

Integrated planning of asset-use and dry-docking for a fleet of maritime assets

Citation for published version (APA):

Dilaver, H. M., Akcay, A., & van Houtum, G-J. (2023). Integrated planning of asset-use and dry-docking for a fleet of maritime assets. *International Journal of Production Economics*, 256, Article 108720. <https://doi.org/10.1016/j.ijpe.2022.108720>

Document license:

CC BY

DOI:

[10.1016/j.ijpe.2022.108720](https://doi.org/10.1016/j.ijpe.2022.108720)

Document status and date:

Published: 01/02/2023

Document Version:

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

[Link to publication](#)

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license above, please follow below link for the End User Agreement:

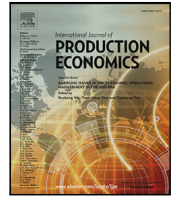
www.tue.nl/taverne

Take down policy

If you believe that this document breaches copyright please contact us at:

openaccess@tue.nl

providing details and we will investigate your claim.



Integrated planning of asset-use and dry-docking for a fleet of maritime assets

Halit Metehan Dilaver, Alp Akçay*, Geert-Jan van Houtum

Department of Industrial Engineering & Innovation Sciences, Eindhoven University of Technology, P.O. Box 513, 5600 MB, Eindhoven, The Netherlands

ARTICLE INFO

Keywords:

Integrated planning
Maintenance
Mandatory inspections
Resource dependence
Mixed Integer Linear Programming

ABSTRACT

In maritime industry, moving assets (e.g., naval ships, dredgers, pilot vessels) are subject to obligatory inspections based on calendar time. These inspections consist of exhaustive operations that need the assets to be towed into specialized facilities referred to as dry-docks. In addition, there are maintenance operations needed as a result of usage-related deterioration of the assets, also requiring the assets to be dry-docked. In practice, a common approach for a fleet of assets is to synchronize these inspection and maintenance operations to avoid unnecessary dry-dockings. However, when and how these operations, some of which are calendar-based and some of which are usage-based, should be synchronized, and whether synchronizing them is always optimal remain as important questions. Since how an asset is used influences when it requires maintenance, answering these questions requires solving an integrated planning problem that combines the planning of asset-use and the planning of dry-docking. Operational constraints such as the locations of assets, limited dry-docking capacity, and the requirement to meet the demand for asset-use in each location make the problem even more challenging. This real-life problem is formulated as a mixed integer linear programming model which minimizes the total discounted cost for a finite time horizon and ensures the full satisfaction of the demand in every time period. The resulting optimal policy is compared with a sequential planning approach to quantify the economic benefit of integrated planning for asset-use and dry-docking. Additionally, two alternative planning approaches are presented for large problem instances. Results of the numerical analysis show that integrated planning can save up to 28.5% of the total cost.

1. Introduction

In many sectors, the maintenance management of physical assets used in production or service (e.g., vessels, aircrafts, trains, electric generators) is a major concern. The maritime sector is one of them. In the maritime sector, comprehensive maintenance actions and inspections require assets to be dry-docked (Deris et al., 1999). The dry-docking refers to taking a maritime asset out of water so that the submerged parts of the hull can be reached and the asset can be fully examined. Since an asset remains out of service during its dry-docking, it is desired to have an effective dry-docking planning (i.e., the time and location of dry-dockings for each asset in a fleet of assets).

In general, two types of strategic-level actions require assets to be dry-docked; so-called mandatory surveys and overhauls. In the maritime sector, the vast majority of assets needs to be surveyed regularly in line with the rules of independent regulatory authorities. These inspections are called *mandatory surveys*, which are generally based on a five-year cycle and consist of three main types: annual surveys, intermediate surveys, and class renewal/special surveys (IACS, 2020). The annual and intermediate surveys do not require an asset to be dry-docked. On the other hand, the class renewal/special surveys, held

every five years, include bottom surveys that aim for detailed hull inspections. In order to be able to apply a hull inspection, assets need to be dry-docked; see Rizzo and Lo Nigro (2008) for more details. In this paper, we focus on the class renewal/special surveys, since the other type of surveys do not require dry-docking. In the remainder of the paper, the term mandatory survey refers specifically to this type of survey. Since mandatory surveys are based on calendar time (i.e., independent of how the assets are used), they can be planned beforehand. A planned dry-docking for a mandatory survey can be considered as a maintenance opportunity. In particular, after some operating hours, critical parts of maritime assets needs to be examined in detail and replaced if necessary. This exhaustive operation is called an *overhaul*. Overhauls require dry-docking similar to mandatory surveys.

Dry-docking planning is a crucial part of the strategic-level maintenance management of maritime assets. With an efficient dry-docking planning, a significant cost reduction in maintenance costs can be achieved. In addition to the cost reduction, availability of maritime assets can be increased since the time of the total dry-docking time can be decreased (Stopford, 2008). To maximize the availability of the assets, dry-docking required maintenance operations need to be

* Corresponding author.

E-mail addresses: h.m.dilaver@tue.nl (H.M. Dilaver), a.e.akçay@tue.nl (A. Akçay), g.j.v.houtum@tue.nl (G.-J. van Houtum).

conducted at the same dry-docking period as much as possible. However, since mandatory surveys and overhauls are based on different drivers, calendar time and usage amount respectively, how and when to overlap them is not trivial. Executing a mandatory survey plan and an overhaul plan created without considering each other may not always be cost-efficient or even feasible.

For the planning of mandatory surveys and overhauls of maritime assets, the limited number of dry-docks in maintenance facilities is a significant constraint. Besides the dry-dock capacity, the geographical location of the maintenance facilities should also be considered. As a matter of fact, a maintenance facility cannot be found in every location of maritime systems. In this paper, a maritime system with multiple locations where only a subset of locations may have a maintenance facility with a fixed number of dry-docks is considered. An additional constraint for many maritime systems is to have a minimum number of operational assets per location. A common approach in strategic level planning of maritime assets is to assure the presence of a minimum number of operational assets for each location, so that any realized demand in a short time window is guaranteed to be fully satisfied. Besides the maritime sector, in many other sectors, the number of available assets in a location at any point of time is a critical constraint for system operability and safety reasons. In this regard, existence of constraints on where the assets can be operated (i.e. the existence of dedicated assets that must be used at a particular location and the existence of flexible assets that can be used in multiple locations) is considered.

In this study, the economic benefit of integrated dry-docking and asset-use planning for multi-asset and multi-location maritime systems under the constraint of full demand satisfaction for every time period is investigated. This problem is motivated by a real-life problem of Loodswezen, which is the company that provides safe and efficient maritime traffic by guiding sea-going vessels into and out of the Dutch and Flemish seaports. Each year, Loodswezen provides guidance to over 90 000 vessels with about 460 registered pilots. Based on the real-life problem of Loodswezen, a maritime system with a limited number of dry-docks with their geographical constraints is considered. The objective is to generate a dry-docking planning by explicitly considering the joint optimization of the timing of mandatory surveys and overhauls. By this way, it is aimed to create optimum dry-docking schedules with guaranteed applicability over the lifespan of the fleet. As a part of overhaul planning (which is driven by the cumulative number of operating hours assigned to each asset), asset-use planning is integrated with dry-docking planning. For these main problem characteristics, a Mixed Integer Linear Programming (MILP) model is built with the objective of minimizing the total discounted cost for a finite time horizon representing the entire lifespan of the fleet (e.g., 25 years), which is divided into time periods of equal length. In the computational experiments of this study, the MILP model is used to generate the optimal integrated planning approach for a new fleet of maritime assets. Also, based on our observations in the current practice of Loodswezen a sequential planning approach, in which dry-docking planning and asset-use planning are made separately, is created. The economic benefit of integrated planning is quantified by comparing the results of the sequential planning approach with the results of the MILP approach that leads to the optimal plan. Then, a sensitivity analysis with respect to the dry-docking cost and the workload in the system is conducted. Based on the sensitivity analysis and the observations on the optimal policies gathered from the MILP approach, two alternative planning approaches called *restricted planning approach* and *problem-based heuristic* are created. The performances of the alternative planning approaches are evaluated by comparing their results with the MILP and sequential planning approaches.

To the best of our knowledge, this paper is the first in literature to investigate the economic benefit of integrated planning of asset-use and dry-docking by optimizing the timing of overhaul and mandatory survey decisions explicitly in one model. This paper also contribute

to the literature with the proposed sequential and restricted planning approaches and by investigating when they can be effective alternatives to the optimal solution of the MILP model under limited solution time and memory capacity of an optimization solver.

The remainder of the paper is organized as follows. Section 2 discusses the related literature, and Section 3 formally describes the problem formulation. An MILP model is created in Section 4 in line with the problem formulation to obtain optimal integrated planning. Section 5 describes the sequential planning approach, which is created in accordance with the real-life practice. Section 6 introduces two alternative planning approaches, i.e. restricted planning approach and problem-based heuristic, for large problem instances. Section 7 presents the results of the numerical simulation where the MILP approach is compared with the other planning approaches. Finally, Section 8 concludes the paper by highlighting the contributions of this paper and the future research directions.

2. Literature review

This paper is related to the following two main research streams: (1) integrated planning of asset-use and maintenance when the degradation of the asset depends on how the asset is used, referred to as load-dependent degradation, and (2) maintenance planning for multi-asset systems with so-called resource dependence. The first research stream can be grouped into two sub-streams based on the following criteria: (1a) the existence of a demand which has to be satisfied, and (1b) the objective to maximize the amount of production while minimizing the total cost.

(1a) *Integrated planning under load-dependent degradation with the existence of a demand which has to be satisfied.* There is a recent interest in literature on jointly planning the asset-use and maintenance by considering the effect of asset use on maintenance timing. There are studies that aim to maximize output as well as studies that examine systems with a demand that has to be met. For example, [Eruguz et al. \(2017a\)](#) consider a k -out-of- n system of a moving asset (i.e., k units need to be active for a system with n parallel and identical units to be functional) and assume an intrinsic age concept to model the degradation process, meaning that the clock ticks at a different pace in different operating modes. In this way, the effect of the operating mode on the degradation of a unit is modeled implicitly. A Markov decision process model is built to decide which units to use in each operating mode that evolves randomly over time. [Biondi et al. \(2017\)](#) build an MILP model to jointly schedule the maintenance and production activities of process plants; their model can select the appropriate operation mode to optimally influence the wear caused by the production on the asset. They assume a deterministic demand for each time period which has to be satisfied. [Feng et al. \(2021\)](#) extend [Biondi et al. \(2017\)](#) by adding a load-dependent degradation model with the possibility of online maintenance (i.e., maintenance tasks that can be performed while the unit is operating). They assume that it is imperative to satisfy the demand, and that it is outsourced at a high cost in case the production is not sufficient. [Olde Keizer et al. \(2018\)](#) consider a 1-out-of- n system (i.e. the system works as long as at least one component is functional), which is inspired by a gas company that must satisfy the demand of companies and households by continuous production. Given economic dependence (i.e., clustering corrective maintenance of failed components can save costs) and load-sharing-dependent failure rates (i.e., the failure rate of components is a function of how the total load is split among functioning components), they formulate a Markov decision process model to obtain the optimal replacement decisions that minimize the long-run average cost rate. [Basciftci et al. \(2020\)](#) solve an integrated condition-based maintenance and operations scheduling problem for a fleet of generators where degradation of generators explicitly depends on how the generators are used. They also consider the restriction of full demand satisfaction with the option of demand curtailment in case of an unexpected loss in production.

