A solution framework for the integrated periodic supply vessel planning and port scheduling in oil and gas supply logistics

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Abstract

In this study, we deal with a real-world problem on oil & gas upstream logistics, comprehending the transport of goods from ports to maritime units, through vessels called Platform Supply Vessels (PSVs). We present an integrated methodology to define the routes of these vessels and port schedules in a three-phase framework. In the first phase, we decompose the problem using a clustering heuristic and then solve periodic supply vessel routing problems for each cluster. The second phase employs a mixed-integer programming model for port scheduling and berth allocation. Finally, in the third phase, given port departure times, the routes are re-sequenced to respect opening time constraints at installations, aiming to reduce waiting times and to balance the intervals between successive services. The framework was validated and evaluated considering a real scenario from an industrial partner located in Rio de Janeiro, Brazil. The experiments' results revealed that the framework could consistently and significantly outperform the solution adopted by the company in terms of economic costs.

Keywords: Offshore logistics; supply vessel planning; berth allocation problem; mixed-integer programming; periodic vessel routing problem

1 Introduction

Owing to high costs and production values, the oil and gas industry cannot afford interruptions of activities due to cargo delays. Therefore, exploration and production operations should be supported by complex logistics systems. Specifically, high-quality transportation is critical to ensure the efficient and timely flow of products while maintaining reduced total logistics costs.

In this study, we analyze a real-world logistics problem faced by an industrial partner in an offshore oil and gas exploration and production area in Southeast Brazil. We focus on the problem's upstream logistics, that is, activities designed to supply facilities with necessary materials [1]. This is accomplished by platform supply vessels (PSVs), which transport supplies from ports to maritime (offshore) units (MUs). Figure 1 shows an outline of the logistical network.

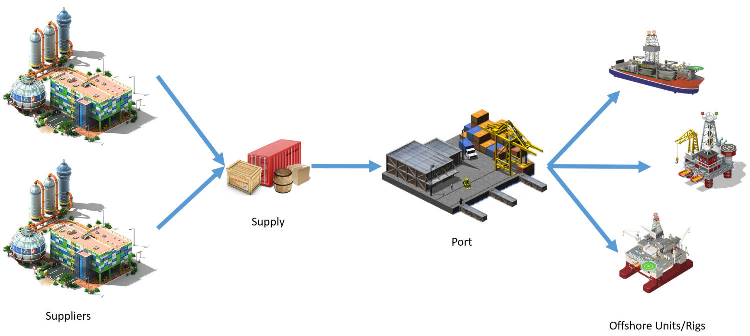

Fig. 1: Offshore supply chain network

Offshore logistics are complex and challenging. In the future, this scenario may be even more arduous, as technological developments and the depletion of mature oil fields have led to the development of fields farther away from the coastline. This highlights the demand for enhanced logistical coordination for the successful implementation of supply operations.

The logistical planning studied in this paper considers multiple aspects, including the weekly routes of PSVs to satisfy each maritime unit's demand. The number of routes and the occupation level of each PSV determine the loading and backloading times at the port; therefore, new or altered routes require a review of port scheduling activities. Furthermore, the interdependence of routing and port scheduling outlines the need for integrated planning of port and PSV activities.

However, due to the combinatorial nature of both problems, an integrated model comprising port operations and PSV routing becomes impractical since a comprehensive analysis of the entire supply chain network may demand extensive computational time, making impossible to incorporate the tool on the periodic planning. In addition, in real operations, it is not desirable to have frequent changes on the entire logistical operation due to administrative issues, hence small weekly changes can be limited to only parts of operation, such as a new port scheduling or eventual routes re-sequencing, for example.

To circumvent this, we developed an innovative methodology through which a solution is found collaboratively within a three-phase framework: PSV routing, port scheduling, and maritime units re-sequencing for time windows adequacy. The methodology introduces gains both in computational time and in flexibility, as it permits both complete decision making procedures or single runs of specific parts of the framework.

In the first step of the framework, we divide the problem into smaller ones using a clustering heuristic, and then we solve a routing problem, considering capacity, maximum port berth time and maximum service time constraints. Note that, in this phase, we do not know port departure times, so it is impossible to forecast arrival times at maritime units and, although important, maritime unit's opening time constraints are not considered. Then, knowing each route's sequence of visits, one can find the loading time on port and in second step of the framework we schedule the activities at the onshore base though a berth allocation problem (BAP). Finally, the third step of the framework uses the port departure times to reformulate the routes and minimize waiting times under opening time constraints. With this strategy, we could deal with both methodological challenges related to obtaining good enough feasible solutions, and practical challenges related to obtaining a solution quickly enough for periodical planning during real operations.

We aim to contribute by proposing an innovative tool that automate the decision-making process in offshore logistics, whilst maintaining the significant characteristics of the real-world problem in the formulation. For instance, we consider vessel's capacity, opening time and total travel time constraints; we also strive to maintain visits to the maritime units well distributed along the time horizon. Although each of these considerations may individually appear in the literature, as far as we know, there is no single modelling framework combining all these these particularities.

Another innovation is the strategy to integrate both port and routing decisions in a single decision support tool. Although working with a comprehensive model, we resort to a solution strategy designed to save computational time, with the decision-making process being made in three steps. Furthermore, in PSV routing, we also resort to a hybrid strategy comprehending a clustering heuristic associated to mathematical programming solved by a solver, further reducing the computational time and enhancing the capacity of handling bigger instances.

The remainder of this paper is organized as follows. Section 2 introduces the problem, followed by a literature review in Section 3. Section 4 presents the proposed framework, while Section 5 validates and evaluates the proposed methodology in light of a real-world example from offshore Brazil. Finally, Section 6 concludes the paper.

2 Problem Definition

Two main types of maritime units provide support for offshore exploration and production of oil and gas, namely oil rigs and production units. While the latter is employed in the production phase, the former supports prospective drilling and work-over operations. Both types of units have a continuous demand for general cargo, fluids, diesel, and food, but their demand profiles differ. Whereas production units feature a relatively stable demand over time, the demand for oil rigs tends to be more variable and prone to emergency deliveries. These distinctions necessitate that each type of installation has its own delivery process, even though the procurement process is integrated.

All demanded items are shipped from a single port to the corresponding maritime units. To manage the loading and unloading operations, each vessel is assigned a time slot in one of the compatible berths at the port. This scheduling should satisfy safety constraints, guarantee maneuverability in and out of the harbor, and incorporate idle times to absorb possible variations in the loading and unloading times. Furthermore, there should also be additional compatibility and operational constraints. For example, some types of cargo may be restricted to certain berths due to weight or equipment limitations, and local environmental regulations prevent the loading of diesel and other fluids on berths facing the beach.

Platform supply vessels (PSVs) traverse specific routes to deliver supplies to maritime units and transport their backloads back to the coast. Operational constraints and contractual obligations impose an upper bound on the duration of each voyage, as well as inferior and superior bounds on the number of stops. In addition, because backloading must precede loading in the space-constrained maritime units, each vessel should depart with sufficient spare room for the backload of the route's first unit. From business specialists knowledge, we know that the backload is always less than or equal to the load, as many products are consumables, such as fluids, cement and others. Likewise, stops with only backload requests are rare. As a consequence, we do not consider it necessary reserve space for backloads on subsequent stops after first unit of the route, since the natural tendency is for the vessel to become increasingly empty.

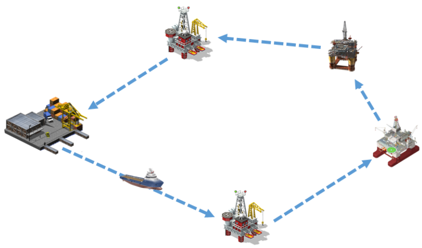

Fig. 2: PSV routes

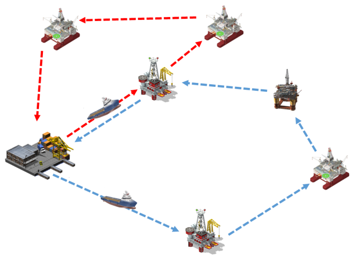

Fig. 3: Conjugate routes

However, if an improbable excessive backload scenario occurs, the remaining cargo can be picked up on the next trip or by an emergency vessel with pre-scheduled loading times at port.

Predicting the availability of individual vessels is very challenging owing to uncertain loading, unloading, and travel times, as well as maintenance requirements. Hence, for planning purposes, the fleet is assumed to be homogeneous with a given deck capacity in square meters equal to the smallest capacity of the fleet and there is no prior commitment between individual vessels and routes. The first reason for making this simplification is that this makes the expected utilization rate of the fleet higher, since the allocation is done dynamically and as soon as a vessel arrives at the port it can be immediately allocated to a new route. In addition, we avoid last minute changes in the vessels assigned routes, since if at the start of loading the assigned vessel were not available, the alternative would be to use whichever one was already available to avoid delays in loading and deliveries. From a practical standpoint, the loss is small because the contracted fleet although not identical, has very similar deck areas. It is also worth mentioning that route planning must also consider demand variation over time to guarantee a prescribed service level.

As illustrated in Figure 2, a route is a sequence of maritime units that start and finish at the port. Every route is traversed twice or thrice a week, attending the same maritime units due to operational constraints. When a maritime unit requires more weekly visits than its counterparts, it is allocated to a pair of so-called *conjugate* routes, both of which include visits to the unit in question. Figure 3 illustrates this route configuration. The planning also considers upper limits for the service (loading and unloading) times, which are estimated according to the expected number of crane movements necessary to complete both backloading and loading. Finally, the visits should respect the operating hours of the maritime units, given that some of these close for loading and unloading at certain times. Typically, the units open for visits either during the day (7 am to 7pm) or at night (7pm to 7am).

