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Research Article

Optimization of Railway Empty Container Repositioning (ECR) with Time Window and Container Type Substitution Based on Genetic Algorithm

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ABSTRACT

ECR is a crucial strategy for enhancing the overall carrying capacity of rail transportation. However, the operational cost is significantly affected by the arrival time of empty containers. When empty containers arrive too early, additional inventory costs are incurred due to idle storage, whereas late arrivals result in opportunity losses. To improve the punctuality of empty container arrival times, this study designs a transportation scheme based on container type substitution. This scheme not only significantly enhances the overall transportation efficiency of the railway system but also further reduces transportation costs. First, a container empty repositioning model based on time windows and container type substitution is constructed. Second, a genetic algorithm is employed to solve the model and determine the optimal substitution strategy. Finally, the effectiveness and unique advantages of the proposed model and algorithm are validated using a case study of a railway freight station with eight container service points. Experimental results demonstrate that the model effectively addresses the ECR problem and yields the optimal repositioning scheme. Under container type substitution, the total cost of ECR is reduced by 11.1% compared to the non-substitution scenario, while inventory costs and opportunity loss costs are reduced by 22.3%. Clearly, container type substitution can lower transportation costs and improve transportation efficiency.

Keywords: ECR; Container Type Substitution; Time Window; Genetic Algorithm.

1. Introduction

Rail freight plays a strategically important role in China's transportation industry, with container transportation being particularly critical under the framework of the Belt and Road Initiative. However, imbalances in economic development between the northern and southern regions and disparities in regional economic levels have led to significant demand for railway ECR. ECR not only consumes railway transport capacity but also imposes additional costs on enterprises, including vehicle rental, marshalling services, locomotive traction, hauling, and track usage fees, substantially increasing operational expenses. Therefore, it is imperative to develop efficient, economical, and reasonable solutions for railway ECR.

Currently, China’s railway container transportation primarily employs two modes: direct trains and ordinary freight trains (Yang, 2019). However, the coverage of direct trains is limited, and ordinary freight trains must share journeys with other cargo and undergo intermediate station sorting, resulting in longer transport times and lower efficiency (Guo, 2011). Additionally, imbalances in container flow and the extensive railway network inevitably lead to extra sorting and waiting times during repositioning, making it challenging to meet customers' container demands promptly (Yang, 2019). To address this issue, China Railway Corporation (now China State Railway Group Co., Ltd.) has established railway container hub stations in various locations. These hubs utilize block train operations for full-train transportation and return ECR while promoting container substitution strategies under suitable conditions to accelerate turnover and improve utilization efficiency.

Although various models and algorithms have been proposed for ECR, they are predominantly based on deterministic scenarios and fail to fully account for the combined impact of time-window constraints and container substitution in railway environments. To address this research gap, this study introduces a container substitution strategy while considering the time-window requirements at demand stations. The goal is to reduce additional costs caused by early or delayed container arrivals and optimize the allocation of empty container resources. Furthermore, to address challenges posed by the extensive scale and limited accessibility of the railway transportation network, a genetic algorithm is employed to solve the proposed model.

The contributions and innovations of this study are as follows:

(1) Combining time-window constraints and container substitution strategies to highlight the impact of varying time periods and container types on ECR costs.

(2) Developing an optimization model based on a genetic algorithm within the railway transportation environment to comprehensively solve complex transport routes and repositioning demands.

(3) Validating, from both theoretical and practical perspectives, that the proposed optimization scheme can significantly reduce operational costs and enhance railway transport efficiency, providing feasible pathways and reference value for future research on railway ECR.

The remainder of this paper is organized as follows: Section 2 reviews related studies on ECR under deterministic and uncertain environments, foldable containers, and China's railway container express system. Section 3 presents the proposed railway ECR model based on time-window constraints and container substitution, along with the corresponding algorithm. Section 4 validates and analyzes the model and algorithm through simulation case studies. Finally, Section 5 concludes the paper and discusses directions for future research.

2. Literature Review

ECR has become an increasingly prominent issue in the field of transportation and logistics due to imbalances in international trade and regional economic disparities. Existing studies have approached this problem from various perspectives, including different transportation modes (e.g., maritime and rail) and optimization techniques (e.g., deterministic and stochastic models, multi-objective optimization, time-window constraints, and container substitution strategies), aiming to reduce costs and enhance transportation efficiency. However, there remain significant research gaps and limitations that warrant further exploration.

2.1 Initial Exploration of Single-Mode Transportation and Deterministic Problems

Early research primarily focused on optimizing ECR under deterministic conditions for single-mode transportation. Meng et al. (2011) proposed a mixed-integer linear programming model to design a hub-and-spoke container liner shipping service network, addressing multi-port calling issues. Song et al. (2012) investigated multi-route, multi-ship, and multi-voyage maritime ECR problems, employing a two-stage solution approach combining shortest path algorithms and heuristics to improve computational efficiency. Zheng et al. (2015) explored inter-company coordination in liner shipping and proposed a two-stage optimization method for ECR.

While these studies laid the groundwork for addressing deterministic ECR problems, their simplified assumptions (e.g., neglecting uncertainties and focusing on single-mode transportation) limited their applicability to real-world complex transportation scenarios. These foundational works provide essential modeling frameworks and optimization ideas for this study but require extensions to account for demand fluctuations, transit time variability, and resource constraints.