(1b) *Integrated planning under load-dependent degradation with the aim of maximizing the production amount while minimizing the total cost.* For a single production unit, [Uit Het Broek et al. \(2020\)](#) study the problem of dynamically adjusting the production rate to control the deterioration (and hence the time to trigger maintenance) of the unit. The so-called *condition-based production* problem is formulated as a Markov decision process model with an objective function that incorporates both the maintenance costs and the production revenues. By controlling the production unit, the model maximizes the revenues until the moment of maintenance which is scheduled upfront. This work is extended by [Uit Het Broek et al. \(2021a\)](#) to two-unit systems, and it is observed that the condition-based production can be beneficial even though there is no economic dependency between the units. For the two-unit systems, a fixed production target is defined corresponding to the total production of the units along with the consideration of a penalty for unsatisfied target and a reward for exceeding the target. More recently, [Uit Het Broek et al. \(2021b\)](#) compare condition-based maintenance with condition based production, and introduce a model that *jointly* optimizes these two policies for systems with production-dependent deterioration. Similar to [Uit Het Broek et al. \(2020, 2021b\)](#) aim to minimize the long-run average cost while maximizing the production revenue. Since the problem investigated in this paper uses the idea of sharing the demand (i.e., operation hours required in a location) among functional units (i.e., assets operating in that location) and requires full satisfaction of the demand in every time period, this paper is mainly contributing to the literature stream (1a). However, the model and findings of this paper can also inspire the researchers contributing to the literature stream (1b) as this paper is also about integrated planning under load-dependent degradation.

Different from the papers in sub-streams (1a) and (1b), in this paper, there is a calendar-based inspection component (i.e., the mandatory surveys), and the presence of economic dependence in the considered problem forms the incentive to reduce costs by overlapping the overhauls and mandatory surveys. Furthermore, it is assumed that the maintenance resources (dry-docking facilities in the problem) have a limited capacity.

(2) *Maintenance of multi-asset systems with resource dependence.* The literature on maintenance planning for multi-asset and multi-component systems has been reviewed by [Cho and Parlar \(1991\)](#), [Wang \(2002\)](#) and [Nicolai and Dekker \(2008\)](#) with a focus on structural, stochastic, and economic dependence between different assets. More recently, [Olde Keizer et al. \(2017\)](#) distinguish a fourth type of dependency, referred to as *resource dependence*. This dependency type is similar to having a negative economic dependence (i.e., the cost increases when the operations are synchronized), but it is more restrictive. In particular, resource dependence exists when there is a limited amount of resources available for performing maintenance of two or more assets at the same time, such as limited amount of time (e.g. [Pandey et al. 2013](#), [Diallo et al. 2018](#), [Do et al. 2015](#), [Khatib and Aghezzaf 2016](#), [Duan et al. 2018](#), [Khatib et al. 2017](#)), maintenance budget (e.g. [Phan and Zhu 2015](#), [Mild and Salo 2009](#)), maintenance crew or tools (e.g. [Armstrong 2002](#), [Safaei et al. 2011a,b](#), [Rasmekomen and Parlikad 2013](#), [Camci 2014, 2015](#), [López-Santana et al. 2016](#), [Phan and Zhu 2015](#)), and spare parts (e.g. [Zhong and Jin 2014](#), [Wang et al. 2008](#), [Joo 2009](#), [Wang et al. 2009](#), [Li and Ryan 2011](#), [En-shun et al. 2012](#), [Olde Keizer et al. 2017](#)). The problem studied in this paper also has resource dependency because dry-docking facilities are necessary to perform overhauls and mandatory surveys, and there is limited capacity for these facilities, i.e., the number of dry-docks in a maintenance facility limits the number of vessels that can be dry-docked at the same moment at that facility. To the best of our knowledge, there is no study that considers resource dependency for multi-unit systems with the idea of controlling the maintenance needs by adjusting the asset-use planning. Also, in this paper, the considered units in such multi-unit systems are heterogeneous (i.e., dedicated or flexible) and moving (i.e., requiring sailing decisions that send an asset from one

location to another at some shipping cost). Thus, the heterogeneity and mobility of the assets are also important for the nature of the problem. This paper is the first that considers all these aspects within the maritime industry.

The review is concluded by emphasizing that there is a literature on dry-docking-required maintenance operations but without an explicit decision on the dry-docking timing. For example, there are studies on the minimization of the duration or cost of dry-docking operations, the estimation of ships' dry-docking duration and labor or the estimation of preferences of decision makers over the dry-docking interval (e.g. [San Cristóbal 2009](#), [Gong et al. 2019](#), [Apostolidis et al. 2012](#), [Dev and Saha 2018](#), [San Cristóbal 2015](#), [Gong et al. 2019](#)). We refer to the review by [Eruguz et al. \(2017b\)](#) for an overview of the studies that consider the existence of dry-docking periods for maintenance activities within the maritime industry. To the best of our knowledge, the only studies that consider a decision on dry-docking timing are [Alhouli \(2011\)](#) and [Alhouli et al. \(2017\)](#). Specifically, they focus on a special type of mandatory survey that must be applied once within a five-year period, and develop a mathematical model to maximize the availability of the ships in the fleet by deciding the dry-docking timing under the constraints of maintenance windows (i.e., predetermined time intervals that the maintenance can be applied) and ship limits (i.e., minimum number of available ships). However, these studies ignore the planning of overhauls. That is, they assume that once the mandatory survey schedule is formed, overhauls are performed accordingly in the same dry-docking moment. In our paper, we relax this assumption and jointly optimize when to perform overhauls and when to perform mandatory surveys over a possibly long time horizon (not just one occurrence of a mandatory survey). This paper is the first to explore the economic benefit of jointly planning the calendar-based mandatory surveys and the asset-use-based overhauls within the stream on dry-docking planning.

3. Problem formulation

Consider a fleet of assets located at multiple locations. Let \mathcal{L} denote the set of all locations and \mathcal{A} the set of all assets. Let $D_{l,t} \in \mathbb{R}^+$ denote the demand to be satisfied at location $l \in \mathcal{L}$ in time period $t \in \mathcal{T}$, where \mathcal{T} denotes the set of time periods of equal length (e.g., time periods of six weeks) numbered as $1, 2, \dots, |\mathcal{T}|$ and \mathbb{R}^+ is the set of non-negative real numbers. The demand at each time period and location needs to be fully satisfied and is expressed in operating hours of assets. There is a maximum amount of operating hours that can be assigned to a specific asset in a period, and this limit is denoted with U . There are two types of locations: main and regular. Let \mathcal{M} denote the set of main locations (i.e., $\mathcal{M} \subseteq \mathcal{L}$). There is a dry-docking facility in each main location $m \in \mathcal{M}$ with a service capacity $S_m \in \mathbb{N}$ with \mathbb{N} denoting the set of positive integers. The parameter S_m can also be interpreted as the number of dry-docks in the main location m . That is, at any time, there can be at most S_m assets dry-docked at the main location m . On the other hand, there is no dry-docking facility in the regular locations. In accordance with the demand satisfaction rule, there is a minimum number of assets that need to be located at location $l \in \mathcal{L}$ at any point of time, denoted by N_l . Therefore, when an asset from a regular location needs to be overhauled or surveyed, it has to move to one of the main locations, and another asset is required in that regular location as a replacement. Moving an asset from location l to j incurs a cost $C_{l,j}^s$. The time to go to a new location is much shorter than the length of a time period, so it is assumed to be negligible.

There are two types of assets: flexible and dedicated. Let \mathcal{F} denote the set of flexible assets (i.e., $\mathcal{F} \subseteq \mathcal{A}$). The flexible assets are free to ship between locations and can operate at any location to satisfy the demand of that location when needed. On the other hand, a dedicated asset $a \in \mathcal{A} \setminus \mathcal{F}$ can only be used to satisfy the demand in its dedicated location, denoted with $I_a \in \mathcal{L}$. At the beginning of the planning horizon, the dedicated assets are assumed to be in their dedicated locations (i.e., not in another location for dry-docking). The initial location of the flexible

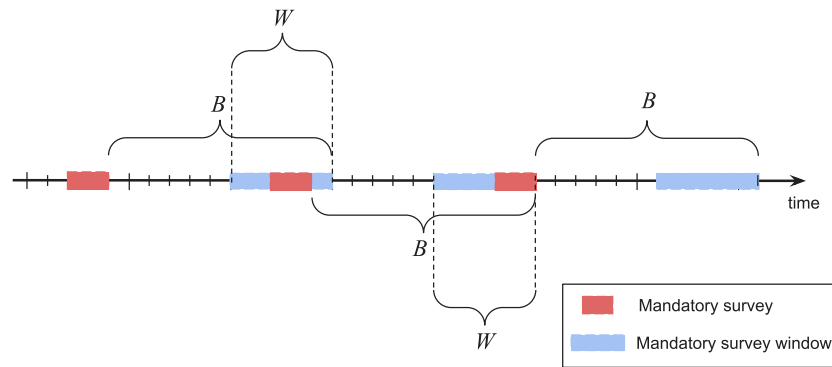


Fig. 1. Illustration of the timeline for mandatory surveys with parameters $B = 11$, $W = 5$, and $p^{ms} = 2$.

asset $f \in \mathcal{F}$ at the beginning of the planning horizon is denoted with $I_f \in \mathcal{L}$.

This study distinguishes between two types of activities that require dry-docking: mandatory surveys and overhauls. A mandatory survey has a duration of p^{ms} time periods, and it needs to be completed no later than B time periods since the completion of the previous mandatory survey. That is, B is the maximum number of time periods between the ends of two subsequent mandatory surveys. Furthermore, a mandatory survey can only take place in time periods close to the end of the allowed time horizon, specifically in the last W time periods with $p^{ms} \leq W \leq B$. Suppose a given mandatory survey takes place in the time periods $t, t + 1, \dots, t + p^{ms} - 1$. Then the parameter B gives the latest time period at which the next mandatory survey has to be completed: $t + p^{ms} - 1 + B$. On the other hand, the earliest period to start the next mandatory survey is $t + p^{ms} - 1 + B - W$. The interval of length W between the earliest time period to start and the latest time period to complete a mandatory survey is called the time window of the mandatory survey. The timeline of mandatory surveys is illustrated in Fig. 1. In practice, it is common to have a value of p^{ms} around multiple weeks, a value of W around multiple months, and a value of B around multiple years. Note that mandatory surveys are based on calendar time, and the requirements on the timing of mandatory surveys do not depend on how the assets are used. At the beginning of the planning horizon, each asset may have a different amount of time until the time window of its first mandatory survey. Let the parameter τ_a denote the time period at which the time window for the first mandatory survey of asset $a \in \mathcal{A}$ starts.

The second type of activity that requires dry-docking is an overhaul. If an asset reaches a certain number of operating hours, it needs to be overhauled. For example, a maritime diesel engine requires an overhaul at around 10 000 operation hours. Let $K \in \mathbb{R}^+$ denote the maximum amount of operating hours that can be performed by an asset until an overhaul. It is possible to overhaul an asset before its operating hours reach the threshold K , but once the threshold has been reached, it is not allowed to continue operating that asset. An overhaul can be considered as a usage-based maintenance operation, and it is assumed that the assets work properly (without failures) until they reach K operating hours after their last overhaul. An overhaul takes p^o time periods. In practice, an overhaul typically takes multiple weeks and often longer than the mandatory survey. Both mandatory surveys and overhauls can only be performed at specialized maintenance facilities with dry-docking capability.