It is also important to guarantee balanced intervals between successive visits according to the number of weekly visits to the maritime unit. To illustrate this need, we consider the schedule proposed in Figure 4. It can be observed that the interval between Monday's and Wednesday's visits (48 hours) is considerably reduced compared to the 120 hours between Wednesday's visit and the subsequent visit next Monday. One would expect the demand for Wednesday's visits to be considerably reduced when compared to that of Monday's visits because of such an imbalance. Hence, to keep the demands balanced, we aim to keep the intervals as close as possible to 84 hours for units visited twice a week and 56 hours for units visited three times a week. In this sense, the model may need to support activities that start in one week and finish in the subsequent week. Therefore, we deal with periodic planning, which is the ability to plan for multiple periods of a fixed length.

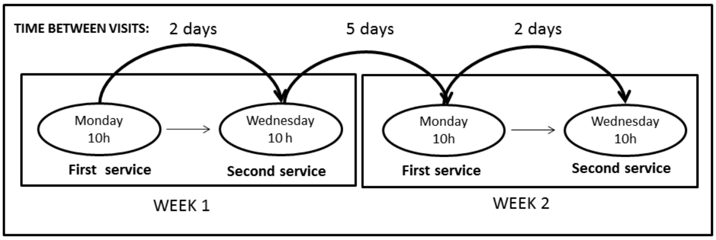

Fig. 4: Example of an unbalanced weekly cycle for two visits a week

The objective of the present work is to provide a methodology to help decision making within the supply chain network from port to maritime units in oil & gas upstream logistics, comprehending both the definition of the PSV's routes and the schedule of the port from where they depart. More specifically, we deal with both a periodic capacitated vehicle routing problem with time windows and homogeneous fleet (PCVRPTW), and a berth allocation problem (BAP). These problems are interconnected: port scheduling affects the timing of the routes, and the composition of the routes affects the requirements, constraints, loading and unloading times at the berth. Aiming a lower computational time and the opportunity of handling bigger instances, we propose a methodology to solve this problem separately in a three-phase framework, which consists of, besides PSV routing, a port scheduling, and an additional route re-sequencing phase to deal with opening time constraints. In addition, before PSV routing, a clustering heuristic divides the problem into smaller ones, to avoid bigger computational times.

PSV routing consists of defining which maritime units should be visited on each route, as well as the order of visits and the amount of supplies to be loaded on each vessel, with the objective of minimizing distance traveled. The main constraints of the problem are the capacities of the vessels and the maximum service, berthing and travel times. The available inputs of the problem are expected demands for each maritime unit (for both load and backload cargoes), quantity of crane movements performed on each maritime unit, the capacity of vessels and maximum service, travel and berthing times. The intended output is a list of routes, each one containing the order of maritime units that should be visited.

When performing the port scheduling, it is necessary to define the time slots and berths for the loading of PSVs assigned to each route and for other port activities, such as berth maintenance, emergency vessel activities, loading of vessels carrying other products outside the scope of this study and crew changes. The planning objective is to minimize the deviation between interval of departures of a route, ensuring visits to the same maritime units with uniform time spacing throughout the week. In relation to problem constraints, besides other usual restrictions related to the berth allocation problems, we also deal with the compatibility between task and berth. The available inputs are the time necessary to execute tasks on berth, slack/maneuver times, the ideal time between departures of a determined route, and compatibility between task and berth. The intended output should contain the time each task should begin on port.

Finally, route re-sequencing consists of reordering previously defined routes which contain any maritime unit with opening constraints. The objective is the minimization of waiting times as well as traveled distance. Compared to PSV routing, there are additional constraints related to the maximum and minimum times between services to ensure that visits to maritime units are well spaced. The available inputs are the opening times on maritime units and the port departure time defined previously. The intended output is, again, a list of routes, each one containing the order of maritime units that should be visited.

3 Literature review

Several planning problems arise in the petroleum industry, which have been studied in the literature. For instance, [2] studied the design of production and transportation network in a gas field and, in contrast, [3] proposed a methodology to support decisions within steel catenary riser design. [4] studied the schedule of resources for well construction, comprehending both drilling and completion activities, and proposed a model similar to the job shop scheduling problem, which was solved through a GRASP metaheuristic. In addition, [5] dealt with the strategic planning of oil supply chains under uncertainty, proposing three mathematical models, each aiming to maximize or minimize different elements of operation: a two-stage stochastic model with fixed recourse, a robust min–max regret model, and a max–min model.

Some years later, [6] proposed a decision support system based on a mixed-integer linear programming model to evaluate different investment alternatives in petroleum downstream logistics, assisting on the selection of the option with costs minimization. [7] proposed methodology based on a capacitance-resistance model to optimize reservoir operations. [8] discussed the problem of offshore oil & gas infrastructure planning and compared the performance of several models. Furthermore, [9] presented a fuzzy stochastic mathematical model to deal with the crude oil scheduling problem by analyzing both vessel transportation to the shore and some other activities related to refining. [10] worked with an integrated planning problem considering both reservoir and surface decisions, dealing with both non-linear mathematical programming aspects and two-stage stochastic models to incorporate uncertainties in oil prices and productivity. [11] dealt with unconventional fields, proposing a methodology based on a mixed-integer linear programming formulation to schedule drilling and hydraulic fracturing of wells. [12] proposed a methodology to support large scale oil field development, in a two phase framework solved by particle swarm optimization-mesh adaptive direct search.

In essence, this work addresses the integration of two principal problems, namely, *periodic supply vessel planning problem* and *berth allocation* (PSVPP-BAP). Sections 3.1 and 3.2 discuss the literature related to each topic.

3.1 Periodic supply vessel planning problem

Periodic supply vessel planning problems are related to vessel routing and scheduling. They share some similarities with specific vehicle routing problems, such as the existence of time windows for individual visits [13]. However, despite the similarities with other types of vehicle routing problems, the particularities of maritime transportation demand specific decision support tools [14].

The studied problem is a type of periodic vehicle routing problem (PVRP), which comprises a planning period of many days containing multiple visits to each individual customer [15]. [16] introduced this problem class while striving to assign compactor trucks for waste collection. Later, [17] employed a series of heuristics to solve a similar problem while enforcing the prescribed service levels. The first integer programming formulation is based on [18], who assigned customers to schedules and routes to vehicles daily.

[19] and [20] introduce PVRP problems applied to offshore logistics with similar characteristics, namely the existence of time windows for the visits to maritime units and upper bound on route times. Specifically, [19] used the traveling salesman problem to define routes, and in the second step, they used integer programming to solve the scheduling problem. In contrast, the two-phase approach by [20] establishes a list of voyages in the first phase and then solves a voyage-based formulation. In a different line of research, [21] discussed the role of supply vessels as well as relevant logistical trade-offs. In addition, [22] dealt with the problem of scheduling cargo supplies to maritime units with time windows at base and clients, with a solution found in a two-step approach: first a heuristic was used to obtain an initial feasible solution, which is them use initialize solver to obtain final optimal schedule.

Related problems were discussed in [23–32]. [23] proposed a methodology to determine optimal fleet on the liner shipping problem, using a multi-trip vehicle routing model with time constraints. [24] dealt with the scheduling of crude oil from maritime units to refineries, proposing several mathematical formulations to solve this problem. [25] proposed a methodology to determine the annual delivery program of a liquefied natural gas (LNG) producer and distributor, dealing with, besides routing and scheduling, also berth and inventory management. [26] combined routing decisions with the disposition of the cargo on deck, [27] modelled selective pickups and [28] considered selective pickups and deliveries. [29] and [30] dealt with both inventory management and routing decisions in maritime applications. A nonlinear model combined onshore and offshore location and routing decisions was presented on the work of [31]. Finally, [32] proposed a methodology integrating a simulation framework of PSV activities with an embedded optimization model to evaluate different fleet management policies and loading strategies on port.

Owing to the complexity of the problem, incorporating uncertainties is challenging. Notwithstanding, the literature contains some level of uncertainty treatment, as observed in the works of [33–35]. In the work of [33], simulation was combined with a recourse optimization procedure to address uncertainties in sailing times and daily production rates within a routing and scheduling problem with time windows. Conversely, [34] employed simulation optimization to account for variations in service time. Finally, [35] prescribed idle times between successive trips to offset unpredictable weather variations.

Considering that mathematical models are limited to small- and medium-sized instances, heuristics are often presented as alternatives to find good solutions with reasonable computational times. In the work of [36], a large neighborhood search (LNS) strategy was used to solve a periodic supply vessel planning problem while also considering fleet composition. By contrast, [37] proposed an adaptation of the genetic search-based heuristic for the PVRP, whereas [38] used arc-flow models to address the same problem. [39] combined their voyage-based approach with an adaptive large neighborhood search (ALNS) heuristic to allow for flexible departure times at the port. [40] studied the problem of transporting crude oil from maritime units, proposing a multi-start heuristic combined with a local search procedure to solve larger instances of the multiship routing and scheduling problem with inventory constraints and pickup-delivery operations. Finally, [41] worked on the problem of rescheduling operations of pipe-laying support vessels (PLSV) after disruptions, which was modeled as an identical parallel machine scheduling problem and solved with an iterated local search (ILS) metaheuristic.

On Table 1, we summarize the similar works presenting alternatives to schedule PSV operations. We highlight objectives, characteristics of the used instances and the gaps which were fulfilled by our work.

