Real time disruption recovery for integrated berth allocation and crane assignment in container terminals

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**ABSTRACT**

This paper studies the disruption recovery optimization for the integrated berth allocation and quay crane assignment problem in container terminals. A reactive recovery strategy which adjusts the initial plan to handle realistic disruptions is proposed. For the proposed recovery strategy, new berthing positions for vessels are restricted within a certain space. Quay cranes are allowed to move to other vessels before finishing current assigned vessels. Meanwhile, vessels requiring early dispatch are particularly considered when conducting recovery planning. With these considerations, a non-linear programming model is proposed to maximize the service quality and minimize the recovery cost at the same time. A heuristic approach based on Squeaky Wheel Optimization is developed to solve the model. Computational experiments are conducted to show the performance and effectiveness of the proposed model and solution method.

**Keywords:** Disruption recovery; Berth allocation; Crane assignment; Container terminal; Squeaky wheel optimization
1 INTRODUCTION

In practice, before a vessel calls a port, the vessel agent will send its estimated time of arrival (ETA), stowage plan, and other information to the port operator who will form an initial berthing and crane scheduling plan before its arrival. However, disruptions may happen during real time operation, such as awful weather, equipment failure, arrival delay, call-port change, etc. Consequently, the initial plan probably turns out to be an infeasible one, or from another aspect, not an optimal one.

While conducting real time re-scheduling for disruption response, port operators usually revise the initial plan manually in their control system according to past experience. Such kind of experience-dependent re-scheduling method is relatively flexible but a systematic view is neglected during this process. Real time recovery requires the resources to be reassigned, and exerts impacts on both vessels that encounter disruptions and those come afterwards. Therefore, the new plan should pay attention to minimize the negative impacts due to rescheduling while striving to maintain a good result with the original objective.

Despite these impacts caused by disruption recovery, in practice when a vessel is delayed in its own schedule, clients often ask ports to accelerate handling to catch up with its schedule. If an acceleration process takes place, for most time in this situation, container terminals will earn some profits either in a monetary form or a reputation for high service quality, which can be seen as compensation to extra costs.

Therefore, the aim of this paper is to propose a real time disruption recovery model that takes the total service time, deviation from the original plan and recovery cost into consideration simultaneously. The remainder of this paper is organized as follows. Following this introduction, Section 2 illustrates the extensive research in the relevant problems. Section 3 describes in detail the recovery problem and develops an optimization model. A Squeaky Wheel Optimization (SWO) meta-heuristic algorithm is presented in Section 4 while Section 5 presents computation results. Section 6 summaries the conclusions and briefly discusses possible future research.

2 LITERATURE REVIEW

For the integration of berth allocation problem (BAP) and quay crane assignment problem (QCAP), Imai et al.(2008) developed a heuristic to solve the integrated problem with the objective of minimizing overall service time. Some real world aspects were considered in Lee and Chen (2009)’s continuous berth scheduling optimization model, in their study, the first-come-first-serve rule, clearance distance between ships, and possibility of ship shifting were considered. In the integration of berth and quay crane (QC) scheduling problems in Han et al.’s study (2010), QCIs were allowed to move to other berths before finishing processing on currently assigned vessels, adding some flexibility to the terminal system. Golias et al. (2010) presented a new formulation for discrete space berth scheduling problem with the objectives of minimizing the total service time and delayed departures as well as the total emissions and fuel consumption for all vessels. In a transshipment container terminal, similar problems are considered. A mixed integer programming model was developed by Lee et al. (2011) to address the integrated problem for bay allocation and yard crane scheduling in a transshipment container terminals with the objective of minimizing total costs, including yard crane cost and delay cost. Der-Horng et al. (2012) integrated terminal allocation for vessels and yard allocation for transshipment container movements both within a terminal and between terminals. While designing a visiting schedule template for feeder vessels and determining storage locations for transshipment containers, they also developed a mixed integer programming formulation with the objective of minimizing both the total distance traveled by transshipment flows between quayside and storage yard and the workload imbalance in time.

BAP under uncertain arrival time or operation time of vessels was considered by Zhen et al. (2011). In their paper, both a proactive strategy to develop an initial schedule that integrated a degree of anticipation of
uncertainty and a reactive recovery strategy adjusting the initial schedule to handle realistic scenarios were proposed. But the scenario based method had limited capabilities when dealing with real situations with large number of possible situations.

While considering the uncertainty of vessel arrival delay and handling time, Xu et al. (2012) adopted the method of inserting time buffers between the vessels occupying the same berthing location to solve the robust berth allocation problem. Zhen and Chang (2012) developed a robust schedule for berth allocation and incorporated a degree of anticipation of uncertain arrival time and operation time by proposing a bi-objective optimization model for minimizing cost and maximizing robustness of schedules. By minimizing the average and the range of the total service times required for serving all vessels, Golias et al. (2014) also provided a robust berth schedule in a discrete berth layout with a bi-objective optimization formulation. Zeng et al. (2011) addressed the problem of recovering berth and quay crane schedules in container terminals with a two-stage strategy.

As the focus of research in this field is evolving toward incorporating uncertainties into the planning process, the proactive strategy and the reactive strategy are gaining interests among researchers. However, studies concerning the reactive strategy are limited, and the recovery cost and vessels requiring early dispatch are seldom considered. Therefore, in this paper, to solve the berth allocation and crane assignment problem (BACAP) under a disrupted circumstance, in addition to minimizing overall service time, we take dynamic QCAP and restricted berthing place reallocation as a recovery strategy to form a reactive plan with the consideration of recovery cost and early dispatch requests.