There is a cost of using a dry-dock in a maintenance facility, denoted with C^d per time period, and this is charged on top of the mandatory survey cost and the overhaul cost, denoted with C^{ms} and C^o , respectively. For example, if an asset is overhauled, it costs $C^o + C^d p^o$. Likewise, the cost $C^{ms} + C^d p^{ms}$ is charged for a mandatory survey. It is known that overhauls and mandatory surveys are independent operations that can be performed at the same time without interfering each other. Hence, they can be conducted in parallel at the same dry-docking

period. Since they do not affect each other, the costs of mandatory surveys and overhauls remain the same in case of overlapping. On the other hand, the overlapping leads to a reduction in the total time of dry-docking and, hence, a reduction in the total dry-docking cost. To be specific, completely overlapping a mandatory survey and an overhaul leads to the total cost of $C^o + C^{ms} + \max\{p^o, p^{ms}\}C^d$, while not overlapping these activities results in the total cost of $C^o + C^{ms} + (p^o + p^{ms})C^d$. However, overlapping mandatory surveys and overhauls may also cause unnecessary surveys or overhauls and, therefore, may increase the total cost in the long run.

At the beginning of the planning horizon, the assets can already have a different number of remaining operating hours until the operating hour limit K . For an asset $a \in \mathcal{A}$, let γ_a denote the remaining operating hours until the limit K at the beginning of the first time period. In order to incorporate the present value of the costs incurred during the planning horizon, the parameter $\alpha^t \in [0, 1]$ that represents the discount factor for the costs generated in time period $t \in \mathcal{T}$ is introduced. The objective is to minimize the total discounted cost by creating an integrated plan that combines the planning of asset-use (i.e., assigning each asset a certain level of operating hours at certain locations to satisfy the demand at all locations and time periods) and the planning of the overhauls and mandatory surveys of the assets (i.e., deciding when and where each asset goes through an overhaul and mandatory survey). The total discounted cost covers the costs of using maintenance facilities, overhauls, mandatory surveys, and shifting the assets between locations. Table 1 summarizes the notation used for the problem formulation.

An example is provided below to illustrate the model and the corresponding notation.

Example 1. Suppose that there are six dedicated assets and one flexible asset (i.e. $\mathcal{A} = \{1, \dots, 7\}$ and $\mathcal{F} = \{1\}$) located in two locations (i.e. $\mathcal{L} = \{1, 2\}$). Let the initial location of the flexible asset be Location 1 (i.e. $I_1 = 1$) and the dedicated assets 2, 3 and 4 be assigned to Location 1 and the dedicated assets 5, 6 and 7 be assigned to Location 2 (i.e. $I_2 = I_3 = I_4 = 1$ and $I_5 = I_6 = I_7 = 2$). The only dry-docking facility is placed in Location 1 (i.e. $\mathcal{M} = \{1\}$) and it has a capacity of one (i.e. $S_1 = 1$). In other words, there can be at most one dry-docked asset in the system at any point of time. Suppose that the timeline is divided into time periods of equal length of six weeks and every day there is 15 operating hours of demand on average at each location (i.e. $D_{1,t} = D_{2,t} = 630 \forall t \in \mathcal{T}$, per period). At any point of time, there have to be at least 3 assets present in each location (i.e. $N_1 = 3, N_2 = 3$). In order to keep the number of assets in each location at those levels, the flexible asset is utilized. Whenever there is a need for a dedicated asset to be dry-docked, the flexible assets is sent to the desired location to satisfy a certain part of the locational demand and the minimum number of assets that needs to be located at the location. When there is no dry-docked asset in the facility, the flexible asset is free to be used at any location. Fig. 2 illustrates a specific moment in this system,

Table 1
Notation for the problem formulation.

\mathcal{L}	The set of all locations
\mathcal{A}	The set of all assets
\mathcal{T}	The set of time periods of equal length numbered as $1, 2, \dots, \mathcal{T} $
$D_{i,t} \in \mathbb{R}^+$	The demand to be satisfied at location $i \in \mathcal{L}$ in time period $t \in \mathcal{T}$
\mathbb{R}^+	The set of non-negative real numbers
U	The maximum amount of operating hours for one asset in a period
\mathcal{M}	The set of main locations (i.e., $\mathcal{M} \subseteq \mathcal{L}$)
$S_m \in \mathbb{N}$	The service capacity of the dry-docking facility in main location $m \in \mathcal{M}$
\mathbb{N}	The set of positive integers
N_i	The minimum number of assets that needs to be located at location $i \in \mathcal{L}$ at any point of time
$C_{i,j}^s$	Shipping cost of an asset from location i to j
\mathcal{F}	The set of flexible assets (i.e., $\mathcal{F} \subseteq \mathcal{A}$)
$\mathcal{A} \setminus \mathcal{F}$	The set of dedicated assets
$I_a \in \mathcal{L}$	The dedicated location of asset $a \in \mathcal{A} \setminus \mathcal{F}$
$I_f \in \mathcal{L}$	The initial location of flexible asset $f \in \mathcal{F}$
p^{ms}	The duration of a mandatory survey in terms of time periods
B	The maximum number of time periods between the ends of two subsequent mandatory surveys
W	The length of the window for a mandatory survey, $p^{ms} \leq W \leq B$
τ_a	The time period at which the time window for the first mandatory survey of asset $a \in \mathcal{A}$ starts
$K \in \mathbb{R}^+$	The maximum amount of operating hours that can be performed by an asset until an overhaul
p^o	The duration of an overhaul in terms of time periods
C^d	The cost of using a dry-dock in a maintenance facility per time period
C^{ms}	The cost of a mandatory survey
C^o	The cost of an overhaul
γ_a	The remaining operating hours of asset $a \in \mathcal{A}$ until the limit K at the beginning of the first time period
$\alpha^t \in [0, 1]$	The discount factor for the costs generated in time period $t \in \mathcal{T}$

where there is no dry-docked asset and the flexible asset is at Location 1. The demand in each location and time period must be distributed to the dedicated and flexible (if any) assets present in that particular location and time period. At most 18 operating hours can be assigned to an asset per day (i.e. $U = 756$ per period). When an asset reaches 14 000 operating hours, the asset has to be overhauled and therefore dry-docked (i.e. $K=14\ 000$). Also, every asset has to be dry-docked for a mandatory survey once in every five years (i.e. $B = 44$ time periods). The mandatory survey window is the last one year (i.e. $W = 9$ time periods) of the five-year mandatory-survey window. Suppose that all of the assets in the fleet are new (i.e. $\gamma_a = K$ and $\tau_a = 36$ periods $\forall a \in \mathcal{A}$). Every overhaul and mandatory survey operation generate costs of €200 000 and €50 000, respectively (i.e. $C^o = 20$ and $C^{ms} = 5$) and takes approximately six weeks (i.e. $p^{ms} = p^o = 1$ period). Also for every period that an asset is dry-docked, a cost of €200 000 is generated (i.e. $C^d = 20$). Lastly, for anytime an asset is shipped between the locations 1 and 2, a cost of €10 000 is incurred (i.e. $C_{1,2}^s = C_{2,1}^s = 1$). Note that for a dedicated asset this can only happen before and after a dry-docking period. The objective is minimizing the total discounted cost for a finite time horizon representing the entire 25 years lifespan of the fleet (i.e. $|\mathcal{T}| = 217$ time periods).

4. MILP approach

In this section, a novel Mixed Integer Linear Program (MILP) formulation for the problem described in Section 3 is presented. First, Section 4.1 introduces the objective function and explains the related notation. Then, Sections 4.2–4.6 present the constraints of the MILP model grouped in distinct categories based on their role in the model formulation. Finally, Section 4.7 presents the type and sign restrictions of the decision variables.

4.1. Objective function

The objective of the model is to minimize the total discounted costs of using maintenance facilities, overhauls, mandatory surveys and

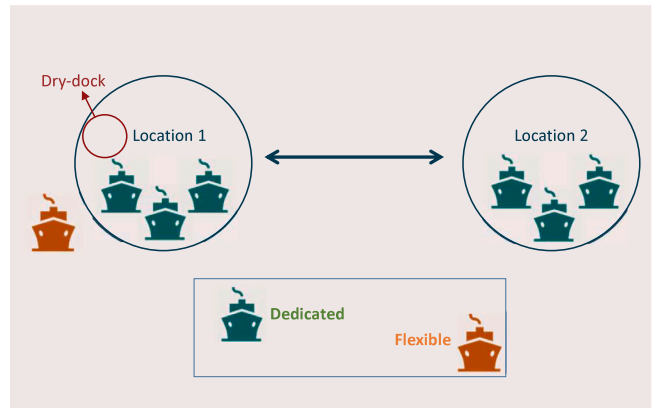


Fig. 2. Visualization of a 2-location system with 6 dedicated assets and 1 flexible asset.

shifting the assets between locations. This objective is captured by the objective function (1) as follows:

$$\begin{aligned}
 \min \quad & \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \alpha^t C^d d_{a,t,m} + \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \alpha^t C^o o_{a,t,m} \\
 & + \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \alpha^t C^{ms} r_{a,t,m} \\
 & + \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{L} | j \neq i} \alpha^t C_{i,j}^s s_{f,t,i,j} \\
 & + \sum_{a \in \mathcal{A} \setminus \mathcal{F}} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \alpha^t (C_{I_a,m}^s + C_{m,I_a}^s) s_{a,t,m} \quad (1)
 \end{aligned}$$

where $d_{a,t,m}$ is a binary variable that is equal to 1 if asset $a \in \mathcal{A}$ is at the maintenance facility in the main location $m \in \mathcal{M}$ in period $t \in \mathcal{T}$. The decision variable $o_{a,t,m}$ is a binary variable that is equal to 1 if an overhaul of asset $a \in \mathcal{A}$ is started in period $t \in \mathcal{T}$ at the maintenance facility in the main location $m \in \mathcal{M}$, and similarly, $r_{a,t,m}$ is a binary variable which is equal to 1 if the asset $a \in \mathcal{A}$ is started to be surveyed in period $t \in \mathcal{T}$ at the maintenance facility in the main location $m \in \mathcal{M}$.

The decision variable $s_{f,t,l,j}$ is a binary variable that is set to 1 if the flexible asset $f \in \mathcal{F}$ is shifted from the location $l \in \mathcal{L}$ to the location $j \in \mathcal{L}, j \neq l$, at the end of the period $t \in \mathcal{T}$.

In the objective function (1), the first two terms represent the total discounted cost of using the maintenance facilities. In the first term, since sailing a dedicated asset to a main location is only necessary when it is shifted there for dry-docking, the sailing cost of dedicated assets from their initial locations to the main locations is added to the cost of using the maintenance facilities. The third and the fourth terms represent the total discounted costs of overhauls and mandatory surveys, respectively. Finally, the fifth term in the objective function represents the total discounted cost of shifting flexible assets between locations.

4.2. Constraints on assigning flexible assets to locations

Since the dedicated assets are preassigned to their specified locations throughout the planning horizon, the only location decision for the dedicated assets is choosing the main location for the maintenance operations, which is captured by the variable $d_{a,t,m}$. On the other hand, the flexible assets can be operated at all locations and must be assigned to a location in each time period. For this purpose, a binary variable $z_{f,t,l}$ is created. This variable is equal to 1 if the flexible asset $f \in \mathcal{F}$ is assigned to the location $l \in \mathcal{L}$ at the time period $t \in \mathcal{T}$. The following constraints are needed to model the assignment of flexible assets to locations:

$$z_{f,1,I_f} = 1 \quad \forall f \in \mathcal{F} \quad (2)$$

$$\sum_{l \in \mathcal{L}} z_{f,t,l} = 1 \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T} \quad (3)$$

$$\sum_{f \in \mathcal{F}} z_{f,t,l} + \sum_{\substack{a \in \mathcal{A} \setminus \mathcal{F} \\ I_a=l}} (1 - \sum_{m \in \mathcal{M}} d_{a,t,m}) \geq N_l \quad \forall l \in \mathcal{L} \setminus \mathcal{M}, \forall t \in \mathcal{T} \quad (4)$$

$$\sum_{f \in \mathcal{F}} (z_{f,t,m} - d_{f,t,m}) + \sum_{\substack{a \in \mathcal{A} \setminus \mathcal{F} \\ I_a=m}} (1 - \sum_{i \in \mathcal{M}} d_{a,t,i}) \geq N_m \quad \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (5)$$

Specifically, constraint (2) denotes that the flexible asset $f \in \mathcal{F}$ is located at its initial location I_f at the beginning of the planning horizon. Constraint (3) ensures that any flexible asset will be assigned to one of the locations $l \in \mathcal{L}$ at any point of time. Finally, constraints (4) and (5) ensure that whenever a dedicated asset is under maintenance, it will be replaced with a flexible asset in order to keep the number of assets at the regular and main locations higher than or equal to N_l , respectively.

