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Sailing through uncertainty: ship pipe routing and the energy transition

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ABSTRACT

The energy transition from fossil fuels to sustainable alternatives makes the design of future-proof ships even more important. In the design phase of a ship, it is uncertain how many and which fuels it will use in the future due to many external factors. In fact, a ship typically sails for decades, increasing the likelihood that it will use different fuels during its lifetime. Pipe route design is expensive and time-consuming, mainly done by hand. Motivated by this, in previous research, we have proposed a mathematical optimization framework for automatic pipe routing under uncertainty of the energy transition. In this paper, we build on the state-of-the-art by implementing design constraints in mathematical models based on discussions with maritime design experts. Additionally, we apply these models to realistic, complex situations of a commercial ship design company. Our experiments show that location-dependent installation costs, which reflect reality, increase the usefulness of stochastic optimization compared to deterministic and robust optimization. Additionally, to prepare for a possible transition to more sustainable fuels, we recommend installing suitable pipes near the engine room upfront to prevent expensive retrofits in the future.

KEY WORDS

Pipe routing; Ship design; Mathematical optimization; Energy transition; Design automation

INTRODUCTION

The maritime industry is responsible for 2-3% of global carbon emissions (International Maritime Organization, 2020). Therefore, new regulations from the IMO and UN state that net zero should be reached by 2050 (International Maritime Organization, 2023). Consequently, ship designers want to consider these measures when designing a new ship. However, Pruyn (2017) states that this is not the case, as most ship owners optimize their ships for the economic situation at the beginning of construction. As a result, ships are not future-proof upon delivery, leading to expensive retrofits in the future.

For sustainability and financial reasons, ship designers must consider future alternative fuels already in the design phase to prevent these retrofits. Using a new fuel typically impacts three essential aspects of a ship: the engine (or the prime mover), the fuel storage, and the pipe routes between them. Although the academic literature elaborately describes the first two aspects (Lindstad et al., 2021; Zwaginga and Pruyn, 2022), the role of pipe routing is not often considered in the academic literature according to Blokland et al. (2023). Automated pipe routing can save time and costs as it is done mainly manually and, consequently, requires over half of the total detail-design labor hours (Park and Storch, 2002). This effort is expected to increase as pipe routing constraints largely depend on the fuel used (Lloyd's Register, 2023).

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In Markhorst et al. (2023), we have proposed a mathematical optimization framework consisting of three models: deterministic, robust, and stochastic optimization. These models route pipes such that they minimize the sum of the installation and retrofit costs while adhering to (some of) the pipe routing rules from Lloyd's Register (2023). In the following, we explain how we have built these models on the current state-of-the-art and what our academic and practical contributions are.

Literature Two extensive works extensively describe the literature on pipe routing (Asmara, 2013; Blokland et al., 2023). They almost exclusively mention works that do not consider any form of uncertainty. More specifically, in their conclusion, Blokland et al. (2023) suggests to include the energy transition uncertainty in pipe routing models. For this, we can model the problem of connecting multiple tank(s) and engine room(s) in a ship as a Steiner Tree Problem (STP); see Ljubić (2021) for a survey. A stochastic version of this problem is called the Stochastic Steiner Tree Problem (SSTP), for which Bomze et al. (2010); Zey (2016); Leitner et al. (2018) have elaborately described exact solution methods. In Markhorst et al. (2023), we consider a generalization of the SSTP called the Stochastic Steiner Forest Problem (SSFP), which connects multiple independent groups of terminals (i.e., tanks and engine rooms). We have built on Schmidt et al. (2021), who describe exact solution methods for the Steiner Forest Problem (SFP).

Our contributions In this work, we build on the state-of-the-art by implementing design constraints in mathematical models based on discussions with maritime design experts. One of the main conclusions from discussions with these experts is that installation costs largely depend on the location in the ship. We apply the models to realistic, complex situations of a commercial ship design company and study different versions of location-dependent costs, which reflect reality, and their impact on the pipe routes and costs. This work aims to show the power of mathematical optimization in the maritime pipe routing domain.

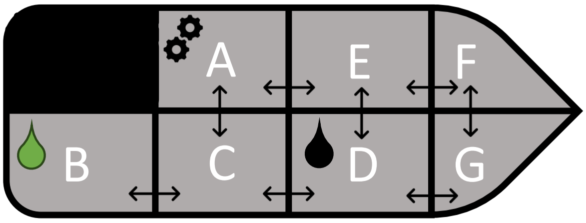
Outline The rest of this paper is structured as follows. First, we describe the three different models using an illustrative example. Then, we describe the data, the experiments, and the corresponding results. Finally, we formulate our conclusions and sketch directions for future research.

METHODOLOGY

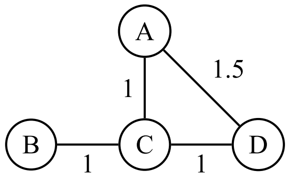
In this section, we formally describe the deterministic and stochastic problem formulation of our pipe routing problem in mathematical terms. To this end, we start with an example that will later show the characteristics of the different models. Then, we continue with the deterministic optimization model and explain why this is a naive benchmark. Finally, we elaborate on the value of adding uncertainty to our models, after which the robust and stochastic optimization models follow. We only sketch the general idea behind the models and refer to Markhorst et al. (2023) for further details.

