Real Time Recovery in Berth Allocation Problem in Bulk Ports

Nitish Umang

Michel Bierlaire

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Nitish Umang

TRANSP-OR EPFL
1015 Lausanne
phone: +41 21 693 93 27
fax: +41 21 693 80 60
nitish.umang@epfl.ch

Michel Bierlaire

TRANSP-OR EPFL
1015 Lausanne
phone: +41 21 693 25 37
fax: +41 21 693 80 60
michel.bierlaire@epfl.ch

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Abstract

In this research, we study the dynamic, hybrid berth allocation problem (BAP) for bulk ports under uncertainty. In practice, the actual arrival times of vessels deviate from their expected values, which can disrupt the original berthing plan and possibly make it infeasible. In this work, we consider a given baseline berthing schedule, and solve the BAP in real time as actual arrival data is revealed. We present an optimization based algorithm and an alternate heuristic approach to recover the schedule in events of disruption with the objective to minimize the total realized costs of the updated schedule. We further discuss certain strategies that the port should adopt and implement to maximize their revenues, and incorporate them as constraints in our recovery algorithms. The approaches are tested and validated by simple numerical experiments in which the baseline schedule is chosen as the solution of the deterministic BAP problem. Preliminary results indicate that the algorithms can be successfully used to solve the BAP in real time, and the optimization approach slightly outperforms the heuristic approach but is computationally expensive.

Keywords

berth allocation, bulk ports, uncertainty, robustness, dynamic recovery, mixed integer programming

1 Introduction

The Berth Allocation Problem (BAP) is one of the most critical and widely studied problems in container terminal operations. The deterministic BAP in bulk ports with dynamic vessel arrival and hyrbid berth layout is studied by Umang *et al.* (2012). In practice, port operations are associated with a high degree of uncertainty owing to weather conditions, equipment breakdown and other factors. Thus the actual arrival times and handling times of vessels can deviate from the estimated values which can potentially disrupt the planned schedule making it infeasible. This calls for quick real time action to minimize the impact of disruptions on the planned schedule. However, traditional methods to model the berth allocation problem do not explicitly account for the uncertainty in information which can potential disrupt the origianlly planned berthing schedule.

There are usually two approaches to deal with uncertainty and stochastic disturbances in transportation schedules. A) Proactive robustness in which the baseline schedule is developed with a certain degree of anticipation of uncertainty and variability in information and occurrence of disruptions during the real execution of the schedule. The methods based on proactive robustness can be divided into two distinct categories: average-best case methods or stochastic optimization and worst case methods or robust optimization. Both these methods explicitly consider the set of all possible realized scenarios, which is characterized by the uncertainty set U. While the stochastic optimization methods aim to find the solution that performs best on average (Birge and Louveaux (1997), Kall and Mayer (2005) and Wallace and Ziemba (1997)), the robust optimization method is more conservative and seeks to find the solution that performs best for the worst case scenario (refer Soyster (1973), Bertsimas and Sim (2003), Ben-Tal and Nemirovski (1998), Ben-Tal and Nemirovski (1999) and Ben-Tal and Nemirovski (2000) and Bertsimas and Sim (2004)). B) Reactive approach or disruption management or online-algorithms which is based on the wait-and-see strategy and deals with adjusting the schedule in real time responding to data changes during execution of the original schedule. The performance of this approach is dependent on the way the data is revealed. One common metric to assess the performance of a reactive algorithm is the competitivity ratio, which is obtained by dividing the value of the solution found by the algorithm by the optimal solution of the deterministic problem Albers (2003). Further, it may be noted that while disruption management and rescheduling are both reactive approaches to modify an existing baseline schedule, they differ in their main objectives. Given a baseline schedule, rescheduling refers to identifying a schedule that is optimal in terms of the original objective function. Disruption management, on the other hand focuses only on minimizing the deviation of the modified schedule from the original planned schedule.

