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Research Article

Disruption Management Approaches for Berth Scheduling in Bulk Terminals

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Maritime terminals are complex transportation systems sensitive to several sources of uncertainty. An alteration in the baseline planning, as a consequence of one or more disruptive events, can lead terminals to a lower quality of the service provided. Therefore, in a context where a terminal strives to maintain or increase competitiveness, it is necessary to consider the uncertainty in the planning and define actions capable of efficiently and effectively mitigating disruptive events. This paper addresses berthing operations at bulk terminals, considering the arrival and handling times as stochastic variables. Hybrid approaches (i.e., proactive-reactive) are proposed in order to provide the port terminal with robust planning capable of reducing the impact of disruptive events by defining uncertainty-tolerant schedules and reactive actions capable of restoring the performance of the terminal when disruptive events arise. Finally, the solution approaches are evaluated together with and without the incorporation of buffer-time management. The computational results corroborate the effectiveness of integrating proactive and reactive approaches in order to maximize the performance of the terminal and reduce the penalty costs derived from alterations in the baseline schedule, with the consequent increase in the terminal competitiveness.

1. Introduction

International freight transport plays an important role in the development and consolidation of important economic sectors such as commerce, industry, or tourism. In this context, the competitiveness and efficiency of maritime ports are essential for the economic and social progress of the regions. A port can be represented as a system, which we refer to as a port system, made up of subsystems or interrelated elements. The nature and granularity of the representation are closely related to the level of detail required and the operational performance of the port. In a port, three clearly defined areas are identified that are related in a complex way to each other: the seaside, the yard/storage area, and the landside.

In this work, we focus the attention on the operations that take place at the seaside of a port and, particularly, on the berth allocation problem (BAP). The purpose of this problem is to assign position and berthing time to each of the vessels that arrive at a maritime terminal, trying to optimize a given objective function. In the scientific literature, we find a wide variety of berth allocation problems, attending mainly to three dimensions, namely, space, time, and cargo. According to the given spatial configuration of the port, the BAP can be continuous, discrete, or hybrid. Considering the temporal dimension, the BAP can be static, dynamic, or time-dependent. Finally, depending on the type of cargo, the BAP can consider bulk freight, containers, or multipurpose. We refer the reader to the survey by Bierwirth and Meisel [1] to study the different variants of the berth allocation problem.

In this work, we address the berth allocation problem in bulk ports (Bulk-BAP) as proposed in Umang et al. [2]. Similarly as in that work, several research papers that solve berth allocation problems consider the input data to be deterministic, and thus, the generated berthing schedules do not take into account stochastic events that may appear and affect those schedules. In real environments, there are many sources of uncertainty (e.g., available information, mechanical failures in facilities and handling material, late arrivals, weather conditions, etc.) [3–5] that can affect to a greater or lesser degree the performance and productivity of the port. Therefore, uncertainty needs to be considered in order to minimize the impact of such stochastic events on the terminal's performance. When the berth allocation problem is solved under realistic scenarios in which disruptive events can occur during the planning horizon, both proactive and reactive approaches can be considered. Proactive approaches have been proposed for the BAP considering stochastic arrival and handling times. Most of them have been applied in container terminal environments (e.g., [3, 5–9], etc). In bulk environments, de León et al. [9] is the only recent work addressing the Bulk-BAP from a proactive point of view. Reactive algorithms are used to handle disruptive events that occur during the planning horizon. The unique work addressing the Bulk-BAP from a reactive perspective is the one proposed by Umang et al. [4], which considers uncertainty on arrival and handling times through probability distributions.

With the purpose of solving the Bulk-BAP under stochastic and dynamic conditions, in which disruptive events can occur during the planning horizon, we propose a hybrid approach combining proactive and reactive approaches to handle stochastic arrival and handling times. In the first place, the proactive approach allows obtaining baseline schedules that take into consideration the variability in the input deterministic data by simulation optimization. When these schedules are implemented in real-time, disruptive events that modify either the handling times or the arrival times of the vessels may occur. In this situation, a reactive approach based on reoptimization adapts the existing solution to deal with the observed disruptions.

Therefore, the main contribution of this paper is the design and analysis of a hybrid approach that combines a proactive phase and a reactive phase to cope with uncertainty in the vessels' handling and arrival time within the Bulk-BAP. To the best of our knowledge, this is the first proactive-reactive optimization approach presented for the Bulk-BAP that combines a proactive simulation-optimization approach with an event-based reactive rescheduling algorithm. The computational results obtained indicate that the hybrid approach allows the bulk port to maximize benefits through efficient management of available resources and, at the same time, to reduce those risks that may negatively influence the quality of service, with its consequent economic penalties and loss of competitiveness.

The rest of the paper is organized as follows. Section 2 presents a comprehensive literature review. Section 3 describes the bulk berth allocation problem. Section 4 describes the solution approaches proposed in this work to solve the problem. The numerical experiments are discussed in Section 5. Finally, Section 6 presents the conclusions together with future research lines.

2. Literature Review

The berth allocation problem aims at assigning positions and berthing times to arriving vessels at a maritime terminal with the aim of optimizing a given objective function (e.g., makespan, the sum of vessels' waiting time, costs, etc.). As such, the BAP has been extensively studied in the literature [1] due to its impact on terminals' performance. The BAP presents different variants grouped into three main groups, namely, space, time, and cargo. Within the spatial restrictions, the quay can be considered (i) discrete: the quay is divided into equal sections called berths [10–13], (ii) continuous: the quay is treated as a continuous section allowing vessels to berth at any point within it [14, 15], and (iii) hybrid: the quay is divided into sections enabling a vessel to occupy more than one section [2, 11]. Moreover, concerning temporal restrictions, the BAP can be treated as (iv) static: all the vessels are at the terminal when the planning is going to be conducted [16], (v) dynamic: the vessels arrive along the planning horizon [11, 17], and (vi) time-dependent: the availability of the berths changes along the time horizon [18, 19]. Regarding the planning level, the BAP can be distinguished as operational (e.g., [11, 17]), tactical (e.g., [20, 21]), or strategic (e.g., [22, 23]). Lastly, depending on the type of cargo, the BAP can consider either bulk, containers, or multipurpose. In this work, we address the Bulk-BAP as proposed in Umang et al. [2]. Given the fact that our work proposes a hybrid proactive-reactive approach for solving this problem, the scope of this literature review is limited to those papers that solve the Bulk-BAP or related problems and consider proactive and reactive approaches. works addressing

From a deterministic problem perspective, Umang et al. [2] propose the Bulk-BAP considering a hybrid quay layout that divides the quay into sections and where each section can only be occupied by a vessel at each instant of time, but a vessel can occupy more than one section. Regarding temporal constraints, the Bulk-BAP is included in the dynamic variant category. The BAP in bulk ports is also studied in [24]. The authors propose a mixed-integer linear program (MILP) model considering maintenance, demurrage, and dispatch values for handling the vessels and an adaptive large neighbourhood search (ALNS) that yields good solutions on a set of instances based on real data. The research work [25] addresses the continuous BAP in order to minimize delays in a bulk terminal taking into account tidal constraints. Two MILP models are proposed, one based on the sequence variables and the other based on time-indexed variables together with a two-phase method in order to enhance the performance of this model. Finally, in [26], a framework for integrating berth allocation and vessel unloader allocation is provided. Two different approaches are proposed, one solves the problems by solving them sequentially, and the other solves both problems simultaneously. A chemical reaction optimization algorithm is proposed to solve the second phase of a sequential approach, and a genetic algorithm is used to solve the first phase of the sequential approach and the integrated approach.

Proactive approaches have been proposed for the BAP considering stochastic arrival and handling times. The majority of them have been applied in container terminal environments (e.g., [3, 5–8], etc.); for a larger literature review on this, the reader is referred to de León et al. [9]. Furthermore, in bulk environments, to the best of our knowledge, the work by de León et al. is the only one that recently addresses the Bulk-BAP. It considers uncertainty in handling and arrival times as well as the inclusion of buffers. The authors proposed a novel variant of a simulation-based optimization framework using metaheuristics (i.e., simheuristics, [27]). Namely, they jointly consider the deterministic and stochastic objectives through a multiobjective approach based on nondominated sorting genetic algorithm II (NSGA-II) [28]. Finally, the authors investigate the proposed algorithms to dynamically manage specific buffer times per vessel to increase the robustness of the proposed solutions. Results indicate that the novel simheuristic scheme provides better solutions than the standard simheuristic. On top of the benefits of incorporating buffers, the authors show that the dynamic management strategy (i.e., buffers vary during the search process) overcomes the static one.