3 MODEL FOR BACAP REAL TIME RECOVERY

3.1 The objectives for real time recovery

Different from the objective of an initial plan which is normally to minimize the total service time, total delay or other manifestation of service quality, the objective of recovery is to minimize the negative impacts of the disruptions. Therefore, the objective of disruption recovery for berth and QCs schedules in this article can be concluded as three parts: the performance of the original plan, the deviation from the original plan as well as the cost to conduct recovery action.

3.1.1 Recovery strategy

The recovery of a plan is a resource rescheduling process based on the certain objectives. In this paper, the recovery strategy mainly involves berth reallocation within a restricted space and dynamic quay crane reassignment process.

As is shown is Figure 1(a), considering of berth space restriction and container horizontal movement, we ensure that the new berthing place of vessel $i$ should be within a restricted range based on its length when reassigning a new berth location. For example, the reallocation space for vessel 3 is confined within the square space in blue in the Figure 1(a). In real world, the number of working QCs can be different for one vessel during its loading and discharging process and the change should not be too sharp. Therefore, we use a dynamic assigning method as in Figure 1(b) and the reassignment process will be conducted in every work shift interval. The number of QCs in two consecutive time steps for a work shift can be different. However, the change in the number QCs should be no more than two for the consideration that large variation would cause frequent QC movements and thus lower the productivity. Figure 1(b) shows a recovery process of vessel 3, the original berthing plan for vessel 3 is represented by the white rectangle, while the actual plan is the gray one. It can be seen that there is an
adjustment in its berthing position and number of assigned QCs which will accelerate its operation to fulfill its
dispatch request. Let \( q_{ih} \) denote that \( q \) QCs are assigned to vessel \( i \) at time step \( h \), in this situation, \( \lambda^{q_{ih}} = 1 \),
otherwise \( \lambda^{q_{ih}} = 0 \). Hence, the average QC number for vessel \( i \) at one time step is:

\[
\sum_{h \in H} \sum_{q \in P_i} q_{ih} q_{in} / \sum_{h \in H} \sum_{q \in P_i} q_{in}
\]

3.1.2 Early dispatch service

When a vessel arrives late, in order to catch up with its planned schedule and to avoid further delay, shipping
companies usually require early dispatch and pay some compensation to container terminals for extra resource
allocation (e.g., more QCs). As for container terminals, they can also provide early dispatching service to some
important clients and take this as a value added action to a reputation of high service quality. This part of earnings
can be regarded as compensation to the container terminal to take recovery action. Container terminals will give
higher priority to this group of vessels when conducting berth reallocation and quay crane reassignment to fulfill
the early dispatch requirement. Therefore, early dispatch requirement should be reflected in the recovery
objectives both on time and cost terms.

3.1.3 Recovery cost

The recovery cost mainly consists of the following three parts: container horizontal transport cost, extra QC-hour
demand cost caused by adjustment of berthing position and QC scheduling process, and the earnings from the
fulfillment of early dispatch for some vessels.

The first part is incurred by the extra horizontal movement distance of the containers when a vessel berths at
a position deviating from its original berthing place. The second part is its extra handling cost for the recovery
operation. It is widely realized that the deviation from the original berthing position will increase the horizontal
transport movement by yard trucks. At the same time, it will also exert impacts on handling cost. Park and Kim
(2003) stated the load of increasing horizontal transport can be partially alleviated by employing more transport
vehicles, while Meisel and Bierwirth (2009) mentioned that a larger number of vehicles decelerates the average
speed and thus reduces the service rate. Therefore, they concluded that an apart berthing position of a vessel leads
to an increase in QC-hour demand. In this study, we use a similar approximation method to describe the extra cost
caused by increased QC-hour demand.
The third part of the recovery cost is the profit earned by offering early dispatch service, which is actually a reduction element for the total cost. Denote $C_3$ as the earning for the early dispatch of one vessel per time unit. The reduction is $C_3 \cdot \Delta D_i$, where $D_i$ refers to the time gap between the actual service time and the expected one for vessels with early dispatch requirement.

### 3.2 Modeling

#### 3.2.1 Assumption

1. There is an initial plan before the recovery process is conducted;
2. Vessels can only be served after arrival;
3. There is no water draft limit for berthing vessels;
4. Each vessel has a certain berthing position in the original plan, and there is no shifting of the berthing position allowed once the operation starts;
5. Each vessel has a maximum and minimum number of QCs to be assigned. Container loading and discharging for vessels does not begin till the minimum numbers of cranes are available.

#### 3.2.2 Notation

**Sets**
- $N$ set of vessels need to be reallocated, $N=\{1,2,\cdots,i,\cdots,n\}$;
- $N^o$ set of vessels under operation, $N^o=\{1,2,\cdots,i^o,\cdots,n^o\}$;
- $N^*$ set of vessels that require early dispatch, $N^* \subseteq N$. $N^*$ is the complementary set of $N^*$, $N^* \cup \overline{N^*} = N$;
- $H$ set of time steps, $H=\{1,\cdots,h\}$. $h$ is the planning span;
- $T$ set of time steps index during one shift length, $T=\{1,\cdots,t^*\}$;
- $H_t$ set of time steps with the index of $t \in T$ within a shift;
- $P_i$ set of QC assignment for the vessel $i \in N$, $P_i = \cup_{t \in T} P_{it}$;
- $\alpha$ set of priority factors of vessels, $\alpha = \{\alpha_1,\alpha_2,\alpha_3,\cdots,\alpha_i,\cdots\}$;
- $\beta$ set of time sensitivity of clients, $\beta = \{\beta_1,\beta_2,\beta_3,\cdots,\beta_i,\cdots\}$;