A key challenge in this research is to determine if the operational costs or realized costs of the modified berthing schedule in response to disruptions, outweigh the planned costs of the original baseline schedule with or without any anticipation of variability in information. This is because we don't know beforehand whether or not any disruptions will occur during the planning horizon when the original planned schedule is executed. Thus given two schedules with different planned costs, one of them may prove better than the other depending on the extent of disruptions during execution phase, on which unfortunately there is no prior information. In this paper, we consider the problem of recovering a berthing schedule in real time as disruptions occur. Our problem derives from the realistic requirements of the port of SAQR in Ras-Al-Kahaimah, UAE, the biggest bulk port in the entire middle east. The underlying model is the dynamic, hybrid berth allocation model developed in context of bulk ports (please refer to Umang *et al.* (2012) for details). The objective is to minimize the total realized costs of the modified berthing schedule, which is the sum of the total service cost of the vessels berthing at the port and the cost of rescheduling respecting certain contractual agreements between the port terminal managers and the shipping companies.

2 Literature Review

Comprehensive literature surveys on the work done on berth allocation problem in container terminals can be found in Bierwirth and Meisel (2010), Steenken *et al.* (2004) and Stahlbock and Voss (2008). To the best of our knowledge, the berth allocation problem in context of bulk ports was studied for the first time by Umang *et al.* (2012). The dynamic, hybrid berth allocation problem was formulated and solved which explicitly takes into account the cargo type on the vessel, using two alternate exact solution approaches based on mixed integer programming and set partitioning, and a heuristic approach based on squeaky wheel optimization.

In container terminals, there have been few studies on robust planning methods for berth allocation problem. The main issue in pro-active robust methods is to define a metric for robustness to measure the degree of stability of a given berthing schedule. For example, robustness of a schedule can be measured by the total slack time or buffer times in the tactical baseline schedule as they can absorb vessel delays to some degree and prevent delay propagation through the schedule. Alternately, for a given set of disruption scenarios, robustness can be defined as the objective function value of the worst case scenario or the expected cost of all scenarios. Primarily two types of approaches have been used to address the problem of pro-active robustness in planned schedule. The first approach is stochastic programming for capturing uncertainty. Zhen *et al.* (2011) use a meta-heuristic approach to solve a two-stage decision model for BAP under uncertainty in which a set of realized scenarios is explicitly defined and the objective is to minimize the total cost of baseline schedule and expected cost of recourse. Han *et al.* (2010) use a simulation based genetic algorithm approach to solve the integrated berth and quay crane scheduling problem with uncertainty in vessel arrival and operation times. For given probability density functions for the vessel arrival and operation, the objective is to minimize the sum of expected value and standard deviation of the service time and the weighted tardiness of the vessels. The second approach in pro-active robust methods is to define surrogate problems that inherit the stochastic nature of the original problem. Moorthy and Teo (2006) use a novel sequence pair approach to design a robust berth template for transshipment hubs in container terminals, in which conflicting objectives are to minimize the total expected delays and deviation from the most preferred berthing locations. Zhen and Chang (2012) define robustness as weighted sum of the free slack times in the berthing schedule, where weights are determined according to the vessel priorities. A bi-objective model is proposed that minimizes cost and maximizes robustness. Xu *et al.* (2012) solve a continuous berth allocation problem with uncertainty in arrival times and operation times of vessels, in which the objective is to balance the level of service using the total departure delay of vessels and robustness measure as defined by the length of buffer time. Hendriks *et al.* (2010) propose a robust optimization model for cyclic berth planning in which the objective is to minimize the maximally required crane capacity. They consider arrival windows for incoming vessels which are agreed upon between the shipping lines and terminal operator instead of using expected arrival time values. Results show that by modifying the nominal arrival times of a small percentage of vessels, it is possible to obtain significant reduction in the crane capacity.

