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A solution framework for the integrated problem of cargo assignment, fleet sizing, and delivery planning in offshore logistics

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ABSTRACT

In order to support deep-sea oil and gas exploration and production operations, platform supply vessel plays a critical role, being the main transport resource to meet the demand of supplies ordered by maritime units. This leads to problems in efficiently allocating supplies to vessels and cost-effectively assessing the fleet size. Aiming to solve these problems, we propose a framework based on the integration of a mixed-integer programming model, which selects the supply set each vessel should provide, and a discrete-event simulator, which realistically represents the offshore operation scenario. We evaluate different fleet management policies, such as distinguishing parts of a fleet with respect to commodity type and multi-commodity transportation. In addition, we analyze the cargo allocation and vessel assignment along scheduled trips, comparing the traditional first-in-first-out delivery strategy with a completely optimization-centered alternative. Our study presents good-quality solutions that can potentially enhance offshore service levels, reduce fleet requirement, and decrease operational costs. We also demonstrate that our framework promotes a further step for improving the current logistics practices of a major oil company operating in Brazilian oil and gas offshore basins.

1. Introduction

The petroleum industry faces challenges in offshore oil and gas exploration and production (E&P) activities with respect to the construction and maintenance technologies for wells, particularly in terms of the logistics of these operations. Such challenges include the need for planning the use of resources and infrastructure and also coordinating the logistics system and other operations related to maritime units (MUs). Examples of these operations include petroleum offloading, arrivals and departures of helicopter flights with crew and specialized personnel, and maintenance diving.

In an established dense offshore E&P logistics network, the MUs correspond to cargo-demanding clients, placing daily requests of deck cargo, fluids, diesel, food, and other goods. Subsequently, all these supplies are collected at a port, from where transportation resources, called as platform supply vessels (PSVs), perform deliveries. According to Daleel Oil and Gas Supply Chain Portal (2018), thus far, the daily hire rates of a PSV range from ∼US$8,000 to US$14,000. Therefore, the transport of supplies, or simply cargo, is a crucial and expensive step in oil and gas business, which can benefit from suitable planning tools. For instance, Iachan (2009) suggested that the application of quantitative tools from the area of operations research assists in achieving large financial gains.

In this context, this study addresses the problems in allocating cargo to multi-capacity PSVs and assessing the appropriate fleet size. We present a decision-support framework that involves discrete-event simulation (DES) and a mixed-integer linear programming (MILP) model to evaluate the logistics plan for cargo delivery, focusing on the maritime portion of the logistics network. We use this framework to evaluate operational policies and their impact on the service level and the fleet size. We compare the approach of identifying vessels with respect to commodities (cargo), i.e., a vessel that transports only one type of commodity, with a multi-commodity transportation, whereby different commodities can be simultaneously transported by a vessel in a

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single trip. In addition, we also analyze the allocation strategies of cargo requests to vessels and compare the first-in-first-out (FIFO) rule with the exact solution obtained via the proposed mathematical model.

There are several contributions of this work to existing literature. First, we present a detailed framework that combines a stochastic DES with an MILP model. Using this approach, it is possible to evaluate in advance the effect of the optimization model on the simulated real system and to subsequently use this model for practical decision making in logistics. It is also possible to identify good cargo allocation policies and determine the fleet size of the associated PSVs under uncertainty. Although simulation–optimization is not a new research topic, it has received limited attention within offshore E&P logistics, an area intrinsically subject to operational and environmental variations.

Second, we introduce a comprehensive stochastic DES model that well reproduces the offshore logistics scenario in Brazilian oil and gas fields, including MUs and their demand, PSVs of varied sizes, and infrastructure of the port of operation. Moreover, this simulation model can be considered either as a testbed for the validation of optimization tools, or as a single, isolated system appropriate for a what-if analysis. Brazilian offshore logistics have not been extensively studied compared to regions such as the Norwegian Sea; thus, using this simulator, we also expect to obtain an improved understanding of the E&P scenario in this area.

Another contribution of the proposed method is the procedure for vessel selection and cargo allocation. In practice, this process is frequently rigid because each route has an expected pre-allocated vessel size. Concurrently, in real-world operations, such a commitment is risky because predictions regarding when a vessel of a certain size will be ready for use and the amount of cargo requested are prone to mismatching owing to uncontrolled uncertainty factors in operation and demand. Typically, researchers deal with eventual delays of vessels using a redundant fleet or a fleet with a vessel from the spot market, which is expensive and unavailable worldwide. Thus, unlike other studies, we propose a form of operation that decides on the demand for the best vessel–cargo schedule to serve each route. In terms of the cargo handling time, “on demand” refers to the instant immediately before a medium-term fixed route commences at the port. Thus, despite dealing with a fixed, predefined scheme of routing and port time slots, our model offers high flexibility in managing deviations in the demand and resource availability, leading to a reduction in cost.

Finally, we aim to provide the decision maker with a better understanding of the effects of different policies on the required fleet size and key indicators of cost, service level, and greenhouse emissions. Thus, we can analyze and compare the impacts of different strategies, such as aggregated versus disaggregated fleet and the allocation optimization model versus the FIFO rule.

2. Literature review

Similar to our study, previous authors have examined oil&gas logistics planning, including the upstream logistics. Among these studies, one of the most recurrent topics is the vehicle routing problem (VRP), in which the allocation of the orders to vehicles and their routes are concomitantly defined. This type of problem, particularly when considering selective deliveries, is slightly similar to the MILP model of our study, because we also need to determine the orders that should be carried by a vessel. Additionally, our problem also resembles the order selection problem (OSP), which only focuses on choosing the deliveries to be carried, while considering the routes to be fixed and predetermined. Finally, similar to our study, several other researchers have employed simulation frameworks to model offshore logistics, focusing on different objectives.

2.1. Upstream logistics planning problems

The oil&gas upstream logistics problem resembles a delivery and pickup problem with time windows, similar to the subject studied by Wang and Chen (2012). Several studies have examined this issue. For example, Kaiser and Snyder (2010) analyzed the Gulf of Mexico panorama and proposed a deterministic model to quantify and predict the service levels on MUs, aiming at its optimization and adequacy to time windows. In addition, Kaiser (2010) proposed an input–output model for the optimization of the number of trips of service vessels in the Gulf of Mexico.

Mattos Ribeiro, Regis Mauri, and Antonio Nogueira Lorena (2011) proposed a methodology to build the schedule of workover rigs responsible to onshore maintenance services, aiming minimal production loss associated with the wells waiting for the service. The developed model is similar to vehicle routing problem with time windows (VRP-TW) and was solved using a simulated annealing metaheuristic.

Yamashita, da Silva, Morabito, and Ribas (2019) studied the problem of delivering crude oil extracted from offshore platforms. They proposed a routing and scheduling model, considering pickup and delivery, time windows, heterogeneous fleet and limited ship capacity. To solve this problem, authors proposed a multi-start heuristic that makes use of intensification and diversification strategies, consisting of two phases: generation of a feasible solution through a constructive heuristic based on dispatching rules and improvement of the solution through a local search heuristic based on insertion and exchange moves. Experimentation considered real instances from Brazilian scenario, as well as comparison with other models in benchmark instances.

Rossit, Gonzalez, Tohme, and Frutos (2019) studied the problem of petroleum upstream logistics in southern Argentina and proposed a model to promote the process of building a distribution schedule for inland transport. As a solution, the authors proposed a three-stage heuristic: clustering of clients, design of routes, and schedule of routes. Although Rossit et al. (2019) dealt with an onshore problem, there are several similarities with offshore logistics.

Several researchers have also investigated the supply vessel planning problem, such as Fagerholt (2000), Aas, Gribkovskaia, Sr, and Shlopak (2007), Halvorsen-Weare et al. (2012), Astoures, Rosa, and Rosa (2016). However, Aas et al. (2007) concluded that despite it being an important problem for the industry, significant research has not been conducted within this field. This conclusion was reinforced in their following study Aas, Sr, and Wallace (2009), in which they stated that the focus has been mainly on the routing problem and not on the supply vessel itself.

In addition to routing, some studies have also considered the effects of various characteristics of operation on the scope of their proposed tool. For example, Amiri, Hassanzadeh Amin, and Tavakkoli-Moghaddam (2019) dealt with a two-echelon periodic location-routing problem with time windows, with the primary objective of determining the fleet composition mix of both offshore and onshore echelons. They proposed a mixed-integer non-linear programming model, whose solutions were obtained via the Lagrangian decomposition method. To avoid large-instance issues, the problem was solved in two steps: onshore and offshore.

In the same context, de Luna Pinto, Vitorugo, de Alvarenga Rosa, Arpini, and Caprini (2018) studied the activities of PSV transporting bulk loads to offshore platforms and developed a methodology capable of defining, in addition to routing related decisions, the two-dimensional arrangement of bulk loads vessel’s deck. The model aims, besides the usual reduction of costs related to fleet size, the minimization of the imbalance of the ship. For the solution, authors proposed a hybrid simulated annealing with ship’s balance (HSA-SB) metaheuristic. In experiments, as well as our work, the Brazilian scenario was considered.

Different from our study, typically, routing problems treat all the orders attendance as constraints. This is not the case in our problem, because there may be scenarios where it is impossible to provide orders owing to a lack in the capacity of the fleet. However, there are some studies including this consideration, such as Gribkovskaia, Laporte, and Shyshou (2008) and Fernández Cuesta, Andersson, Fagerholt, and Laporte (2017).

Table 1
Comparative analysis of studies that used optimization strategies to analyze offshore planning problems.

Work	Type of problem	Fleet	Order selection?	Solution method	Case study
Mattos Ribeiro et al. (2011)	Scheduling, similar to VRP-TW	No capacity	No	Simulated Annealing	Offshore Brazil
Yamashita et al. (2019)	VRP and scheduling	Heterogeneous	No	Multi-start heuristic	Offshore Brazil
Rossit et al. (2019)	Scheduling	Heterogeneous	No	Constructive heuristic	Onshore site in southern Argentina
Fagerholt (2000)	VRP	Heterogeneous	No	Tabu search heuristics	Offshore Norway
Aas et al. (2007)	VRP	Homogeneous (single vessel)	No	Exact method with CPLEX	Offshore Norway
Halvorsen-Weare et al. (2012)	PVRP	Heterogeneous	No	Voyage-based solution method	Offshore Norway
Astoures et al. (2016)	VRP with Intermediate Replenishment Facilities	Homogeneous/ Heterogeneous	No	Exact method with CPLEX	Offshore Brazil
Amiri et al. (2019)	Two-echelon periodic location-routing	Heterogeneous	No	Lagrangian decomposition	Persian Gulf and the sea of Oman
de Luna Pinto et al. (2018)	VRP and arrangement of deck	Heterogeneous	No	combination of two different simulated annealing metaheuristics	Offshore Brazil
Gribkovskaia et al. (2008)	VRP	Homogeneous	Yes (for pickups)	Classical construction and improvement/Tabu search heuristics	CVRP instances of VRPLIB
Fernández Cuesta et al. (2017)	VRP	Homogeneous	Yes	Exact method with Gurobi/ ALNS	Offshore Brazil
Andersson et al. (2015)	OSP	Homogeneous	Yes	Exact method with Xpress	Offshore Brazil
Cuesta et al. (2018)	VRP with order selection and OSP	Homogeneous	Yes	Exact method with Gurobi	Offshore Brazil
Halvorsen-Weare and Fagerholt (2011)	Scheduling	Heterogeneous	No	Voyage-based	Offshore Norway
Bassi et al. (2012)	Scheduling	No capacity	No	Greedy algorithm or GRASP metaheuristic	Offshore Brazil
Halvorsen-Weare et al. (2013)	VRP-TW	Heterogeneous	No	Exact method with Express	Offshore Norway
Norlund et al. (2015)	Vessel Planning Problem	Homogeneous	No	Exact method with Xpress-Optimizer	Offshore Norway
Norlund and Gribkovskaia (2017)	Vessel Planning Problem	Homogeneous	No	Exact method with Xpress-Optimizer	Norway
Eskandari and Mahmoodi (2016)	Fleet sizing problem	Heterogeneous	No	Simulation	Persian Gulf
Halvorsen-Weare and Fagerholt (2016)	Vessel Planning Problem	Heterogeneous	No	Exact method with Xpress-Optimizer	Offshore Norway
Kisialiou et al. (2018)	Robust VRP and scheduling	Heterogeneous	No	ALNS	Offshore Norway
Kisialiou et al. (2019)	Periodic Supply Vessel Planning Problem (PSVPP)	Heterogeneous	No	ALNS	Offshore Norway
Our work	OSP embedded on simulation framework	Heterogeneous	Yes	Exact method with Gurobi	Offshore Brazil

Gribkovskaia et al. (2008) presented a routing problem with deliveries and pickups for a homogeneous fleet. Although deliveries are continuously transported, the pickups to be carried can be selected depending on the capacity constraints of the vessel.