**Parameters**
- $L$ length of the quay;
- $l_i$ length of quay vessel $i$ will occupy including the vessel length and the safety distance between its adjacent vessels;
- $ETA_i$ expected time of arrival of vessel $i$;
- $AR_i$ actual arrival time of vessel $i$;
- $ET_i$ expected time of the completion of handling of vessel $i$;
- $Q^h$ maximum QCs available at time step $h$;
- $b_i$ berthing position of vessel $i$ in the original plan;
- $q_{ih}$ $q$ QCs are assigned to vessel $i$ at time step $h$, $q_{ih} \in P_i\{R_{min},\cdots,R_{max}\}$, $R_{max}$ is the technically maximum number of QC for vessel $i$;
- $m_i$ QC-hours required by vessel $i$;
- $W_i$ TEUs that required to be loaded or discharged on vessel $i$;
- $C_0$ time cost for each time unit;
- $C_1$ horizontal movement cost for one container every unit distance;
- $C_2$ operation cost of one QC-hour;
- $C_3$ early dispatch earning rate;
\[ \begin{align*}
\theta & \quad \text{berth deviation factor;} \\
\mu & \quad \text{QC productivity interference exponent;} \\
up_i & \quad \text{upper bound of berthing position deviation distance of vessel } i; \\
q_i & \quad \in \{0, 1\}, \forall i \in N. 1 \text{ if vessel } i \text{ asks for early dispatch, } 0 \text{ otherwise}; \\
M & \quad \text{a sufficiently large constant} \\
k & \quad \text{weighted factor for different objectives, } 0 \leq k \leq 1
\end{align*} \]

Decision variables

\[ \begin{align*}
ST_i & \quad \text{actual operation start time of vessel } i; \\
ET_i & \quad \text{actual operation completion time of vessel } i; \\
b_i^t & \quad \text{actual berthing position of vessel } i; \\
x_{ij} & \quad \in \{0, 1\}, \forall (i, j) \in N. 1 \text{ if vessel } j \text{ is berthed after vessel } i, 0 \text{ otherwise;} \\
y_{ij} & \quad \in \{0, 1\}, \forall (i, j) \in N. 1 \text{ if vessel } j \text{ is berthed on the left of vessel } i, 0 \text{ otherwise;} \\
\rho_i^o & \quad \in \{0, 1\}, \forall i \in N, \forall h \in H. 1 \text{ if the operation process for vessel } i \text{ is started at time step } h, 0 \text{ otherwise;} \\
\lambda_{qih} & \quad \in \{0, 1\}, \forall i \in N. 1 \text{ if } q \text{ QC}s \text{ are assigned to vessel } i \text{ at time step } h, 0 \text{ otherwise;}
\end{align*} \]

3.3.3 Model formulation

The BACAP recovery problem is formulated as a mixed integer nonlinear programming model. It particularly considers total service time, deviation from original plan, recovery cost and early dispatch requests which are seldom considered in most previous models. The mathematical formulation for the BACAP recovery is as follows:

\[ \begin{align*}
Z = \mathop{\text{Min}} k \cdot f_1 + (1 - k) \cdot f_2 \quad (1)
\end{align*} \]

\[ \begin{align*}
f_1 = C_0 \cdot \left( \sum_{i \in N} \alpha_i (ET_i - AR_i) + \sum_{i \in N} \beta_i (ET_i - ET_i) + \sum_{i \in N} \alpha_i (ET_i - AR_i) + \sum_{i \in N} \beta_i (ET_i - ET_i) \right) \quad (2)
\end{align*} \]

\[ \begin{align*}
f_2 = C_1 \sum_i W_i |b_i^t - b_i| + C_2 \sum_i \left( \frac{1 + \theta |b_i^t - b_i|}{\sum_{h \in H} \sum_{q \in P_i} \lambda_{qih} q_{ih}} - m_i \right) \quad (3)
\end{align*} \]

\[ \begin{align*}
\text{S.t.} \\
AR_i - ST_i \leq (1 - \rho_i^h) M \quad \forall i \in N, \forall h \in H \quad (4)
\end{align*} \]

\[ \begin{align*}
ET_i - ST_i = \sum_{h \in H} \sum_{q \in P_i} \lambda_{qih} \quad \forall i \in N \quad (5)
\end{align*} \]

\[ \begin{align*}
\sum_{h \in H} \sum_{q \in P_i} \lambda_{qih} q_{ih}^\mu \geq (1 + \theta |b_i^t - b_i|) m_i \quad \forall i \in N, \forall q \in P_i, \forall h \in H \quad (6)
\end{align*} \]

\[ \begin{align*}
ET_i \geq \rho_i^h \cdot (h + 1) \quad \forall i \in N, \forall h \in H \quad (7)
\end{align*} \]

\[ \begin{align*}
ST_i \leq \rho_i^h \cdot h + H \cdot (1 - \rho_i^h) \quad \forall i \in N, \forall h \in H \quad (8)
\end{align*} \]

\[ \begin{align*}
b_i^t + l_i \leq b_j^t + M(1 - y_{ij}) \quad \forall i \in N, \forall j \in N, i \neq j \quad (9)
\end{align*} \]

\[ \begin{align*}
b_i^o + l_i^o \leq b_i^t + M(1 - y_{i^o j^o}) \quad \forall i \in N, \forall i^o \in N^o \quad (10)
\end{align*} \]
\[ ET'_{i} \leq ST_{j} + M(1 - x_{ij}) \quad \forall i \in N, \forall j \in N, \ i \neq j \] (11)

\[ ET'_{i \theta} \leq ST_{i} + M(1 - x_{i \theta}) \quad \forall i \in N, \forall \theta \in N^{\theta} \] (12)

\[ x_{ij} + x_{ji} + y_{ij} + y_{ji} \geq 1 \quad \forall i \in N, \forall j \in N, \ i \neq j \] (13)

\[ y_{i \theta} + y_{i \theta'} + x_{i \theta} + x_{i \theta'} \geq 1 \quad \forall i \in N, \forall \theta, \theta' \in N^{\theta} \] (14)

