergency towing service and the expected penalty costs due to insufficient preparedness. We solve the problem using Sample Average Approximation in combination with a self-developed heuristic. Our results indicate that we can achieve a sufficient preparedness level with six tugboats.

Keywords: Maritime preparedness · Set covering problem · Uncertainty.

1 Introduction

A safe and reliable maritime transportation system is of great economic importance to Norway: Approximately 83% of all international cargoes (in tonnes) and about 44% of all domestic cargoes (in tonne-kilometres) are carried on board ships [11]. In addition, overall ship traffic (in kilometres) along the coast of Norway is predicted to increase by 41% until 2040. However, maritime transportation is risky and the number of accidents is also expected to increase by as much as 30% during the same period [15].

A recent example of the risk in maritime transportation is the incident involving the MV Eemslift Hendrika that was abandoned off the west coast of Norway in April 2021. The ship drifted for 2 days before tugboats were able to secure the ship and avert grounding of the ship. Up to 350 tonnes of heavy fuel oil and up to 50 tonnes of diesel fuel could have caused severe environmental pollution in the area if the ship's hull had been damaged [23].

To assist drifting vessels and prevent them from grounding or colliding in coastal waters, Norway has established an emergency towing service [4]. The ambition is to be able to reach and assist a drifting vessel with the necessary tugboats to prevent an accident from happening [18]. The tactical problem of how to dynamically position these tugboats according to current vessel traffic has been extensively studied, see e. g. [2], [3], [5] or [6]. However, these approaches all focus on the allocation of existing resources and consider the number of available tugboats as given. In this paper, we consider the strategic problem of determining both the optimal location and number of tugboats to achieve a satisfying maritime preparedness level.

A common characteristic of emergency response planning is that the location decisions have to be made before the actual emergency is known. Approaches considering uncertainty are therefore common in the literature. Some recent and relevant examples of this literature are: [16] discusses the problem of locating ambulances to serve random road crashes. [19] uses a maximal covering formulation to evaluate the effectiveness of different fleets when responding to emergencies. [14] introduces a robust formulation of the set covering problem for locating emergency service facilities. In [1], two variants of the probabilistic set covering problem are discussed: the first variant considers a problem with uncertainty regarding whether a selected set can cover an item, while the second variant aims at maximizing the minimum probability that a selected set can cover all items. For a more thorough overview over covering models in the literature see [10]. See also [13] for an overview of the literature on covering models used for emergency response planning.

We propose a two-stage stochastic programming model for the strategic Tugboat Location Problem (TLP) under uncertainty that covers nominal preparedness requirements in the first stage and uses the second-stage decisions to evaluate the quality of the first-stage decisions by calculating the expected costs in case accidents cannot be prevented. To solve the model, we use Sample Average Approximation (SAA) combined with a self-developed heuristic.

The remainder of this article is structured in the following way: The problem is presented in more detail in Section 2, before the mathematical model is introduced in Section 3. Subsequently, the solution scheme is presented in Section 4 and followed by a description of our case study and computational results in Section 5. Lastly, we conclude in Section 6.

2 Problem Description

In this section, we present the TLP in more detail. First, we introduce the problem before discussing the uncertainty in the problem and its consequences.

2.1 Problem Structure

The overall goal of the strategic TLP is to determine the optimal fleet of tugboats in the emergency towing service and to locate the tugboats in ports such that they can respond to vessels in need of assistance. As the decision which tugboats to locate where has to be made before the location of the vessels in need of assistance is known, this gives rise to a two-stage structure of the problem where the first-stage decisions include the number and type of required tugboats and which ports to locate them in. The second-stage decisions are made after a vessel calls for assistance and cover which tugboat(s) to deploy to the incident site to assist the vessel.

The first-stage decisions have to satisfy dimensioning criteria for Norway's emergency towing service. The dimensioning criteria are derived from dimensioning incidents that represent the assistance needs of high-risk vessels such as large oil tankers [17]. The maximum time to reach the vessel is determined by the vessel's drifting time, whereas the tugboats' time to assist the vessel consists of mobilization and sailing time as well as hook-up time. In addition, we include a safety margin to enforce even stricter requirements for high-risk areas and vessels. We formulate these criteria as minimal covering requirements for maritime preparedness, ensuring that a sufficient number of tugboats are able to reach any vessel in any area within the required time.