The translation from maritime design to mathematics

For this work, we consider a ship that sails on diesel but *could* transition to methanol in the future. In the following simplistic example, we assume that the methanol and diesel tanks are placed on the starboard side of the ship and that the engine room is placed on the port side. Schematically, we represent this ship, where each room may contain one or more engines or fuel tanks, as a graph; see Figure 1. For simplicity, we only consider rooms A, B, C, and D in the corresponding graph representation. Additionally, we assume that installing a pipe between adjacent rooms costs €1, except for the connection between room A and E, which costs €0.5, hence an installation cost of €1.5 for the connection between A and D. The undirected graph $G = (\mathcal{V}, \mathcal{E})$ consists of a set of vertices $\mathcal{V}$ (the rooms in a ship) and a set of edges $\mathcal{E}$ (the possible connections between the rooms). Later, we will assume that the ship's graph representation G remains the same when considering future scenarios.



(a) Simplistic top-down view of a ship.



(b) Graph with the first stage installation costs.

Figure 1: Example of the mathematical representation of a ship with 8 rooms. The icons in Figure 1a indicate the function of a room: A denotes the engine room, while C, E, F, and G represent voids, and vertices B and D denote the methanol and diesel tanks, respectively. For simplicity, we only consider rooms A, B, C, and D in the graph representation. The arrows indicate possible pipes and the black square denotes a room through which we cannot route any pipes.

In our problem, we want to connect the fuel tank(s) with the engine room(s). Because we consider different fuel types, we must route according to different rules for pipe routing. For example, diesel pipes cannot be routed through rooms adjacent to water due to regulations from, for example, Lloyd's Register (2023). Consequently, we consider two different terminal groups. One group corresponds to diesel, whereas the other corresponds to methanol. For now, we assume that we only need to connect the diesel tank with the engine room. To do so, we can use a set of types $\mathcal{P}$ denoting the set of feasible pipes for diesel, which are single and double walled pipes in this case. Introducing these sets of pipes allows us to consider different fuel types in the future. The installation cost of a pipe p at a particular edge (u, v) is given by $\gamma_{puv} > 0$.

Due to regulations from Lloyd's Register (2023), we cannot route some dangerous fuel types through certain areas in a ship. For instance, we cannot route diesel through rooms adjacent to the waterside. To model this, we introduce the set of admissible edges, which contains the edges that can be used for the installation of pipes to connect the tank(s) and engine room(s) for the fuel type under consideration. This model choice enables us to consider different fuel types in the future.

Our problem consists of three components: (i) a graph consisting of vertices and (feasible) edges; (ii) a set of (feasible) pipes, which depends on the fuel type under consideration; and (iii) the cost parameters for the installation of a pipe on an edge. A feasible solution connects each terminal group's tank(s) and engine room(s), only uses feasible pipes and edges, and can install pipes in advance that might be redundant for now but may become useful in the future.

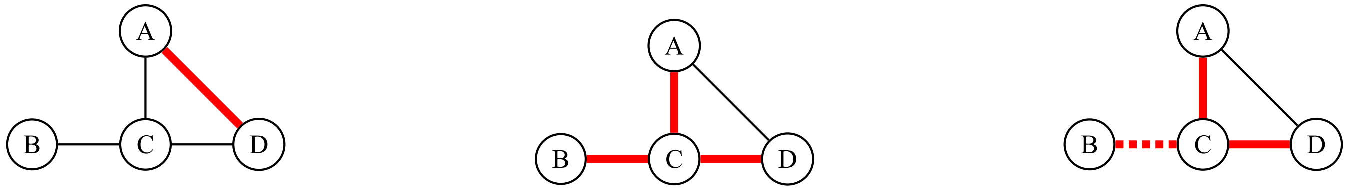
Deterministic optimization: a naive benchmark model

Deterministic optimization aims to connect the terminal group's tanks(s) and engine room(s) while only using feasible pipes and edges with as little installation costs as possible. Mathematically, we can formulate the deterministic mathematical optimization problem as

$$\textbf{(DO)} \qquad \min_{\mathbf{S} \in \mathcal{M}(I)} F(I, \mathbf{S}_0, \mathbf{S}) = \min_{\mathbf{S} \in \mathcal{M}(I)} \sum_{(p,(u,v)) \in \mathbf{S} \setminus \mathbf{S}_0} \gamma_{puv}. \tag{1}$$

We denote our problem by I and the set of all feasible solutions by $\mathcal{M}(I)$. We introduce the set $\mathbf{S}_0$ of pipe-edge pairs that describe which pipes already exist on which edge to consider previous stages in time. For example, $(p, (u, v)) \in \mathbf{S}_0$ represents pipe p which is installed at edge (u, v). We denote the cost of solution $\mathbf{S} \in \mathcal{M}(I)$ for instance I when pipe-edge pairs $\mathbf{S}_0$ are present by $F(I, \mathbf{S}_0, \mathbf{S})$. In (1), we find the feasible solution with the lowest installation costs that are required to connect each terminal group's tank(s) with the engine room(s). We compute these costs per feasible solution by summing the installation costs of all the pipe-edge pairs that we have to install except for the ones that are already "pre-installed". For deterministic optimization, it holds that $\mathbf{S}_0 = \emptyset$ as no pipes have been pre-installed.

We cannot directly solve the problem described in (1) with (commercial) solvers, but we need the corresponding Integer



(a) Deterministic optimization.

(b) Robust optimization.

(c) Stochastic optimization for $p_2 = 0.4$.

