APEM journal

Advances in Production Engineering & Management
Volume 12 | Number 4 | December 2017 | pp 363–374
https://doi.org/10.14743/apem2017.4.264

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Container assignment optimization considering overlapping amount and operation distance in rail-road transshipment terminal

Wang, L.[a,*]**, Zhu, X.**[a]**, Xie, Z.**[a,b]

[a]School of Traffic and Transportation, Beijing Jiaotong University, Beijing, P.R. China
[b]State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, P.R. China

A B S T R A C T

Container assignment strategy is crucial to the operation efficiency of rail-road container transshipping system. An effective container assignment approach can markedly improve integral operation efficiency of rail-road container transshipping system. In this paper, the container assignment problem in rail-road transshipment terminal was described and formulated as a two-stage optimization model considering overlapping amount and operation distance of crane. The first stage optimization model was to optimize container assigning positions for minimizing the total overlapping amount caused by container assigned in the considered block at one planning period, and an iterative solution procedure was proposed to obtain container assignment sets. Based on the container assignment sets obtained by the first stage, the second stage optimization model was to optimize the container assigning sequence for decreasing the total operation distance of crane, and a genetic algorithm was designed to obtain the optimal container handling sequences in container assignment process. Computational experiments on the data from a rail-road transshipment terminal in China were implemented to test efficiency of the proposed approach. Computational results showed that the proposed approach was effective to reduce overlapping amount and operation distance in container assignment process. The proposed approach is significant for the production and management of rail-road container transshipping terminals.

A R T I C L E I N F O

Keywords:
Intermodal transportation
Container assignment
Terminal scheduling
Rail-road transshipment terminal
Optimization
Genetic algorithms

**Corresponding author:*
liwang@bjtu.edu.cn
(Wang, L.)

Article history:
Received 25 January 2017
Revised 21 October 2017
Accepted 26 October 2017

1. Introduction

Intermodal transportation is defined as the successive use of various modes of transportation (road, rail, air and water) without any handling of the goods themselves during transfers between modes [1]. In rail-road intermodal transshipping system, massive quantities of containers are carried by railway for long distances, and short distance transshipping and delivery are undertaken by container trucks. To enable containers efficiently transferred between trains and trucks, modern rail-road transshipment terminals are required, which have advanced modern handling resources and efficient scheduling strategies.

As a key resource of rail-road transshipment terminals, storage space is used for temporarily stockpiling inbound and outbound containers unloaded from container trains and trucks. Storage space allocation is a critical scheduling strategy defined as the temporary allocation of the inbound/outbound containers to the storage blocks at each period with aim of balancing the workload between blocks in order to minimize the storage/retrieval times of containers [2]. Container assignment is an important decision making problem in storage space allocation strategy, which is a vital constraint for other strategies. Therefore, it is necessary for rail-road transshipment terminals to optimize their container assignment.

Outbound containers assignment problem was formulated as a mixed-integer linear programming model, whose objectives were to utilize space efficiently and make loading operations more efficient [3]. The location assignment for arriving outbound containers during container-receiving stage was formulated as two novel dynamic programming models, and compared with existent model on small-scale instances [4]. A novel mixed-integer programming model was developed to integrate storage space allocation and ship scheduling for achieving high space utilization, low material loss, and low transportation costs [5]. For improving the operations efficiency for retrieving inbound container in container terminal, three optimization models under different strategies of storing containers were proposed, namely, a non-segregation model, a single-period segregation model, and a multiple-period segregation model [6]. An ant-based model was present for the storage space allocation problem to balance operational quantities among different blocks, and minimize the moving distance of internal trucks between container yards and berths [7].

For solving container assignment problem, several heuristic algorithms were developed. An efficient GA was proposed to solve the extensional container assignment problem in container terminal [2]. For large-scale SSAP instances, a two-stage heuristic was proposed. For the first stage, a neighborhood searching heuristic was present to generate the priority sequence; a rollout-based heuristic was developed to improve the incumbent solution in the second stage [8]. An outer–inner cellular automaton algorithm (CAOI) was developed to solve SSAP, using YBAP and SAP as an integrated optimization process [9].

According to the literature review above, most of studies focused on container assignment problem in maritime container terminals. These studies generally decomposed the problem into two stages, and developed different heuristic algorithms to solve the problem. By contrast, specific literature on rail-road transshipment terminal is scarce. A two-stage optimization model was proposed to balance operational quantities and reduce overlapping amount of inbound containers [10]. A container slot allocation model based on mixed storage mode was present to minimize container overlapping amounts and a heuristic algorithm was designed for solving the model [11]. These studies only focused on decreasing the overlapping amounts, and did not consider the crane operation distance together in container assignment optimizing process. The operation distance is also an important indicator for storage space allocation in rail-road transshipment terminals. Some studies focused on crane operation optimization without considering container overlapping amount [12, 13].

Therefore, we simultaneously consider overlapping amount and operation distance in container assignment process. The main contributions of this paper are as follows. First, we present a two-stage approach for formulating the container assignment problem to minimize overlapping amount and total operation distance of crane. Second, a rolling horizon implement strategy is designed for obtain an approximate optimal solution. The proposed approach is effective for different size of planning periods.

The remainder of this paper is organized as follows. The container assignment problem in rail-road transshipment terminals is described in Section 2, and formulated in Section 3. A rolling horizon implement strategy is developed in Section 4. Computational results are discussed in Section 5. Section 6 covers the conclusion.

2. Problem description

A typical container transshipping system of rail-road transshipment terminals is mainly composed by three subsystems, including loading-unloading subsystem, storage space allocation subsystem and transport subsystem, which is shown in Fig. 1.