The number of reactive approaches for the BAP, when compared to proactive approaches, is much more limited. Also, similarly, as with proactive approaches, the majority are applied in container terminal environments (see, e.g., [29–31]). The unique work addressing the Bulk-BAP from a reactive perspective is the one proposed by Umang et al. [4]. In that work, the authors consider uncertainty on arrival and handling times through probability distributions. With the objective of minimizing the cost of scheduling, they propose a reactive approach for the real-time rescheduling of vessels in case of disruptive events and new information. They develop two recovery algorithms to reschedule before the occurrence of disruptive events, one based on the optimization model and the other based on a greedy method. To assess the robustness of the proposed solutions, each solution is subjected to 100 disruptive scenarios. The reported results indicate that although the optimization-based method outperforms the other heuristic approaches in terms of vessels' waiting time, the greedy method performs better in terms of adherence to the originally planned schedule.

Reactive algorithms are commonly used to cope with improbable and unexpected variations or events. Depending on the application domain, their response time might be limited to a very short time frame. Because of that, it is relevant to combine such approaches with proactive ones that already contain some built-in flexibility. Although there are no approaches that jointly consider both offline (proactive) and online (reactive) planning in bulk berth scheduling, there are a few proposed for container terminals (i.e., [32–34]). Those works share in common that they generate a baseline schedule proactively and, for all possible scenarios (known in advance), the best recovery plan. As indicated in [33], this type of approach requires scenario information that in some real-environment is hard to obtain due to a lack of data. This also presents a shortcoming when the data is not shared within the same platform or is stored in a different form.

Considering the above literature review, the main contribution of this work is the combination of a novel approach that considers baseline schedules proactively generated via simulation-optimization adapted from [9] and a reactive approach that is based on reoptimization that permits coping with events during the realization of the planning. The strategy to face events is, thus, event-based and not scenario-based. That is, all possible scenarios are not known in advance. Thus, to the best authors' knowledge, this is the first proactive-reactive optimization approach for the Bulk-BAP and, if applied in container terminal contexts, the first one combining a simheuristic-based proactive approach with reactive reoptimization strategies for the berth allocation problem.

3. Bulk Berth Allocation Problem

The bulk berth allocation problem (Bulk-BAP) [2] models the berth scheduling operations at bulk terminals where the objective is to minimize the total service time of the vessels that arrive there within a well-defined planning horizon. For this, it is necessary to define a feasible schedule that establishes the berthing position and time for each incoming vessel. A schedule is considered feasible as long as it satisfies the time and space constraints described below.

Considering space constraints, the quay layout corresponds to a hybrid layout in which the quay is divided into well-defined sections and where a vessel can occupy more than one section if necessary. However, two vessels cannot occupy the same section at the same time, even if there is no overlap between them. In addition, there are restrictions associated with berthing a vessel in a specific section depending on the type of cargo being transported. This is because each type of cargo requires specific facilities (mobile and fixed) for processing. In this regard, both the quay and the yard have specific characteristics to adapt to the processing of different types of cargo. First of all, several storages are distributed across the yard depending on the type of cargo. Secondly, each section of the quay is associated with a set of facilities for cargo processing. For this reason, a vessel may only be berthed in a section that has the necessary facilities to process its cargo. As cranes are mobile facilities (available across the quay), there are no berthing restrictions for cargo vessels in need of the said facility. However, there are fixed facilities that are only available in a subset of the quay sections, that is, pipelines and conveyors. This is why berthing is limited to sections where these facilities are available if cargo processing requires pipelines or conveyor belts. On the other hand, taking into account the time constraints, the Bulk-BAP is considered dynamic, as vessels can arrive at any time within the planning horizon.

Formally, the Bulk-BAP defines a quay with length, L, that is divided into a heterogeneous set of m sections, $M = \{1, \ldots, m\}$, and where a set of n vessels must be berthed, $N = \{1, \ldots, n\}$. As previously stated, each section has associated characteristics such as the number of available cranes, the type of cargo it can process, and its location and dimensions on the quay, among others. In addition, each vessel carries a quantity and type of cargo, has an estimated time of arrival, and has its own physical characteristics (e.g., length of vessel), among others. Finally, the deterministic objective of the Bulk-BAP is to minimize the total service time, which is defined in equation (1), where m_i, ETA_i, and c_i represent the service start time, arrival time at the terminal, and handling time for vessel $i \in N$, respectively. For further information about the constraints and modelling of the Bulk-BAP, it is recommended to consult the paper by Umang et al. [2].

$$f(s) = \sum_{i=1}^{|N|} (m_i - ETA_i + c_i). \quad (1)$$

The assumptions and constraints contemplated in the Bulk-BAP are the following:

(i) Each vessel $i \in N$:

(1) can only be berthed after their arrival at the port.
(2) can occupy more than one section $k \in M$.
(3) can only carry a single type of cargo.
(4) can only be assigned to one starting section.
(5) starting at section $k \in M$ cannot exceed the length of the quay.
(6) can only be berthed in a compatible section $k \in M$.
(7) cannot be reallocated once it has been berthed.
(8) is allowed to berth before its scheduled berthing time.

(ii) The vessel length implicitly considers safety margins to avoid overlapping between vessels. Similarly, handling time includes berthing and unberthing time.

(iii) The vessel's handling time depends on the sections where the vessel is berthed.

(iv) Each section $k \in M$ can only be occupied by a vessel $i \in N$ at the same time.

(v) Capacity restrictions in the yard are not considered.

(vi) Resources (e.g., handling equipment, facilities, or workforce) are considered to be available at the terminal.

(vii) Expected arrival and handling times are known in advance.

Figure 1 illustrates a simplified example of the Bulk-BAP showing the two areas that make up the terminal, that is, the yard and the quay. In this example, only two storages are in the yard for different types of cargo: (i) oil and (ii) grain. The quay is divided into three sections where five vessels are berthed. Section 3 has pipelines to process liquid cargo, while the other sections do not have fixed facilities. In relation to the cargo carried by the vessels, vessel 1 is transporting oil, while the other vessels are carrying grain. Taking into account the constraints stated above, vessel 1 can only berth in Section 3, while the other vessels can berth at any section of the quay (including 3, see vessel 5). Finally, Section 2 cannot be occupied by vessel 2, while vessel 3 is still berthed there, although it could do so without there being an overlap between the vessels.

The description above corresponds to the Bulk-BAP under deterministic conditions. Under these conditions, the problem parameters or the variables calculated from them (e.g., handling time) do not undergo any type of alteration after solving the problem. However, if during the realization of the schedule, the terminal undergoes any type of alteration; then the environment is stochastic; and thus, the deterministic solution has to be revised.

3.1. Bulk Berth Allocation Problem under Stochastic Conditions. In real environments, the vessels or terminal information may experience variations due to the appearance of disruptive events or information updates during the planning horizon, for example, facilities breakdown, unexpected increase in terminal congestion, or updated information regarding the time or physical characteristics of a vessel (e.g., late arrival, change of workload, etc.). In literature, it is possible to observe that the uncertainty in berth operations is usually modelled by defining the estimated time of arrival and the handling time of the vessels as stochastic variables. In addition, it is also observed that the probability distributions vary between the research papers, as they must be extracted from the historical data of the port. Therefore, this paper uses the probability distributions defined by Umang et al. [4] after his observations at Saqr Port, Ras Al Khaimah, United Arab Emirates (UAE). Specifically, the estimated time of arrival follows a uniform distribution in the range $[ETA_i - \delta, ETA_i + \delta]$, where δ defines the level of uncertainty. Regarding the handling time of the vessels, a truncated exponential distribution is defined in the interval $[H_{ik}, \gamma H_{ik}]$, where H_{ik} and γ represent the handling time of vessel i berthed at section k and the level of uncertainty, respectively.