Figure 2: Optimal pipe routes for Figure 1b according to the three mathematical models. The red solid and dotted lines represent the pipes we installed in the first and second stages, respectively. Note that for simplicity, we have not yet distinguished between single- and double-walled pipes. In Figure 2c, p_2 denotes the probability that the methanol tank must be connected to the engine room. We will discuss these probabilities later.

Linear Optimization (ILO) model. If we apply this model to the pipe routing problem sketched in Figure 1b, we install a pipe on the edge between vertices A and D, as shown in Figure 2a. However, a possible retrofit to methanol would be expensive, especially when installation costs increase, which is typically the case in the maritime industry. Our deterministic optimization model is naive as it does not consider any other (future) scenario than the present. Throughout the rest of this work, this model will mainly serve as a benchmark to compare with the other two models, which will be explained in the following section.

Adding uncertainty is useful for future-proof design

Pruyn (2017) states that ship owners typically design their ships for the current economic situation, leading to future sub-optimality. Retrofitting a ship is not preferable as it comes with considerable costs due to its downtime and complex maintenance. To prevent these high costs, ship designers must consider alternative fuels in the design phase.

In practice, however, we do not yet know which alternative fuel will be used in the future as this depends on external factors, such as technology improvements, availability, and future costs (Prussi et al., 2021). To capture this uncertainty over time, we consider two time periods in our framework: the present (i.e., first stage) and the future (i.e., second stage). Figure 3 shows these two stages, of which we know the possible outcomes. For instance, we know the fuel a ship will sail on in the present, typically diesel. However, in the future, this could change to a sustainable alternative, such as green methanol, which has different pipe route requirements than diesel. For instance, it can be routed through rooms next to the waterside and requires double-walled pipes. At each stage, we can install pipes to connect the engine room(s) and the fuel tank(s). Unfortunately, the future outcome is unknown due to uncertainty, adding another layer of complexity to the problem.

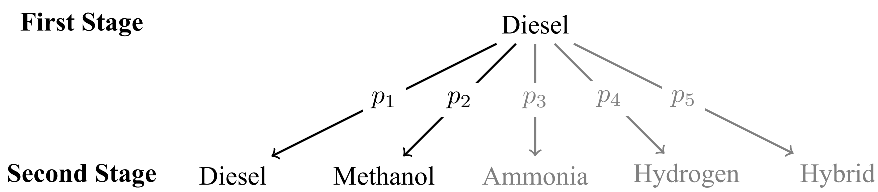


Figure 3: Two-stage scenario tree which describes our problem setting: we start with the diesel scenario in the present, but it is unknown which scenario will take place in the future. We assume that we can install pipes in the first- and second-stage and that we know the probabilities of each future scenario, i.e., p_1 corresponds to the probability of a future diesel scenario. This work only considers two future scenarios, diesel and methanol, which are colored black in the scenario tree. The other scenarios are not studied in this work and are therefore colored gray.

To illustrate the value of considering future scenarios, we use the example from Figures 1 and 2. In the first stage, the ship sails on diesel, whereas in the second stage, it is uncertain whether a transition to methanol is required. As Figure 2a shows, the deterministic optimization model suggests installing a pipe on the edge between the diesel tank (vertex A) and the engine room (vertex D), leading to high second-stage costs in case a transition to methanol takes place. To prevent this situation, we can prepare for the transition by connecting both the diesel and methanol tank (vertices B and D) to the engine room (vertex A), as shown in Figure 2b. We call this way of modeling robust optimization, which is rather expensive and might yield redundant pipes. The route in Figure 2c lies between deterministic and robust optimization. The pipe installation between the void (vertex C) and the methanol tank depends on the probability of the methanol scenario and the installation costs on that edge. This way of modeling is a form of the stochastic optimization model. Although this route seems inefficient for the diesel scenario, it prepares the ship for a possible transition to methanol in the future and balances current and (expected) future costs.

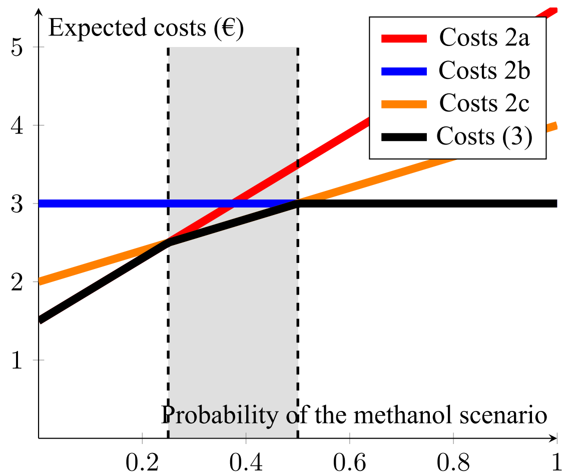


Figure 4: Expected costs of the three routes shown in Figure 2 and the stochastic optimization model (3). As (3) considers the probabilities of the future scenarios, it follows the minimum of the expected costs of the three routes shown in Figure 2.

Figure 4 shows the expected costs of the three pipe routing options for our example on the y-axis and the probability of the methanol scenario on the x-axis. Here, we assume that installing a pipe on an edge in the second stage is twice as expensive as the corresponding first-stage costs. Hence, we can compute the route costs shown in Figure 2a with $1.5 + 4p_2$ where $p_2 \in [0, 1]$ represents the probability of the methanol scenario. In contrast, the robust route costs shown in Figure 2b yield a horizontal line at €3 as the costs do not depend on any probability. Finally, we can compute the costs from the route of Figure 2c with $2 + 2p_2$. The grey dashed area indicates where stochastic optimization outperforms deterministic and robust optimization. Hence, this toy example illustrates that the only way to make the best pipe routing decisions is to explicitly include uncertainty in our mathematical models.

