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# Multi-Port Stowage Planning for Inland Container Liner Shipping Considering Weight Uncertainties

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**ABSTRACT** The multi-port stowage planning problem investigates the ship's whole route to make the stowage plans for multiple ports. This paper formulates the multi-port stowage planning problem for inland container liner shipping on the Yangtze River that hedges against container weight uncertainties. A mathematical formulation based on stochastic programming of this problem is presented. Three solution approaches, which include an exact approach based on robust optimization, an exact approach based on stochastic chance-constrained programming, and a hybrid neighborhood search algorithm based on heuristics are presented. Experimental results showed that the exact approaches and hybrid neighborhood search algorithm could robustly solve the problem. With increasing ship size, numbers of operational ports, and vessel loading rates, the exact approaches cannot guarantee the solutions for some large-scale experiments within the time limit. The hybrid neighborhood search algorithm finds solutions for all the instances with an average gap 1.67 %, and it outperforms the exact approaches with respect to calculation time and solution quantity for the large-scale experiments.

**INDEX TERMS** Stowage planning, container weight uncertainty, stochastic programming, robust optimization, heuristics.

## I. INTRODUCTION

Inland container liner shipping connects domestic and foreign markets and plays an important role in trade for inland cities. In China, the total economic output of the Yangtze River Economic Belt in 2017 had exceeded 40% of the country as a whole. The fast development of urban economies in the Yangtze River Economic Belt has enabled the rapid development of container transport along the Yangtze River. In the past 6 years, the container capacity of the Yangtze River increased from 13.6 million Twenty-Foot Container Equivalent Units (TEUs) to 16.5 million TEUs. By 2020, it is expected that the container capacity of the Yangtze River will reach 20 million TEUs. Figure 1 shows the container shipping network of the Yangtze River. In the network, Chongqing, Wuhan, Nanjing, and Shanghai are hub ports belonging to the trunk line of the river, while other ports serve as feeders for the hub ports.

Container transport between different ports of the Yangtze River is undertaken by inland container ships. Typical inland container ships on the Yangtze River are made by refitting bulk-cargo ships, which results in small ship size and no hatch

covers being installed (Figure 2). The ship is divided into several sections called bays. Within each bay, there are several stacks for stowing containers. Each stack has several slots, with each slot representing a 1 TEU holding capacity.

Inland container liner shipping along the Yangtze River primarily involves containers that are standard sized (i.e., 20-ft containers, 40-ft containers), and the ratio of other container types (i.e., hazardous containers, reefer containers, and out-of-gauge containers) is very low. For hazardous containers, laws and regulations formulated by the government have resulted in most of the inland ports of the Yangtze River not qualifying to operate these containers. The excessive management costs of these containers also make inland ports not willing to undertake their transport. Due to the influence of domestic consumption, there is a small market for cold-chain logistics in China, and those cargos are mainly transported by road. Additionally, shipping companies do not usually transport reefer containers due to their long shipping times and high transport costs. The number of out-of-gauge containers (e.g., 45-ft containers and high-cube containers) is quite small, and they are stowed into the top



FIGURE 1. The container shipping network of the Yangtze River.

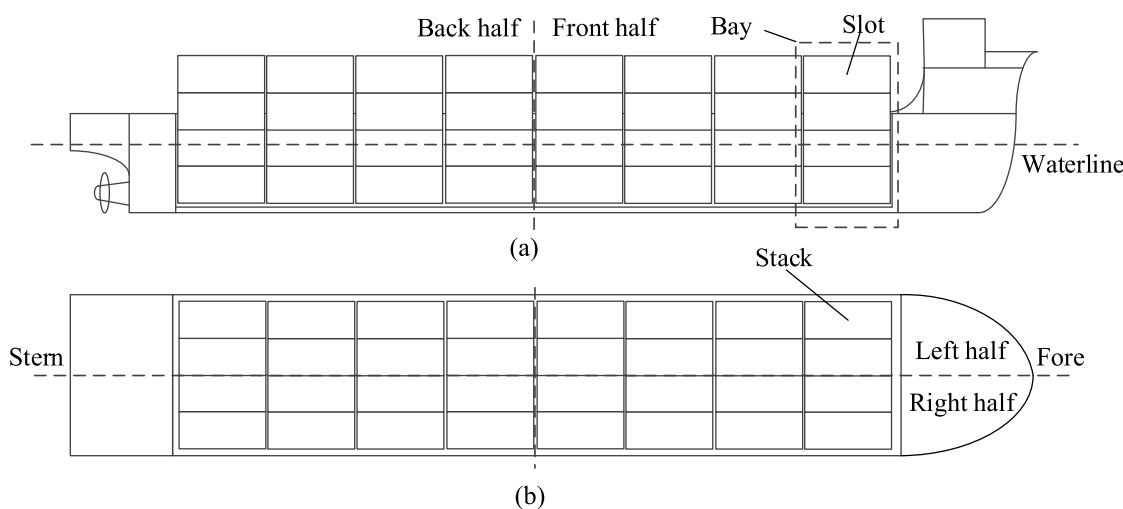


FIGURE 2. The structure of typical inland container ships.

positions of stacks after stowing standard containers in practical slots. Therefore, inland container liner shipping on the Yangtze River primarily concerns the transport of standard containers.

Nowadays, economic competition between the inland container ports of the Yangtze River has led to the ship owners having dominant positions in the inland container transport industry. Due to the surplus transport capacity in container shipping, ship owners emphasize higher capacity utilization in stowage planning. However, stowage planning for container ships on the Yangtze River remains at the level of single-port planning and relies on human experience. Single-port stowage planning lacks consideration of stowage plans necessary at subsequent ports along the route, which may cause several re-handles at future ports. Re-handles are the extra operations required to move containers within a ship or temporarily unload containers to gain access to containers stowed below them. Meanwhile, the physical characteristics of inland ships (i.e., small size and no hatch covers) leave them fewer options for using ballast water to ensure stability. If the manually made stowage plan is

unreasonable, re-handles may also be necessary for ship stability. Additionally, inland ports on the Yangtze River generally do not weigh each container, so container weights are usually reported by the cargo owner, which results in inconsistencies between the actual and reported container weights. Thus, stowage plans generated from reported container weights would cause insufficient ship stability, necessitating many re-handles. Therefore, existing stowage planning methods for inland container liner shipping along the Yangtze River force re-handles, which negatively effect operational efficiency.

To meet the practical requirements of stowage planning for inland container liner shipping along the Yangtze River, the following aspects should be considered. First, multi-port stowage planning for the full route should be incorporated rather than single-port stowage planning. Second, higher ship capacity utilization is emphasized rather than minimizing the ship’s stay at ports. Third and more difficult to achieve, is coordinating stability adjustments and efficiently using full ship capacity. Finally, there are container weight uncertainties. These characteristics make stowage

planning for inland container liner shipping different from that of maritime shipping.

The contribution of this article is that we formulated a stochastic programming model (SPM) for multi-port stowage planning that considered container weight uncertainties. Three approaches were introduced to solve the problem: 1) an exact approach based on a robust optimization model (ROM); 2) an exact approach based on a stochastic chance-constrained programming model (SCPM); and 3) a hybrid neighborhood search (HNS) algorithm based on heuristics. Finally, the solving performance and robustness of the different methods were analyzed to give suggestions for practical application.

The rest of the article is organized as follows: a review of relevant literature is presented in Section 2; details of the problem are described in Section 3; a mathematical model for the problem based on stochastic programming is developed in Section 4; three approaches to solving the problem are introduced in Section 5; details of experiments performed to assess optimization of these approaches are described in Section 6; and finally, conclusions and future work are discussed in Section 7.

## II. LITERATURE REVIEW

The existing research on stowage planning problems typically concerns maritime container shipping and is divided into single-port stowage planning problems and multi-port stowage planning problems. Single-port stowage planning problems only consider making a stowage plan for a single port, i.e. the plan of how to stow containers destined for different ports into the container ship at current port. Multi-port stowage planning problems take the whole route of the ship into account to generate stowage plans for multiple ports over the full route.