3.2 Port scheduling problems

The berth allocation problem (BAP) refers to the allocation of a specific vessel to a physical location in a port for handling operations conducted over a certain period. In addition to quay layout and planning horizon, attributes such as vessel length and depth, vessel arrival time, and handling time should be considered [44]. It is worth noting that the BAP has been proven to be a

Table 1: Summary of supply vessel planning similar works

Work	Objective	Method	Instance	Gaps fulfilled by our work
[19]	PSV scheduling	Heuristics and integer programming	Norway	Time windows, total travel time constraints, and backloads
[20]	PSV fleet size and schedule	Voyage-based model	Statoil	Time windows, and backloads
[22]	PSV scheduling with time windows	Heuristics and integer programming	Western Australia	Port departure times and backloads
[26]	PSV scheduling and ship's deck load arrangement	Simulated Annealing with Ship's Balance	Brazil	Port departure times and backloads
[28]	PSV scheduling with selective pickups and deliveries	Solver and ALNS	45 artificial instances	Time windows, and port departure times
[31]	Fleet size and routes on both maritime and onshore echelons	Lagrangean decomposition & non-linear programming	Persian Gulf and the Sea of Oman	Berth capacity and backloads
[32]	PSV fleet management evaluation and loading strategies	Simulation with cargo allocation through optimization	Brazil	Vessel and port schedules
[35]	PSV scheduling with weather uncertainties	Optimization-simulation & ALNS	Statoil	Berth loading capacity, port activities allocation, and backload
[36]	PSV fleet size and schedule	LNS	Statoil	Time windows, total travel time constraints, backloads, and berth capacity & scheduling
[37]	PSV fleet size and schedule	Genetic algorithm	Statoil	Time windows, backloads, and berth capacity & scheduling
[38]	PSV fleet size and schedule, with speed & weather uncertainties	Voyage-based model	Statoil	Port departure times calculation and backloads
[39]	Multiple vessel scheduling with different levels of robustness	Optimization-simulation & ALNS	Statoil	Port departure times calculation and backloads
[42]	Berth allocation, fleet composition and vessel schedules	Multi step model approach & ALNS	Brazil	Time windows
[43]	Berth allocation, fleet composition and vessel schedules	Branch-and-cut & ALNS	Brazil	Time windows
Our work	Innovative framework that integrates periodic PSV routing and port scheduling. We consider time windows, total times constraints and backloads	Heuristics and integer programming	Data from Brazil	–

non-deterministic polynomial-time hard (*NP*-hard) problem related to the set partitioning problem [45] and the bi-dimensional cut problem [46].

Several constraints may exist, which yield considerable variety in BAP problem formulations [44]. For example, [44] presented three problem classes regarding the berth layout:

(a) Discrete layout: The quay has discrete partitions (berths), and only one vessel can be served at each berth at a given time.

(b) Continuous layout: There is no quay partitioning, which may facilitate improved space utilization. However, on the other hand, the planning problem becomes more complex compared to the discrete version.

(c) Hybrid layout: Analogous to the discrete layout in which the quay is partitioned. However, despite that, smaller vessels can share the same berth, thus configuring partitioned continuous layouts.

[47] considered the dynamic BAP with vessel service priorities. The model proposed in that study was solved using a subgradient method, as proposed by [48]. The relaxed model yielded a quadratic assignment problem, which led the authors to implement a solution method based on genetic algorithms. [49] also presented a Lagrangian relaxation algorithm to solve the problem of dynamically scheduling ships to multiple continuous berth spaces. Some properties of the problem structure were used to update the multipliers and obtain feasible solutions. Further, [50] solved the BAP problem for bulk cargo using a branch-and-price algorithm, while [51] used a set partitioning formulation with a squeaky wheel heuristic for feasible solution construction and optimization. [52] also proposed a tool for the berth allocation problem in maritime container terminals, with the tactical level objective of obtaining a weekly plan, which could have its allocation decisions adjusted by a simulation procedure at the operational level. In addition, [53] presented a methodology for determining the container handling schedule and storage policy at multimodal terminals, obtaining a solution with branch-and-bound techniques or genetic algorithms for larger instances.

[54] focused on the comparison of a set of competing formulations, as well as tabu search, with the objective of minimizing waiting times for both continuous and discrete berth layouts. Among the competing solution procedures, we found genetic algorithms [47, 48, 55] and a hybrid heuristic that combined simulated annealing and clustering [56]. Finally, a multi-objective formulation was addressed via genetic algorithms in [57].

[58] introduced a BAP formulation considering tidal movements, water depths, and vessel drafts, as well as time windows. To solve this problem, they employed two different parallel machine scheduling formulations along with a heuristic procedure. A distinct space-time network formulation has also been advocated [59]. [60] introduced involved meta-heuristic procedures that incorporate an existing mathematical programming formulation. More recently, [42] simultaneously integrated berth allocation decisions with the determination of heterogeneous fleet composition and vessel schedules, considering continuous and flexible departures from the base and historical data to model the berth

allocations and departures. [43] also dealt with the same problem, although with innovative solution strategies, comprehending a branch-and-cut algorithm and an adaptive large neighborhood search (ALNS) heuristic.

Perhaps due to the difficulty in solving deterministic formulations, stochastic formulations of BAP are scarce. Regardless, many sources of randomness exist, such as lead times for acquired supplies, failures and unavailability of resources, and varying loading and offloading times. Previously, [61] considered stochastic loading and offloading times within a bi-objective optimization framework that contrasted waiting times with schedule deviations. Another study incorporated random arrival times and uncertain loading and offloading within a chance constraint formulation [62], whereas [63] opted for a robust programming formulation to tackle the same uncertainties. Finally, [64] proposed a stochastic dynamic programming approach to characterize optimal policies under stochastic arrival and loading and offloading times for different vessel types.

On Table 2, we summarize the similar works presenting alternatives for berth allocation. Again, we highlight objectives, characteristics of the used instances and the gaps which were fulfilled by our work.

3.3 Our Contributions

In relation to the strategy to build routes, the main contribution of our work is the incorporation of several characteristics of real operations in the model. In this context, the model presents some real-life-related constraints, such as total travel time, preservation of spare room for the backload of the first maritime unit on route, opening hours of maritime units, and cycle time constraints. In addition, the strategy of dividing the procedure of building routes into two models – routing and route re-sequencing models – can also be considered as an innovative approach.

In addition, to the best of our knowledge, there are no berth allocation optimization methods with the same level of detail or generality in the literature. For example, some studies addressed the management of a discrete quay layout using integer programming [47, 48, 57, 58]. Others have focused on scheduling aspects [41, 65–67]. This study combines all these aspects and presents additional innovations to the literature. This includes a flexible model that guarantees moorings at fixed times, considers precedence relations between moorings, and tackles periodic mooring planning. Then, it allows to keep the assignment of the routes even with small changes in the port schedule or in the time windows.

Finally, regarding the strategy of dealing with port scheduling and periodic routing in an integrated way, as far as we know, considering all real operation particularities as ours. For instance, the most similar works, [42] and [43], did not consider time windows constraints. In addition, their strategy to have a good spread of the visits along the week consists on using tolerance parameters, which do not guarantee the best balanced intervals between successive visits

Table 2: Summary of berth allocation similar works

Work	Objective	Method	Instance	Gaps fulfilled by our work
[47]	Dynamic BAP	Subgradient method and genetic algorithms	Artificial instances	Evenly spread departure times and integration of berth-vessel planning
[48]	Dynamic BAP	Genetic algorithm	Port of Kobe	Same as previous
[49]	Dynamic BAP	Lagrangian relaxation	Shanghai Baoshan complex	Same as previous
[50]	BAP and yard assignment	Branch-and-price	SAQR port, UAE	Same as previous
[51]	Dynamic BAP	Squeaky wheel heuristic	SAQR port, UAE	Same as previous
[52]	Tactical and operational level BAP	Beam search, simulated annealing and simulation	Gioia Tauro, Italy	Same as previous
[53]	Container handling and storage policy	Branch-and-Bound & genetic algorithms	Fisherman Islands Port, Australia	Same as previous
[54]	Discrete and continuous BAP	Branch-and-Bound & Tabu Search	Gioia Tauro, Italy	Same as previous
[48]	Dynamic BAP	Genetic algorithm	Port of Kobe	Same as previous
[55]	Container terminals design	Genetic algorithm	Estimated handling times	Same as previous
[56]	Dynamic BAP	Simulated annealing	Gioia Tauro, Italy	Same as previous
[57]	BAP on container port	Multi-objective modeling	Port of Kobe	Same as previous
[58]	BAP considering tidal movements, drafts, and time windows	Custom heuristics	Artificial instances	Same as previous
[59]	Dynamic BAP with flexible spaces	Custom algorithm	Taiwan	Same as previous
[60]	BAP considering tidal & water depth	POPMUSIC matheuristic	Pearl River Delta port, China	Same as previous
[61]	BAP with time uncertainties	Evolutionary heuristic	Artificial instances	Same as previous
[62]	BAP with time uncertainties	Genetic algorithm	Artificial instances	Same as previous
[63]	BAP with time uncertainties	Genetic algorithm	Artificial instances	Same as previous
[64]	BAP with time uncertainties	Stochastic programming	Port of Izmir, Turkey	Same as previous
[42]	BAP, fleet size & vessel schedules	Multi step model approach	O&G supply port in Brazil	Minimize distance from perfectly spread departures instead of using tolerance parameters
[43]	BAP, fleet size & vessel schedules	Branch-and-cut & ALNS	O&G supply port in Brazil	Same as previous
Our work	Find a viable schedule that keeps route departures as well-spaced as possible	Integer programming	O&G supply port in Brazil	–

compared to our strategy, which solution is reached through the minimization of the deviations from the ideal interval between consecutive trips of a route.