Once an incident becomes known, tugboats are deployed to assist the vessel in distress. However, due to weather conditions at the time of the incident, not only drifting speed of the vessel but also sailing speed of the tugboat and hook-up time can be different from the nominal values used in the first stage. It is therefore possible that tugboats arrive too late and an accident occurs. In this case, a penalty cost is incurred.

Each located tugboat has a chartering and operating cost associated with it and can provide a certain bollard pull. The combined bollard pull of all deployed tugboats has to be higher than the required bollard pull to assist the vessel in distress. If multiple tugboats are deployed, hook-up to the vessel will start once all tugboats have arrived at the scene.

Some ports in Norway serve as bases for a large number of privately operated vessels with tugboat capabilities. When the number of these tugboats is sufficiently large, we assume that a small number can contribute to maritime preparedness. We therefore account for them when considering the minimal covering requirements. However, the cost of these tugboats does not become part of the objective function as they are not paid for by the emergency towing service.

The objective is to minimize the sum of the costs of publicly operated tugboats in the emergency towing service and expected penalty costs due to insufficient preparedness. Incident-dependent operational costs are not included in the model as these are usually paid for by the vessel in need of assistance.

Note that the probability of a vessel starting to drift is small. This implies that the probability of two or more drifting incidents happening simultaneously is extremely low, and these incidents are therefore neglected in this paper. This is a common simplification in preparedness planning, see e.g. [2] and [20].

2.2 Geography, Vessel Types and Tugboat Types

We divide the Norwegian coast into geographical zones, as illustrated in Figure 1. Every zone is described by its seabed characteristic, ecosystem vulnerability, weather conditions and traffic density. Each zone also contains an impact point and a set of one or more corridors where vessels are sailing. A zone is defined

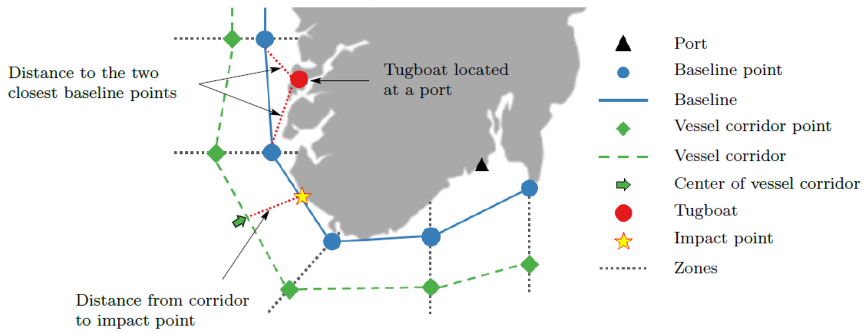

Fig. 1. Representation of the Norwegian coastline.

from the coastline to the corridor located farthest away from the shore. When a vessel encounters a problem leading to loss of propulsion, it will start to drift from the center of its corridor towards the coast. If no tugboats are able to assist the drifting vessel before it reaches the impact point, an accident happens. The impact point is located in the middle of each zone's baseline.

We categorize vessels by vessel type. A vessel type is defined by its size, cargo type and sailing corridor. All vessel belonging to a given vessel type are considered to be identical. Tugboats are grouped by tugboat type. Each tugboat type is described by its bollard pull and maximal sailing speed, with all tugboats belonging to a tugboat type having the same properties.

2.3 Uncertain Parameters

We define date and location of an incident, characteristics of the involved vessel and wind speed (as a proxy for weather conditions) as uncertain parameters affecting the potential consequences of the incident and the lateness of the tugboats deployed to assist the vessel in distress. See Figure 2 for an illustration of how these parameters relate to each other and the penalty cost. Both consequence, lateness and penalty cost are explained in more detail below.

Consequence Consequences result from an accident when the deployed tugboats are not able to assist a drifting vessel before it reaches the impact point. The consequences depend on vessel and seabed characteristics as well as the vulnerability of the ecosystem. The vessel characteristics, and cargo type in particular, influence the expected consequence of an accident. Incidents involving passenger vessels put human lives at stake whereas spills from oil tankers have higher consequences in more vulnerable ecosystems. The ecosystem vulnerability is changing throughout the year and differs across areas. We assume that grounding on a rocky seabed will cause a greater fracture in the vessel's hull than a sandy seabed, thus leading to a greater spill.

