Effective Container Allocation Strategies for Multi-Yard Inland Container Depots

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***Abstract*—Efficiently assigning incoming containers to inland container depots is critical for reducing operational disruptions and improving overall terminal efficiency. This paper addresses the container depot selection problem with the objective of minimizing container relocations, a key factor influencing terminal performance. We propose an integrated approach that accounts for both immediate relocation costs incurred upon container arrival and future relocation risks estimated via Monte Carlo simulation. The proposed method provides a balanced decision-making framework that considers both short-term and long-term relocation factors. To evaluate the effectiveness of our proposed method, computational experiments were conducted under diverse conditions, including varying container volumes, initial yard occupancy levels, and weighting parameter.**

***Index Terms*—Container relocation, multi-depot systems, yard selection, monte-carlo simulation, operational optimization.**

I. Introduction

Global containerized trade continues to grow steadily, with volumes projected to increase by approximately 3 percent annually between 2024 and 2028 [1]. This sustained growth is driven by the ongoing global economic recovery, the rapid expansion of e-commerce, and evolving international trade patterns. As a result, congestion at maritime terminals is intensifying worldwide [2], [3]. To manage the increasing volume of containers and alleviate quayside congestion, major ports have adopted operational strategies that involve transferring containers from maritime terminals to nearby Inland Container Depots (ICDs), where containers are temporarily stored before being delivered to final customers [4], [5].

In ICD-based operations, containers are ideally stacked according to their planned departure dates. Those scheduled to depart earlier are placed on upper tiers, while those departing later are stored below [6]. However, the continuous arrival of new containers frequently disrupts this optimal stacking order, resulting in container relocations (reshuffling). These relocations increase crane operation time, interfere with yard truck movements, raise operational costs, and ultimately reduce terminal efficiency [7].

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Previous studies on the container relocation problem (CRP) have primarily focused on minimizing relocations within individual yards through various optimization algorithms and mathematical modeling [8]–[11]. In addition, heuristic and AI-based approaches have proven particularly effective in reducing reshuffling operations and improving overall efficiency in single-yard environments [12]–[14].

However, the involvement of multiple ICDs in modern port operations presents a new operational challenge in selecting the most suitable ICD for each newly arriving container. Yard-selection strategies that focus solely on minimizing immediate relocation costs may appear effective in the short term but often result in significant long-term operational inefficiencies. Concentrating containers in a limited number of ICDs can lead to imbalanced yard utilization and accelerate overall yard saturation. Moreover, when containers with varying departure schedules are stored together in the same ICD, the complexity and frequency of future relocations can increase substantially, leading to a sharp rise in operational workload. These compounded inefficiencies gradually degrade the overall performance of the ICD system and constrain the logistical throughput of the entire port. To overcome these challenges, it is essential to adopt yard-selection strategies that systematically consider both immediate relocation costs and anticipated future relocation risks.

To address this challenge, this paper proposes an effective ICD selection strategy that jointly considers immediate relocation costs and future relocation risks. Specifically, we develop a heuristic-based algorithm that estimates the number of relocations required upon container arrival and assesses future relocation risks using Monte-Carlo simulation. This integrated approach enables terminal operators to make informed and balanced ICD selection decisions, supporting both short-term operational efficiency and long-term system stability.

The remainder of the paper is organized as follows. Section II formally defines the ICD selection problem. Section III presents the proposed heuristic algorithm. Section IV validates the proposed approach through experimental results. Finally, Section V concludes the paper and outlines potential directions for future research.