For the single-port stowage planning problem, Avriel *et al.* [1] proposed a suspensory heuristic procedure. Later, Ding and Chou [2] developed a heuristic algorithm that performed better than this suspensory heuristic procedure. Dubrovsky *et al.* [3] used the genetic algorithm to solve the problem. To study stowage planning as a whole, their research assumed that container ships comprised a single rectangular bay, and they formulated monolithic models for the problem. However, this kind of grossly abstracted model of container ship spaces made their findings unsuitable for practical stowage planning.

Along with research that studied this problem as a whole, there has been considerable research into solving this problem through a two-phase decomposition approach. This work comes from Wilson and Roach [4], [5] and Wilson *et al.* [6], where the stowage planning problem was decomposed into two sub-problems, i.e. the master bay planning problem (MBPP) and the slot planning problem (SPP). For MBPP, the master bay plan was generated to distribute containers into ship bay sections. For SPP, the master bay plan was treated as the input to make the slot plan for stowing containers into slots. Kang and Kim [7] proposed

two heuristics for the sub-problems, i.e. a greedy heuristic for solving MBPP and a tree search method for solving SPP. Additional studies have also focused on one of the sub-problems. Sciomachen and Tanfani [8] solved MBPP through a heuristic method, while Ambrosino *et al.* [9], [10] proposed a basic 0–1 linear programming model for MBPP, and designed a heuristic procedure and a three-step heuristic tabu-based search. In Moura *et al.* [11], a mixed integer programming (MIP) model combining MBPP with the ship routing problem was presented. To solve SPP, Delgado *et al.* [12] presented a constraint programming model and an integer programming model. These studies took into consideration single-port stowage planning, where potential stowage planning at subsequent ports along the route is missing. This may cause re-handles and does not meet the requirement of stowage planning for full container liner shipping routes.

The multi-port stowage planning problem can also be studied as a whole or can be decomposed into two sub-problems, i.e. multi-port master planning problem (MP-MBPP) and SPP. In Imai *et al.* [13], the problem was formulated as an integer programming model, which was solved by a heuristic algorithm based on the genetic algorithm. Azevedo *et al.* [14] formulated the problem, which they called the “3D containership loading planning problem,” as a linear programming model. Three meta-heuristics, including the genetic algorithm, simulated annealing, and beam search, were combined to solve the problem. Along with these studies that addressed the problem as a whole, some studies have adopted decomposition approaches. Zhang *et al.* [15] solved MP-MBPP and SPP by different tabu search heuristics based on the bin-packing problem. Pacino *et al.* [16] presented an integer programming model for MP-MBPP, and a constraint programming and a local search procedure for SPP. In Ambrosino *et al.* [17]–[19], they focused on MP-MBPP and proposed a MIP model and heuristic algorithms to solve the problem. These studies assumed that the container information at ports is fixed and lacked considerations of the uncertainties in multi-port stowage planning.

Studies investigating uncertainties in container shipping have been primarily focused on scheduling problems, such as the liner ship route schedule (Wang and Meng [20]; Meng and Wang [21]; Dong *et al.* [22]), liner ship fleet deployment (Ng [23], [24]), cargo mix problems (Ang *et al.* [25]), empty container repositioning (Zhang *et al.* [26]), and berth allocation (Han *et al.* [27]; Ursavas and Zhu [28]). Among these studies, Wang and Meng [20] proposed a mixed-integer non-linear stochastic programming model for the liner ship route schedule design problem that considered time uncertainties at sea and at port. In Meng and Wang [21], a two-stage stochastic integer programming model for the short-term liner ship fleet planning problem was presented that considered the uncertain container shipment demand. Dong *et al.* [22] formulated a two-stage stochastic programming model for the problem of joint service capacity planning and dynamic container routing in liner shipping with uncertain demands.

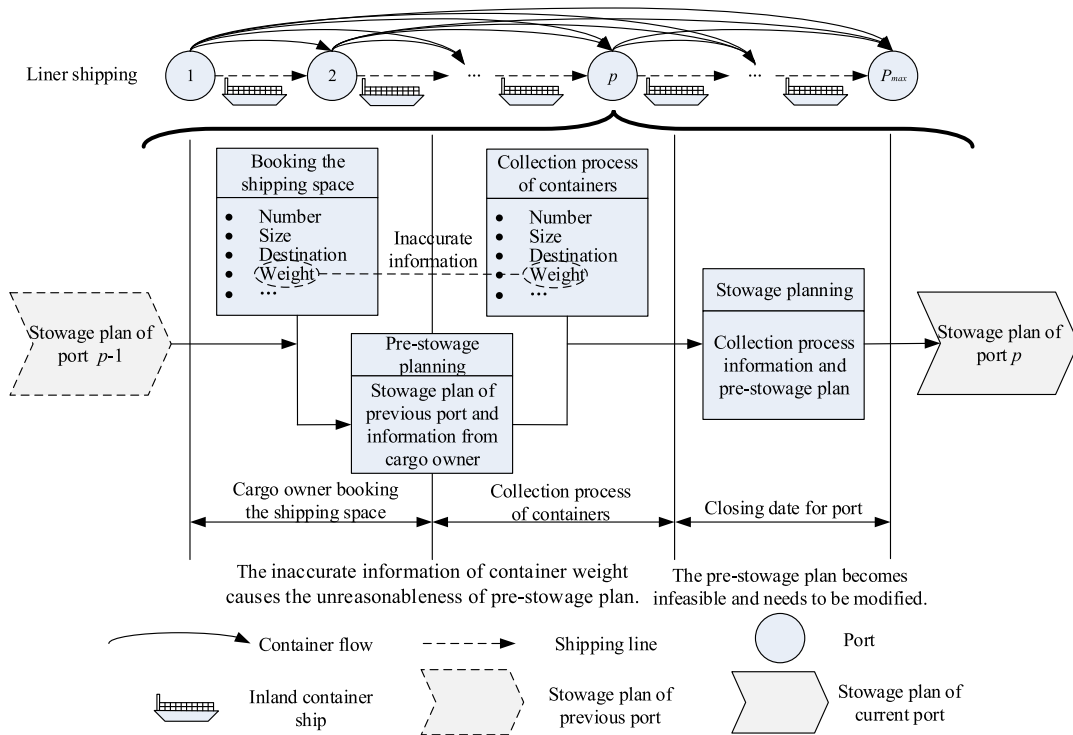


FIGURE 3. Multi-port stowage planning for inland container liner shipping along the Yangtze River.

Ng [23], [24] investigated the liner ship fleet deployment problem with stochastic dependencies in shipping demand and proposed stochastic programming models. Ang *et al.* [25] presented a two-stage stochastic integer programming model for the cargo mix problem under uncertainty in the parameters of some scenarios. Zhang *et al.* [26] considered the empty container repositioning problems between multi-port routes with stochastic demand and lost sales based on stochastic programming. Han *et al.* [27] addressed the simultaneous discrete berth and quay crane scheduling problem with stochastic arrival and handling times through a mixed-integer stochastic programming model. In Ursavas and Zhu [28], the berth allocation problem with stochastic arrival and handling times was modeled by a framework based on the stochastic dynamic programming approach. These studies showed that stochastic programming can be used to formulate scheduling problems that consider the uncertainties in container shipping.

In practice, there are other uncertainties in stowage planning for inland container liner shipping, especially container weight uncertainties. Therefore, we focused on container weight uncertainties in this study of the multi-port stowage planning problem for inland container liner shipping along the Yangtze River. To the best of our knowledge, this is the first time to propose this specific problem considering container weight uncertainties in inland container liner shipping.

### III. PROBLEM STATEMENT

In multi-port stowage planning for inland container liner shipping, the whole route of the ship must be investigated

to generate stowage plans for multiple ports over the full route. In Figure 3, the inland container ship visits multiple ports over the course of its voyage, while containers flow from the current to subsequent ports through the shipping line of the Yangtze River. The ship-side stowage planner uses container information (e.g., number, size, destination, and weight) provided by the cargo owner when booking shipping space to generate the pre-stowage plan of the current port. Then the port-side stowage planner combines the process information and the pre-stowage plan to complete the stowage plan for the ship.