2.2 Advanced Research on Uncertainty and Multi-Objective Optimization

To better reflect real-world transportation conditions, researchers have incorporated uncertainty and multi-objective optimization into the study of ECR. Dong et al. (2009) examined dynamic and uncertain conditions, addressing multi-ship, multi-port, and multi-voyage ECR using genetic algorithms. Liu et al. (2022) integrated uncertain laden and empty container demands into liner shipping network optimization. Duan et al. (2012, 2015) addressed uncertainties in empty container supply, demand, and transit times, validating their models' effectiveness. Song et al. (2022) tackled demand and supply uncertainties in multi-port environments using particle swarm optimization algorithms. Li et al. (2022) introduced robust stochastic optimization to address demand and carbon trading price uncertainties. Bakir et al. (2022) employed a rolling time-domain framework to account for future demand fluctuations. Feng et al. (2024) focused on the coordination of bulk cargo transportation and ECR, optimizing leasing decisions under uncertain demand. Song et al. (2022) approached ECR from an inventory control perspective, incorporating spatial imbalances, dynamic operations, and leasing phenomena under uncertainty.

These studies have broadened the scope and depth of research on ECR, incorporating more realistic complexities into their models. However, the majority of these efforts have concentrated on maritime transportation, with limited exploration of how to effectively address uncertainty factors in railway systems. Additionally, while some studies have considered time constraints, in-depth research on strict or flexible time-window requirements in railway systems remains insufficient.

2.3 Optimization of Time-Window Constraints and Repositioning Strategies

In practice, demand stations often impose time-window constraints on empty container arrivals. Yang et al. (2021) introduced time-window constraints, pick-up and delivery orders, and multi-container configurations into container transportation problems, solving them with mixed-integer programming models. Liu et al. (2022) incorporated time-window constraints in liner shipping routes affected by disruptions, using adaptive mutation particle swarm optimization. Min et al. (2012) addressed time-window-induced accumulation costs and opportunity losses in maritime ECR using an improved genetic simulated annealing algorithm.

However, these studies on time-window constraints primarily focus on maritime scenarios, with limited attention to the unique operational modes and constraints of railway transportation. Furthermore, the potential impacts of container substitution strategies on repositioning costs and efficiency under time-window constraints remain underexplored.

2.4 Exploration of Substitution Strategies such as Foldable Containers

To improve resource utilization, some studies have introduced foldable containers to reduce repositioning and storage costs. Moon et al. (2013) validated the economic feasibility of foldable containers in maritime ECR. Zhang et al. (2022) and Wang et al. (2024) examined the application of foldable containers in river-sea intermodal transport and hub location problems, demonstrating the cost-reduction and efficiency-enhancing potential of such substitution strategies.

While container substitution strategies have been studied in maritime contexts, their application to railway transportation, particularly under time-window and uncertainty considerations, remains a research gap. Existing studies lack a systematic exploration of substitution strategies combined with time-window constraints and transit time uncertainties in the context of China's railway systems.

2.5 Current Status and Limitations in the Context of China's Railways

In China's railway sector, Li (2018) categorized the development of rail express services and proposed strategies based on transport and cargo organization. Song et al. (2022) developed a model for maximizing railway enterprise revenue by optimizing the joint transportation of empty and loaded containers using passenger trains. Duan et al. (2011, 2012, 2015)extensively studied priority rankings for suitable cargo (2012), technical station operations (2011), and time-window constraints (2015). Xia et al. (2023) proposed an integer linear programming model to optimize repositioning under daily demand fluctuations.

While these studies offer valuable references for railway container repositioning, they often focus on single dimensions, such as time-window constraints, uncertainties, or substitution strategies, without integrating these aspects into a comprehensive framework. There is a lack of research addressing the combined effects of time-window requirements, transit time uncertainties, and substitution strategies to reduce costs and enhance efficiency.

2.6 Research Gaps and Directions

In summary, while existing research has expanded the understanding of ECR, several gaps remain:

(1) Most studies focus on maritime transportation, with relatively few addressing railway container repositioning, particularly in the context of China's rail express services.

(2) While uncertainty has been extensively studied, systematic models incorporating time-window requirements and transit time variability in railway scenarios are scarce.

(3) Although substitution strategies such as foldable containers have shown potential benefits, their integration with railway-specific time-window and uncertainty factors remains unexplored.

This study aims to address these gaps by developing an optimization model that integrates transit time uncertainty, time-window constraints, and substitution strategies in the context of China's railway transportation system. The proposed model will be solved using intelligent optimization algorithms, offering new theoretical, methodological, and practical insights into railway container repositioning.

3. Modeling

3.1. Description of the Problem

In a railway container transportation network, there are n container demand stations and m container supply stations, with supply and demand exhibiting spatial and temporal imbalances. The network provides several types of empty containers (assumed to be k types in total), each with different sizes or functionalities suitable for varying cargo loading requirements.

Time-Window Constraints: In practical transportation scenarios, each demand station has specific requirements for the arrival times of empty containers. Early arrivals incur additional storage costs (e.g., occupying space and requiring additional labor for maintenance), while late arrivals may prevent customers from loading or shipping on time, reducing the reputation of the transportation company and resulting in opportunity costs or potential revenue losses.