Based on these probability distributions, it is possible to define a disruptive scenario for a specific instance of the Bulk-BAP. An example is presented below showing how a disruptive scenario disturbs the baseline schedule if no decision is made. That is, the vessels are not reallocated in other sections; the order in which they are berthed in the sections is not modified; and they cannot be berthed before the scheduled berthing time. Table 1 defines the disruptive scenario, showing for each vessel the estimated (ETA) and current (ATA) arrival time, as well as the estimated (EHT) and current (AHT) handling time. There are vessels that arrive at their ETA (vessels 1 and 5), vessels that arrive earlier (vessel 2), or vessels that arrive later (vessels 3 and 4). In addition, there are vessels with a handling time longer than the scheduled time (vessels 1 and 2). Finally, the number in parentheses indicates the exact time at which the disruptive event occurs. Figure 2 shows how the baseline schedule is disturbed by the events defined in Table 1 until the end of the service at the time $t = 13$. Therefore, after starting the planning horizon, at $t = 0$, vessel 1 is at the terminal and is berthed according to the baseline schedule, but vessel 3 is delayed and its new estimated time of arrival is at time 2. At $t = 1$, the arrival time of vessel 2 is updated, which arrives at

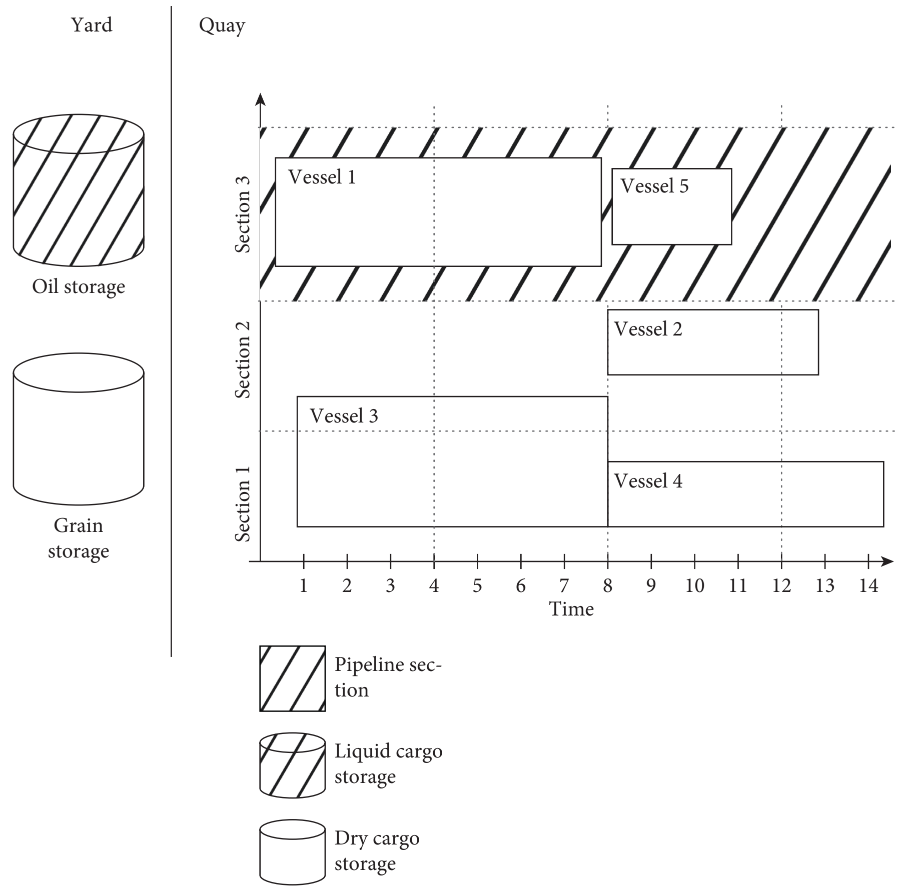

FIGURE 1: Example solution for Bulk-BAP with five vessels and three sections.

TABLE 1: Example of disruptive scenario.

Vessel	ETA	EHT	ATA	AHT
1	0	5	0	6 (updated at $t = 2$)
2	6	5	1 (updated at $t = 1$)	6 (updated at $t = 9$)
3	0	5	2 (updated at $t = 0$)	5
4	2	5	7 (updated at $t = 5$)	5
5	5	5	5	5

the terminal at the same time. It should be recalled that although Section 2 is free due to the delay of vessel 3, vessel 2 must wait for vessel 3 to be berthed and finish being processed so that the baseline schedule is respected. At $t = 2$, a disruptive event occurs that increases the handling time of vessel 1, and vessel 3 is berthed. Due to the delay of vessel 3 and the increased handling time of vessel 1, it is necessary to modify the schedule of vessels 2, 4, and 5 so that no overlappings occur. Disruptive events continue to occur until the end of service at $t = 13$. At this point, it is possible to observe how the final schedule has been disrupted and how it differs from the baseline one.

Given that a baseline schedule can be altered after the appearance of disruptive events, and before conducting recovery actions, it is necessary to define the constraints to be considered to properly take them. In this paper, a vessel is allowed to advance its scheduled berthing time without incurring penalties, since the resources are considered to be available at the terminal. However, a penalty is incurred when a vessel is reallocated in another section, derived from the cost of moving material and human resources along the quay. Under this context, the following equation [4] is defined as the objective function used to evaluate the performance of the realized schedule s' with respect to the baseline schedule s:

$$f(s,s') = \sum_{i=0}^{|N|} \left(m_i^{s'} - ETA_i^{s'} + c_i^{s'} + \left| g_i^{s'} - g_i^{s} \right| \cdot c_1 \right). \qquad (2)$$

The objective function defined in equation (2) receives as input the baseline schedule s and the realized schedule s' to be evaluated. The first three terms of the summation correspond to the vessels' total service time (see equation (1)), while the last term corresponds to the penalty cost, c_1, derived from modifying the berthing position g_i of vessel i with respect to the baseline schedule. This paper uses a penalty cost equal to 0.002.

4. Solution Approaches

Previous research (i.e., [9]) addressed the Bulk-BAP under uncertainty conditions through a purely proactive approach, which gives robust schedules capable of absorbing the impact of disruptive events on the performance of the terminal. In that paper, the schedule is generated before the planning

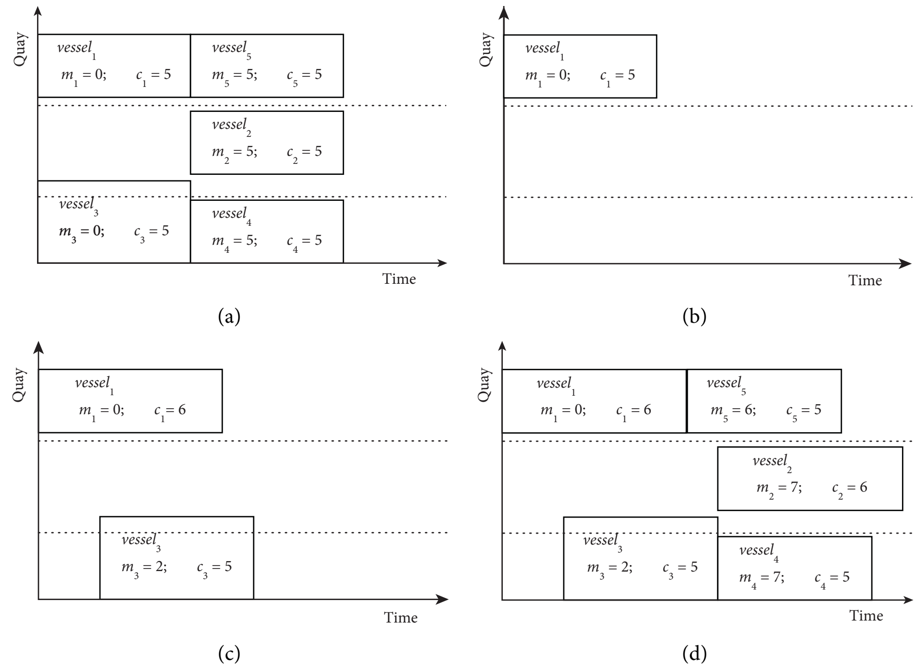

Figure 2: Evolution of baseline schedule under uncertainty conditions. (a) Baseline schedule. Solution makespan = 10. (b) Current schedule at $t = 0$. Unchanged with respect to the baseline schedule. (c) Current schedule at $t = 2$ where the handling time of vessel 1 is lengthened one time unit and vessel 3 is delayed two time units. (d) Current schedule at $t = 13$ where the service start time of vessels 2, 4, and 5 has been delayed due to events occurred at $t = 2$. Solution makespan = 13.

horizon begins, and it is not possible to make real-time decisions based on the new information obtained during the planning horizon.

However, the ability to alter the baseline schedule in the case of disruptive events is presented as an important strategy to increase the terminal's performance. In order to improve the results previously obtained, this paper proposes a solution approach that combines proactive and reactive approaches to manage uncertainty, that is, a hybrid approach. This hybrid framework is presented in Section 4.1. Subsequently, in Sections 4.2 and 4.3, the proactive and reactive phases are detailed, respectively. Finally, Section 4.4 describes the a posteriori approach used to obtain a lower bound against which to compare the hybrid approach.

4.1. Hybrid Reactive-Proactive Framework. The hybrid approach proposed in this work considers two phases, that is, before and during the realization of the schedule. Namely, before the planning horizon begins, the baseline schedule is determined proactively by considering the uncertainty. On the other hand, the reactive phase is applied during the realization of the planning when unexpected events happen. This enables the real-time management of any disruptive events. This way, through jointly considering proactive and reactive approaches, the robust baseline planning can be adapted in real-time according to updated port data.