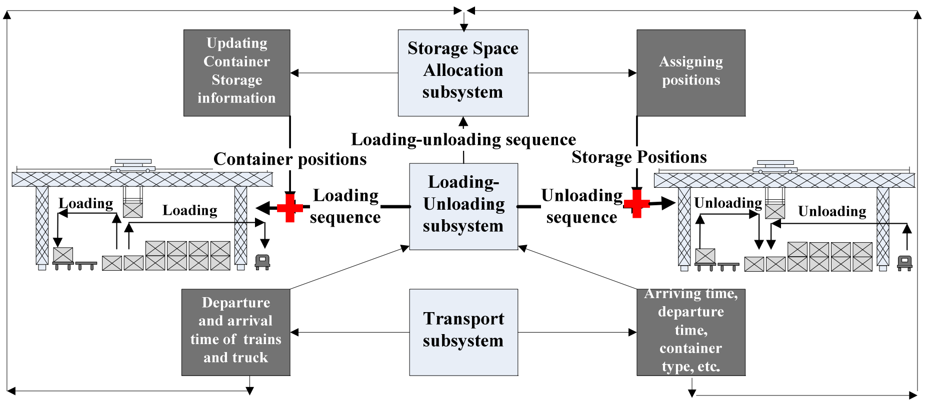


Fig. 1 A typical container transshipping system in rail-road transshipment terminals

These three subsystems ensure outbound and inbound containers can be quickly transferred in rail-road transshipment terminals. The main mission of storage space allocation subsystem is to assignment containers to the suitable positions. The assignment processing has two tasks, first is to allocated containers to blocks, and the other is to assign container to slots. Our study only focuses on the second task to assign containers in considered block.

As observed in Fig. 1, assigned containers in rail-road transshipment terminals can be classified into the following two kinds.

- Rail vehicle unloading containers (RVUC): inbound containers are on rail vehicles before unloaded and assigned to container yard.
- Truck unloading containers (TRUC): outbound containers are on trucks before unloaded and assigned to container yard.

The operations of two type assigned containers are shown in Fig. 2.

By simultaneously considering overlapping amount and operation distance, we can decompose the container assignment problem into two stages.

- First stage: Assign optimal positions for TRUCs and RVUCs to minimize overlapping amount and obtain container assignment sets.
- Second stage: Optimize assigning sequence to minimize the total operation distance of crane based on assignment sets obtained in the first stage. Because arriving time of TRUC is uncertain and discrete, TRUC assigning sequence cannot be optimized. Therefore, this stage optimization is only for the RVUCs, and TRUCs are assigned according to arriving sequence.

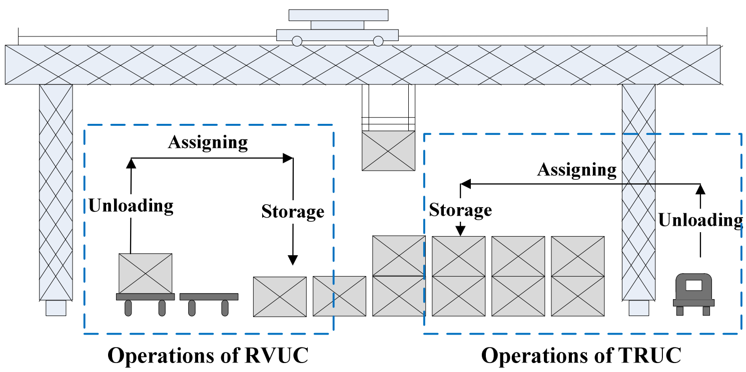


Fig. 2 Operations of two type allocated containers

3. Problem formulation

Based on the problem described above, the container assignment problem in rail-road transshipment terminal is formulated as two-stage optimization model.

3.1 Assumptions

The problem is formulated based on the following assumptions.

1) Initial assigning amount of RVUCs and TRUCs are assumed to be known at beginning of each planning epoch.
2) Arrival and departure time of containers are got beforehand and no delay happens at planning period.
3) There are enough resources, i.e., gantry cranes, container slots, to assign containers to the considered block.
4) Containers in the model are the same size.

3.2 Notations and variables

The notations and variables of two-stage optimization model are shown in Table 1.

Table 1 Notations and variables

Indexes	
q, r :	row index, $1 \le q \le R, 1 \le r \le R$
a, b :	bay index, $1 \le a \le B, 1 \le b \le B$
e, l :	layer index, $1 \le e \le L, 1 \le l \le L$
(r, b, l) :	container slot (r row, b bay, l layer)
i, j :	assigning index
Parameters	
N :	total amount of RVUCs and TRUCs
B :	bay amount in considered block
R :	row amount in considered block
L :	maximum layer height
$det_{(r,b,l)}$:	departure time of container in (r, b, l)
Sets	
$\tilde{S}_{RV}$:	container set of RVUCs
$\tilde{S}_{TR}$:	container set of TRUCs
$\tilde{S}_b$:	container slots set in considered block
Variables	
$S_{(r,b,l)}$:	1, if (r, b, l) has container; 0, otherwise.
$S^i_{(r,b,l)}$:	1, if assigning the i^{th} container to (r, b, l) ; 0, otherwise.
$K^{RVUC}_{(r,b,l),(r,b,l-e)}$:	overlapping of $(r, b, l-e)$ generated by RVUC assigned to (r, b, l) . 1, if $det_{(r,b,l)} < det_{(r,b,l-e)}$; 0, otherwise.
$K^{TRUC}_{(r,b,l),(r,b,l-e)}$:	overlapping of $(r, b, l-e)$ generated by TRUC assigned to (r, b, l) . 1, if $det_{(r,b,l)} < det_{(r,b,l-e)}$; 0, otherwise.
CW_i :	1, if the i^{th} container is RVUC; 0, otherwise.
$d^i_{(r,b,l)}$:	operation distance of the i^{th} container
$X^{ji}_{(q,a,e),(r,b,l)}$:	1, if the j^{th} container assigned immediately begins after the i^{th} container assignment has been finished; 0, otherwise.