Container Type Substitution: Due to regional economic disparities and variations in industrial structures, the types and inventory levels of empty containers at different stations are often unbalanced. Some stations may have a surplus of certain container types, while others face severe shortages. When the required type of empty container is unavailable at the target demand station or must be transported from a distant supply station, this can lead to high transportation costs or failure to meet the time-window requirements. To improve resource utilization efficiency, a "container substitution" strategy can be adopted, allowing compatible or similar container types to replace the originally required type, provided they meet the actual loading requirements.

For instance, as illustrated in Figure 1, a railway container transportation network comprises stations A_1, A_2, and A_3, which handle containers, and two types of containers, U_1 and U_2. During a specific time period, demand station A_1 urgently requires U_1 containers. If U_1 containers can only be transported from a distant supply station, A_3, and cannot arrive on time, while a closer supply station, A_2, has surplus U_2 containers that can meet the loading requirements of A_1, substituting U_2 for U_1 would satisfy the time-window requirements and reduce transportation costs.

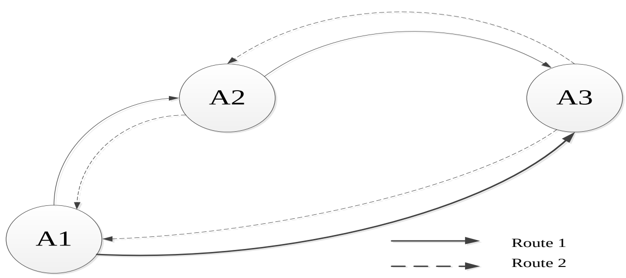


Figure 1: Railway container transportation network diagram

3.2. Model Assumptions

The railway transportation system is a complex network composed of various forms of transportation organizations. Given the specific characteristics and constraints of container transportation, it is essential to simplify the model to capture the general aspects of the problem when establishing a railway ECR model. This paper adopts the following assumptions and principles:

(1) Container Types: Only two types of containers (U_1 and U_2) are considered for repositioning, with no consideration of transshipment scenarios.

(2) Transportation Vehicles: It is assumed that there are always sufficient transportation vehicles available to ensure immediate loading of empty containers.

(3) Single Transportation Mode: Only railway transportation between container stations is considered, as it is currently the primary mode of ECR in railway systems.

(4) Cost Simplification: Costs such as empty container handling fees, locomotive traction fees, and vehicle service fees are aggregated into the transportation costs at each origin-destination (OD) container handling station.

3.3. Symbolic Description

S: The set of empty container supply stations.

D: The set of empty container demand stations.

U: The set of empty container types.

E: The set of directed edges, $E = S \times D$, That is $(i, j) \in E, i \in S, j \in D$.

k: The empty container type, and $k \in U$.

a_i^k: The number of empty containers of the type k contained in the empty container supply station i.

b_j^k: The number of empty containers of the type k required by the empty container demand station j.

a_j^k: The empty container substitution factor, if the empty container needed by the demand station j can be substituted by a different type of empty container at the supply station, then $a_j^k = 1$, otherwise $a_j^k = 0$.

β_j^k: The substitution cost when the substitution coefficient $a_j^k = 1$.

c_{ij}^k: The cost of transporting empty containers of type k per unit from station i to station j.

$\left[e_j^k, l_j^k\right]$: The time window of the demand for empty containers k at station j.

t_i^k: The departure time of the empty container at the station i.

t_{ij}^k: The travel time of the container k from the station i to the station j.

T_j^k: The actual time of arrival of the empty container of type k at station j, $t_i^k + t_{ij}^k = T_j^k$.

u_j^k: The backlog cost incurred by an empty container that arrives at the station j earlier than the time window.

v_j^k: The cost of losses incurred by empty containers arriving at the station j later than the time window.

x_{ij}^k: The number of empty containers of type k repositioning from station i to station j.

3.3. Objective Function Establishment

Establish the objective function as equation (1)~(6)

$$\min\left\{\sum_i\sum_j\sum_k x_{ij}^k\left(c_{ij}^k+\beta_{ij}^k\right)\right\}+\sum_i\sum_j\sum_k x_{ij}^k\left(u_j^k\max\left\{e_j^k-T_j^k,0\right\}+v_j^k\max\left\{T_j^k-l_j^k,0\right\}\right) \tag{1}$$

$$s.t.\ \sum_i x_{ij}^k \le M\cdot\alpha_j^k \tag{2}$$

$$\sum_j\sum_k x_{ij}^k \le a_i^k \tag{3}$$

$$\sum_i\sum_k x_{ij}^k \ge b_j^k \tag{4}$$

$$x_{ij}^k \le r_{ij}^k \tag{5}$$

$$x_{ij}^k \ge 0 \ \ \textit{and an integer} \tag{6}$$

Where: M denotes the number of empty containers of type k at station i; r_{ij}^k is the transport capacity on the path (i, j) in terms of the number of containers.

