DISRUPTION MANAGEMENT MODEL AND ITS ALGORITHMS FOR BERTH ALLOCATION PROBLEM IN CONTAINER TERMINALS

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Abstract. In this paper, the disruption management problem of berth allocation is studied to deal with the unforeseen disruptions in container terminals. A berth allocation model considering the scheduling of quay crane is developed first. Then a disruption management model is developed to recover the berth schedule when unexpected events happen, and simulation optimization approach is proposed to solve the model. To improve the computation efficiency of simulation optimization approach, algorithms based on local rescheduling and tabu search is designed. Numerical experiments indicate that local rescheduling based algorithm can improve the computation efficiency comparing to full rescheduling based algorithm. Moreover, the disruption management model considers the benefit of different parties, thus increases the scientifi city of recovery schedule.

Keywords: Berth scheduling, Disruption management, Simulation optimization, Container terminals

1. Introduction. Berths are important resources of container terminals and the good scheduling of berths can improve customers’ satisfaction, increase throughput and lead to higher revenues of container terminals. The objective of the berth scheduling is to determine the berthing times and positions of containerships in container terminals, thus to minimize the penalty cost resulting from delays in the departures of ships and the additional handling costs resulting from non-optimal locations of ships in a container terminals.

Quay cranes (QCs) scheduling problem is another vital factor for efficient terminal operations. The scheduling of QCs signifi cantly affects the operation efficiency of container terminals, and thus determines the makespan of a container vessel, which is the latest completion time of all operation tasks of a container vessel. QC operation rate is one of the most important indexes to measure the performance of operation system in container terminals. Moreover, berth allocation and QC scheduling are two inter-related problems, e.g., the change of QC-to-Vessel assignment influences the operation times of container vessels. Therefore, the integration solution of BAP and QCSP is needed.

Numerous studies have been conducted regarding the improvement of the efficiency of berth allocation and QC scheduling. And many models and algorithms are developed to optimize the berth allocation and QC scheduling. However, during operation, the planned schedules often have to be revised because of disruptions caused by severe weather, equipment failures, technical problems and other unforeseen events. Once these
disruptions happen, the initial plan may be infeasible, and modification of current or future schedule should be undertaken to minimize the negative impacts of the disruption, which is called disruption management.

This paper addresses the problem of recovering berth schedule during disruptions. The objective is to decrease the influence of unforeseen disruptions to operation system and decrease the addition cost resulting from disruptions. And this paper is organized as follows.

2. Literature Review. Issues related to container terminal operations have gained attention and have been extensively studied recently due to the increased importance of container transport. And there have been a growing number of studies that deal with the berth allocation problem (BAP) as well as quay crane scheduling (QCSP).

Existing studies about BAP can be classified into discrete and continuous types. In the discrete cases, the quay line is partitioned into a number of sections, called berths, where one vessel can be served at a time. Nishimura et al. [1] constructed a discrete assigning model in terms of public berths. Imai et al. [2] further considered the docking privileges of different shipping company to assign the berth. Kim and Moon [3] solved the discrete berth assignment model with simulated annealing. In continuous cases, Imai et al. [4] have developed a continuous berth assignment model to minimize the total service times, and in 2007 they further studied the berth assignment problem in the context of indented berths [5]. Wang et al. [6] took berth assignment problem as a multi-stage decision making problem.

The problem of QCSP was first studied by Daganzo [7], he designed an algorithm for determining the number of QCs assigned to ship-bays of multiple vessels. Kim and Park [8] developed a mixed-integer programming model considering various constraints related to the operation of QCs. Lee et al. [9] developed a mixed integer programming model for QC scheduling problem. Tavakkoli et al. [10] presented a mixed-integer programming model for the QC scheduling and assignment problem. A. V. Goodchild and C. F. Daganzo [11] described the double-cycling problem.

BAP and QCSP are two inter-related problems. The simultaneous BAP and the QCSP was first considered by Park and Kim [12]. A MIP and a heuristic solution method based on a Lagrangean relaxation were proposed to determine the berthing positions, berthing times, and the QC assignments. Imai et al. [13] developed a model for simultaneous berth and QC allocation problem, and the discrete BAP is considered in the model. Meisel and Bierwirth [14] studied the combined problem of berth allocation and QC assignment. Liang et al. [15] also developed a model for simultaneous berth and quay crane scheduling problem.

