HIGH TECHNOLOGY LETTERS | Vol. 24 No. 4 | Dec. 2018 | pp. 351 ~ 361

doi:10.3772/j.issn.1006-6748.2018.04.003

Berth-crane allocation under uncertainty: dynamic modeling and nested Tabu search①

Han Xiaole(韩笑乐), Qian Lina, Lu Zhiqiang②
(School of Mechanical Engineering, Tongji University, Shanghai 201804, P. R. China)

Abstract

The integrated berth-crane allocation problem at container terminals is addressed under the uncertainty of vessel arrival time at operational level. To ensure both robustness and flexibility of the 2-stage decision processes, a dynamic decision framework is proposed based on the dynamic analysis of information and operation at container terminal. A mixed integer programming model is established aiming at minimizing total cost of all vessels, including the cost of fixed to-be-executed decisions in the 1st stage and expected cost of the adjustable stochastic-scenario-based decisions of all scenarios in the 2nd stage. A multi-layer nested Tabu search is proposed for each epoch dynamically. Finally numerical experiments have been conducted to testify the effectiveness and efficiency of the proposed model and algorithm.

Key words: container terminal, berth and crane, uncertainty, Tabu search

0 Introduction

Berth and quay cranes are both key resources of the seaside operations at container terminals. As highlighted by Refs[1,2], it's necessary and important to integrate both berth and crane resources to optimize seaside operations. Such berth-crane allocation problem can be viewed as an extension to the resource-constrained project scheduling problem, and it is complicated due to the practical constraints involved, e.g. the contiguity of berth segments assigned to each vessel, the amount of intervals of crane-to-vessel assignment, the interference relationships between cranes, etc. Refs[3-8] have solved such problem from different aspects in certain circumstances.

During practical operations at container terminals, the influence of uncertainties is inevitable. Possible uncertainties include variation of vessel arrival time, fluctuation of vessel processing time, reliability of cranes and weather condition, etc., among which the vessel arrival time is usually the most common and inevitable one[9]. This parameter reveals vessel by vessel as time elapsing. The closer to a vessel's expected arrival time, the more accurate information about its actual arrival time can be obtained.

However, as a practical and realistic issue, how to effectively deal with the impacts of uncertain factors becomes the focus of recent researches. Considering the uncertainty of vessel arrival time, Ref.[9] addressed the berth template from the tactic perspective. The problem was modeled as a rectangle packing problem on a cylinder and a sequence pair based on simulated annealing algorithm which is adopted. Under the uncertainty of vessel operation time, Ref.[10] regarded the berth allocation problem as a bi-objective problem with the objectives of minimizing the risk and total service time. An evolutionary algorithm based heuristic and simulation-based Pareto front pruning algorithm was proposed to solve this problem effectively. Ref.[11] investigated the berth allocation problem at tactical-level with the uncertainty of vessel's operation time. A robust berth allocation schedule was developed to cope with such stochastic formulation. With the uncertainty of vessels arrival and operation times, Ref.[12] proposed a bi-objective robust berth allocation model considering the balance between cost and customer satisfaction, and an adaptive grey wolf optimizer algorithm was developed to solve this model, while Ref.[13] developed a conceptual model of ship-to-berth allocation problem with collaborative approach to reduce the total handing time and improve resources utility. Since the initial data obtained could be changed, Ref.[14] proposed a multi-objective optimization model to minimize the total service time and maximize the robustness or buffer time coping with the deviation between actual

① Supported by the National Natural Science Foundation of China (No. 71502129, 61473211).
② To whom correspondence should be addressed. E-mail: zhiqianglu@tongji.edu.cn
Received on Oct. 10, 2017

information and initial data. While considering the quay crane setup time of shifting along quay, Ref. [15] established two robust optimization models to deal with data uncertainties. A genetic algorithm (GA) and an insertion heuristic algorithm were proposed to solve these models respectively. Since the marginal productivity of quay cranes was decreased and the handing time was increased due to the deviation from the desired position, Ref. [16] proposed a novel valid inequality and variable fixing methods with an adaptive large neighborhood sarch (ALNS) heuristic.

When facing disruptions, Ref. [17] used quay crane rescheduling and berth reallocation strategy to handle the disruptions. Ref. [18] focused on the disruption of quay crane breakdowns during the execution of scheduling; the behavior perception-based disruption models was developed to minimize the negative deviation from the originally planning. Considering the objective of minimizing the total realized cost of modified berth scheduling with a given baseline scheduling, Ref. [19] developed the optimization based algorithm and alternate heuristic approach to solve the hybrid berth allocation problem (BAP) for bulk ports under uncertainty of vessels arrival time, while Ref. [20] studied the BAP on a rolling horizon under the uncertainty of vessels arrival time and handing time.

Generally, the typical strategies coping with the uncertainties include proactive planning with reactive policies[21-23], and dynamic planning under rolling horizon[20, 24]. Generally, the former strategy emphasizes on the robustness of planning by taking account of and hedging against the possible scenarios of uncertainties ahead of time. While the latter strategy emphasizes on the flexibility of planning by utilizing the latest information on uncertainties, and delaying the decisions is till indeed required.

In this paper, the dynamic decision framework is proposed to integrate the robustness and flexibility mentioned above, which adopts a 2-stage approximate-model of the 2-stage stochastic optimization process[25]. On one hand, at each epoch, the robustness of 1st stage to-be-executed plan is enhanced by proactively preparing contingent plans for stochastic scenarios of 2nd stage. On the other hand, the flexibility of 2nd stage decision is retained by reserving its right to be modified at later epochs, so that the continuously updated information can be better used. Since the proactive plans of the 2nd stage are the extended decisions of the 1st stage, it can be modified at later epochs. Considering the accuracy of processing time, instead of using the average quay crane value, the operation of a single vessel is based on quay crane scheduling problem (QCSP) formulation[26].

The rest of this paper is organized as follows: Section 1 describes the problem as a 2-stage approximate scheme, a dynamic decision framework is proposed. A multi-layer nested Tabu search for the decision making at each consecutive epoch is proposed in Section 2. The numerical experiments are conducted in Section 3. Finally, Section 4 concludes the whole paper.

1 Decision mechanism and modeling

1.1 Dynamic description

For building a dynamic decision-making framework based on 2-stage approximate optimization model, the following illustration is done.