Equation (1) is the objective function, which consists of three parts: container allocation cost, container type substitution cost, early arrival inventory, and late arrival penalty cost;

Equation (2) represents the empty container substitution constraint, which indicates that the number of empty containers of container type k from station i to station j where substitution occurs is less than or equal to the number of empty containers of type k at station i multiplied by the substitution factor.

Equation (3) represents the empty container supply constraint, indicating that the number of container-type k empty containers from station i to station j where the allocation occurs is less than or equal to the supply of station i type k empty containers;

Equation (4) represents the empty container demand constraint, which indicates that the number of container type k empty containers for which an allocation occurs from station i to station j is greater than or equal to the demand for type k empty containers at station j;

Equation (5) represents the route capacity constraint, which indicates that the number of empty containers of container type k for which an allocation occurs from station i to station j is less than or equal to the capacity of the containers on the transportation path (i, j);

Equation (6) is a variable declaration indicating that the number of empty containers of container type k for which an allocation occurs from station i to station j is greater than or equal to zero and an integer.

4. Algorithmic Solving

The Genetic Algorithm (GA) was proposed by American scientist Holland in 1975. This algorithm is an adaptive stochastic search optimization method based on the simulation of natural evolution and selection mechanisms. Through operations such as genetic encoding, population generation, fitness calculation, selection, crossover, and mutation, genetic algorithm iteratively filters out relatively optimal solutions within the model. Genetic algorithms are widely applied to complex and nonlinear optimization problems and typically achieve satisfactory computational results.

4.1. Initial Population

For the transportation problem, Real-valued encoding is used to generate an initial feasible solution. A certain number of chromosomes are randomly generated, with each chromosome representing a feasible solution to the problem. All individuals form a population. The transportation problem is represented using a matrix, and each chromosome C_p is composed of two parts: X_p and Y_p.

$$X_p = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{7}$$

$$Y_p = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{8}$$

Where m is the number of supply stations and n is the number of demand stations; X_p represents the Pth chromosome, and x_{ij} is the chromosome gene in the matrix, which represents the number of type k containers allocated from supply station i to demand station j; Y_p represents the Pth chromosome, and y_{ij} in the matrix is a chromosome gene indicating the number of containers in the substitution from supply station i to demand station j.

4.2. Fitness Function

The fitness of a chromosome is evaluated using the objective function value, denoted as eval (C_p), which represents the fitness function value of chromosome C_p. The fitness function for the model is expressed as follows (Equation 9):

$$eval(C_p) = \left\{ \sum_i \sum_j \sum_k x_{ij}^k \left(c_{ij}^k + \beta_{ij}^k \right) \right\} + \sum_i \sum_j \sum_k x_{ij}^k \left(u_j^k \max\left\{ e_j^k - T_j^k, 0 \right\} + v_j^k \max\left\{ T_j^k - l_j^k, 0 \right\} \right) \tag{9}$$

4.3. Selecting Operation

Based on the fitness of each individual, the cumulative probability for each individual is calculated, and the roulette wheel method is used to select individuals for the next generation. The probability of an individual being selected is proportional to its fitness value. Chromosomes with higher fitness scores have a greater likelihood of being selected. The probability $P(x_i)$ of selecting a chromosome is given by:

$$P(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{10}$$

where $P(x_i)$ is the probability of selecting a chromosome, $f(x_i)$ is the fitness value of chromosome x_i, and N is the total number of chromosomes in the population.

4.4. Crossover Operation

A parameter P_c is defined to represent the probability of crossover. Chromosomes X_1 and X_2 are randomly selected as parent chromosomes for crossover based on the crossover probability P_c, where $X = (X_{ij})$.

For each pair, a random number R is generated within the range (0, 1). If $R < P_c$, the following method is used to generate offspring chromosomes X_3 and X_4:

$$X_3 = X_1 + R * (X_2 - X_1) \tag{11}$$

$$X_4 = X_2 + R * (X_1 - X_2) \tag{12}$$

Then, the feasibility of each offspring is verified. If all offspring are feasible, they replace their parent chromosomes. If any offspring are infeasible, only the feasible offspring are retained. Subsequently, new random numbers are generated, and the crossover operation is repeated until the required number of feasible offspring is obtained or a predefined iteration limit is reached.

4.5. Variation Operation

Define P_m as the probability of mutation. Suppose a chromosome C_p consists of genes $C_1, C_2, \cdots C_n$, where each gene C_i must satisfy $lb_i \le C_i \le ub_i$, with lb_i as the lower bound and ub_i as the upper bound.

For each chromosome in the population, genes are randomly selected for mutation based on the mutation probability P_m.

Thus, the gene C_i undergoes mutation with a probability of P_m.

$$C_i^{'} = C_i \pm \Delta\delta \tag{13}$$

Where $C_i^{'}$ the new gene is after the mutation, C_i is the pre-mutation gene, and $\Delta\delta$ is a randomly varying quantity that determines the range of variation in gene values.

Here, $C_i^{'}$ represents the mutated gene, C_i is the original gene before mutation, and $\Delta\delta$ is a random variable within the interval [−d,d], determining the range of gene mutation.

If the mutated gene exceeds the defined boundaries, boundary adjustments are applied:

If $C_i^{'} \le lb_i$, set $C_i^{'} = lb_i$ (lower bound).