In real time when conflicts occur, there are several reactive strategies to cope up with the disruptions and minimize their impact on the original planned schedule. For example, the vessels are rescheduled by considering the analogous time space diagram, and shifting rectangles representing vessels along the time axis. Another strategy could be rescheduling the unassigned conflicting vessels in the event of a disruption which amounts to solving a complex optimization problem in real time. Zeng *et al.* (2012) address the problem of disruption recovery in the integrated berth and quay crane assignment problem in container terminals. They develop optimization models for berth reallocation and quay crane rescheduling, and solve the disruption recovery problem using local rescheduling and tabu search methods. Du *et al.* (2010) use a feedback procedure to develop a robust berth allocation plan and a reactive strategy that takes into account the priorities assigned to the vessels and the congestion at the port. To the best of our knowledge, very few scholars have addressed the problem of real time recovery in berth allocation problem in port operations using optimization based approaches. While in context of bulk ports, the problem has not been studied at all. This paper makes an exploratory study in this field.

$N =$	set of vessels
$M =$	set of sections
$k =$	1,...,$\|M\|$ sections along the quay
$i =$	1,...,$\|N\|$ vessels berthing at the port
$A_i =$	expected arrival time of vessel i
$e_i =$	estimated departure time of vessel i
$D_i =$	draft of vessel i
$L_i =$	length of vessel i
$Q_i =$	quantity of cargo for vessel i
$W_i =$	set of cargo type(s) to be loaded or discharged from vessel i indexed from w=1 to w=$\|W_i\|$
$d_k =$	draft of section k
$\ell_k =$	length of section k
$b(k) =$	starting coordinate of section k
$h_k^w =$	handling time for unit quantity of cargo type w for vessel berthed at section k
$L =$	total length of quay
$H =$	total duration of planning horizon

Table 1: Input Parameters in the determination of baseline schedule

3 Problem Statement and Implementation

Our research problem derives from the realistic requirements of the port of SAQR in Ras-Al-Kahaimah, UAE. We study the problem of solving the dynamic, hybrid BAP for bulk ports in real time for a given baseline schedule. The baseline schedule can be any feasible solution to the BAP or alternately it can be obtained by solving the deterministic version of the problem without accounting for any uncertainty. Please refer to Umang *et al.* (2012) for details regarding the implementation and solution of the deterministic problem. A list of the input parameters used in the modeling of the deterministic problem is as given in Table (1).

In practice, the actual arrival times of vessels deviate from their estimated values, which can potentially disrupt the baseline schedule making it infeasible. In this research, we solve the BAP in real time accounting for the deviation in arrival times of vessels, by introducing additional constraints and variables in our model. Once a baseline berthing schedule is developed for the vessels arriving at the port, the port authorities allocate various resources such as human labour, handling equipment and cargo availibility depending on the requirements of the vessels berthing over the planning horizon. In the event of disruptions, these resources need to be reallocated over time and/or space, and this incurs additional cost to the port. Thus for a given baseline schedule, our objective is to minimize the sum of the total service cost of vessels berthing at the port, and the inconsistent cost of rescheduling in the event of disruptions as measured by the weighted sum of the time and space deviation of the updated schedule from the original one.

Furthermore, we explicitly consider and model certain contractual agreements between the bulk terminal managers and shipping companies. In practice, in container terminals the port authorities and shipping lines have an agreement that guarantees a maximum threshold processing time and departure time for any incoming vessel if its arrival is within a certain arrival time window (Hendriks et al. (2010)). We propose the bulk terminal managers to enforce a similar agreement, where the processing time of the vessel is below a certain nominal value if the actual arrival time a_i of vessel i lies within the arrival time window [A_i-U_i, A_i+U_i]. The nominal handling time value of any vessel can be taken as a factor η times larger than the handling time of the vessel in the baseline schedule or the minimum handling time h_i^{min} of the vessel for the most preffered berthing location of the vessel along the quay. If the arrival is outside the arrival window, the processing time is bounded by the maximum handling time value as given by the least preferred berthing location of the vessel along the quay. Figure 1 represents the maximum threshold handling time envelope for different values of the actual arrival times. To mathematically model this, we introduce an additional auxiliary binary decision variable $\theta_i(t)$, which is equal to 1 if time t lies within the arrival time window of vessel i, and 0 otherwise. This results in the following:

$$h_i \leq \eta h_i^{min} + M(1 - \theta_i(t)) \tag{1}$$

$$a_i + M(1 - \theta_i(t)) \geq A_i - U_i \tag{2}$$

$$a_i \leq A_i + U_i + M(1 - \theta_i(t)) \tag{3}$$

$$\sum_{t=A_i-U_i}^{A_i+U_i} \theta_i(t) = 2U_i + 1 \tag{4}$$

An analysis of the total cost incurred by the port under different disruption scenarios for a given baseline schedule, should enable us to come up with appropriate pricing strategies that the port can adopt to earn revenues from late arriving vessels. For example, there could be contractual agreements between the port managers and shipping lines according to which the port may charge an extra penalty fees to the vessel operators, if the actual arrival time of the vessel is beyond the right end of its arrival time window given by A_i + U_i. It would be of interest to study the trade-off between the revenues earned by the port from the late arriving vessels, and the cost incurred by the port due to rescheduling in events of disruption. The penalty cost P_i imposed on vessel i could be any complex function of the delay g_i beyond the right end of the arrival window. This is illustrated graphically in Figure 2 in which a linear relationship is assumed for sake of simplicity. For linear relationship, we have:

$$g_i = maximum(a_i - (A_i + U_i), 0) \tag{5}$$

$$P_i = c_3 g_i \tag{6}$$

Here, c_3 is a parameter than can be determined from a more in-depth study of the results of the BAP recovery in real time.