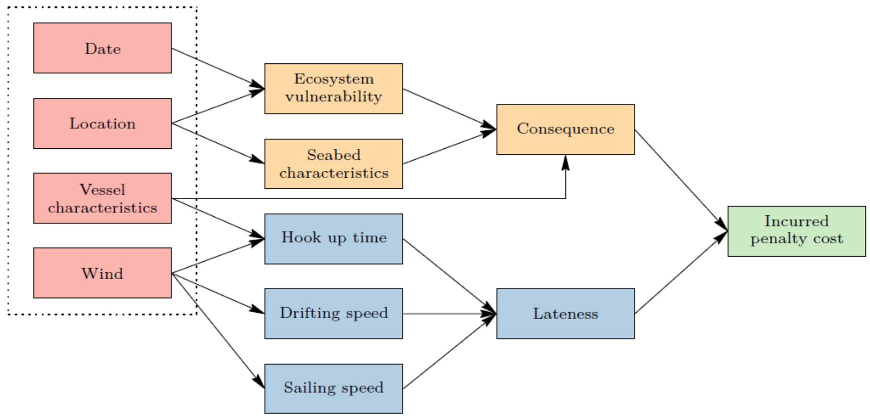

Fig. 2. Uncertain parameters and their relationship to the incurred penalty cost.

Lateness By lateness we describe the tugboat's ability to assist the vessel in time. Drifting speed increases with wind speed and determines how much time the tugboats have to reach and assist the vessel in distress. The hook-up time is the time is takes to connect the tugboat's tugline to the vessel. We assume that the hook-up time increases with higher wind speed and heavier vessels. The tugboat's sailing speed determines how long it takes to sail from port to the incident site. Sailing speed is negatively correlated with wind speed.

Lateness is positive if the sum of the tugboat's mobilization time, sailing time and hook-up time is larger than the vessel's drifting time. In the other case, the accident is avoided and lateness is zero.

Penalty cost We introduce a fictitious penalty cost function depending on lateness to penalize accidents. The penalty cost reflects that it might not always be possible to prevent accidents from happening, but that is often beneficial to have vessels quickly at the site of the accident to reduce its consequences, for example through search-and-rescue operations or oil-spill mitigation. By adjusting the penalty cost function, e. g. for accidents involving high-risk vessels or in high-risk areas, a policy maker can analyze how different expected costs of accidents influence the optimal number and location of the tugboats.

We have chosen to model the penalty cost as a piecewise linear and convex function, see Figure 3. Large lateness in arriving at the accident site is therefore penalized more severely than small lateness. We keep weights $\alpha^t_{\underline{k}}$ and α^c_k constant in our modeling approach and adjust the maximum lateness, $\overline{T}$, and maximum penalty cost, $\overline{C}$, according to seabed characteristics, ecosystem vulnerability and vessel characteristics. Note that for passenger vessels, the maximal penalty costs $\overline{C}$ apply already at a lateness of 0.

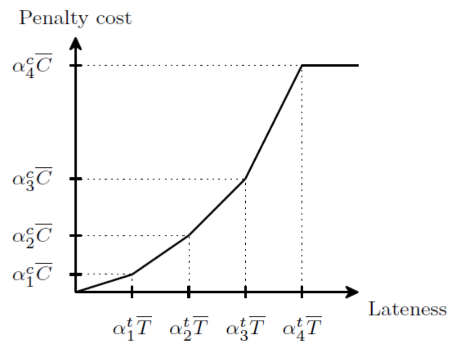

Fig. 3. Penalty cost as a function of lateness.

3 Model Formulation

We formulate the problem of optimizing maritime preparedness as a two-stage stochastic programming problem. The objective is to minimize the sum of the costs of tugboats in the emergency towing service and the expected penalty costs resulting from accidents.

Let us first introduce the following notation for our problem formulation:

Sets

$\mathcal{B}$	Set of tugboat types.
$\mathcal{K}$	Set of breakpoints of the penalty cost function.
$\mathcal{P}$	Set of ports.
$\mathcal{S}$	Set of scenarios.
$\mathcal{V}$	Set of vessel types.
$\mathcal{Z}$	Set of zones along the coast.