4.3. Constraints on operating hours assignment and demand satisfaction

In this section, the constraints on operating hours assignment and demand satisfaction are presented. For this purpose, the variables $x_{a,t} \in [0, U]$ and $x_{f,t,l} \in [0, U]$, where $x_{a,t}$ denotes the amount of operating hours (in terms of operating hours) assigned to the dedicated asset $a \in \mathcal{A} \setminus \mathcal{F}$ and $x_{f,t,l}$ denotes the amount of operating hours assigned to the flexible asset $f \in \mathcal{F}$ at location $l \in \mathcal{L}$ at the time period $t \in \mathcal{T}$ are introduced.

$$x_{a,t} \leq U \times \left(1 - \sum_{m \in \mathcal{M}} d_{a,t,m} \right) \quad \forall a \in \mathcal{A} \setminus \mathcal{F}, \forall t \in \mathcal{T} \quad (6)$$

$$x_{f,t,l} \leq U \times z_{f,t,l} \quad \forall f \in \mathcal{F}, \forall l \in \mathcal{L} \setminus \mathcal{M}, \forall t \in \mathcal{T} \quad (7)$$

$$x_{f,t,m} \leq U \times (z_{f,t,m} - d_{f,t,m}) \quad \forall f \in \mathcal{F}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (8)$$

$$\sum_{f \in \mathcal{F}} x_{f,t,l} + \sum_{\substack{a \in \mathcal{A} \setminus \mathcal{F} \\ I_a=l}} x_{a,t} = D_{l,t} \quad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \quad (9)$$

Constraint (6) states that if a dedicated asset $a \in \mathcal{A} \setminus \mathcal{F}$ is taken into a maintenance facility, it will be out of service and no operating

hours can be assigned to it, otherwise it is bounded by U . Similarly, constraints (7) and (8) state that a flexible asset $f \in \mathcal{F}$ can only operate at the location $l \in \mathcal{L}$ where it is assigned at the time period $t \in \mathcal{T}$ as long as it is not in a maintenance facility. Constraint (9) ensures that the demand $D_{l,t}$ will be fully satisfied and allocated among the assets which are assigned to the particular location $l \in \mathcal{L}$ at the time period $t \in \mathcal{T}$.

4.4. Constraints on calculation of the usage until overhaul limit

In this section, a modeling approach to calculate how close the usage of an asset is to the overhaul limit, denoted with K , is presented. For this purpose, a continuous variable $y_{a,t} \in [0, K]$, which represents the remaining operating hours to the overhaul limit K for asset $a \in \mathcal{A}$ at the end of time period $t \in \mathcal{T}$, is created. The variable $y_{a,t}$ starts with its upper bound K . Its value is updated in each period by decreasing it by the amount of the operating hours assigned to the corresponding asset, and it is reset to K after an overhaul:

$$y_{a,0} = Y_a \quad \forall a \in \mathcal{A} \quad (10)$$

$$y_{a,t} \geq y_{a,t-1} - x_{a,t} \quad \forall a \in \mathcal{A} \setminus \mathcal{F}, \forall t \in \mathcal{T} \quad (11)$$

$$y_{f,t} \geq y_{f,t-1} - \sum_{l \in \mathcal{L}} x_{f,t,l} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T} \quad (12)$$

$$y_{a,t} \leq y_{a,t-1} - x_{a,t} + K \sum_{m \in \mathcal{M}} o_{a,t,m} \quad \forall a \in \mathcal{A} \setminus \mathcal{F}, \forall t \in \mathcal{T} \quad (13)$$

$$y_{f,t} \leq y_{f,t-1} - \sum_{l \in \mathcal{L}} x_{f,t,l} + K \sum_{m \in \mathcal{M}} o_{f,t,m} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T} \quad (14)$$

$$y_{a,t} \geq K \sum_{m \in \mathcal{M}} o_{a,t,m} \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T} \quad (15)$$

$$y_{a,t} \leq K \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T} \quad (16)$$

For each asset $a \in \mathcal{A}$, constraint (10) specifies the usage until the overhaul limit (i.e., the remaining amount of operating hours until the overhaul limit) at the beginning of the planning horizon. Constraints (11)–(16) aim to calculate the remaining amount of operating hours until the overhaul limit for all the assets throughout the planning horizon. Specifically, whenever a certain amount of operating hours is assigned to an asset, constraints (11) and (13) and constraints (12) and (14) assure that the remaining usage until the overhaul limit is decreased accordingly for the dedicated assets and for the flexible assets, respectively (if the asset is not overhauled). If the asset is overhauled, constraints (15) and (16) assure that the remaining usage until the overhaul limit is reset to the upper bound K .

4.5. Constraints on overhauls and mandatory surveys

Next the constraints related to the execution of overhauls and mandatory surveys are presented:

$$d_{f,t,m} \leq z_{f,t,m} \quad \forall f \in \mathcal{F}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (17)$$

$$p^0 o_{a,t,m} \leq \sum_{i=t}^{t+p^0-1} d_{a,i,m} \quad \forall a \in \mathcal{A}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (18)$$

$$p^{ms} r_{a,t,m} \leq \sum_{i=t}^{t+p^{ms}-1} d_{a,i,m} \quad \forall a \in \mathcal{A}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (19)$$

$$\sum_{a \in \mathcal{A}} d_{a,t,m} \leq S_m \quad \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (20)$$

$$\sum_{i=\tau_a}^{\tau_a+W-1} \sum_{m \in \mathcal{M}} r_{a,i,m} \geq 1 \quad \forall a \in \mathcal{A} \quad (21)$$

$$\sum_{i=t}^{t+B-W-1} \sum_{m \in \mathcal{M}} r_{a,i,m} \leq 1 \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T} \quad (22)$$

$$\sum_{i=t}^{t+B-p^{ms}-1} \sum_{m \in \mathcal{M}} r_{a,i,m} \geq 1 \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T} \quad (23)$$

Specifically, constraint (17) states that the flexible asset $f \in \mathcal{F}$ needs to be assigned to the location $m \in \mathcal{M}$ in order to be taken into the maintenance facility at the particular location m . Constraints (18) and (19) control the duration of the overhauls and mandatory surveys in terms of time periods, respectively. Constraint (20) limits the number of assets under maintenance simultaneously at the maintenance facility located at the location $m \in \mathcal{M}$ by S_m . Constraint (21) is used to initialize the process of mandatory surveys of each asset $a \in \mathcal{A}$ and constraints (22) and (23) control the process of the mandatory surveys.

4.6. Constraints on shipping assets between locations

Recall from objective function (1) that the binary variables $s_{a,t,m}$ and $s_{f,t,l,j}$, which represent if the dedicated asset a is moved from its dedicated location I_a to m , or if the flexible asset f is moved from location l to j , respectively, at the end of period $t \in \mathcal{T}$, need to be equal to 1 to charge the corresponding shipment cost. The following constraints are added to assure this:

$$s_{a,t-1,m} \geq d_{a,t,m} - d_{a,t-1,m} \quad \forall a \in \mathcal{A} \setminus \mathcal{F}, \forall m \in \mathcal{M} | m \neq I_a, \forall t \in \mathcal{T} \setminus \{1\} \quad (24)$$

$$s_{f,t-1,l,j} \geq z_{f,t,j} + z_{f,t-1,l} - 1 \quad \forall f \in \mathcal{F}, \forall l, j \in \mathcal{L} | j \neq l, \forall t \in \mathcal{T} \setminus \{1\} \quad (25)$$

Constraint (24) assures that the variable $s_{a,t-1,m}$ is set to 1 when the binary variable $d_{a,t,m}$ is equal to 1 and $d_{a,t-1,m}$ is equal to 0, representing a change in the location of the dedicated asset due to a dry-docking. Similarly, constraint (25) assures that the variable $s_{f,t-1,l,j}$ is set to 1 when the binary variables $z_{f,t,j}$ and $z_{f,t-1,l}$ are both equal to 1, representing a change in the location of the flexible asset. Note that m is not allowed to be equal to I_a in (24) because it is assumed that a dedicated asset $a \in \mathcal{A} \setminus \mathcal{F}$ can only be shipped for its maintenance needs and it is located at its dedicated location I_a for the rest of the time. Since shipment decisions are only defined for sailing between two locations, constraint (24) is only defined for $m \neq I_a$.

4.7. Sign restrictions of the decision variables

The model formulation is finalized by listing the decision variables and their sign restrictions. The list of the decision variables can be found in Table 2.

$$x_{a,t} \geq 0 \quad \forall a \in \mathcal{A} \setminus \mathcal{F}, \forall t \in \mathcal{T} \quad (26)$$

$$x_{f,t,l} \geq 0 \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T}, \forall l \in \mathcal{L} \quad (27)$$

$$y_{a,t} \geq 0 \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T} \cup \{0\} \quad (28)$$

$$z_{f,t,l} \in \{0, 1\} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T}, \forall l \in \mathcal{L} \quad (29)$$

$$d_{a,t,m} \in \{0, 1\} \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M} \quad (30)$$

$$r_{a,t,m} \in \{0, 1\} \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M} \quad (31)$$

$$o_{a,t,m} \in \{0, 1\} \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M} \quad (32)$$

$$s_{a,t,m} \in \{0, 1\} \quad \forall a \in \mathcal{A} \setminus \mathcal{F}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M} | m \neq I_a \quad (33)$$

$$s_{f,t,l,j} \in \{0, 1\} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T}, \forall l, j \in \mathcal{L} | j \neq l \quad (34)$$

The constraints (26)–(34) indicate the domains and sign restrictions of the decision variables.

5. Sequential planning approach

In industry, it is commonly observed that the dry-docking planning and the asset-use planning are separately done by the different departments of a company. For ease of explanation, we call those departments the maintenance department and fleet management department, respectively. The maintenance department creates a dry-docking schedule based on mandatory survey windows and sends it to the fleet management department. According to the received dry-docking plan, the

fleet management department creates an asset-use plan and the related overhaul schedule. Each department searches for the best planning for its own planning problem and ignores the planning of the other department.