1) Decisions are made at the beginning of each epoch, although some uncertainties are revealed during an epoch, new decisions won't be made until next epoch begins.

2) The vessel arrival time is the only stochastic parameter, and it is revealed at least during the previous epoch of its actual arrival. In other words:

i) When an epoch begins, all the uncertain information in this epoch has already been revealed, i. e., the arriving vessels and their actual arrival time.

ii) When an epoch ends (the begin of the next epoch), all the uncertain information of next epoch will be revealed.

iii) Note that some information may be revealed ahead of time by more than one epochs, but it's not necessary to make final decisions for it at once, i. e., even if making right now, decisions can be changed till its actual arriving epoch.

3) The distribution of each vessel arrival time is independent, and the stochastic information of each vessel is given by scenarios.

4) For the convenience of yard operation, each vessel's berth position should be determined at least one epoch ahead of its arrival time.

A simple example is provided in Fig. 1 to illustrate the seaside resources allocation plan. Based on the dynamic description above, at k (the beginning of epoch k), three types of vessels can be confirmed, as shown in Fig. 1, including.

- Vessels that are started at k but unfinished. Some arrived before epoch $k-1$, some during epoch $k-1$ (Vessel 1, 2).
- Vessels that are un-started at k but will arrive during epoch k (before epoch $k+1$). Some arrived before k (Vessel 3), some will arrive during epoch k (Vessel 4-6). Some will be started in epoch k (Vessel 3-5), some planned to be delayed after epoch k (Ves-

sel 6).

- Vessels that are stochastically arriving during epoch $k+1$ through epoch $k+s$ (Vessel 7-13, $s=3$).

Label these three types of vessels A, B and C respectively, and the known parameters and decisions include:

- For type-A vessels: known parameters include arrival time (A^A), berthing position (b^A), crane number (c^A), start time ($s^A = k$).

At epoch k, complete the remaining operation with the crane number already distributed.

- For type-B vessels: known parameters include arrival time (A^B), berthing position (b^B).

Firstly, decide the value of delay indicator (u), if the vessel is planned to be delayed after epoch k, then set $u = 1$, otherwise $u = 0$. As a decision parameter u divides V^B into V^{B0} and V^{B1}. For (V^{B0}) ($u = 0$), fixed to-be-executed decisions will be made in the 1st stage, including start time (s^{B0}) and crane number (c^{B0}), while other vessels ($u = 1$) will make the adjustable stochastic-scenario-based decisions in the 2nd stage, their schedule plans can be adjusted in the subsequent decision-making epoch.

- For type-C vessels: known parameters include arrive time (A^C_ω) in all possible scenarios.

Unique berthing location (b^C) is determined in the 1st stage, while other stochastic-scenario-based decisions, e. g. start time (s^C_ω) and crane number (c^C_ω) will be determined in the 2nd stage. All the stochastic-scenario-based decisions can be revised in the following epochs.

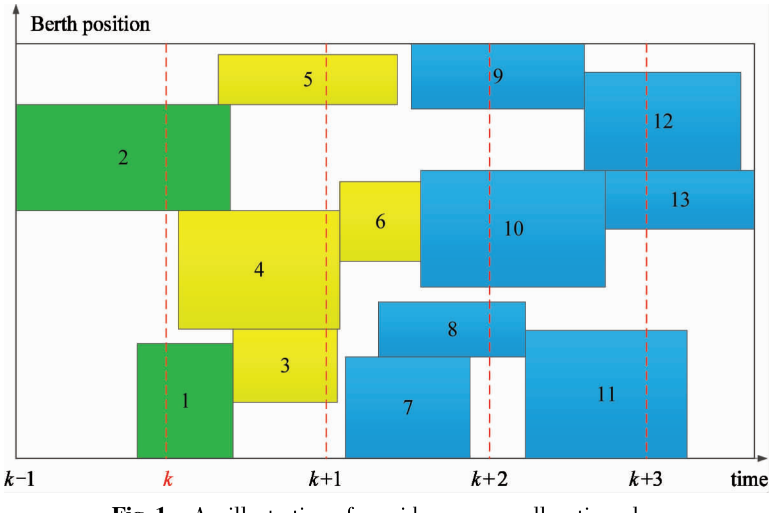

Fig. 1 An illustration of seaside resource allocation plan

In general, the parameters can be divided into two parts: determined parameters of the 1st stage and the stochastic-scenarios-based parameters of the 2nd stage, opposite to the fixed to-be-executed decisions of the 1st stage and the adjustable stochastic-scenario-based decisions of the 2nd stage. The fixed decisions in the 1st stage is used for actual execution, while the adjustable decisions in the 2nd stage of all scenarios are temporary, and are used to estimate the former one. At epoch k, the 2-stage decision structure is showed in Table 1.

At each decision time k, the objective is to minimize the sum of fixed and expected of adjusted costs, measured by total dwell times. Mathematically written as:

$$\min f(x_k) + E_\omega[f(x_{k+1} \mid x_k)] \quad (1)$$

where, $x_k = \{u, s^{B0}, c^{B0}, b^C\}$,

$x_{k+1} = \{s^{B1}_\omega, c^{B1}_\omega, s^C_\omega, c^C_\omega\}$

Table 1 The 2-stage decision-making structure in epoch k

1st stage	Parameter	Decision
A	A^A, b^A, c^A, s^A	–
B	A^B, b^B	u, s^{B0}, c^{B0}
C	–	b^C
2nd stage	Parameter	Decision
B1	A^B, b^B, u, s^{B0}, c^{B0}	s^{B1}_ω, c^{B1}_ω
C	A^C_ω, b^C	s^C_ω, c^C_ω

1.2 Mathematical model

Evaluate the effectiveness and efficiency of the fixed decisions made in the 1st stage through the stochastic-scenario-based decisions in the 2nd stage under uncertain circumstances. Making full use of the certain and uncertain information obtained, taking into account of both robustness and feasibility during decision-making process, a scenario-based 2-stage approximate optimization model is proposed. In epoch k, the model is formulated as follows.