Parameters

A_{bpvz}	1 if tugboat type b in port p is close enough to vessel type v in zone z, 0 otherwise, $b \in \mathcal{B}, p \in \mathcal{P}, v \in \mathcal{V}, z \in \mathcal{Z}$.
C_b^B	Cost of chartering and operating a tugboat of type b, $b \in \mathcal{B}$.
$\overline{C}^s$	Maximal penalty cost in scenario s, $s \in \mathcal{S}$.
F_b	Bollard pull of tugboat type b, $b \in \mathcal{B}$.
$\hat{F}_b^s$	Effective bollard pull of tugboat type b in scenario s, $b \in \mathcal{B}, s \in \mathcal{S}$.
Q_v	Number of tugboats required by vessel type v, given the minimal covering requirement, $v \in \mathcal{V}$.
$\hat{Q}^s$	Number of tugboats required, depending on the characteristics of the drifting vessel in scenario s, $s \in \mathcal{S}$.
T_{bp}^s	Lateness of tugboat type b in port p in scenario s, $b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}$.
$\overline{T}^s$	Maximal lateness in scenario s, $s \in \mathcal{S}$.
W_v	Total bollard pull required by vessel type v, given the minimal covering requirement, $v \in \mathcal{V}$.

$\hat{W}^s$ Total effective bollard pull required, depending on the characteristics of the drifting vessel in scenario s, $s \in \mathcal{S}$.
X_{bpz} 1 if a privately operated tugboat of type b in port p has zone z within its operating range, 0 otherwise, $b \in \mathcal{B}, p \in \mathcal{P}, z \in \mathcal{Z}$.
$\hat{X}_{bp}^s$ 1 if the range of privately operated tugboat type b in port p includes the drifting vessel in scenario s, 0 otherwise, $b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}$.
α_k^c Breakpoint k's weight of the maximal penalty cost, $k \in \mathcal{K}$.
α_k^t Breakpoint k's weight of the maximal lateness, $k \in \mathcal{K}$.
p^s Probability of scenario s, $s \in \mathcal{S}$.

Decision variables
u_{bp}^s 1 if tugboat type b located in port p is deployed in scenario s, 0 otherwise, $b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}$.
t^s Maximum lateness in scenario s, $s \in \mathcal{S}$.
x_{bp} 1 if tugboat type b is located in port p, 0 otherwise, $b \in \mathcal{B}, p \in \mathcal{P}$.
y_{bvz} 1 if tugboat type b is able to rescue vessel type v in zone z, given the minimal cover requirement, 0 otherwise, $b \in \mathcal{B}$, $v \in \mathcal{V}, z \in \mathcal{Z}$.
μ_k^s Weight of breakpoint k in scenario s, $k \in \mathcal{K}, s \in \mathcal{S}$.

In the first stage of the two-stage stochastic programming problem, the number of tugboats and their locations are decided upon. In the second-stage, tugboats are deployed in order to prevent a specific drifting accident. The resulting model formulation is given below:

$$\min \sum_{b \in \mathcal{B}} \sum_{p \in \mathcal{P}} C_b^B x_{bp} + \sum_{s \in \mathcal{S}} p^s \mathcal{Q}^s(x) \tag{1}$$

subject to

$$\sum_{p \in \mathcal{P}} A_{bpvz} \cdot (x_{bp} + X_{bpz}) \geq y_{bvz} \qquad b \in \mathcal{B}, v \in \mathcal{V}, z \in \mathcal{Z}, \tag{2}$$

$$\sum_{b \in \mathcal{B}} y_{bvz} \geq Q_v \qquad v \in \mathcal{V}, z \in \mathcal{Z}, \tag{3}$$

$$\sum_{b \in \mathcal{B}} F_b \cdot y_{bvz} \geq W_v \qquad v \in \mathcal{V}, z \in \mathcal{Z},, \tag{4}$$

$$x_{bp} \in \{0,1\} \qquad b \in \mathcal{B}, p \in \mathcal{P}, \tag{5}$$

$$y_{bvz} \in \{0,1\} \qquad b \in \mathcal{B}, v \in \mathcal{V}, z \in \mathcal{Z}, \tag{6}$$