The objective of above studies is to optimize the berth and QC schedule before operations of vessels begin. However, during operation, the planned schedules often have to be revised because of disruptions. Once these disruptions happen, the initial plan may be infeasible, and modification of current or future schedule should be undertaken to minimize the negative impacts of the disruption.

Recently, management of disruptions attracts more and more attentions, and models were developed to tackle the disruptions in supply chain, machine scheduling and airlines operation, etc. Yu [16] developed disruption model for airline scheduling problem and designed a system called Crew-Solver based on heuristics algorithms to solve the model. Xiao et al. [17] studied the coordination of supply chain management when disruptions happens, and proposed method to improve the robust of initial plan. Petrovic et al. [18] and Qi et al. [19] developed disruption model for flow shop problem and designed solution algorithms. Walker et al. [20] developed an optimization model to resolve disruptions to
an operating schedule in the rail industry.

In this paper, the problem of disruption recovery for berth allocation and QC scheduling is studied. The problem is formulated into a mix-integer programming model. And simulation is integrated with optimization algorithms to obtain the recovery schedule. To improve the computation efficiency, algorithms based on local rescheduling and genetic are designed. Finally, numerical tests are provided to illustrate the validity of the proposed model and algorithms.

3. Model for Berth Allocation.

3.1. Problem descriptions. When allocating berth, the berthing time and position of every vessel must be determined. BAP consists of assigning a berthing position and a berthing time to each vessel within a given planning horizon. These decisions are made considering the different priorities, lengths, arriving and handling times of each vessel.

In the BAP, the handling time of each vessel is usually assumed to be fixed and known in advance. However, QCs are scarce resource in container terminals, if several vessels berth simultaneously, the handling time of each vessel is influenced by QC assignment plan which is restricted by the total number of QCs. In addition, the number of QCs serving a vessel is often restricted by a minimum number and technically allowable maximum number.

For this reason, when determine the berth allocation plan, the assignment of QC should be considered. We call it simultaneous berth allocation and QC scheduling problem (BACSP). This problem consists of two sub-problems: the first one is berth allocation and QC assignment problem which is to determine the berth allocation plan and the number of QCs assigned to each vessel, and the second one is QC scheduling problem which is to determine the QC routing plan.

3.2. Model formulation. For berth allocation and QC assignment problem, we make the following assumptions:

(a) The QC productivity is proportional to the number of QCs that simultaneously serve a vessel.
(b) There are no physical or technical restrictions such as vessel draft and water depth.
(c) There is a best berthing position for each vessel, in this location, yard trailers have the least delivery cost.
(d) Vessel handling requires a minimum number of QCs and it does not begin till that the number of QCs are available.

Let $L$ denote the total length of a quay line which is denoted by the number of 10-m segments, $N$ denote the number of vessels, $Q$ denote the number of QCs, $T$ denote the set of 1-h periods, $a_i$ denote the expected arrival time of vessel $i$, $d_i$ denote the latest completion time of vessel $i$ without penalty cost, $l_i$ denote the length of vessel $i$ given as the number of 10-m segments, $b_i$ denote the best berthing location of vessel $i$, in this location, the yard trailers have the least delivery cost, $q_{i}^{\text{min}}$ denote the minimum number of QCs needed to serve vessel simultaneously, $q_{i}^{\text{max}}$ denote the maximum number of QCs allowed to serve vessel $i$ simultaneously, $c_{1i}$ denote the additional travel cost per unit distance for delivering the containers of vessel $i$, resulting from non-optimal berthing location, $c_{2i}$ denote the penalty cost per unit time of vessel $i$, resulting from the departure delayed beyond the required due time, $c_{3}$ denote the operation cost rate of QCs given as USD per QC-hour, $w_i$ denote the QC capacity demand by vessel $i$ given as number of QC-hours, $M$ denote a sufficient large constant.
Let $x_i$ denote the berthing position of vessel $i$, $y_i$ denote the time starting operation of vessel $i$, $e_i$ denote the time finishing operation of vessel $i$. $z^x_{ij}$ is set to 1 if vessel $i$ is located to the left of vessel $j$ on the berth line, and 0 otherwise. $z^y_{ij}$ is set to 1 if vessel $i$ is berthed before vessel $j$ in time, and 0, otherwise. $r_{itq}$ is set to 1 if at least one QC is assigned to vessel $i$ at time $t$, and 0, otherwise. $r_{itq}$ is set to 1 if $q$ QCs are assigned to vessel $i$ at time $t$, and 0, otherwise.