Parameters	
$i \in V = \{1,\cdots,V\}$	Set of vessels
$q \in Q = \{1,\cdots,Q\}$	Set of quay cranes
$t \in T = \{1,\cdots,T\}$	Set of discretized time period, regard k as relative 0 point
$\omega \in \Omega = \{1,\cdots,\Omega\}$	Set of scenarios
T^0	The relative time of decision point $k+1$ to the point k, $T^0 \leqslant T$
L	Length of the quay (discrete segment)
L_i	Length of vessel i
$A_{i,\omega}$	Arrival time of vessel i in scenario ω
$R_i^{\max}$	Minimum allowed QC number assigned to vessel i
$R_i^{\min}$	Maximum allowed QC number assigned to vessel i
C_{iQ}	Task time of vessel i by q QCs
V^A, V^B	Subset of three kinds of vessels
b_i^A, c_i^A	Actual berth position and assigned QC number of type-A vessels i
b_i^B	Actual berth location of type-B vessels i

Decision variables	
b_i	Berthing position of vessel i
$s_{i,\omega}$	Start processing time of vessel i in scenario ω
$e_{i,\omega}$	End processing time of vessel i in scenario ω
$c_{i,\omega}$	Number of assigned QCs of vessel i in scenario ω
y_{ij}	$=1$, if $b_i + L_i < b_j$; $=0$, otherwise
$z_{ij,\omega}$	$=1$, if $e_{i,\omega} < s_{j,\omega}$; $=0$ in scenario ω, otherwise
$r_{it,\omega}$	$=1$, if vessel i is being served at time t in scenario ω; $=0$, otherwise
$x_{it,\omega}$	QC number assigned to vessel i at time t in scenario ω
$v_{iq,\omega}$	$=1$, if vessel i assigned q quay cranes in scenario ω $=0$, otherwise
u_i	$=1$, if $i \in V^B$ and vessel i is delayed after epoch k; $=0$, otherwise

Objective function:

$$\text{Minimize} \sum_{I,\omega} (e_{i,\omega} - A_{i,\omega})/\Omega \tag{2}$$

Subject to:

$$b_{i,\omega} = b_i^A,\ \forall i \in V^A,\ \omega \tag{3}$$

$$c_{i,\omega} = c_i^A,\ \forall i \in V^A,\ \omega \tag{4}$$

$$s_{i,\omega} = 0,\ \forall i \in V^A,\ \omega \tag{5}$$

$$e_{i,\omega} = e_{i,1},\ \forall i \in V^A,\ \omega \tag{6}$$

$$b_{i,\omega} = b_i^B,\ \forall i \in V^B,\ \omega \tag{7}$$

$$-Q \cdot u_i \leqslant c_{i,\omega} - c_{i,1} \leqslant Q \cdot u \,\forall i \in V^B, \omega \tag{8}$$

$$-T \cdot u_i \leqslant s_{i,\omega} - s_{i,1} \leqslant T \cdot u \,\forall i \in V^B, \omega \tag{9}$$

$$T \cdot (u_i - 1) \leqslant s_{i,\omega} - T^0 \leqslant T \cdot u \,\forall i \in V^B, \omega \tag{10}$$

$$-T \cdot u_i \leqslant e_{i,\omega} - e_{i,1} \leqslant T \cdot u \,\forall i \in V^B, \omega \tag{11}$$

$$(t+1) \cdot r_{it,\omega} \leqslant e_{i,\omega},\ \forall i,\ t,\ \omega \tag{12}$$

$$t \cdot r_{it,\omega} + T \cdot (1 - r_{it,\omega}) \geqslant s_{i,\omega},\ \forall i,\ t,\ \omega \tag{13}$$

$$\sum_i r_{it,\omega} = e_{i,\omega} - s_{i,\omega}, \forall i, \omega \tag{14}$$

$$\sum_q v_{iq,\omega} = 1,\ \forall i,\ \omega \tag{15}$$

$$\sum_q q \cdot v_{iq,\omega} = c_{i,\omega},\ \forall i,\ \omega \tag{16}$$

$$\sum_q C_{iq} \cdot v_{iq,\omega} = e_{i,\omega} - s_{i,\omega},\ \forall i,\ \omega \tag{17}$$

$$Q \cdot (-r_{it,\omega}) \leqslant x_{it,\omega} \leqslant Q \cdot r_{it,\omega},\ \forall i, t, \omega \tag{18}$$

$$Q \cdot (r_{it,\omega} - 1) \leqslant x_{it,\omega} - q_{i,\omega} \leqslant Q \cdot (1 - r_{it,\omega}),\ \forall i, t, \omega \tag{19}$$

$$\sum_i x_{it,\omega} \leqslant Q,\ \forall t, \omega \tag{20}$$

$$b_j + L \cdot (1 - y_{ij}) \geqslant b_i + L_i,\ \forall i \neq j \tag{21}$$

$$s_{j,\omega} + T \cdot (1 - Z_{ij,\omega}) \geqslant e_{i,\omega} + L_i,\ \forall i \neq j, \omega \tag{22}$$

$$y_{ij} + y_{ji} + z_{ij,\omega} + z_{ji,\omega} \geqslant 1,\ \forall i \neq j, \omega \tag{23}$$

$$b_i \in \{1, \cdots, L - L_i + 1\},\ \forall i \tag{24}$$

$$s_{i,\omega},\ e_{i,\omega} \in \{A_{i,\omega}, \cdots, T\},\ \forall i, \omega \tag{25}$$

$$c_{i,\omega} \in \{R_i^{\min}, \cdots, R_i^{\max}\},\ \forall i, \omega \tag{26}$$

$$y_{ij},\ z_{ij},\ r_{it,\omega},\ v_{iq,\omega} \in \{0 \tag{27}$$

$$x_{it,\omega} \in \{0\} \cup \{R_i^{\min}, \cdots, R_i^{\max}\},\ \forall i, \omega \tag{28}$$

$$u_i \in \{0,1\},\ \forall i \in V^B \tag{29}$$

The objective function Eq. (2) minimizes expected cost of all scenarios at epoch k, which is measured by the vessels total dwell time. Since the constrained relationships are expressed by scenarios, for the fixed decisions of type-A and type-B vessels, adding functions Eqs(3) – (11) as fixed constrains to reconcile the decisions in all scenarios, make sure function Eq. (1) is equal to function Eq. (2) in essence. Constraint Eqs(12) – (13) define $r_{it,\omega}$ based on $s_{i,\omega}$, $e_{i,\omega}$. Constraint Eq. (14) ensures that each vessel can be processed without interrupting. Constraint Eqs(15) – (16) define $v_{iq,\omega}$ based on $c_{i,\omega}$. Constraint Eq. (17) ensures the processing time is based on the QCSP optimization. Note that C_{iq} in constraint Eq. (17) is calculated by the QCSP formulation. Constraint Eqs(18) – (19) define $x_{it,\omega}$ based on $r_{it,\omega}$. Constraint Eq. (20) confines the upper and lower bound of QC available for terminal. Constraint Eqs(21) – (22) are the definition of y_{ij} and $z_{ij,\omega}$. Constraint Eq. (23) makes sure that one berth location can't be occupied by different vessels at one time. Constraint Eqs(24) – (29) are the domains of definitions for decision variables.