where $\mathcal{Q}^s(x)$ is the solution to the following second-stage problem:

$$\mathcal{Q}^s(x) = \min \sum_{k \in \mathcal{K}} \alpha_k^c \overline{C}^s \mu_k^s \tag{7}$$

subject to

$$u_{bp}^s \leq x_{bp} + \hat{X}_{bp}^s \qquad b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}, \tag{8}$$

$$\sum_{b\in\mathcal{B}} \sum_{p\in\mathcal{P}} u_{bp}^s \geq \hat{Q}^s \qquad s \in \mathcal{S}, \tag{9}$$

$$\sum_{b\in\mathcal{B}} \sum_{p\in\mathcal{P}} \hat{F}_b^s \cdot u_{bp}^s \geq \hat{W}^s \qquad s \in \mathcal{S}, \tag{10}$$

$$t^s \geq T_{bp}^s u_{bp}^s \qquad b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}, \tag{11}$$

$$t^s = \sum_{k\in\mathcal{K}} \alpha_k^t \overline{T}^s \mu_k^s \qquad s \in \mathcal{S}, \tag{12}$$

$$\sum_{k\in\mathcal{K}} \mu_k^s = 1 \qquad s \in \mathcal{S}, \tag{13}$$

$$\mu_k^s \geq 0, \ \text{SOS2} \qquad k \in \mathcal{K}, s \in \mathcal{S}, \tag{14}$$

$$u_{bp}^s \in \{0, 1\} \qquad b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}. \tag{15}$$

The first-stage problem (1)-(6) is formulated as a covering problem, satisfying the dimensioning criteria for planning maritime preparedness. The first-stage objective (1) minimizes the sum of the tugboats' chartering and operating costs and the expected penalty costs. Constraints (2) ensure that tugboat type b located in port p has to be close enough to zone z to rescue a vessel of type v. Constraints (3) make sure that the number of available tugboats for rescuing vessel type v in zone z exceeds the required number of tugboats. Constraints (4) ensure that the combined bollard pull of the available tugboats is sufficiently large. Constraints (5) and (6) are the binary restrictions on x_{bp} and y_{bvz}, respectively.

The second-stage problem is given by (7)-(15). The second-stage objective (7) minimizes the penalty costs of responding to an incident. Constraints (8) ensure that a tugboat type b has to be located in port p in order to be deployed in scenario s. Restrictions (9) and (10) ensure that a sufficient number of tugboats with a sufficiently large combined effective bollard pull are deployed to assist the drifting vessel. Constraints (11) determine the lateness for a given scenario. Lateness for a scenario is defined by the lateness of the last deployed tugboat to reach the drifting vessel. Constraints (12) link the scenario lateness to the penalty cost in the objective function (7) through weights μ_k^s on the breakpoints of the penalty cost function. Constraints (13) in combination with constraints (14) define variable μ_k^s as a special ordered set of type 2 (SOS2), see e. g. [24] for more details. The binary requirements on variable u_{bp}^s are imposed through constraints (15).

4 Solution Approach

We first introduce the scenario generation procedure, before we briefly present our solution approach. Our approach combines Sample Average Approximation to determine a lower bound to the problem with a heuristic for finding upper bounds.

4.1 Scenario Generation

A scenario is mainly characterized by 3 groups of uncertain parameters: location, date and incident type. The location of the incident affects the seabed characteristics and, together with the date of the incident, the vulnerability of the ecosystem. The date also provides the weather conditions for the given location and wind speed in particular. The incident type specifies the vessel characteristics such as vessel type and size as well as its cargo.

The date of the incident is drawn randomly from the datasets of available wind data. We use historical weather data from the ERA-Interim dataset [7], made available by the European Centre for Medium-Range Weather Forecasts (ECMWF). One might assume that locations with extreme weather conditions are more likely to experience an incident. However, human error and technical conditions of the vessel actually have a greater impact on the probability of an incident [9]. We therefore sample date and location of an incident independent of each other. The probability distribution for the location of an incident is based on the accidents statistics provided by the Norwegian Maritime Authority. The incident type is sampled based on historical marine traffic information from the Norwegian Coastal Administration.