\[ \rho^{h}_{i} = \max \{0, \sum_{q \in P_{i}} \lambda^{q_{ih}} - \sum_{q \in P_{i}} \lambda^{q_{ih-1}}\} \quad \forall i \in N, \forall h \in H \] (15)

\[ \sum_{i \in N} \sum_{q \in P_{i}} \lambda^{q_{ih}} q_{ih} \leq Q^{h} \quad \forall h \in H \] (16)

\[ q_{ih+t} - q_{ih} - 2 \leq M(1 - \lambda^{q_{ih}}) \quad \forall i \in N, \forall h \in H, \forall t \in T, q \in P_{i} \quad (17) \left| b'_{i} - b_{i} \right| \leq u_{p_{i}} \quad \forall i \in N \] (18)

\[ 0 \leq b'_{i} \leq L - l_{i} \quad \forall i \in N \] (19)

\[ x_{ij} \in \{0,1\}, \forall (i,j) \in N \] (20)

\[ y_{ij} \in \{0,1\}, \forall (i,j) \in N \] (21)

\[ \rho^{h}_{i} \in \{0,1\}, \forall i \in N, \forall h \in H \] (22)

\[ \lambda^{q_{ih}}_{i} \in \{0,1\}, \forall i \in N, q \in P_{i}, \forall h \in H \] (23)

\[ ST_{i} \geq 0 \quad \forall i \in N \] (24)

\[ ET'_{i} \geq 0 \quad \forall i \in N \] (25)

Objective function (2) minimizes the time cost from service time and deviation from vessels’ expected departure time. Objective function (3) minimizes total recovery cost of all vessels, including container horizontal transport cost, extra QC demand cost caused by adjustment of berthing position and QC scheduling process, and earnings from the fulfillment of early dispatch for some vessels. (1) combines the two with a weighted parameter \( k \). Constraint (4) ensures that vessels are served after its arrival. Constraints (5)–(8) set the start time and ending time for the operation of vessel \( i \). Constraints (9) and (10) state the relationship of berthing position between vessels. The time relationship between vessels is defined by constraints (11) and (12) in a similar way. Constraints (13) and (14) ensure that there is no overlapping both in berthing space and time. Constraint (15) links variable \( \rho^{h}_{i} \) and \( \lambda^{q_{ih}}_{i} \). Constraints (16) and (17) impose the QC resource restriction. Constraint (18) defines the largest deviation from the original berthing place. The range of decision variables is specified in constraints (19)–(25).

To better explain the extra handling cost for recovery, a brief illustration is given below. Since \( C_{2} \) denote the operation cost per QC-hour, and \( m_{i} \) denotes the original QC hour demand of vessel \( i \), the extra handling cost can be roughly described as \( C_{2} \cdot \Delta m_{i} \), where \( \Delta m_{i} = m_{\text{increase}} - m_{\text{original}} \). Hence, the new QC capacity demand of a vessel positioned away from original berthing position is \( (1 + \theta |b'_{i} - b_{i}|)m_{i} \) QC-hours. Considering of the
interference effects between QCs, the productivity of QCs for vessel \( i \) is \((\sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}} q_{ih} / \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}})^\mu\).

Therefore, the total handling time for vessel \( i \) is

\[
\frac{(1 + \theta |b'_i - b_i|) m_i}{(\sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}} q_{ih} / \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}})^\mu}
\]

From the equation above, we can obtain the increased working hours for vessel \( i \):

\[
\frac{(1 + \theta |b'_i - b_i|) m_i \times \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}} q_{ih} / \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}}}{(\sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}} q_{ih} / \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}})^\mu}
\]

Therefore, the extra handling cost for recovery in the objective function is presented as:

\[
C_2 \sum_i \left( \frac{(1 + \theta |b'_i - b_i|) m_i \times \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}} q_{ih} / \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}}}{(\sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}} q_{ih} / \sum_{h \in H} \sum_{q \in P_i} \lambda^{q_{ih}})^\mu} - m_i \right)^+
\]

4 ALGORITHM

4.1 General framework

As BAP was already proved to be a NP-hard problem by Lim in 1998, where NP refers to Non-deterministic Polynomial (Lim, 1998) and the objective function in this model is nonlinear, we solve this BACAP with a meta-heuristic algorithm called Squeaky Wheel Optimization. The main idea of the solution method is (1) to insert \( N \) vessels into the two-dimensional time-space plane one by one with a given inserting sequence, and (2) to improve the inserting sequence by local search procedure.

The SWO algorithm can provide an approach to improve the resource utilization by rearranging the work sequence hence improve the final solutions of a scheduling problem. (Joslin and Clements, 1999). In SWO, firstly a greedy algorithm will be used to construct a solution which is then analyzed to find those elements that are likely to improve the objective value. The results of the analysis are used to generate new priorities that determine the order in which the greedy algorithm constructs the next solution. This Construct/Analyze/Prioritize cycle continues until stopping condition is reached, or an acceptable solution is found. The reason we choose Squeaky Wheel Optimization algorithm is for its excellent performance on the improvement of resource utilization. By updating the inserting sequence iteration by iteration, the SWO algorithm tries to assign appropriate priorities among vessels and improve the overall performance of the berth allocation and quay crane assignment plan.

The initial inserting sequence is usually determined according to vessels’ estimated arrival time. Given an inserting sequence, a random generation method is applied to construct feasible solutions (e.g., decision variables of the model). Considering the randomness of the construct process, we propose a probability distribution of potential berthing place and number of assigned QCs. With a set of constructed feasible solutions corresponding to the same inserting sequence, the best objective function value of these solutions is regarded as the fitness (i.e., performance evaluation) of the sequence.