If $C_i^{'} \ge ub_i$, set $C_i^{'} = ub_i$ (upper bound).

The mutated gene value then replaces the original gene, forming a new chromosome.

4.6. Algorithm Steps

The genetic algorithm operates by initializing a population, evaluating fitness, and iteratively performing selection, crossover, and mutation operations. Once the stopping condition is met, the individual with the best fitness is output as the feasible solution. The basic flowchart of the algorithm is shown in Figure 2, and the steps are as follows:

(1) Initialization: Generate a set number of individuals as the initial population.

(2) Fitness Evaluation: Evaluate each individual in the population based on the objective function of the problem and calculate its fitness value.

(3) Iteration and Update: Perform selection, crossover, and mutation operations during each iteration and update the current population.

(4) Stopping Condition: Stop the iteration when the maximum number of iterations or the fitness threshold is reached.

(5) Output Results: The individual with the highest fitness is output as the optimal feasible solution for the ECR problem.

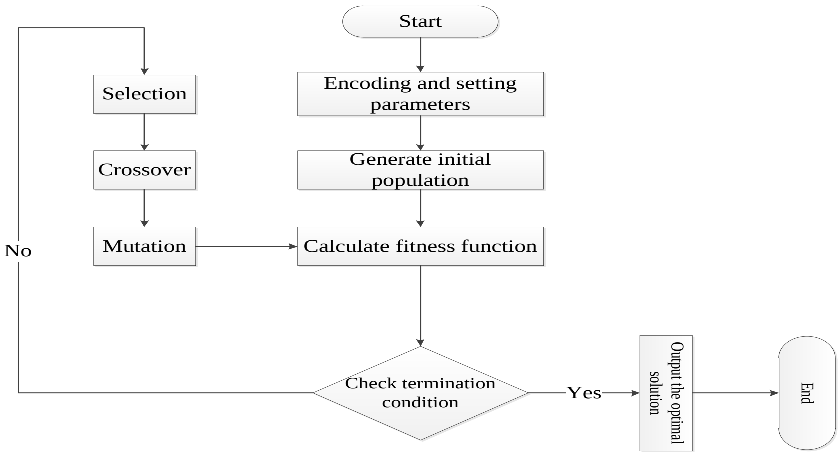


Figure 2. Genetic algorithm flowchart

5. Algorithm Analysis

5.1. Case Date

A railroad bureau has 8 stations for container business, 4 stations for the railroad empty container supply station, A_1, A_2, A_3, and A_4; 4 stations need containers to meet the transport, for the empty container demand station B_1, B_2, B_3, and B_4. There are two types of containers, U_1 and U_2, and U_2 is considered as a substitute in case of insufficient U_1. The example solution considers two cases of container substitution and no substitution. A planned period of empty container supply station information is shown in Table 1, empty container demand station information is shown in Table 2, and Table 3 for the supply station and the demand station between the traveling time, ECR cost as shown in Table 4, Table 5 for the cost of substitution for U_2 substitution of U_1 cost.

Consider a railway bureau with eight stations handling container operations. Among these, four stations serve as railway empty container supply stations, denoted as A_1, A_2, A_3, and A_4, while the remaining four stations act as empty container demand stations, denoted as B_1, B_2, B_3, and B_4. Two types of containers, U_1 and U_2, are available, and U_2 can be used as a substitute when U_1 is insufficient. The case study examines two scenarios: with and without container substitution. During a specific planning period, the information on empty container supply stations is provided in Table 1, while Table 2 lists the information for empty container demand stations. Table 3 presents the transit times between supply and demand stations, Table 4 provides the ECR costs, and Table 6 specifies the substitution costs for using U_2 as a replacement for U_1.

Table 1. Information on empty container supply station

Supply station	A_1		A_2		A_3		A_4	
container type	U_1	U_2	U_1	U_2	U_1	U_2	U_1	U_2
Supply of container types/CTN	32	23	17	16	15	24	21	35
departure time	2:00	2:00	3:00	3:00	8:00	8:00	7:00	7:00

Table 2. Information on empty container demand station

Demand Station	**container type**	**Empty container demand**/CTN	**Time window**	**Early arrival cost/(CNY/(CTN •h))**	**Late arrival cost/(CNY/(CTN •h))**
B_1	U_1	30	[12：00，19：00]	3	5
	U_2	21	[11：00，17：00]	5	7
B_2	U_1	18	[20：00，23：00]	3	5
	U_2	10	[19：00，23：00]	5	7
B_3	U_1	15	[11：00，12：00]	3	5
	U_2	12	[12：00，24：00]	5	7
B_4	U_1	19	[14：00，21：00]	3	5
	U_2	15	[15：00，22：00]	5	7

Table 3. Travel time between supply and demand stations (h)

Supply station	**Demand station**			
	B_1	B_2	B_3	B_4
A_1	24	19	15	19
A_2	17	18	10	7
A_3	11	2	6	15
A_4	5	12	6	10

Table 4. ECR cost (CNY/CTN)

Supply station	**Demand station**			
	B_1	B_2	B_3	B_4
A_1	244/366	187/281	149/224	193/290
A_2	167/250	183/275	99/149	70/105
A_3	107/161	22/33	63/95	155/233
A_4	45/68	119/179	60/90	99/149

[1] Figures before "/" indicate U_1 repositioning costs; figures after "/" indicate U_2 repositioning costs.