4.2 Sample Average Approximation for Estimating a Lower Bound

A common challenge in stochastic programming is that the problems often become computationally intractable when using an appropriately large number of scenarios. We therefore apply Sample Average Approximation (SAA) to obtain a lower bound estimate for our problem [12]. SAA is based on the idea that it is often easier to solve multiple smaller optimization problems than one single large problem.

By solving M problems with N scenarios each, we can derive a statistical lower bound for our problem. Note that the scenario trees for the M problems are generated independent of each other and that the number of scenarios N used to solve the problem is small compared with the true problem size. See [12], [21] or [22] for detailed descriptions of the algorithm.

4.3 Search Heuristic for Determining an Upper Bound

To calculate an upper bound for the problem, we need to evaluate a feasible solution over a reference sample of N'_{ref} scenarios. The reference sample is sampled independently from the $M \cdot N$ scenarios of the SAA-problems and usually $N'_{\mathrm{ref}} \gg N$.

The solutions for the different SAA problems can be used as candidate solutions for calculating an upper bound, but they may be infeasible for the reference sample. We therefore use a search heuristic that generates feasible solutions in the neighbourhood of the solutions provided by the SAA problems. A solution's neighbourhood is defined as the closest surrounding ports and tugboat types. For example, if a tugboat of type B is located in port 13, its neighbourhood are tugboat types A–C located in ports 12–14. We group the different unique solutions from the SAA problems according to the number of used tugboats and then generate the neighbourhood solutions for the best solutions of each group. These solutions are then checked for feasibility and infeasible solutions are discarded. The remaining feasible solutions are then evaluated in the reference sample.

However, in many cases it is impractical to evaluate all solutions in the reference sample N'_{ref} as the computational time could be huge. We therefore apply a stepwise approach to evaluating feasible solutions: All feasible candidate solutions are evaluated over a relatively small sample N'_1. Solutions that perform poorly in N'_1 are assumed to be bad and are discarded, while the K_1 best solutions are evaluated a second time. In the second evaluation, the sample size is larger, $N'_2 \approx 100 \cdot N'_1$, thus providing a better estimate of the true objective function value. The K_2 best solutions in N'_2 are evaluated a third time, now in the reference sample N'_{ref}. The best objective function value from the reference sample is then used as an upper bound estimate.

Note that our heuristic can only search a neighbourhood where all solutions use a predefined number of tugboats. We therefore denote the upper bound for solutions using n tugboats UB_n with the corresponding solution $x^{(n)}$.

5 Computational Results

In this section we present our computational study of locating tugboats along the Norwegian coast. We first introduce the input data and the problem instance in Section 5.1, before presenting our results in Section 5.2.

5.1 Problem Instance

This section discusses how the parameters used in the model are calculated and estimated. First the geography, vessel and tugboat characteristics are introduced. Then penalty costs are presented before the calculations of the time-related parameters are provided.

Geography and Ports The Norwegian coastline is divided into 38 zones of approximately equal width. The coastline itself is represented as a set of line segments, referred to as the baseline. The impact point is located in the middle of the baseline and its seabed characteristics and ecosystem vulnerability are representative for the entire zone.

The seabed in a zone is categorized as either sandy, rocky or cliffy. The ecosystem vulnerability is classified as low, medium or high, depending on the season [8]. Both of these factors have an impact on the penalty cost function described below.

Only ports satisfying the International Ship and Port Facility Security (ISPS) Code are regarded as sufficiently large to be used for tugboat operations. Among the 640 ISPS ports in Norway, 30 ports close to relatively large densely populated areas are chosen as possible base locations for tugboats.

Vessel Types and Tugboat Characteristics A vessel type is categorized by cargo type as either "passenger", "oil", or "other", sailing in the inner or outer corridor depending on cargo type. The size of the vessels is classified as either "light" or "heavy", with a required effective bollard pull of 45 tonnes and 95 tonnes, respectively.

A tugboat type is defined by its bollard pull, sailing speed and chartering and operating cost. We define four tugboat types, A–D, as shown in Table 1. The types represent different real-world tugboats, from smaller harbour tugs to larger tugboats used in the offshore oil & gas industry. Effective bollard pull and sailing speed are adjusted for wind speed according to a linear reduction function. The maximal reduction occurs when the wind speed is 28 m/s, corresponding to violent storm on the Beaufort wind force scale, reducing bollard pull and sailing speed by 20% and 30% respectively.