The berth allocation and QC assignment problem can be formulated as follows (M1):

$$\text{Min} \sum_{i=1}^{N} \left\{ c_{1i} |x_i - b_i| + c_{2i}(e_i - d_i)^+ + c_3 \sum_{t \in T} q_{itq} \right\}$$  \hspace{1cm} (1)

s.t. $\sum_{i \in N} \sum_{q \in R_i} q \times r_{itq} \leq Q$, $\forall t \in T$  \hspace{1cm} (2)

$\sum_{q \in R_i} r_{itq} = r_{it}$, $\forall i = 1, \ldots, N$, $\forall t \in T$  \hspace{1cm} (3)

$\sum_{t \in T} r_{it} = e_i - y_i$, $\forall i = 1, \ldots, N$  \hspace{1cm} (4)

$\sum_{q \in R_i} q \times r_{itq} \geq w_i$, $\forall i = 1, \ldots, N$  \hspace{1cm} (5)

$x_i + l_i \leq x_j + M(1 - z^x_{ij})$, $\forall i, j = 1, \ldots, N$, $i \neq j$  \hspace{1cm} (6)

$e_i \leq y_j + M(1 - z^y_{ij})$, $\forall i, j = 1, \ldots, N$, $i \neq j$  \hspace{1cm} (7)

$z^x_{ij} + z^x_{ji} + z^y_{ij} + z^y_{ji} \geq 1$, $\forall i, j = 1, \ldots, N$, $i \neq j$  \hspace{1cm} (8)

$y_i \geq a_i$, $\forall i = 1, \ldots, N$  \hspace{1cm} (9)

$x_i \in \{0, 1, \ldots, L - l_i\}$, $\forall i = 1, \ldots, N$  \hspace{1cm} (10)

$R_i \in (q^\text{min}_i, q^\text{max}_i)$, $\forall i = 1, \ldots, N$  \hspace{1cm} (11)

$z^x_{ij}, z^y_{ij} = 1$ or 0, $\forall i, j = 1, \ldots, N$, $i \neq j$  \hspace{1cm} (12)

The objective function (1) is to minimize the departure delays of vessels, the additional handling costs resulting from non-optimal locations of vessels in a container terminal, and the operation cost of QCs. Constraints (2) ensure that at most $Q$ QCs are utilized simultaneously. Constraints (3) – (5) denote the starting time and ending time for each vessel. Constraints (6) denote the location relations between two vessels, which are effective only when $z^x_{ij} = 1$. Constraints (7) denote the berthing time relations between two vessels, which are effective only when $z^y_{ij} = 1$. Constraints (8) exclude the case where two vessels are in conflict with each other with respect to the berthing time and the berthing position. Constraints (9) ensure that a vessel cannot berth before it arrives at a container terminal. Constraints (10) ensure that every vessel must be berthed within the berth length. Constraints (11) restrict the number of QCs can be assigned to vessel $i$.

Next, given the berth allocation scheme and the number of QCs assigned to each vessel as above model (M1), QCs scheduling, namely the routing of QCs can be determined. To formulate the problem, we make the following assumptions:

(a) QCs are mounted on rails and run on the same track, and cannot pass each other.

(b) Once a QC begins to serve a vessel, it can move to another vessel only when the operations of the vessel are finished.

(c) The operation starting and ending time of each vessel is determined by the model described by Equations (1) – (12). If more QCs are assigned to a vessel, the ending time may be earlier than planned. In this occasion, QCs will move to other vessels until the planned ending time.
The following notations are used for model formulation:

\( i, j \)  
Vessels to be served, with \( i, j = 0, 1, \ldots, N, N + 1 \). Where, 0 is the source node and \( N + 1 \) is the sink node.