4 Framework

This section introduces a three-phase framework for PSV routing and port scheduling that considers the limited availability of vessels to load and offload cargo by means of prescribed time windows. Figure 5 illustrates the three phases of the framework. The first step of Phase 1 is a clustering procedure designed to divide the original problem into smaller, more manageable problems. For each cluster, Phase 1 solves a capacitated vehicle routing problem (CVRP) to construct the routes that platform supply vessels should follow. According to the newly constructed routes, it is possible to know the expected occupation of the vessel assigned to each route, as well as the expected loading and unloading times at the port and maritime units. Then, in Phase 2, the newly acquired data is used as an input to the berth allocation problem (BAP) that produces a full schedule for the port. Finally, Phase 3 uses the vessel departure times from Phase 2 to reformulate the routes when necessary, to minimize costs while respecting the actual operating time constraints (time windows) of each maritime unit. Sections 4.1, 4.2, and 4.3 discuss each phase in detail.

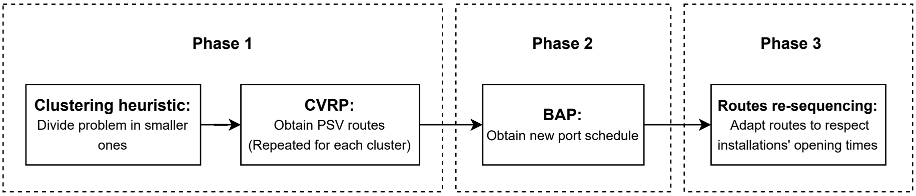

Fig. 5: Framework steps.

4.1 Phase 1: clustering and routing

In this phase, we model the CVRP as a mixed-integer linear programming (MILP) problem. It is well known that the CVRP is *NP*-hard [68]; therefore, large real-world instances rapidly become computationally intractable. For instance, the studied case deals with up to 60 maritime units on the same planning, which could lead to big computational times if solved at once. As we need an agile tool to use repeatedly every time a new weekly plan is performed or any change require a planning review, we start by clustering the maritime units into smaller subsets that produce manageable instances that could be solved within a reasonable time frame from an operational standpoint. Then, by aggregating the solutions of the smaller instances, we can find a near-optimal solution to the original problem while maintaining the computational time within reasonable bounds.

4.1.1 Clustering heuristic

The objective of the clustering heuristic is to divide the maritime units into smaller subsets that are processed separately in subsequent vessel routing. In this sense, the objective is to obtain sequenced lists of maritime units representing each cluster. The objective function to be minimized consists of the sum of the hypothetical distances required to travel between all maritime units, considering the clusters as routes.

The heuristic proposed in this work is based on that of [69], but it incorporates some modifications. To improve the solution, a two-step iterative improvement step was performed until the stopping criterion was satisfied.

The process starts with an initial solution that can be chosen randomly or based on previously operated routes. The first step improves the solution by analyzing all possible pairwise swaps between two maritime units, encompassing units from the same or different clusters. The process is repeated, along what we define as inner iterations, with newly obtained solutions until no further improvement is verified or a maximum number of iterations is attained. This procedure is illustrated in Figure A1 on Appendix.

The second step, illustrated in Figure A2 on Appendix, aims to further improve the current solution by reconfiguring the clusters. First, we set the geometric center of each current cluster as a seed. Then, we rebuild the clusters around the seeds using the regret function in (1). Let $\mathcal{C} \in \mathbb{N}$ be the set of maritime units, and S, $\|\mathcal{S}\| \leq \|\mathsf{C}\|$ be the set of seeds, where S and C denote the number of elements in sets S and C, respectively. Let d_{ij} denote the distance between maritime unit $i \in \mathcal{C}$ and seed $j \in \mathcal{S}$, and define

$$Regret(i) = d_{ij^2} - d_{ij^1}, \quad j^1 = \arg\min_{j \in \mathcal{S}} d_{ij}, \quad j^2 = \arg\min_{j \in \mathcal{S},\, j \neq j^1} d_{ij}. \tag{1}$$

Hence, $Regret(i)$, $i \in \mathcal{C}$ can be deemed as a penalty for assigning maritime unit i to the second nearest seed instead of the nearest one.

To reallocate the maritime units to the newly constructed clusters, we sort them out from the highest to the lowest value of the regret function, allocating the ones with the highest values first. Therefore, we expect to prioritize maritime units that are more isolated, and which allocation to more distant clusters can result in the poorest solutions.

This process is repeated for all maritime units. When the maximum quantity of elements in the cluster is reached, the maritime unit is assigned to increasingly distant clusters. We also use Tabu Search to prevent cycles and improve the efficiency of the algorithm [70].

The algorithm repeats Steps 1 and 2 along what we define as outer iterations, until a maximum number of iterations is reached. The process is performed as follows:

Algorithm 1 Clustering heuristic

```
Generate initial solution, randomly or based on actual routes
Best Solution:=Initial solution
while Max number of outer iterations not reached do
    Evaluated solution := Best Solution
    while Max number of inner iterations not reached and new solution being found do
        for All 2-position changes in evaluated solution do
            Calculate the objective function
            if New Best solution is found then
                Best Solution:=Current solution
            end if
        end for
    end while
    Define the geometric center of the current clusters as seeds
    for All maritime units, ordered according to the Regret function value do
        if Nearest seed's cluster did not reach capacity then
            Allocate maritime units to clusters originating from the nearest seed
        else
            Try to allocate to increasingly distant clusters.
        end if
    end for
    if Solution already visited according to Tabu Search then
        Generate new random solution
    end if
end while
```

4.1.2 Capacitated routing

The main objective of this step is to obtain the maritime units attended on each route, and consequently demands and load times on each route. Indirectly, it is possible to obtain the berth loading times, which are important for calculations in the subsequent port scheduling phase.

Consequently, after assigning maritime units to clusters, we solve a capacitated vehicle routing problem (CVRP) with total travel time constraints for each cluster to create routes that respect the capacity constraint of the demand flow, and the total travel and berthing time. Note that opening time constraints are not considered at this stage. This happens because it is not yet possible to predict the departure and arrival times on the ports and, consequently, arrival times at maritime units. These times would only be available a posteriori because, to define the port schedule, it is necessary to know the loading times of the vessel, which depends on its occupancy according to the maritime units served on each route.

In our problem, the maritime units require two or three services per week, but in this phase we need only to solve the problem for a single visit, as the same sequence of visits would occur on all repetitions of the route throughout the week. From a practical standpoint, maintaining the same sequence of visits on all trips leads to a better distribution of visits to the maritime units throughout a week and facilitates the company's management of the weekly operations. Indeed, keeping the sequence of visits unaltered on all trips was a strong recommendation of the company.

Formally, the problem is defined as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where $\mathcal{V}$ represents the set of nodes and $\mathcal{A}$ represents the set of arcs. Set $\mathcal{V}$ is defined as $\mathcal{V} = \{0\} \cup \mathcal{C}$, where node 0 represents the port and $\mathcal{C}$ represents the subset of maritime units.

The arc set $\mathcal{A}$ contains all pairs of nodes $(i,j), i \neq j, i,j \in \mathcal{V}$. The problem is defined over a finite time horizon, typically one week.

Each unit $i \in C$ has associated: a service time s_i , lifts z_i , demand k_i, and backload ρi. The distance from node i to node j is represented by d_{ij}, $(i,j) \in A$. R is a maximum travel time, H represents the maximum berthing time, α and β are coefficients of the regression used to determine berthing time, and M is a big number. The maximum capacity of the vessels is denoted C_{max}.

Eight types of variables are used in the mathematical model: x_{ij}, $i,j \in V$ is a binary variable taking value 1 if the arc between nodes i and j is part of a route, zero otherwise; f_{ij} and g_{ij} are non-negative real variables representing demand flows expressed in square meters and crane movements respectively, passing through arc (i,j) for $i \in V$ and $j \in C$; and finally, h_i is a non-negative real variable that indicate the arrival times at node $i \in C$.

Parameters:

s_i – Service time on maritime unit i;
z_i – Number of crane movements performed for loading and unloading at maritime unit i;
k_i – Demand on maritime unit i;
ρi – Backload on maritime unit i;
d_{ij} – Distance from node i to node j;
t_{ij} – Travel time from node i to j;
R – Maximum travel time;
C_{max} – Maximum capacity of vessels;
H – Maximum berthing time;
α – Average loading/unloading craning time on port;
β – Average loading/unloading setup time on port.

Decision Variables:

x_{ij} – Binary variable, equals to 1 when arc (i,j) belongs to some trip, and 0 otherwise;
f_{ij} – Demand flow (expressed in square meters) through arc (i,j) related to the vessels' loading space;
g_{ij} – Demand flow (expressed in crane movements) through arc (i,j) related to the loading and unloading times on the maritime units;
h_i – Arrival time in maritime unit i.