Table 1. Overview of tugboat types used in the model.

Tugboat type	**A**	**B**	**C**	**D**
Maximal sailing speed [knots]	15	14	13	12
Bollard pull [tonnes]	200	150	100	80
Chartering and operating cost [MNOK/year]	51	36	33	18

We include two tugboats of type B located in Bergen and Oslo in our analysis to reflect the availability of privately operated tugboats in those areas.

Generation of Penalty Cost Functions The penalty costs for not being able to provide assistance in time depend on the severity of the accident. The expected spillage in case of an accident depends on the given seabed characteristics. We assume no leakage if the seabed is classified as sandy, only leakage from the fuel tank if rocky and leakage from the fuel and oil tanks if cliffy.

Human lives are generally considered more important than environmental damage. Therefore, we regard all incidents involving "passenger" vessels as equally bad and worse than any other accidents. Consequently, neither $\overline{C}$ nor $\overline{T}$ depend on seabed characteristics or ecosystem vulnerability.

Vessels with cargo type "oil" spill from both the fuel tank and the oil tank, depending on the seabed characteristics at the impact point. The consequences in case of an accident are determined by spill size (with heavy vessels spilling more oil than light vessels) and ecosystem vulnerability. In case the vessel is grounding on a sandy seabed, no fuel or oil spill is expected. Thus, the penalty cost is in this case independent of ecosystem vulnerability.

Vessels with cargo type "other" can by definition only spill fuel, as they do not have an oil tank. This means that the consequences of grounding on a cliffy and rocky seabed are the same, resulting in the same penalty cost function as long as the ecosystem vulnerability does not change.

We model the penalty cost function as an approximated quadratic function using five breakpoints $(\alpha^t\overline{T}, \alpha^c\overline{C})$, where the weights are chosen as $\alpha^t = (0\ \frac{1}{4}\ \frac{2}{4}\ \frac{3}{4}\ 1)$ and $\alpha^c = (0\ \frac{1}{20}\ \frac{1}{4}\ \frac{5}{9}\ 1)$. The actual values for maximal penalty cost $\overline{C}$ and maximal lateness $\overline{T}$ depend on the combination of cargo type, seabed characteristics and ecosystem vulnerability at the time of the accident and are therefore calculated for each scenario. The values used in the model range from 100 to 10 000 MNOK for $\overline{C}$ and 0 to 10 hours for $\overline{T}$.

Preprocessing $\boldsymbol{A_{bpvz}}$ and $\boldsymbol{T^s_{bp}}$ The incidence matrix $\mathbf{A}$ is used in the first-stage problem to identify which tugboats at which ports can contribute to satisfying the covering requirements. Its values are mainly determined by the nominal dimensioning criteria for maritime preparedness. We calculate the nominal time for tugboat assistance as the sum of a tugboat b's mobilization and sailing time from port p to zone z, T^B_{bpz}, the hook-up time T^H_{vz} for connecting the tugboat to the vessel v in zone z and a safety margin T^S_{vz} dependent on vessel v and zone z. The value of the incidence matrix is then set based on whether the nominal time for tugboat assistance is less than vessel v's nominal drifting time to the impact point in zone z, T^V_{vz}. So, if (16) holds, we set $A_{bpvz} = 1$ and $A_{bpvz} = 0$ otherwise.

$$T^B_{bpz} + T^H_{vz} + T^S_{vz} \leq T^V_{vz} \qquad v \in \mathcal{V}, b \in \mathcal{B}, p \in \mathcal{P}, z \in \mathcal{Z}. \tag{16}$$

Matrix $\mathbf{T}$ is needed in the second-stage problem and depends on the realization of the uncertain parameters. Its values, T^s_{bp}, represent the lateness of tugboat b located in port p in scenario s. Lateness is non-negative and cannot be larger than the maximal lateness $\overline{T}$. As each scenario s only considers a single incident, the location, date and vessel type are known. We can therefore preprocess lateness for different combinations of tugboat type b and port p as the difference between the time needed by tugboat type b in port p to reach the drifting vessel in scenario s, $T^B_{bp}(s)$, the corresponding hook-up time $T^H(s)$, and the vessel's actual drifting time, $T^V(s)$. Hence, the values of matrix $\mathbf{T}$ are determined by (17):

$$T^s_{bp} = \max\left\{0, \min\left\{\overline{T}, T^B_{bp}(s) + T^H(s) - T^V(s)\right\}\right\} \quad b \in \mathcal{B}, p \in \mathcal{P}, s \in \mathcal{S}. \tag{17}$$