\( k \)  
QCs, where \( k = 1, \ldots, Q \). QCs are ordered in increasing order of their relative location along the berth line.

\( t_{ij} \)  
The travel time of a QC from vessel \( i \) to vessel \( j \), where, \( t_{0i} = 0, t_{i,N+1} = 0 \).

\( d_{ij} \)  
The travel time of a QC from vessel \( i \) to vessel \( j \), where, \( d_{0i} = 0, d_{i,N+1} = 0 \).

\( c_4 \)  
Cost rate of QCs travel given as USD per QC-hour.

\( p_i \)  
The time needed to perform vessel \( i \).

\( X_{ijk} \)  
1, if QC \( k \) performs vessel \( j \) immediately after performing task \( i \); and 0 otherwise.

\( D_i \)  
The real completion time of vessel \( i \). \( D_i \) may earlier or later than planned completion time \( e_i \). If \( D_i < e_i \), QCs serving vessel \( i \) will move to other vessels until the planned ending time; and if \( D_i > e_i \), the delay (\( D_i - e_i \)) should less than the interval of two consecutive vessels determined by berth allocation plan.

\( c_5 \)  
Penalty cost rate of QCs idling given as USD per QC-hour. For example, if \( D_i < e_i \), QCs serving vessel \( i \) will move to other vessels after waiting a period of \( (e_i - D_i) \). This may induce the waste of QC resources and thus decrease the utilization efficiency of QCs. Therefore, penalty cost is considered.

\( Z_{ij} \)  
1, if the operation of vessel \( j \) starts later than the completion time of vessel \( i \); 0 otherwise. This decision variable can be obtained by solving model M1.

Then the model for QCs scheduling can be formulated as follows (M2):

\[
\text{Min} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{Q} c_4 t_{ij} X_{ijk} + c_5 \sum_{i=1}^{N} \left\{ (e_i - D_i)^+ \sum_{i=0}^{N} \sum_{k=1}^{Q} X_{ijk} \right\}
\]

s.t. \( \sum_{j=1}^{N} X_{0jk} = 1, \quad \forall k = 1, \ldots, Q \) \hspace{1cm} (14)

\( \sum_{i=1}^{N} X_{i,N+1,k} = 1, \quad \forall k = 1, \ldots, Q \) \hspace{1cm} (15)

\( \sum_{j=1}^{N} X_{ijk} - \sum_{j=1}^{N} X_{jik} = 0, \quad \forall i = 1, \ldots, N, \quad \forall k = 1, \ldots, Q \) \hspace{1cm} (16)

\( D_i = y_i + w_i / \sum_{i=0}^{N} \sum_{k=1}^{Q} X_{ijk}, \quad \forall i = 1, \ldots, N \) \hspace{1cm} (17)

\( e_i + t_{ij} - y_j \leq M(1 - X_{ij}), \quad \forall i, j = 1, \ldots, N \) \hspace{1cm} (18)

\( D_i + t_{ij} - y_j \leq M(1 - z_{ij}^u + z_{ij}^x), \quad \forall i, j = 1, \ldots, N \) \hspace{1cm} (19)

\( \sum_{v=1}^{k} \sum_{u=1}^{N} X_{uv} - \sum_{v=1}^{k} \sum_{u=1}^{N} X_{uv} \leq M(Z_{ij} + Z_{ji}), \quad \forall i, j = 1, \ldots, N, \) \hspace{1cm} (20)

\( x_i < x_j, \quad \forall k = 1, \ldots, Q \)

\( X_{ijk} = 1 \text{ or } 0, \quad \forall i, j = 1, \ldots, N, \quad \forall k = 1, \ldots, Q \) \hspace{1cm} (21)

\( D_i \geq 0, \quad \forall i = 1, \ldots, N \) \hspace{1cm} (22)

The objective function (13) is to minimize the travel and penalty costs of QCs. Constraints (14) and (15) select the first and last tasks for each QC. Constraints (16) are
flow balance constraints ensuring that all vessels are performed in well-defined sequences. Constraints (17) denote the real finishing time of each vessel. Constraints (18) determine the relation between planned completion times (obtained by M1) of all vessels with routings of QCs. Constraints (19) ensure that the delay of a vessel (the real completion time is later than planned one, namely, $D_i > e_i$) can not induce the delay of the successor vessel. Constraints (20) are to avoid the interference among QCs.