4.2. Proactive Phase. The proactive phase sets out to obtain a robust baseline schedule that considers uncertainty. To do so, the proposed solution approach described in our previous paper [9] is used, which included several proposals to proactively manage uncertainty in the Bulk-BAP. For this paper, the solution approaches based on the NSGA-II are used, since, in general terms, they outperform the other approaches. This multiobjective optimization algorithm provides a Pareto front by simultaneously optimizing the value of the objective function (see equation (1)) and the estimated penalty cost due to the delay in vessel departure. This estimated penalty cost is obtained by simulating disruptive events. Finally, we also studied the contribution of using buffer times during the proactive phase. Therefore, this paper studies the performance of the hybrid reactive-proactive approach when vessel-specific buffer times are considered during the planning.

4.2.1. Use of Buffer Times. Buffer times absorb the impact of disruptive events by reserving a section for a period of time, even if, based on the estimated or expected data, it is unused. This period of time means that if a vessel is delayed or its handling time is lengthened, the rest of the schedule is not disrupted. See the example shown in Figure 3. Although the handling time of vessel 1 is lengthened and vessel 3 is delayed, the rest of the vessels continue to start being processed at the scheduled time due to the buffer times. See [9] for a detailed description of how the buffer time values are heuristically determined for each vessel and how they are integrated during the NSGA-II search process. It is necessary to consider that buffer times increase the robustness at the cost of underusing the terminal's resources, so its value must be chosen carefully.

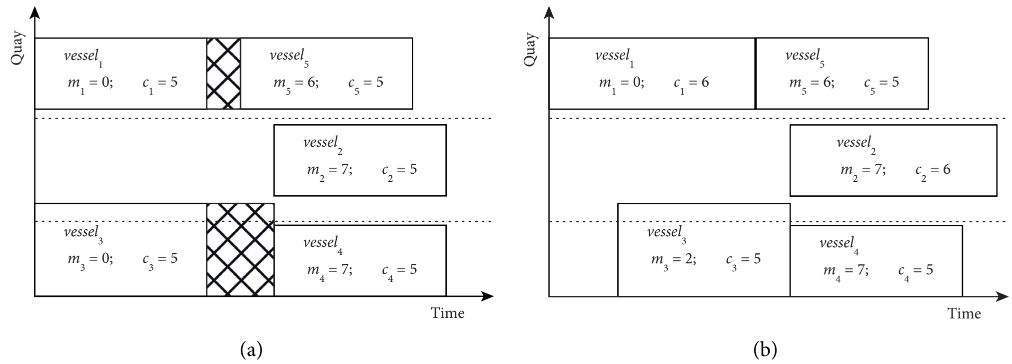

Figure 3: Example of baseline schedule with buffer times. (a) Baseline schedule where buffer time had been defined for vessels 1 and 3. Solution makespan = 12. (b) Current schedule at $t = 13$ where the handling time of vessels 1 and 2 is lengthened one time unit and vessel 3 is delayed two time units. Solution makespan = 13.

4.3. Reactive Phase. After completing the proactive phase, feasible planning is obtained and time begins to pass within the planning horizon. At this point, the reactive approach, based on the events that occur during the realization of the planning horizon, provides recovery or improvement actions that modify the baseline schedule provided in such a way as to minimize the impact of various disruptive events. It is necessary to consider that because the reactive phase is applied as soon as a new event happens, there are certain actions that might not be feasible. Specifically, at time t, it is not possible to modify the decisions taken before said moment (e.g., at time $t = 10$, it is not possible to modify the berthing position of a vessel berthed at time $t = 0$). Likewise, disruptive events are not known in advance but appear during the course of the planning horizon. Therefore, it is necessary to have metrics capable of evaluating the deviation from the baseline schedule and the impact of disruptive events on the terminal. With this objective, the following metrics are used in this paper: (*i*) penalty cost due to the delay in vessel departure with respect to the baseline schedule, (*ii*) the objective function $f(s, s')$ defined above in equation (2), and (*iii*) deviation ratio with respect to the baseline schedule.

4.3.1. Reactive Phase Metrics

(1) Penalty Cost due to Delay in Vessel Departure with Respect to the Baseline Schedule. Several papers in literature [35–37] define the vessels' departure delay from the terminal with respect to the baseline schedule as a metric of the terminal's performance under stochastic conditions. Given a baseline schedule s and the realized schedule that was finally carried out s', the calculation of the total delay in vessel departure is performed by Algorithm 1. In line 3, the departure delay of vessel $i \in N$ is calculated, where m_i^s and c_i^s represent the service start time and the handling time in the schedule s, respectively. Ocean carriers may impose financial penalties as a consequence of a deviation from the agreed service [38]. In this sense, it is possible to obtain the penalty cost due to the delay in vessel departure by multiplying the total delay returned by Algorithm 1 by a penalty cost (see equation (3)). This paper uses a cost of $\Gamma = \$800$ per unit of time of delay [37].

$$h(s, s') = \text{delay}(s, s') \cdot \Gamma. \tag{3}$$

(2) Deviation Ratio with Respect to the Baseline Schedule. During the proactive phase, two objectives are used to guide the search process: (i) the deterministic objective function value and (ii) the estimated penalty cost due to the delay in the vessel departure. After completing the proactive phase, the decision-maker obtains a Pareto front and chooses the schedule that best suits the needs of the terminal. Due to the simulation component, the decision-maker obtains a metric that tells them the penalty cost that would be expected for the selected schedule. Once the planning starts, it is possible to make decisions that modify the baseline schedule based on the new information available. These decisions should, as far as possible, maintain or improve the performance and penalty expectations associated with the selected baseline schedule. This way, the goal is to reduce the ratio deviation between the baseline schedule and the realized one. In this paper, given a baseline schedule s and a realized schedule s', the deviation ratio is calculated according to the following equation:

$$\text{deviationRatio} = \left(f(s, s')/fS\right) + \left(h(s, s')/hS\right). \tag{4}$$

In equation (4), it can be seen that the deviation ratio is calculated from the sum of two terms: (i) ratio of the value of the objective function and (ii) penalty cost ratio. In that equation, $f(s, s')$ and $h(s, s')$ represent the value of the objective function (see Section 3.1) and the penalty cost (see Section 4.3.1) of schedule s' with respect to the baseline schedule s, respectively. Moreover, fS represents the value of the deterministic objective function of the baseline schedule, while hS represents the average penalty cost resulting from the simulation of the baseline schedule. The goal of using ratios is to achieve the following:

(i) During the reactive phase, a multiobjective approach is not followed, so both objectives are added together to obtain a single objective with which to guide the process. By adding the ratios, instead of the original values, the goal is to reduce the problems derived from the scale of the metrics. This respects the decision-maker choice and does not ignore any of the objectives used during the proactive phase.

(ii) If it is improved, the ratio will be less than 1, which means that the search process can be guided towards higher-quality solutions. On the other hand, if the ratio is greater than 1, it suggests that there has been a deterioration compared to the baseline schedule.

Finally, by means of the procedure set out in Algorithm 2, it is possible to use this metric to evaluate the realized schedule so far s'. The algorithm receives as input the baseline schedule s, the value of the deterministic objective function fS for baseline schedule s, the estimated penalty cost hS for baseline schedule s, the realized schedule s', and the current time t. The first operation of the algorithm is to obtain a new schedule s'' from the realized schedule so far s' (line 1). This means that all vessels not yet berthed will be berthed according to the baseline schedule s in terms of berthing order (lines 2–6). That is, in the event of overlapping when trying to follow the baseline schedule s, the berthing time of the vessel will be modified to avoid such overlapping. It is relevant to indicate that the berthing section is never modified, nor will it be possible to berth before the current time t. The algorithm ends by returning the deviation ratio (line 7).

4.3.2. Reactive Rescheduling-Based Approach. The reactive phase considers a reoptimization strategy that evaluates possible changes as soon as new events appear. Algorithm 3 depicts the proposed reoptimization procedure. It receives as input the schedule generated in the proactive phase s as well as the value of the deterministic objective function fS and estimated penalty cost hS for that schedule. Before starting the planning horizon, the realized schedule so far s' is empty (line 1). Next, the reactive process begins, which is repeated as long as the realization of the planning horizon is not over (line 3). At each time, the available information regarding the stochastic components of the problem is updated (line 4), and a reoptimization process determines the berthing of the vessels based on this new information (lines 5–31). The first step in this reoptimization process is to obtain the current deviation ratio (see Section 4.3.1) of s' with respect to s (line 8). Afterward, the optimization process aims at determining the berthing assignment of vessel i to section j to minimize the deviation ratio (lines 11–26). To do this, each vessel-section pair is evaluated where vessel i should be at the terminal (line 12), should not have been berthed at s' (line 12), and should be allowed to berth in section j (line 14). If the above conditions are met, an auxiliary schedule s'' is created for that pair vessel i section j. This auxiliary schedule is based on the realized schedule so far s' (line 15) and considers the information updated. This way, online 16, the reoptimization is conducted by reallocating vessel i in section j at the best available time $(\geq t)$ within s''. For that new variation, the deviation ratio is determined (line 17), and if improves the best-known deviation ratio, then that change vessel section is stored (lines 18–22). Finally, once all vessels and sections have been analyzed for the event at hand and if the solution was updated, then the schedule is updated (line 28). The reoptimization algorithm will continue after no further improvements can be made (lines 6 and 29).