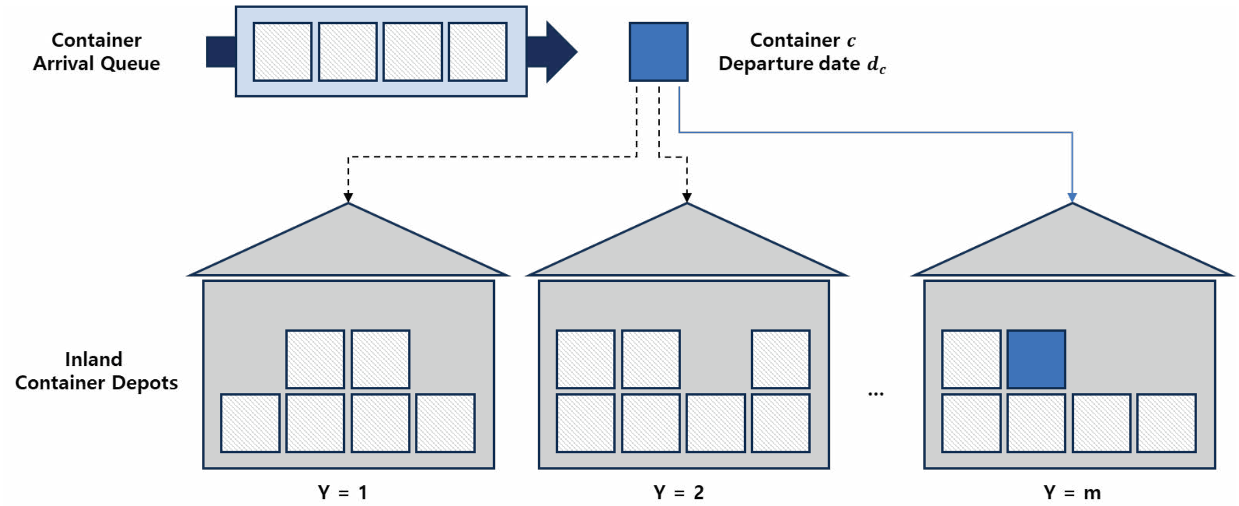


Fig. 1: Illustration of the container assignment process from an incoming container queue to multiple ICDs.

II. Problem Definition

Consider a container storage environment consisting of multiple Inland Container Depots (ICDs), indexed by the set $Y = \{1, 2, \ldots, m\}$. Each ICD $y \in Y$ comprises multiple container stacks arranged in a bay-row configuration, each with a maximum allowable height H. Containers within stacks should ideally be ordered based on their planned departure dates, with containers scheduled to depart earlier placed above those scheduled to depart later.

Given a queue of arriving containers Q, each container $c \in Q$ is assigned immediately to one of the ICDs upon its arrival, as illustrated in Fig. 1. To maintain operational efficiency, the assignment should minimize the total expected number of relocations across all ICDs. The ICD selection problem can be formally defined as the following optimization problem:

$$\text{minimize} \quad \sum_{c \in Q} \sum_{y \in Y} R(y, c)\, x_{yc} \tag{1}$$

$$\text{subject to} \quad \sum_{y \in Y} x_{yc} = 1, \quad \forall c \in Q \tag{2}$$

$$x_{yc} \in \{0, 1\}, \quad \forall y \in Y, c \in Q \tag{3}$$

where x_{yc} is a binary decision variable equal to 1 if container c is assigned to ICD y, and 0 otherwise, and $R(y, c)$ denotes the estimated number of relocations incurred when assigning container c to ICD y.

The objective is to determine an assignment of incoming containers to ICDs that collectively minimizes the total expected relocations. Each container must be immediately allocated to exactly one ICD upon arrival, which reflects realistic operational constraints. Due to the combinatorial complexity of this problem, we propose an efficient heuristic approach, detailed in Section III, designed to provide effective and computationally tractable solutions suitable for real-time operational decision-making.

III. Methodology

In this section, we present a heuristic approach to address the ICD selection problem described in the previous section. The proposed heuristic aims to assign each arriving container to the most suitable ICD by considering two important types of container relocations: immediate relocations and anticipated future relocations. An immediate relocation occurs when assigning a newly arriving container disrupts the optimal stacking order within an ICD, requiring other containers to be moved immediately in order to maintain the correct sequence. On the other hand, anticipated future relocations refer to the expected relocations that may occur later due to subsequent container arrivals, capturing the potential long-term operational disruptions.

Our heuristic approach integrates both immediate and future relocation costs, consisting of three core components: (1) estimation of immediate relocation costs for each ICD upon container arrival, (2) assessment of anticipated future relocation risks using Monte-Carlo simulations, and (3) combination of these two estimates into an unified decision-making criterion. Each of these components is detailed in the following subsections.

A. Immediate Relocation Cost Estimation

When assigning a newly arrived container $c \in Q$ to an ICD $y \in Y$, it is essential to maintain containers stacked according to their planned departure dates. Ideally, containers scheduled for earlier departure should always be positioned above those departing later. Violations of this stacking order inevitably trigger immediate relocations of containers, directly impacting operational efficiency.