At the same time, a local search procedure is employed to improve the quality of inserting sequence iteration by iteration. In this paper, the ‘analyze’ and ‘prioritize’ process of SWO is equivalent to finding a new inserting sequence by analyzing the contribution of the arranged vessels to the objective results. The one with the larger contribution to the results will be moved ahead in the new sequence. The new inserting sequence then can be used
to create new generation of solutions again, and the performance of the new sequence can be evaluated by the best solution that is found.

The whole search process of the SWO solution algorithm terminates according to the following criteria: the best objective value stays unchanged for $N$ consecutive iterations or the maximum number of iterations is reached.

The following describes the main procedure:

Step 1: Obtain the initial group of solutions, let $N=1$.

Step 1.1 Given an initial sequence $seq_0$.

Step 1.2 Based on $seq_0$, obtain $N_s$ solutions through “Construct”.

Step 1.3 Calculate the objective value of $N_s$ solutions, find the best solution through “Analyze” and denote it as $F(seq_0)$.

Step 2: Repeat the following steps until one of stopping conditions becomes true.

Step 2.1 Generate $N_{seq}$ neighbor sequences of seq, i.e., $seq_n, n \in \{1,2,\cdots N_{seq}\}$, namely the “Prioritize” process.

Step 2.2 For $n=1$: $N_{seq}$

Step 2.2.1: Based on $seq_n$, obtain $N_s$ solutions through “Construct”.

Step 2.2.2: Calculate the objective value of $N_s$ solutions, find the best solution and denote it as $F(seq_n)$ (“Analyze” phase).

Step 2.2.3: If $F(seq_n) < F(seq_{n-1})$, set seq = seq$_n$.

Step 2.3 Set $N=N+1$.

4.2 Construct phase

To generate the initial group of solutions for a given sequence, the first step is to randomly generate berthing positions for vessels that need to be inserted. As we have constrained the range of berthing place for vessels, we propose a probability distribution according to which the berthing position is randomly determined. The cumulative distribution function to generate the re-berthing place is presented below:

$$F(X_i) = \begin{cases} 
\frac{x_i - b_i + l_i}{l_i/3} \cdot 0.05 & x_i \in (b_i - l_i, b_i - 2l_i/3) \\
\frac{x_i - b_i + 2l_i/3}{l_i/3} \cdot 0.15 + 0.05 & x_i \in (b_i - 2l_i/3, b_i - l_i/3) \\
\frac{x_i - b_i + l_i/3}{l_i/3} \cdot 0.6 + 0.2 & x_i \in (b_i - l_i/3, b_i + l_i/3) \\
\frac{x_i - b_i - l_i/3}{l_i/3} \cdot 0.15 + 0.8 & x_i \in (b_i + l_i/3, b_i + 2l_i/3) \\
\frac{x_i - b_i - 2l_i/3}{l_i/3} \cdot 0.05 + 0.95 & x_i \in (b_i + 2l_i/3, b_i + l_i)
\end{cases}
$$

(26)

Considering that a remote actual berthing position from its original one will increase the recovery cost and even be infeasible for some large vessels, thus the reallocation space for this vessel is defined within a distance of its own vessel length in this situation. For example, a vessel should be reallocated within the range of $[b_i - l_i, b_i + l_i]$ . The probability of reallocating vessel $i$ in the range A, B, C is set as 60%, 30% and 10% respectively with the same length of A, B, C as $2\ l_i/3$.

The same method is applied for randomly generating a QC assignment plan at each time step. The feasible number of QCs that can be assigned for a vessel is within the discrete interval $[R_{min}, \min (R_{max}, \text{available QC})]$. For each element $X_i$ in the discrete interval, denote $\Delta_i = X_i - R_{min} + 1$. Then, the probability of assigning $X_i$ number of QCs for the vessel follows the distribution in (26). For example, for feasible number of QCs set $[2, 4]$, the probability of assigning 2, 3 and 4 QCs is 1/6, 1/3 and 1/2, respectively.
\[ p(X_i) = \frac{\Delta_i}{\sum \Delta_i} \quad X_i \in [R_{\text{min}}, \min\{R_{\text{max}}, \text{availableQC}\}] \]  

After the determination of berth allocation and crane assignment for vessel \( i \), the coordinates of vessel \( i \) in the time-space plane is identified. The next step is to check whether it overlaps with the formerly inserted vessels. If overlapping exists, the berthing position of vessel \( i \) will be adjusted. If a feasible position is found, turn to inserting the next vessel; otherwise, the crane assignment of vessel \( i \) needs to be modified until a feasible solution is found. This process ends when all the vessels are inserted. Then a group of initial solutions are obtained. The generation of a group of initial plans is the process of “Construct”. The main flowchart for this process is shown below:

**FIGURE 2 Flowchart for “Construct”**
4.3 Analyze and prioritize phase

As a group of solutions have been obtained through the above construct phase, the core of “Analyze and Prioritize” process is to find a neighborhood sequence for the given sequence in order to improve the solution in sequence space. We explore the neighborhood space by finding neighborhood sequences with the size of $S$. The $S$ new sequences are obtained by the following steps: (1) calculate the contribution of each vessel to the final result. We use the value of the combined objective function for vessel $i$ as an evaluation of its contribution. Therefore, the evaluation of contribution of vessel $i$ is $v(i) = k \cdot f_1(i) + (1 - k) \cdot f_2(i)$, where $k$ is a parameter varying from 0.1 to 0.9; (2) randomly select two vessels from the best solution in last iteration; (3) compare values of these two vessels. If value of vessel $i <$ vessel $j$, this two vessels will be swapped, which means vessel $j$ will be inserted before vessel $i$ in the next iteration to gain more priority in terms of resource allocation. In the same way, we obtain sequence 2,3 ..., and sequence $S$. This process is in accordance with the “Analyze and Prioritize”, namely, the priorities of vessels are analyzed and the sequence of vessel inserted is reset to improve the quality of final solution.