Extending the deterministic model: robust and stochastic optimization

As discussed, we want to include uncertainty in our models. Stochastic optimization (SO) and robust optimization (RO) consider uncertainties and variability in real-world optimization problems, but each follows a different approach. While SO requires distribution information and, in our case, optimizes the *average* case, RO uses the support of the uncertain parameters and optimizes the *worst* case. We refer the reader to Birge and Louveaux (2011); Klein Haneveld et al. (2020) and Ben-Tal et al. (2009); Gorissen et al. (2015) for extensive discussions on SO and RO, respectively. Their application in the context of ship pipe routing is novel.

To model different future scenarios, we introduce a set of second-stage scenarios $s \in \mathcal{S}$, where each scenario corresponds to one fuel type. We can almost exactly reuse the notation for the deterministic optimization model: we only introduce a superscript (s) for scenario s. For example, $I^{(s)}$ denotes a pipe routing problem in scenario s and $\mathbf{S}^{(s)}$ represents the decisions taken in scenario s. The installation costs of a pipe p at a particular edge (u, v) is given by $\gamma_{puv}^{(s)} = \gamma_{puv} \cdot \nu_{uv}$ where $\nu_{uv} \geq 1$ is the increase rate.

Robust Optimization We formulate the robust optimization model in which we anticipate the *worst-case* future scenario as follows:

(RO)

$$\min_{\mathbf{S}\in\mathcal{M}(I)} \left(F(I,\emptyset,\mathbf{S}) + \max_{s\in\mathcal{S}} \min_{\mathbf{S}^{(s)}\in\mathcal{M}(I^{(s)})} \left(F(I^{(s)},\mathbf{S},\mathbf{S}^{(s)}) \right) \right) \tag{2a}$$

$$= \min_{\mathbf{S}\in\mathcal{M}(I)} \Bigg(\underbrace{\sum_{(p,(u,v))\in\mathbf{S}\setminus\mathbf{S}_0} \gamma_{puv}}_{\text{First stage costs}} + \underbrace{\max_{s\in\mathcal{S}} \min_{\mathbf{S}^{(s)}\in\mathcal{M}(I^{(s)})} \sum_{(p,(u,v))\in\mathbf{S}^{(s)}\setminus\mathbf{S}} \gamma^{(s)}_{puv}}_{\text{Second stage (retrofit) costs}} \Bigg). \tag{2b}$$

The minimization in (2b) depends on the first- and second-stage costs. For the first-stage costs, we do not have to consider the pipe-edge pairs from the set $\mathbf{S}_0$ as these are pre-installed. For the second-stage costs, we minimize the total installation costs of the worst-case scenario, hence the combination of minimization and maximization. The pipe-edge pairs installed in the first stage can be considered as "pre-installed" in the second stage and do not have to be considered when computing the second-stage costs.

Stochastic Optimization The stochastic optimization problem (SO), which aims to minimize the *sum of expected costs*, can be formulated as:

(SO)

$$\min_{\mathbf{S}\in\mathcal{M}(I)} \left(F(I,\emptyset,\mathbf{S}) + \mathbb{E}_{\mathbb{S}} \left[\min_{\mathbf{S}'\in\mathcal{M}(I^{\mathbb{S}})} \left(F(I^{\mathbb{S}},\mathbf{S},\mathbf{S}') \right) \right] \right) \tag{3a}$$

$$= \min_{\mathbf{S}\in\mathcal{M}(I)} \Bigg(\underbrace{\sum_{(p,(u,v))\in\mathbf{S}\setminus\mathbf{S}_0} \gamma_{puv}}_{\text{First stage costs}} + \underbrace{\mathbb{E}_{\mathbb{S}} \Bigg[\min_{\mathbf{S}'\in\mathcal{M}(I^{\mathbb{S}})} \sum_{(p,(u,v))\in\mathbf{S}^{(s)}\setminus\mathbf{S}} \gamma^{(s)}_{puv} \Bigg]}_{\text{Second stage (retrofit) costs}} \Bigg), \tag{3b}$$

where $\mathbb{E}$ denotes the expectation and $\mathbb{S}$ represents a discrete random variable for the future scenario with a known distribution, i.e., $\Pr(\mathbb{S} = s)$ is known for all $s \in \mathcal{S}$. The minimization from (3b) differs from (2b) in the second-stage costs. Instead of minimizing the costs of the worst-case scenario, the expected costs over the future scenarios are computed.

RESULTS

We concluded from discussions with maritime experts that pipe installation costs largely depend on the location in the ship. Therefore, we study the impact of a location-dependent cost increase on the pipe route and the corresponding costs. In the following, we elaborate on the used data and then explain the experimental setup. After this, we provide the results of our numerical experiments, including a discussion and analysis of the value for considering uncertainty. To solve the models from (1), (2), and (3) with (commercial) solvers, we use the corresponding ILO formulations.

Ship modelling and data

For this work, we have collaborated with a commercial shipyard company that provided us with data from a state-of-the-art ship consisting of four decks. As it is not trivial to visualize the original data, a 3D network of 75 compartments on the ship and 156 edges, we use four 2D graphs. Figure 5 shows the result, where the vertex colors indicate whether a room contains an engine, a fuel tank, or a void. We have data on the location of diesel and methanol tanks due to the work of Minderhoud (2023). We chose this specific ship as it contains a moonpool, which makes pipe routing more complex as it restricts routes.