In this section, the sequential planning approach that mimics the procedure mentioned above is introduced. The main idea behind this approach is to use the time of mandatory surveys as opportunities for overhauls since the assets are already dry-docked (and hence out-of-service) during a mandatory survey. First, the mandatory survey moments with minimum cost are identified and then the asset-use and overhaul planning by considering the dry-docking moments of the already scheduled mandatory surveys as opportunities for overhauls are optimized. To be specific, it is a two-step process. In the first step, a mandatory survey schedule that generates the minimum mandatory-survey-related costs (i.e., the total dry-docking and mandatory survey costs) is created by solving the following model (M1) optimally.

$$\begin{aligned} \min \quad & \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \alpha^t C^d d_{a,t,m} + \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \alpha^t C^{ms} r_{a,t,m} \\ \text{s.t.} \quad & \text{Constraints (2)–(5)} \\ & \text{Constraints (17), (19)–(23)} \\ & \text{Constraints (29)–(31)} \end{aligned} \quad (M1)$$

Let $\{r_{a,t,m}^* | a \in \mathcal{A}, t \in \mathcal{T}, m \in \mathcal{M}\}$ denote the mandatory survey schedule (i.e., the values of the variables $r_{a,t,m}$) in the optimal solution of this model. These values are considered as fixed in the second step. Specifically, given the mandatory survey schedule from the first step, the asset-use and the related overhaul planning that incur the minimum total cost are created in the second step by solving the following model (M2) optimally.

$$\begin{aligned} \min \quad & \text{Objective Function (1)} \\ \text{s.t.} \quad & \text{Constraints (2)–(34)} \\ & r_{a,t,m} = r_{a,t,m}^* \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M} \end{aligned} \quad (M2)$$

The result of the second step is declared as the result of the sequential planning approach which is a complete asset-use and dry-docking planning. This approach is used as a benchmark to evaluate the economic benefit of integrated planning in the numerical results.

6. Alternative solution approaches

In this section, two alternative planning approaches are introduced for large problem instances, where finding the optimal MILP policy may not be possible under limited computational time. The main motivation behind these alternative planning approaches is the common practice of maximally overlapping mandatory surveys with overhauls in industry. The preliminary computational experiments have shown that, except in the cases where the dry-docking cost is 0, the policy that minimizes the number of dry-docking periods (by maximally overlapping mandatory surveys and overhauls) turns out to be the best policy. However, overlapping which overhauls with which mandatory surveys is still not obvious. Based on the observation of the good performance of overlapping mandatory surveys and overhauls, the following alternative solution approaches are constructed: the *restricted planning approach* and the *problem-based heuristic*.

6.1. Restricted planning approach

This approach is based on solving the MILP model presented in Section 4 in a more restricted way. To be specific, the restriction used under this approach is that an overhaul can only start when a mandatory survey starts. Therefore, the following constraint is added to the MILP model

$$o_{a,t,m} \leq r_{a,t,m} \quad \forall a \in \mathcal{A}, \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \quad (35)$$

Table 2
Model notation for the MILP approach.

$x_{a,t}$	The amount of operating hours (in terms of operating hours) assigned to dedicated asset $a \in \mathcal{A} \setminus \mathcal{F}$
$x_{f,l,t}$	The amount of operating hours assigned to flexible asset $f \in \mathcal{F}$ at location $l \in \mathcal{L}$ at time period $t \in \mathcal{T}$
$y_{a,t}$	The remaining operating hours to the overhaul limit K for asset $a \in \mathcal{A}$ at the end of time period $t \in \mathcal{T}$
$z_{f,l,t}$	Binary variable that is equal to 1 if flexible asset $f \in \mathcal{F}$ is assigned to location $l \in \mathcal{L}$ at time period $t \in \mathcal{T}$
$d_{a,t,m}$	Binary variable that is equal to 1 if asset $a \in \mathcal{A}$ is at the maintenance facility in main location $m \in \mathcal{M}$ in period $t \in \mathcal{T}$
$r_{a,t,m}$	Binary variable that is equal to 1 if asset $a \in \mathcal{A}$ is started to be surveyed in period $t \in \mathcal{T}$ at the maintenance facility in main location $m \in \mathcal{M}$
$o_{a,t,m}$	Binary variable that is equal to 1 if an overhaul of asset $a \in \mathcal{A}$ is started in period $t \in \mathcal{T}$ at the maintenance facility in main location $m \in \mathcal{M}$
$s_{a,t,m}$	Binary variable that is equal to 1 if dedicated asset $a \in \mathcal{A}$ is moved from its dedicated location I_a to $m \in \mathcal{M}$
$s_{f,l,t,j}$	Binary variable equals to 1 if flexible asset f is moved from location l to j at the end of period $t \in \mathcal{T}$

where $o_{a,t,m}$ is equal to 1 if the overhaul of asset $a \in \mathcal{A}$ is started in period $t \in \mathcal{T}$ and $r_{a,t,m}$ is equal to 1 if asset $a \in \mathcal{A}$ is started to be surveyed in period $t \in \mathcal{T}$ at main location $m \in \mathcal{M}$. Constraint (35) implies that an overhaul cannot be started on an asset if the asset is not being taken into mandatory survey at that period. The MILP model that is used to find the integrated plan under the restricted planning for overhauls is as follows:

$$\begin{aligned} \min \quad & \text{Objective Function (1)} \\ \text{s.t.} \quad & \text{Constraints (2)–(35)} \end{aligned}$$

In maritime systems, where the number of overhauls is less than the number of mandatory surveys, it can be reasonable to consider mandatory surveys as opportunities for overhaul, and hence, to adopt the timing of mandatory surveys as restrictions for time of overhauls. (For systems with the number of overhauls greater than the number of mandatory surveys, the restricted approach can be adjusted by changing the direction of the inequality sign in (35) to allow overhauls as opportunities for mandatory surveys). The main motivation for this is keeping the number of dry-docking periods as low as possible by minimizing dry-docking costs. Our computational experiments show that (see Table 5 in Section 7.2) restricting the MILP approach by adding Constraint (35) often improves its solution performance. For further discussion, see Section 7.2.

6.2. Problem-based heuristic (PBH)

This approach aims to improve the result of the sequential planning approach iteratively. This is done by solving the models $M1$ and $M2$ (see the description of the sequential planning approach in Section 5) and adding new constraints to $M1$ based on the solution of $M2$ after each iteration. The intention of adding a new constraint is to shift some particular mandatory surveys to earlier periods (the shift is backward in time since $M1$ already delays the mandatory surveys as much as possible due to discount factor). The aim of shifting mandatory surveys to earlier periods is to create overhaul opportunities in later periods (so that the asset is fully utilized before hitting the overhaul limit). In this way, it is aimed to decrease the cost of overhauls (and hence the total cost) despite a slight increase in the cost of mandatory surveys.

Two parameters are introduced for the problem-based heuristic: *residual* for each overhaul (of each asset), and the so-called picking parameter P . The residual of an overhaul for an asset represents the amount of operating hours that could still be performed by the asset before that overhaul. The picking parameter P is used to identify the P th mandatory survey without an overhaul after the first overhaul with residual (if any). To clarify, note that it is already mentioned that the PBH aims to shift mandatory surveys backwards in time to be able to explore improved overhaul plans. The picking parameter is introduced

to choose which mandatory survey to shift. We illustrate how the PBH works in Fig. 3.

To initialize the heuristic, the maximum number of iterations I is specified and the picking parameter P is set to 1. Afterward, the algorithm proceeds to the first part, which searches for an overhaul plan in which the remaining operating hours (i.e., residuals) are equal to zero for all the overhauls. To be specific, in each iteration, the first-step model of the sequential planning approach, $M1$, is solved. The dry-docking moments are fixed as in the result of $M1$, and then the second-step model of the sequential planning approach, $M2$, is run to optimize the asset use and overhaul planning in accordance with the fixed dry-docking moments from $M1$. If the objective value of $M2$ is lowest so far, then the objective and the dry-docking plan of $M2$ are recorded as *Bestcost* and *Bestplan*, respectively. Afterward, the residuals at the time of the overhauls are checked for each asset. If there is a positive residual, the earliest overhaul with a positive residual is identified and the P th mandatory survey without a simultaneous overhaul after that overhaul is determined. If there is such a mandatory survey, a constraint is added to $M1$ to restrict this identified mandatory survey (i.e., here ‘restrict’ means preventing that mandatory survey happening at that moment, and hence allowing it to be moved backward). The first part is run until a plan with no residual is found or the iteration limit I is reached.

In the second part, first the memory of the additional constraints of the model $M1$ is cleared. Then it is checked if the found overhaul plan is different from the one in the previous iteration. Note that it is possible to reach zero residuals by changing the mandatory survey moments, which may lead to a different asset-use plan but the same overhaul moments. In this case, the algorithm may not be able to minimize the objective further even if it decreases the total residuals to zero. To avoid this, the picking parameter P is increased by one in the algorithm to search for new mandatory survey schedules in order to create shifting opportunities for overhauls. If the overhaul plan is different from the planning in the previous iteration, then the algorithm sets $P = 1$ and fixes the overhaul moments for $M1$. Then, it goes back to the first part to look for further improvements. If the iteration limit I is reached or the number of mandatory surveys without a synchronized overhaul after the first overhaul with residual is less than P , then the algorithm returns the best result and the corresponding integrated plan as the solution.

Algorithm 1 in Appendix provides a detailed outline of the steps of PBH. The results of the PBH are presented along with the results of the restricted planning approach and compared with the results of the MILP approach in Section 7.2.

7. Numerical simulation and results

In this section, the results of the computational experiments are presented. In Section 7.1, the MILP approach and the sequential planning

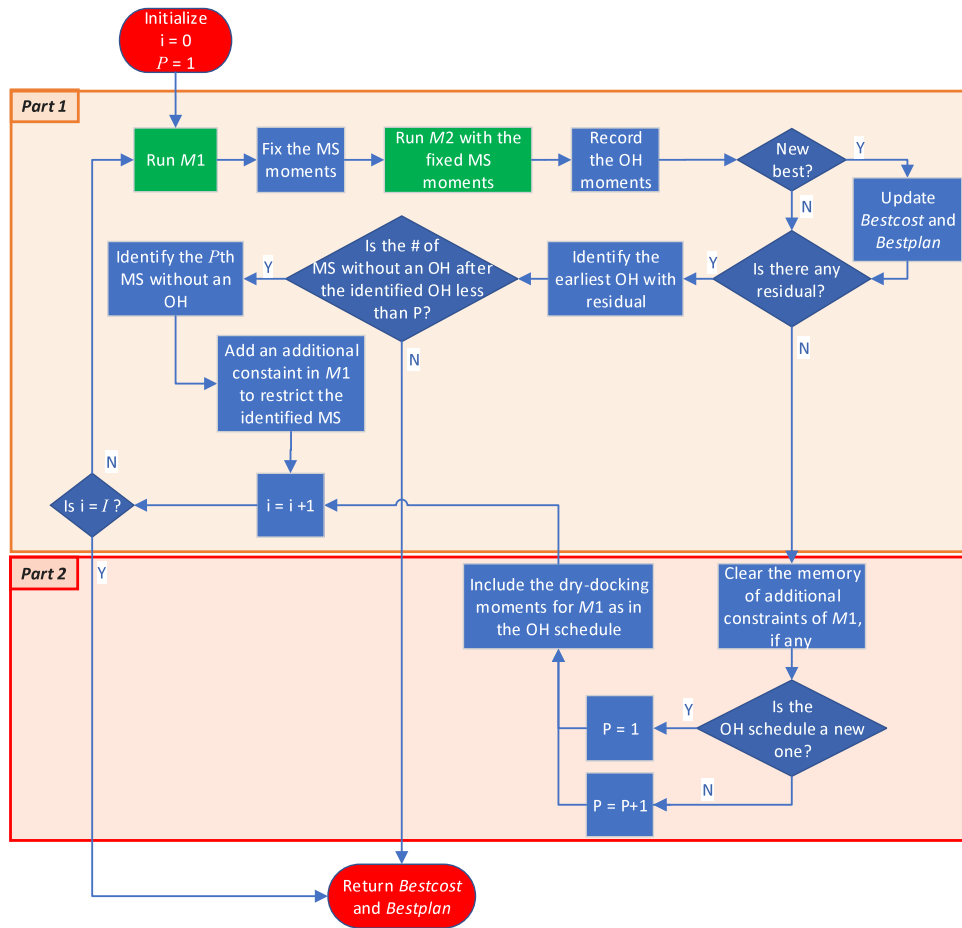


Fig. 3. Flowchart of the problem-based heuristic (OH: overhaul, MS: mandatory survey).

approach are used for multiple problem instances with varying choices for the network size and structure. In Section 7.2, the results of the two alternative planning approaches (i.e., the restrictive planning approach and the problem-based heuristic) are presented, and compared with the MILP and sequential planning approaches. In all of the computational experiments in this study, a new fleet throughout a life cycle of 217 time periods (i.e., this corresponds to a life cycle of about 25 years assuming that each time period is 6 weeks) is considered. The algorithms for the implementation of the alternative solution approaches are coded in JAVA and all of the experiments are conducted on a machine with 8 cores (2.30 GHz each) and 32 GB RAM. The MILP models are optimized via CPLEX Optimization Studio 20.1.0 with the default settings (under a time limit of 12 h).