Fernández Cuesta et al. (2017) proposed a formulation of the VRP with selective pickups and deliveries for a homogeneous fleet in an offshore scenario. In regard to the impossibility of delivering an order, two alternatives were presented: reallocation of a delivery on an emergency route or sending a delivery to an order pool for posterior delivery. Although this previously stated problem can be solved using a commercial solver, the adaptive large-neighborhood search (ALNS) approach was also presented to avoid long computational times.

Although the studies by Gribkovskaia et al. (2008) and Fernández Cuesta et al. (2017) are similar to our investigation, there are still differences. We consider routes that are already determined a priori; therefore, this issue cannot be considered as a routing problem. Indeed, there is another class of problems similar to those in our proposal, named as the order selection problem (OSP).

The OSP was formulated by Andersson, Cuesta, Fagerholt, Gausel, and Hagen (2015). In their study, they proposed a mixed-integer programming model to determine the orders that need to be served or postponed for a fixed route. Experiments were conducted using the historic data from a Brazilian oil company, comparing four different planning strategies, including FIFO. It should be noted that, although the fleet size in the Brazilian case study is heterogeneous, the solution is obtained under the assumption that all the fleets possess the same capacity.

Subsequently, Cuesta, Andersson, and Fagerholt (2018) also discussed the same problem. This study compares the OSP and the VRP based on selective pick-ups and deliveries (VRPSPD). In their experiments, the Brazilian case scenario was used.

Indeed, the OSPs presented in Andersson et al. (2015) and Cuesta et al. (2018) are similar to our problem. However, the authors considered a homogeneous fleet, and because all the vehicles were identical, vessel allocation was not required. In reality, the capacity considered in such a model may be lower than its actual value, leading to solutions that are not optimal. It is important to note that, because it is not easy to predict an available vessel at a certain instant, this can be a valid simplification. In contrast, we propose an approach different from those in other studies, because we consider that our decision-making process is achieved in real time precisely before vessel arrival, with available information regarding the vehicles. We did not introduce any simplification, and the fleet was considered heterogeneous, leading to an advanced order selection model.

In Table 1, we summarize the studies that employed optimization strategies to analyze offshore logistics planning problems.

2.2. Simulation frameworks

According to Aas et al. (2007), uncertainty exists in offshore logistics because changes in weather conditions and delivery and pickup demands of installations are typically unexpected events. Consequently, it is difficult to use purely deterministic approaches, and several researchers have preferred using traditional simulation approaches

Table 2
Comparative analysis of studies that use simulation strategies to analyze offshore planning problems.

Work	Type of vehicle	Stochasticity	Spot contracts?	Approach	Case Study
Shyshou et al. (2010)	AHTS	Weather conditions and duration of activities	Yes	Simulation	Offshore Norway
Maisiuk and Gribkovskaia (2014)	PSV	Weather conditions and future spot vessel rates	Yes	Simulation	Offshore Norway
Norstad et al. (2017)	PSV and helicopters	Transport demands	–	Simulation	Offshore Arctic
Anselmo et al. (2017)	PSV	Environmental, diesel consumption, demands, etc.	No	Simulation	Offshore Brazil
Moreira et al. (2019)	PSV transporting diesel	Environmental, diesel consumption, demands, etc.	No	Simulation	Offshore Brazil
Our work	PSV	Several activities	No	Simulation framework with optimization embedded	Offshore Brazil

(mainly discrete-event stochastic simulation) as suitable methods for analyzing these problems.

For example, Shyshou, Gribkovskaia, and Barceló (2010) employed a DES to model the impacts of spot rates and vessel allocations on the total vessel hiring costs in the fleet-sizing problem arising in the scheduling of anchor handling tug supply (AHTS) vessels supporting offshore oil and gas drilling operations. The annual vessel hiring cost, consisting of the long-term and spot hire costs, is used as an efficiency measure. Furthermore, the trade-off between long-term and spot contracts is considered, with spot rates being frequently higher than the long-term ones. Moreover, stochastic factors, such as weather conditions and the duration of anchor-handling operations, are considered.

Subsequently, Maisiuk and Gribkovskaia (2014) addressed the supply vessel planning problem. A model simulating the sequence of voyages was proposed in their study; this model was implemented according to the annual set of weekly schedules. Each weekly vessel schedule comprised the finite set of voyages performed by each vessel. If an assigned vessel was unavailable by the time its own schedule commenced, another vessel could be contracted in the spot market to maintain the operation. The sailing time of a vessel depended on the stochastic weather conditions modeled using the time-series analysis applied to data provided by the Norwegian Meteorological Institute. The output analysis revealed that its fleet configuration was cost-effective.

Norstad, Gribkovskaia, Johnsen, and Lindstad (2017) worked on a simulation tool for upstream logistics of offshore operations in the Arctic (and potentially other remote regions). The simulation tool was used to assist ship design and fleet sizing, considering stochasticity from the transport demand. The objective was to determine the most economical fleet configuration that can ensure necessary requirements, such as safety, emergency preparedness, and environmental performance.

Very few studies have focused on Brazilian offshore logistics as well as our research. For example, Anselmo, Moreira, and Leite (2017) performed simulations to test several scenarios and determined the best PSV fleet size in Campos Basin, Brazil. The authors also proposed a multipurpose strategy, which was also evaluated in our study, considering the transport of both diesel and the deck cargo. Subsequently, the same simulation framework was also used by Moreira, Penna Leite, and Silva (2019) to determine the activities after the construction of a new port, discussing if it is preferable to continue using a tanker as a diesel hub to fulfill PSVs or if the port infrastructure should be considered for this purpose.

Table 2 lists the studies that used simulation to analyze related problems.

2.3. *Studies Integrating optimization and simulation*

Besides the simulation approach, there are studies that have integrated simulation and optimization approaches as well as our method. In de Sousa Junior, Barra Montevechi, de Carvalho Miranda, and Teberga Campos (2019), authors present a systematic literature review about works integrating both themes, comprehending a total of 663 different researches. For instance, Legato, Mazza, and Gulli (2014) worked with berth allocation problem in maritime container terminals, and proposed a tool comprehending an optimization model to obtain weekly plan in tactical level and simulation to adjust allocation decisions in the operational level. Similarly, Martins, Amorim, Figueira, and Almada-Lobo (2017) developed a tool to help on pharmaceutical's distribution network redesign, comprehending a optimization model to redesign decisions in strategic level, and simulation to evaluate solution in operational level.

In addition, there exists several works in oil & gas logistics area that also incorporates simulation and optimization approaches. Important examples are the studies of Halvorsen-Weare and Fagerholt (2011), Bassi, Ferreira Filho, and Bahiense (2012), Halvorsen-Weare, Fagerholt, and Ronnqvist (2013), Norlund, Gribkovskaia, and Laporte (2015), Norlund and Gribkovskaia (2017), Eskandari and Mahmoodi (2016), Halvorsen-Weare and Fagerholt (2016), Kisialiou, Gribkovskaia, and Laporte (2018), and Kisialiou, Gribkovskaia, and Laporte (2019).

Halvorsen-Weare and Fagerholt (2011) suggested that, because of uncertainty, it is considerably difficult to implement a planned schedule, e.g., in relation to the delays caused by weather conditions. Thus, they proposed a robust optimization for the fleet sizing and scheduling problem. In this approach, all possible voyage configurations are simulated, thereby generating the input for the primary model.

Similar to Mattos Ribeiro et al. (2011), Bassi et al. (2012) also proposes a method to schedule rig's operation, minimizing opportunity costs related to some operating constraints. The main innovation of this work is that it considers the uncertainties in service time through a simulation-optimization approach. The strategy consists on performing several replications of optimization, each one considering a random sample of service times generated. For mathematical model solution, two alternatives a proposed: a greedy algorithm and the GRASP metaheuristic.

Halvorsen-Weare et al. (2013) worked with the liquefied natural gas ship routing and scheduling problem with pick-up time windows. To consider uncertainties in sailing times and daily production rates, authors constructed a tool in which solutions are evaluated using a simulation model with a recourse optimization procedure.

Norlund et al. (2015) and Norlund and Gribkovskaia (2017) developed a simulation–optimization tool to measure differences in the greenhouse gas emissions of PSVs considering weather conditions and evaluated variable-speed optimization strategies. They performed simulations to generate different weather condition scenarios, which were then used as the inputs for the optimization procedure.

Eskandari and Mahmoodi (2016) compared two alternatives for vessel routing: routing based on a fixed schedule and routing based on platform demands. The study used a simulator to determine near-optimal solutions for the fleet composition problem with minimal costs, satisfying the minimum platform service level. In this study, the fleet composition was chosen from a set of available long-term and spot

Table 3
Comparative analysis of studies that use simulation with optimization strategies to analyze offshore planning problems.

Work	Type of vehicle	Stochasticity	Spot contracts?	Approach	Case Study
Halvorsen-Weare and Fagerholt (2011)	PSV	Weather conditions	Yes	Simulate scenarios for posterior optimization	Offshore Norway
Bassi et al. (2012)	Rigs	Service time	No	Simulation to generate input to optimization	Offshore Brazil
Halvorsen-Weare et al. (2013)	LNG ships	Sailing times and daily production rates	Yes	Optimization and simulation to evaluate solutions	Offshore Norway
Norlund et al. (2015)	PSV	Weather conditions	–	Simulation to generate optimization inputs	Offshore Norway
Norlund and Gribkovskaia (2017)	PSV	Weather conditions	–	Simulation to generate optimization inputs	Offshore Norway
Eskandari and Mahmoodi (2016)	PSV	Operation duration, vessel rates, platform demands and weather	Yes	Simulation-based optimization	Persian Gulf
Halvorsen-Weare and Fagerholt (2016)	PSV	Weather conditions	–	Simulation to generate optimization inputs	Offshore Norway
Kisialiou et al. (2018)	PSV	Weather conditions	–	Simulation to evaluate optimization results	Offshore Norway
Kisialiou et al. (2019)	PSV	Demands at installations	Yes	Simulation to evaluate optimization results	Offshore Norway
Andersson et al. (2015)	PSV	Ordering behavior	No	Simulation to generate optimization inputs	Offshore Brazil
Cuesta et al. (2018)	PSV	Ordering behavior	No	Simulation to generate optimization inputs	Offshore Brazil
Our work	PSV	Several activities	No	Simulation framework with optimization embedded	Offshore Brazil

Table 4
Request list example.