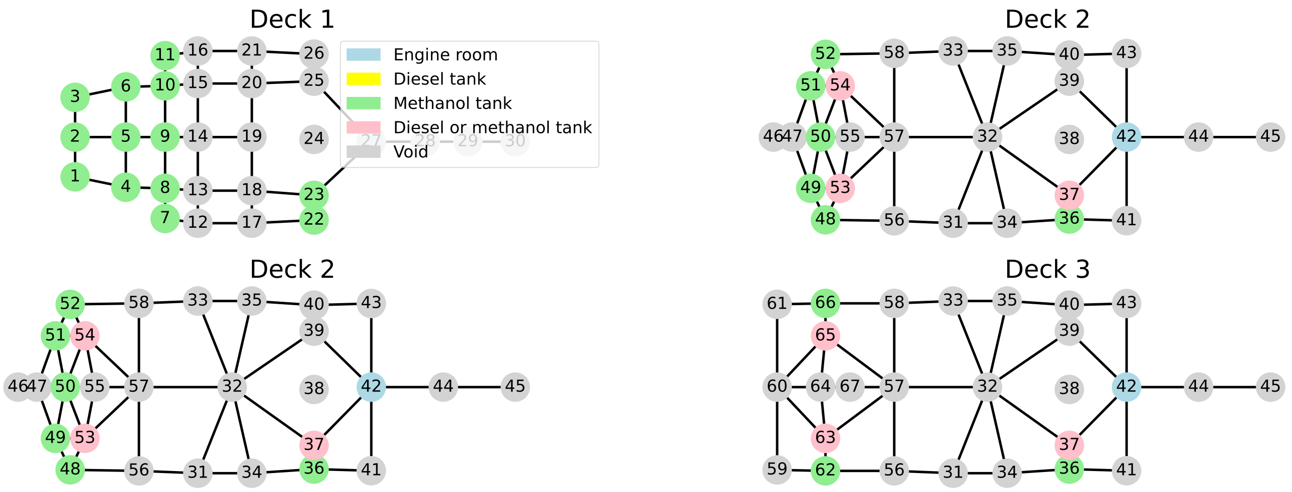


Figure 5: Four 2D graphs representing the data we obtained from the shipyard and Minderhoud (2023). The vertex colors indicate whether a room contains an engine or tank or can be seen as a void, and indicate that there are rooms that can be both diesel and methanol tanks. Note that there are no rooms that can only contain diesel (and no methanol) tanks, hence no vertex is colored yellow. The lines indicate the edges on which we can install pipes. Vertices 24, 38, and 70 correspond to the moonpool.

Similarly to the example in Figure 2, we assume that we start with diesel in the first stage and might transition to diesel or methanol in the second stage. The locations of the diesel and methanol tanks and the engine room are shown in Figure 5. We cannot route diesel pipes through the double bottom or rooms adjacent to the water. Furthermore, we can use single- or double-walled pipes for diesel, but only double-walled pipes for methanol.

Experimental setup

We carried out numerical experiments to study the impact of the cost increase from single- to double-walled pipes (η) and the cost increase from first to second stage (ν_{uv}) on the pipe route and the corresponding costs. First, we use the Manhattan distance between the vertices for the costs γ_{1uv} of installing a single-walled pipe in the first stage, or mathematically: $\gamma_{1uv} = d(u, v)$, where $d(u, v)$ denotes the Manhattan distance between the vertices u and v. We chose this distance measure because it reflects the natural distance a pipe travels. Next, we assume that double-walled pipes are more expensive than single-walled:

$$\gamma_{2uv} = \eta \cdot \gamma_{1uv},$$

where typically $\eta = 2$. However, in our experiments, we will study the impact of η on the pipe route and its corresponding costs. We introduce ν_{uv}, which is the increase rate from first- to second-stage costs for installing a pipe on edge $(u, v) \in \mathcal{E}$:

$$\gamma^{(s)}_{puv} = \nu_{uv} \cdot \gamma_{puv}.$$

The simplest parameter definition for ν_{uv} is a homogeneous cost increase rate, which we assume to be equal to 2 for now

$$\nu_{uv} = 2, \forall (u, v) \in \mathcal{E}, \tag{4}$$

In other words, the increase rate from the first- to the second-stage costs is the same for each pipe-edge pair. As suggested by the maritime experts, it is more realistic to make ν_{uv} dependent on the location in the ship. For example, they suggested that retrofitting the pipe network might be more expensive in rooms adjacent to the engine room or tanks than in a void.

We have incorporated this intuition into two parameter definitions, one only depends on the distance to the engine room whereas the other depends on the function of the rooms. We chose these definitions to study the difference in impact on pipe routes and the costs. First definition looks as follows

$$\nu_{uv} = \frac{\max_{(a,b)\in\mathcal{E}}\{d(a,\mathrm{ER}) + d(b,\mathrm{ER})\}}{d(u,\mathrm{ER}) + d(v,\mathrm{ER})}, \tag{5}$$

where ER denotes the vertex representing the engine room. In (5), the value of ν_{uv} decreases as the distance between ER and the vertices u and v increases. Note that ν_{uv} is always bigger than or equal to 1 for all edges. The intuition behind (5) is that the further an edge lies from the engine room, the lower the complexity of the retrofit and hence the lower the increase rate for the second stage costs. The second definition for ν_{uv} looks as follows:

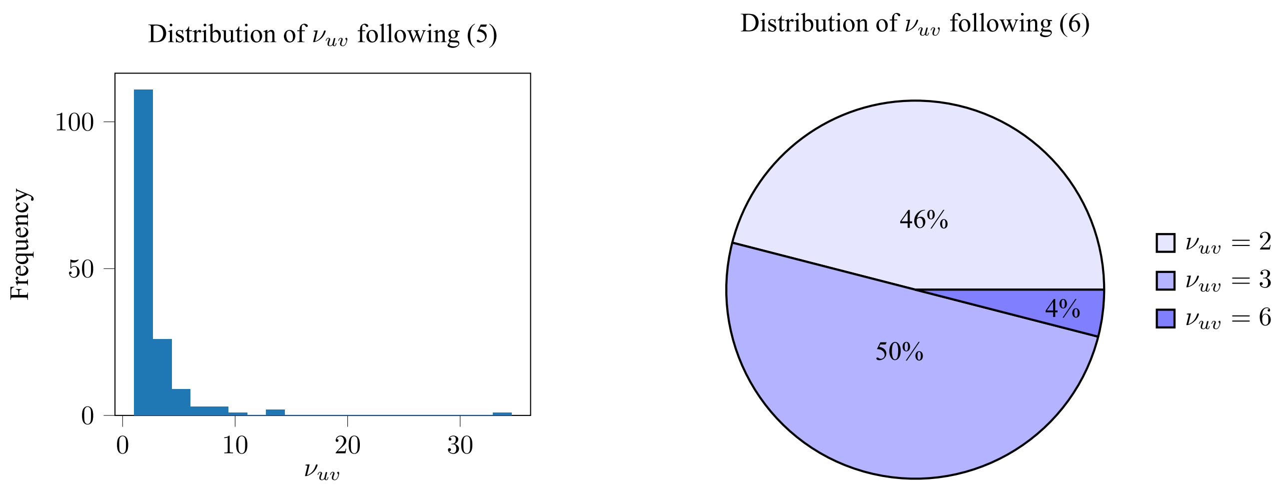
$$\nu_{uv} = \begin{cases} 6 & \text{if } u \text{ or } v \text{ is ER}, \\ 3 & \text{if } u \text{ or } v \text{ is a tank}, \\ 2 & \text{otherwise}. \end{cases} \tag{6}$$

The intuition behind (6) is that retrofits near the engine room are the most expensive, as many essential elements of the ship are close to each other in a narrow space. Additionally, retrofitting through a tank is expensive as additional safety measures are required for the pipe routing. Finally, routing through a void is cheaper but still relatively expensive, as we should consider the costs of not sailing and the complexity of the installation.

Finally, all experiments are executed on a laptop with four cores and CPU 1.2GHz using the Gurobi solver Gurobi Optimization, LLC (2023) for our Python code, which is available upon request.

Numerical experiments: studying the impact of two cost increase rates (ν_{uv} and η)

In the following, we will divide our numerical experiments, which consist of a parameter study, into two parts: the impact of ν_{uv} and η on the pipe route and the corresponding costs.



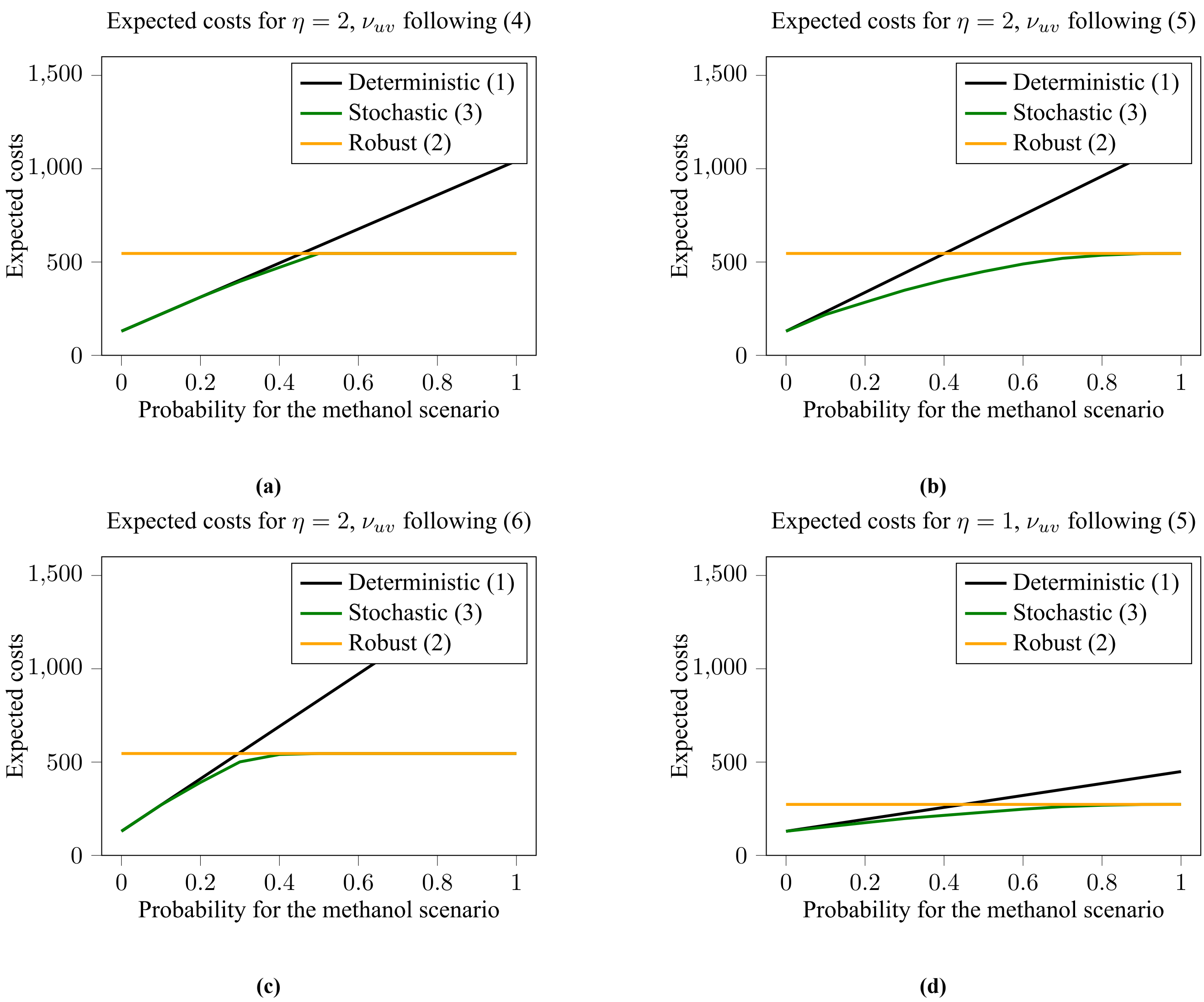
(a) Distribution of ν_{uv} following (5). We see that most edges yield relatively low increase rates, and one extreme value corresponds to the edge (27, 42).