The mathematical model is:

$$\min \sum_{i\in\mathcal{V}} \sum_{j\in\mathcal{V}} d_{ij} x_{ij} \tag{2}$$

s.t.

$$\sum_{i \in \mathcal{C}} x_{ij} = 1 \qquad j \in \mathcal{C} \tag{3}$$

$$\sum_{j \in \mathcal{C}} x_{ij} = 1 \qquad i \in \mathcal{C} \tag{4}$$

$$\sum_{j \in \mathcal{C}} x_{0j} = \sum_{i \in \mathcal{C}} x_{i0} \tag{5}$$

$$\sum_{i \in \mathcal{V}} f_{ij} - \sum_{i \in \mathcal{V}} f_{ji} = k_j \qquad j \in \mathcal{C} \tag{6}$$

$$\sum_{i \in \mathcal{V}} g_{ij} - \sum_{i \in \mathcal{V}} g_{ji} = z_j \qquad j \in \mathcal{C} \tag{7}$$

$$f_{0j} \leq (C_{max} - \rho_j) x_{0j} \qquad i, j \in \mathcal{V}, \tag{8}$$

$$f_{ij} \leq C_{max} x_{ij} \qquad i, j \in \mathcal{C} \tag{9}$$

$$g_{ij} \leq M x_{ij} \qquad i, j \in \mathcal{V} \tag{10}$$

$$\alpha g_{0i} + \beta \leq H \qquad i \in C \tag{11}$$

$$h_i + s_i + t_{ij} - M(1 - x_{ij}) \leq h_j \qquad i, j \in \mathcal{C} \tag{12}$$

$$h_j + s_j + t_{j0} - M(1 - x_{j0}) \leq R \qquad i, j \in \mathcal{C}, \tag{13}$$

$$x_{ij} \in \{0, 1\} \qquad i, j \in \mathcal{V} \tag{14}$$

$$h_i, f_{ij}, g_{ij} \geq 0 \qquad i, j \in \mathcal{V} \tag{15}$$

The objective function (2) minimizes the total distance traversed by all vessels. The single assignment constraints (3) and (4) ensure that there is only one incoming arc and one outgoing arc for each maritime unit. Constraint (5) guarantees that the quantity of arcs leaving and entering the port must be the same. Constraint (8) ensures that vessel departs with sufficient space available for the backload of the first maritime unit attended, as the backload must be done before loading the platform. Note that the flow variable f_{0j} to the first chosen unit j will be limited to at most the capacity of the vessel discounting the backload ρ_j of the unit $(C_{max} - \rho_j)$, and this constraint is only activated when the network variable x_{0j} is 1.

The demand flow must be expressed and limited in two formats: the occupied surface and the amount of crane movements necessary to load the vessel. Then, the constraints (6) and (7) define the demand flows in each arc, area, and crane movements, respectively, whereas the constraints (9) and (10) are the upper bounds for these demands. Constraint (11) limits the berthing time according to the coefficients set by the company to transform the crane movement in loading hours. Constraint (12) defines the relationship between the arrival time from a maritime unit to its successor. Constraint (13) limits the sum of travel time, aiming to balance the interval between visits.

Finally, constraints (14) and (15) enforce the integrality and non-negativity conditions on the variables.

4.2 Phase 2: Port scheduling via Berth Assignment Problem

After defining the routes performed by the PSVs, it is now possible to know quantity of cargo transported by the vessel and, consequently, the necessary loading time on port. Since we are dealing with a periodic behavior problem with opening time constraints, it is necessary to have an estimation of the arrival time at the maritime units. For this reason, the port departure times must be defined through a berth allocation modeling. The objective of Phase 2 is to allocate tasks, that is, PSV loading activities, to port berths. The berth and task sets are denoted by B and R, respectively. A set O of integer numbers denotes the possible positions of a task in the berth. Following is a description of the sets, parameters, and decision variables:

Sets:

B – Set of berths;
R – Set of tasks to be allocated;
O – Set of position orders for a task;
$C \subset R \times R$ – Set of conjugate pairs;

Parameters:

$Bincomp_{i,j}$ – Equal to 1 if berth i is compatible with task j;
$PREC_{j,r}$ – Equal to 1 if task j precedes task r;
$Tmax$ – Planning horizon;
D_j – Time needed to execute task j at port
LW_j – Time window Lower bound of task j;
UW_j – Time window upper bound of task j;
SK_j – Slack/maneuver times after task j;
$L_{j,r}$ – Ideal time interval between trips in the same route;
$LC_{j,r}$ – Ideal time interval between conjugate routes;
T_j – Fixed start time of task j;

Decision Variables:

$y^k_{i,j} \in \{0,1\}$ – Binary variable equals to 1 if mooring j is the k-th task handled at berth i, and 0 otherwise;
$s_j \in \mathbb{R}$ – time at which task j begins.
$dp^+_{j,r}, dp^-_{j,r} \in \mathbb{R}$ – Slack times in relation to the ideal time interval between the pair of trips $j, r \in R$;
$dc^+_{j,r}, dc^-_{j,r} \in \mathbb{R}$ – Slack times in relation to the ideal time interval between trips for conjugate routes.
$l^r_{i,j} \in \{0,1\}$ – Binary variable equals to 1 if task j is assigned before r at berth i, and 0 otherwise;
$x_{i,j} \in \{0,1\}$ – Binary variable equals to 1 if task j is assigned to berth i, and 0 otherwise;

The mathematical model is:

$$\min \sum_{(j,r)|PREC_{j,r}} (dp^+_{j,r} + dp^-_{j,r}) + \sum_{(j,r)\in C} (dc^+_{j,r} + dc^-_{j,r}), \tag{16}$$

s.t.

$$\sum_{i\in B} x_{i,j} = 1 \qquad \forall j \in R \tag{17}$$

$$s_r \geq sj + D_j + SK_j - Tmax(1 - l^r_{i,j}) \qquad \forall i \in B, j, r \in R \mid j \neq r \tag{18}$$

$$l^r_{i,j} + l^j_{i,r} \leq \frac{1}{2}(x_{i,j} + x_{i,r}), \qquad \forall i \in B, j, r \in R \mid j < r \tag{19}$$

$$l^r_{i,j} + l^j_{i,r} \leq x_{i,j} + x_{i,r} - 1, \qquad \forall i \in B, j, r \in R \mid j < r \tag{20}$$

$$\sum_{i\in B}\sum_{j\in R} Bincomp_{i,j} \cdot x_{i,j} = 0. \tag{21}$$

$$s_r = s_j + L_{j,r} + dp^+_{j,r} - dp^-_{j,r}, \qquad \forall j, r \in R \mid PREC_{j,r} \tag{22}$$

$$s_r = s_j + LC_{j,r} + dc^+_{j,r} - dc^-_{j,r}, \qquad \forall (j,r) \in C \tag{23}$$

$$s_j = T_j, \qquad \forall j \in R \mid T_j \geq 0 \tag{24}$$

$$s_j \geq LW_j, \qquad \forall j \in R \mid LW_j \geq 0 \tag{25}$$

$$s_j + D_j \leq UW_j, \qquad \forall j \in R \mid UW_j \geq 0 \tag{26}$$

$$s_j + Tmax(1 - l^r_{i,j}) \geq s_r + D_r + SK_j - Tmax, \qquad \forall i \in B, j, r \in R \mid j \neq r \tag{27}$$

$$x_{i,j}, l^r_{i,j} \in \{0, 1\}, \qquad \forall i \in B, j \in R \tag{28}$$

$$dp^+_{j,r}, dp^-_{j,r} \in \mathbb{R}_+, \qquad \forall j, r \in R \mid PREC_{j,r} \tag{29}$$

$$dc^+_{j,r}, dc^-_{j,r} \in \mathbb{R}_+, \qquad \forall (j,r) \in C. \tag{30}$$

The objective function (16) minimizes the sum of the deviations from the ideal interval between consecutive trips over a set of routes. Constraint (17) ensures that only one berth is allocated for a given task. Inequalities (18) forbid task overlap. Constraints (19) and (20) ensure non-anticipativity of the task order on each berth such that, for a given pair of tasks (j, r), only one can precede the other if both are performed on the same berth. Equation (21) concerns the berth and task compatibility. Constraints (22) and (23) calculate the slack variables necessary for feasibility. Equation (24) guarantees that the fixed start time of a task will be respected. Constraints (25) and (26) correspond to the time window limits for task realization.

Inequalities (27) facilitate periodic scheduling. Assume that tasks j and r were performed on the same berth i. If j was performed before r, then $l^r_{i,j}$ was equal to one. Suppose also that task r had a duration longer than the remaining

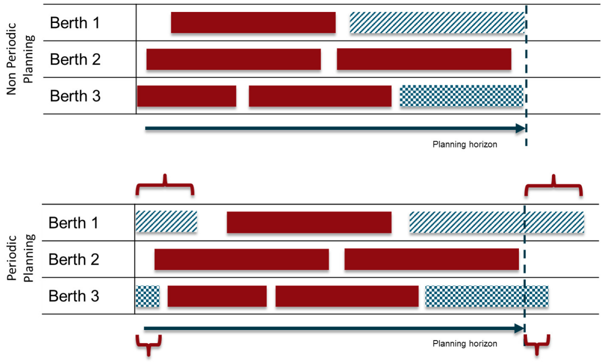

Fig. 6: Non Periodic Planning vs. Periodical Planning

time before the end of the planning horizon (e.g., $s_r = 160$ and $D_r = 10$). Thus, for a feasible schedule, s_j must be greater than the remaining time for task r after the start of the new week plus its slack times ($s_r + D_r + SK_j - Tmax$). This situation is illustrated in Figure 6, where the overlaps in the bottom illustrate this flexibility, whereas the top part depicts a hard weekly plan. Finally, constraints (28)–(30) establish the variable domains.

4.3 Phase 3: Maritime units re-sequencing for time windows adequacy

After determining the port scheduling and departure times, phase 3 is performed. In this phase, the model only deals with routes with at least one maritime unit with opening time constraints. We aimed to make no changes to the maritime units visited on each route; however, changes in the order of visits may be made to respect these constraints. Contrary to Phase 1, now we consider that different repetitions of the same route along a week may have different order of visits to the maritime units.

If a maritime unit is reached before its opening time, the vessel should wait to start loading. Therefore, the objective of the model is to minimize these waiting times while maintaining the cycle time of each unit around 3.5 days (for the case with two visits per week). For instance, consider the case of Figure 7, in which we considered a maritime unit with two visits per week. If the PSV arrives on Monday night, it needs to perform a long wait time of 8 h because of the opening hours constraint. Then, after the re-sequence, the result in Figure 8 shows a better solution without waiting times.