4.4. A Posteriori Approach. If the Bulk-BAP under stochastic conditions is solved after the occurrence of all disruptive events, then the problem is reduced to solving the deterministic Bulk-BAP where all disruptions are known in advance. That rich instance already incorporating all events' information can be solved by means of an efficient solution method, and as a result, a reference solution or lower bound can be obtained. This reference solution can be used to evaluate stochastic approaches as a lower bound. As all disruptive events are known in advance, no rescheduling is necessary and, therefore, there is no reallocating penalty involved.

Because the Bulk-BAP is an NP-Hard optimization problem, in this experiment, a large neighbourhood search (LNS, [39]) is implemented to obtain this lower bound. It is worth indicating that since the LNS algorithm is not capable of guaranteeing optimality, the lower bound used is not the best possible lower bound but a competitive one.

The LNS defines the search environment by alternating between two well-defined stages until a given stopping criterion is reached. In this work, the proposed LNS starts from a feasible solution generated using the greedy randomized algorithm (GRA) [40]. Subsequently, as long as a certain stopping criterion is not reached, a destruction phase and a repair phase are executed sequentially. During the destruction phase, a subset of vessels is randomly removed from the schedule. The number of vessels removed is defined by a metaheuristic parameter called the degree of destruction. At this point, for the repair phase, the GRA is used to reinsert the removed vessel into the schedule.

The GRA is used to generate the baseline solution as well as to repair the solution after the destruction phase. The algorithm, at each iteration, generates all feasible allocations for each vessel that is not already on the schedule. Each allocation is defined by the triplet: vessel, section, and the incremental contribution of that allocation to the solution's objective function. Based on the incremental evaluation, a subset of k allocations is selected, from which a restricted list of candidates (RLC) is built. Finally, an allocation is randomly selected from the RLC, and the schedule is updated accordingly. This process is repeated until all the vessels are allocated.

5. Numerical Experiments

This section presents the different computational experiments carried out to evaluate and validate the performance of the proposed solution approaches described in the previous section.

The computational experiments included in this paper were performed on an Intel CPU with a 3.3-GHz i7-5820k processor and 8 GB of RAM. Meanwhile, the used instances correspond to a set of 54 instances based on real data from Saqr Port, Ras Al Khaimah, UAE, provided by Umang et al. [2]. Likewise, the probability distributions used to simulate the uncertainty are provided in [4]. Due to the stochasticity of the solution approaches made, each experiment is performed 30 times.

It is necessary to indicate that in a real environment, after the proactive phase, the decision-maker might obtain a set of possible solutions [41], and based on it, a Pareto front of different schedules can be determined. At this point, the decision-maker must choose which schedule will be used taking into account the value of the objective function and the robustness of the schedule so that they fit the needs of the terminal. Notice that such selection of the schedule can be automated to select the best schedule according to a given optimization objective or another metric. Once the realization of it begins, the chosen baseline schedule is followed, and in the case disruptive events arise, decisions might be taken to adapt the said schedule given the information collected from new events. It can also be observed that the decision-maker obtains a set of berthing schedules during the proactive phase, while only one schedule is used during the reactive phase. Unlike a real-life environment, this paper applies the reactive phase to all the solutions in the Pareto front generated during the proactive phase. This makes it possible to study the behaviour and performance of the hybrid approach regardless of the chosen solution by the decision-maker. On the other hand, this permits the assessment of the behaviour of the reactive phase in diverse cases, for example, when the solution is the most robust or when optimizes the value of the objective function.

In this context, the rest of the section is organized as follows. Section 5.1 provides a description of the parameter tuning performed. Section 5.2 describes how the disruptive scenarios used during the experiments have been generated. The validity of the LNS metaheuristic as a reference point is discussed in Section 5.3. The solution approaches proposed to handle the impact of disruptive events are compared with each other in Section 5.4. Namely, the purely proactive approach, the purely reactive approach, and the hybrid approach are compared. The solution approaches proposed are compared to the LNS metaheuristic by managing the uncertainty a posteriori in Section 5.5. Finally, Section 5.6 discusses and evaluates the main findings from a managerial point of view.

5.1. Parameter Tuning. Since the reactive phase of the proposed approach is a deterministic algorithm, it does not require configuration parameters. Concerning the proactive approach, the same parameters as those used in [9] are employed as follows:

(i) The initial population is generated by GRA with $|RLC| = 4$
(ii) The population size is set to 500
(iii) The time limit for the solver is set to 30 seconds
(iv) Mutation rate is set to 1%
(v) Each pair instance algorithm has been executed 30 times

Moreover, in [42], an exhaustive study was carried out to select the best algorithm and parameters to solve the deterministic version of the Bulk-BAP. In that work, parameter tuning was conducted for the LNS used in this work. Based on the information provided in said paper, the parameters used in the LNS are as follows:

(i) Stop criterion: 3,000 iterations
(ii) Degree of destruction: 0.4

In addition, a study is carried out to compare the LNS with other approaches and assess its validity to be later used as a reference point when assessing the proposed disruption management approaches (see Section 5.3).

5.2. Generation of Disruptive Scenarios. In a real environment, during the course of the planning horizon, different disruptive events or updates on parameter information might occur. To evaluate our approaches and simulate this context, a set of disruptive scenarios are defined. Each scenario defines the set of disruptive events (e.g., vessel arrival delay, longer handling time, etc.) that are going to occur and the time at which they occur. Those events are not known by the reactive approaches until the time at which they occur is reached. Namely, the disruptive events considered in this work can be of two types [4]: (i) modification of the estimated time of arrival of the vessel and (ii) modification of the handling time of the vessel once it is berthed. This way, a large set of 1,000 disruptive scenarios is defined for each of the 54 problem instances, resulting in a total of 54,000 scenarios. These scenarios are used to evaluate the performance of the proposals made during the reactive phase. It is worth noticing that these scenarios were only generated to evaluate the performance of the proposed approaches but are not necessary for the approaches to work, that is, they are not needed when implementing such approaches in a real environment.

With the aim of defining the set of disruptive events affecting each vessel, the probability distributions described in Section 3.1 are followed, and the different events that modify the ETA and EHT of each vessel are defined. During the comparison between solution approaches, the following values are used for the variables ruling uncertainty and extracted from the historical data presented by Umang et al. [4]:

(i) Uncertainty in arrival times: $\delta = 7.5$
(ii) Uncertainty in handling times: $\gamma = 1.15$

5.3. LNS Validity as a Reference Point. In order to establish a reference point to compare the different stochastic approaches, we analyze the performance of a metaheuristic for the case where all disruptions are known in advance and provided to the method as input.

For that, this experiment evaluates the validity of the LNS metaheuristic (see Section 4.4) as the method to provide this reference point. To do this, the set of 54 instances is solved deterministically and compared with the results reported by

Require: Bulk-BAP baseline schedule s
Require: Bulk-BAP schedule s'
totalDelay = 0
for $i \in N$ **do**
  delay = $(m_i^{s'} + c_i^{s'}) - (m_i^{s} + c_i^{s})$
  if delay >= 0 **then**
    totalDelay = totalDelay + delay
  end if
end for
return totalDelay

Algorithm 1: Total delay in vessel departure with respect to the baseline schedule.

Umang et al. [2]. Finally, it should be noted that when solving the instances in a deterministic setting, only the deterministic objective function (see equation (1)) can be used.

Table 2 reports the results for the optimization model (MILP), the generalized set-partitioning problem (GSPP) model, the squeaky wheel optimization (SWO), and the LNS. The results are grouped by instance size (i.e., $|N|x|M|$). In the table, the first three sets of columns, MILP, GSPP, and SWO, contain the values as provided in [2]. For the MILP model, the value of the objective function (Obj.), the relative error provided by the solver (Gap), and the time required to find a feasible solution within the two-hour time limit (Time) are provided. It is important to note that the MILP model is sometimes unable to reach the optimal solution within the time limit ("—"). Also, for the GSPP model, the objective values and computational times are provided. The results obtained by SWO and LNS are the average values of the objective function, the average computation time measured in seconds, and the relative error with respect to the GSPP model (RE). Each instance-algorithm pair has been executed 30 times. For small instances (10 vessels), the MILP model provides the best solution, but for medium (25 vessels) and large (40 vessels) instances, the optimal solutions are unknown. Therefore, SWO and LNS are compared using the solutions provided by the GSPP model.