In the inland container liner shipping example in Figure 3, all ports over the full route are characterized by a set  $P$ . The container flow from the original port  $o$  ( $o \in P$ ) to the destination port  $d$  ( $d \in P$ ) is characterized by an  $o - d$  shipping pair  $a$ ,  $a = (o, d) \in Q(p)$ ,  $\forall p \in P$ . The  $o - d$  shipping pair set  $Q(p)$  at port  $p$  includes two  $o - d$  shipping pair subsets  $Q_s(p)$  and  $Q_t(p)$ .  $Q_s(p)$  includes all the  $o - d$  shipping pairs that start at port  $p$ , and  $Q_t(p)$  includes all the  $o - d$  shipping pairs that indicate the  $o - d$  shipping pass through port  $p$ . The stowage plan of the previous port  $p - 1$  ( $p - 1 \in P$ ) will be the input for the stowage planning of the current port  $p$  ( $p \in P$ ) in the multi-port stowage planning.

All the container weight classes including light, medium and heavy ones are characterized by a set  $G$ . For port  $p$ , all the containers with weight class  $g$  in  $o - d$  shipping pair  $a$  should be loaded aboard,  $\forall a = (p, d) \in Q_s(p)$ ,  $p \in P$ ,  $g \in G$ . The ship's stability constraint can be satisfied if the longitudinal and horizontal weight tolerances at port  $p$  are both within their limits  $\Delta LG$  and  $\Delta CG$  respectively,

TABLE 1. Mathematical notations for the multi-port stowage planning model.

Sets	
$P$	Set of ports over the full route
$Q(p)$	Set of $o-d$ shipping pairs at port $p$ , $Q(p) = Q_i(p) \cup Q_o(p)$ , $\forall p \in P$
$Q_i(p)$	Subset of $o-d$ shipping pairs passing through port $p$ , $Q_i(p) = \{a   o, p, d \in P, o < p < d, a = (o, d)\}$
$Q_o(p)$	Subset of $o-d$ shipping pairs starting at port $p$ , $Q_o(p) = \{a   o, p, d \in P, o = p < d, a = (o, d)\}$
$G$	Set of container weight classes (light, medium, heavy), $G = \{1, 2, 3\}$
$J$	Set of ship stacks, $J = J_F \cup J_A = J_L \cup J_R$
$J_F$	Subset of ship stacks in the front half of the ship
$J_A$	Subset of ship stacks in the back half of the ship
$J_L$	Subset of ship stacks in the left half of the ship
$J_R$	Subset of ship stacks in the right half of the ship
Parameters	
$N_g(a)$	Number of containers loaded at port $p$ with weight class $g$ and destined for port $d$ (Unit: TEU), $\forall a = (p, d) \in Q_i(p), p \in P, g \in G$
$w_g$	Average weight of containers with weight class $g$ (Unit: ton), $\forall g \in G$
$\Delta w_g$	Maximum weight deviation of containers with weight class $g$ (Unit: ton), $\forall g \in G$
$\tilde{w}_g$	Weight of containers with weight class $g$ (Unit: ton), $\tilde{w}_g \in [w_g - \Delta w_g, w_g + \Delta w_g]$ , $\forall g \in G$
$\Delta LG$	Maximum longitudinal weight tolerance of the ship (Unit: ton)
$\Delta CG$	Maximum horizontal weight tolerance of the ship (Unit: ton)
$SW_j$	Maximum load weight of stack $j$ of the ship (Unit: ton), $\forall j \in J$
$ST_j$	Maximum stacking tiers (or capacity limit) of stack $j$ of the ship (Unit: TEU), $\forall j \in J$
$L$	A large number, $L = 1000$
Variables	
$x_{jg}(a)$	Number of containers of weight class $g$ loaded into stack $j$ at port $p$ with the original port $o$ and destination port $d$ . $\forall g \in G, j \in J, a = (o, d) \in Q(p), p \in P$
$y_j(a)$	$y_j(a) = 1$ , if stack $j$ stowed containers at port $p$ with the original port $o$ and destination port $d$ ; otherwise $y_j(a) = 0$ . $\forall j \in J, a = (o, d) \in Q(p), p \in P$

$\forall p \in P$  (Ambrosino et al. [9]). To calculate the longitudinal and horizontal weight tolerances, the ship stacks are divided into different stack sets according to the front half, back half, left half, and right half of the ship, as shown in Figure 2. Meanwhile, the loading weight and capacity limits of ship stack  $j$  ( $j \in J$ ) at port  $p$  should satisfy the ship's constraints  $SW_j$  and  $ST_j$  respectively,  $\forall j \in J, p \in P$ .

The parameter  $w_g$  represents the average weight of containers of weight class  $g, \forall g \in G$ . The inconsistency between the actual and reported weights of containers within weight class  $g$  is described using the maximum weight deviation of containers  $\Delta w_g, \forall g \in G$ . The parameter  $\tilde{w}_g$  is used to describe the uncertain weight of containers within weight class  $g$ , and should satisfy  $\tilde{w}_g \in [w_g - \Delta w_g, w_g + \Delta w_g], \forall g \in G$ .

This article explores the multi-port stowage planning problem for inland container liner shipping along the Yangtze River considering container weight uncertainties. This problem concerns assigning containers at each port of the route into the ship's stacks. The ship's constraints of stability, strength and capacity need to be satisfied at each port of the route. The objective of the proposed solution is to minimize the number of occupied stacks in the ship over the full route. Keeping containers with same  $o-d$  shipping pair

clustered and using as few stacks as possible can help increase utilization of the ship's capacity and decrease re-handles at future ports. Moreover, re-handles are avoided in this problem by constraints that do not allow stowing containers from different  $o-d$  shipping pairs into one stack.

#### IV. THE MULTI-PORT STOWAGE PLANNING MODEL

The multi-port stowage planning model is inspired by that of Ambrosino et al. [19] which considered the storage areas called bay locations and the determined container weights. For the model proposed in this article, the smaller storage units in the bay locations called stacks are considered and the container weights are described as the stochastic parameters based on the practical operations in the inland container liner shipping. Mathematical notations for the multi-port stowage planning model are described in detail in Table 1.

Based on these mathematical notations, the proposed problem was formulated as a SPM:

$$f = \min \sum_{p \in P} \sum_{a \in Q(p)} \sum_{j \in J} y_j(a) \tag{1}$$

$$\sum_{j \in J} x_{jg}(a) = N_g(a), \quad \forall p \in P, a \in Q_s(p), g \in G \tag{2}$$



$$\sum_{j \in J} y_j(a) \geq 1, \quad \forall p \in P, a \in Q(p) \quad (3)$$

$$\sum_{a \in Q(p)} y_j(a) \leq 1, \quad \forall p \in P, j \in J \quad (4)$$

$$y_j(a) \leq \sum_{g \in G} x_{jg}(a) \leq L \cdot y_j(a), \quad \forall j \in J, a \in Q(p), p \in P \quad (5)$$

$$\sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \leq ST_j, \quad \forall j \in J, p \in P \quad (6)$$

$$\sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \cdot \tilde{w}_g \leq SW_j, \quad \forall j \in J, p \in P \quad (7)$$

$$\left| \sum_{a \in Q(p)} \sum_{g \in G} \left( \sum_{j \in J_F} x_{jg}(a) \cdot \tilde{w}_g - \sum_{j \in J_A} x_{jg}(a) \cdot \tilde{w}_g \right) \right| \leq \Delta LG, \quad \forall p \in P \quad (8)$$

$$\left| \sum_{a \in Q(p)} \sum_{g \in G} \left( \sum_{j \in J_L} x_{jg}(a) \cdot \tilde{w}_g - \sum_{j \in J_R} x_{jg}(a) \cdot \tilde{w}_g \right) \right| \leq \Delta CG, \quad \forall p \in P \quad (9)$$