Since the mandatory surveys have to be applied based only on calendar time, the decision of dry-docking must be made on a regular basis, even if an asset is not used. Due to the minimum number of mandatory surveys that has to be applied on an asset, in any planning approach, there exists a so-called inevitable cost. The results of all four planning approaches are presented after the elimination of this inevitable part of the mandatory survey and dry-docking costs. Also, the optimality gap (i.e., by subtracting the inevitable cost from both the best solution and the best bound) gathered from the optimization solver is recalculated by subtracting the inevitable cost from both the results of the mathematical models and the best bound found by the solver.

7.1. Comparison of the MILP approach and the sequential planning approach

In this section, we compare the MILP and sequential planning approaches. The parameter values used in the experiment are summarized

in Table 3. For the sake of confidentiality, we cannot provide the precise real-life values from our industry partner, Loodswezen, for the cost parameters (C^d , C^o , C^{ms} , $C_{i,j}^s$), the upper bound for the daily usage of an asset U , the operating-hour threshold K , and the duration of the maintenance actions (p^o , p^{ms}). However, these parameter values are chosen to be representative of real-life situations as much as possible. The parameters W and B , which determine the mandatory survey timeline as illustrated in Fig. 1, are in line with the maritime practice (see IACS 2020, Rizzo and Lo Nigro 2008). The initialization parameters γ_a and τ_a are set to reflect the characteristics of a new fleet of maritime assets, i.e., setting γ_a equal to K implies that all assets have the maximum amount of hours until a required overhaul, and setting τ_a equal to 36 reflects that the first mandatory survey of each asset must take place in a time window that starts around just after 4 years since the start of the planning horizon.

Table 4 presents our problem instances together with the number of binary variables, the total number of variables, and the total number of constraints in the corresponding MILP formulations. In Table 4, the size of the fleet is denoted with A , and the number of the flexible assets within the fleet is denoted with by F (i.e., $A = |A|$ and $F = |F|$). The number of locations is denoted with L , and the number of main locations (i.e., the locations that house a maintenance facility) is denoted with M (i.e., $L = |L|$ and $M = |M|$). In the experiments, it is necessary to specify how many dedicated assets exist per location as well as the location of each flexible asset at the beginning of the planning horizon: A balanced distribution is assumed for the number of flexible and dedicated assets located in different locations. This means that, if it is possible, an equal number of flexible and dedicated assets are assigned to each location. When it is not possible, the balance

Table 3
Parameter selection for the problem instances of Table 4.

C^d	20 (x €10 000)
C^o	20 (x €10 000)
C^{ms}	5 (x €10 000)
$C_{i,j}^s, \forall i, j \in \mathcal{L} j \neq i$	1 (x €10 000)
$\gamma_a, \forall a \in \mathcal{A}$	K
$\tau_a, \forall a \in \mathcal{A}$	36 (i.e., approximately 4 years)
p^{ms}	1 (i.e., 6 weeks)
p^o	1 (i.e., 6 weeks)
$D_{l,i}, \forall l \in \mathcal{L}, \forall i \in \mathcal{T}$	210 h × # of dedicated asset at location l
W	9 (i.e., approximately 52 weeks)
U	756 h (18 h a day for 6 weeks)
B	44 (i.e., approximately 5 years)
K	14 000 h
α	0.99
N_l	# of dedicated assets assigned to location l

is kept as much as possible by assigning assets to locations one by one, starting with the flexible ones and continuing with dedicated ones after the flexible ones are all assigned. For instance, in a three-location system with 2 flexible and 6 dedicated assets, the assignment in locations 1-2-3 is given by 3-3-2 (composed of 1-1-0 flexible assets and 2-2-2 dedicated assets). In a three-location system with 1 flexible and 5 dedicated assets, the assignment is 2-2-2 (composed of 1-0-0 flexible assets and 1-2-2 dedicated assets).

For each problem instance, Table 4 provides the solution time, the objective value ('Obj. Val'), and the optimality gap ('Gap%') associated with the MILP approach. Here the optimality gap is gathered from CPLEX and it represents the percentage gap between the best (i.e., lowest cost) feasible solution and the best (i.e., highest) lower bound found by CPLEX. The presented values of 'Gap%' are the results after eliminating the inevitable part of the cost from both the best feasible solution and the best lower bound. This recalculation is applied to better reflect the economic benefit of the MILP approach. Note that not all instances could be solved optimally. Some of the instances ended either due to the time limit (denoted as 12H solution time) or due to the RAM capacity (denoted by writing the solution time in *italic*). For these cases, the objective value associated with the best solution found is presented. In Table 4, the performance of the sequential planning approach is also presented. To be specific, the 'Obj. Val.' under the 'Sequential' column represents the objective value of the sequential planning approach, and 'Gap%' represents the percentage gap defined as $(Seq - MILP)/Seq$, where $MILP$ is the objective value associated with the MILP approach and Seq is the objective value associated with the sequential planning approach. The solution time of the sequential planning approach is less than 15 min for each of the instances.

Table 4 presents instances in three groups. The first group consists of the first 17 instances, where the focus is on systems with a single main location and a single flexible asset. The second group consists of instances 18–29, where the economic benefit of having more flexible assets in the fleet and the complexity due to the increased flexibility is investigated. In the last group (instances 30–34), instances with multiple main locations are considered to evaluate the benefit of possible decomposition ideas (i.e., splitting the network into multiple mutually exclusive sub-networks, and formulating the integrated planning problem in each sub-network as a separate MILP model). In the remainder of this subsection, first the results of the MILP approach are examined in itself. Then, the results of the sequential planning approach are compared with the MILP approach in order to highlight the economic benefit of integrated planning.

The first group of the instances shows that the problem of integrated asset-use and dry-docking planning is computationally challenging in many aspects. As the number of assets in a location (e.g., instances 5–6) or the total number of locations (e.g., instances 13–17) is increased, the complexity of the problem increases drastically. In a single location system, the optimal approach for a fleet with at most 6 assets could be

found. In a two-location system, the highest number of assets that could be optimally solved is only 4. Notice that, for even small numbers of assets, the instances with 3 locations could not be solved to optimality. Our interpretation is that increasing the number of assets at a location only increases the computational complexity of the asset-use planning. On the other hand, increasing the number of locations also increases the number of sailing decision variables (to make asset movement decisions) exponentially.

In the second group of instances, the effect of having more flexibility in the system is investigated. This is done by increasing the number of flexible assets for a fleet of a given size. This means the number of dedicated assets in the fleet is decreased accordingly since the fleet size is assumed to be fixed. However, recall from Table 3 that the parameters N_l and $D_{l,i}$ depend on the number of dedicated assets at location l . In order to be able to compare the results of the first and the second group of instances, the values of these parameters are kept the same as in the first group of instances. In instances 18–23, instances with two flexible assets are considered, and in instances 24–29 it is considered that the entire fleet is flexible. Even for the two-flexible asset instances, the computational complexity of the problem turns out to be beyond our limits for any fleet size. This is in line with the observation of increasing computational complexity associated with an increase in the number of sailing decision variables that come with the additional flexibility. However, as the optimal costs found for instances 7 and 8 are compared with the near-optimal costs found for instances 24 and 25, it can be already seen that adding flexibility is beneficial in terms of the total cost. For example, while the optimal cost is 31.1 for instance 7, the cost of the solution in instance 24 (whose reported cost is guaranteed to be no less than the optimal cost) is less than this, only 29.3. As a matter of fact, shipment cost of the systems is higher when there are more flexible assets but the gain in the cost of maintenance can be even higher. In Table 4, comparing instances 7 and 8 with instances 18 and 19, respectively, it can be further observed that even the systems with two flexible assets are more cost beneficial than their single flexible-asset counterparts.

In the third group of instances, the effect of having more maintenance locations is investigated. In order to use the benefit of having more than one main location, the number of flexible assets is increased to the same extent. A common practice, which is also observed at Loodswezen, is to consider a network with multiple main locations as decomposable into sub-networks and perform asset-use and overhaul planning within each sub-network. In order to check the performance of this approach, instances 30–34 are created by combining the instances in the first group. For example, instance 31 is the combination of instances 1 and 2, instance 30 is the combination of 1 with itself, and instance 32 is the combination of instance 2 with itself. This set of instances shows that considering systems with multiple main locations as a whole leads to better results in terms of cost. For example, the observed cost is 39.9 in instance 30, while the total cost of two systems as described in instance 1 is 42. Even for the systems with a maintenance facility and a flexible asset at each location, it can be beneficial to consider the system as a whole. Furthermore, it can be seen that the economic benefit of considering systems with multiple main locations as a whole is decreasing as the number of assets in the system is increased (see instances 31 and 32).

When the results of the MILP approach are compared with the sequential planning approach, for both single and multi-location systems, the objective value of the sequential planning approach is relatively higher than the objective value of the MILP policy. The gap presented in the last column, Gap%, of Table 4 shows that planning mandatory surveys and overhauls separately is generally inefficient. This sequential planning approach mostly generates a higher cost than the MILP approach because of several reasons. First, the sailing decisions and costs of the assets are ignored during the dry-docking planning step of the sequential planning approach. Second, optimizing mandatory survey planning in the first step leads to dry-docking moments for mandatory

Table 4
The results for the MILP approach.