5.2 Case Study

We use the SAA method, solving $M = 20$ problems with $N = 60$ scenarios each. The resulting lower bound estimate LB is 179.8 with a corresponding standard deviation σ_{LB} of 2.67%. We observe that the minimum number of tugboats satisfying the minimal covering requirement is 6. To not exclude possibly better solutions with more tugboats, we use a search heuristic to generate neighbourhood solutions for the solutions containing 6, 7 and 8 tugboats, respectively.

For each neighbourhood, the solutions are evaluated using $N'_1 = 500$, $K_1 = 500$, $N'_2 = 50\,000$ and $K_2 = 20$. The best solutions are then evaluated in the reference sample N'_{ref} containing 700 000 scenarios. These numbers are chosen based on experience from initial testing. Table 2 shows that the best upper bound estimate found by the search heuristic is $UB^{(6)} = 245.3$ for a solution with 6 tugboats, resulting in an optimality gap of approx. 36%. Furthermore, Table 2 indicates that solutions with 7 and 8 tugboats perform considerably worse when evaluated in the reference sample, even though the neighbourhoods are ~100 times larger.

Table 2. Upper bound estimates found by the search heuristic and the corresponding neighbourhood size. Values for UB in MNOK.

Solution	**Upper bound**		**Neighborhood size**	
	$UB^{(n)}$	$\sigma_{UB^{(n)}}$	*All solutions*	*Feasible solutions*
$x^{(6)}$	245.300	0.03%	41 472	3 888
$x^{(7)}$	257.431	0.05%	6 531 264	315 792
$x^{(8)}$	257.055	0.04%	6 398 388	537 408

To provide a better estimate on the lower bound, we solve the SAA problems again, but force the number of tugboats in the solution to be either 6, 7 or 8. The lower bounds and optimality gaps from these constrained SAA problems are shown in Table 3.

Table 3. Results for the constrained SAA problems. The upper bounds are found by the search heuristic and the confidence interval is at 90%. Values for LB and UB in MNOK.

Solution	**Lower bound**		**Upper bound**		**Optimality gap**	
	$LB^{(n)}$	$\sigma_{LB^{(n)}}$	$UB^{(n)}$	$\sigma_{UB^{(n)}}$	*Estimate*	*Confidence interval*
$x^{(6)}$	245.113	8.03%	245.300	0.03%	0.08%	10.36%
$x^{(7)}$	202.255	5.97%	257.431	0.05%	21.44%	27.44%
$x^{(8)}$	189.308	1.92%	257.055	0.04%	26.35%	28.17%

Table 3 shows that the optimality gap estimate from the constrained problem with 6 tugboats is less than 0.1%. The optimality gap estimates for the constrained problem with 7 and 8 tugboats are still above 20%. However, due to the lower upper bound for the 6 tugboat solution and the stable performance of the tested solutions in the evaluation procedure, we believe that the optimal solution consists of 6 tugboats with an objective value of approx. 245 MNOK.

6 Conclusions

The goal of this work is to develop an optimization framework that can support the design of maritime preparedness systems. In our case, we want to compose the tugboat fleet and locate the tugboats along the Norwegian coast such that they can assist vessels in distress before accidents happen. We therefore formulate a two-stage stochastic programming model with the objective to find the optimal trade-off between the costs of tugboats in the emergency towing service and expected penalty costs from accidents that could not be prevented.

Our results indicate that six tugboats are sufficient to satisfy the dimensioning criteria for maritime preparedness along the Norwegian coast. Restricting the original problem, we can show that our approach is capable of identifying near-optimal locations and tugboat types for the six tugboats.

Areas of future research include studying how a more detailed description of the Norwegian coastline, i. e. a larger problem instance, affects runtime and solution quality of the approach presented in this paper. It should also be possible to use a formulation based on facility location models to design the maritime preparedness system. In addition, further work is needed to better understand how different penalty costs impact the optimal number and location of the tugboats.

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