3.3 First stage optimization model

In the first stage, RVUCs and TRUCs are assigned to optimal container slots in each planning period. The optimization model is written as follows.

$$\min \sum_{i=1}^{N} [CW_i \sum_{e=1}^{l-1} K^{RVUC}_{(r,b,l),(r,b,l-e)} + (1 - CW_i) \sum_{e=1}^{l-1} K^{TRUC}_{(r,b,l),(r,b,l-e)}] \tag{1}$$

$$S^i_{(r,b,l)} - S_{(r,b,l-1)} \le 0, \forall i \in \tilde{S}_{RV} \cup \tilde{S}_{TR}, \forall (r,b,l), (r,b,l-1) \in \tilde{S}_b \tag{2}$$

$$(1+\sum_{e=1}^{l-1} S^{i}_{(r,b,l-e)})\sum_{n=1}^{i-1} S^{n}_{(r,b,l)} - 1 \le 0, \forall i \in \tilde{S}_{RV} \cup \tilde{S}_{TR}, \forall (r,b,l),(r,b,l-e) \in \tilde{S}_b \tag{3}$$

$$\sum_{i=1}^{N}\sum_{r=1}^{R/2-1}(1-CW_i)S^{i}_{(r,b,l)} - \sum_{i=1}^{N}\sum_{r=R}^{R/2+1}(1-CW_i)S^{i}_{(r,b,l)} \ge 0, \forall (r,b,l) \in \tilde{S}_b \tag{4}$$

$$\sum_{i=1}^{N}\sum_{r=1}^{R/2-1} CW_i S^{i}_{(r,b,l)} - \sum_{i=1}^{N}\sum_{r=R}^{R/2+1} CW_i S^{i}_{(r,b,l)} \ge 0, \forall (r,b,l) \in \tilde{S}_b \tag{5}$$

The objective function (Eq. 1) is to minimize the total overlapping amount in considered block at one planning period. The first part is the overlapping amount caused by RVUCs, and the other part is the overlapping amount caused by TRUCs. Constraint (Eq. 2) indicates that position upon empty container slot cannot be assigned. Constraint (Eq. 3) means that the subsequent operation container does not allow to be assigned below the previous operation containers. Constraint (Eq. 4) is assignment preferences of TRUCs, which ensures assigning positions of TRUCs should be near to rail handling tracks in order to decrease loading time of container trains. Constraint (Eq. 5) is assignment preferences of RVUCs, which ensures assigning positions of RVUCs should be near to truck lane for reducing loading time of trucks.

3.4 Second stage optimization model

In the second stage, based on container assignment sets obtained from the first stage, RVUCs assigning sequence will be optimized to decrease the total operation distance of crane. The optimization model is written as follows.

$$\min \sum_{i=1}^{N} S^{i}_{(r,b,l)} d^{i}_{(r,b,l)} \tag{6}$$

$$d^{i}_{(r,b,l)} = (|b-i|+r)+(|b-j|+r)X^{ji}_{(q,a,e),(r,b,l)}, \forall i,j \in \tilde{S}_{RV} \cup \tilde{S}_{TR}, \forall (r,b,l),(q,a,e) \in \tilde{S}_b \tag{7}$$

$$\sum_{j=1}^{N} X^{ji}_{(q,a,e),(r,b,l)} \le 1, \forall i \in \tilde{S}_{RV} \cup \tilde{S}_{TR}, \forall (r,b,l),(q,a,e) \in \tilde{S}_b \tag{8}$$

$$\sum_{i=1}^{N} X^{ji}_{(q,a,e),(r,b,l)} \le 1, \forall j \in \tilde{S}_{RV} \cup \tilde{S}_{TR}, \forall (r,b,l),(q,a,e) \in \tilde{S}_b \tag{9}$$

$$\frac{S^{i}_{(r,b,l)} \cdot S^{j}_{(r,b,e)}}{(i-j)(l-e)} \ge 0, \forall i,j \in \tilde{S}_{RV} \cup \tilde{S}_{TR}, \forall (r,b,l),(r,b,e) \in \tilde{S}_b \tag{10}$$

The objective function (Eq. 6) is to minimize RVUCs operation distance in considered block at one planning period. Constraint (Eq. 7) represents operation distance calculation of each RVUCs. The distance includes two parts. The first is loaded moving distance between the initial and final position of RVUC. The other is the unloaded moving distance from the final position of one operation to the initial position of its subsequent operation. Constraint (Eq. 8) and constraint (Eq. 9) are assigning sequence constraints, which ensure that each RVUC assigning operation at most has one pre-order operation and one subsequent operation. Constraint (Eq. 10) indicates that the assigned RVUCs must be operated in well-defined sequence.

4. Solution algorithm

For solving the two-stage optimization model present above, a rolling horizon implement strategy is developed in this section. The two-stage optimization model is solved in each planning period based on RVUCs and TRUCs initial information at beginning of each planning epoch. The implement process is shown in Fig. 3.