Inst.	A	F	L	M	#Bin. Var.	Total #Var.	#Const.	MILP			Sequential	
								Soln. time (s)	Gap%	Obj. Val.	Obj. Val.	Gap%
1	3	1	1	1	2170	3475	6951	15.7	0.0%	21.0	23.4	10.3%
2	4	1	1	1	2821	4561	8906	41.8	0.0%	34.2	35.7	4.2%
3	5	1	1	1	3472	5647	10861	132.4	0.0%	46.3	48.2	3.9%
4	6	1	1	1	4123	6733	12816	16277.3	0.0%	61.5	69.1	11.0%
5	7	1	1	1	4774	7819	14771	12H	2.3%	75.6	79.1	4.4%
6	8	1	1	1	5425	8905	16726	12H	2.1%	88.0	94.7	7.1%
7	3	1	2	1	3037	4559	8250	15303.1	0.0%	31.1	32.6	4.6%
8	4	1	2	1	3904	5861	10421	2215.1	0.0%	45.4	49.5	8.3%
9	5	1	2	1	4555	6947	12376	12H	5.8%	57.9	60.4	4.1%
10	6	1	2	1	5422	8249	14547	12H	3.6%	76.9	86.6	11.2%
11	7	1	2	1	6073	9335	16502	12H	8.5%	93.3	94.2	1.0%
12	8	1	2	1	6940	10637	18673	12H	7.2%	108.8	119.4	8.9%
13	4	1	3	1	4989	7163	11936	8358.8	20.3%	55.9	56.7	1.4%
14	5	1	3	1	5856	8465	14107	12H	18.3%	72.1	71.1	-1.4%
15	6	1	3	1	6723	9767	16278	12H	16.2%	90.5	92.6	2.3%
16	7	1	3	1	7374	10853	18233	12H	14.5%	103.1	107.2	3.8%
17	8	1	3	1	8241	12155	20404	12H	19.9%	126.9	121.9	-4.1%
18	3	2	2	1	3689	5428	9118	10933.4	7.9%	30.2	33.4	9.6%
19	4	2	2	1	4556	6730	11289	12318.0	8.5%	42.7	42.6	-0.2%
20	5	2	2	1	5207	7816	13244	12H	8.5%	55.5	55.5	0.0%
21	6	2	2	1	6074	9118	15415	12H	8.2%	74.9	79.9	6.3%
22	7	2	2	1	6725	10204	17370	12H	7.5%	86.9	89.0	2.4%
23	8	2	2	1	7592	11506	19541	12H	8.2%	104.3	108.2	3.6%
24	3	3	2	1	4557	6513	10202	10474.3	13.5%	29.3	32.0	8.4%
25	4	4	2	1	6076	8684	13241	17853.1	7.9%	44.5	45.1	1.3%
26	5	5	2	1	7595	10855	16280	12H	16.4%	56.7	56.4	-0.5%
27	6	6	2	1	9114	13026	19319	12H	12.4%	75.4	80.8	6.7%
28	7	7	2	1	10633	15197	22358	12H	17.5%	90.6	90.4	-0.2%
29	8	8	2	1	12152	17368	25397	12H	20.4%	109.9	111.4	1.4%
30	6	2	2	2	11276	14320	19966	15206.4	11.0%	39.9	55.8	28.5%
31	7	2	2	2	13010	16489	22787	23118.7	5.4%	54.9	64.6	15.0%
32	8	2	2	2	14744	18658	25608	12H	5.6%	68.5	83.5	18.0%
33	7	2	3	2	14532	18445	24735	12H	12.3%	67.9	73.6	7.7%
34	8	2	3	2	16050	20398	27340	12H	13.2%	82.1	89.5	8.3%

survey operations at the latest possible moments. However, this might lead to overhaul decisions for assets when they have still significant numbers of remaining operating hours. This is a result of the economic benefit of having the minimum number of dry-docking operations. As overhauls are more expensive operations than mandatory surveys, prioritizing the planning of the mandatory surveys increases the total cost. Observe that, in 28 out of 34 instances, the MILP approach returns better results than the sequential planning approach although most of the instances could not be optimally solved under the time and RAM capacity limits. In only one instance, both approaches found the same result which is not proven to be optimal. In the remaining five instances, which are returned from CPLEX with a high percentage of gap, MILP approach is outperformed by the sequential planning approach under the time and RAM capacity limits. The comparison of the MILP and sequential planning approaches highlights the economic benefit of integrated planning for multi-asset systems. Although many instances in Table 4 could be solved optimally, it is shown that integrally optimized planning can provide up to 28.5% improvement (i.e., in a multi-main-location instance).

7.2. Comparison of the alternative solution approaches with the MILP approach

In this section, the results of the numerical simulation for the alternative planning approaches are presented and compared with the MILP planning approach in Table 5. For those results, the same parameter values in Table 3 and the same problem instances in Table 4 are used. For each problem instance, the objective values of the sequential, restricted and PBH planning approaches, are presented. In Table 5, the results of the MILP and sequential planning approaches are also presented, and the results of the MILP approach are compared with the results of the other three approaches. For this comparison, ‘Gap%

is defined as (objective value of the presented approach — objective value of MILP approach)/(objective value of the MILP approach). For instance, for the sequential approach, $\widehat{Gap\%}$ under the column ‘Sequential’ represents $(Seq - MILP)/MILP$. In the columns $\widehat{Gap\%}$, the negative values show that the presented approach managed to find better results than the MILP approach under the same computation time and RAM capacity limits. For each instance, the lowest objective value(s) and the corresponding $\widehat{Gap\%}$ value(s) are presented in bold.

The mathematical model built for the restricted planning approach in Section 6.1 could not be solved for all instances under a limited computation time of 12 h. However, all instances that could be solved optimally in Table 4 are also solved optimally under the restricted approach. Furthermore, for large problem instances, we found either close to or even better results than the MILP approach under the same computation time and RAM capacity limits. The restricted approach is better in 18 instances, while the MILP approach is only better in 7 instances under a limited computation time of 12 h. In the rest of the instances, they returned the same objective value. Therefore, under limited computation time, the restricted planning approach is a good alternative over the MILP approach. Besides, these results show that the restricted approach is convenient for the systems where the number of overhauls is smaller than the number of mandatory surveys. However, for some initial conditions or demand levels, this approach may lead to infeasibility (while for the corresponding instance a feasible solution is obtained under the MILP approach).

The results of the PBH and its comparison with the results of the MILP planning approach also are presented in Table 5, where I is set equal to 100. In 26 instances, PBH is able to improve the result of the sequential planning approach. The results show that PBH can obtain better results than the MILP approach under a time limit. Furthermore, PBH can improve the result of the sequential planning approach beyond the result of the MILP approach, even though the sequential planning

Table 5
Comparison of the sequential, restricted and PBH approaches with the MILP approach.

Inst.	MILP	Sequential		Restricted		PBH	
	Obj. Val.	Obj. Val.	Gap%	Obj. Val.	Gap%	Obj. Val.	Gap%
1	21.0	23.4	11.4%	21.0	0.0%	21.6	2.9%
2	34.2	35.7	4.4%	34.2	0.0%	35.0	2.3%
3	46.3	48.2	4.1%	46.3	0.0%	48.1	3.9%
4	61.5	69.1	12.4%	61.5	0.0%	65.5	6.5%
5	75.6	79.1	4.6%	75.6	0.0%	79.1	4.6%
6	88.0	94.7	7.6%	87.9	-0.1%	92.3	4.9%
7	31.1	32.6	4.8%	31.1	0.0%	31.4	1.0%
8	45.4	49.5	9.0%	45.4	0.0%	45.4	0.0%
9	57.9	60.4	4.3%	57.9	0.0%	58.9	1.7%
10	76.9	86.6	12.6%	77.2	0.4%	82.5	7.3%
11	93.3	94.2	1.0%	90.9	-2.6%	94.2	1.0%
12	108.8	119.4	9.7%	108.4	-0.4%	113.0	3.9%
13	55.9	56.7	1.4%	55.5	-0.7%	54.6	-2.3%
14	72.1	71.1	-1.4%	71.1	-1.4%	70.8	-1.8%
15	90.5	92.6	2.3%	91.7	1.3%	91.3	0.9%
16	103.1	107.2	4.0%	103.4	0.3%	105.4	2.2%
17	126.9	121.9	-3.9%	122.5	-3.5%	121.4	-4.3%
18	30.2	33.4	10.6%	29.6	-2.0%	31.8	5.3%
19	42.7	42.6	-0.2%	42.2	-1.2%	42.6	-0.2%
20	55.5	55.5	0.0%	54.7	-1.4%	55.5	0.0%
21	74.9	79.9	6.7%	72.5	-3.2%	79.8	6.5%
22	86.9	89.0	2.4%	87.1	0.2%	89.0	2.4%
23	104.3	108.2	3.7%	103.4	-0.9%	106.9	2.5%
24	29.3	32.0	9.2%	29.1	-0.7%	30.5	4.1%
25	44.5	45.1	1.3%	44.2	-0.7%	45.1	1.3%
26	56.7	56.4	-0.5%	57.1	0.7%	56.4	-0.5%
27	75.4	80.8	7.2%	75.9	0.7%	77.2	2.4%
28	90.6	90.4	-0.2%	89.2	-1.5%	90.4	-0.2%
29	109.9	111.4	1.4%	107.8	-1.9%	108.4	-1.4%
30	39.9	55.8	39.8%	39.9	0.0%	52.4	31.3%
31	54.9	64.6	17.7%	54.8	-0.2%	61.7	12.4%
32	68.5	83.5	21.9%	67.2	-1.9%	75.3	9.9%
33	67.9	73.6	8.4%	68.7	1.2%	73.4	8.1%
34	82.1	89.5	9.0%	81.1	-1.2%	89.3	8.8%

approach is worse (see Instances 13 and 29). It is noted that the solution time of the PBH is much shorter compared to the MILP and restricted approaches. Each problem instance is concluded in less than 4 h with an average of 28 min.

In Table 5, the objective values in bold show that the restricted approach, which finds the best result in 24 instances, is the best approach under the 12-hour computation time limit. It is followed by the MILP approach with 15 instances. However, both the MILP and restricted planning approaches require high computational power and time limits to reach those results. On the other hand, PBH is able to improve the results of the sequential planning approach significantly while its solution time is much shorter than the MILP and restricted approaches. Thus, the decision makers can adopt the problem-based heuristic for getting quick results of good quality. If they are seeking higher quality results (in terms of cost minimization), they should either use the MILP approach itself or the restricted planning approach if there is limited computation time.

8. Conclusion

This paper studies the integrated planning of dry-docking and asset-use for multi-asset maritime systems with the constraint of full demand satisfaction in every time period. For this purpose, a novel MILP modeling approach is proposed. In order to obtain a benchmark for the MILP approach, an approach inspired by real life applications is introduced. In the computational experiments, the economic benefit of integrated planning is quantified for both single and multi-location systems. In addition, managerial insights such as the benefit of allowing assets to operate in different locations (to be flexible) and the benefit of considering systems with multiple maintenance facilities as a whole are generated. It is shown that even for small dry-docking cost or high levels of demand, it is optimal to minimize the total number of dry-docking periods by overlapping mandatory surveys and overhauls as

much as possible. Based on this observation, two practically applicable alternative planning approaches, i.e. restricted planning approach and problem-based heuristic, are introduced. The results show that in 80% of the problem instances, the restricted approach leads to either equal or better results than the results of the MILP approach under the computation time limit of 12 h. Also, the results of the problem-based heuristic can outperform the results of the MILP approach (while the sequential planning approach is worse than the MILP approach). Note that the problem introduced in this study is commonly observed in real-life maritime systems. However, the generated insights and the planning approaches can also be applied to other systems with moving assets (e.g., trains, airplanes) where the usage-based and calendar-time-based maintenance operations are both present and require the same specialized maintenance facility.

We suggest three possible directions as future research. First of all, specialized heuristic approaches can be designed for large problem instances. Secondly, in this paper we assume a fleet of identical assets. It can be practically relevant to look into the problem with multiple asset types having different maintenance needs. A third possible extension can be the consideration of multiple fleets using the same dry-docking facilities. Since not every fleet has its own private dry-docking facility, this is a situation encountered in the maritime sector. In such cases, asset-use planning problems are independent of each other since every fleet is responsible for a separate set of demand. However, dry-docking planning has to be created in accordance with each other to prevent possible conflicts and therefore infeasibilities. This problem of multiple fleets can be considered as a multi-agent planning problem with conflicting objectives.

Data availability

Data will be made available on request.

Acknowledgment

This publication is part of the project “Maritime remote control tower for service logistics innovation (MARCONI)” (project number 439.18.309) of the research programme “Integrator - Logistics as enabler for enhancing society”, which is (partly) financed by the Dutch Research Council (NWO).

Appendix. Problem-based heuristic algorithm

In this section, the pseudo-code of the problem-based heuristic (see Section 6) is presented. Here, *memory* is a parameter that is used to keep and clear the memory of additional constraints added to $M1$. The picking counter p is created to count the number of mandatory surveys while identifying the P th mandatory survey after the earliest overhaul with residual. *Bestplan* and *Bestcost* keep the record of the best solution found so far and its objective value, respectively. The binary variables $\bar{O}_{a,t,m}$ and $\hat{O}_{a,t,m}$ keep the overhaul decisions found in the previous and the current iterations, respectively, for asset a at time t and location m . Similarly, $\bar{M}_{a,t,m}$ represents the fixed mandatory survey decision after solving $M1$.