Notice that all the certain information revealed during epoch k is about the vessels which are going to arrive in epoch $k+1$, and would not have influence on the resource assignment and actual execution in the current epoch, thus no reactive strategy needs to be prepared in operation process under such dynamic framework proposed above. Actually reactive policy of uncertainty exists in the stochastic-scenario-based decisions of the 2^{nd} stage, which keeps its adjustment opportunities in the following epochs.

2 Tabu search

2.1 Framework

Based on the modeled 2-stage decision sequence, a multi-layer nested Tabu search is proposed, whose framework is shown in Fig. 2.

TS_1 is based on a given initial priority list L: searching for space $\{L\}$; for each L, decode to its initial 1^{st}-stage decision ξ_k^0, and call TS2.

TS_2 is based on ξ_k^0, given from initial 1^{st}-stage decision by TS_1: move on c^{B0} and re-decode to search for space $\{\xi_k\}$; for each given ξ_k supply its initial 2^{nd}-stage decision ξ_{k+2}^0, then call TS_3.

TS_3 is based on ξ_{k+1}^0 made in TS_2: searching space $\{L_2\}$ in all scenarios re-supple to get more 2^{nd}-stage decisions ξ_{k+1}.

The Tabu search procedure is provided in Table 2.

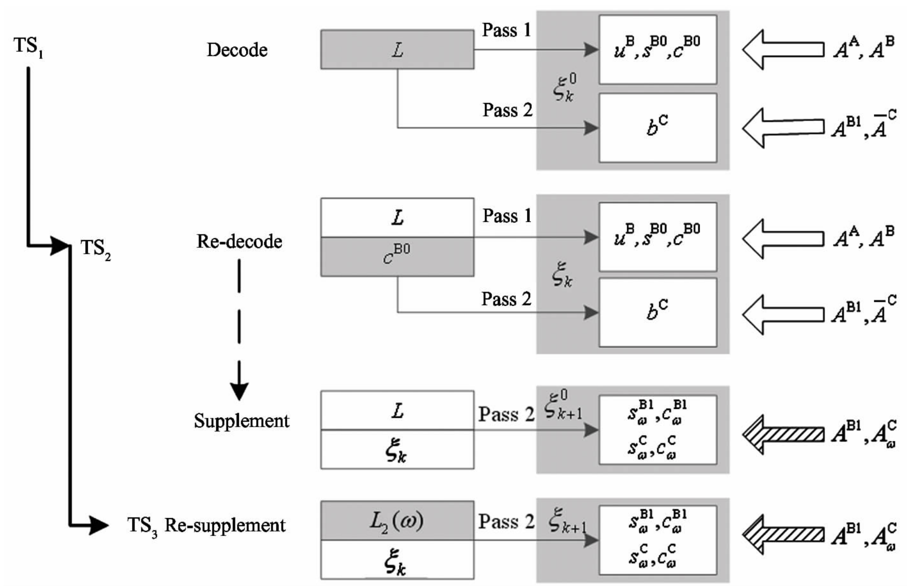

Fig. 2 Multi-layer nested Tabu search framework under uncertain vessel arrival time

Table 2 Procedure of nested Tabu search: 1-phase, 3-layer, 2-stage

Get initial L^0. $L^* := L^0$.

TS_1 start

Construct $N(L^*)$: swap$\Rightarrow L[\,]$. (L^* is included in the 1^{st} iteration)

For $L \in N(L^*)$, If $\Pi(L)$ not tabued

  First Fit$\Rightarrow \xi_k^0$

  $\xi_k^* := \xi_k^0$

  TS_2 start

  Construct $N(\xi_k^*)$: $\{L, (C^{B0})^M\} \Rightarrow \xi_k[\,]$. ($\xi_k^*$ is included in the 1^{st} iteration)

  For $\xi_k \in N(\xi_k^*)$, If $\Pi(\xi_k)$ not tabued

    First Fit$\Rightarrow \xi_{k+1}^0$

    $\xi_{k+1}^* := \xi_{k+1}^0$

    For scenario ω

      TS_3 start

      Construct $N(\xi_{k+1,\omega}^*)$: $\{\xi_k, L_2(\omega)^M\} \Rightarrow \xi_{k+1,\omega}[\,]$. ($\xi_{k+1,\omega}^*$ is included in the 1^{st} iteration)

      For $\xi_{k+1,\omega} \in N(\xi_{k+1,\omega}^*)$, If $\Pi(L_2(\omega)^M)$ not tabued

Continued Table 2

Locate $\xi^L_{k+1,\omega} \in N(\xi^*_{k+1,\omega})$ with the least cost
$\xi^*_{k+1,\omega} := \xi^L_{k+1,\omega}$, update Tabu3. Iterate, repeat to construct $N(\xi^*_{k+1,\omega})$
TS$_3$ end, return sampled cost of ξ_k
Repeat scenario ω for expected cost of ξ_k
Locate $\xi^L_k \in N(\xi^*_k)$ with the least expected cost
$\xi^*_k := \xi^L_k$, update Tabu2. Iterate, repeat to construct $N(\xi^*_k)$
TS$_2$ end, return cost of L
Locate $l \in N(L^*)$ with the least cost
$L^* := l$, update Tabu1. Iterate, repeat to construct $N(L^*)$
TS$_1$ end

2.2 TS$_1$: priority list L

Priority list L is used to generate the fixed decisions in the 1st stage (decode to get initial in TS$_1$ and re-decode to more get in TS$_2$), and then generate the initial 2nd-stage decision with given (supplement to initial in TS$_2$), which consists of two segments: vessels {A} and {B, C}. The type-A vessels have the top priority in any feasibility L since their resumption at epoch k is enforced. The type-B and C vessels are mixed in L, since they have equivalent priorities in decision making process. The initial list L^0 is generated empirically: sort type-A vessels by EDD rule, and sort type-B and type-C vessels by FCFS rule. According to the classification of vessels in Section 1.2, vessels' priority list is generated. An example of priority list is shown in Fig. 3.