Request	Product	Quantity	Customer	Route	Due date
1	Diesel	792	4	9	265
3	Diesel	238	14	5	319
4	Diesel	377	25	2	468
5	GC	1	1	8	144
6	GC	1	1	8	288
7	GC	1	1	8	288
8	GC	1	2	12	168
9	GC	1	2	12	168
10	GC	1	3	13	120

contracts.

Halvorsen-Weare and Fagerholt (2016) proposed an arc-flow model and a voyage-based model to determine the optimal fleet size, mix of offshore supply vessels (OSV), as well as its routes and its schedules. To consider uncertainties such as those pertaining to weather conditions, they employed a simulation model to simulate each possible voyage and determined its robustness measure, which was then used for the optimization.

Kisialiou et al. (2018) proposed a methodology for the robust sequencing of PSVs, considering the uncertainty related to weather conditions, particularly during the winter. To address this unpredictability, the authors proposed adding idle times to the vessels between and during each trip. The scheduling solution was achieved using the ALNS. In this study, discrete simulation was performed to evaluate the service levels of the achieved solutions subjected to different weather scenarios.

In addition, Kisialiou et al. (2019) also proposed the formulation of supply vessel routing and scheduling, while considering uncertain demands in association with a discrete simulator. The methodology proposed uses ALNS to generate several vessel schedules; following the DES, which computes the expected solution costs. The most significant innovation of this study is that it solves, for the first time, a large-scale PSV planning problem with a stochastic demand.

In Andersson et al. (2015) and Cuesta et al. (2018), as well as a previously discussed optimization, simulations were also conducted. In these studies, a simulation model was used to generate demands, which were employed in the optimization procedures performed for each vessel trip. Although the demand information is revealed over time and with the performance of new trips, the simulation model is implemented immediately, prior to the optimization procedures. In our study, comparatively, the simulation is more comprehensive and significantly more interdependent on the optimization model; therefore, both the methods need to be implemented simultaneously.

In our framework, the optimization procedure is embedded within the simulation. Although not highly uncommon in literature, there are a few studies that employed similar approaches. For example, Kuo, Miller-Hooks, and Mahmassani (2010) studied the train slot selection problem to determine freight train timetables. The authors proposed a binary integer program to model the problem, solving it through column generation. Owing to elastic demand, this problem contains uncertainty; thus, for the experiments, a simulation framework was constructed, with optimization as an internal step.

Subsequently, Nourinejad and Roorda (2014) also proposed a similar approach. The authors studied the car sharing vehicle relocation problem, aiming to determine the fleet size and vehicle relocation policy. To achieve this, they proposed a dynamic model, with the optimization model embedded in the DES. For the optimization part, they proposed a binary integer programming model with a piecewise convex objective function. The solution was achieved using particle swarm metaheuristics.

Therefore, our model is embedded in the simulation framework, similar to those in Kuo et al. (2010) and Nourinejad and Roorda (2014). However, herein, we propose employing this model for the offshore logistics planning problem, which is an unprecedented application.

In addition, because our research is based on a Brazilian scenario, we expect the results to assist in gaining knowledge regarding regional practices. A few studies have proposed the translation of a Brazilian case to a simulation framework, such as Anselmo et al. (2017) and Moreira et al. (2019). Therefore, we expect to consider the tool itself as another important contribution.

Table 3 lists the studies that conducted studies integrating simulation and optimization to analyze related problems.

3. Problem description

In our problem, clients serve as production units, rigs, and other special service units. For simplification, we refer to them as MUs.

Table 5
Port schedule example.

Route	Client sequence	Berth time	
		1st trip	2nd trip
1	[49, 50, 56, 55, 57]	71	152
2	[27, 25, 60, 61, 62]	56	141
3	[22, 23, 35, 28]	19	105
4	[26, 21, 80, 29]	19	106
5	[15, 14, 47, 78, 18]	3	88
6	[54, 84, 51, 53, 52]	38	125
7	[17, 58, 79, 13, 48]	54	137
8	[30, 1, 31]	68	153
9	[4, 5, 44, 77, 46]	3	87
10	[39, 83, 42, 45, 41]	0	87

Table 6
Example of available fleet.

Vessel	Capacity			ETA
	CG	Diesel	Water	
1	88	1360	1850	0
2	85	1440	1450	293
3	85	1440	1450	384
4	95	1040	1350	264
5	85	1040	1400	384
6	85	1540	1600	0
7	56	740	1500	0
8	56	640	1350	320
9	56	640	1350	0
10	85	1480	1800	0

Periodically, the MUs place delivery requests for three types of products—deck cargo, diesel, and water—as well as cargo backloads. Each request comprises the quantity of the commodity and the delivery due date. Table 4 presents an example of a request.

To fulfill these demands, a vehicle supplies these products from a single depot. These deliveries are made according to pre-defined fixed routes. Owing to inventory limitations of clients and to maintain the stability of operations, each route has a weekly delivery frequency and is uniformly spread through the planning horizon.

In our problem, the port represents the depot, i.e., the location where all the goods are collected and kept ready for delivery. It has unlimited storage capacity; however, there are a few limitations on the working hours and infrastructure, owing to the number of berths and machine productivity. Another limitation on the port is the availability of the port channel, which allows limited maneuvering of vessels to and from the port. To deal with these limitations, time windows are assigned to determine when the loads can occur and the duration of these loads. Table 5 presents an example of the timetables of these operation. Each route has an order in which the customers should be served and the scheduled starting times for loading windows on the port.

In our study, the vehicles are PSVs. The fleet is heterogeneous with multiple compartments; therefore, each vehicle has its own storage capacity for each commodity. These vehicles may be available in the anchoring queue, in transit-making deliveries, or may be unavailable because of scheduled maintenance or failures. Table 6 exemplifies an available fleet at a determined instant. Each vessel has the capacity for each class of products and is associated with an expected time of arrival on port, which is equal to 0 if the vessel is already in the port anchoring queue.

Considering the strategic, operational, and tactical decision levels of supply chain management, different policies and trade-offs can be analyzed for this problem. With the objective of comparing policy alternatives, a discrete-event simulator was developed and used to represent offshore operations, while considering stochasticity.

To meet the requested demands of the MUs, different fleet management policies can be used. In this study, we evaluate two possibilities. The first is a commonly used policy in the offshore Brazilian scenario, i.e., the disaggregated fleet policy. As a second alternative, with a potential cost reduction, we propose the aggregated fleet policy. These two strategies are summarized in Figs. 1 and 2.

The disaggregated fleet policy is illustrated in Fig. 1. In this operation, a fleet is segmented by its cargo. Thus, one fleet is dedicated to the deck cargo and water (blue and red arrows), whereas another is used to transport diesel (black arrows). Being highly regular and predictable, the deck cargo and water deliveries can follow pre-scheduled routes with few problems in case of delays. However, diesel shortages can easily lead to unplanned shutdowns, which can cause significant losses. Therefore, dedicated diesel delivery vehicles make deliveries on demand, transporting oil from the larger tank ships strategically distributed throughout the basin.

Among the multiple compartments, the fleet may include idle compartments that can be used to deliver other products via another strategy. Therefore, we propose the aggregated fleet policy, as illustrated in Fig. 2. This strategy enables the simultaneous transportation of different

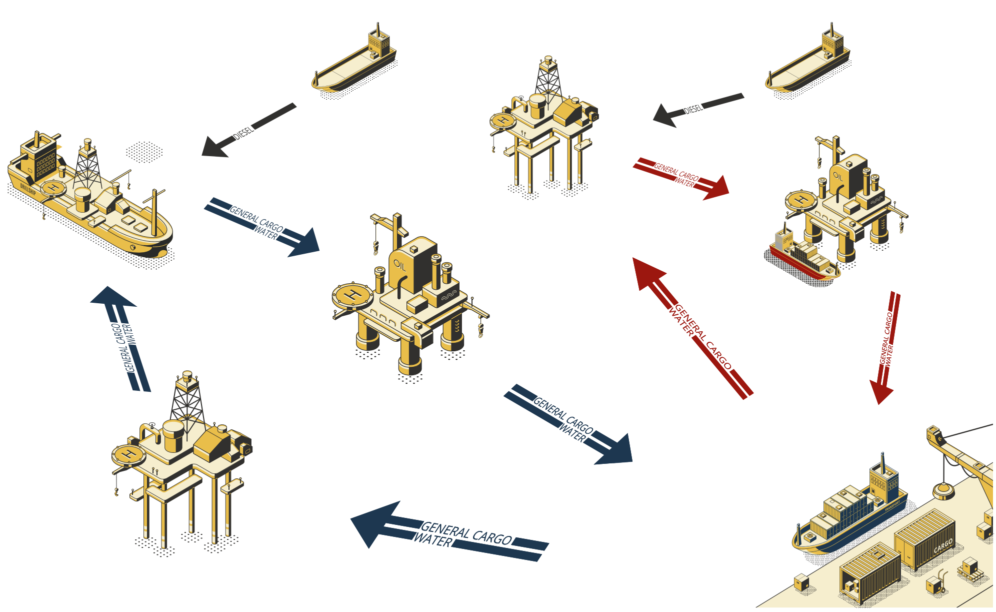

Fig. 1. Operation outline for disaggregated fleet.

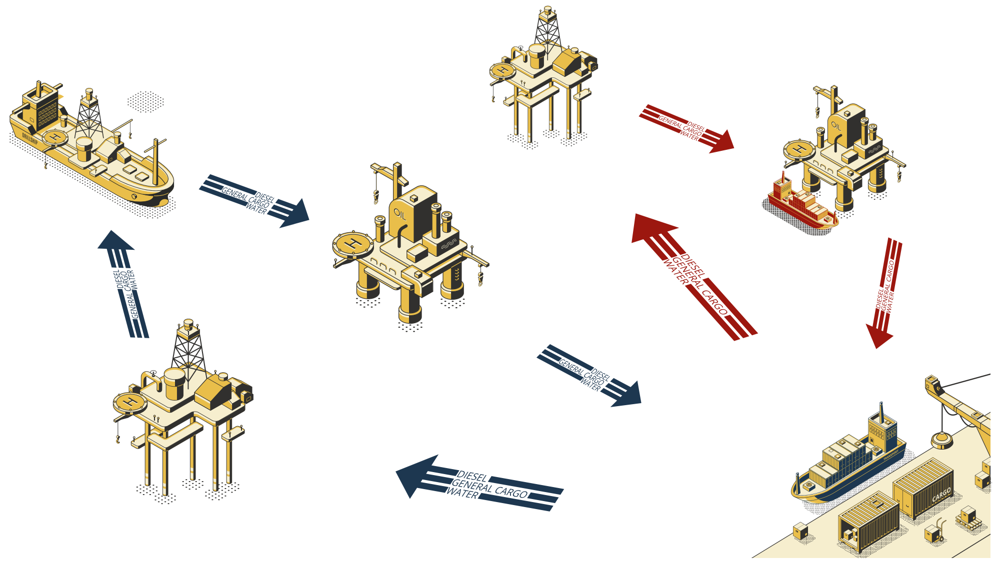

Fig. 2. Operation outline for aggregated fleet.

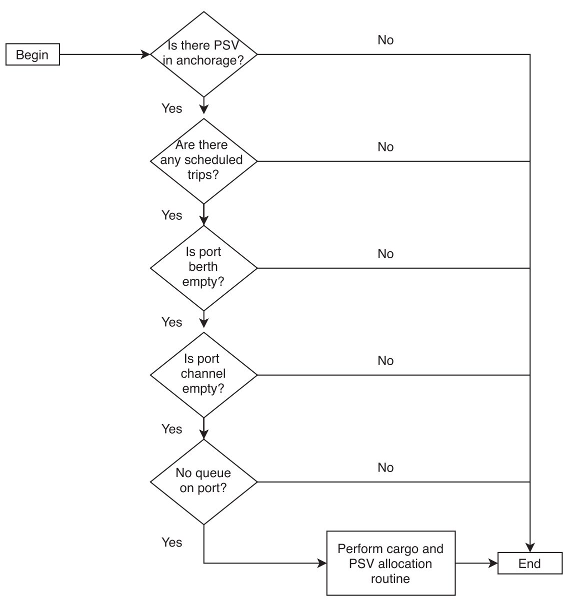

Fig. 3. Cargo allocation.

products through the same vessel, resulting in economic savings. While previous strategies are based on realizing a high level of readiness, this method prioritizes planning.