Phase 3 uses the same flow model from Phase 1, but with some changes in the sets and additional constraints. In summary, now we solve the PVRPTW considering departure times previously defined in the Phase 2. The set $\mathcal{C} = \mathcal{P} \cup \mathcal{B}$ represents the maritime units that are artificially duplicated and partitioned into two sets: $\mathcal{P} = \{$ units visited at the first travel$\}$ and $\mathcal{B} = \{$the same units served at the second travel$\}$. We also define $\mathcal{T} \subseteq C$ as the set of units with opening time constraints in such a way that $\mathcal{T} = \mathcal{D} \cup \mathcal{N}$, where

Travel 1								
Port	UM1	UM2	UM3	UM4	UM5	UM6	UM7	Port
Tuesday 20h	Wednesday 7h	Wednesday 19h	Thrusday 8h	Thrusday 12h + 0	Thrusday 18h	Friday 1h	Friday 8h	Sunday 14h
Travel 2								
Port	UM1	UM2	UM3	UM4	UM5	UM6	UM7	Port
Sunday 6h	Sunday 17h	Monday 5h	Monday 18h	Monday 23h +8	Monday 13h	Monday 20h	Tuesday 3h	Tuesday 17h

Arrival + waiting times

Fig. 7: Routes without re-sequencing, with bigger wait times

Travel 1								
Port	UM6	UM1	UM2	UM5	UM3	UM4	UM7	Port
Tuesday 20h	Wednesday 4h	Wednesday 15h	Thrusday 3h	Thrusday 15h	Friday 9h	Friday 13h	Friday 22h	Saturday 17h
Travel 2								
Port	UM6	UM1	UM2	UM5	UM7	UM3	UM4	Port
Saturday 6h	Saturday 14h	Monday 1h	Monday 13h	Monday 1h	Monday 17h	Tuesday 8h	Tuesday 13h	Wednesday 1h

Arrival times within opening hours   Time between visits in 3,5 days

Fig. 8: Routes after re-sequencing, without wait times

$\mathcal{D}$ = { represents the set of units to be served in daytime} and $\mathcal{N}$ = {the set of units to be served at night time}. Finally, to allow different departure times from port 0, we created a set $\mathcal{S}$ of auxiliary nodes such that $\mathcal{S} = \mathcal{S}^1 \cup \mathcal{S}^2$, where $\mathcal{S}^1$ contained the nodes corresponding to the first travel and $\mathcal{S}^2$ contained the nodes corresponding to the second travel. The problem is defined over a finite time horizon, typically a week, on the set J of days.

Additional Parameters:

$[a_i^d, b_i^d]$ – Opening hours in maritime unit $i \in \mathcal{T}$;

γ_i^d – Port departure times for unit $i \in \mathcal{S}$, in a day $d \in \mathcal{J}$;

$[n_{min}, n_{max}]$ – Cycle time interval;

μ – Weight that vary according to the magnitude of the sum of the distances.

Additional Decision Variables:

y_i^d – Binary variable, equal to 1 if the day d is chosen for the service on maritime unit $i \in \mathcal{T}$ and zero otherwise;

w_i – Wait times to server the maritime unit $i \in \mathcal{T}$.

The objective function (31) minimizes the weighted sum of the traveled and waiting times.

$$\min \sum_{i \in \mathcal{V}} \sum_{j \in \mathcal{V}} t_{ij} x_{ij} + \mu \sum_{i \in \mathcal{T}} w_i \tag{31}$$

Assignment and flow constraints were maintained in this model (constraints (3), (4), (6), and (7) with $i \in \mathcal{C} \cup \mathcal{S}$). Constraint (12) turned into the new constraints (32), which define the relation between arrival time from a maritime unit to his successor, including the wait times when opening hours must be respected. Constraint (13) turned into the new constraint (33), as the first maritime unit became the auxiliary node that represents the port departure time.

$$h_i + w_i + s_i + t_{ij} - M(1 - x_{ij}) \leq h_j \qquad i, j \in \mathcal{C} \tag{32}$$

$$h_j + s_j + t_{j0} - h_i - M(1 - x_{j0}) \leq R \qquad i \in \mathcal{S}, j \in \mathcal{C}. \tag{33}$$

In addition, there are constraints that are not on the Phase 1 routing model, as they ensure the opening times in the installations and the maximum and minimum time between services:

$$x_{ij} = 0 \qquad i \in \mathcal{C}, j \in \mathcal{S} \tag{34}$$

$$x_{ij} = 0 \qquad i \in \mathcal{P}, j \in \mathcal{B} \tag{35}$$

$$\sum_{d \in J} y_i^d = 1 \qquad i \in \mathcal{D} \tag{36}$$

$$\sum_{d \in J} y_i^d = 1 \qquad i \in \mathcal{N} \tag{37}$$

$$h_i = \gamma_i^d \qquad i \in \mathcal{S}, d \in \mathcal{J} \tag{38}$$

$$n_{min} \leq h_i - h_j \leq n_{max} \qquad i = j, i \in \mathcal{P}, j \in \mathcal{B}. \tag{39}$$

$$a_i^d y_i^d \leq h_i \qquad i \in \mathcal{T}, d \in \mathcal{J}, \tag{40}$$

$$h_i + s_i \leq b_i^d y_i^d + M(1 - y_i^d) \qquad i \in \mathcal{T}, d \in \mathcal{J}, \tag{41}$$

$$w_i = 0 \qquad i \notin \mathcal{T} \tag{42}$$

$$y_i^d \in \{0, 1\} \qquad i \in \mathcal{V}, d \in J \tag{43}$$

$$h_i, w_i \geq 0 \qquad i, j \in \mathcal{V} \tag{44}$$

Equations (34) guarantee that the artificial departure nodes are attended first. Equation (35) ensures that active arcs only exist between the maritime units from the same travel. The choice of a day of the week to serve daytime and nighttime only maritime units are ensured by Equations (36) and (37), respectively. Equation (38) ensures that the arrival time to the auxiliary nodes should be equal to the beginning of the time window given by the port schedule.

Constraint (39) guarantees that the cycle time between the first and second travels must lie within a given interval.

Constraints (40) and (41) ensure that the service must be realized within the day or night operation period. Constraints (32), (33), and (40) were linearized by introducing a sufficiently large number M. Equations (42) define the null waiting times for nodes that do not belong to the set of units with opening hours constraints. Finally, constraint (44) establishes the variable domains.

5 Realistic Case Study

Experiments based on operational data from an offshore area in Brazil's Southeast between 2014 and 2017 were conducted to evaluate the effectiveness of the proposed methodology. The instances contained maritime units to be serviced divided into two operational areas: Area A and Area B. We also considered a scenario integrating these operational areas which we name as I. Description of instances is on Table 3.

Table 3: Instances description

Instance	Number of installations
A-1	41
A-2	42
A-3	40
B-1	18
B-2	18
B-3	19
I-1	59
I-2	60
I-3	59

Among these installations, two had opening time constraints: one of them opened only during the day, and the other opened only at night. The operation occurred from a single port with six berths, and the PSV fleet had a homogeneous capacity of 600 m^2 of the deck area.

The clustering heuristic was coded in C++, and mathematical models were solved using GUROBI in platform Aimms version 3.13. Data communication was conducted using Microsoft Excel spreadsheets using VBA macros. For clustering, routing, and maritime unit re-sequencing, the computer used in the experiments had the following configuration: Intel(M) Core i7 processor running at 3.0 GHz, with 8 GB of RAM and Windows 8 operating system. For port scheduling, the computer used in the experiments had the following configuration: Xeon E5-2620 processor, with 160 GB RAM and a Windows server. In Sections 5.1, 5.2, and 5.3, we discuss the results for each of the steps of the proposed framework.

5.1 Phase 1: Supply vessel routing

There were two important parameters to be determined in the clustering heuristic: the number of heuristic iterations (IH) and the number of clusters (NG). To determine these values, we performed several experiments.

In Figure 9, we show the average, worst, and best solutions achieved by the heuristic along the outer iterations, after 10 replications. Note that results may vary positively and negatively depending on the number of iterations, as we performed separate experiments concerning different decisions related to the number of iterations. We concluded that after $IH = 200$ outer iterations, the objective began to stabilize. However, it was also possible to observe some small decreases until $IH = 1000$ iterations.

Heuristic parameters also impact the routing solution. Therefore, we evaluated how the routing objective function changed according to the number of heuristic parameter settings. The variation coefficient ($coef$) for the values found was lower than $coef < 0,001$, indicating that the heuristic had generated good results for routing with 200 outer iterations.

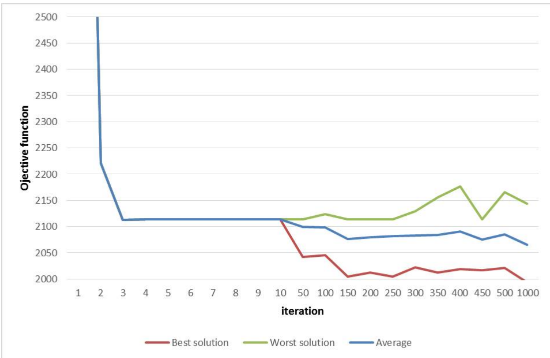

Fig. 9: Calibration to decide number of outer iterations of clustering heuristic

To define the number of groups that maritime units should be divided (NG) into, we evaluated the routing solution and computational time considering different numbers of clusters, considering scenarios with 1–4 maritime unit clusters. The results of these experiments are listed in Table 4. We note that dividing installations into 2-3 groups produces good solutions. To reduce the computational time, three clusters were sufficient for instances B-1, B-2, and B-3 and four clusters were sufficient for instances A-1 and A-3, respectively. However, it is important to note that an excessive number of clusters may lead to poorer routing objective function values.