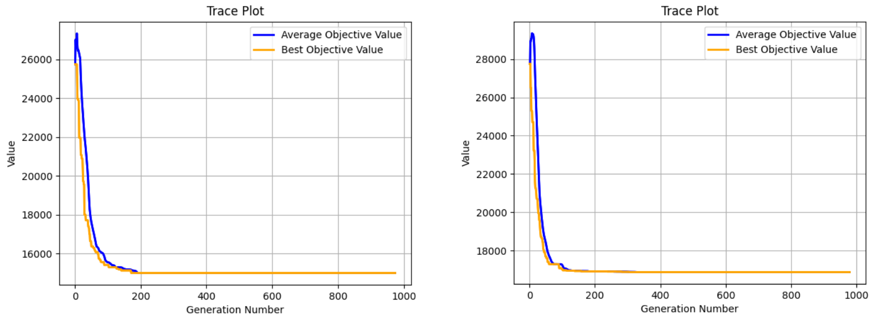
Table 5. Empty container substitution cost (CNY/CTN)

Supply station	**Demand station**			
	B_1	B_2	B_3	B_4
A_1	366	281	224	290
A_2	250	275	149	105
A_3	161	33	95	233

A_4	68	179	90	149

5.2. Solution Process

Using the genetic algorithm solution steps, ECR was performed for an 8-station network. When the initial population size N_p=500N, crossover probability P_c=0.8, mutation probability P_m=0.1, and the number of algorithm iterations *gen*=1000, the performance was found to be optimal. Computer simulations were conducted using Python software, and the convergence behavior of the algorithm under scenarios with and without container substitution is shown in Figure 3. As observed in the figure, the algorithm exhibits a fast convergence rate, with significant convergence occurring around the 200th generation. The convergence speed in the scenario without container substitution is faster compared to the scenario with substitution.



(a) (b)

Figure 3. Iterative convergence diagram of the genetic algorithm: (**a**) Iterative convergence diagram of the algorithm under empty container substitution; (**b**) Iterative convergence plot of the algorithm under empty container non-substitution.

A computer simulation of the above example is carried out to analyze the results of the calculations in terms of the repositioning scheme corresponding to one of the solutions.

Separate orders:

$$f_1 = \sum_i \sum_j \sum_k x_{ij}^k c_{ij}^k \text{, } f_2 = \sum_i \sum_j \sum_k x_{ij}^k \beta_{ij}^k$$

$$f_3 = \sum_i \sum_j \sum_k x_{ij}^k \left(u_j^k \max\left\{ e_j^k - T_j^k, 0 \right\} + v_j^k \max\left\{ T_j^k - l_j^k, 0 \right\} \right)$$

Based on the results of Python operations, the cost of each part of the optimal solution in the case of substitution and non-substitution of empty containers is obtained as shown in Table 6, and the repositioning scenarios are shown in Tables 7 and 8.

Table 6. Cost of each part of the optimal solution for substitution and non-substitution cases (CNY)

	f_1	f_2	f_3	F
Type of container substitution	12066	1639	1305	15010
Type of container non-substitution	15206	0	1679	16885

Table 7. Repositioning scheme under the substitution of container types (CTN)

Handling station	Repositioning of U_1 containers				Repositioning of U_2 containers				U_2 Substitute U_1 container			
	B_1	B_2	B_3	B_4	B_1	B_2	B_3	B_4	B_1	B_2	B_3	B_4
A_1	0	2	0	4	0	0	2	4	0	0	0	0
A_2	1	1	6	9	2	0	3	9	0	0	0	2

A_3	1	13	1	0	9	5	7	0	0	2	1	0
A_4	12	0	5	4	10	5	0	2	16	0	2	0

Table 8. Repositioning scheme under the non-substitution of container types (CTN)

Handling station	Repositioning of U_1 containers				Repositioning of U_2 containers			
	B_1	B_2	B_3	B_4	B_1	B_2	B_3	B_4
A_1	12	9	5	3	0	0	0	0
A_2	7	4	0	6	0	0	0	15
A_3	1	3	10	1	0	10	0	0
A_4	10	2	0	9	21	0	12	0

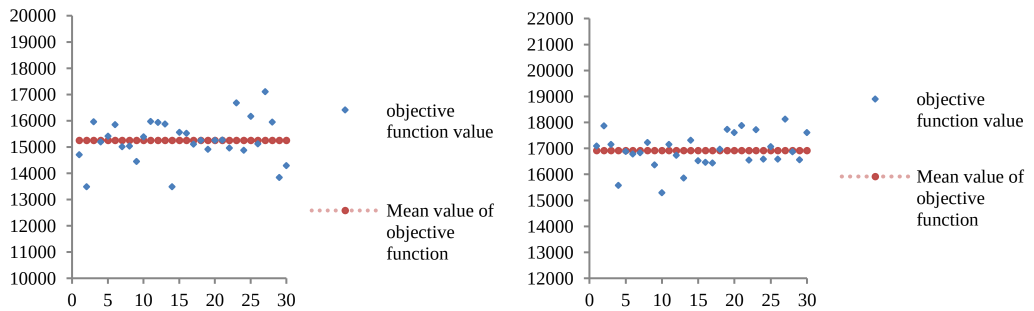
5.3. Analysis of Results

The simulation case study was solved using Python, effectively validating the rationality of the model and algorithm. The optimization of railway ECR was conducted considering time-window constraints and container substitution, resulting in an optimal repositioning scheme that satisfies the objective function and its constraints. Multiple computer simulations were conducted to verify the feasibility of the proposed scheme. The key parameters for the genetic algorithm were set as follows: initial population size N_p=500, crossover probability P_c=0.8, mutation probability P_m=0.1, and the number of algorithm iterations gen=1000. Notably, the solution began to converge significantly around the 200th iteration.