In addition to the abovementioned fleet management policies, deciding the shipping orders and their allocation to a vehicle is another interesting management problem. We analyzed two different procedures: the FIFO rule and a more advanced optimization technique.

The FIFO rule is a traditional and common approach. In this strategy, the oldest orders placed by the customers are delivered by the longest available vehicle at the anchoring. This technique is used by the company considered in our case study; hence, we use it as a benchmark. Different from the FIFO rule, we propose a new decision method, formulated as the following mathematical problem: (*i*) Given a set of clients associated with (*ii*) a set of delivery requests for products expected to be fulfilled in a certain time horizon, and (*iii*) a heterogeneous fleet of PSVs. We are interested in determining (*a*) which vessel will perform each trip (*b*), which requests will be carried in each trip, (*c*) and the time at which each vessel will reach the locations (clients and supply base). The objective is to maximize the service level (defined by the percentage of requests delivered on time), while simultaneously avoiding request refusals and stockouts. The main constraints are the capacities of the vessels and the time windows of the berths. We determine the optimal solution in order to enhance the service levels, thereby enabling fleet reduction in both the fleet policies.

4. Framework

The framework, named as APOLO (Offshore Support Logistics Evaluator), is based on a flexible DES model, which enables the analysis of all the offshore supply chain logistics and the prediction of the impact of the proposed improvements. One of the steps of the simulation is cargo allocation to a vehicle, which is performed at the port. For this step, as well as a simple FIFO approach, we propose a more advanced optimization strategy by which an optimization step is embedded in the simulation.

In this section, we first provide a description of the DES, highlighting the most important operation sequence aspects and its implementation within the framework. Subsequently, we highlight the order allocation step.

4.1. Discrete-event simulator

The logistics processes are represented considering several random variables:

- Product handling - loading flow of diesel (port, MUs, and tank ships), loading flow of water (port and MUs), and handling rates of deck and backload cargo (port and MUs);
- MU demands - demand of deck cargo, consumption of diesel and water, production of water, and production of backload cargo;
- Fleet management - navigation speed, inoperative events and their duration, time spent in docking, and time spent to change the crew in oilers; and
- External influences - the necessity of the fleet to wait to operate in the MUs or tank ships, owing to some weather condition or limiting events in the units (diving operation, helicopter landing, operation of shuttle tanker, and others). In simulation, this is represented through waiting times.

Concerning the logical sequence of operations in the simulation, we can divide the PSVs in two groups. The first group considers PSVs that

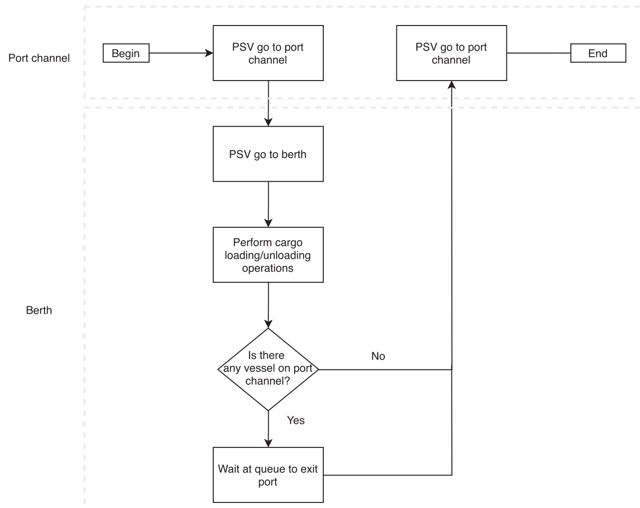

Fig. 4. Port operations.

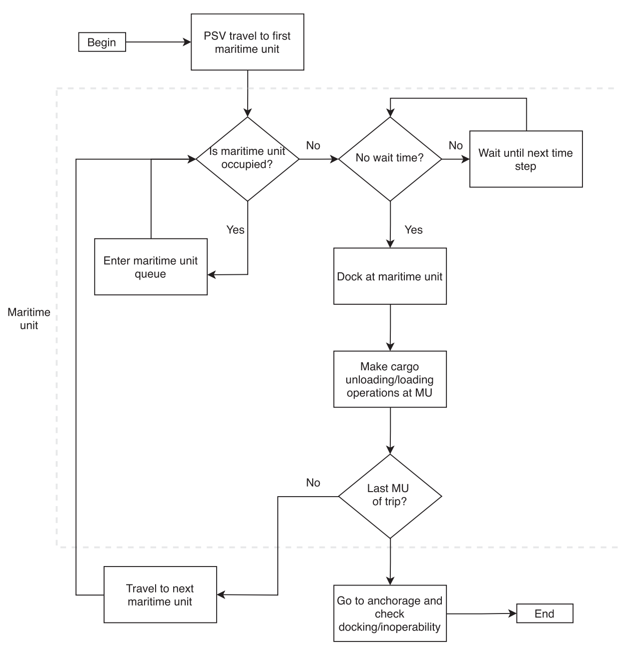

Fig. 5. Cargo delivery operations.

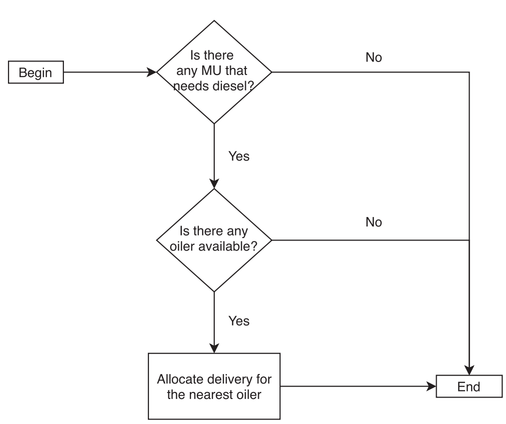

Fig. 6. Cargo allocation for oiler operations.

simultaneously deliver the deck cargo, diesel, and water under the aggregated fleet policy. It also includes traditional PSVs simultaneously delivering the deck cargo and water in the disaggregated fleet policy; we name this as type A operation. The second group considers PSVs delivering strictly oil; we name this as type B operation. In the following sections, we present an in-depth analysis of each of these operations.

4.1.1. *Type A operation (port PSV)*

In this type of operation, we term the vehicles as port PSVs. On each simulator time step, simulator checks several items, as detailed on logical sequence of Fig. 3. If all the items are satisfied, the simulator requires an appropriate allocation strategy to select the vehicle and the cargoes that will be loaded, according to loading planning detailed on SubSection 4.2. To perform loading, the selected PSV moves from port channel to berth and perform activities as detailed on Fig. 4.

After loading operations on port, PSV starts a route to attend a set of maritime units, which is described on Fig. 5. After returning to the anchor area, the PSV can experience unintended events, leading to temporary malfunctioning. Eventually, it has to return to a dry dock for planned maintenance. During all the operations, the PSVs consume diesel at different self-consumption rates, depending on their states and locations.

4.1.2. *Type B operation (oiler)*

This type of operation refers to the oiler PSVs. Periodically, all the MUs examine whether their diesel stock is below an operational quota, placing delivery requests if necessary, as illustrated on Fig. 6. If this is the case, an MU places a delivery request and enters in a queue to be attended, ordered by the ascending time until a stockout scenario. The first MU in the queue receives the nearest available oiler, and the process continues until no oilers are available or no MUs are in the queue.

When an oiler arrives at the MU, it proceeds with activities as explained on Fig. 7. Every time a loading operation is completed, the oiler checks whether its own tank needs restocking; if necessary, vessel moves to a buoy for restocking, as also explained on Fig. 7. In addition, it also checks if there is a need for crew change, and vessel travels to the port and makes an operation similar to port loading previously explained, if necessary. Finally, if no operation is necessary, the oiler becomes available and waits for a new diesel request, not making any additional movement. Diesel consumption in this operation is similar to that in Type A operation.

4.1.3. *Structures*

Similar to a traditional DES, our simulation model is composed of entities, locations, and resources. Entities initiate and respond to simulation events. We consider the following entities:

- Scheduled trips: operational time windows when departures to a determined route are allowed with weekly frequency; and
- Requests: goods demanded by clients, including water, diesel, and deck cargo. Each request has specific attributes, such as the product ordered, quantity, and due date.

Locations represent fixed spots where all types of operations are performed. They can have an associated capacity constraint or not. The locations in the model are as follows:

- Anchor area: waiting area where vessels arrive from a trip and from where they depart to the port, modeled as an unlimited capacity location. In addition, during inoperative and dry-docking scenarios, vessels are located in this area.
- Port channel: the narrow passage connecting the anchor area to the port and the port to the basin.
- Port berths: where PSV loading/unloading operations and crew change occur. A berth only receives a single vessel at a time. The capacity of the port is the number of active berths.

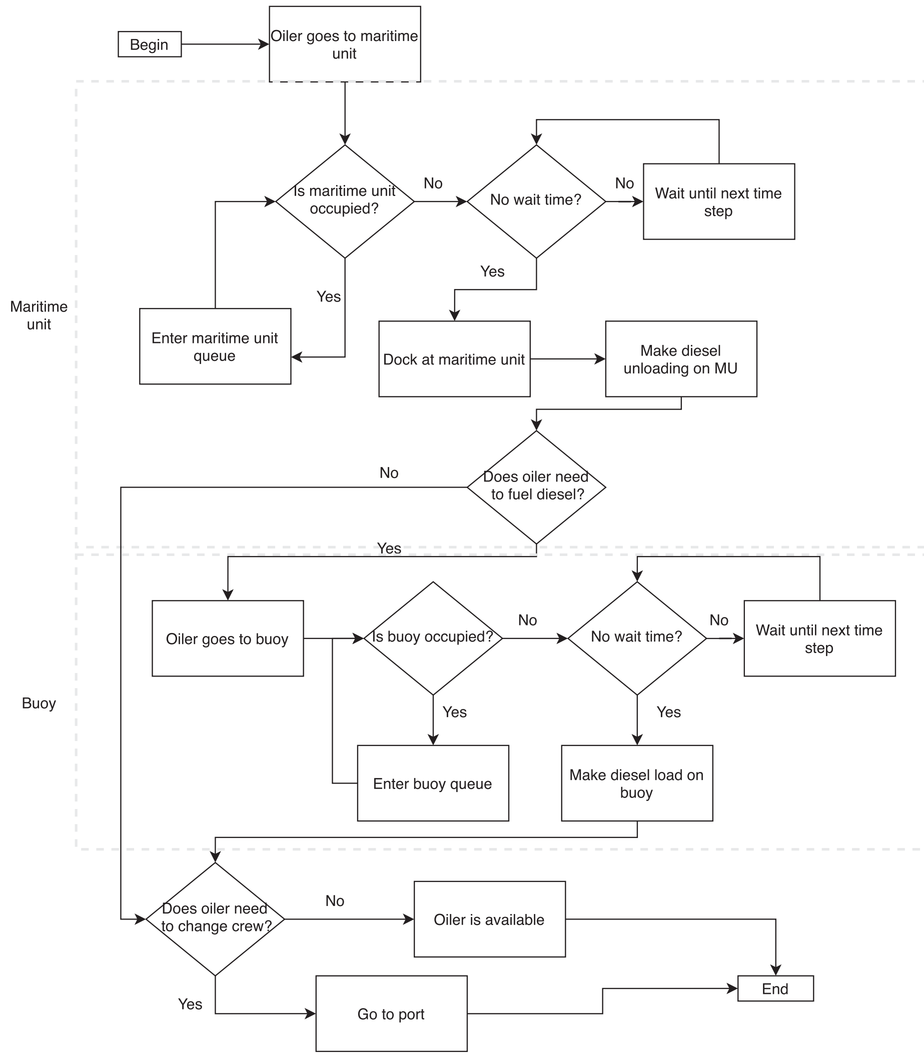

Fig. 7. Oiler vessel cargo delivery operations.