$$x_{jg}(a) \geq 0, \quad x_{jg}(a) \in Z, \quad \forall j \in J, g \in G, a \in Q(p), p \in P \quad (10)$$

$$y_j(a) = \{0, 1\}, \quad \forall j \in J, p \in P, a \in Q(p) \quad (11)$$

The objective function (1) minimizes the number of occupied stacks in the ship over the full route to help increase utilization of the ship’s capacity and decrease re-handles at future ports. Constraint (2) ensures that all containers can be loaded aboard at each port along the route. The fact that all containers of same  $o-d$  shipping pair should occupy at least one stack is enforced by constraint (3). Constraint (4) guarantees that each stack can at most be occupied by containers of the same  $o-d$  shipping pair which means all the containers in one stack have the same destination ports to avoid re-handles. Relationships between different variables are defined by constraint (5). If there are containers of  $o-d$  shipping pair  $a$  loaded in stack  $j$  at port  $p$ ,  $x_{jg}(a) > 0$  and  $y_j(a) = 1$ ; otherwise,  $x_{jg}(a) = 0$  and  $y_j(a) = 0$ . Constraints (6) and (7) represent the capacity and load weight constraints of each stack at each port. The longitudinal and horizontal weight tolerances of the ship are within their required limits at each port by constraints (8) and (9). Constraints (10) and (11) define the values of decision variables.

### V. SOLUTION APPROACHES FOR THE MULTI-PORT STOWAGE PLANNING PROBLEM

The SPM formulated in section 4 cannot be solved by conventional optimization methods or solvers (Al-Dhaheri *et al.* [29]). Thus, three solution approaches were developed to optimize the multi-port stowage planning problem considering container weight uncertainties for inland container liner shipping along the Yangtze River.

First, a solution method based on robust optimization is presented to transform SPM into a ROM. Second, a solution method based on stochastic chance-constrained programming is proposed to build a SCPM based on SPM, which is then solved through the deterministic equivalent method. These two exact approaches can compute exact solutions in a limited time. Third, because the exact approaches cannot find solutions for some experiments within the time limit, a HNS algorithm based on heuristics was designed to efficiently find solutions.

#### A. EXACT APPROACH BASED ON ROBUST OPTIMIZATION

Following the approach of Goerigk *et al.* [30], strict robustness in robust optimization was adopted to transform SPM into a MIP model. In this approach, the strictly robust solution was obtained over the worst-case scenarios. Constraints (7)–(9), which contain the stochastic parameters in SPM were replaced following the descriptions below:

First,  $E_{pg}$  or  $F_{pg}$  in equation (12) or (13) were defined to represent the quantity difference of containers within the same weight class between the front and back halves or left and right halves of the ship at each port.

$$E_{pg} = \sum_{a \in Q(p)} \left( \sum_{j \in J_F} x_{jg}(a) - \sum_{j \in J_A} x_{jg}(a) \right), \quad \forall g \in G, p \in P \quad (12)$$

$$F_{pg} = \sum_{a \in Q(p)} \left( \sum_{j \in J_L} x_{jg}(a) - \sum_{j \in J_R} x_{jg}(a) \right), \quad \forall g \in G, p \in P \quad (13)$$

Then, according to the definitions of  $E_{pg}$  and  $F_{pg}$ , constraints (7)–(9) can be replaced by:

$$\sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \cdot (w_g + \Delta w_g) \leq SW_j, \quad \forall j \in J, p \in P \quad (14)$$

$$\left| \sum_{g \in G} E_{pg} \cdot (w_g + \Delta w_g) \right| \leq \Delta LG, \quad \forall p \in P \quad (15)$$

$$\left| \sum_{g \in G} F_{pg} \cdot (w_g + \Delta w_g) \right| \leq \Delta CG, \quad \forall p \in P \quad (16)$$

Constraints (14)–(16) ensure that the loading weight of each stack, the longitudinal weight tolerance, and the horizontal weight tolerance of the ship are all within their maximum allowable values over the worst-case scenarios at each port. Finally, the ROM for the proposed problem was formulated as follows:

$$(ROM) \left\{ \begin{aligned} f = \min \sum_{p \in P} \sum_{a \in Q(p)} \sum_{j \in J} y_j(a) : \\ (2) \sim (6), (12) \sim (16), (10), (11) \end{aligned} \right\}.$$

**B. EXACT APPROACH BASED ON STOCHASTIC CHANCE-CONSTRAINED PROGRAMMING**

The SCPM is characterized by the rule that probabilities of stochastic constraints being satisfied should be no less than the confidence requirement. Studies have shown that the SCPM can be solved through deterministic equivalents or the hybrid intelligent algorithm (Charnes and Cooper [31], Zhao and Liu [32]). The stochastic constraints (7)–(9) in SPM were described using chance constraints, and then the SCPM for the proposed problem was formulated as follows:

$$\Pr \left\{ \sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \cdot \tilde{w}_g \leq SW_j \right\} \geq \alpha, \quad \forall j \in J, p \in P \tag{17}$$

$$\Pr \left\{ \left| \sum_{a \in Q(p)} \sum_{g \in G} (\sum_{j \in J_F} x_{jg}(a) \cdot \tilde{w}_g - \sum_{j \in J_A} x_{jg}(a) \cdot \tilde{w}_g) \right| \leq \Delta LG \right\} \geq \alpha, \quad \forall p \in P \tag{18}$$

$$\Pr \left\{ \left| \sum_{a \in Q(p)} \sum_{g \in G} (\sum_{j \in J_L} x_{jg}(a) \cdot \tilde{w}_g - \sum_{j \in J_R} x_{jg}(a) \cdot \tilde{w}_g) \right| \leq \Delta CG \right\} \geq \alpha, \quad \forall p \in P \tag{19}$$

The chance constraints (17)–(19) guarantee the probability of each stochastic event occurrence satisfying the confidence requirement ( $\alpha = 0.95$ ).

$$\text{(SCPM)} \left\{ f = \min \sum_{p \in P} \sum_{a \in Q(p)} \sum_{j \in J} y_j(a) : \right. \\ \left. (2) \sim (6), (17) \sim (19), (10), (11) \right\}.$$

According to the deterministic equivalent method of Charnes and Cooper [31], if a stochastic parameter is subject to a normal distribution, the chance constraint can be transformed into the deterministic constraint. To obtain tractable results, the stochastic weights of containers within different weight classes were assumed fall within normal distributions of their average weights. As defined in the mathematical notations, the stochastic weight of containers with weight class  $g$  should satisfy:

$$\begin{aligned} \beta &= \Pr(w_g - \Delta w_g \leq \tilde{w}_g \leq w_g + \Delta w_g) \\ &= \phi\left(\frac{w_g + \Delta w_g - \mu}{\sigma}\right) - \phi\left(\frac{w_g - \Delta w_g - \mu}{\sigma}\right) \approx 1, \quad \forall g \in G \end{aligned} \tag{20}$$

In this equation,  $\beta$  represents the probability of parameter  $\tilde{w}_g \in [w_g - \Delta w_g, w_g + \Delta w_g], \forall g \in G, \mu$  and  $\sigma$  represent the expectation and standard deviation of the normal distribution, respectively, and  $\phi(\cdot)$  represents the standard normal distribution function. Then, the parameter  $\tilde{w}_g$  is subject to the normal distribution below by setting  $\beta = 0.995$ .

$$\tilde{w}_g \sim N(w_g, (\frac{\Delta w_g}{2.81})^2), \quad \forall g \in G \tag{21}$$

To use the deterministic equivalents of Charnes and Cooper [31], according to equations (12) and (13), constraints (18) and (19) were transformed as:

$$\Pr \left\{ \sum_{g \in G} |E_{pg}| \cdot \tilde{w}_g \leq \Delta LG \right\} \geq \alpha, \quad \forall p \in P \tag{22}$$

$$\Pr \left\{ \sum_{g \in G} |F_{pg}| \cdot \tilde{w}_g \leq \Delta CG \right\} \geq \alpha, \quad \forall p \in P \tag{23}$$

Then Constraints (17), (22) and (23) were transformed based on the deterministic equivalents as follows:

$$\sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \cdot w_g + (\frac{\Delta w_g}{2.81}) \cdot \phi^{-1}(\alpha) \sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \leq SW_j, \quad \forall j \in J, p \in P \tag{24}$$

$$\sum_{g \in G} |E_{pg}| \cdot w_g + (\frac{\Delta w_g}{2.81}) \cdot \phi^{-1}(\alpha) \sum_{g \in G} |E_{pg}| \leq \Delta LG, \quad \forall p \in P \tag{25}$$

$$\sum_{g \in G} |F_{pg}| \cdot w_g + (\frac{\Delta w_g}{2.81}) \cdot \phi^{-1}(\alpha) \sum_{g \in G} |F_{pg}| \leq \Delta CG, \quad \forall p \in P \tag{26}$$

Then the chance constraints (17)–(19) in SCPM can now be replaced by constraints (24)–(26) to obtain its deterministic equivalent form.