5 COMPUTATIONAL EXPERIMENT

In this section, comprehensive computational experiments are conducted to validate the performance of the proposed BACAP model and the solution approach. We firstly report the test instance generation process and the parameter settings of the SWO heuristic method. Then, the efficiency and effectiveness of the developed model and heuristic approach are assessed. Besides, various disruption scenarios are also generated and tested to further evaluate its performance in actual situations. Finally, parameter sensitivity analysis is conducted to see the effect of the interference exponent and berth deviation factor. The SWO heuristic are coded in Matlab 7.14. All of the computational experiments are conducted on a PC with 2 GHz CPU and 2 GB RAM.

5.1 Test instance generation

Test instances are randomly generated according to the empirical data shown in Table 1 (Meisel and Bierwirth, 2009). Three vessel classes, namely Feeder, Medium and Jumbo, are considered whose attributes, including vessel length, QC-hour demand and loading/discharging workload, follow a uniform distribution as presented in Table 1. For example, the vessel length of a Feeder follows a uniform distribution between 8 and 21 length unit, namely 80m to 210m. Similarly, the Medium is from 210m to 300m, the Jumbo is from 300m to 400m. The minimum and maximum QCs that can be assigned at the same time for each vessel class are also reported. Considering the improvement of the discharging efficiency in container terminals, we revise the QC demand and minimum QC for different vessel class accordingly. We randomly generate three test instance sets according to the size of vessel set (10, 20, and 30 vessels) each of which consists of ten instances.
TABLE 1 Technical specifications for different vessel classes and experimental parameters

<table>
<thead>
<tr>
<th>Vessel classes</th>
<th>Class</th>
<th>Vessel length</th>
<th>QC demand</th>
<th>Minimum QC</th>
<th>Maximum QC</th>
<th>TEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medium</td>
<td>U[21,30]</td>
<td>U[15,36]</td>
<td>1</td>
<td>4</td>
<td>U[3500,5000]</td>
<td></td>
</tr>
<tr>
<td>Jumbo</td>
<td>U[30,40]</td>
<td>U[36,48]</td>
<td>3</td>
<td>6</td>
<td>U[5000,7500]</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Instance parameters</th>
<th>Test set ID</th>
<th>N</th>
<th>N*</th>
<th>λ</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1 - 01~05</td>
<td>10</td>
<td>2</td>
<td>1/5</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>Set 1 - 05~10</td>
<td>10</td>
<td>2</td>
<td>1/2</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>Set 2 - 01~05</td>
<td>20</td>
<td>3</td>
<td>1/5</td>
<td>168</td>
<td></td>
</tr>
<tr>
<td>Set 2 - 05~10</td>
<td>20</td>
<td>3</td>
<td>1/2</td>
<td>168</td>
<td></td>
</tr>
<tr>
<td>Set 3 - 01~05</td>
<td>30</td>
<td>4</td>
<td>1/5</td>
<td>168</td>
<td></td>
</tr>
<tr>
<td>Set 3 - 05~10</td>
<td>30</td>
<td>4</td>
<td>1/2</td>
<td>168</td>
<td></td>
</tr>
</tbody>
</table>

Problem related parameters:
- Interference exponent $\mu = 0.9$;
- Berth deviation factor $\theta = 0.01$;
- Cost rate $C_1 = 0.05$, $C_2 = 0.3$, $C_3 = 0.8$;
- Priority factors for vessels requiring early dispatch $\alpha^*_i = \beta^*_i = 0.95$, $\forall i \in N$

Algorithm related parameters:
- Total iteration: 1000
- Number of solutions for each iteration in solution space: n=25;
- Number of solutions for each iteration in sequence space: n=10;
- Weighted parameter $k$ for objective function is changing by step size of 0.1 from 0.1 to 0.9;
- Termination condition: there is no improvement in the solution for consecutive 100 iterations or the total number of iterations is reached.

For each set of instance, 60% of vessels belong to class Feeders, 30% are class Medium and 10% are Jumbo. The planning horizon is set to be three days to one week, namely from 72h to 168h. The length of quay is set as 160 (1600m). And the vessels’ inter-arrival time follows an exponential distribution with parameter $\lambda = \frac{1}{2}$, and $\lambda = \frac{1}{5}$ respectively. The vessels with arrival delay are randomly selected, and 30% of the expected handling time is set to be the amount of delay for those delayed vessels. The number of vessels requiring early dispatch is set as 10%-15% of the total vessel number. The original berthing location for vessel $i$ is randomly generated according to the uniform distribution: $U[0, L - l_i]$, and its priority factor is generated from $U[0,0.8]$. Considering a moderate QC productivity losses, the interference exponent is set to 0.9, and the berth deviation factor is set to 0.01. An overall view of instance and algorithm parameters settings are illustrated below:

For instance, as for the set 2, the total number of vessel is 20 and the number of vessels with early dispatch requirement is 3, the exponent parameter $\lambda$ is set as 0.5 and 0.2 respectively for each 5 instances. The planning horizon is 168h.