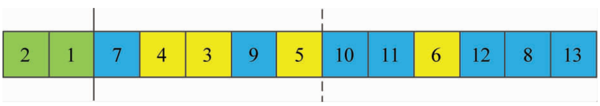

Fig. 3 An illustrative example of list

As mentioned above, the type-B vessels will be divided into two categories: {B0} (with $u = 0$) is planned to start in current epoch k, while {B1} (with $u = 1$) is planned to postpone their starting time until not earlier than the next epoch. Note that such division of type-B vessels belongs to the 1st-stage decision ξ_k itself. As a result the type-B0 and B1 vessels are mixed in the L, i. e., no division has to be explicitly specified in L, instead, given L, the types of B0 and B1 will be naturally revealed once decoding ξ_{k+1} into ξ_k.

To search the neighbor of L, make single swap moves within a randomized neighborhood[27]. Since type-A vessels are nothing to do with the actual decision, the swap operation only needs to be done in the segments of type-B and type-C vessels. The Tabu object is the swap operation of upper moves: Tabu number is randomly generated between Tabu_max and Tabu_min, the Tabu search will be processed till the maximum cycle number iter_max.

To decode to ξ^0_k from given L, add vessels into partial plan one by one using the first fit (FF) policy according to L, considering the remaining resources of berth and QC available. There are two passes: first pass decodes for the type-A and B vessels, and the second pass decodes for the type-C vessels.

For each vessel in L

If type-A: retain b^A, c^A and continue processing from the time k.

If type-B: retain b^A, and find the minimum s between time k and $k+1$ with a maximum feasible c. Set $u = 0$, $s^{B1} = 0$, $c^{B1} = c$ if found, set $u = 1$ otherwise.

Else type-C: skip.

For each vessel in L

If type-B1: retain b^B, and find the earliest s after time $k+1$ with a maximum feasible c.

Else if type-C: find the earliest s after estimated time of arrival (ETA) with a maximum feasible c and a minimum feasible b. Set $b^c = b$.

Else skip.

Note that in the first pass, type-B vessels that are unable to start before time $k+1$ are determined to be type-B1, and no further decisions of the 1st stage have to be made for them. However in the second pass, determining their provisionary s, c values helps to determine some decisions (b^c) of type-C vessels in the 1st stage.

2.3 TS$_2$: 1st stage ξ_k

Since the quay crane resource has a decisive role in the seaside operation, once the allocated quay crane has changed, the processing time of a vessel will be changed accordingly. For getting more feasible decisions in the 1st stage, re-decoding has been done to get more ξ_k in TS$_2$.

To search neighbor of ξ_k which is decoded (or re-decoded) from some list L, first make moves on c by shifting c_i, c_j values between selected pairs of vessels (i, j), and then re-decode L to a neighbor ξ_k' based on the newly fixed c_i', c_j' values.

The vessel pair (i, j) will be selected if both vessel i and j are type-B0 vessels, and if vessel i and j are simultaneously under processing for at least one time segment. Each feasible number of shifted cranes (δ) between vessel i and j will be a possible move, as long as vessel i and j don't break their requirements on the maximum and minimum crane numbers, i. e., as long as

$$R_i^{\min} \leqslant c_i - \delta \leqslant R_i^{\max}, \text{ and } R_j^{\min} \leqslant c_j - \delta \leqslant R_j^{\max}.$$

The re-decoding procedure is similar to the decoding in TS_1, except for the provisional setting of $R_i^{\min} = R_i^{\max} = c_i' = c_i + \delta$, and $R_j^{\min} = R_j^{\max} = c_j' = c_j - \delta$.

The Tabu object is the swap operation of c_i and c_j.

To supple from given ξ_k to ξ_{k+1}^0, add type-B1 and type-C vessels into partial plan of ξ_k one by one using the FF policy according to priority list L in scenario ω considering remaining available berth and crane resources. For each respective scenario ω, there is only one pass that decides for the type-B1 and C vessels, which is similar to the 2^{nd} pass of decoding procedure in TS_1, except that b^C values are already fixed for type-C vessels.

For each Scenario ω

For each vessel in L

If type-B1: retain b^B, and find the earliest s_ω after time $k+1$ with a maximum feasible c_ω. Set $s_\omega^{B1} = s_\omega$, $c_\omega^{B1} = c_\omega$.

If type-C: retain b^C, and find the earliest s_ω after A_ω^C with a maximum feasible c_ω. Set $s_\omega^C = s_\omega$, $c_\omega^C = c_\omega$

Else skip.

2.4 TS_3: 2^{nd} stage ξ_{k+1}

To search the neighbor of ξ_{k+1}, ξ_{k+1} is supplemented or re-supplemented from some ξ_k which has been decoded (or re-decoded) from some list L. In scenario ω, first make single swap moves on $L_2(\omega)$ which is a partial list consisted of type-B1 and C vessels, and then make re-supplement for ξ_k to get a neighbor ξ_{k+1} based on new $L_2(\omega)$.

The single swap moves are similar to those in TS_1. The re-supplement is the same as the supplement procedure in TS_2

The Tabu object in scenario ω is the reverse of swap operation, as in TS_1.

3 Numerical experiment

3.1 Experiment environment

Using the parameter distribution provided in Ref. [28], information of vessels in two weeks is generated, including each vessel's expected arrival time, minimum and maximum allowed QC number, predicted workload and length.