To efficiently estimate immediate relocation costs, denoted as $R_{\text{now}}(y, c)$, we propose a practical heuristic comprising two main phases. In the first phase, the heuristic identifies stacking violations introduced by inserting the incoming container. Specifically, it identifies and counts containers positioned

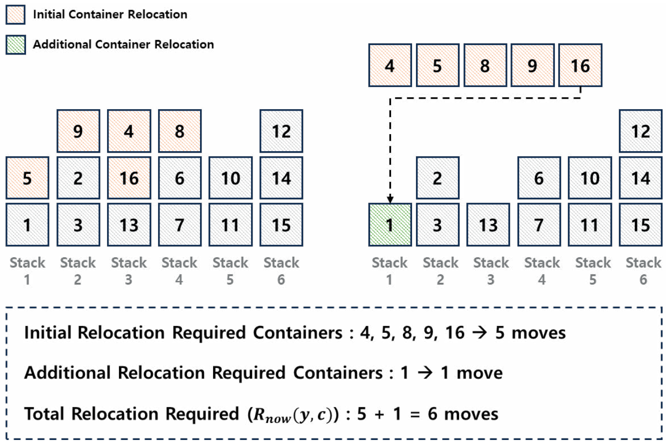


Fig. 2: An illustrative example demonstrating the estimation of immediate relocations. In this example, containers are initially stacked in a random order, violating the ideal stacking sequence based on departure dates. The heuristic first identifies the containers violating the desired stacking order (Initial Container Relocation, colored in red). Subsequently, these containers are removed temporarily and reassigned to stacks, considering additional relocations (Additional Container Relocation, colored in green).

incorrectly, which refers to containers stacked above others scheduled to depart earlier, as initial relocation requirements. In the second phase, the heuristic addresses cases where these improperly positioned containers cannot be directly relocated without additional relocations. If the departure date of an improperly positioned container is later than that of all properly stacked containers currently available at stack tops, additional container relocations are required. The heuristic selects the stack requiring the minimum number of extra moves to resolve these secondary violations and incrementally updates the total relocation estimate. An illustrative example demonstrating this process is provided in Fig. 2.

B. Future Relocation Cost Estimation

While immediate relocation costs address disruptions caused by a newly arriving container, anticipated future relocation costs consider potential relocations arising from containers arriving subsequently. Due to the inherent uncertainty regarding future container arrivals, precise calculation of future relocations is challenging. Therefore, we employ a Monte-Carlo simulation-based approach to robustly estimate the anticipated future relocation burden, denoted as $R_{\text{future}}(y, c)$, incurred by assigning container c to ICD y.

The heuristic begins by hypothetically placing the newly arrived container c into ICD y and temporarily updating the ICD's state. Then, N independent future arrival scenarios are simulated, each involving a single additional container. For each scenario, the simulated container's departure date is randomly generated from a predefined probability distribution, such as a uniform distribution over the next 30 days.

For each simulated arrival, the heuristic estimates the immediate relocation cost $R_{\text{now}}(y, c_n^{sim})$, using the procedure described in the previous subsection. The anticipated future relocation cost for ICD y is then computed as the average of these immediate relocation costs across all N scenarios:

$$R_{\text{future}}(y, c) = \frac{1}{N} \sum_{n=1}^{N} R_{\text{now}}(y, c_n^{sim}) \tag{4}$$

where c_n^{sim} represents the container arrival simulated in scenario n.

C. Integrated ICD Selection Policy

The final stage of our heuristic integrates both immediate and anticipated future relocation costs into a unified decision-making criterion. Given the immediate relocation cost $R_{\text{now}}(y, c)$ and the anticipated future relocation cost $R_{\text{future}}(y, c)$ for container c and ICD y, we define an integrated cost measure $J(y, c)$ as a weighted sum:

$$J(y, c) = \alpha R_{\text{now}}(y, c) + (1-\alpha) R_{\text{future}}(y, c), \quad 0 \leq \alpha \leq 1 \tag{5}$$

The weighting parameter α controls the relative importance placed on immediate versus future relocations. A higher value of α prioritizes immediate operational convenience, while a lower value emphasizes long-term operational stability and resilience against future disruptions.

For each incoming container c, the heuristic evaluates $J(y, c)$ across all candidate ICDs and assigns the container to the ICD y^* with the lowest integrated cost:

$$y^* = \arg\min_{y \in Y} J(y, c) \tag{6}$$

This integrated selection policy provides a balanced, interpretable, and practical solution that can be directly applied to real-time container assignment decisions, effectively addressing both short-term operational demands and long-term ICD utilization efficiency.

IV. Experimental Results

In this section, we evaluate the performance of the proposed heuristic ICD selection strategy through a series of computational experiments. Specifically, we investigate how effectively the heuristic reduces container relocations under varying conditions, including different numbers of arriving containers, initial yard occupancy levels, and the weighting parameter. We compare the proposed approach against two baseline heuristics (immediate-only and future-only) and a random selection strategy.