Algorithm 1 Problem-Based Heuristic

```

Specify  $I$ . Set  $memory = 0$ ,  $p = 0$ ,  $P = 1$ ,  $Bestcost = 1000000$ ,  $Bestplan = \bar{0}$ ,
 $i = 0$ 
Set  $\bar{O}_{a,t,m} = 0$ ,  $\hat{O}_{a,t,m} = 0$ ,  $\bar{M}_{a,t,m} = 0 \quad \forall a \in \mathcal{A}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T}$ 
while  $i < I$  do
  Run  $M1$  with the additional constraints  $C_j \quad \forall j \mid memory \leq j < i$  and
 $r_{a,t,m} \geq \bar{O}_{a,t,m} \quad \forall a \in \mathcal{A}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T}$ 
  Update  $\bar{M}_{a,t,m}$  as in the solution of  $M1$ 
  Run  $M2$  with the additional constraints  $r_{a,t,m} = \bar{M}_{a,t,m} \quad \forall a \in \mathcal{A}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T}$ 
  Update  $\hat{O}_{a,t,m}$  as in the solution of  $M2$ 
  if Objective of  $M2$  is less than  $Bestcost$  then Update  $Bestcost$  and
 $Bestplan$ 
  Let  $p = 0$ ,  $residual = 0$ 
  for  $t \leftarrow 1$  to  $T$  do
    for  $a \leftarrow 1$  to  $A$  do
      for  $m \leftarrow 1$  to  $M$  do
        if  $o_{a,t,m} \times y_{a,t-1} > 0$  then
           $residual = residual + o_{a,t,m} \times y_{a,t-1}$ 
          for  $\hat{t} \leftarrow t + 1$  to  $T$  do
            for  $\hat{a} \leftarrow 1$  to  $A$  do
              for  $\hat{m} \leftarrow 1$  to  $M$  do
                if  $r_{\hat{a},\hat{t},\hat{m}} = 1$  and  $o_{\hat{a},\hat{t},\hat{m}} = 0$  then
                   $p \leftarrow p + 1$ 
                  if  $p = P$  then
                    Create  $C_i := \{r_{\hat{a},\hat{t},\hat{m}} = 0\}$ 
                    break (all for loops)
            if  $p < P$  then
              return  $Bestcost$ ,  $Bestplan$ 
          if  $residual = 0$  then
             $memory = i$ 
            if  $\hat{O}_{a,t,m} = \bar{O}_{a,t,m}$  then
               $P = 1$ 
            else  $P = P + 1$ 
             $\bar{O}_{a,t,m} \leftarrow \hat{O}_{a,t,m}$ 
             $i \leftarrow i + 1$ 
  return  $Bestcost$ ,  $Bestplan$ 

```

References

Alhouli, Y., 2011. Development of Ship Maintenance Performance Measurement Framework to Assess the Decision Making Process to Optimise in Ship Maintenance Planning (Doctoral Dissertation, PhD Thesis). The University of Manchester, United Kingdom.

- Alhouli, Y., Alardhi, M., Elhag, T., 2017. Preventive maintenance scheduling of ship fleet using integer programming. *IJSET-Int. J. Innov. Sci. Eng. Technol.* 4 (8), 270–285.
- Apostolidis, A., Kokarakis, J., Merikas, A., 2012. Modeling the dry-docking cost - the case of tankers. *J. Ship Prod. Design* 28, 134–143.
- Armstrong, M.J., 2002. Age repair policies for the machine repair problem. *European J. Oper. Res.* 138 (1), 127–141.
- Basciftci, B., Ahmed, S., Gebraeel, N., 2020. Data-driven maintenance and operations scheduling in power systems under decision-dependent uncertainty. *IIEE Trans.* 52 (6), 589–602.
- Biondi, M., Sand, G., Harjunkoski, I., 2017. Optimization of multipurpose process plant operations: A multi-time-scale maintenance and production scheduling approach. *Comput. Chem. Eng.* 99, 325–339.
- Camci, F., 2014. The travelling maintainer problem: integration of condition-based maintenance with the travelling salesman problem. *J. Oper. Res. Soc.* 65 (9), 1423–1436.
- Camci, F., 2015. Maintenance scheduling of geographically distributed assets with prognostics information. *European J. Oper. Res.* 245 (2), 506–516.
- Cho, D.I., Parlar, M., 1991. A survey of maintenance models for multi-unit systems. *European J. Oper. Res.* 51 (1), 1–23.
- Deris, S., Omatu, S., Ohta, H., Shaharudin Kutar, L., Abd Samat, P., 1999. Ship maintenance scheduling by genetic algorithm and constraint-based reasoning. *European J. Oper. Res.* 112 (3), 489–502.
- Dev, A., Saha, M., 2018. Dry-docking time and labour. *Trans. R. Inst. Nav. Archit.* A 160, 337–378.
- Diallo, C., Venkatadri, U., Khatib, A., Liu, Z., 2018. Optimal selective maintenance decisions for large serial k-out-of-n: G systems under imperfect maintenance. *Reliab. Eng. Syst. Saf.* 175, 234–245.
- Do, P., Vu, H.C., Barros, A., Bérenguer, C., 2015. Maintenance grouping for multi-component systems with availability constraints and limited maintenance teams. *Reliab. Eng. Syst. Saf.* 142, 56–67.
- Duan, C., Deng, C., Gharaei, A., Wu, J., Wang, B., 2018. Selective maintenance scheduling under stochastic maintenance quality with multiple maintenance actions. *Int. J. Prod. Res.* 56 (23), 7160–7178.
- En-shun, G., Qing-min, L., Hua, L., 2012. Condition-based maintenance for multi-component systems using proportional hazards model. In: *Proceedings of the 31st Chinese Control Conference*. IEEE, pp. 5418–5422.
- Eruguz, A.S., Tan, T., van Houtum, G.-J., 2017a. Optimizing usage and maintenance decisions for k-out-of-n systems of moving assets. *Nav. Res. Logist.* 64 (5), 418–434.
- Eruguz, A.S., Tan, T., van Houtum, G.-J., 2017b. A survey of maintenance and service logistics management: Classification and research agenda from a maritime sector perspective. *Comput. Oper. Res.* 85, 184–205.
- Feng, W., Feng, Y., Zhang, Q., 2021. Multistage distributionally robust optimization for integrated production and maintenance scheduling. *AIChE J.* 67, e17329.
- Gong, C., Frangopol, D.M., Cheng, M., 2019. Risk-based life-cycle optimal dry-docking inspection of corroding ship hull tankers. *Eng. Struct.* 195 (June), 559–567.
- IACS, 2020. Classification societies—what, why and how? International Association of Classification Societies, www.iacs.org.uk, Accessed: 2021-05-29.
- Joo, S.-J., 2009. Scheduling preventive maintenance for modular designed components: A dynamic approach. *European J. Oper. Res.* 192 (2), 512–520.
- Khatib, A., Aghezzaf, E.-H., 2016. Selective maintenance optimization when quality of imperfect maintenance actions are stochastic. *Reliab. Eng. Syst. Saf.* 150, 182–189.
- Khatib, A., Aghezzaf, E.H., Diallo, C., Djelloul, I., 2017. Selective maintenance optimization for series-parallel systems alternating missions and scheduled breaks with stochastic durations. *Int. J. Prod. Res.* 55 (10), 3008–3024.
- Li, R., Ryan, J.K., 2011. A Bayesian inventory model using real-time condition monitoring information. *Prod. Oper. Manage.* 20 (5), 754–771.
- López-Santana, E., Akhavan-Tabatabaei, R., Dieulle, L., Labadie, N., Medaglia, A.L., 2016. On the combined maintenance and routing optimization problem. *Reliab. Eng. Syst. Saf.* 145, 199–214.
- Mild, P., Salo, A., 2009. Combining a multiattribute value function with an optimization model: An application to dynamic resource allocation for infrastructure maintenance. *Decis. Anal.* 6 (3), 139–152.
- Nicolai, R.P., Dekker, R., 2008. Optimal maintenance of multi-component systems: a review. *Complex Syst. Maint. Handb.* 263–286.
- Olde Keizer, M., Flapper, S., Teunter, R., 2017. Condition-based maintenance policies for systems with multiple dependent components: a review. *European J. Oper. Res.* 261 (2), 405–420.
- Olde Keizer, M.C., Teunter, R.H., Veldman, J., Babai, M.Z., 2018. Condition-based maintenance for systems with economic dependence and load sharing. *Int. J. Prod. Econ.* 195, 319–327.
- Pandey, M., Zuo, M.J., Moghaddass, R., Tiwari, M., 2013. Selective maintenance for binary systems under imperfect repair. *Reliab. Eng. Syst. Saf.* 113, 42–51.
- Phan, D.T., Zhu, Y., 2015. Multi-stage optimization for periodic inspection planning of geo-distributed infrastructure systems. *European J. Oper. Res.* 245 (3), 797–804.
- Rasmekomen, N., Parlikad, A.K., 2013. Maintenance optimization for asset systems with dependent performance degradation. *IEEE Trans. Reliab.* 62 (2), 362–367.
- Rizzo, C.M., Lo Nigro, A., 2008. A review of ship surveys practices and of marine casualties partly due to aging effects. In: *International Conference on Offshore Mechanics and Arctic Engineering*, Vol. 48197. pp. 807–818.

- Safaei, N., Banjevic, D., Jardine, A.K., 2011a. Bi-objective workforce-constrained maintenance scheduling: a case study. *J. Oper. Res. Soc.* 62 (6), 1005–1018.
- Safaei, N., Banjevic, D., Jardine, A.K., 2011b. Workforce-constrained maintenance scheduling for military aircraft fleet: a case study. *Ann. Oper. Res.* 186 (1), 295–316.
- San Cristóbal, J.R., 2009. A goal programming model for vessel dry docking. *J. Ship Prod.* 25 (02), 95–98.
- San Cristóbal, J.R., 2015. A cost forecasting model for a vessel drydocking. *J. Ship Prod. Des.* 31 (01), 58–62.
- Stopford, M., 2008. *Maritime Economics* 3e. Routledge.
- Uit Het Broek, M.A., Teunter, R.H., De Jonge, B., Veldman, J., 2021a. Joint condition-based maintenance and load-sharing optimization for two-unit systems with economic dependency. *European J. Oper. Res.* 295 (3), 1119–1131.
- Uit Het Broek, M.A., Teunter, R.H., de Jonge, B., Veldman, J., 2021b. Joint condition-based maintenance and condition-based production optimization. *Reliab. Eng. Syst. Saf.* 214, 107743.
- Uit Het Broek, M.A., Teunter, R.H., de Jonge, B., Veldman, J., Van Foreest, N.D., 2020. Condition-based production planning: Adjusting production rates to balance output and failure risk. *Manuf. Serv. Oper. Manage.* 22 (4), 792–811.
- Wang, H., 2002. A survey of maintenance policies of deteriorating systems. *European J. Oper. Res.* 139 (3), 469–489.
- Wang, L., Chu, J., Mao, W., 2008. An optimum condition-based replacement and spare provisioning policy based on Markov chains. *J. Qual. Maint. Eng.* 14 (4), 387–401.
- Wang, L., Chu, J., Mao, W., 2009. A condition-based replacement and spare provisioning policy for deteriorating systems with uncertain deterioration to failure. *European J. Oper. Res.* 194 (1), 184–205.
- Zhong, C., Jin, H., 2014. A novel optimal preventive maintenance policy for a cold standby system based on semi-Markov theory. *European J. Oper. Res.* 232 (2), 405–411.