As Ref. [28], the quay length is 1 000 m and discretized by 10 m, the time horizon is discretized by 1hr, the total quay crane number is 10. The small, median and large problem scales involved are respectively 20, 30 and 40 vessels per week. The epoch length is set to be 24 h, and the horizon of 2^{nd} stage decision to be 24 h. The arriving times of 3 latest vessels are modified to be 0 as the type-A vessels and also pre-specify berthing locations and cranes allocation for type-A and B vessels of the 1^{st} epoch. Furthermore, the processing time of a single vessel is based on the QCSP optimization, and the scenarios of uncertain arriving time of potential type-C vessels are generated following the normal distribution $N(ETA_i, \sigma_i^A)$, and $\sigma_i^A = 3$.

At the beginning of each epoch k, information of tasks to be processed is firstly updated: type-A vessels are identified and their remained workloads are calculated based on decisions of epoch $k-1$; type-B vessels are renewed based on the 1^{st} stage decisions as well as the newly reviewed uncertainty during epoch $k-1$; the scenarios of uncertain arrival time of potential type-C vessels are re-generated. The scenario pool size is 2 000, and the sample size in TS_3 is 30. The actual scenario is randomly selected from the scenario pool, unrelated to the samples.

By the end of the 7^{th} epoch, the arrival time of finished and in-process vessels are known with certainty. The posterior optimization can be conducted for these vessels, using Cplex or TS to get the contrast solution from the deterministic model.

The algorithm is coded in C# and run on a PC with 2.6 GHz CPU and 4 G RAM. Parameters of Tabu search are set as in Table 3.

Table 3 Parameters for Tabu search

Parameters	TS_1	TS_2	TS_3
α	5	–	5
β	10	–	10
γ	5	–	5
Iter _ max	10	10	1
Tabu _ min	|list|/2	2	2
Tabu _ max	|list|	5	5

Based on the parameters and the sets of test, five kinds of experiment environment tests are made for comparing. The specific sets are shown in Table 4.

Table 4 Comparison of tested environment in numerical experiment

Test environment	Certain		Uncertain		
Test number	1.1	2	1.2	3	4
Information type	Completely posterior	Partial posterior	Completely posterior	Random scenario	Expert scenario
Decision method	Single	Rolling	Single	Rolling	Rolling
Algorithm	Cplex	Cplex	TS	TS	Cplex
Resolution model	1-stage (7 epochs)	2-stage approximate	2-stage approximate (1 + 6epochs)	2-stage approximate	2-stage approximate
Method set	Directly call	Directly call 1 scenario in the 2nd stage *s*	6 epochs with 1 scenario in the 2nd stage	30 scenarios randomly selected from scenario pool in the 2nd stage	Directly call 1 scenario in the 2nd stage

Detailed setup is as follows.

Test 1: Certain environment, based on the completely posterior information.

Test 1.1: Using Cplex, solving the modified 1-stage optimization model (including 7 epochs) in a single way.

Test 1.2: Using the simplified multi-layer nested Tabu search, solving the modified 2-stage approximate optimization model in a single way, including 1 epoch in the 1^{st} decision stage, and 6 epochs with 1 scenario in the 2^{nd} stage.

Test 2: Certain environment, based on partial posterior information, at each decision point, only the uncertainty of the next epoch can be revealed. In each epoch, solving the 2-stage approximate model by Cplex with rolling horizon (including 1 epoch in the 1^{st} stage and 1 epoch with 1 scenario in the 2^{nd} stage).

Test 3: Uncertain environment, based on the certain information in current epoch and random scenario based information of the following epoch. In each epoch, solving the 2-stage approximate model by multi-layer nested Tabu search with rolling horizon (including 1 epoch in the 1^{st} stage and 1 epoch with 30 scenarios randomly selected from scenario pool in the 2^{nd} stage).

Test 4: Uncertain environment, based on the certain information in current epoch and expert scenario information of the next epoch. In each epoch, solving the 2-stage approximate model by Cplex (including 1 epoch in the 1^{st} stage and 1 epoch with 1 scenario in the 2^{nd} decision stage).

3.2 Experiment results

Experiment results are shown in Table 5. The 'obj' column reports the object value of each method. The 'gap' column reports the gap between 'obj' value and 1.1 'obj' values. "*" means the low bound of Cplex, accuracy solution otherwise. And the average computing time of each scale is shown in Table 6.

Table 5 Results of numerical experiment

V	#	Posterior					Randomly scenario		Expert scenario	
		1.1Cplex	2 Cplex		1.2TS		3TS		4Cplex	
		obj	obj	gap	obj	gap	obj	gap	obj	gap
20	1	194	194	0.00%	194	0.00%	196	1.03%	203	4.64%
	2	264	264	0.00%	264	0.00%	264	0.00%	268	1.52%
	3	167	167	0.00%	167	0.00%	176	5.39%	176	5.39%
	4	243	243	0.00%	243	0.00%	246	1.23%	250	2.88%
	5	182	182	0.00%	182	0.00%	185	1.65%	199	9.34%
	6	174	174	0.00%	174	0.00%	174	0.00%	178	2.30%
	7	196	196	0.00%	196	0.00%	204	4.08%	208	6.12%
	8	201	201	0.00%	201	0.00%	201	0.00%	207	2.99%

Continued Table 5

	9	155	155	0.00%	155	0.00%	155	0.00%	155	0.00%
	10	197	197	0.00%	197	0.00%	197	0.00%	198	0.51%
Average				0.00%		0.00%		1.34%		3.57%
40	1	248	250	0.81%	250	0.81%	249	0.40%	259	4.44%
	2	335	335	0.00%	335	0.00%	336	0.30%	336	0.30%
	3	239	239	0.00%	239	0.00%	252	5.44%	253	5.86%
	4	335	335	0.00%	335	0.00%	341	1.79%	346	3.28%
	5	267	267	0.00%	269	0.75%	269	0.75%	276	3.37%
	6	261	261	0.00%	264	1.15%	267	2.30%	273	4.60%
	7	278	278	0.00%	283	1.80%	291	4.68%	303	8.99%
	8	281	281	0.00%	281	0.00%	281	0.00%	281	0.00v
	9	255	255	0.00%	255	0.00%	256	0.39%	263	3.14%
	10	288	288	0.00%	291	1.04%	303	5.21%	325	12.85%
Average				0.08%		0.55%		2.13%		4.68%
60	1	328	331	0.91%	335	2.13%	340	3.66%	350	6.71%
	2	430 *	462	7.44%	459	6.74%	467	8.60%	470	9.30%
	3	330 *	334	1.21%	336	1.82%	354	7.27%	366	10.91%
	4	381 *	424	11.29%	429	12.60%	429	12.60%	443	16.27%
	5	356 *	370	3.93%	380	6.74%	380	6.74%	403	13.20%
	6	364 *	364	0.00%	366	0.55%	373	2.47v	404	10.99%
	7	365	386	5.75v	390	6.85%	401	9.86%	423	15.80%
	8	371 *	371	0.00%	371	0.00%	374	0.81%	393	5.93%
	9	428	433	1.17%	435	1.64%	435	1.6%4	448	4.67%
	10	378	402	6.35%	404	6.88%	419	10.85%	458	21.16%
Average				3.81%		4.59%		6.45%		11.50%