4. Disruption Management Model.

4.1. Problem descriptions. The objective of above two models is to obtain an optimal berth & QC schedule before operations begin. However, during operation, there may be disruptions caused by severe weather, equipment failures, technical problems and other unforeseen events. Once these disruptions happen, the initial plan may be infeasible, and interventions or modifications are needed to recover the berth & QC schedule.

To solve this problem, disruption management method can be used. The primary difference between disruption management and rescheduling is that rescheduling focuses on the identification of a schedule which is optimal in terms of the original objective function whereas disruption management also aims to minimize the deviation of the updated schedule from the original one [19]. The disruption management problem for berth & QCs schedule in this paper takes the form of a bi-criterion scheduling problem. The first criterion is the origin objective function and the second is a measure of the deviation from the original schedule.

4.2. Model formulation. The disruption management problem for berth & QCs schedule can be divided into two phases. The first phase is berth allocation, whose objective is to search new berthing position and berthing order of each vessel, and the second phase is QCs scheduling whose objective is to optimize QCs rescheduling based on the first phase.

For the first phase, the objective function is to minimize the deviation of vessel completion time in new berth schedule from original one, and the addition cost resulting from non-optimal locations.

Let $e_i$ be the completion time of vessel $i$ in the new schedule when disruption happens. Then the difference between $e_i$ and $\bar{e}_i$ can be used to evaluate the deviation between original and new schedule.

Let $N'$ denote the number of uncompleted vessels left when disruption occurs, $T_0$ denote the time when disruptions happen. $x'_i$, $y'_i$ denote the berthing position and berthing time of vessel $i$ in new schedule. $z'_{ij} = 1$, if ship $i$ is located to the left of ship $j$ in the new schedule; and 0 otherwise. $y'_{ij} = 1$, if ship $i$ is berthed before ship $j$ in time in the new schedule; and 0, otherwise.

Then first phase model (M3) for disruption management of berth & QCs schedule can be formulated as follows:

$$\text{Min } \sum_{i=1}^{N'} \left\{ c_{1i} |x'_i - b_i| + c_{2i}(e'_i - e_i)^+ \right\}$$

s.t. $\sum_{i \in N'} \sum_{q \in R_i} q \times r_{itq} \leq Q$, $\forall t \in (T_0, T)$

$$\sum_{q \in R_i} r_{itq} = r_{it}, \quad \forall i = 1, \ldots, N', \quad \forall t \in (T_0, T)$$

$$\sum_{t \in (T_0, T)} r_{it} = e_i - y'_i, \quad \forall i = 1, \ldots, N'$$
\[
\sum_{q \in R_i} q \times r_{iq} \geq w_i, \quad \forall i = 1, \ldots, N'
\]  
(27)

\[
x'_i + l_i \leq x'_j + M(1 - z_{ij}^x), \quad \forall i, j = 1, \ldots, N', \quad i \neq j
\]  
(28)

\[
e'_i \leq y'_i + M(1 - z_{ij}^{y_i}), \quad \forall i, j = 1, \ldots, N', \quad i \neq j
\]  
(29)

\[
z_{ij}^x + z_{ji}^x + z_{ij}^{y_i} + z_{ji}^{y_i} \geq 1, \quad \forall i, j = 1, \ldots, N', \quad i \neq j
\]  
(30)

\[
y'_i \geq a_i, \quad \forall i = 1, \ldots, N'
\]  
(31)

\[
x'_i \in \{0, 1, \ldots, L - l_i\}, \quad \forall i = 1, \ldots, N'
\]  
(32)

\[
R_i \in (q_i^{\min}, q_i^{\max}), \quad \forall i = 1, \ldots, N'
\]  
(33)

\[
\overline{z}_{ij}^x, \overline{z}_{ij}^{y_i} = 1 \text{ or } 0, \quad \forall i, j = 1, \ldots, N', \quad i \neq j
\]  
(34)

For the second phase, the objective of QC rescheduling phase is to minimize the deviation of vessel completion time in new schedule from initial one, which can be obtained by solving model M2 based on the results obtained by M3.