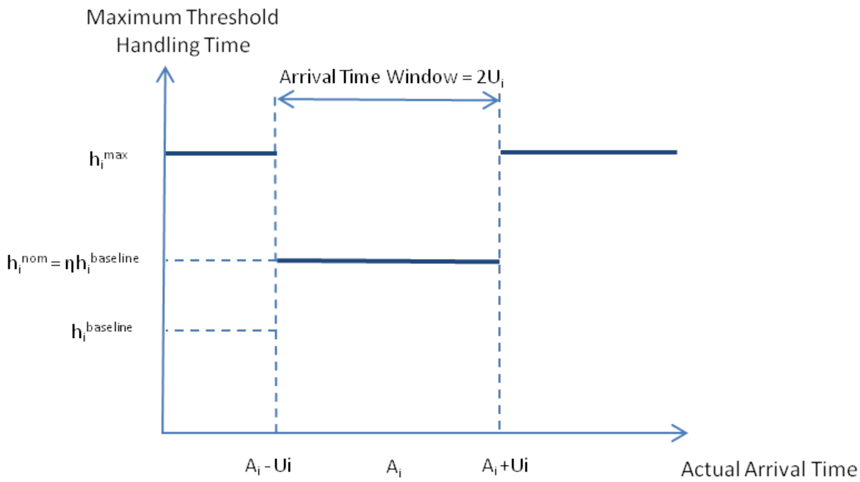

Figure 1: *Handling Time Envelope for varying arrival time values*

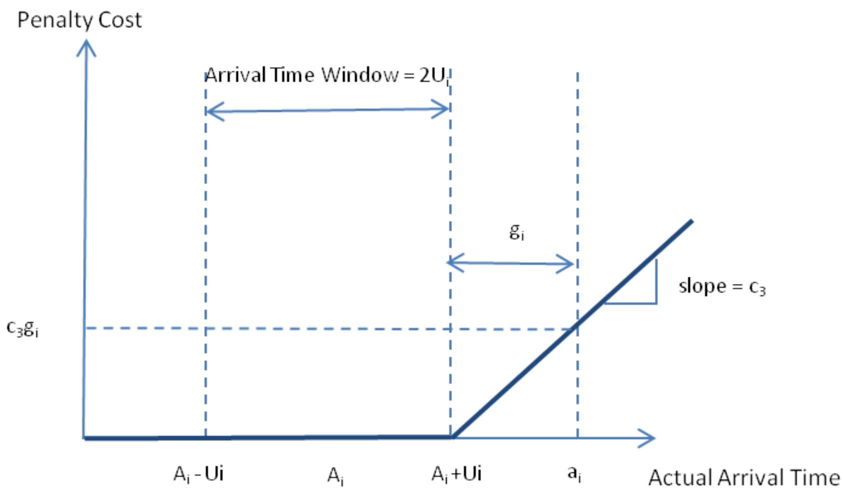

Figure 2: *Penalty Cost for varying arrival time values*

We further consider different service priorities μ_i for the incoming vessels berthing at the port. In practice, if a vessel with higher priority arrives late, it could still be given preference over a vessel with low service priority. Thus, the service priorities of the vessels are explicitly taken into consideration. Thus at any given time instant in the planning horizon, the objective function to be minimized is the sum of the total service cost of the realized schedule and the cost of rescheduling given by the weighted sum of the departure delay deviation and berthing location deviation from the original baseline schedule for all unassigned vessels N_u at that time instant. Let $b_i(k')$ denote the actual starting berthing location of vessel i and e'_i denote the actual departure time of vessel i in the realized schedule. Then the objective function cost is given by:

$$minZ = \sum_{i \epsilon N_u} (m_i - A_i + h_i) + \sum_{i \epsilon N} (c_1|b_i(k') - b_i(k)| + c_2\mu_i|e'_i - e_i|) \tag{7}$$

subject to constraints related to the deterministic berth allocation problem (for details refer to Umang *et al.* (2012)) and constraints (1)-(6). Here, c_1 and c_2 are weighting parameters for the space and time deviation respectively.

The main assumptions in our recovery algorithm for the berth allocation problem can be summarized as follows:

- As discussed earlier, the performance of any real time algorithm largely depends on the way the actual data is revealed. In our algorithm, we consider that each incoming vessel updates its exact arrival time a certain fixed time period before its actual arrival time. This time period represented by the parameter τ in our model is assumed equal to 5 hours. It is further assumed that once the arrival time of the vessel is updated, it does not change again.

- As the arrival delay information is released in real time only τ hours before the actual arrival, we re-optimize the berthing schedule every time the arrival time of any vessel is updated and it deviates from its expected value. Once the arrival time of a vessel is updated, its berthing assignment is determined by re-optimization of all the unassigned vessels in the schedule with the objective function (7) and the assignment of that vessel remains unchanged thereafter. Thus, at any given instant in the planning horizon H, the berthing schedule of all vessels whose exact arrival time is updated is considered frozen and unchangeable.

- In the optimization process, we only consider unassigned vessels at that time instant. The arrival time of any unassigned vessel that has not been updated up to that instant is assumed to be equal to its expected value if current time t is less than $A_i - \tau$, or otherwise assumed equal to $t + \tau$. The handling time restrictions are imposed accordingly.

The implementation of the optimization based recovery algorithm can be described by Algorithm 1.

The optimization based algorithm described above is implemented using set-partitioning ap-

Algorithm 1 Algorithm for implementation of optimization based recovery algorithm to solve BAP in real time