Table 6 Average computing time of numerical experiment

V	1.1 Cplex (min)	2 Cplex (min)	1.2 TS (min)	3 TS (min)	4 Cplex (min)
20	0.8	0.3	0.1	1.2	0.3
30	9.6	0.6	0.9	14.4	1.6
40	111.1	176.6	5.1	33.9	280.7

In Test 1.1, the small and median cases can be effectively solved by Cplex, optimal solutions are found in average 0.8 min and 9.6 min respectively. Otherwise, only 3 large cases can be solved within 5 h, costing 111.1 min on average, and the rest of 7 large cases can't be solved in 5 h. It is thus clear that based on the completely posterior information, large cases can't be solved effectively by Cplex. The optimal solutions and the lower bound in this experiment provide a reference for further experiments.

Based on the partial posterior information, Test 2 uses Cplex to solve 2-stage approximate model in a rolling horizon. Most of the cases can be solved effectively. Compared with Test 1.1, Test 2 can get the same or approximate solutions, even much faster, the average gaps of different scales are 0%, 0.08%, 3.81% respectively. It shows the importance of uncertain information in the 2^{nd} stage during dynamic decision-making process, and also indicates the necessary of 2-stage optimization in each epoch. If the uncertain information of the next epoch can be obtained accurately, the 2-stage optimization based decision-making framework can have a great performance compared with the completely posterior information.

Test 1.2 based on the completely posterior which is the same as Test 1.1, solves the test by the modified multi-layer nested Tabu search. In small cases, it can have the same performance as decisions in Test 1.1 and Test 2, even much faster, only 0.1min on average. In median cases, the decision quality has no obvious differences from the singe or the rolling Cplex, the gap is 0.55% on average, and its calculating time is around 0.9 min, which is less than single Cplex and approximate to the rolling Cplex. In large cases, the average gap is 4.59%, calculating time is 5.1 min on average, which is far less than the single and rolling Cplex. It shows that the multi-layer nested Tabu search proposed has a great performance in certain circumstance: the differences in quality and computing speed are both within the acceptable range comparing with Cplex.

Test 3 uses the dynamic decision-making framework proposed with multi-layer nested Tabu search under uncertain circumstance. In each epoch, the 2-stage approximate optimization model is solved with certain information in current epoch and the randomly scenario information of following epochs. The average gap of different scales is 1.34%, 2.13%, 6.45%, respectively.

Compared with Test 2 and Test 1.2, the increment is not notable, which means the adjustable decisions in the 2^{nd} stage can effectively response to the uncertainties, a better decisions in the 1^{st} stage can be obtained, the posterior optimality of the 2-stage decision can be enhanced. Since the adjustable decisions should be made in all scenarios selected, the average computing time of large scale is 33.9 min, still within the acceptable range.

Test 4 is similar to Test 2, using Cplex in rolling horizon, based on the expect information of next epoch's randomly scenarios instead. The average gaps of different scales are 3.57%, 4.68%, 11.5%, respectively, far more than the corresponding value in Test 3. It indicates that using expert information in 2^{nd} stage can't deal with the uncertainties very well even using Cplex. It also shows the value and importance of random scenario based information in the 2-stage approximate optimization model with decision-making framework proposed.

3.3 Sensitivity analysis

The sensitivity analysis is made for the uncertainty of vessels arrival time, of which value is set as 2, 3 and 4 under different stochastic circumstances. The sensitivity of gaps is obtained as Section 3.2 does. The trend of average gap value in each scale case is shown in Fig. 4.

It can be observed that there are still consistent conclusions as Section 3.2 under different values of σ_i^A. In addition, with the increases of σ_i^A, the increase of Test 3 gap is not notable, while the difference between Test 4 and Test 3 is increased, which shows that the dynamic stochastic-scenario-based decision framework proposed has a more pronounced effect when the degree of uncertainty is increasing.

4 Conclusion

This paper addresses the integrated berth and quay crane allocation problem under uncertain circumstances. Set vessel arrival time as stochastic parameters with continuous berth position. Based on the analysis of the characteristics of information and operation in 2-stage stochastic optimization process, a 2-stage approximate model is proposed. A dynamic decision-making framework is developed with the stochastic-scenario-based decisions in the 2^{nd} stage, and the multi-layer nested Tabu search is proposed to deal with this mixed integer programing effectively. The numeral experiments show that such decision-making framework with multi-layer nested Tabu search can get an approximate optimal solution which is much close to the theoretical optimization in completely posterior situation.

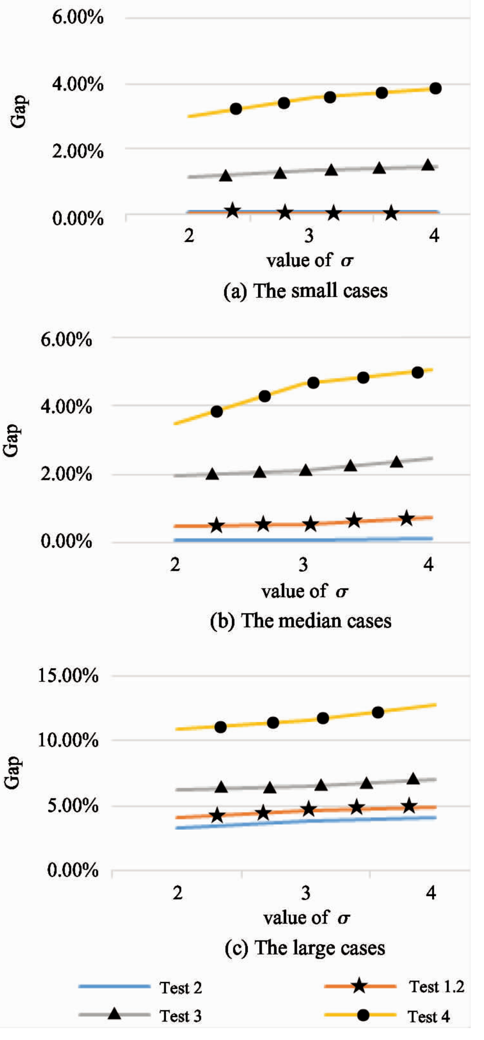

Fig. 4 Sensitivity of gaps under different σ values for different scale cases

References

[1] Bierwirth C, Meisel F. A survey of berth allocation and quay crane scheduling problems in container terminals [J]. *European Journal of Operational Research*, 2010, 202(3):615-627