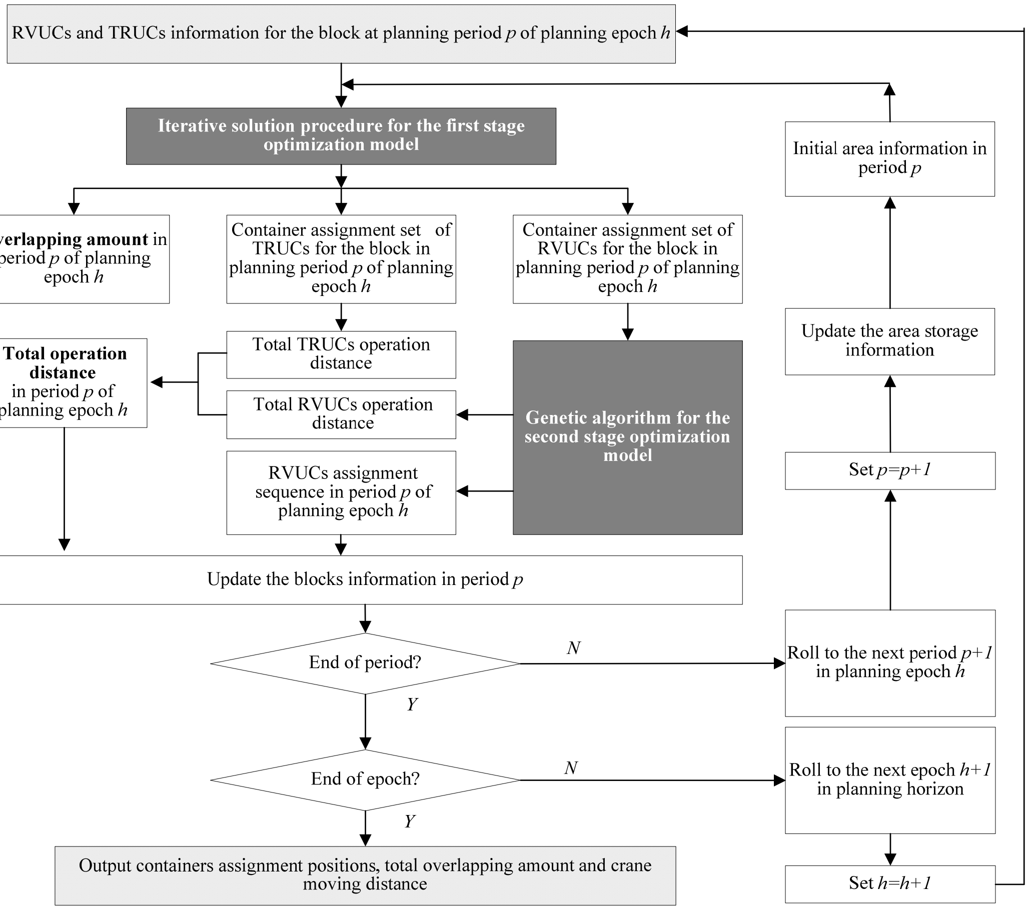


Fig. 3 A rolling horizon implement process

4.1 Iterative solution procedure for the first stage

In implement process, we introduce an iterative solution procedure for the first stage optimization model to minimize overlapping amount and obtain container assignment sets at one planning period. The related notations are described in Table 2.

In iterative solution procedure, for the i^{th} container, we firstly need distinguish the container type. For TRUC, we search the optimal assigning positions from the row near the loading-unloading track, and for RVUC, the search begins at the row near the truck operation lane. After the iterative solution procedure, we can obtain container assignment set for the i^{th} container. The details of iterative solution procedure are shown in Table 3.

Table 2 Notations of iterative solution procedure

n :	solution index
$\tilde{K}$:	overlapping amount sets
$\tilde{F}_i$:	feasible assigning set of the i^{th} container
$\tilde{A}_i$:	minimum overlapping amount set of the i^{th} container which belongs to RVUCs
$\tilde{B}$	TRUCs assignment set with minimum overlapping amounts
$\tilde{S}_{ss}$	optimal RVUCs assignment set with minimum total overlapping amounts
K_i^{RVUC}	overlapping amount of the i^{th} container belongs to RVUCs
K_i^{TRUC}	overlapping amount of the i^{th} container belongs to TRUSs
K_n^{VU}	overlapping amounts generated by the n^{th} feasible solution of RVUCs
K_n^{RU}	overlapping amounts generated by the n^{th} feasible solution of TRUSs
I	an arbitrary positive big number