Require: Baseline schedule of set N of vessels, set M of sections
  Initialize set N_u of unassigned vessels $\rightarrow N$
  Initialize boolean array arrivalUpdated of size N = false $\forall i \in N$
  Initialize counter = 0
  while $|N_u|$ > 0 and $counter \leq |H|$ **do**
    Initialize boolean shouldOptimize = false
    for $i = 1 \rightarrow N$ **do**
      if arrivalUpdated[i] = false and counter $\geq a_i$ - τ and $a_i \neq A_i$ **then**
        Set arrivalUpdated[i] $\rightarrow$ true
        Set $A_i \rightarrow a_i$
        Set shouldOptimize $\rightarrow$ true
      end if
    end for
    if shouldOptimize **then**
      Re-optimize for all $i \in N_u$
    end if
    for $i = 1 \rightarrow N_u$ **do**
      if counter = latest updated start time m'_i **then**
        Assign vessel i to latest updated location $b_i(k')$
        Set $N_u \rightarrow N_u - \{i\}$
      end if
    end for
    counter++
  end while

proach by generating all feasible assignments of unassigned vessels every time there is a disruption. Since the approach involves several optimization runs, it is computationally very expensive as validated from simple numerical experiments. Thus, instead of optimizing the schedule every time, we consider an alternate heuristic approach for recovering the schedule. In this approach, every time there is an incoming vessel arriving at the port we scan the entire quay and assign it to the set of sections where the total cost of unassigned vessels given by (7) is minimized at or after its estimated berthing time according to the original baseline schedule. While determining the cost at a given instant in the planning horizon, we make the same assumptions for future vessel arrivals as discussed for Algorithm 1, and that every unassigned vessel is assigned to the estimated set of sections at or after their estimated berthing time as per the original baseline schedule. This heuristic algorithm is as described in Algorithm 2.

4 Preliminary Results

In this section, we present some preliminary results on disruption recovery in berth allocation problem in real time. We conduct some simple numerical experiments to test and validate

Algorithm 2 Algorithm for implementation of recovery heuristic algorithm to solve BAP in real time

Require: Baseline schedule of set N of vessels, set M of sections
  Initialize set N_u of unassigned vessels $\rightarrow N$
  Initialize boolean array arrivalUpdated of size N = false $\forall i \in N$
  Initialize counter = 0
  while $|N_u|$ > 0 and $counter \leq |H|$ **do**
    for Berthing Schedule: b **do**
      if b.hasArrived AND !b.isAssigned **then**
        Set boolean foundSection = false
        for $k = 1 \rightarrow M$ **do**
          if isStartSectionAvailable(b.vessel,k) **then**
            foundSection = true;
            break;
          end if
        end for
        if foundSection AND counter $\geq$ b.estimatedBerthingTime **then**
          Scan the entire quay and assign the vessel to the set of sections with minimum total cost $\forall i \in N_u$
        end if
      end if
    end for
    counter++
  end while

D_v	Optimization based algorithm		Heuristic Algorithm
	Realized Cost	Time	Realized Cost
0	586.0	0.07	586.0
2	645.0	48.5	695.5
6	745.0	56.5	761.2
10	842.3	85.7	884.3
14	871.5	108.6	897.9
18	904.3	115.8	910.8

Table 2: Total realized costs for the optimization based algorithm and heuristic algorithm for different values of D_v

the two algorithms discussed in the previous section, and analyze the impact of some input parameters in the model. All experiments are conducted for an instance of size $|N|$=25 vessels and $|M|$= 10 sections for a congested arrival scenario where all expected vessel arrivals are within a time range of 5 hours. The baseline schedule is obtained from the solution of the deterministic BAP for the dynamic vessel arrivals and hybrid berth layout, developed in context of bulk ports (refer to Umang *et al.* (2012) for details regarding the implementation). In all tested instances, the parameter c_1 in the objective function (7) is chosen as 0.002 and parameter c_2 is chosen as 1, which implies that shifting the berthing location of a vessel by 500 meters is considered equivalent to one additional hour of delay. The arrival window for imposition of