**C. THE HNS ALGORITHM**

Zhao and Liu [32] proposed a hybrid intelligent algorithm to effectively solve the SCPM. Inspired by their approach, a HNS algorithm is proposed, which consists of sample data generation, neural network training, and neighborhood search heuristics. First, for sample data generation, sample data including input and output data were generated by solving a non-objective model to train the neural network. Then, during neural network training, a neural network was trained and saved for testing the feasibility of stowage plans. Finally, in the neighborhood search heuristics, an initial stowage plan was first constructed and then improved by neighborhood search strategies if it could not pass the test of trained neural network.

**1) SAMPLE DATA GENERATION**

Monte Carlo stochastic simulation was used to generate the sample data for training the neural network to approximate the uncertain function  $U(x) : x \rightarrow (U_1(x), U_2(x), U_3(x))$  below. The parameter  $\tilde{w}_g$  is randomly generated within  $[w_g - \Delta w_g, w_g + \Delta w_g]$  at each time,  $\forall g \in G$ . The sub-functions (27)–(29) represent the possibility values of each stochastic event occurrence, i.e. the loading weight of each stack, the longitudinal weight tolerance, and the horizontal weight tolerance of the ship are within their respective limits

at each port.

$$U_1(x) = \Pr \left\{ \sum_{a \in Q(p)} \sum_{g \in G} x_{jg}(a) \cdot \tilde{w}_g \leq SW_j \right\}, \quad \forall j \in J, p \in P \quad (27)$$

$$U_2(x) = \Pr \left\{ \sum_{a \in Q(p)} \sum_{g \in G} \left| \sum_{j \in J_F} x_{jg}(a) \cdot \tilde{w}_g - \sum_{j \in J_A} x_{jg}(a) \cdot \tilde{w}_g \right| \leq \Delta LG \right\}, \quad \forall p \in P \quad (28)$$

$$U_3(x) = \Pr \left\{ \sum_{a \in Q(p)} \sum_{g \in G} \left| \sum_{j \in J_L} x_{jg}(a) \cdot \tilde{w}_g - \sum_{j \in J_R} x_{jg}(a) \cdot \tilde{w}_g \right| \leq \Delta CG \right\}, \quad \forall p \in P \quad (29)$$

*Step 1:* The non-objective optimization model (CSM1:  $\{f = 0 : (2) \sim (6), (10), (11)\}$ ) was defined to determine the assignments between containers and ship stacks.

*Step 2:* Define the sample data capacity for training the neural network.

*Step 3:* Solve CSM1 to produce the input data (i.e., stowage plan- $x_{jg}(a)$ ) for  $U(x)$ .

*Step 4:* Adopt the Monte Carlo stochastic simulation to get the output data (i.e., the possibility values of sub-functions (27)–(29)) for  $U(x)$  with the input data from *Step 3*. Then one sample is obtained for the neural network training.

*Step 5:* Repeat *Steps 3–4* until reaching sample data capacity.

## 2) NEURAL NETWORK TRAINING

With the sample data from the Monte Carlo stochastic simulation, a neural network was trained to approximate  $U(x)$ . The neural network consisted of one input layer, one hidden layer, and one output layer. The back propagation method was adopted to update weights between different layers.

The trained neural network could output values of three sub-functions in with a stowage plan as input. Then, the feasibility of the stowage plan could be decided by comparing these values with the confidence requirement.

## 3) NEIGHBORHOOD SEARCH HEURISTICS

### a: CONSTRUCTING A SOLUTION

*Step 1:* Grouping containers: Containers at the current port are grouped based on their characteristics of  $o - d$  shipping pairs and weight classes. Containers with the same destination ports and weight classes are clustered into one container group.

*Step 2:* Sorting container groups: Container groups are then sorted by the rules ‘destination port from far to near’ and ‘weight class from heavy to light.’

*Step 3:* Numbering ship stacks: Ship stacks are numbered successively by the rules ‘from the fore to the stern’ and ‘from the left to the right.’

*Step 4:* Stowing container groups into ship stacks: Container groups are then stowed into ship stacks one-by-one considering some conditions, i.e. the capacity constraints of each stack, and the constraint that does not allow stowing containers of different  $o - d$  shipping pairs into one stack.

The heuristic rules above ignore the loading weight and stability constraints of the ship. The number of occupied stacks  $M(a)$  for each  $o - d$  shipping pair  $a$  can be obtained as a lower bound through *Steps 1–4*.

*Step 5:* Solving the model to obtain an initial stowage plan: For each  $o - d$  shipping pair  $a$ ,  $M(a)$  is used to solve the non-objective optimization model (Containers to Stack Model 2, CSM2). Constraint (30) defines the number of ship stacks that containers with  $o - d$  shipping pair  $a$  should occupy. For the loading weight constraint of each stack, constraint (14) is considered in CSM2.

$$\sum_{j \in J} y_j(a) = M(a), \quad \forall a \in Q_s(p) \quad (30)$$

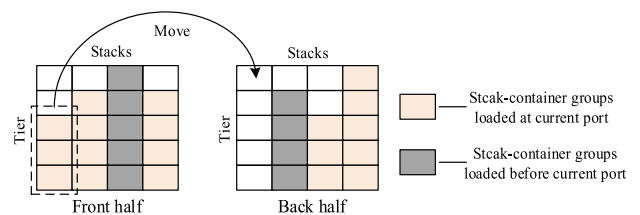
(CSM2) $\{f = 0 : (2) \sim (6), (14), (30), (10), (11)\}$ .

If CSM2 cannot be solved within the time limit,  $M(a)$  is updated to  $M(a) = M(a) + 1$ . Then, repeat *Step 5* until all the container groups at the current port have been stowed into ship stacks to get an initial stowage plan. The plan does not take into account the longitudinal and horizontal weight tolerances of the ship.

### b: IMPROVED SOLUTION

The longitudinal and horizontal weight tolerances of the ship may not be satisfied with the constructed solution. Thus, three different neighborhood search strategies were designed to modify longitudinal and horizontal weight tolerances.

*Strategy 1:* Moving containers into another stack. All containers in one stack at the front (or back) half of the ship are moved into an empty stack at the other end of the ship as shown in Figure 4.



**FIGURE 4.** Moving containers in one stack into an empty stack on the other side of the ship.

*Strategy 2:* Swapping containers between different stacks. All containers in two different stacks from opposite ends of the ship are swapped as shown in Figure 5.

*Strategy 3:* Splitting and moving containers. Containers in one stack at the front (or back) half of the ship are split and moved to an empty stack at the other side of the ship.



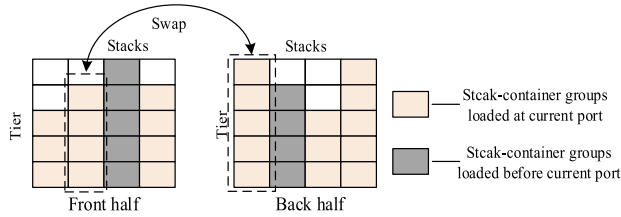


FIGURE 5. Swapping all containers from two different stacks at opposite ends of the ship.