Table 3 Iterative solution procedure

Iterative solution procedure
Step 1: Parameter initialization. Set $i=1$, $r=1$, $b=1$, $\tilde{K}=\phi$, $\tilde{S}_{ss}=\phi$, $\tilde{A}_i=\phi$, $\tilde{B}=\phi$, $\tilde{F}_i=\phi$, $K_i^{RVUC}=I$, $K_i^{TRUC}=I$, go to step 2.
Step 2: Distinguish type of the i^{th} container, get $\tilde{F}_i$ based on the constraint (2) and (3). If the i^{th} container belongs to TRUC, go to step 3. Otherwise, let $r=R$, then go to step 6.
Step 3: If $(r,b,l)\notin \tilde{F}_i$, go to step 4. Otherwise, assign the i^{th} container to (r,b,l), calculate K_n^{RU}, and compare with K_i^{TRUC}. If $K_n^{RU} > K_i^{TRUC}$, go to step 4. Otherwise, let $K_i^{TRUC}=K_n^{RU}$, $\tilde{B}=\{S_{(r,b,l)}^i\}$, and go to step 4.
Step 4: Let $b=b+1$. If $b\le B$, go to step 3. Otherwise, let $r=r+1$, then go to step 5.
Step 5: If $r\le R$, go to Step 3. Otherwise, let $\tilde{K}=\tilde{K}\bigcup\{K_i^{TRUC}\}$, $\tilde{B}=\tilde{B}\bigcup\{S_{(r,b,l)}^i\}$, then go to step 10.
Step 6: If $(r,b,l)\notin \tilde{F}_i$, go to step 7. Otherwise, assign the i^{th} container to (r,b,l), calculate K_n^{VU}, and compare with K_v^{RVUC}. If $K_n^{VU} > K_i^{RVUC}$, go to step 7. Otherwise, go to step 9.
Step 7: Let $b=b+1$. If $i-3\le b\le i+3$, go to step 6. Otherwise, let $r=r-1$, then go to step 8.
Step 8: If $r\ge 1$, go to step 6. Otherwise, let $\tilde{K}=\tilde{K}\bigcup\{K_i^{RVUC}\}$, $\tilde{A}_i=\tilde{A}_i\bigcup\{S_{(r,b,l)}^i\}$, then go to step 10.
Step 9: If $K_n^{VU}=K_i^{RVUC}$, let $\tilde{A}_i=\tilde{A}_i\bigcup\{S_{(r,b,l)}^i\}$, then go to step 7. Otherwise, let $K_i^{RVUC}=K_n^{VU}$, $\tilde{A}_i=\{S_{(r,b,l)}^i\}$, and go to step 7.
Step 10: The i^{th} container assignment is finished. Let $r=1$, $b=1$, $i=i+1$. If $i>N$, go to step 11, otherwise, go to step 2.
Step 11: Procedure terminates. Obtain overlapping amount of the period p based on $\tilde{K}$, get $\tilde{S}_{ss}$ based on the constraint (3) and the mapping relationship of $\tilde{A}_i$.

4.2 Genetic algorithm for the second stage

Based on the optimal container assignment sets obtained from the first stage, a genetic algorithm is developed for optimizing assigning sequences to minimize total RVUCs operation distance at one planning period. Main steps of genetic algorithm implementation are introduced in the following subsections.

Chromosome representation

Two-dimensional encoding is employed for chromosome representation in this paper. Each chromosome represents a possible assigning sequence of RVUCs at one planning period, and includes genes are RVUCs amount in considered block at one planning period. Each gene includes five parts, which are RVUC index, row, bay and layer index of assignment slot, and arrival period of RVUC. The sequence of gene from the left to right represents the assigning sequence. A sample of chromosome representation is shown in Fig. 4. In the sample, there are 6 RVUCs to be assigned, gene1 represents the 5th RVUC arriving at the second period is assigned to the container slot (5,7,1), and the whole chromosome means the six RVUCs are assigned according to the sequence of 5-(5,7,1)-1-(2,9,1)-4-(4,6,2)-6-(1,11,1)-2-(6,9,2)-3-(4,10,2).

	Gene 1	Gene 2	Gene 3	Gene 4	Gene 5	Gene 6
RVUC index	5	1	4	6	2	3
Row index of assignment slot	5	2	4	1	6	4
Bay index of assignment slot	7	9	6	11	9	10
Layer index of assignmet slot	1	1	2	1	2	2
Arrival period of RVUC	2	2	2	2	2	4

Fig. 4 A Sample of chromosome representation

Evaluation of fitness value

Some of chromosomes generated by the genetic operators do not violate constraint (10). Therefore, every chromosome must be verified whether its corresponding sequence satisfies the constraint. If it satisfies constraints (10), calculate the chromosome fitness value based on Eq. (11). Otherwise, set its fitness value to zero.

$$Fitness\ value = \frac{1}{\sum_{i=1}^{N} S^{i}_{(r,b,l)} d^{i}_{(r,b,l)}} \tag{11}$$

Genetic operators design

In the developed GA, initial generation is randomly generated, and tournament selection is employed as selection operator.

- Crossover operator
  Based on constraints (Eq. 8) to (Eq. 10), the values of RVUC index cannot to be lost and repeated in offspring, so the order crossover operator is employed in this paper. The crossover operator works as follows, and a sample of crossover operating is shown in Fig. 5.
  Setp1: Randomly select a substring from each parent.
  Step2: Copy the selected substring into the front of other parent to produce a proto-child.
  Step3: Scan the first layer of proto-child from left to right, and delete repeated gene values behind the substring. An offspring is produced.

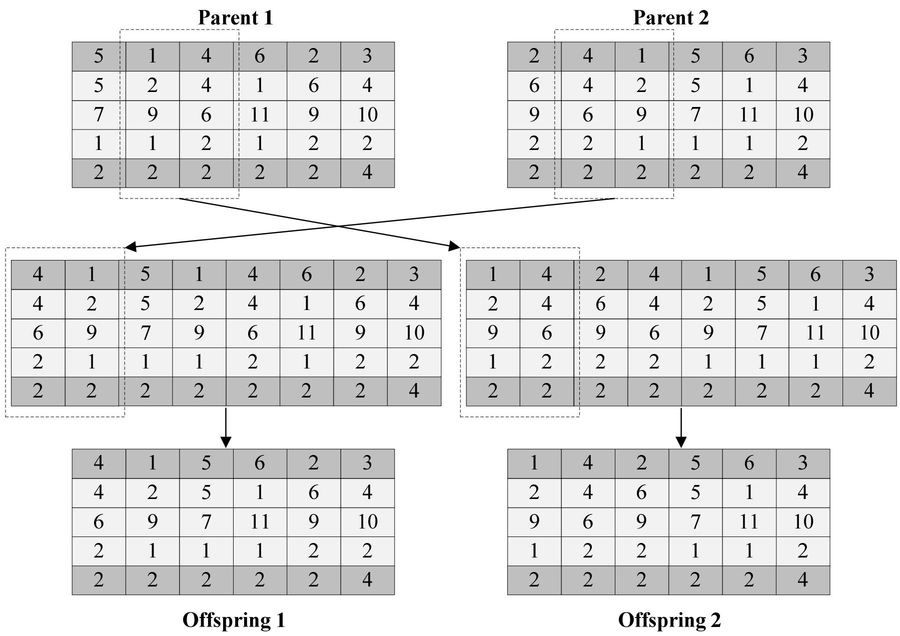


Fig. 5 A sample of crossover operating

- Mutation operator
  To avoid losing and repeating of RVUC index in offspring, we use the inversion mutation operator, which firstly chooses two mutation points randomly, then inverts two points genes. A sample is shown in Fig. 6.