According to Table 2, it can be deduced that the RE obtained by SWO and the gap obtained by the MILP grow as the instance size increases, unlike the RE obtained by LNS. As can be seen, the LNS metaheuristic is capable of obtaining an average relative error of 5.07% with respect to the solutions provided by GSPP, compared to 9.46% obtained by SWO. Furthermore, the LNS is capable of obtaining these results within an average computation time of around 0.2 seconds. Also, it can be seen that for medium (25 vessels) and large (40 vessels) instances, the LNS provides higher-quality solutions in terms of the value of the objective function than SWO. Due to this, it can be concluded that the LNS metaheuristic is capable of providing high-quality solutions in reduced computational times, which is why it is valid for use as a reference point in the following sections.

5.4. Comparison between Proactive, Reactive, and Hybrid Approaches. This section assesses the performance of the following disruption management approaches:

(1) Without an uncertainty management approach (i.e., no opt): the deterministic Bulk-BAP is solved by the LNS metaheuristic described in Section 4.4 in order to obtain the baseline schedule. During the course of the planning horizon, no aspect of the baseline schedule is modified. This means that the vessels are not reallocated in other sections, the order in which they are berthed in the sections is not modified, and they cannot be berthed before the scheduled berthing time.

(2) Proactive approach: the baseline schedule is generated using the NSGA-II evolutionary algorithm integrated with simulation as briefly described in Section 4.2. This approach performs purely proactive uncertainty management; no aspect of the baseline schedule is modified in real-time when conducting the planning.

(3) Reactive approach: this approach uses the baseline schedule generated by a nonproactive approach such as the LNS used for solving the deterministic Bulk-BAP described in Section 4.4. During the course of the planning horizon, the reactive phase described in Section 4.3 is applied. This way, the contribution of the reactive approach without the influence of the proactive one can be assessed.

(4) Hybrid approach: starting from the schedule generated by the proactive approach, the reactive approach is used every time a disruption or parameter update happens (see Section 4). As such, this combines the previous two approaches.

Because proactive and hybrid approaches share the same proactive phase to generate the baseline schedule and in order to evaluate the impact of the reactive phase, both solution approaches use the same baseline schedule. That is, for a given instance, the proactive approach is used first to generate a Pareto front made up of different schedules (i.e., during the proactive phase). Subsequently, each baseline schedule is subjected to the corresponding set of 1,000 disruptive scenarios (see Section 5.2), and the performance of each proposed solution approach to mitigate the disruptions is evaluated. In the case of the proactive approach, no changes to the baseline schedule are made. Furthermore, the performance of both the proactive and hybrid

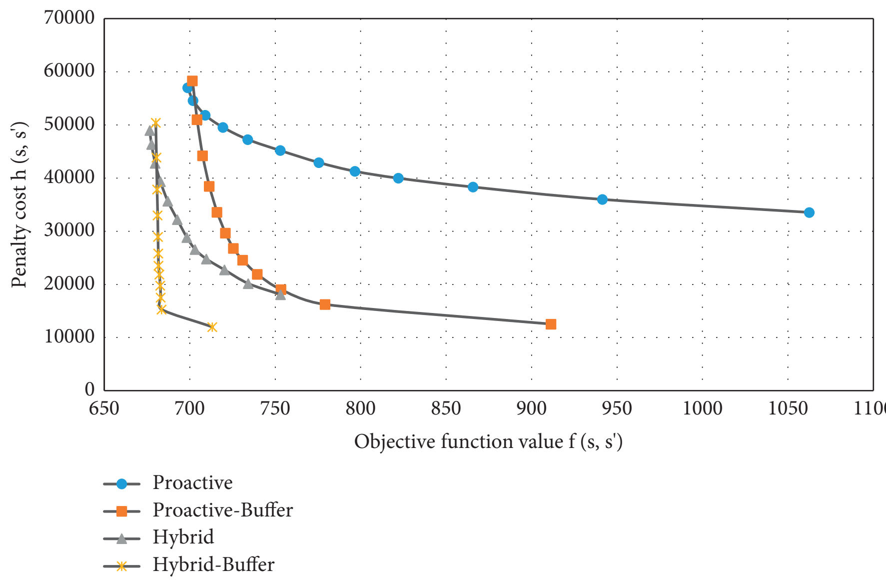

Figure 4: Performance comparison between proactive and hybrid solution approaches.

approaches is evaluated, whether or not they include the use of buffers. In order to evaluate the contribution of only having a reactive approach, but none proactive nor hybrid approaches, the results of the fully deterministicand reactive approaches are reported.

Figure 4 shows the results obtained by the proactive and hybrid approaches when addressing the set of 54 instances under conditions of uncertainty. The abscissa axis represents the value of the objective function $f(s, s')$. Meanwhile, the ordinate axis represents the penalty cost derived from the total delay in vessel departure $h(s, s')$. It should be recalled that although in a real environment a single schedule would be selected from among all those in the Pareto front generated during the proactive phase, this paper applies the reactive phase to all the solutions in the said front. Due to this, Figure 4 shows a Pareto front for each of the proposed solution approaches evaluated. Finally, because each solution approach is executed 30 times for each instance, the reported values correspond to the average ones.

In addition, Table 3 shows the detailed results obtained by each of the solution approaches indicated above. For each of them, two sets of columns are shown: (i) the value of the objective function $f(s, s')$ and (ii) the penalty cost $h(s, s')$. While Figure 4 uses the medians to represent the average behaviour of the baseline schedule under conditions of uncertainty (1,000 disruptive scenarios), Table 3 shows the minimum value (Min.), first quartile (Q1), median (Median), third quartile (Q3), and maximum (Max.) value for both sets of columns. For proactive and hybrid approaches, subsets of the solutions present in the different Pareto fronts shown in Figure 4 have been selected:

(i) Schedule that minimizes the value of the objective function $f(s, s')$ denoted as s'_f

(ii) Schedule with the lowest normalized distance (considering $f(s, s')$ and $h(s, s')$) to the origin of coordinate denoted as s'_{fh}

(iii) Schedule that minimizes the penalty cost $h(s, s')$ denoted as s'_h

Figure 4 and Table 3 both show that regardless of the use of buffer-time management strategies, the hybrid approach manages to improve the results of purely proactive and reactive strategies. Furthermore, this improvement is observed both in the value of the objective function $f(s, s')$ and in the delay in vessels' departure. The latter results in a reduction in penalty costs. In this regard, although purely proactive approaches are capable of reducing the impact of disruptive events (as shown in [9]), the use of reactive actions, capable of adapting the schedule, is presented as an effective strategy to increase the resilience of the port terminal against the occurrence of such events.

Firstly, it can be seen how the approach without uncertainty management reports 706.70 and 61,664 for the median value of the objective function and the median penalty cost, respectively. Note how, by not managing uncertainty, the highest penalty cost of all the evaluated solution approaches is obtained. Moreover, in the case of seeking to only minimize the objective function value, the rest of the approaches are able to provide higher quality solutions with lower penalty costs. That is, the approach without uncertainty management is dominated by the other approaches, whereas the reactive approach manages to improve these results by adapting the baseline schedule, reporting 684.57 and 52,680 for the median $f(s, s')$ and $h(s, s')$, respectively. Considering only the value of the objective function, the reactive approach is able to provide better solutions than the proactive approach; however, the latter generates a Pareto front where there are solutions with lower penalty costs. Therefore, the proactive approach is able, in general terms, to improve the results provided by the reactive approach regarding the penalty cost. Moreover, providing a Pareto front allows the decision-maker to select the baseline schedule that best suits the terminal's needs, while the reactive approach only provides a single

```
Require: Bulk-BAP baseline schedule s
Require: Deterministic objective function value fS for baseline schedule s
Require: Estimated penalty cost hS for baseline schedule s
Require: Bulk-BAP reactive schedule s'
Require: Current instant t
s'' = s'
for i∈N do
   if i has not been berthed at s'' then
      berth (s'', s, i, t)
   end if
end for
return (f (s, s'')/fS) + (h (s, s'')/hS)
```

ALGORITHM 2: Deviation ratio with respect to the baseline schedule.

```
Require: Bulk-BAP baseline schedule s
Require: Deterministic objective function value fS for baseline schedule s
Require: Estimated penalty cost hS for baseline schedule s
s' = ∅
t = 0
while t ≤ |H| do
   update AT_HT
   scheduleUpdated= true
   while scheduleUpdated do
      scheduleUpdated= false
      bestDeviationRatio = deviationRatio (s, fS, hS, s', t)
      bestSec = −1
      bestVessel = −1
      for i ∈ N do
         if i has arrived and i has not been berthed then
            for j ∈ M do
               if feasible berthing of vessel i at section j then
                  s'' = s'
                  berth (s'', i, j, t)
                  deviationRatio = deviationRatio (s, fS, hS, s'', t)
                  if deviationRatio ≤ bestDeviationRatio then
                     bestSec = j
                     bestVessel = i
                     bestDeviationRatio = deviationRatio
                  end if
               end if
            end for
         end if
      end for
      if bestVessel ≠ −1 then
         berth (s', bestVessel, bestSec, t)
         scheduleUpdated = true
      end if
   end while
   t++
end while
```

ALGORITHM 3: Real-time rescheduling algorithm.

solution. Regarding the purely proactive and reactive approaches, the results suggest that if the objective function value is to be minimized, the reactive approach should be used, while if the penalty cost is to be minimized, the proactive approach should be selected.