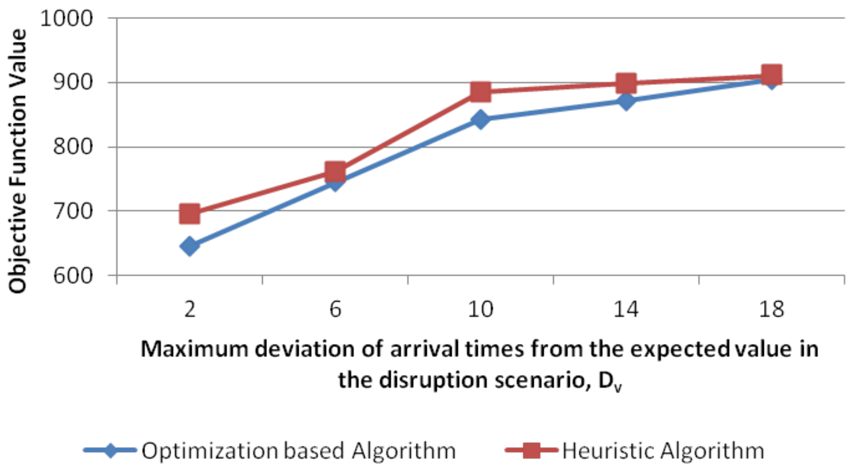

Figure 3: *Comparison between optimization based approach and heuristic approach (values averaged over 10 disruption scenarios)*

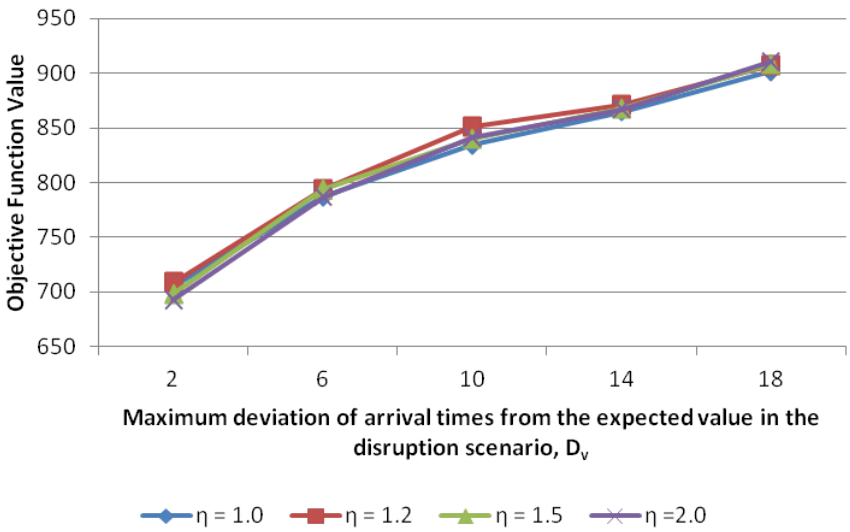

Figure 4: *Variation in total realized cost with change in D_v for different η values (values averaged over 100 disruption scenarios)*

handling time restrictions, U_i is chosen as 8 hours for all vessels, parameter τ relating to the release of arrival information is chosen as 5 hours, and the parameter η is assumed equal to 1.2 unless specified otherwise. The vessel priorities μ_i are chosen as more than 1 for two out of 25 vessels, and chosen exactly equal to 1 for the remaining 23 vessels.

The parameter D_v represents the maximum deviation of arrival time from the expected arrival time values in the disruption scenario applied on the baseline schedule. The arrival scenarios are generated by randomly generating actual arrival time values within the pre-specified range [A_i-D_v, A_i+D_v] for each vessel i. Table (2) shows the comparison between the optimization based algorithm and the heuristic approach. The numbers are averaged over 10 different disruption scenarios for each value of D_v. It can be inferred that although the optimization based algorithm