5. Simulation Optimization Approach. It is well known that BAP is a NP-hard problem. It is doomed unable to obtain optimal solutions for large-scale problems. Hence, heuristic algorithms are wildly used to obtain near-optimal solutions efficiently. However, because of the numerous constraints, it is difficult to evaluate a scheduling scheme in the process of heuristic algorithms, especially the calculation of \(c_{ij} |x'_i - b_i|\). Discrete event simulation has been a useful tool for evaluating the performance of such systems. However, simulation can only evaluate a given design, not provide more optimization function. Therefore, the integration of simulation and optimization is needed [21].

The framework of simulation optimization modeling integrates a schedule simulation model and an optimization solver. It starts by activating the schedule simulation model to identify and assess the disruptions. The optimization solver is used to search a new schedule, and the schedule is evaluated by simulation model.

When the berth reschedule needs to be optimized after disruption happens, simulation model must be built first, and then the optimization algorithm is designed to optimize the parameters of simulation model. The setup of input and output variables, such as initial solution, constraints of decision variables, objective function and repetition time of simulation in simulation model is done in optimization algorithm. As optimization algorithm running, it would create a set of feasible design variables, and transfer them to the simulation model by data interface; then the simulation model applies these variables to reconfigure the simulation parameters in real time, and run the simulation, then simulation results are returned to the optimization algorithm; according the results, the algorithm adjusts the direction of optimal solution searching and creates a new set of feasible solutions. The process would repeat until the stop criterion is satisfied. Finally, optimized design variables and best scheduling scheme are output.


6.1. Algorithm descriptions. To improve the computation efficiency of simulation optimization, and thus provide online decision support for disruption management of berth scheduling, we design algorithms integrating local rescheduling method with tabu searching.

The objective of disruption management is to find a new schedule which is optimal not only in terms of original objective, but minimization the deviation of new schedule from original one. Therefore, disruption management does not simply optimize all future operations, and a good idea is taking the existing schedule into account to do local resc-
6.2. Framework of local rescheduling based algorithm. Suppose \( t_c \) denote the current time (i.e., the time when disruptions happen) and \( t_e \) denote the end of considered horizon. The considered time window is defined by a lower bound \( t_l^i \) and an upper bound \( t_u^i \) for iteration \( i \), with \( i = \{1, \ldots, n\} \). Let \( s_c \) denote the position of the first disrupted vessel and \( s_e \) denote the end of quay line. The considered space window is defined by a lower bound \( s_l^i \) and an upper bound \( s_u^i \) for iteration \( i \). Suppose that the lower bounds for time and space window are fixed, which are denoted by \( t_c \) and \( s_c \) respectively. The process of local rescheduling is as follows:

Step 1: initialize time window \((t_c, t_u^0)\) and space window \((s_c, s_u^0)\);
Step 2: optimize the reschedule within the time window and space window using tabu search, \( i = i + 1 \);
Step 3: if \( i \leq n \), go to Step 4 and Step 6, otherwise;
Step 4: update the upper bound by step size \( p_i \), \( p_i' \), and \( p_i = \frac{t_e - u_0}{n} \), \( p_i' = \frac{s_e - s_c}{n} \);
Step 5: go to Step 2;
Step 6: end.

7. Numerical Experiments. Numerical experiments are conducted to evaluate the validity of the proposed model and algorithms. Real data of a berth and size of vessels are collected from Tianjin Five Continents International Container Terminal, a container terminal of Tianjin Port in China. The length of berth is 1202m, and the number of QCs is 12. The operation efficiency of QCs is about 30moves/hour. Data for vessels are collected from October, 2007. Considering the practical situation in Tianjin port and taking the results of Kim [3], \( c_{1i} \) and \( c_{2i} \) are set to be 100$/li$ and 20000$/li$ respectively. And \( c_3 \), \( c_4 \), \( c_5 \) are set to be 200, 120, 100 USD respectively.