(1) Heuristic Algorithm Efficiency

The genetic algorithm is a heuristic algorithm that seeks the optimal solution within the current population in each iteration. However, in an uncertain environment, the railway ECR optimization problem cannot guarantee that every solution obtained is the global optimum. Therefore, the case study was run 30 times randomly, and a scatter plot of the objective function values from these 30 runs was generated to observe the variations between the results with and without container substitution, as shown in Figure 4. From the figure, it can be observed that the optimal objective values obtained from 30 Python simulation runs exhibit minimal differences and fluctuate uniformly around a straight line. This indicates that the proposed transportation scheme is reasonable and demonstrates good stability.

In conclusion, the feasibility of the model has been validated, and multiple trials confirmed the effectiveness of the genetic algorithm in solving the proposed model.



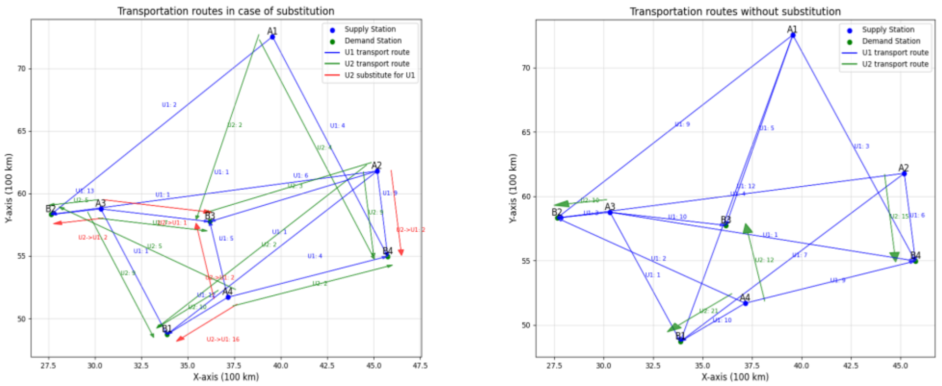
(a) (b)

Figure 4. Scatterplot of objective function values for 30 runs of the algorithm: **(a)** Scattered distribution of objective function values under empty container substitution; **(b)** Scattered distribution of objective function values under empty container no-substitution.

(2) Routing Analysis

The transportation paths for ECR under scenarios with and without substitution are illustrated in Figure 3. Circles represent supply or demand station points, and directed lines represent ECR paths. Blue lines indicate the repositioning paths for U_1 containers, green lines represent the repositioning paths for U_2 containers, and red lines show the paths where U_2 substitutes for U_1 containers. Taking station A_2 as an example under the container substitution scenario, this supply station transports both U_1 and U_2 containers to demand stations B_1, B_3, and B_4, while only U_2 containers are transported to B_2. Additionally, U_2 containers are used as substitutes for U_1 containers in the repositioning to B_4.

From the ECR path diagram, it is evident that the transportation scheme does not involve detours, indicating that the scheme is reasonable. In the non-substitution scenario, there are instances of long-distance transportation, such as the repositioning of U_1 containers from supply station A_1 to demand station B_1, which represents the longest distance between two stations. However, in the substitution scenario, no such long-distance repositioning occurs. Clearly, container substitution reduces long-distance transportation and optimizes the transportation paths.



(a) (b)

Figure 3. Empty container transportation route map: **(a)** Transportation path diagram with container substitution;**(b)** Transportation path diagram non-container substitution

(3) Optimal Objective Value and Cost Comparison

To evaluate the effectiveness of the container type substitution strategy, the model was run under two scenarios: with substitution and without substitution. Table 9 presents the optimal solution for a typical case and compares the average costs over 30 random iterations for each scenario. It was observed that introducing container substitution reduced the total transportation cost from 16,885 CNY to 15,010 CNY, achieving an 11.1% cost reduction. The results of multiple random experiments (container type substitution average: 15,254 CNY vs. without container type substitution average: 16,912 CNY) further demonstrate that the container type substitution strategy maintains a cost advantage under various disturbance conditions.

Table 9. Comparison of optimal solution costs between container substitution and non-substitution scenarios (CNY)

Scenarios	Optimal cost	Average value over 30 random runs
Type of container substitution	15010	15254
Type of container non-substitution	16885	16912
Reduction rate	-11.10%	-9.80%

Notably, in this case, there were five instances where U_2 containers were substituted for U_1 containers, incurring a substitution cost of 1,639 CNY. While the substitution cost accounts for a small proportion of the overall cost savings, it significantly enhanced flexible optimization at critical stations or during key time periods. This indicates that the container type substitution strategy allows for greater flexibility in equipment type allocation, particularly in situations where certain container types are scarce or long-distance transportation is uneconomical, delivering substantial economic benefits.