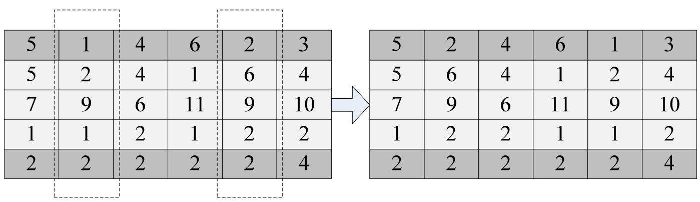


Fig. 6 A sample of mutation operating

5. Computational experiments: Results and discussion

To illustrate the approach proposed above, computational experiments are conducted by using the data from a rail-road transshipment terminal in China. For evaluating efficiency of the proposed approach, some comparisons are made. All experiments are implemented based on a personal computer with Intel Core(TM) i5-2450M @ 2.50GHz processors and 4 GB RAM.

Parameters related to the rail-road transshipment terminal are introduced as follows. The container yard of terminal has four blocks. Each block includes 20 bays, 6 rows and 2 layers. Most of RVUCs and TRUCs are handled no more than two days after they assigned to blocks, so we set two days as a planning horizon, one day as a planning epoch and six hours as a planning period. Therefore, each planning horizon has two planning epochs or eight planning periods.

Firstly, we choose a planning epoch to implement the proposed approach. The initial information of RVUCs and TRUCs in considered block at one planning epoch is shown in Table 4.

Based on the initial information in Table 4, the iterative solution procedure for the first stage is conduct to obtain RVUCs and TRUCs assignment sets with minimum overlapping amount. For evaluating improvement of the proposed approach (PA), we make a comparison with random search algorithm (RSA) which is used in rail-road transshipment terminals. Computational results of the first stage are shown in Table 5.

Table 4 Initial information at one planning epoch

Planning period 1				Planning period 2				Planning period 3				Planning period 4			
No.	T	At	Dt	No.	T	At	Dt	No.	T	At	Dt	No.	T	At	Dt
1	I	2	34	1	I	6	38	1	II	13	26	1	II	18	72
2	I	2	19	2	I	6	32	2	II	13	26	2	II	18	72
3	I	2	17	3	I	6	20	3	II	15	26	3	II	20	48
4	I	2	32	4	I	6	32	4	II	15	48	4	II	20	72
5	I	2	38	5	I	6	40	5	II	17	72	5	I	21	55
6	I	2	32	6	I	6	40	6	I	17	34	6	I	21	55
7	I	2	34	7	I	6	40	7	I	17	56	7	I	21	64
8	I	2	32	8	I	6	38	8	I	17	37	8	I	21	45
9	I	2	38	9	I	6	32	9	I	17	37	9	I	21	58
10	I	2	20	10	II	7	26	10	I	17	38	10	I	21	40
11	I	2	20	11	II	7	26	11	I	17	32	11	I	21	67
12	I	2	35	12	II	9	26	12	I	17	32	12	I	21	62
13	I	2	22	13	II	9	48	13	I	17	44	13	I	21	38
14	I	2	38	14	II	9	48	14	I	17	36	14	I	21	38
15	I	2	56	15	II	10	48	15	I	17	36	15	I	21	62
16	I	2	15	16	II	10	48	16	I	17	36	16	I	21	59
17	I	2	34	17	II	10	48	17	I	17	40	17	II	22	48
18	I	2	38	18	II	10	48	18	I	17	40	18	II	22	48
19	I	2	63	-	-	-	-	19	I	17	34	19	II	23	48
20	I	2	20	-	-	-	-	20	II	18	48	20	II	23	72
21	I	2	36	-	-	-	-	21	II	18	72	21	II	23	72
22	II	4	26	-	-	-	-	22	II	18	72	-	-	-	-
23	II	6	26	-	-	-	-	-	-	-	-	-	-	-	-
24	II	6	48	-	-	-	-	-	-	-	-	-	-	-	-

Notes: T denotes Type (I—RVUC, II—TRUC); At denotes the arrival period of containers in a planning horizon; Dt denotes the departure period of containers in a planning horizon.

Table 5 Comparison between PA and RSA in the first stage at one planning epoch

Planning period	Overlapping amount (PA)	Overlapping amount (RSA)	GAP[1]
1	4	9	55.6 %
2	2	5	60.0 %
3	3	7	57.1 %
4	2	4	50.0 %
Total amount	11	25	56.0 %

Notes: GAP[1]= (overlapping amount obtained by RSA - overlapping amount obtained by PA) · 100/ overlapping amount obtained by RSA.