To decrease the number of occupied stacks in the ship over the full route, the stack that stows containers with the nearest destination port is preferentially chosen for split as shown in Figure 6.

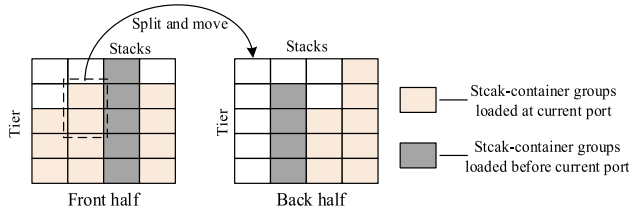


FIGURE 6. Splitting and moving some containers to an empty stack at the other end of the ship.

The pseudo code of HNS is shown in detail in Algorithm 1. After obtaining the sample data and training the neural network, the algorithm began generating stowage plans for each port one-by-one through first constructing a solution, and successively improving it by the neighborhood search strategies. The algorithm ends when a multi-port stowage plan for the full route has been generated.

VI. EXPERIMENTS

A. EXPERIMENTAL SETUP

Three typical inland container ships on the Yangtze River are listed in Table 2 according to the Chinese national standard GB/T 19283-2010.

TABLE 2. Inland container ships on the Yangtze River.

Type	Bay	Stack	SW/t	Capacity/TEU	$\Delta LG/t$	$\Delta CG/t$
S1	8	32	45	96	30	30
S2	12	48	60	192	30	30
S3	12	72	75	360	40	40

Here, a series of test scenarios based on these ships are designed to validate the effectiveness of the solution approaches. Table 3 lists the number of operational ports for four shipping lines on the Yangtze River. For each line, three vessel loading rates were randomly generated corresponding to real-life scenarios of inland container ships (Table 4).

TABLE 3. Inland container shipping lines on the Yangtze River.

Shipping line	L1	L2	L3	L4
Number of ports	4	5	6	7

Algorithm 1 HNS for SCPM

```

Require: CSM1, Containers to Stack Model 1
U(x), Uncertain function
Pop, Sample data capacity
N1, Stochastic simulation times
N2, Training times for each sample
P, Set of ports over the full route, P = {1, 2, ..., p_max}
Sp0, Initial stowage plan of port p, p ∈ P
Fp0, Objective function value of Sp0, p ∈ P
Sp, Stowage plan of port p, p ∈ P
Fp, Objective function value of solution Sp, p ∈ P
TNN, Trained neural network
Ensure: S: Multi-port stowage plan, F: Objective function value of S
1: if sample data do not reach Pop
2:   repeat
3:     Input data of U(x) ← Solving CSM1 by using Gorubi
4:     if stochastic simulation times do not reach N1
5:       repeat
6:         Output data of U(x) ← Monte Carlo stochastic simulation with input data
7:       until stochastic simulation times reach N1
8:     until sample data reach Pop
9:   end if
10:  Sample data ← (Input data, Output data)
11:  if training times for each sample do not reach N2
12:    repeat
13:      TNN ← Neural network training with sample data
14:    until training times reach N2
15:  end if
16:  Initialization p = 1
17:  if p does not reach p_max
18:    repeat
19:      {Sp, Fp} ← {Sp0, Fp0} from construction solution
20:      if Sp cannot pass TNN test
21:        repeat
22:          {Sp, Fp} ← Update {Sp, Fp} with Strategy 1
23:        until Sp cannot be improved
24:      end if
25:      if Sp cannot pass TNN test
26:        repeat
27:          {Sp, Fp} ← Update {Sp, Fp} with Strategy 2
28:        until Sp cannot be improved
29:      end if
30:      if Sp cannot pass TNN test
31:        repeat
32:          {Sp, Fp} ← Update {Sp, Fp} with Strategy 3
33:        until Sp cannot be improved
34:      end if
35:    return the stowage plan solution {Sp, Fp} of port p, p ∈ P
36:    p ← p+1
37:  until port p reaches p_max
38:  end if
39:  return the multi-port stowage plan solution {S, F} over the full route

```

TABLE 4. Different vessel loading rates for the ship.

NO.	C45	C65	C85
loading rate	45%	65%	85%

All test instances are coded similar to S1-L1-C45. The first part (S1) represents the ship type, the second part (L1) represents the shipping line, and the third part (C45) represents the vessel loading rate of 45%.

TABLE 5. Results of the different models and HNS for ship S1.

Instance	LBM		SPM			ROM			SCPM			HNS		
	<i>f</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>
S1-L1-C45	48	0.94	48	0	60	48	0	60	48	0	60	49	2.08	16.63
S1-L1-C65	67	4.87	67	0	60	67	0	60	67	0	60	68	1.49	81.26
S1-L1-C85	85	0.77	85	0	60	86	1.18	60	86	1.18	60	86	1.18	16.21
S1-L2-C45	60	1.5	60	0	60	60	0	60	60	0	60	60	0	32.14
S1-L2-C65	84	0.98	84	0	457.15	84	0	600	84	0	600	86	2.38	53.84
S1-L2-C85	113	1.84	115	1.77	60	114	0.88	60	116	2.65	60	114	0.88	39.04
S1-L3-C45	84	14.49	84	0	60	84	0	60	84	0	60	85	1.19	69.88
S1-L3-C65	101	6.1	103	1.98	60	102	0.99	60	102	0.99	60	101	0	66.25
S1-L3-C85	154	60	154	0	600	155	0.65	600	156	1.3	600	155	0.65	139.77
S1-L4-C45	99	60	99	0	60	99	0	60	99	0	60	99	0	146.25
S1-L4-C65	130	60	132	1.54	60	131	0.77	60	130	0	60	130	0	175.43
S1-L4-C85	173	60	175	1.16	600	174	0.58	600	177	2.31	600	175	1.16	186.79
<b>Average</b>	<b>99.83</b>	<b>22.62</b>	<b>100.50</b>	<b>0.54</b>	<b>183.10</b>	<b>100.33</b>	<b>0.42</b>	<b>195</b>	<b>100.75</b>	<b>0.70</b>	<b>195</b>	<b>100.67</b>	<b>0.92</b>	<b>85.29</b>

TABLE 6. Results of the different models and HNS for ship S2.

Instance	LBM		SPM			ROM			SCPM			HNS		
	<i>f</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>
S2-L1-C45	63	0.74	63	0	2.22	65	3.17	60	65	3.17	60	64	1.59	22.48
S2-L1-C65	93	0.75	96	3.23	60	96	3.23	60	96	3.23	60	96	3.23	34.39
S2-L1-C85	121	0.94	122	0.83	60	122	0.83	60	122	0.83	60	122	0.83	29.44
S2-L2-C45	86	1.49	86	0	60	86	0	60	86	0	60	87	1.16	66
S2-L2-C65	125	1.49	125	0	5.44	126	0.8	60	126	0.8	60	128	2.4	59.98
S2-L2-C85	164	1.7	164	0	60	164	0	60	164	0	60	164	0	46.03
S2-L3-C45	111	2.75	111	0	12.83	111	0	6.5	111	0	8.26	111	0	92.98
S2-L3-C65	146	1.79	150	2.74	60	150	2.74	60	150	2.74	60	150	2.74	152.05
S2-L3-C85	205	3.25	205	0	60	205	0	60	207	0.98	60	207	0.98	107.07
S2-L4-C45	145	60	146	0.69	60	146	0.69	60	146	0.69	60	150	3.45	286.17
S2-L4-C65	190	60	191	0.53	60	191	0.53	60	190	0	60	193	1.58	280.22
S2-L4-C85	249	19.04	249	0	60	249	0	60	249	0	60	249	0	282.22
<b>Average</b>	<b>141.50</b>	<b>12.83</b>	<b>142.33</b>	<b>0.67</b>	<b>46.71</b>	<b>142.58</b>	<b>1</b>	<b>55.54</b>	<b>142.67</b>	<b>1.04</b>	<b>55.69</b>	<b>143.42</b>	<b>1.50</b>	<b>121.59</b>

To compare performances of the different approaches, the lower bound model (LBM) of the proposed problem was developed by deleting constraints (7)–(9) in SPM. LBM results can be used as the lower bound because it ignores load weight and stability constraints of the ship.

$$(LBM) \left\{ f = \min \sum_{p \in P} \sum_{a \in Q(p)} \sum_{j \in J} y_j(a) : (2) \sim (6), (10), (11) \right\}.$$

**B. EVALUATING THE PROPOSED APPROACHES**

All mathematical models proposed in this article were solved using the standard solver Gurobi 7.5.1. Stochastic parameters in SPM were calculated with their average weights. The HNS algorithm was programmed in Python 3.6. All tests were run on an Intel Core I7-5500U 2.40 GHz processor with 4 GB of RAM.