- MUs: facilities located in the basin, responsible for the E&P operations and in charge of order generation. They can only be attended by one PSV at a time.
- Buoys: these are located across the basin; oilers can moor at these areas to fill their diesel tanks.

Resources are the elements that perform the simulation operations and have limited capacity. The modeled resources are as follows:

- Port PSVs: the vessels responsible for supplying MU requests. They alternate among the following statuses during the simulation: loading and unloading cargo, traveling, waiting, nonfunctioning, and dry-docking. They can visit the anchor area, port channel, port, and MUs.
- Oilers: the vessels responsible for supplying diesel requests in the disaggregated fleet policy. They alternate among the following statuses during the simulation: loading and unloading cargo, traveling, waiting, crew changing, nonfunctioning, and dry-docking. They can visit the anchor area, port channel, port, MUs, and buoys.
- Tank ships: ships located next to the buoys. They are responsible for supplying diesel to several types of vessels in the basin. They need to periodically travel to the diesel terminals at the port to fill their tanks. They alternate among the following statuses during the simulation: loading and unloading cargo and traveling. They can visit the buoys and the port.

4.2. *Allocation strategies*

The selection of the vessel and cargo allocation for each route are important decision areas in offshore logistics. Therefore, we investigated two allocation strategies: (i) a greedy heuristic known as FIFO and (ii) the proposed MILP optimizer.

4.2.1. *FIFO*

The FIFO rule of allocation is a greedy heuristic that assigns the PSV that has remained in the anchor area for a longer duration to the subsequent trip. The simulator orders the deck cargo requests of a route based on the due date and selects the maximum number of requests (following an ascending order) that fits the PSV deck. Each MU of the trip receives its scheduled deck cargo loaded in the port.

The diesel and water schedules in the port follow the same approach. The operation fills the PSV water and diesel tanks only if the tank stock is below the operational quota for each good.

There is no pre-defined schedule for unloading water and diesel at the MUs. When the PSV arrives at an MU, it checks whether its tank stock is below the operational quota for each good; if it is, the PSV loads the tank to the maximum limit.

4.2.2. *Mathematical programming*

Table 7 summarizes the notations adopted in the models.

Let C be the set of MUs, or customers, scattered in the ocean. Each of

Table 7
Notations used for sets, parameters, and decision variables.

Notation	
Sets:	
$t \in \mathcal{T}$	Trip t and ordered set of active trips $\mathcal{T}$
$v \in \mathcal{V}$	Vessel v and set $\mathcal{V}$ of PSVs
$p \in \mathcal{P}$	Products p and set of Products, $\mathcal{P}$
$c \in \mathcal{C}$	Customers c and set of customers, $\mathcal{C}$
$\kappa(t) \subset \mathcal{C}$	Ordered set of customers c to be served in t
$\rho(t) \subset \mathcal{R}$	Ordered set of requests r to be delivered in trip t
$\zeta(c) \subset \mathcal{R}$	Set of requests made by client c
Parameters:	
Q^p_r	Quantity of product p demanded on request r
C^p_v	Vessel v capacity for product p
ETA_v	Expected time of arrival of vessel v
B_t	Trip t starting berth working time
UB_t	Deadline for trip t berth operations
$S_{i,j}$	Travel time between consecutive locations i and j
DD_r	Request r delivery due date
HC^p_c	Handling time per unit of product p at customer c
HP^p	Handling time per unit of product p at port
$\alpha(t)$	Trip t first customer
$\eta(i)$	Successor of location i
Decision Variables:	
$z^r_t \in \{0,1\}$	1 if request r is delivered on trip t
$y^t_v \in \{0,1\}$	1 if vessel v is assigned to trip t
$l_r \in \{0,1\}$	1 if request r is delivered on time
$h_r \in \{0,1\}$	1 if request r is refused
$x^t_{p,v} \in \mathbb{R}_+$	Amount of product p loaded on vessel v for trip t
$f^t_{p,v} \in \mathbb{R}_+$	Capacity slack in vessel v for product p on trip t
$tl^t_c \in \mathbb{R}_+$	Time at which the vessel arrives at customer c on trip t
$t_r \in \mathbb{R}_+$	Time at which request r is delivered
$w^t_c \in \mathbb{R}_+$	Working time of customer c on trip t
$wp^t \in \mathbb{R}_+$	Working time at harbor for trip t

these clients gradually generates requests $r \in \mathcal{R}$ for a certain quantity Q^p_r of product $p \in \mathcal{P}$ with due date DD_r.

All the clusters are serviced at a certain frequency during the week. The sum of these attendances characterizes a set T of the trips. If a vessel is assigned for a trip $t \in \mathcal{T}$, it must be ready-to-use at the anchoring when the working time at the berth commences, as given by B_t. In addition, the total working time at the berth should not exceed a certain upper bound UB_t.

A route, or a cluster, is defined as a set $\kappa(t) \subset C$ of customers who are served consecutively. A location $j \in C \cup \{base\}$ is called a successor of $i \in C \cup \{base\}$ if $i \wedge j \in K$ and i supply service precedes j, if the travel time from i to j is given by $S_{i,j}$.

Let V be the vessels set. Each vessel $v \in \mathcal{V}$ has a capacity C^p_v to carry each product. Furthermore, the fleet is distributed, either waiting in the anchoring of the port for a new service or in transit. Therefore, each vessel has an expected arrival time at the anchoring, ETA_v. In case the vessel is already at the anchoring, $ETA_v = 0$.

With regard to the handling time, the time required to move one unit of product p is defined as HP^p if the movement occurs in the harbor and as HC^p_c if the movement occurs at the client.

Because there may be insufficient capacity available to accept all requests, it is possible that some delivery requests are refused. Therefore, our objective is to maximize the service level defined by the percentage of requests that are delivered on time. For calculation purposes, we consider a request delivered after its due date or a refused one as delayed. Thus, we have

$$\min \sum_r \left(h_r - \frac{l_r}{|R|}\right) + \sum_{p,v,t} \left(\frac{\max(B_t) - B_t}{B_t \cdot |P| \cdot |V|} \cdot f^t_{p,v}\right) \tag{1}$$

s.t.

$$\sum_v x^t_{p,v} \geqslant \sum_{r \in \rho(t)} Q^p_r \cdot z^r_t \forall p \in \mathcal{P}, t \in \mathcal{T} \tag{2}$$

$$\sum_t z^r_t \leqslant 1 \forall r \in \rho(t) \tag{3}$$

$$\sum_v y^t_v \leqslant 1 \forall t \in \mathcal{T} \tag{4}$$

$$\sum_t y^t_v \leqslant 1 \forall v \in \mathcal{V} \tag{5}$$

$$x^t_{p,v} + f^t_{p,v} = C^p_v \cdot y^t_v \forall p \in \mathcal{P}, t \in \mathcal{T}, v \in \mathcal{V} \tag{6}$$

$$ETA_v \cdot y^t_v \leqslant B_t \forall v \in \mathcal{V}, t \in \mathcal{T} \tag{7}$$

$$h_r + \sum_t z^t_r = 1 \forall r \in \mathcal{R} \tag{8}$$

$$h_r + l_r \leqslant 1 \forall r \in \mathcal{R} \tag{9}$$

$$M \cdot l_r + t_r \geqslant DD_r \forall r \in \mathcal{R} \tag{10}$$

$$M \cdot (l_r - 1) + t_r \leqslant DD_r \forall r \in \mathcal{R} \tag{11}$$

$$t_r \geqslant tl^t_c - M \cdot (1 - z^r_t) \forall t \in \mathcal{T}, c \in \kappa(t), r \in \rho(t) \tag{12}$$

$$t_r \leqslant tl^t_c + M \cdot (1 - z^r_t) \forall t \in \mathcal{T}, c \in \kappa(t), r \in \rho(t) \tag{13}$$

$$tl^t_{\eta(i)} \geqslant tl^t_i + w^t_i + S_{i,\eta(i)} \forall t \in \mathcal{T}, i \in C \cup \{base\} \tag{14}$$

$$tl^t_{\alpha(t)} \geqslant B_t + wp^t + S_{base,\alpha(t)} \forall t \in \mathcal{T} \tag{15}$$

$$w^t_c \geqslant \sum_{p \in \mathcal{P}} \sum_{r \in \zeta(c)} (HC^p_c \cdot Q^p_r \cdot z^t_r) \forall t \in \mathcal{T}, c \in \kappa(t) \tag{16}$$

$$wp^t \leqslant UB_t \forall t \in \mathcal{T} \tag{17}$$

$$wp^t \geqslant HP^p \cdot x^t_{p,v} \forall p \in \mathcal{P}, t \in \mathcal{T}, v \in \mathcal{V} \tag{18}$$

The objective function, 1, is divided into two parts. The first sum seeks to deliver the most requests on time, i.e., the function increases with the number of requests delivered on time and is penalized by those refused. The second portion seeks to measure how late each vessel performs its activity on port and prioritize the use of available space over time. This is important because, between the decision of the optimizer and the effective loading at the ports of latest scheduled trips, additional requests might be generated, imposing the need for a new optimization. Therefore, it is important to maximize the utilization of vessels departing in the near future in order to obtain more space in the subsequent vehicles for these additional requests. The greater the value of B_t, the lower is the ratio, $\frac{\max(B_t) - B_t}{B_t \cdot |P| \cdot |V|}$, imposing a reduction in the free space, $f^t_{p,v}$, to improve the objective function.

The first constraint, (2), ensures that the quantity of the product shipped is at least the quantity of each request assigned to that trip. The constraint in (3) imposes that a request r must be assigned to at most one trip of its respective cluster. Eq. (4) imposes that the same vessel may not be assigned to more than one trip, which is a good assumption as other optimization calls on future simulation time steps may successfully deal with subsequent trips of the vessel. The inequalities in (5) ensure that no more than one vessel is assigned to the same trip.

The constraint in (6) prevents the vessels from being loaded with

Table 8
Key performance indicators selected for validation.

Category	Indicator	Fleet	Description
Time	Voyage	PSV delivering deck cargo and water	Average time interval required for vessel mooring procedure and movement to waiting area
Time	Waiting for MU operation	PSV delivering deck cargo and water and oiler	Average time interval required to start vessel operation at MU. This interval results from waiting for safe environmental conditions or some other MU issue preventing transfer of supplies
Time	Downtime	PSV delivering deck cargo and water and oiler	Average time interval vessel is in downtime state. Typically, short vessel downtime occurs because of corrective maintenance
Time	Unloading in MU	PSV delivering deck cargo and water and oiler	Average time interval required for vessel loading or unloading operations in MU
Time	Loading in port	PSV delivering deck cargo and water	Average time interval required when vessel is loading or unloading in port
Cargo	Diesel per visit	Oiler	Average volume of diesel delivered per visit in MU
Cargo	Water per visit	PSV delivering deck cargo and water	Average volume of water delivered per visit in MU
Cargo	Deck cargo per voyage	PSV delivering deck cargo and water	Average deck cargo carried by vessel

Table 9
Validation results.