The number of considered vessels is 26 (the vessels are numbered according to arriving time), and the considered time is 7 days. Initial berth allocation and QCs schedule can be obtained by solving M1 and M2. Tabu search algorithm is used to solve the models.

The considered vessels are numbered in increasing order according the arriving time. We design 7 scenarios supposing that the vessel 3, 4, 5, 7, 13, 14 and 18 are delayed respectively. And each vessel is delayed 8 hours. Using these data, two methods are compared:

(1) Local rescheduling with tabu search algorithm, namely the algorithm described in Section 6, and the iteration for QCs rescheduling is 40.

(2) Full rescheduling: To optimize all future operations, and tabu search is used.

We compare the objective function obtained by these two methods. The objective function includes total vessel delay cost caused by disruption which is given as \( \sum_{i=1}^{N'} c_{2i}(\bar{e}_i - e_i)^+ \), and penalty cost resulting from non-optimal locations of vessels which is given as additional yard truck cost between new and initial schedule. Results are given in Table 1.
Table 1. Results of different methods

<table>
<thead>
<tr>
<th>Experiment scenarios No</th>
<th>Delayed vessel</th>
<th>Local rescheduling Objective value</th>
<th>Computation time(s)</th>
<th>Full rescheduling Objective value</th>
<th>Computation time(s)</th>
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<td>25,493</td>
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</table>

Results show that local rescheduling can improve the computation efficiency to obtain the new schedule coping with disruptions comparing with full rescheduling. The local rescheduling method performs particularly well if the considered problem is complex and if the time available to response to disruption is little. E.g., when the number of uncompleted vessels is small (e.g., scenario 7), the difference of the two methods is small; and when the number of vessels is large (e.g., scenario 1), the solution computation time of full rescheduling is longer than local rescheduling greatly. The characteristics of disruption management require the high speed and efficiency of solution algorithms, thus the local rescheduling based method is more suitable to disruption management problem.

Moreover, the influence of different number of iterations \((n)\) is studied. Scenario 1 in Table 1 is used. Results are shown in Figure 1 and Figure 2.

![Figure 1. Computation time in different iterations](image)

Figure 1 indicates that with the increase of iterations first, the computation time decreases first, and then increases when the number of iteration is greater than 24. With the increase of iterations, the algorithm may find a relative good reschedule locally, which can save the time to search full solution space. However, when the iterations are too large, the step size of the algorithm is too small and the algorithm may not find a feasible solution in the small time window or space window, thus induce the decrease of computation efficiency.

From Figure 2, we can find that the total penalty increase with the increase of iterations, which indicate the solution quality decrease with the increase of iterations. This is because that with the increase of iterations, the step size is decreases, and thus makes the algorithm more local-based. Results of Figure 2 indicate that local rescheduling method decreases the solution quality comparing with full rescheduling.
The characteristics of disruption management require the high speed and efficiency of solution algorithms, thus the local rescheduling based method is more suitable to disruption management problem. In addition, in the optimization process, the simulation model can evaluate the influence of new schedule accurately, which can improve the scientificity of the new schedule.

8. Conclusions. In this paper, the disruption management problem of berth scheduling is studied. The disruption management model for the simultaneous optimization of berth and QC reschedule is developed. And a simulation optimization approach is proposed to assess the influence of disruptions and optimize the new berth schedule coping with disruptions. To improve the computation efficiency of simulation optimization model, an algorithm based on local rescheduling and tabu search is designed. Numerical experiments indicate that the algorithm based on local rescheduling and tabu search can improve the computation efficiency. Moreover, the disruption management model considers the benefit of different parties, thus increases the scientific of disruption recovery schedule.

In this paper, the constraints are supposed to be unchanged in the process of disruption management. However, with the development of disruptions, some constraints may be unnecessary or inappropriate, and new constraints may be needed. Therefore, the constraints for disruption management model should be dynamic, namely some constraints should be omitted while other constraints should be added. This is a problem needed to be studied further.

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