A. Experimental Setup

The simulation environment consisted of multiple ICDs, each configured with 3 bays, 4 rows, and a maximum stack height of 5 tiers. Container arrival scenarios were generated randomly, with departure dates uniformly distributed between 1 and 30 days from the arrival date. For each test scenario,

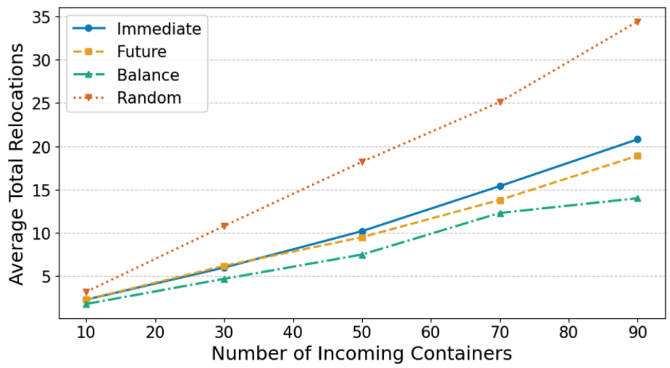


Fig. 3: Effect of the number of incoming containers on total relocations (Initial yard occupancy = 50%, α = 0.5).

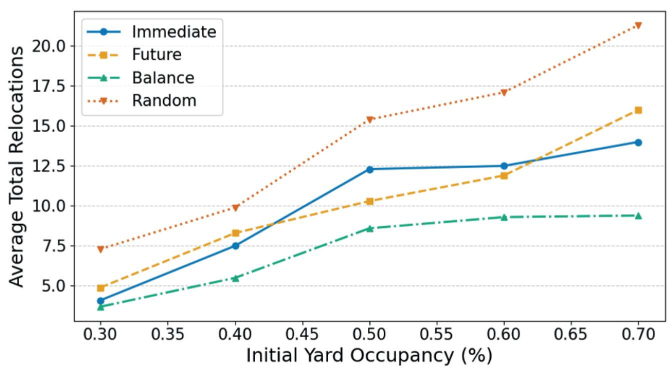
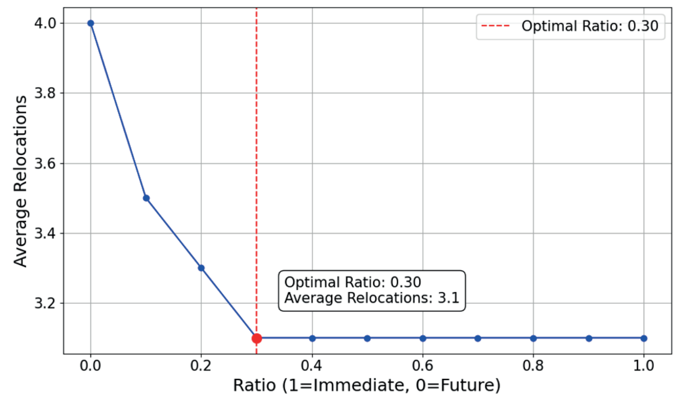
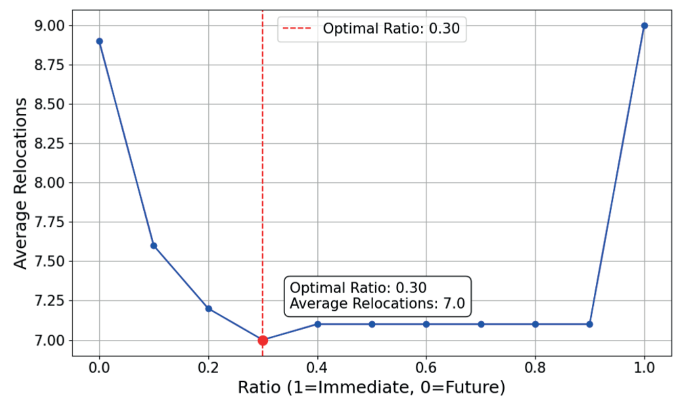


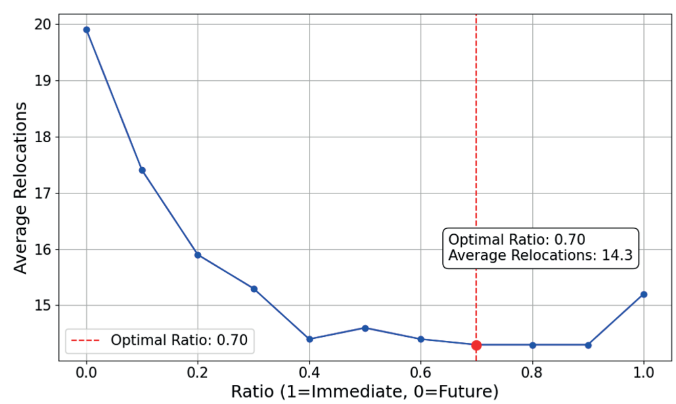
Fig. 4: Effect of initial yard occupancy on total relocations (Number of incoming containers = 50, α = 0.5)