Vessel	Indicator	Base simulator	Proposed simulator	Error (%)
PSV delivering deck cargo and water	Voyage (days)	4.03	4.07	0.98
	Waiting for MU operation (days)	0.46	0.46	0
	Downtime (days)	2.43	2.29	5.76
	Unloading in MU (h)	7.18	7.18	0
	Loading in port (hours)	13.25	13.37	0.9
	Water per visit (m^3)	258.64	258.80	0.06
	Deck cargo per voyage	59.09	59.12	0.05
Oiler	Waiting for MU operation (days)	0.49	0.50	2.04
	Downtime (days)	2.19	2.30	5.02
	Unloading in MU (h)	10.74	10.54	1.86
	Diesel per visit (m^3)	632.28	618.78	2.13

products exceeding their capacity; this is the result of adding the quantity of the loaded product ($x^t_{p,v}$) to the capacity slack ($f^t_{p,v}$). The inequality in (7) dictates that a vessel cannot be assigned to a trip whose loading window starts before its time of arrival (ETA) at the anchoring.

The next block of constraints addresses the service level and the time measurements. The constraint in (8) measures whether a request r was refused—if r is not assigned to any trip, i.e., $\sum_t z^t_r = 0, h_r$ must be 1. If a request is refused, then it is also considered as delayed, as expressed in (9). The constraints in (10) and (11) determine whether the request is delivered on time, i.e., if $t_r \leqslant DD_r$, then l_r must be 1. To calculate the time at which a request is delivered, (12) and (13) impose that the delivery time is the time when the vessel reaches the customer.

The time of arrival of the vessel to the customer is calculated using the constraints in (14) and (15). The time at which the vessel arrives at a successive location i, defined as $\eta(i)$, is at least equal to the time it arrives at the previous location (i) of the route, i.e., the sum of the travel and working times. In addition, the time at which the vessel arrives at the first customer of the route ($\alpha(t)$) is at least equal to the sum of the starting time for loading (B_t) and the handling time in the port and the travel time from the port to the first customer of the trip ($\alpha(t)$).

Finally, there are restrictions concerning the loading times. By considering that one type of product is moved at a time at client (sequential loading), (16) imposes that the working time at the customer on a specific trip (w^t_c) is greater than or equal to the sum of the loading times of all the products delivered to the client on this specific visit, for each client that is part of this trip ($c \in \kappa(t)$).

With regard to the port, there are two types of constraints. The first constraint in (17) is an upper bound of the total time spent at the berth. In addition, we consider that loading at the port occurs in parallel, i.e., different types of products can be loaded simultaneously, resulting in the constraint in (18).

5. Computational experiments

The computational experiments consisted of two steps:

- Validation: To ensure that the APOLO simulator appropriately represents an actual offshore operation system.
- Case study: To compare the benchmark activities with proposed changes in the policies, considering a real offshore operation scenario from Brazil.

The discrete-event simulator (APOLO) and the allocation approaches—both the FIFO rule and the optimizer—were implemented in Python, with parameters imported from a spreadsheet. To solve the optimization problem, we used Gurobi 8.0. The validation model was achieved in Promodel 14.0. The tests were implemented on a machine with the following configuration: Intel Xeon CPU E5-2620 v4 @ 2.10 GHz with two processors, 256 GB of RAM memory, and Windows Server operational system.

5.1. Validation

The validation process is an important stage when building a discrete-event simulator, because it can ensure that the simulation accurately represents reality. In an ideal validation, we compare important performance indicators obtained during an actual operation against the results obtained via a simulator. However, real values are not always available. One alternative, presented by Sargent (2010), is the comparison to other models; this indirect validation is an alternative method that can be used when there is a lack of information, comparing the results obtained using a simulator previously validated against real data.

Owing to the unavailability of real data, we conducted an indirect validation against the simulator proposed by Anselmo et al. (2017), named as base simulator. Their tool was previously validated against large and real data supplied by Petrobras, to fit statistical distributions and establish basic parameters. For this purpose, they selected a group of key indicators in collaboration with maritime transport specialists and compared the results with real data to determine the model capability of reproducing real-world performance. They used Stat::Fit software during the fitting process and statistical tests of Kolmogorov–Smirnoff with a significance level of 5% to rank and select the distributions suggested by the software.

We use the same statistical distributions from the base simulator, which are presented in Appendix A. To validate our model, we select 11 key performance indicators (KPIs). These indicators can describe important operational aspects of the problem and were also used for the base simulator validation. Table 8 lists these KPIs.

For the validation, we implemented both the simulation models for 180 days, with 30 replications. The warm-up time was 90 days. We considered the disaggregated fleet policy scenario, with the FIFO

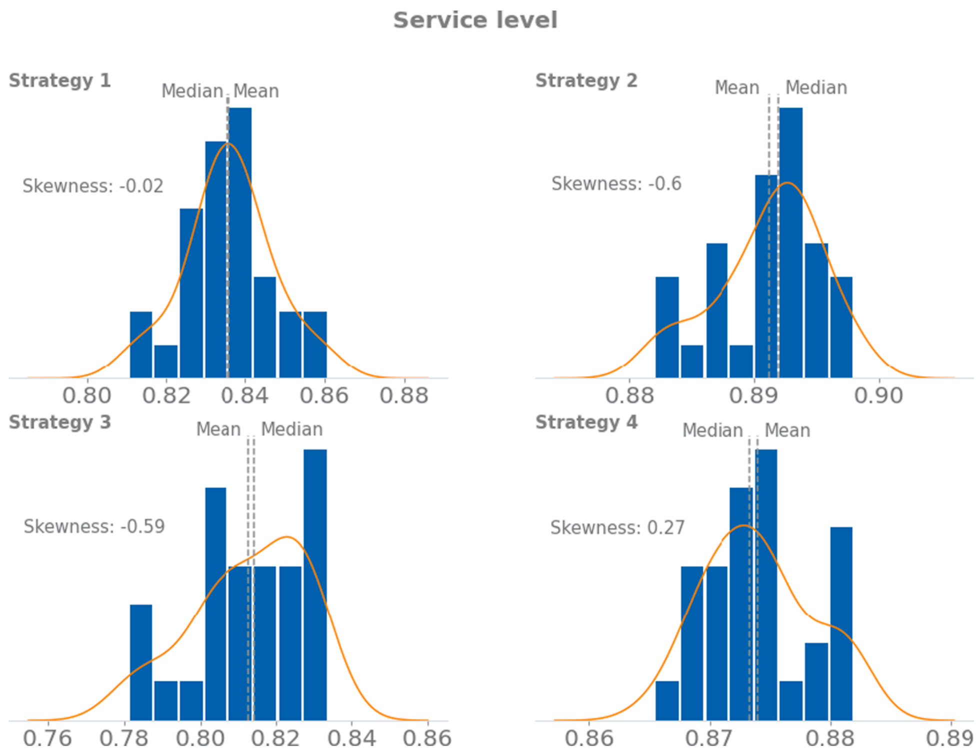

Fig. 8. Service level histograms for all four simulated cases.

Table 10
Confidence interval for 30 replications.

Strategy	Mean	s (sample standard deviation)	Method	Confidence level	h	% of interval variation
(i)	0.8359	0.0112	t-Student	95%	0.0042	0.5%
				99%	0.0056	0.67%
(ii)	0.8912	0.0042	Bootstrap	95%	0.0015	0.17%
				99%	0.002	0.22%
(iii)	0.813	0.0148	Bootstrap	95%	0.0054	0.66%
				99%	0.0071	0.87%
(iv)	0.874	0.0045	t-Student	95%	0.0017	0.19%
				99%	0.0023	0.26%

Table 11
Case study configuration.

General measures of case scale		Main scenario parameters	
Weekly consumption of diesel (m^3)	14222.3	MUs	90
Weekly consumption of water (m^3)	12656.8	Clusters	23
Weekly production of water (m^3)	6841.7	Basin	Espírito Santo and Campos
Weekly delivery deck cargo demand (units)	2740	Port	Açu
Weekly pickup deck cargo demand (units)	2380	Port berths	6
Total distance travelled per trip (km)	422.84	Tank ships	5
Total distance travelled per trip (km)	422.84	Deck cargo and water PSVs	35
Distance between port and MU (km)	177.49	Diesel dedicated PSVs	7

allocation model. Table 9 summarizes the results.

The results obtained with both the simulators as well as the discrepancy between them are provided in Table 9. Among the total of 11 KPIs, 55% have an error less than 1%, 82% have an error less than 2.5%, and 100% have an error less than 6%. These values confirm the accuracy of the framework in reproducing the base simulator system and consequently validate it.

To ensure that the number of replications, n, is correct, we performed additional tests, analyzing the service level of the deck cargo, an important indicator of the operation. For $n = 30$, we studied 4 cases: (i) disaggregated fleet policy using FIFO as the allocation approach; (ii) disaggregated fleet policy using optimization as the allocation approach; (iii) aggregated fleet policy using FIFO as the allocation approach; and (iv) aggregated fleet policy using optimization as the allocation approach.

Fig. 8 shows the histogram for each case with the skewness value highlighted. According to Bulmer (1979), distributions with skewness absolute values between 0 and 0.5 are considered symmetrical, while values between 0.5 and 1 have moderate skew. Wang (2001) showed the good performance of the bootstrap strategy to generate confidence interval for asymmetrical and non-normal distributions, therefore we applied bootstrap resampling method for cases (ii) and (iii) in order to estimate the confidence intervals. For cases (i) and (iv), the critical value and half of the confidence interval based on the t-Student distribution is $h = (t_{n-1,\alpha/2} \cdot s)/\sqrt{n}$. The results are summarized in Table 10.

We consider the following two criteria to ensure the validation of the process:

Table 12
Main indicators of benchmark scenario compared to Strategy 1 with fleet reduction.

	Benchmark			Disaggregated fleet with FIFO		
	Lower	Mean	Upper	Lower	Mean	Upper
Service level	83.33%	83.85%	84.63%	83.17%	83.59%	84%
Diesel stockouts	0	0.17	0.34	0	0.1	0.21
Water stockouts	0	0	0	0	0.03	0.1

Table 13
Strategies tested on experiments.

Strategy	Policy	Approach	Fleet composition
1	Disaggregated	FIFO	33 PSVs for deck cargo and water; 9 PSVs for diesel
2	Disaggregated	Optimization	33 PSVs for deck cargo and water; 9 PSVs for diesel
3	Aggregated	FIFO	33 PSVs for deck cargo, diesel, and water
4	Aggregated	Optimization	33 PSVs for deck cargo, diesel, and water

Table 14
Evaluated performance indicators.

Operation	Indicator	Description
Deck cargo	Service level	Percentage of deck cargo delivered on time to MU
Deck cargo	Lead time	Average time spent since cargo request until its delivery
Diesel	Stockouts	Occurrences of empty diesel tanks in MU
Diesel	Idle space	Idle space in PSV diesel tank after load operation at port (only in aggregated policy)
Water	Stockouts	Occurrences of empty water tanks in MU
Fleet management	Fuel consumption	Total fuel consumption of fleet (oilers and cargo and water fleet)

- With a confidence level of 95%, half of the confidence interval should be less than or equal to 1% of the mean.
- With a confidence level of 99%, half of the confidence interval should be less than or equal to 2% of the mean.

For all the strategies, both the criteria were satisfied. Thus, the 30 replications were sufficient to confirm the validation of the process..

5.2. *Case study*

We use the proposed framework to simulate a large-scale scenario on the southeastern Brazilian coast; a majority of the country's petroleum is produced at this location. In Table 11, we summarize the instance configuration. It consists of supplying 90 MUs, divided between 23 routes located in the Espírito Santo and Campos basins along the Espírito Santo and Rio de Janeiro coasts. Each MU has delivery demands of deck cargo, water, and diesel, apart from cargo pickup orders. The current fleet consists of 10 oilers and 35 PSVs responsible for delivering the deck cargo and water. The port, used to support these operations, is Açu, with six berths dedicated to supplying offshore operations. In a cyclical period of 7 days, the port has 46 scheduled slots for PSV loading.