5.2 Test results

To illustrate the effectiveness and efficiency of the proposed heuristic, we compare the final results obtained from SWO with plans recovered with the FCFS rule. $C_0$ is set as 100. The results are shown in Table 2. In the column of combined total, the weighted parameter $k$ is set as 0.1, 0.3, 0.5, 0.7, 0.9 every 5 instance in a set. For example, in set 1, $k$ is set as 0.1 in instance 01 and 05, 0.3 in instance 02 and 06, 0.5 in instance 03 and 07, etc.
### TABLE 2 Computational results

<table>
<thead>
<tr>
<th>Instance ID</th>
<th>SWO</th>
<th>FCFS</th>
<th>Improvement (%)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time cost</td>
<td>Recovery cost</td>
<td>Combined total</td>
<td>Time cost</td>
</tr>
<tr>
<td>Set1-01</td>
<td>6109</td>
<td>13336</td>
<td>12613</td>
<td>14489</td>
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<td>Set1-02</td>
<td>8298</td>
<td>8323</td>
<td>8316</td>
<td>9200</td>
</tr>
<tr>
<td>Set1-03</td>
<td>10230</td>
<td>7443</td>
<td>8837</td>
<td>10445</td>
</tr>
<tr>
<td>Set1-04</td>
<td>4570</td>
<td>7643</td>
<td>5492</td>
<td>5505</td>
</tr>
<tr>
<td>Set1-05</td>
<td>4246</td>
<td>11094</td>
<td>4931</td>
<td>8323</td>
</tr>
<tr>
<td>Set1-06</td>
<td>10556</td>
<td>12815</td>
<td>12589</td>
<td>22134</td>
</tr>
<tr>
<td>Set1-07</td>
<td>5205</td>
<td>15470</td>
<td>12391</td>
<td>10506</td>
</tr>
<tr>
<td>Set1-08</td>
<td>14204</td>
<td>16259</td>
<td>15232</td>
<td>13247</td>
</tr>
<tr>
<td>Set1-09</td>
<td>8856</td>
<td>24570</td>
<td>13570</td>
<td>11585</td>
</tr>
<tr>
<td>Set1-10</td>
<td>5804</td>
<td>15411</td>
<td>6765</td>
<td>11476</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Instance ID</th>
<th>SWO</th>
<th>FCFS</th>
<th>Improvement (%)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time cost</td>
<td>Recovery cost</td>
<td>Combined total</td>
<td>Time cost</td>
</tr>
<tr>
<td>Set2-01</td>
<td>32201</td>
<td>28765</td>
<td>29109</td>
<td>50406</td>
</tr>
<tr>
<td>Set2-02</td>
<td>24210</td>
<td>41481</td>
<td>36300</td>
<td>39808</td>
</tr>
<tr>
<td>Set2-03</td>
<td>25104</td>
<td>33508</td>
<td>29306</td>
<td>47210</td>
</tr>
<tr>
<td>Set2-04</td>
<td>10450</td>
<td>32626</td>
<td>17103</td>
<td>25607</td>
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<td>Set2-05</td>
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<td>40221</td>
<td>31742</td>
<td>62805</td>
</tr>
<tr>
<td>Set2-06</td>
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<td>45371</td>
<td>46274</td>
<td>74204</td>
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<tr>
<td>Set2-07</td>
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<td>40344</td>
<td>42372</td>
<td>95410</td>
</tr>
<tr>
<td>Set2-08</td>
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<td>46178</td>
<td>49593</td>
<td>56107</td>
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<tr>
<td>Set2-09</td>
<td>41507</td>
<td>36547</td>
<td>40019</td>
<td>53704</td>
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<tr>
<td>Set2-10</td>
<td>39060</td>
<td>62209</td>
<td>41375</td>
<td>64402</td>
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</table>

<table>
<thead>
<tr>
<th>Instance ID</th>
<th>SWO</th>
<th>FCFS</th>
<th>Improvement (%)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time cost</td>
<td>Recovery cost</td>
<td>Combined total</td>
<td>Time cost</td>
</tr>
<tr>
<td>Set3-01</td>
<td>52445</td>
<td>47928</td>
<td>48380</td>
<td>65305</td>
</tr>
<tr>
<td>Set3-02</td>
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<td>63647</td>
<td>60676</td>
<td>43500</td>
</tr>
<tr>
<td>Set3-03</td>
<td>71202</td>
<td>60373</td>
<td>65788</td>
<td>87720</td>
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<td>62608</td>
<td>62480</td>
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</tr>
<tr>
<td>Set3-05</td>
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<td>95703</td>
<td>68846</td>
<td>90930</td>
</tr>
<tr>
<td>Set3-06</td>
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<td>72349</td>
<td>75369</td>
<td>134330</td>
</tr>
<tr>
<td>Set3-07</td>
<td>103631</td>
<td>97232</td>
<td>99152</td>
<td>111002</td>
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<tr>
<td>Set3-08</td>
<td>104106</td>
<td>113454</td>
<td>108780</td>
<td>119501</td>
</tr>
<tr>
<td>Set3-09</td>
<td>121040</td>
<td>120567</td>
<td>120989</td>
<td>134230</td>
</tr>
<tr>
<td>Set3-10</td>
<td>101540</td>
<td>126041</td>
<td>103990</td>
<td>140504</td>
</tr>
</tbody>
</table>

The comparison between SWO and FCFS when $k = 0.1$ and 0.9 is shown in Figure 3. As can be seen from these figures, both SWO and FCFS have an increasing trend in time and recovery cost as the number of vessels grows. Since the increase in the number of arriving vessels in a given period reduces the recovery flexibility for berth allocation and crane assignment, a larger scale adjustment may need to be performed. Thus, both the time and recovery costs are larger when $\lambda = 0.5$ compared with $\lambda = 0.2$. However, it is evident that SWO can obtain...
a better result than FCFS both in terms of time and recovery cost. Therefore, it can be concluded that the shifting of the initial inserting sequence can greatly improve the resource allocation process thus reduce the total service time and delay as well as recovery cost.