(a) Initial Yard Occupancy = 30%



(b) Initial Yard Occupancy = 50%



(c) Initial Yard Occupancy = 70%

Fig. 5: Effect of the weighting parameter α on average relocations under different initial yard occupancy levels (Number of incoming containers = 50).

container yards were randomly initialized while maintaining a predefined occupancy rate. To estimate the anticipated future relocation costs, Monte-Carlo simulations were conducted with 100 repetitions per container assignment. The performance metric for evaluation was the total number of container relocations incurred throughout the simulation.

B. *Effect of the Number of Incoming Containers*

We investigated the impact of the number of incoming containers, ranging from 10 to 90, while maintaining an initial yard occupancy of 50% and setting the weighting parameter α = 0.5. As depicted in Fig. 3, the proposed strategy (*Balance*) consistently outperformed all other methods, recording the lowest number of relocations across the entire range. While the immediate-only heuristic (*Immediate*) performed adequately with a smaller number of incoming containers, its efficiency declined notably as container volumes increased. In contrast, the integrated approach maintained robust performance and significantly lower relocation counts, even at higher container volumes. This demonstrates its ability to effectively balance immediate and anticipated future relocation costs. These results highlight that focusing solely on immediate relocation costs overlooks potential future disruptions, which become increasingly significant as container traffic grows.

C. *Effect of Initial Yard Occupancy*

We also examined the influence of initial yard occupancy levels by varying occupancy rates from 30% to 70%, while fixing the number of incoming containers at 50 and the weighting parameter α = 0.5. Results shown in Fig. 4 illustrate that the proposed method consistently achieved the fewest number of relocations across all occupancy levels. At lower occupancy rates, the immediate-only heuristic produced results comparable to the balanced heuristic, but its effectiveness deteriorated significantly as yard congestion increased beyond 50%. The future-only heuristic (*Future*) consistently underperformed compared to the balanced method, but occasionally outperformed the immediate-only heuristic at higher occupancy levels. This suggests that accounting for future relocation risks becomes particularly advantageous under congested yard conditions. The random strategy (*Random*) consistently showed the poorest performance across all occupancy levels, highlighting the importance of strategic decision-making. Overall, these results indicate that the proposed heuristic effectively mitigates operational disruptions even as yard congestion intensifies.

D. Effect of the Weighting Parameter α

To examine how the balance between immediate and future relocation costs affects the performance, we varied the weighting parameter $\alpha \in [0, 1]$ under three yard occupancy conditions: 30%, 50%, and 70%. The parameter α determines the trade-off between immediate and future relocation costs, where α=1 considers only immediate costs, and α=0 considers only future relocation risks. In each setting, the number of incoming containers was fixed at 50.

As shown in Fig. 5a–5c, the number of relocations followed a U-shaped trend across all occupancy levels, indicating the presence of an optimal weight parameter value. When the yard occupancy was relatively low (30% and 50%), the optimal performance was achieved with $\alpha = 0.3$, suggesting that giving greater importance to future relocation risks leads to more stable stacking in the long term. Under heavy congestion (70% occupancy), the optimal value shifted to $\alpha = 0.7$, highlighting that avoiding immediate disruption becomes more critical when space is limited.

These findings indicate that the most effective weighting between immediate and future relocation costs varies depending on yard occupancy. In more spacious environments, planning for future relocations is advantageous, while under congested conditions, minimizing immediate reshuffling becomes essential.

V. Conclusion

This study addressed the container assignment problem in multi-yard inland container depots by proposing a heuristic strategy that balances immediate relocation costs and anticipated future relocation risks. Through Monte Carlo simulation and a unified cost formulation, the proposed heuristic demonstrated robust adaptability and performance across diverse operational scenarios. Simulation results showed that the heuristic consistently outperformed baseline strategies, particularly under high traffic volumes and congested yard conditions, by reducing total relocation counts and mitigating future operational disruptions.

These findings validate the importance of integrating both short-term and long-term considerations into yard allocation decisions. Furthermore, the weighting parameter offers a flexible control mechanism to tailor the decision-making process according to specific operational preferences and priorities. As future work, we plan to explore the dynamic adjustment of the weighting parameter based on real-time yard conditions and extend the framework to multistage decision-making settings that incorporate container priorities and departure uncertainties.

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