All the case study tests were conducted for 90 days of warm-up and 180 days of valid simulation, with 30 replications. The obtained results have a confidence interval of 95%.

5.2.1. *Comparison with benchmark*

The current used policy in Brazilian offshore operations considers a disaggregated fleet and the FIFO rule for cargo allocation, which we name as Strategy 1. In the benchmark scenario, besides these characteristics, the fleet is composed of 10 oilers and 35 PSVs delivering the deck cargo and water.

In the first step of our analysis, we use the proposed framework to determine the performance indicators for the benchmark scenario. Subsequently, we determine the fleet reduction that can be achieved using Strategy 1, while maintaining the same deck cargo service level of the benchmark and restricting occurrences of diesel and water stockouts near zero.

The reduction in the oilers from 10 to 9 does not generate additional occurrences of diesel stockouts. In addition, the reduction in the PSVs delivering the deck cargo and water from 35 to 33 neither worsens the service level of the deck cargo nor generates additional occurrences of water stockouts. The results are summarized in Table 12.

Subsequently, we tested the new policies proposed herein: the aggregated fleet policy and the new cargo allocation strategy based on a mathematical model. All the tested strategies are defined in Table 13.

For the analysis, we considered the performance indicators that could cover all the main aspects of operation and their qualities, which are listed in Table 14. The deck cargo service level and the stockouts of

Table 15
Results of indicators for all strategies.

Indicator	Confidence interval	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Deck cargo Service level	Lower	83.17%	88.96%	80.74%	87.24%
	Mean	83.59%	89.12%	81.30%	87.40%
	Upper	84.00%	89.28%	81.85%	87.57%
Deck cargo Lead time	Lower	4.43	4.14	4.53	4.24
	Mean	4.45	4.15	4.56	4.25
	Upper	4.47	4.16	4.60	4.26
Stockouts of diesel	Lower	0.00	0.00	0.00	0.00
	Mean	0.10	0.10	0.20	0.25
	Upper	0.21	0.21	0.43	0.51
Diesel tank idle space	Lower	–	–	253	717
	Mean	–	–	256	720
	Upper	–	–	258	722
Stockouts of water	Lower	0.00	0.00	0.00	0.00
	Mean	0.03	0.3	0.00	0.33
	Upper	0.10	0.75	0.00	0.6
Fuel consumption	Lower	39026	39095	33101	33098
	Mean	39255	39338	33197	33158
	Upper	39484	39581	33293	33218

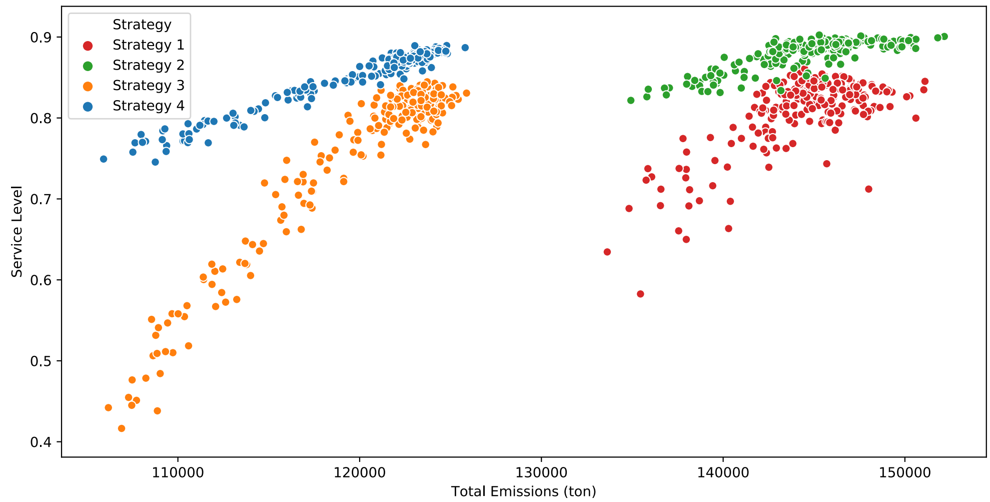

Fig. 9. Total emissions versus service level.

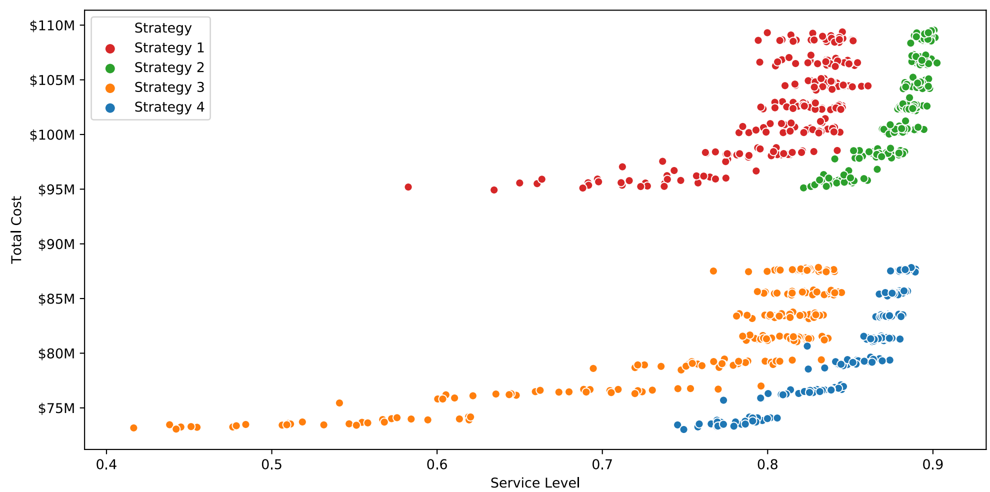

Fig. 10. Total cost versus service level.

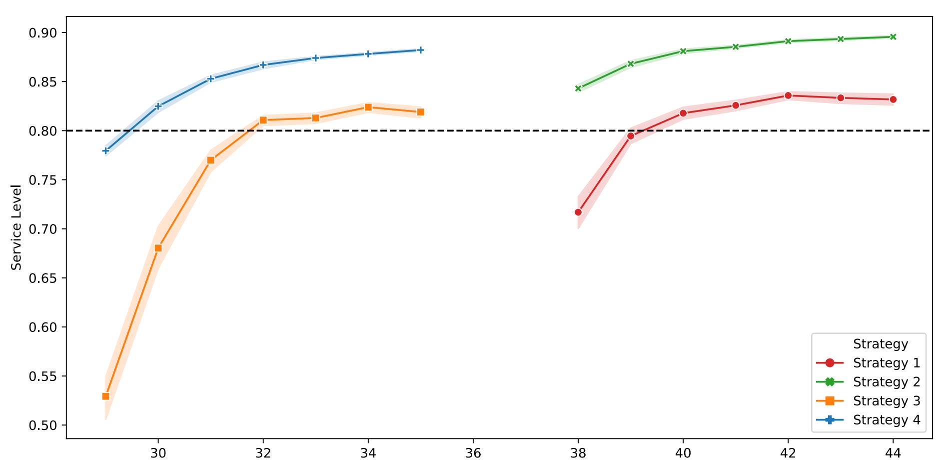

Fig. 11. Entire fleet vs service level.

diesel and water are the most important indicators of operation. The service level represents the capacity to cover the MU cargo deliveries before the due date. The occurrences of stockouts of diesel and water must have levels near zero to avoid the shutdown of the MU. Table 15 summarizes the simulation results for each indicator.

The use of optimization in strategies 2 and 4 to solve the allocation problem results in a consistent increase in the deck cargo service level compared to the results obtained using the FIFO rule in strategies 1 and

Table 16
Results of fleet size considering a service level of 80%.

		Strategy 1	Strategy 2	Strategy 3	Strategy 4
Service Level	Lower	81.12%	83.91%	80.54%	81.84%
	Mean	81.78%	84.31%	81.08%	82.48%
	Upper	82.45%	84.70%	81.62%	83.13%
	Cost	$79,200,000	$75,240,000	$63,360,000	$59,400,000
Fleet	PSV	31	29	32	30
	Oiler	9	9	0	0
	Total	40	38	32	30
Fuel Cost	Lower	$21,206,283	$20,403,650	$17,952,315	$16,989,270
	Mean	$21,341,696	$20,548,157	$18,006,926	$17,106,036
	Upper	$21,477,109	$20,692,664	$18,061,538	$17,222,802
Total Emissions	Lower	143,939	138,491	121,852	115,316
	Mean	144,858	139,472	122,223	116,108
	Upper	145,777	140,453	122,594	116,901

Table 17
Optimization model results.

Indicator	Disaggregated policy		Aggregated policy	
Optimized fleet size	33	30	33	30
Average Optimization time (s)	0.04	0.01	0.03	0.01
GAP (%)	0	0	0	0
Constraints	1915	953	1512	950
Variables	2904	1087	2028	1003
Simulation time (s)	193	101	156	105

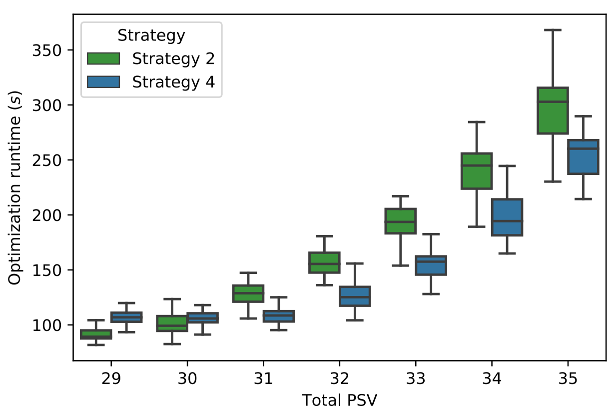

Fig. 12. Optimization computational time.

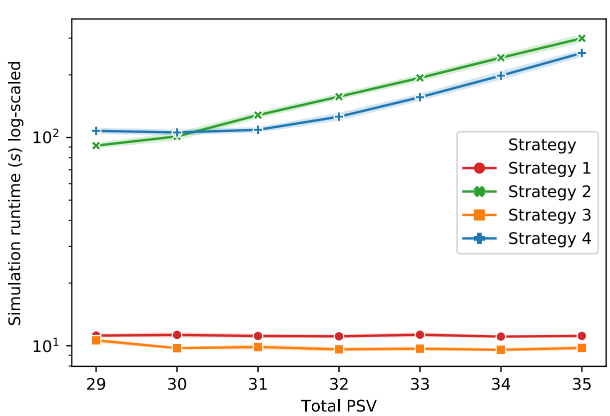

Fig. 13. Simulation computational time.

3. Simultaneously, a reduction in the lead time of the cargo on the deck, i.e., the time between order generation and its arrival at the client, is also representative, leading to an increase in the reliability of the operation.

The disaggregated policies achieve better results in terms of the deck cargo service level compared to the aggregated policies, using the same allocation strategy. The time saved during the diesel loading operations at the port and the MUs reduces the total operation time. Consequently, the deck cargo is delivered within a shorter period of time, thereby increasing the service level.

In all the scenarios, low mean occurrences of diesel and water stockouts are achieved, with the lower confidence level being zero. These indicators with values near zero ensure that the possibility of an MU ceasing operation because of a diesel or water shortage is remote.