(b) Distribution of ν_{uv} following (6). We see a minority of the edges connected to the engine room and the majority to a fuel tank.

Figure 6: Distribution of the ν_{uv}-values under the two parameter defintions (5) and (6).

Increase rate from first- to second-stage costs (ν_{uv}) The two proposed parameter definitions (5) and (6) yield considerably different distributions for ν_{uv} as shown in Figure 6. In Figure 6a, which displays the values of ν_{uv} on the x-axis and the frequency on the y-axis, we see a skewed distribution, which indicates that most edges have relatively low increase rates, whereas only a few yield extreme values. In Figure 6b, which is a pie chart of the ν_{uv}-values, we see a small number of edges connected to the engine room and many edges connected to a fuel tank.

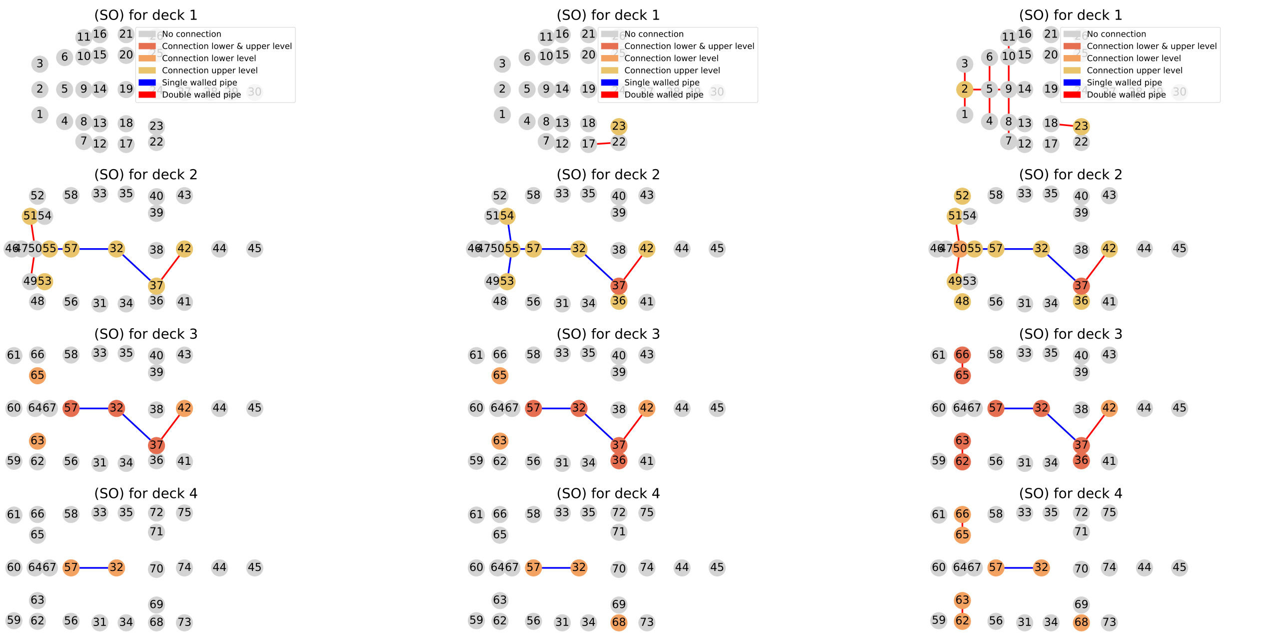
Recall that we use three parameter definitions for ν_{uv}: (4), (5), and (6). A consequence of these different definitions is a difference in expected costs between the mathematical models as shown in Figure 7, where $\eta = 2$. The three figures display the probability of the methanol scenario on the x-axis, the expected costs on the y-axis, and the three mathematical models colored by different colors. Figure 7a shows that the stochastic optimization model slightly outperforms the deterministic and robust optimization model in a small range of probability values. This gap becomes larger in Figure 7c and even larger in Figure 7b, which shows that the heterogeneity of ν_{uv} yields more cost efficiencies for the stochastic optimization models than for the deterministic and robust optimization models. Hence, we conclude that the value of stochastic optimization is enhanced by heterogeneous cost increase rates.