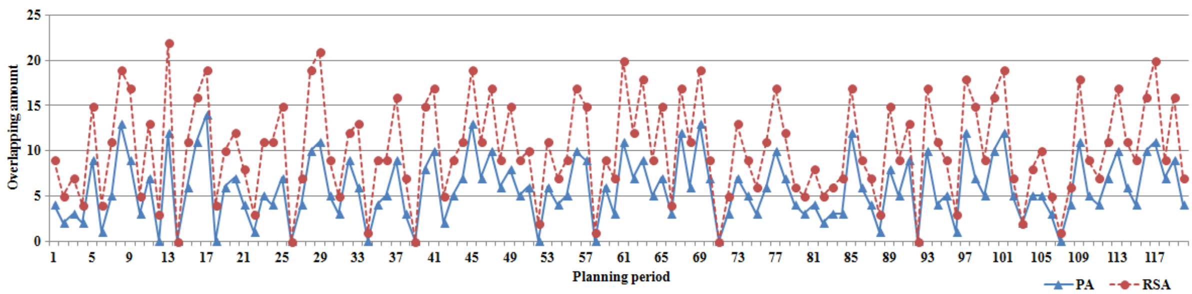
As observed in Table 5, the overlapping amount has been decreased in each planning period. Based on RVUCs assignment sets obtained by the first stage, genetic algorithm for the second stage is conducted to optimize assigning sequence. For 50 independent runs, the average time consumption of each planning period is 2.3 min, the average time consumption of each planning epoch is 11.7 min, which can meet requirement of practical operations in rail–truck transshipment terminals. In order to evaluate our approach, we compare the operation distance obtained by our approach with average operation distance of RVUC assignment sets (AOD). The computational results of the second stage are shown in Table 6.

As shown in Table 6, operation distance has been reduced by optimizing assigning sequence at each planning period. The decrease of operation distance can directly improve container assignment efficiency. For further evaluating performance of the proposed approach, computational experiments on 30 days are implemented. The experimental results are shown in Fig. 7.

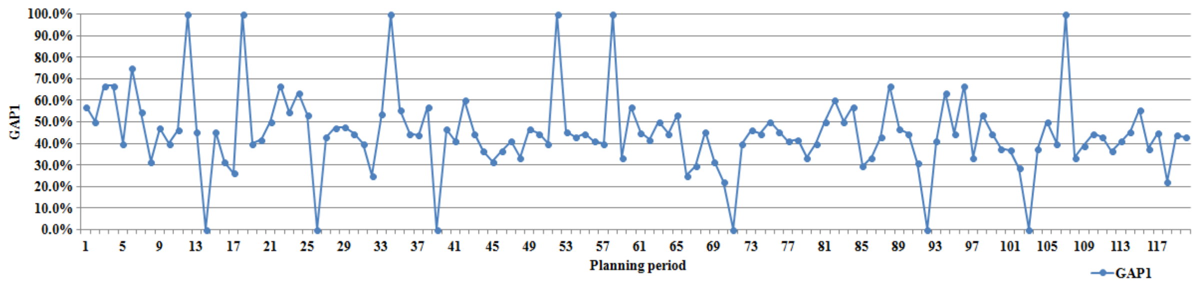
Table 6 Comparison between PA and AOD in the second stage at one planning epoch

Planning period	Operation distance (PA) (m)	Operation distance (AOD) (m)	GAP2
1	836.4	875.5	4.5 %
2	340.6	356.5	4.5 %
3	597	622	4.0 %
4	476.4	507.5	6.1 %
Total amount	2250.4	2361.5	4.7 %

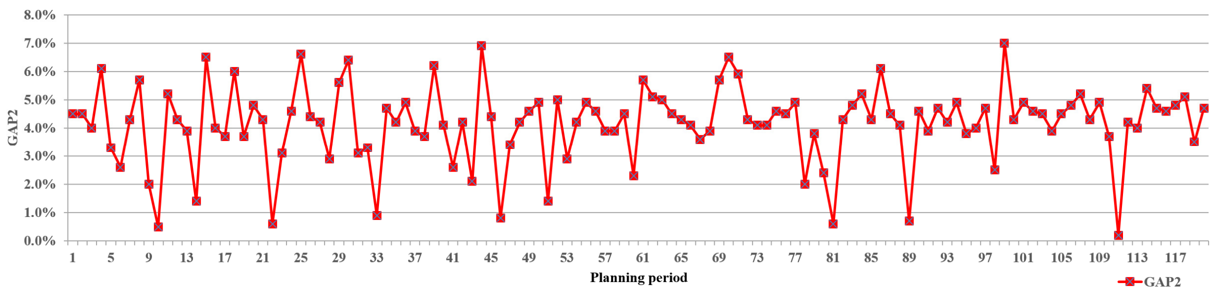
Notes: GAP2= (operation distance obtained by AOD - operation distance obtained by PA) • 100/ operation distance obtained by AOD.



(a)



(b)



(c)

Fig. 7 Overlapping amount in 30 days: (a) overlapping amount comparison between PA and RSA in 30 days; (b) GAP1 in 30 days; (c) GAP2 in 30 days

As observed in Fig. 7(a) and (b), the overlapping amount caused by RVUCs and TRUCs assigned are prominently reduced at each period of 30 days, and average of GAP[1] is 44.8 %. Almost half of container re-handling operations have been eliminated by optimizing assignment of RVUCs and TRUCs. On the basis of minimum overlapping amount, RVUC assignment sequences are optimized to minimize the operation distance at each period, and the average of GAP[2] is 4.1 % shown in Fig. 7(c). The decreases of overlapping amount and operation distance can directly improve container loading-unloading operation and cranes utilization efficiency. The experimental results of different size planning periods indicate that the proposed approach is effective and efficient for container assignment in rail-road transshipment terminals.