Diesel tank idleness is a parameter that can only be evaluated in case of the aggregated fleet policy, because in the disaggregated fleet, none of the PSVs transport this type of product. In strategy 4, using the optimizer, tank idleness is almost three times greater than that using the FIFO rule in strategy 3. This gain suggests that the PSV fleet is traveling lighter and with lower amounts of stocked diesel. The reduction in the amount of diesel stocked in the PSVs is indicative of better management of the diesel resources at the port, with lower amounts of undelivered diesel being transported during each PSV trip.

The total fuel consumption of the entire fleet does not vary with the allocation strategy and is only dependent on the fleet policy adopted. Owing to a smaller fleet, the aggregated policies attain a reduction of ~20% in fuel consumption as compared to the disaggregated policies.

5.3. Managerial insights

In actual scenarios, the conclusions of a decision maker based on the available information are highly important. We select three KPIs to assist managerial choices.

- Service level: We define it as the percentage of the cargo delivered on time. The objective is to achieve the minimum acceptable level defined in an agreement or a level that ensures client satisfaction.
- Greenhouse emissions: We consider two primary greenhouse gases for this analysis: carbon dioxide (CO_2) and sulfur dioxide (SO_2). We use a conversion rate of 3.17 for CO_2 and 1.184 for SO_2, from a ton of diesel to a ton of gas. The objective of most companies is to minimize the emissions of greenhouse gases, as this is currently a sensitive topic.
- Operational cost: It is composed of the charter fleet cost and the consumed fuel cost. The goal of a company is to reduce the operational cost. We consider a charter fee of 11,000.00 USD per day, which is the average of the costs stated by Daleel Oil and Gas Supply Chain Portal (2018). For the fuel cost, we considered an expense of 2.06 USD per cubic meter of diesel, based on the average of daily

prices in 2018, calculated using data from U.S. Energy Information Administration (2020).

From this perspective, the proposed framework allows the analysis of these indicators for different fleet sizes for each strategy, yielding a confidence interval that suggests robustness in the analyses. The trade-off between service level and emissions is presented in Fig. 9, where an increase in the service level leads to an increase in greenhouse emissions. When strategies 3 and 4 with the aggregated fleet policy are used, there is a substantial reduction in emissions. The optimization leads to an increase in the service level, while maintaining emissions at the same level.

The results for similar analyses of the service level and the operational costs are shown in Fig. 10. An increase in the service level leads in an increase in the operational cost, charter cost, and fuel consumption. Using the aggregated fleet policy provides a significant cost reduction. In addition, using the optimizer can lead to improved service levels, while maintaining the same cost as the FIFO. Moreover, strategy 4 dominates over the others.

Fig. 11 illustrates the evolution of the service level with the changes in fleet size. As mentioned previously, a smaller fleet leads to a lower service level. Therefore, we need to stipulate a minimal service level. Considering a hypothetical service level of 80%, the fleet sizing results for each strategy are listed in Table 16 along with the managerial indicators and their confidence intervals. Table 16 summarizes the results observed thus far. Strategy 4 operates at the same service level using the smallest fleet size, thus reducing the operational cost and emissions.

These results inform the decision maker that strategy 4 is superior to the others and that efforts pertaining to its implementation should be implemented. It is necessary to note that, during real operations, additional aspects need to be considered, such as contractual issues and process change management. These aspects can have a significant impact on cost and operational flexibility, which are beyond the scope of this study.

5.4. Framework overview

The simulation induced instances for the optimization model are described on Appendix B. Note that, on this table, we refer only to the number of PSVs available for allocation on model, i.e. the vessels at the anchor area near the port. In addition, on this table, we calculate the computational time as the sum of the time required for both model construction and solution.

To evaluate the performance and viability of this optimization methodology and its interaction with the discrete-event simulator, we selected five indicators that could provide an overview of the optimizer and its actions.

Optimality gap (i.e., the difference between the current upper and lower bounds divided by the best bound and expressed in percentage) and optimization time were used to evaluate optimization performance. The number of constraints and the number of variables provide an estimate of the problem size. The simulation time reflects the interaction with the discrete-event simulator; it is the sum of the simulation time and the time for all optimization processes.

Table 17 lists the optimization indicator results for fleets with 33 and 30 PSVs operating in the port with strategies 2 and 4. Note that, different from Appendix B, the fleet on Table 17 considers the whole fleet (both PSVs available in anchor area and those unavailable performing any other activity). In addition, in this case, the optimization time only accounts the time needed to obtain model solution.

An analysis of Table 17 indicates the efficiency of the optimizer. Although the problem has numerous constraints and variables, it can typically reach the optimal solution within a short computational time, ensuring feasible application in actual industrial practices.

It is necessary to observe the computational times because the optimization is implemented repetitively, i.e., 48 times per week. In Figs. 12 and 13, we present the computational times achieved using our framework. Even in the worst case scenario, the replication time is less than 300 s for strategies using the optimizer for allocation, as compared to the time of less than 12 s for strategies using FIFO to perform allocation. For a smaller fleet, the problem size decreases, thereby expediting the optimization–simulation framework.

6. Conclusion

In this paper, we presented a tool integrating optimization with simulation in order to represent upstream logistics operations in Brazil. Using this tool, we could mimic current operations, combining a disaggregated fleet policy and the FIFO strategy for cargo selection at the port. In addition, we proposed new scenarios considering the aggregated fleet policy and the use of the optimization model for vessel selection and cargo allocation at the port.

Using this tool, we could assess the impacts of new policies on important operational cost indicators: service level and greenhouse emissions. Particularly, the proposed framework provides important highlights regarding the effects of each policy on the trade-off between fleet sizing and KPIs; this information is expected to enable decision makers to choose the best alternative based on the objectives of companies in different areas.

As a general conclusion for policy selection, it can be stated that transporting multiple types of cargo in the same supply vessel is feasible, because we can significantly reduce operation costs and the emissions of greenhouse gases, while maintaining a high service level of cargo delivery. In addition, the coupled allocation–optimization approach guarantees gains in the service level for the same fleet size. Although employing optimization as an internal process of the simulation system increased the execution time from a few seconds to a few minutes, the gain in the quality of the solution was significant.

Therefore, we could achieve the previously stated objectives of this study. We constructed a framework integrating simulation with optimization for assisting decision-making procedures in upstream logistics. In addition, this framework helped us comprehend the Brazilian oil & gas logistics scenario, which has not been studied extensively. In addition, we developed an optimization model for cargo allocation and vehicle selection at the port, which was embedded in the simulation framework; however, this model can also be used alone for daily operations. Finally, we believe that the discussions presented herein contribute toward clarifying managerial aspects of the problem.

The theme addressed in this study is broad and challenging. Through this paper, we introduced different aspects and approaches that can be topics of future research and development. We highlight the following: evaluation of the loading operations for fluids and cement; including multiple ports; considering seasonal weather conditions that influence fleet speed; and system optimization to improve the operation time for better fleet management and scheduling of routes and ports, supporting planning, current system focus, and scheduling. From a methodological perspective, addressing this problem via stochastic optimization is a prospective research direction.

CRediT authorship contribution statement

Gustavo Cunha de Bittencourt: Methodology, Software, Writing – original draft. **Rennan Danilo Seimetz Chagas:** Methodology, Software, Writing – original draft, Visualization. **Victor Anselmo Silva:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data Curation. **Igor Girão Peres Vianna:** Software, Writing – original draft, Investigation, Visualization. **Rafael Pedro Longhi:** Software, Writing – review & editing. **Paulo Cesar Ribas:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data Curation, Supervision. **Virgílio José Martins Ferreira Filho:** Conceptualization, Supervision, Project administration, Funding acquisition.

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Appendix A. Statistical distributions used in simulator

Table A.18.

Table A.18
Statistical distributions used in simulator.

Component	Event	Distribution	Comments
MU	Diesel consumption	Uniform	Each MU has different consumption possibilities. Everyday, one of these values is randomly selected
MU	Diesel loading flow	Triangular, Beta, Uniform	Distribution depends on volume
MU	Water consumption	Inverse gamma, Weibull, Uniform, Beta prime, Beta	Each MU has distribution
MU	Water production	Beta prime, Weibull, Beta, Triangular, Uniform, Inverse Gamma, Normal	Each MU has distribution
MU	Water loading flow	Triangular	–
MU	Deck cargo demand	Uniform, Beta, Weibull, Triangular, Normal, Gamma, Beta prime, Lognormal	Each MU has a distribution
MU	Backload cargo generation	Beta, Beta prime, Gamma, Weibull, Uniform, Triangular	Each MU has distribution
MU	Handling rate of deck and backload cargo	Uniform, Inverse gamma, Beta prime, Wald, Lognormal, Normal	Distribution depends on quantity of cargo and MU's type
MU	Necessity of PSV to wait for start of operation	Percentage	Probability depending on MU type, of the event occurrence
MU	PSV waiting time until start of operation	Beta prime, Lognormal, Weibull	Distribution depends on MU type
MU	Necessity of oiler to wait for start of operation	Percentage	Probability of event occurrence
MU	Oiler waiting time until start of operation	Lognormal	Distribution depends on type of MU
PSV/Oiler	Navigation speed in case of short distance	Normal	–
PSV/Oiler	Navigation speed in case of long distance	Weibull	–
PSV/Oiler	Probability of innoperance occurrence	Percentage	Probability of event occurrence
PSV/Oiler	Innoperance time	Lognormal	–
PSV/Oiler	Docking time	Beta Prime	–
Oiler	Crew change time	Triangular	–
Tank ship	Necessity to wait for start of operation	Percentage	Probability of event occurrence
Tank ship	Waiting time until start of operation	Beta	–
Tank ship	Diesel Loading flow	Weibull, Uniform	Distribution depends on volume
Berth	Diesel loading flow	Uniform	–
Berth	Water loading flow	Uniform	–
Berth	Handling rate of deck and backload cargo	Normal	–

Appendix B. Optimization model instances characterization

Table B.19.

Table B.19
Descriptive summary of instances used on optimization experiments.

PSVs	Calls	Number of MUs			General cargo requests			Diesel requests			Water requests			cpu (s)		
		min	mean	max	min	mean	max	min	mean	max	min	mean	max	min	mean	max
1	24	3	3.79	5	32	57.17	90	0	324.58	1146	0	40.79	374	0.02	0.02	0.03
2	33	6	7.42	11	56	109.94	164	0	375.03	1562	0	141.30	712	0.02	0.03	0.05
3	101	9	11.36	16	98	166.60	228	0	842.65	2939	0	221.67	1133	0.02	0.04	0.08
4	162	12	15.57	20	126	219.00	287	0	1064.73	3210	0	398.27	1599	0.03	0.06	0.11
5	215	15	19.66	24	153	271.56	385	0	1303.26	3764	0	508.14	1858	0.05	0.08	0.19
6	210	18	23.65	29	235	322.02	481	0	1669.91	4452	0	642.56	1989	0.06	0.11	0.27
7	199	21	28.27	34	278	367.68	491	210	1905.65	4649	0	834.09	2263	0.08	0.15	0.33
8	145	24	32.52	39	308	416.37	563	496	2070.90	4616	0	1008.99	2623	0.11	0.20	0.63
9	56	27	36.09	42	317	440.57	581	871	2303.25	4945	0	1095.62	2586	0.12	0.24	0.62
10	21	30	41.38	46	370	522.33	658	1224	2689.48	4943	0	1602.62	2723	0.15	0.34	0.62
11	5	41	45.20	51	468	567.40	644	1807	2502.60	3717	1086	1719.60	2649	0.31	0.47	0.69
12	6	39	43.67	54	567	647.33	692	1222	2281.67	3177	0	888.00	2612	0.36	0.40	0.42
13	3	45	51.33	57	567	667.33	760	1795	2347.67	2953	536	1557.00	2501	0.56	0.61	0.69
14	3	57	58.67	60	839	871.00	906	2843	3103.67	3330	2263	2384.67	2464	0.63	0.81	0.97

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