In addition, the strategy of using a clustering heuristic proved to bring better results also to routing itself. Dividing the problem into smaller ones helped reduce the computational time required or the gap, in case of reaching

Table 4: Results for phase 1 – PSV routing

	Division in one cluster			Division in two clusters		
Instance	Objective	GAP(%)	Time(s)	Objective	GAP(%)	Time(s)
A-1	3269.70	40.59	3600	2431.44	5.7	3600
A-2	2790.48	43.31	3600	2602.40	19.96	3600
A-3	2682.46	21	3600	2681.6	3.5	3600
B-1	1474.27	2.84	1800	1511.28	0	5.5
B-2	1607.02	24.25	1800	1623.35	0	25
B-3	1653.81	3.4	1800	1965.23	0	35
I-1	4867.71	39.83	3600	3694.47	6.1	3600
I-2	5176.92	51.46	3600	4231.48	35.7	3600
I-3	18996.3	81.96	3600	4386.65	19.6	3600

	Division in three clusters			Division in four clusters		
Instance	Objective	GAP(%)	Time(s)	Objective	GAP(%)	Time(s)
A-1	2413.44	1.4	1800	2708.19	0	5
A-2	2641.19	30.05	1800	2918.30	39.8	1800
A-3	2668.75	28	1800	3031.8	0	5
B-1	1962.39	0	1.5	–	–	–
B-2	1933.89	0	5	–	–	–
B-3	1964.18	0	5	–	–	–
I-1	3709.51	8.1	3600	4022.19	1.5	3600
I-2	4262.11	23.3	3600	4459.78	24.9	3600
I-3	4525.68	25.1	3600	4851.64	0	3600

maximum computational time. Observe that, as instances I-1, I-2 and I-3 consider an integrated operation of areas A and B, the number of maritime units is significantly larger than in the other experiments. Hence, a larger gap was expected. Nevertheless, it is still possible to observe a gap reduction when the problem is divided into more clusters. Note that the large gap in the instance A-2 even if the installations are divided into four clusters happens due to the bigger size of the instance with respect to the others, and because of the presence of maritime units with opening time constraints.

5.2 Phase 2: Port scheduling

We considered four realistic cases, as listed in Table B1. The first column contains the task name, followed by its duration. In the third and fourth columns, we specify slack times to absorb handling time uncertainties and maneuver times. The fifth column shows the number of trips or the frequency of the task, if the operation must occur on a specific day of the week and the specific time of the day. The eighth column states the task time windows, and finally, the last columns give the berth compatibility of each task. Concerning the tasks, we have

(i) One reserved time for maintenance at berths 1 and 2, beginning at 09:00 on Wednesday;
(ii) Thirteen production unit routes (P1 - P13);
(iii) Three oil rig routes (R1 - R3);

Table 5: Results for phase 2 – port scheduling

Scenario	Obj. Func.	Maximum deviation	CPU (s)	Variables	Constraints
WC	106	4.75	18000	22890	45285
OC	50	4	18000	22874	45261
EWC	0	0	30.95	28222	55848
EOC	0	0	5.24	28206	55824

(iv) Seven periods reserved for emergency vessels (Extra01-Extra07), beginning every day at 02:00;
(v) Four periods of 8 h reserved for crew-changing operations (Crew01-Crew04) on Mondays, Tuesdays, Wednesdays, and Thursdays with a time window of 07:00 to 18:00;
(vi) Exclusive reservation of berth 3 for pumping and fluid operations due to operational and equipment constraints;
(vii) One route of pipe deliveries.

The data listed in Table B1 were evaluated for the conjugate pairs listed as those marked with the same symbol (†, ‡, ✠) and for the following four scenarios (Table 5):

1) With conjugate routes (WC);
2) Without conjugates (OC);
3) Capacity expansion with conjugates (EWC); we suppose that fluid and pumping operations can be transferred and that berth 3 is released for the performance of all other tasks;
4) Capacity expansion without conjugates (EOC).

Table 5 demonstrates that the obtained solutions are very satisfactory, despite the fact that we could not find a proven optimal solution for the WC and OC scenarios. The deviation variables were no larger than 5 h (Maximum Deviation column). As expected, the problem was easier to solve without conjugate routes. The most impressive aspect was the decrease in processing time obtained by adding only a single additional berth. In response, the processing time for this problem decreased from the time limit of 5 h to only a few seconds. Note that the problem size grew significantly with this extra berth, once again, demonstrating the importance of port idleness to facilitate finding the optimal solution.

5.3 Phase 3: Route re-sequencing for time windows adequacy

Considering the port scheduling solution with conjugate routes and no expansion scenario, we evaluated the results for route re-sequencing. Table 6 shows the value of the objective function (OF) before and after re-sequencing, as well as the computational time and improvement rate compared to the company's solution. The table also depicts the computational time and improvement rate compared to the company's solution. In general, the results are good, with lower costs compared with company routes. The new values of the objective function (OF) highlight improvements in both travel times and wait times after

Table 6: Results for phase 3 – route re-sequencing

	Company		Three-phase method			
Instance	travel	wait	travel	wait	CPU(s)	Improvement (%)
A-1	460.62	68.61	364.45	11.3	1800	2.89
A-2	445.51	40.14	472.47	5.65	1800	1.55
A-3	471.96	13.41	337.98	3.67	1800	29.61
B-1	298.76	26.78	236.17	2.33	3600	20.17
B-2	238.06	20.64	188.37	7.65	3600	24.26
B-3	239.63	24.57	222.95	5.34	3600	13.59
I-1	759.38	95.39	712.92	22.43	3600	13.97
I-2	683.57	60.78	593.73	9.11	3600	19.01
I-3	711.59	37.98	583.42	12.78	3600	20.46
Average	478.78	43.14	420.65	8.64	3000	16.16

Table 7: Comparison of the number of routes per instance

	Number of trips	
Instance	Company	three-phases method
A-1	9	7
A-2	9	7
A-3	9	8
B-1	4	4
B-2	4	4
B-3	6	5
I-1	13	10
I-2	13	11
I-3	13	12
Total	80	68

re-sequencing the maritime units. The improvement in route times is around 13%, while the wait times for new routes are on average 5 times shorter than the company's. Such savings reduce the use of vessels and have a direct influence on the reduction of the number of routes, since the vessel can serve more installations within the maximum allowed travel time.

In Table 7, we introduce a new metric to account for the number of routes, comparing company's strategy and the new planning formulated by our three-phases method. Our final solutions require fewer routes than the company's to service all maritime units, with a reduction of one to three itineraries. Considering the instances from area I, which are equivalent to the integration of areas A and B, we also conclude that the company can also save one more extra route if they change the current administrative rule that separate the operation of these two areas. This is extremely important, as these vessels rent can cost several million dollars, and fewer routes mean fewer necessary vessels, leading the company to significant savings, or even allowing the company to grow and expand its operations without large investments in new vessels. Therefore, these results show that the company should evaluate its way of administratively grouping the MUs.

Finally, we show a graphical representation of the routes along the coast of Brazil for the I-3 instance. In Figure 10, we show the routes of the company's solution, in Figure 11 the routes formed by the clustering-routing method. We note that the change in the shape of the solution is significant, reinforcing

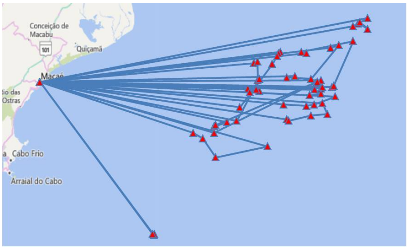

Fig. 10: Routes according to company solution

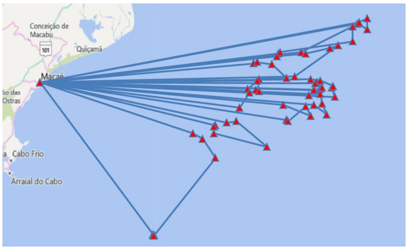

Fig. 11: Routes according to framework methodology

again the idea that our solution has improved not only the appearance of the routes,but also in the grouping and sequence of UMs in each route.

6 Conclusions

In this study, we provided an integrated framework to help in the decision-making process of offshore logistics. The tool encompasses three main problems, for which we presented mathematical formulations: PSV routing, berth allocation, and route re-sequencing. The proposed method proved to be a powerful alternative for practical use, as it can replace many hours or even days of manual work, providing good-quality solutions.

Another goal of this study was to introduce a new type of berth allocation problem. Traditional literature has primarily focused on methods to solve dynamic berth allocation problems for commercial port operators. In this study, we considered a different paradigm, that is, a dedicated terminal in which the vessel waiting times are irrelevant to the offshore unit service levels.

In relation to the routing part of our problem, although the biggest challenge has been already overcome, as the characteristics of the problem may lead to difficulties even to find a feasible solution, there are still several possible directions for future works. There may be a strengthening the polytope of the exact model or the inclusion of new valid cuts, since it was found that the the generation of good dual bounds may represent a challenge. It would also be interesting to test an approach via heuristics and/or metaheuristics such as the LNS, ALNS, and ILS to solve the problem.

In relation to the berth allocation model, there are plans to enhance the objective function, approximate solutions to operational goals, and accelerate optimization. In addition, other optimization techniques can be used, such as the Lagrangian relaxation method with column generation or metaheuristics for the construction of an initial solution.

Finally, stochasticity is an important area to be studied. Several parameters, such as vessel capacity, are defined considering safety margins. For example, in port, we considered a security gap of two hours before different loading operations. These numbers were defined arbitrarily, according to specialists' experience, but studying the operation's stochasticity can help in selecting better operation parameters.