(a) (b) (c) (d)

Figure 7: Expected costs of the three mathematical models under different parameter settings. It shows that more heterogeneous cost rates lead to more cost efficiencies for the stochastic optimization models than the deterministic and robust optimization models.

Besides the expected costs of the three models, we are also interested in how the corresponding optimal pipe route looks. Figure 8 shows the result of stochastic optimization with equal probabilities for each future scenario using the parameter settings $\eta = 2$ and ν_{uv} according to (4), (5), and (6). The blue and red lines indicate an installation of a single- or double-walled pipe on the corresponding edge, respectively. The vertex colors tell if a vertex is connected to a lower and/or upper deck via a pipe. We see that the pipes go via the ship's starboard side due to rooms 22, 23, 36, and 37 that contain fuel tanks. We make two observations in Figure 8. First, Figure 8a contains the least pipes and second, does not contain many double-walled pipes. On the other hand, Figure 8c contains the most pipes and already installs double-walled pipes in the double-bottom to prepare for the methanol scenario. In other words, we see that Figure 8b and Figure 8c prepare better for a possible methanol scenario than Figure 8a as shown in the first decks. As Figure 8a is based on homogeneous cost increase rates, they do not differ between edges based on their location in the ship. We already installed double-walled pipes between vertices 17, 22, and 23 in Figure 8b as these are close to the engine room and are relatively expensive to install in the second stage. Additionally, we see a difference in the pipe routes between Figure 8b and Figure 8c. We explain this result using the difference between Figure 6a and Figure 6b, where (5) mostly yields considerably smaller values for ν_{uv} than (6) despite the fact that the outliers from (5) are considerably higher than the highest value for ν_{uv} in (6). Consequently, the second stage becomes more expensive for (6), and stochastic optimization will install more pipes in the first stage to prevent expensive retrofits.



(a) Optimal pipe route when $\eta = 2$ and ν_{uv} follows (4).

(b) Optimal pipe route when $\eta = 2$ and ν_{uv} follows (5).

(c) Optimal pipe route when $\eta = 2$ and ν_{uv} follows (6).

Figure 8: Optimal pipe routes based on (3) under different parameter settings with equal probabilities for the two future scenarios. Figure 8a contains the least pipes, whereas Figure 8c contains the most.

Increase rate from single- to double walled pipes (η) To illustrate the findings of the numerical experiments, we compare Figures 7b and 7d, which correspond to ν_{uv} following (5) with $\eta = 2$ and $\eta = 1$, respectively. These values were chosen for simplicity reasons. We see that η positively correlates with the expected costs because it directly impacts both first- and second-stage costs. For example, the costs for robust optimization are considerably higher for $\eta = 2$ in Figure 7b than for $\eta = 1$ in Figure 7b. Additionally, η influences the relative cost behavior: stochastic optimization still outperforms deterministic and robust optimization, but the range of probabilities under which this happens changes with η. Figures 7b and 7d a larger probability range for $\eta = 1$ than for $\eta = 2$. In other words, when the installation costs of double- and single-walled pipes become more similar, which is realistic, the stochastic solution becomes more powerful compared to deterministic and robust optimization.

CONCLUSION

Motivated by ship pipe routing under the uncertainty of the energy transition, we have applied the mathematical framework to realistic, complex situations of realistic ship data from a commercial ship designer. In collaboration with maritime design experts we have implemented design constraints in these models: deterministic, robust, and stochastic optimization models. Using these models, we analyzed the impact of realistic location-dependent costs for installing pipes on the pipe route and the corresponding costs. For a more elaborate overview of the different models, we refer the reader to Markhorst et al. (2023).

We find that realistic, heterogeneous cost increase rates depending on the location in the ship enforce the usefulness of stochastic optimization compared to deterministic and robust optimization. More specifically, in our experiments, this effect also depends on the relation between double- and single-walled pipe costs. We see this difference in the corresponding optimal pipe routes as well because the rooms containing an engine or tank get considerably more expensive for retrofits in the future. Consequently, we install most pipes near these sensitive areas in the first stage. Our results show the value of considering uncertainty in ship pipe routing for which our models can be used. Discussions with the maritime experts show that our methods can lead to cost reduction and decreased (financial) risk for ship owners. Additionally, our methods allow the engineers to consider various degrees of preparation for the energy transition with limited effort in the early design stage.

Future research could focus on methods that solve larger instances of the SSFP, which enable ship designers to include even more details in the (graph-)data. Furthermore, we could include more constraints from Lloyd's Register (2023), allow multiple fuel types (i.e., hybrid solutions) in one scenario, and include multiple decision stages over time to make the models more realistic. Finally, we could add other piping and cable infrastructure that may interact with the fuel piping system to our optimization models, to further reduce both costs and risks.

CONTRIBUTION STATEMENT

B.T. Markhorst Conceptualization; Methodology; Software; Formal analysis; Investigation; Data Curation; Writing - Original Draft; Visualization **J. Berkhout** Validation; Writing - Original Draft; Writing - Review & Editing supervision; Supervision. **A. Zocca** Writing - Review & Editing; Supervision. **J.F.J. Pruyn** Resources; Writing - Review & Editing; Supervision; Project administration; Funding acquisition. **R.D. van der Mei** Resources; Writing - Review & Editing; Supervision; Project administration; Funding acquisition.

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