Average container weights within different weight classes were set as 7, 14 and 21 ton, respectively

(Ambrosino et al. [19]). The maximum weight deviation of containers within each weight class was set as 1 ton according to regulations from the Ministry of Transport of China, i.e.  $\Delta w_g = 1, \forall g \in G$ .

When solving the models with Gurobi, the CPU time limit was first set at 60 s. If the model could not be optimally solved, the time limit was extended to 600 s. The solution results of different ships are shown in Tables 5–7. In Tables 5–7, *f* represents the number of occupied stacks in the ship over the full route; *T* represents CPU time (unit: s); *gap* represents the gap in units of *f* compared with LBM from different models (SPM, ROM, and SCPM) and HNS (unit: %); and \* represents that a model could not be solved within the time limit of 600 s.

Tables 5–7 show the number of occupied stacks in the ship over the full route and CPU time results for each situation. Table 5 shows that for the ship S1, the number of occupied stacks in the ship from solving different models (SPM, ROM, SCPM) and HNS were

**TABLE 7. Results of the different models and HNS for ship S3.**

Instance	LBM		SPM			ROM			SCPM			HNS		
	<i>f</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>	<i>f</i>	<i>gap</i>	<i>T</i>
S3-L1-C45	98	1.61	98	0	600	98	0	600	102	4.08	600	102	4.08	58.52
S3-L1-C65	141	2.54	141	0	60	141	0	60	141	0	60	145	2.84	105.26
S3-L1-C85	190	60	190	0	600	190	0	600	190	0	600	193	1.58	104.43
S3-L2-C45	134	57.65	134	0	60	140	4.48	60	141	5.22	60	140	4.48	171.66
S3-L2-C65	190	60	190	0	600	190	0	600	190	0	600	195	2.63	165.07
S3-L2-C85	252	60	*	*	600	*	*	600	*	*	600	259	2.78	170.25
S3-L3-C45	181	60	184	1.66	600	181	0	600	182	0.55	600	183	1.10	246.97
S3-L3-C65	236	60	245	3.81	600	238	0.85	600	238	0.85	600	243	2.97	282.75
S3-L3-C85	311	60	*	*	600	*	*	600	*	*	600	316	1.61	283.92
S3-L4-C45	221	60	223	0.90	600	223	0.90	600	223	0.9	600	229	3.62	464.58
S3-L4-C65	294	60	296	0.68	600	299	1.70	600	299	1.7	600	299	1.70	447.59
S3-L4-C85	382	60	*	*	600	*	*	600	*	*	600	389	1.83	447.69
<b>Average</b>	<b>219.17</b>	<b>50.15</b>	<b>189.33</b>	<b>0.78</b>	<b>510</b>	<b>188.89</b>	<b>0.88</b>	<b>510</b>	<b>189.56</b>	<b>1.48</b>	<b>510</b>	<b>224.42</b>	<b>2.59</b>	<b>245.72</b>

quite close. HNS performed better in CPU time than the models.

In Table 6, SPM had a lower average gap against other models and HNS for ship S2. SPM performed better than ROM, SCPM and HNS in solution quality and CPU time. The differences between ROM and SCPM were quite small, while HNS had a longer CPU time and a bigger average gap.

In Table 7, the increased ship size increased the difficulty of solving each instance. For ship S3, solving the models (SPM, ROM and SCPM) could not guarantee a feasible solution within the time limit (e.g. S3-L2-C85, S3-L3-C85, and S3-L4-C85). When the models could be solved, SPM had a lower average gap against ROM and SCPM. The CPU time for solving SPM, ROM, and SCPM was the same. HNS could solve all instances and performed better in CPU time.

In conclusion, SPM found better solutions by calculating stochastic parameters within the average weights, which means it lacks considerations of container weight uncertainties. When ship size increases, ROM and SCPM cannot guarantee a solution within the time limit. HNS performed better than the exact approaches, especially for solving the large-scale experiments. Finally, HNS had a reasonable average gap (1.67%) for all instances, which is small and acceptable in realistic scenarios.

**C. ROBUSTNESS ANALYSIS**

Monte Carlo stochastic simulation was adopted to analyze the robustness of different approaches. A container weight with weight class was randomly generated within at each time, . Each instance was simulated 1000 times continuously, and the results are listed in Table 8. The number in Table 8 represents the passing rate of different stowage plans per 1000 simulations. \* represents that a model could not find a solution within the time limit of 600 s.

The results in Table 8 show that SPM can only ensure that eight situations pass the test, while the others could not satisfy the confidence requirement ( $\alpha = 0.95$ ), which means it had the worst robustness for solving the problem. ROM and SCPM ensured that all solved instances passed the test.

**TABLE 8. Monte Carlo stochastic simulation results.**

Instance	SPM	ROM	SCPM	HNS
S1-L1-C45	0.761	1	1	1
S1-L1-C65	0.750	1	1	1
S1-L1-C85	0.762	1	1	1
S1-L2-C45	0.748	1	1	1
S1-L2-C65	0.746	1	1	1
S1-L2-C85	0.753	1	1	1
S1-L3-C45	1	1	1	1
S1-L3-C65	0.736	1	1	1
S1-L3-C85	0.754	1	1	1
S1-L4-C45	1	1	1	1
S1-L4-C65	0.769	1	1	1
S1-L4-C85	0.747	1	1	1
S2-L1-C45	0.746	1	1	0.991
S2-L1-C65	1	1	1	1
S2-L1-C85	0.763	1	1	0.953
S2-L2-C45	0.746	1	1	0.962
S2-L2-C65	0.758	1	1	1
S2-L2-C85	1	1	1	0.963
S2-L3-C45	0.758	1	1	0.985
S2-L3-C65	0.757	1	1	0.999
S2-L3-C85	0.755	1	1	1
S2-L4-C45	0.769	1	1	1
S2-L4-C65	0.768	1	1	0.954
S2-L4-C85	0.759	1	1	0.958
S3-L1-C45	0.734	1	1	1
S3-L1-C65	0.768	1	1	1
S3-L1-C85	1	1	1	0.983
S3-L2-C45	0.734	1	1	0.999
S3-L2-C65	1	1	1	1
S3-L2-C85	*	*	*	1
S3-L3-C45	1	1	1	0.980
S3-L3-C65	1	1	1	0.987
S3-L3-C85	*	*	*	0.971
S3-L4-C45	0.761	1	1	0.988
S3-L4-C65	0.763	1	1	0.992
S3-L4-C85	*	*	*	0.961

HNS guaranteed that all stowage plans satisfied the confidence requirement. These results reveal that for practical application in inland container liner shipping along the

Yangtze River, ROM and SCPM are more suitable for making stowage plan decisions for small- and medium-size ships, while HNS is the preferred method for making stowage plans for large ships.

## VII. CONCLUSION

In this study, multi-port stowage planning for inland container liner shipping considering container weight uncertainties was concerned. A SPM for the problem was proposed with the objective of minimizing the number of occupied stacks in the ship over the full route. As the model could not be addressed by conventional optimization methods or solvers, three different solution approaches were presented to solve the problem: two exact approaches, which transformed SPM into MIP models based on robust optimization and stochastic chance-constrained programming, respectively, and were solved using a standard solver, and third, a HNS algorithm was also designed.