6. Conclusion

In this paper, container assignment problem of rail-road transshipment terminals was considered and formulated as a two-stage optimization model. The first stage was to optimize assignment positions to minimize overlapping amount, and the second stage was to optimize assigning sequence to minimize the operation distance. For solving the model, an iterative solution procedure was proposed to minimize overlapping amount in the first stage, and a genetic algorithm was developed to minimize operation distance in the second stage. Computational experiments were conducted by using real-life data, and results showed that our approach could reduce overlapping amount and operation distance while containers assigning, and remarkably improve efficiency of containers storage allocation.

The proposed approach cannot be directly used to optimize other container logistics system, etc. water-rail and water-road transshipment system. Because each system has its specific container assignment rules, optimization problem has different constraints. These logistics processes optimization can draw on our problem solving procedure, and proposed similar approach based on these characteristics. Our approach can serve as an important reference for container assignment problem.

In future, considering the uncertainty of container arrival-departure time which caused by the delay of trains and trucks, to propose the automatic container assignment optimization model under uncertainty is a possibility for further research.

Acknowledgement

This work was supported by the Major Program of National Natural Science Foundation of China (grant number 71390332), Specialized Research Fund for the Doctoral Program of Higher Education (grant number 20130009110001), Fundamental Research Funds for the Central Universities (grant number 2015JBM056), Talented Faculty Funds of Beijing Jiaotong University (Grant no. 2016RC045) and China Postdoctoral Science Foundation (grant number 2015M570925).

References

[1] Boysen, N., Fliedner, M. (2010). Determining crane areas in intermodal transshipment yards: The yard partition problem, *European Journal of Operational Research*, Vol. 204, No. 2, 336-342, doi: 10.1016/j.ejor.2009.10.031.

[2] Bazzazi, M., Safaei, N., Javadian, N. (2009). A genetic algorithm to solve the storage space allocation problem in a container terminal, *Computers & Industrial Engineering*, Vol. 56, No. 1, 44-52, doi: 10.1016/j.cie.2008.03.012.

[3] Kim, K.H., Park, K.T. (2003). A note on a dynamic space-allocation method for outbound containers, *European Journal of Operational Research*, Vol. 148, No. 1, 92-101, doi: 10.1016/S0377-2217(02)00333-8.

[4] Zhang, C., Wu, T., Zhong, M., Zheng, L., Miao, L. (2014). Location assignment for outbound containers with adjusted weight proportion, *Computers & Operations Research*, Vol. 52, 84-93, doi: 10.1016/j.cor.2014.06.012.

[5] Tang, L., Sun, D., Liu, J. (2016). Integrated storage space allocation and ship scheduling problem in bulk cargo terminals, *IIE Transactions*, Vol. 48, No. 5, 428-439, doi: 10.1080/0740817X.2015.1063791.

[6] Yu, M., Qi, X. (2013). Storage space allocation models for inbound containers in an automatic container terminal, *European Journal of Operational Research*, Vol. 226, No. 1, 32-45, doi: 10.1016/j.ejor.2012.10.045.

[7] Sharif, O., Huynh, N. (2013). Storage space allocation at marine container terminals using ant-based control, *Expert Systems with Applications*, Vol. 40, No. 6, 2323-2330, doi: 10.1016/j.eswa.2012.10.032.

[8] Hu, W., Wang, H., Min, Z. (2014), A storage allocation algorithm for outbound containers based on the outer–inner cellular automaton, *Information Sciences*, Vol. 281, 147-171, doi: 10.1016/j.ins.2014.05.022.

[9] Boysen, N., Fliedner, M., Jaehn, F., Pesch, E. (2013). A survey on container processing in railway yards, *Transportation Science*, Vol. 47, No. 3, 312-329, doi: 10.1287/trsc.1120.0415.
[10] Wang, L., Zhu, X., Xie, Z. (2014). Storage space allocation of inbound container in railway container terminal, *Mathematical Problems in Engineering*, Vol. 2014, 1-10, doi: 10.1155/2014/956536.
[11] Wang, L., Zhu, X.-N., Yan, W., Xie, Z.-Y., Li, Q.-B. (2013). Optimization Model of Mixed Storage in Railway Container Terminal Yard, *Journal of Transportation Systems Engineering and Information Technology*, Vol. 2, 172-178, doi: 10.3969/j.issn.1009-6744.2013.02.026.
[12] Guo, P., Cheng, W., Zhang, Z., Zhang, M., Liang, J. (2013). Gantry crane scheduling with interference constraints in railway container terminals, *International Journal of Computational Intelligence Systems*, Vol. 6, No. 2, 244-260, doi: 10.1080/18756891.2013.768444.
[13] Wang, L., Zhu, X., Xie, Z. (2016). Rail mounted gantry crane scheduling in rail-truck transshipment terminal, *Intelligent Automation & Soft Computing* Vol. 22, No. 1, 61-73, doi: 10.1080/10798587.2015.1041764.
[14] Tang, M., Gong, D., Liu, S., Zhang, H. (2016). Applying multi-phase particle swarm optimization to solve bulk cargo port scheduling problem, *Advances in Production Engineering & Management*, Vol. 11, No. 4, 299-310, doi: 10.14743/apem2016.4.228.
[15] Grubišić, N., Dundović, Č., Žuškin, S. (2016). A split task solution for quay crane scheduling problem in mid-size container terminals, *Tehnički vjesnik – Technical Gazette*, Vol. 23, No. 6, 1723-1730, doi: 10.17559/TV-20150914110215.
[16] Rajkovic, R., Zrnic, N. Stakic, D. (2016). Application of a mathematical model for container transport flow of goods: From the Far east to Serbia, *Tehnički vjesnik – Technical Gazette*, Vol. 23, No. 6, 1739-1746, doi: 10.17559/TV-20140629203730.