Table 2: LNS performance results for deterministic Bulk-BAP.

$N \times M$	MILP			GSPP		SWO			LNS		
	Obj.	Gap	Time	Obj.	Time	Obj.	RE (%)	Time	Obj.	RE (%)	Time
10×10	222.90	0.01	13.47	223.88	5.65	223.42	−0.22	16.60	226.89	1.33	0.02
10×30	182.03	0.01	136.92	183.05	90.75	189.44	3.35	49.15	194.53	5.97	0.05
25×10	793.91	26.29	—	793.09	14.55	840.40	6.02	22.68	829.65	4.50	0.07
25×30	654.19	22.27	—	639.21	222.28	727.87	13.89	101.54	715.73	11.53	0.25
40×10	1,173.92	60.99	—	1,086.03	62.05	1,243.21	14.60	31.52	1,122.08	3.42	0.18
40×30	949.64	61.69	—	878.75	1,117.45	1,054.12	19.12	176.72	910.25	3.65	0.60
Average	662.77	28.54	75.19	634.00	252.12	713.08	9.46	66.37	666.52	5.07	0.20

Note. Time: average computational time measured in seconds, Obj.: average objective function value, Gap: relative error calculated with respect to the linear bounds, and RE: relative error with respect to the best solution provided by the GSPP optimization model.

Table 3: Performance comparison between proactive, reactive, and hybrid solution approaches.

Buffer time management	Uncertainty management	Schedule	Value of the objective function, $f(s,s')$					Penalty cost, $h(s,s')$				
			Min.	Q1	Median	Q3	Max.	Min.	Q1	Median	Q3	Max.
Without buffer time management	Proactive	s_h'	991.77	1,042.77	1,062.52	1,098.05	1,187.93	456	19,136	33,544	67,536	135,432
		s_{fh}'	728.09	778.75	796.74	821.79	898.86	1,008	26,648	41,272	64,736	126,752
		s_f'	636.93	684.30	698.83	713.73	771.22	5,136	43,512	57,000	70,968	121,032
	Hybrid	s_h'	658.70	730.34	753.18	777.41	881.62	320	11,560	18,080	25,632	70,224
		s_{fh}'	626.46	685.22	703.19	721.99	795.96	672	17,856	26,584	36,720	86,040
		s_f'	610.79	661.65	676.67	692.15	754.63	3,728	36,648	48,944	62,120	116,448
	Reactive	—	617.01	669.18	684.57	700.51	767.16	4,752	39,936	52,680	66,328	123,760
	No opt	—	642.94	691.67	706.70	722.00	779.80	6,448	47,560	61,664	75,960	125,008
With buffer time management	Proactive	s_h'	862.11	900.85	911.45	922.07	960.90	72	8,456	12,520	17,104	36,592
		s_{fh}'	675.17	714.49	725.55	737.00	781.83	744	18,480	26,752	35,992	73,848
		s_f'	639.87	687.20	701.58	716.26	772.42	5,672	44,752	58,304	72,144	121,256
	Hybrid	s_h'	632.42	694.25	713.30	733.31	813.42	16	7,920	11,984	16,776	50,704
		s_{fh}'	613.04	666.27	681.80	697.65	759.55	600	16,024	23,544	32,312	75,264
		s_f'	613.64	665.14	680.17	695.62	757.84	4,208	37,928	50,408	63,640	117,400

Note. s_h': schedule that minimizes the penalty cost $h(s,s')$, s_{fh}': schedule with the lowest normalized distance (considering $f(s,s')$ and $h(s,s')$) to the origin of coordinate, and s_f': schedule that minimizes the value of the objective function $f(s,s')$.

In the case of the proactive and hybrid approaches without buffer time management, it can be observed how the solutions of the Pareto front that tend to minimize the value of the objective function obtain less benefit when using the reactive phase compared to the solutions of the Pareto front that seek to minimize the penalty cost. Specifically, when comparing the proactive and hybrid approaches, an absolute difference is observed in the median value of the objective function equal to 309.34 (i.e., 1062.52 − 753.18 = 309.34), 93.55, and 22.16 for the schedule s_h', the schedule s_{fh}', and the schedule s_f', respectively. Similarly, an absolute difference of 15,464, 14,688, and 8,056 is observed for the penalty cost. Meanwhile, the solutions provided by the proactive approach are distributed along the abscissa axis in the range [699, 1,063] and on the ordinate axis in the range [33,544, 57,000], while the hybrid approach provides solutions in the range [677, 753] and [18,080, 48,944] on the abscissa and ordinate axis, respectively. Based on the previous results, we can point out that the hybrid approach considerably improves the results provided by the purely proactive and reactive approaches. It should be noted that the hybrid approach without buffer time management provides better performance than the proactive approach with it.

Regarding solution approaches with buffer time management, it can be observed that the hybrid approach with buffers dominates the one without it, as well as purely proactive and reactive approaches. Moreover, it can be observed that the solutions provided by the hybrid method with buffer time management are aligned around the same point of the abscissa axis. Generally, this is because the Pareto front generated during the proactive phase with buffer time management is made up of solutions that represent the same schedule but with different values of buffer times. Due to the use of these buffers, and despite being the same schedule, different values of the objective function and different penalty costs are observed. In addition, because vessels are allowed to berth before their scheduled time, the buffers do not alter the final schedule. This means that all the solutions that represent the same schedule, but with different buffer times, end up leading to the same final schedule with the same objective function value but a different penalty cost. In this regard, it can be observed that the median value of the objective function reported by the schedule s_f' and the schedule s_{fh}' are very similar, 680.17 and 681.80, respectively. However, this similarity is not observed in the median penalty cost. Specifically, the schedule s_f' reports a penalty cost equal to 50,408, while the schedule s_{fh}' reports 23,544. That is, schedules are obtained with a similar quality in terms of the objective function but with disparate penalties. Therefore, under the framework proposed in this paper, if during the selection of the baseline schedule (retrieved from the

Table 4: Performance comparison between a posteriori uncertainty management and proactive, reactive, and hybrid solution approaches.

Buffer time management	Uncertainty management	Schedule	Value of the objective function $f(s, s')$					RE	RE	RE	RE	RE
			Min.	Q1	Median	Q3	Max.	min.	Q1	median	Q3	max.
Without buffer time management	Proactive	s'_h	991.77	1,042.77	1,062.52	1,098.05	1,187.93	65.14	63.74	64.04	66.84	68.67
		s'_{fh}	728.09	778.75	796.74	821.79	898.86	21.24	22.28	23.01	24.86	27.62
		s'_f	636.93	684.30	698.83	713.73	771.22	6.06	7.45	7.89	8.44	9.50
	Hybrid	s'_h	658.70	730.34	753.18	777.41	881.62	9.68	14.68	16.28	18.12	25.18
		s'_{fh}	626.46	685.22	703.19	721.99	795.96	4.31	7.59	8.56	9.70	13.01
		s'_f	610.79	661.65	676.67	692.15	754.63	1.70	3.89	4.47	5.17	7.15
	Reactive	—	617.01	669.18	684.57	700.51	767.16	2.74	5.08	5.69	6.43	8.93
	No opt	—	642.94	691.67	706.70	722.00	779.80	7.06	8.61	9.11	9.70	10.72
With buffer time management	Proactive	s'_h	862.11	900.85	911.45	922.07	960.90	43.55	41.45	40.72	40.10	36.43
		s'_{fh}	675.17	714.49	725.55	737.00	781.83	12.42	12.19	12.02	11.98	11.01
		s'_f	639.87	687.20	701.58	716.26	772.42	6.55	7.91	8.32	8.83	9.67
	Hybrid	s'_h	632.42	694.25	713.30	733.31	813.42	5.31	9.01	10.12	11.42	15.49
		s'_{fh}	613.04	666.27	681.80	697.65	759.55	2.08	4.62	5.26	6.00	7.84
		s'_f	613.64	665.14	680.17	695.62	757.84	2.18	4.44	5.01	5.69	7.60
A posteriori (LNS)			600.56	636.85	647.72	658.16	704.30	—	—	—	—	—

Note. s'_h: schedule that minimizes the penalty cost $h(s, s')$, s'_{fh}: schedule with the lowest normalized distance (considering $f(s, s')$ and $h(s, s')$) to the origin of coordinate, and s'_f: schedule that minimizes the value of the objective function $f(s, s')$.

proactive phase), there are two equal schedules, but with different buffer times, the selection should focus on the robustness of the schedule. That means that penalty costs derived from departure delays are minimized and the quality in terms of the objective function value of the final schedule is maintained.