Experimental results demonstrated that SPM had the worst robustness. ROM, SCPM and HNS could robustly make multi-port stowage plans over the full route. The exact approaches and HNS algorithm were all effective for solving the proposed problem. Although the average gaps of the exact approaches were better than the algorithm, the HNS algorithm found solutions for all instances with an average gap 1.67% and it outperformed the exact approaches in CPU time and solution quantity for large-size ships.

In future studies, multi-port stowage planning for inland container liner shipping considering quantity uncertainties will be researched. This problem also exists in real-world shipping scenarios along the Yangtze River, as the quantity of foreign trade containers continuously changes due to customs inspections at port.

## REFERENCES

- [1] M. Avriel, M. Penn, N. Shpirer, and S. Witteboon, "Stowage planning for container ships to reduce the number of shifts," *Ann. Oper. Res.*, vol. 76, pp. 55–71, Jan. 1998.
- [2] D. Ding and M. C. Chou, "Stowage planning for container ships: A heuristic algorithm to reduce the number of shifts," *Eur. J. Oper. Res.*, vol. 246, pp. 242–249, Oct. 2015.
- [3] O. Dubrovsky, G. Levitin, and M. Penn, "A genetic algorithm with a compact solution encoding for the container ship stowage problem," *J. Heuristics*, vol. 8, no. 6, pp. 585–599, 2002.
- [4] I. D. Wilson and P. A. Roach, "Principles of combinatorial optimization applied to container-ship stowage planning," *J. Heuristics*, vol. 5, no. 4, pp. 403–418, 1999.
- [5] I. D. Wilson and P. A. Roach, "Container stowage planning: A methodology for generating computerised solutions," *J. Oper. Res. Soc.*, vol. 51, pp. 1248–1255, Nov. 2000.
- [6] I. D. Wilson, P. A. Roach, and J. A. Ware, "Container stowage pre-planning: Using search to generate solutions, a case study," *Knowl.-Based Syst.*, vol. 14, pp. 137–145, Jun. 2001.
- [7] J.-G. Kang and Y.-D. Kim, "Stowage planning in maritime container transportation," *J. Oper. Res. Soc.*, vol. 53, no. 4, pp. 415–426, 2002.
- [8] A. Sciomachen and E. Tanfani, "A 3D-BPP approach for optimising stowage plans and terminal productivity," *Eur. J. Oper. Res.*, vol. 183, pp. 1433–1446, Dec. 2007.
- [9] D. Ambrosino, A. Sciomachen, and E. Tanfani, "Stowing a containership: The master bay plan problem," *Transp. Res. A, Policy Pract.*, vol. 38, pp. 81–99, Feb. 2004.
- [10] D. Ambrosino, D. Anghinolfi, M. Paolucci, and A. Sciomachen, "A new three-step heuristic for the master bay plan problem," *Maritime Econ. Logistics*, vol. 11, pp. 98–120, Mar. 2009.
- [11] A. Moura, J. Oliveira, and C. Pimentel, "A mathematical model for the container stowage and ship routing problem," *J. Math. Model. Algorithms Oper. Res.*, vol. 12, no. 3, pp. 217–231, 2013.
- [12] A. Delgado, R. M. Jensen, K. Janstrup, T. H. Rose, and K. H. Andersen, "A constraint programming model for fast optimal stowage of container vessel bays," *Eur. J. Oper. Res.*, vol. 220, pp. 251–261, Jul. 2012.
- [13] A. Imai, K. Sasaki, E. Nishimura, and S. Papadimitriou, "Multi-objective simultaneous stowage and load planning for a container ship with container rehandle in yard stacks," *Eur. J. Oper. Res.*, vol. 171, no. 2, pp. 373–389, 2006.
- [14] A. T. de Azevedo, C. M. Ribeiro, G. J. de Sena, A. A. Chaves, L. L. N. Salles, and A. C. Moretti, "Solving the 3D container ship loading planning problem by representation by rules and meta-heuristics," *Int. J. Data Anal. Techn. Strategies*, vol. 6, no. 3, pp. 228–260, 2014.
- [15] W.-Y. Zhang, Y. Lin, and Z.-S. Ji, "Model and algorithm for container ship stowage planning based on bin-packing problem," *J. Marine Sci. Appl.*, vol. 4, no. 3, pp. 30–36, 2005.
- [16] D. Pacino, A. Delgado, R. M. Jensen, and T. Bebbington, "Fast generation of near-optimal plans for eco-efficient stowage of large container vessels," in *Proc. Int. Conf. Comput. Logistics*, 2011, pp. 286–301.
- [17] D. Ambrosino, M. Paolucci, and A. Sciomachen, "Experimental evaluation of mixed integer programming models for the multi-port master bay plan problem," *Flexible Services Manuf. J.*, vol. 27, pp. 263–284, Sep. 2015.
- [18] D. Ambrosino, M. Paolucci, and A. Sciomachena, "A MIP heuristic for multi-port stowage planning," *Transp. Res. Procedia*, vol. 10, pp. 725–734, Jul. 2015.
- [19] D. Ambrosino, M. Paolucci, and A. Sciomachen, "Computational evaluation of a MIP model for multi-port stowage planning problems," *Soft Comput.*, vol. 21, no. 7, pp. 1753–1763, 2017.
- [20] S. Wang and Q. Meng, "Liner ship route schedule design with sea contingency time and port time uncertainty," *Transp. Res. B, Methodol.*, vol. 46, no. 5, pp. 615–633, 2012.
- [21] Q. Meng, S. Wang, and T. Wang, "Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand," *Eur. J. Oper. Res.*, vol. 223, no. 1, pp. 96–105, 2012.
- [22] J.-X. Dong, C.-Y. Lee, and D.-P. Song, "Joint service capacity planning and dynamic container routing in shipping network with uncertain demands," *Transp. Res. B, Methodol.*, vol. 78, pp. 404–421, Aug. 2015.
- [23] M. W. Ng, "Distribution-free vessel deployment for liner shipping," *Eur. J. Oper. Res.*, vol. 238, pp. 858–862, Nov. 2014.
- [24] M. W. Ng, "Container vessel fleet deployment for liner shipping with stochastic dependencies in shipping demand," *Transp. Res. B, Methodol.*, vol. 74, pp. 79–87, Apr. 2015.
- [25] J. S. K. Ang, C. Cao, M. Parlar, and H. Q. Ye, "Two-stage stochastic integer programming model for multiperiod sea cargo mix problem in container shipping industry," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 39, no. 2, pp. 460–465, Mar. 2009.
- [26] B. Zhang, C. T. Ng, and T. C. E. Cheng, "Multi-period empty container repositioning with stochastic demand and lost sales," *J. Oper. Res. Soc.*, vol. 65, no. 2, pp. 302–319, 2014.
- [27] X.-L. Han, Z.-Q. Lu, and L.-F. Xi, "A proactive approach for simultaneous berth and quay crane scheduling problem with stochastic arrival and handling time," *Eur. J. Oper. Res.*, vol. 207, pp. 1327–1340, Dec. 2010.
- [28] E. Ursavas and S. X. Zhu, "Optimal policies for the berth allocation problem under stochastic nature," *Eur. J. Oper. Res.*, vol. 255, pp. 380–387, Dec. 2016.
- [29] N. Al-Dhaheeri, A. Jebali, and A. Diabat, "A simulation-based genetic algorithm approach for the quay crane scheduling under uncertainty," *Simul. Model. Pract. Theory*, vol. 66, pp. 122–138, Aug. 2016.
- [30] M. Goerigk, S. Knust, and X. T. Le, "Robust storage loading problems with stacking and payload constraints," *Eur. J. Oper. Res.*, vol. 253, pp. 51–67, Aug. 2016.
- [31] A. Charnes and W. W. Cooper, "Deterministic equivalents for optimizing and satisficing under chance constraints," *Oper. Res.*, vol. 11, no. 1, pp. 18–39, 1963.
- [32] R. Zhao and B. Liu, "Stochastic programming models for general redundancy-optimization problems," *IEEE Trans. Rel.*, vol. 52, no. 2, pp. 181–191, Jun. 2003.



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