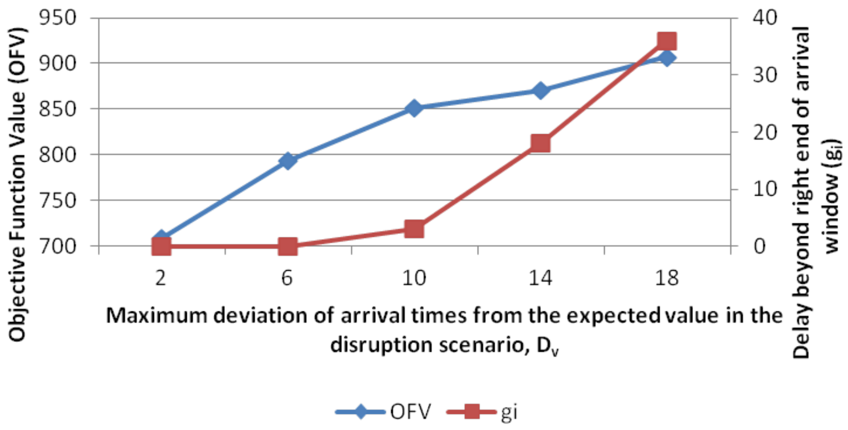

Figure 5: *Variation in total realized cost and g_i with change in D_v for η = 1.2 (values averaged over 100 disruption scenarios)*

slightly outperforms the heuristic algorithm, it is computationally much more expensive. The computation time for the heuristic based algorithm was not reported since it returns output almost instantaneously. The comparison is also shown graphically in Figure 3. As expected, it can be seen that total realized costs increase with increase in D_v. It is important to note here that the optimization based algorithm also makes assumptions regarding future vessel arrival times at a given instant in the planning horizon. Thus, the solution obtained from this approach is also not the best one, and it is possible that the heuristic approach may outperform the optimization based approach in certain cases in terms of the total realized costs of the modified schedule.

Figure 4 shows the variation of the total realized costs of the modified berthing schedule against different values of D_v. The results are intuitive as the costs increase with increasing maximum deviation in arrival time values from the expected value. Note that in this plot, the values are averaged over 100 disruption scenarios, and obtained from the heuristic algorithm since it is computationally much faster. An interesting observation is that for a given value of D_v, the total realized cost does not vary significantly over different values of η. This implies that the port managers can insert larger buffer times for the processing of vessels, without significantly increasing the total realized costs. This is a key aspect that definitely needs to be looked into greater depth in future research.

As discussed earlier, if the port decides to impost a penalty cost on all the vessels which are late beyond the right end of their permissible arrival window, the port can earn more revenue to cover their operational costs and earn higher profits. As shown in Figure 5 with increase in realized costs for increasing values of D_v, the total hours of delay g_i for all vessels beyond the right end of the arrival window is also higher. A more in-depth analysis may enable us to come up with appropriate pricing strategies and a penalty cost function dependent on the arrival delay g_i.

5 Conclusions and Future Work

In this work, we solve the problem of recovering a baseline berthing schedule in real time as disruptions occur. The underlying model is the dynamic, hybrid berth allocation model developed in context of bulk ports. To the best of our knowledge, very few scholars have attempted to study the problem of real time recovery using optimization based approaches in port operations, while the problem has not been studied at all in context of bulk ports. We present an optimization based recovery approach and a heuristic approach to solve the BAP in real time for a given baseline schedule. Preliminary results suggest that the approaches can be successfully applied to minimize the impact of disruptions in real time. The optimization based approach slightly outperforms the heuristic approach, but is computationally much more expensive.

Regarding future work, a more in-depth analysis based on extensive numerical experiments is needed in order to come up with appropriate values of the different input parameters c_1 and c_2 related to the cost of shifting the vessel along the quay and departure delay of a vessel with respect to the baseline schedule respectively, and parameters related to cost functions and handling time restrictions that can maximize the revenue earnings of the port.

Another possible extension of the work done so far is to develop a robust formulation for the berth allocation problem with a certain degree of anticipation of delays and variability in information. The recovery algorithm can be applied on both the deterministic and robust formulations and the performance can be compared in terms of loss of revenue at the planning stage and recovery savings in the event of disruptions.

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