[2] Bierwirth C, Meisel F. A follow-up survey of berth allocation and quay crane scheduling problems in container terminals[J]. *European Journal of Operational Research*, 2015, 244(3): 675-689

[3] Rodriguez-Molins M, Salido M A, Barber F. A GRASP-

based metaheuristic for the berth allocation problem and the quay crane assignment problem by managing vessel cargo holds[J]. *Applied Intelligence*, 2014, 40(2):273-290

[4] Elwany M H, Ali I, Abouelseoud Y. A heuristics-based solution to the continuous berth allocation and crane assignment problem[J]. *Alexandria Engineering Journal*, 2013, 52(4):671-677

[5] Hu Q M, Hu Z H, Du Y. Berth and quay-crane allocation problem considering fuel consumption and emissions from vessels[J]. *Computers & Industrial Engineering*, 2014, 70:1-10

[6] Hsu H P. A HPSO for solving dynamic and discrete berth allocation problem and dynamic quay crane assignment problem simultaneously[J]. *Swarm & Evolutionary Computation*, 2016, 27:156-168

[7] Lin S W, Ting C J. Solving the dynamic berth allocation problem by simulated annealing[J]. *Engineering Optimization*, 2014, 46(3):308-327

[8] Agra A, Oliveira M. MIP approaches for the integrated berth allocation and quay crane assignment and scheduling problem[J]. *European Journal of Operational Research*, 2018, 264:138-148

[9] Moorthy R, Teo C P. Berth management in container terminal: the template design problem[J]. *OR Spektrum*, 2006, 28(4):495-518

[10] Karafa J, Golias M M, Ivey S, et al. The berth allocation problem with stochastic vessel handling times[J]. *The International Journal of Advanced Manufacturing Technology*, 2013, 65(1):473-484

[11] Zhen L. Tactical berth allocation under uncertainty[J]. *European Journal of Operational Research*, 2015, 247(3):928-944

[12] Xiang X, Liu C, Miao L. A bi-objective robust model for berth allocation schedulingunder uncertainty[J]. *Transportation Research Part E*, 2017, 106:294-319

[13] Budipriyanto A, Wirjodirdjo B, Pujawan N, et al. Berth allocation problem under uncertainty: a conceptual model using collaborative approach[J]. *Procedia Manufacturing*, 2015, 4:429-437

[14] Rodriguez-Molins M, Ingolotti L, Barber F, et al. A genetic algorithm for robust berth allocation and quay crane assignment[J]. *Progress in Artificial Intelligence*, 2014, 2(4):177-192

[15] Shang X T, Cao J X, Ren J. A robust optimization approach to the integrated berth allocation and quay crane assignment problem[J]. *Transportation Research Part E Logistics & Transportation Review*, 2016, 94:44-65

[16] Iris C, Pacino D, Ropke S. Improved formulations and an adaptive large neighborhood search heuristic for the integrated berth allocation and quay crane assignment problem[J]. *Transportation Research Part E Logistics & Transportation Review*, 2017, 105:123-147

[17] Zeng Q, Yang Z, Hu X. Disruption recovery model for berth and quay crane scheduling in container terminals[J]. *Engineering Optimization*, 2011, 43(9):967-983

[18] Liu C, Zheng L, Zhang C. Behavior perception-based disruption models for berth allocation and quay crane assignment problems[J]. *Computers & Industrial Engineering*, 2016, 97:258-275

[19] Umang N, Bierlaire M. Disruption management and rescheduling in berth allocation problem in bulk ports[J]. *Pure & Applied Chemistry*, 2012, 77(7):1173-1181

[20] Umang N, Bierlaire M, EreraA L. Real-time management of berth allocation with stochastic arrival and handling times[J]. *Journal of Scheduling*, 2017,20(1):67-83

[21] Zhen L, Lee L H, Chew E P. A decision model for berth allocation under uncertainty[J]. *European Journal of Operational Research*, 2011, 212(1):54-68

[22] Xu Y, Chen Q, Quan X. Robust berth scheduling with uncertain vessel delay and handling time[J]. *Annals of Operations Research*, 2012, 192(1):123-140

[23] Zhen L, Chang D F. A bi-objective model for robust berth allocation scheduling[J]. *Computers & Industrial Engineering*, 2012, 63(1):262-273

[24] Chang D, Jiang Z, Yan W, et al. Integrating berth allocation and quay crane assignments[J]. *Transportation Research Part E Logistics & Transportation Review*, 2010, 46(6):975-990

[25] Zhang G, Smilowitz K, Erera A. Dynamic planning for urban drayage operations[J]. *Transportation Research Part E Logistics & Transportation Review*, 2011, 47(5): 764-777

[26] Lu Z, Han X, Xi L, et al. A heuristic for the quay crane scheduling problem based on contiguous bay crane operations[J]. *Computers & Operations Research*, 2012, 39(12):2915-2928

[27] Ak A. Berth and quay crane scheduling: problems, models and solution methods[D]. Atlanta: Georgia Institute of Technology, 2008

[28] Meisel F, Bierwirth C. Heuristics for the integration of crane productivity in the berth allocation problem[J]. *Transportation Research Part E: Logistics and Transportation Review*,2009, 45(1): 196-209

Han Xiaole, born in 1983. He received his Ph. D degree from Shanghai Jiaotong University in 2013. He is currently an assistant professor in the School of Mechanical Engineering, Tongji University. His research focuses on the operational optimization of container terminal.