![Comparison between SWO and FCFS](image1)

(a) Cost comparison between SWO and FCFS ($\lambda = 0.2, k = 0.1$)  (b) Cost comparison between SWO and FCFS ($\lambda = 0.5, k = 0.1$)

![Comparison between SWO and FCFS](image2)

(a) Cost comparison between SWO and FCFS ($\lambda = 0.2, k = 0.9$)  (b) Cost comparison between SWO and FCFS ($\lambda = 0.5, k = 0.9$)

**FIGURE 3** Comparison between SWO and FCFS ($k = 0.1$ or 0.9)

### 5.3 Scenario analysis

In this session, six scenarios are generated with vessel number of 20. For scenario 1, suppose the operations of 30% vessels are delayed, each vessel being delayed for 12 hours. For scenario 2, two QCs are supposed to fail; 40% vessels require early dispatch in scenario 3 and two situations stated in the above take place at the same time in scenario 4. The performance of schedules under different scenarios (20 vessels) is shown in Table 10. Scenario parameter (1) refers to percentage of vessels arrive delay or early; (2) means number of failure crane and (3) indicates number of early dispatch vessels. Schedule 1 and the 4 is the one with shortest time and the one with

<table>
<thead>
<tr>
<th>Vessel number</th>
<th>SWO Cost</th>
<th>FCFS Cost</th>
<th>SWO Recovery Cost</th>
<th>FCFS Recovery Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>15</td>
<td>0</td>
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<tr>
<td>20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

![Diagram](image3)
least recovery cost respectively, while schedule 2 and 3 are plans between them. The results are presented in Table 3.

### TABLE 3 Results of scenario analysis

<table>
<thead>
<tr>
<th>Scenarios parameters</th>
<th>Time-oriented (1)</th>
<th>Cost-oriented (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Schedule 1 time</td>
<td>Schedule 2 time</td>
</tr>
<tr>
<td></td>
<td>cost</td>
<td>cost</td>
</tr>
<tr>
<td>10% 0 0</td>
<td>28808 107638</td>
<td>20911 68830</td>
</tr>
<tr>
<td>20% 0 0</td>
<td>36392 70731</td>
<td>35107 43783</td>
</tr>
<tr>
<td>30% 0 0</td>
<td>35455 43675</td>
<td>33117 47577</td>
</tr>
<tr>
<td>40% 0 0</td>
<td>35479 45878</td>
<td>38317 31635</td>
</tr>
<tr>
<td>50% 0 0</td>
<td>32484 100641</td>
<td>27236 74003</td>
</tr>
<tr>
<td>20% 1 0</td>
<td>14246 45471</td>
<td>19780 70154</td>
</tr>
<tr>
<td>20% 2 0</td>
<td>19315 45054</td>
<td>20648 85468</td>
</tr>
<tr>
<td>20% 3 0</td>
<td>29964 48528</td>
<td>25312 55873</td>
</tr>
<tr>
<td>20% 4 0</td>
<td>33054 58221</td>
<td>24720 63993</td>
</tr>
<tr>
<td>20% 5 0</td>
<td>40288 60586</td>
<td>28302 34187</td>
</tr>
<tr>
<td>20% 6 0</td>
<td>27259 69708</td>
<td>28136 46240</td>
</tr>
<tr>
<td>20% 7 0</td>
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<td>35279 64198</td>
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<td>34745 60428</td>
</tr>
<tr>
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<tr>
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</tr>
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<tr>
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<td>24457 27555</td>
</tr>
<tr>
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<td>25787 45525</td>
<td>34237 38721</td>
</tr>
<tr>
<td>50% 2 5</td>
<td>33908 56534</td>
<td>35286 50310</td>
</tr>
</tbody>
</table>

As input data in scenario 1 are different, the impacts of numbers of delayed vessels are not that obvious. However, we can still find that time-oriented plan can provide nearly the shortest service time and delay compared with other plans but with a little sacrifice of recovery cost. It is almost the same with the cost-oriented plan. For the impacts of failed crane, we can see that both time and cost have an increase in the situation of more failed crane, and the ascending trend of time is more evident in time-oriented plan than in a cost-oriented plan, which also happens in increasing trend of the recovery cost. From scenario 3, we can see some impacts from vessels requiring early dispatch. There is an increasing trend in time and recovery cost, then with the growth in number of early dispatched vessels, both of them go downwards. Therefore, we can conclude that if there are sufficient resources to fulfill the early dispatch requirement, the terminal operator can embrace a lower recovery cost.

### 5.4 Parameter sensitivity analysis

The interference exponent \( \mu \) and berth deviation factor \( \theta \) also affect the total time and recovery cost. Therefore, the sensitivity of these two parameters will be investigated to shown their influence in this session. In Figure 4(a), \( k \) is set as 1. \( \theta \) is kept as 0.01 while \( \mu \) varying from 0.6 to 0.9 with a step of 0.1. Figure 4(b) shows the result with \( \theta \) varying in a range from 0.01 to 0.025 while \( \mu \) is held constant as 0.9, \( k = 0 \). Considering the varying range of the single objective (\( k = 1 \) and 0), it can be observed that \( \mu \) has a larger impact on the time aspect than \( \theta \), while the impact of \( \theta \) on recovery cost is larger than \( \mu \). The reason for this could be that QC productivity is the major influence on the service time. On the contrary, the horizontal cost caused by berthing position deviation accounts more in the recovery cost.
In this paper, we propose a reactive strategy for the integrated berth allocation and quay crane assignment problem once some disruptions (e.g., service interruption, vessel delay) are realized. The recovery strategy is proposed to make full use of the resources while taking into account the recovery cost. At the same time, vessels requiring early dispatch are considered which embodies more real world aspects. Finally, a heuristic approach based on Squeaky Wheel Optimization is developed and computational experiments are conducted to show its efficiency and effectiveness. As can be seen, the proposed solution method has high computational efficiency. And during the recovery process, crane productivity is the major factor that influence total service time, while the deviation from original berthing position accounts more in the recovery cost. However, these two factors are also interrelated. If the crane capability is sufficient to fulfill more early dispatch requirements, the recovery cost will eventually develop towards a declining trend.

For further research, we are interested in integrating more scenarios of disruptions into the model and enrich the recovery strategy to gain a more flexible recovery approach.

6 CONCLUSION
ACKNOWLEDGEMENT

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REFERENCE