In terms of computational time, the reactive phase requires an average computational time of around 15 seconds to address a single disruptive scenario, which would recommend its application in real-world environments. The improvement in the results provided by the hybrid approach compared to the purely proactive and reactive approaches, together with a negligible computational time, suggests the application of hybrid approaches instead of the other studied options for efficient berth management at bulk terminals.

5.5. A Posteriori Analysis. This a posteriori analysis aims at obtaining a reference point to compare the performance of the stochastic solution approaches. Specifically, the LNS is used to address the 54,000 scenarios defined in Section 5.2 where all dynamic information is known beforehand. As the resolution is made knowing already all disruptive events in advance, there is no baseline schedule, and therefore, there is no delay in departure, nor any penalty for reallocating the vessels. Therefore, only the values obtained for the objective function are compared.

The results for this comparison are summarized in Table 4, where, for each proposed solution approach, the minimum value (Min.), first quartile (Q1), median (Median), third quartile (Q3), and maximum (Max.) of the objective function value are reported, and for each of the said values, the relative error with respect to the results obtained by LNS is calculated. The last row in the table corresponds to the results obtained by a posteriori approach, and they are used as reference values when calculating the relative error. For example, the schedule s'_{fh} generated by the hybrid approach with buffer-time management obtains 613.04 as the minimum value of the objective function value and, therefore, has a relative error equal to 2.08% (i.e., $((|613.04 - 600.56|)/600.56) \cdot 100 = 2.08$).

As can be observed in Table 4, the hybrid approaches achieve an average relative error of less than 10% for the schedule s'_{fh}. It should be noted that the hybrid approaches obtain a relative error of less than 20% for solutions that seek to minimize vessel delay, s'_h, while purely proactive approaches obtain values greater than 40%. These values indicate the ability of the hybrid approaches to improve the quality of schedule even though they were originally generated with the goal of minimizing the delay in departure and not minimizing the value of the objective function. Also, it can be observed that as the schedule is minimized according to the objective function, the difference obtained concerning the relative error reported by the proactive and hybrid approaches decreases. For example, the schedule s'_h generated by the proactive approach without buffer time management reports a median relative error equal to 64.04%, while the hybrid approach with buffers reports a relative error equal to 10.12%. That is, there is a difference of 53.92%. However, for schedule s'_f, the reported median relative error is equal to 7.89% and 5.01% for the proactive and hybrid approaches, respectively, which leaves a difference of only 2.88%. In turn, the reactive approach and the one without uncertainty management obtain a RE of less than 10%. In this regard, the reactive approach improves the performance exhibited by the proactive approach regardless of the use of buffers. However, the hybrid approach exhibits slightly better performance. Specifically, for the hybrid approach with buffer time management, the schedules s'_{fh} and s'_f reports a median RE equal to 5.26 and 5.01, respectively, against 5.69 reported by the reactive approach. Lastly, as expected, none of the solution approaches could equal or improve the results of the a posteriori LNS given that they do not know the events in advance. Nevertheless, the results indicate that the best one approach over all is the hybrid one with and without buffers when only optimizing the objective function of the main problem.

5.6. Managerial and Algorithmic insights. This section summarizes and discusses the managerial and algorithmic insights extracted from the above computational results.

5.6.1. Disruption Management. As expected, it can be observed how not considering the uncertainty inherent in the terminal and not acting to mitigate it impacts results concerning economic penalties, despite the fact that the baseline schedule was of high quality. In this sense, the approaches that manage uncertainty, regardless of the strategy followed for this purpose, are able to reduce the economic penalties. This reduction in penalties derives from an improvement in the quality of the service by not delaying the departure of vessels compared to the baseline schedule. Therefore, the reduction of costs and improvement of the service would result in increasing profits, competitiveness, and better use of the resources available at the terminal. Furthermore, delays in the departure and handling of vessels have a direct impact on the rest of the interconnected problems or systems that make up the terminal, so the use of disruption management strategies at the berthing operation positively impacts the overall terminal's performance. Lastly, it should be noted that maximizing the terminal's uncertainty handling capacity allows for accurate strategic decision-making according to the real functioning of the terminal and not due to the underutilization of available resources.

5.6.2. Proactive-Reactive Synergy. The computational results indicate that combining proactive and reactive approaches significantly enhances the results obtained by purely proactive and reactive approaches, irrespective of whether or not buffer times are incorporated. The use of buffer times is an important resource to reduce the impact of disruptive events, especially in environments where vessels' delays can be predicted or handling times delays can be anticipated. However, such buffer times may lead to the underutilization of quayside resources and therefore need to be carefully managed. In this sense, as the hybrid approach is able to modify the current schedule, it can provide a better manage buffer times in such a way that its drawbacks are reduced. Such improved results provided by the hybrid approach within a short computational time highlight the hybrid approach as a feasible and adequate strategy to achieve efficient and robust management of bulk terminals.

5.6.3. Use of Simulation. It should be noted that due to the multiobjective nature of the proactive phase, the decision-maker of the terminal obtains a Pareto front during the planning phase and should, therefore, select the schedule that best suits the terminal's needs before the realization of the planning. As discussed in Section 5, the selection of such a baseline schedule has a major impact on the results obtained during the reactive phase. At this stage, simulation is a relevant component, as it allows the decision-maker to forecast the average performance of each schedule under uncertain conditions based on the port's historical data. In this sense, maritime terminals can define certain criteria to facilitate the selection of the solution that best suits their preferences and needs based on the different objectives.

5.6.4. Algorithmic Benefit. Lastly, solving Bulk-BAP under stochastic conditions requires high computational effort, and therefore, it is necessary to consider the computing time that would be required to apply the hybrid approach in real environments. In this regard, the proposed proactive phase is capable of providing a Pareto front within a short time. The computation time of the proactive phase is limited to 30 seconds in this research, but this value can be adjusted according to the terminal at hand. Due to the stochastic nature of the proactive approach, a reduced computational time allows different runs of the approach to obtain a larger set of possible solutions to select the one that best fits the terminal's needs. Furthermore, during the course of the planning disruptive events might occur, thus, it is needed to define and implement response actions in the shortest possible time and, at the same time, minimize their impact. In that regard, the proposed reactive phase is executed in a few seconds (around 15 seconds). This feature allows the port terminal to quickly get a recovery plan and react to the various disruptive events occurring during the realization of the planning.

6. Conclusions and Future Research

In this paper, the bulk berth allocation problem considering uncertainty in vessels' arrival and handling times is studied. In order to minimize the impact of disruptive events on the terminal's performance, a hybrid solution approach is proposed where uncertainty is managed both, proactively and reactively. The solution approach starts by generating a baseline schedule proactively upon considering the uncertainty based on port data. Later, during the course of the planning horizon, a reactive approach is applied in which real-time decisions are capable of modifying the baseline schedule. Two versions of this solution approach have been evaluated, that is, with and without the use of buffers, which are intended to cushion the impact of disruptive events.

The computational results evaluate the terminal's performance using purely proactive and reactive strategies as well as their combination through the hybrid approach. In this sense, the computational results indicate that the combination of proactive and reactive actions (i.e., hybrids) not only cushions the impact of unforeseen events but also improves the quality of schedule in terms of the value of the objective function with respect to purely proactive or reactive actions. The proposed solution approach that uses buffers shows a better performance than the solution approach that does not use them. It is necessary to consider that the highest computational cost, both in time and computing power, is performed during the proactive phase, while during the reactive phase (i.e., real-time), this cost is relatively negligible. This, together with the fact that the integration of a reactive phase considerably improves the results, shows that hybrid uncertainty management approaches are suitable strategies for port terminals affected by uncertainty.

Based on the numerical results, we can observe that for those baseline schedules that are less tolerant to uncertainty, it is more difficult for the proposed hybrid solution approach to mitigate the effects of disruptive events. Thus, in future work, we aim at studying ways of measuring and assessing this uncertainty tolerance as well as analyzing different reactive and hybrid strategies to cope with such types of cases. Complementary, studying, and designing a meta-learning system [43, 44] capable of assessing and responding to disruptions given a set of possible reactive strategies will also be a topic of future research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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