We accomplished to develop a framework that contemplates the issues that the company faces on its daily operation. Although the intermediate solutions of each model are not proven optimal, they are obtained in reasonable times and provide satisfactory results with improvement over the company's practice. In addition, due to the large number of operational constraints that need to be considered, one of the hardest challenges was to obtain a feasible solution, something that was rarely achieved manually by the decision makers. Therefore, we consider that the objectives have been satisfactorily met. Our framework provides not only planning alternatives that respect business constraints, but also promote efficiency gains.

Acknowledgments. We acknowledge the cooperation of Petroleo Brasileiro S.A. (Petrobras), which suggested this problem to us as a real demand for them and provided data sets and funding in the form of research grants. This work was conducted during scholarships supported by the Brazilian Federal Agency for Support and Evaluation of Graduate Education (CAPES), National Council for Scientific and Technological Development (CNPq), and Petrobras - Petroleo Brasileiro S.A.

Appendix A Clustering heuristic flowcharts

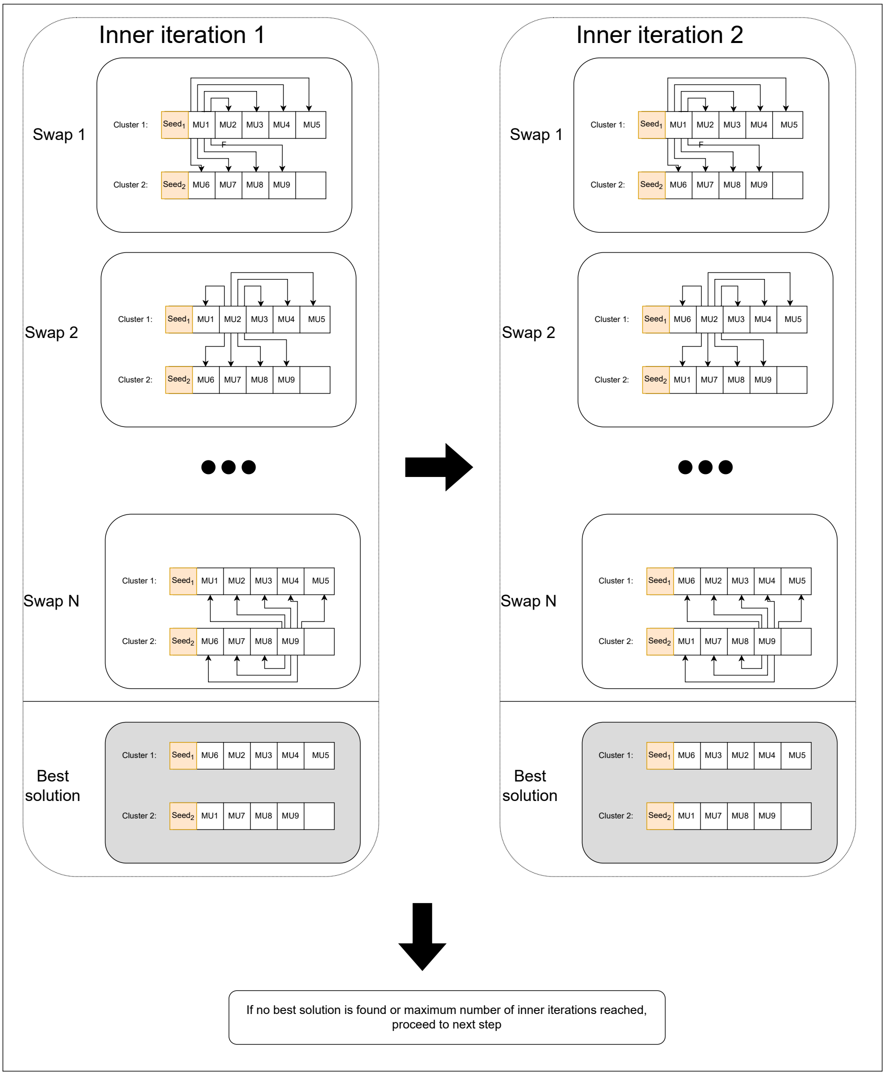

Fig. A1: Clustering heuristic – step 1.

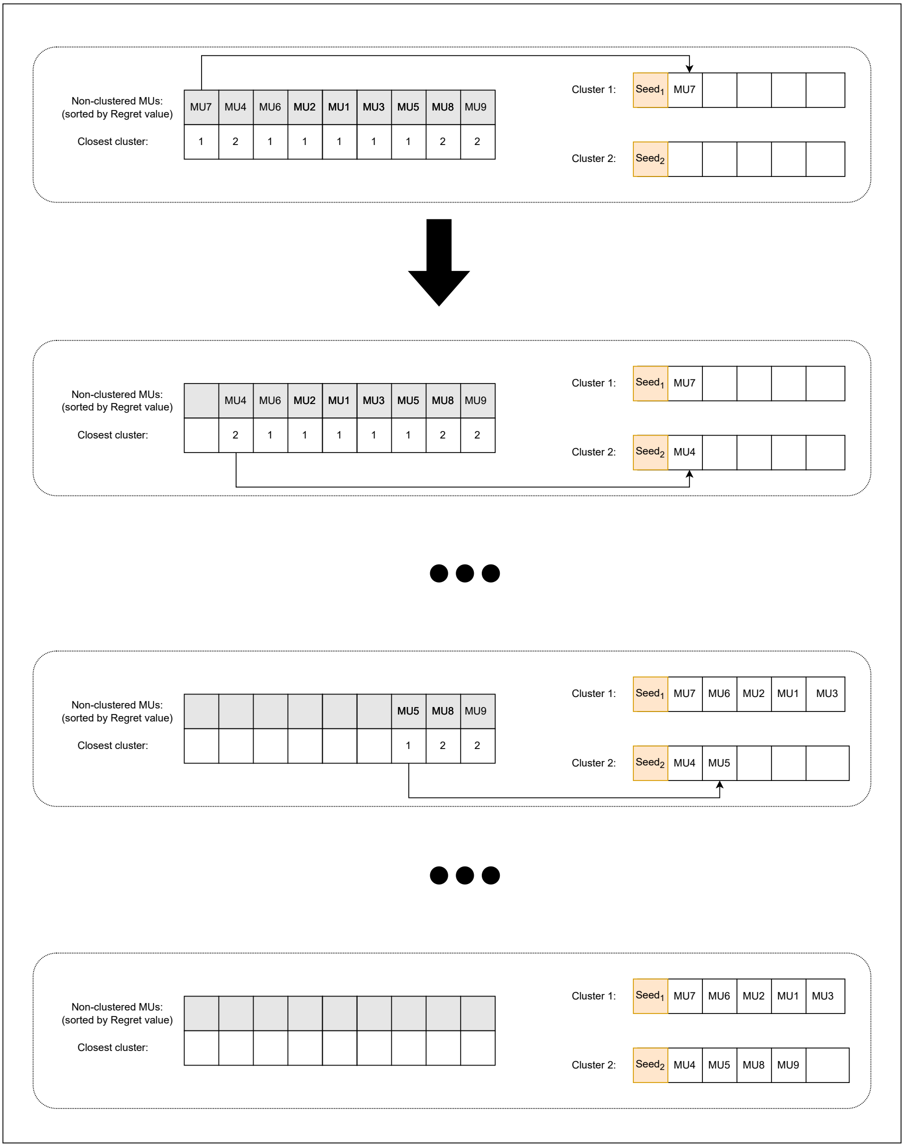

Fig. A2: Clustering heuristic – step 2.

Appendix B Berth allocation problem instance

Table B1: Realistic case instance

Task	Duration	Slack time	Maneuver time	Trips	Day	Time	Time windows		B1	B2	B3	B4	B5	B6
Pumping	38		1	1	Sat.	9	-	-			✓			
Special units	12	2	1	2		-	-	-	✓	✓	✓	✓	✓	
Fluids	100		1	1		-	-	-			✓			
Maintenance	10		1	1	Wed.	9	-	-	✓					
Maintenance	10		1	1	Wed.	9	-	-		✓				
Pipes	14	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
R1	14	2	1	3		-	-	-	✓	✓	✓	✓	✓	✓
R2	14	2	1	3		-	-	-	✓	✓		✓	✓	✓
R3	14	2	1	3		-	-	-	✓	✓		✓	✓	✓
P1 †	14	2	1	2		-	-	-	✓	✓		✓	✓	✓
P2 †	14	2	1	2		-	-	-	✓	✓		✓	✓	✓
P3 ‡	14	2	1	2		-	-	-	✓	✓		✓	✓	✓
P4 ‡	14	2	1	2		-	-	-	✓	✓		✓	✓	✓
P5 ✠	13	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P6 ✠	13	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P7	13	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P8	16	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P9	11	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P10	14	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P11	14	2	1	2		-	-	-	✓	✓		✓	✓	✓
P12	16	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
P13	15	2	1	2		-	-	-	✓	✓	✓	✓	✓	✓
Extra01	7		1	1	Mon.	2	-	-		✓		✓	✓	✓
Extra02	7		1	1	Tue.	2	-	-		✓		✓	✓	✓
Extra03	7		1	1	Wed.	2	-	-		✓	✓	✓	✓	✓
Extra04	7		1	1	Thu.	2	-	-		✓		✓	✓	✓
Extra05	7		1	1	Fri.	2	-	-		✓		✓	✓	✓
Extra06	7		1	1	Sat.	2	-	-		✓		✓	✓	✓
Extra07	7		1	1	Sun.	2	-	-		✓		✓	✓	✓
Crew01	8		1	1	Mon.	-	7	18		✓		✓	✓	✓
Crew02	8		1	1	Tue.	-	7	18		✓		✓	✓	✓
Crew03	8		1	1	Wed.	-	7	18		✓	✓	✓	✓	✓
Crew04	8		1	1	Thu.	-	7	18		✓		✓	✓	✓

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