(4) Impact of Time Window Constraints

In ECR, some containers may arrive at demand stations either earlier or later than required, incurring inventory costs or opportunity loss costs, respectively. Table 10 presents the additional costs caused by time-window violations for the same case.

Table 10. Comparison of time-window constraint costs between container substitution and non-substitution scenarios

Scenarios	Early arrival count	Late arrival count	Additional costs for early and late arrivals
Type of container substitution	4	6	1305
Type of container non-substitution	5	5	1679
Reduction rate			-22.30%

As shown in the table, while the container type substitution scheme also involves early and late arrivals, the additional costs amount to only 1,305 CNY, compared to 1,679 CNY for the non-substitution scheme, representing a 22.3% difference. This indicates that container substitution enables certain key demand stations to utilize containers from closer or more flexible sources, thereby reducing waiting or storage times and effectively lowering time-window violation costs.

6. Discussion

In this study, we developed a railway ECR optimization model based on time-window constraints and container substitution, solved using a genetic algorithm. Through experimental simulations, we demonstrated the effectiveness of the genetic algorithm in addressing the ECR problem, identifying near-optimal repositioning schemes. Comparing scenarios with and without container substitution, we found that container substitution effectively reduces total repositioning costs and transportation expenses. Additionally, analyzing the arrival times within the specified time windows, we observed that most repositioning schemes ensured empty containers arrived within the time window, though a small number exceeded the time constraints. Therefore, to meet customer container timing requirements and minimize inventory and opportunity loss costs, further optimization is necessary to ensure that empty containers arrive within the specified time window as much as possible.

There is limited research on railway container substitution. Among the existing studies, Zhang (2015), Chang (2008), Qiao (2010), and Fan et al. (2015) investigated substitution between 20-foot and 40-foot containers. These studies concluded that container substitution can effectively reduce repositioning costs and improve transportation efficiency, which aligns with the findings of this study. Min et al. (2012) constructed a shipping container repositioning model with time-window constraints, aiming to minimize total costs. They introduced simulated annealing into the genetic algorithm to solve the model, and their case studies indicated that early and late arrivals of containers at ports incur costs. Similarly, Hu et al. (2020) considered time-window costs and minimum empty container clearance requirements between stations, constructing a bi-level programming model to optimize ECR. Their results showed that the cost of meeting minimum clearance requirements is negatively correlated with unit inventory and opportunity loss costs within the time window.

This study incorporates practical considerations and general characteristics of railway container types to analyze substitution among different containers. Additionally, the study accounts for time-window requirements, demonstrating that container substitution can effectively address scenarios where insufficient container availability or long-distance repositioning increases transportation costs. To ensure customer container timing requirements are met and to minimize early inventory and late opportunity loss costs, the repositioning scheme must be optimized to ensure container arrivals within the specified time window.

The railway ECR problem is a complex issue involving multiple factors. This study explored the uncertainty of demand timing, but the ECR system is a dynamic and uncertain complex system. In actual repositioning activities, parameters such as container demand and supply quantities, timing, and internal system influencing factors are often uncertain. Moreover, unexpected events during repositioning, such as delays caused by weather, container damage, or operational errors, may disrupt the execution of repositioning plans. These uncertainties often hinder the smooth execution of repositioning schemes as planned. Therefore, when studying and optimizing the railway ECR system, it is essential to account for and address these uncertainties to enhance the system's flexibility and robustness and ensure efficient repositioning operations.

Numerous uncertainties influence the railway ECR problem. This study focused on the uncertainty of demand timing and optimized repositioning schemes using container substitution to address customer timing requirements. Future research will further explore uncertainties related to transit times and uncertain optimization methods.

7. Conclusions

Efficient container transportation plays a vital role in supporting economic development, but imbalances in supply and demand across regions result in significant ECR challenges. This study proposes a robust optimization model for ECR that incorporates time window constraints and container type substitution. Employing a genetic algorithm, the model effectively solves the problem and offers optimal substitution strategies, as demonstrated through computational experiments.

The results reveal that the container type substitution approach not only reduces transportation costs by 11.1% compared to non-substitution but also minimizes inventory and opportunity costs by 22.3%. The substitution strategy proves particularly effective in mitigating logistical inefficiencies, such as long-distance transport, by enabling flexible container usage based on cargo characteristics. This adaptability enhances the robustness and efficiency of the transportation network, particularly in scenarios where specific container types are in limited supply or economically impractical for certain routes.

Furthermore, the study highlights that a well-designed transportation plan prioritizes timely container arrivals within prescribed time windows, thereby reducing early-arrival inventory costs and late-arrival opportunity losses. The findings also emphasize the importance of dynamic adjustments to container allocation strategies to accommodate uncertainties in demand and transport conditions.

In summary, the integration of container type substitution in repositioning strategies provides a promising pathway to optimize operational efficiency, lower costs, and improve service reliability in railway container logistics. Future research may explore the scalability of this approach in larger networks and under varying demand scenarios to further generalize its applicability.

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