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Balanced Truck Dispatching Strategy for Inter-Terminal Container Transportation with Demand Outsourcing

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Abstract

This study proposes a balanced truck dispatching strategy for inter-terminal transportation (ITT) in large ports, incorporating proactive demand outsourcing to address stochastic and imbalanced ITT demand. A portion of ITT tasks are intentionally outsourced to third-party public trucks at a higher cost, so that self-owned trucks can be reserved for more critical tasks. The ITT system is modeled as a closed Jackson network, in which self-owned trucks circulate among terminals and routes. An optimization model is developed to determine the optimal proactive outsourcing ratios for origin–destination terminal pairs and the appropriate fleet size of self-owned trucks, aiming to minimize total transportation costs. Reactive outsourcing is also included to handle occasional truck shortages. A mean value analysis method is used to evaluate system performance with given decisions, and a differential evolution algorithm is employed for optimization. The case study of Shanghai Yangshan Port demonstrates that the proposed strategy reduces total system cost by 9.8% compared to reactive outsourcing. The results also highlight the importance of jointly optimizing outsourcing decisions and fleet size. This study provides theoretical insights and practical guidance for ITT system management under demand uncertainty.

Keywords: inter-terminal transportation; outsourcing; truck dispatching; closed Jackson network; port logistics

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1. Introduction

The continuous growth of global containerized shipping has driven the expansion of major ports worldwide. Large ports usually consist of multiple seaside terminals serving mega vessels, along with value-added facilities such as rail yards and warehouses located on the landside. The transfer of containers between shipping lines and transport modes gives rise to inter-terminal transportation (ITT), which refers to the movement of containers among terminals and facilities within the same port [1,2]. Trucks are the most representative tool for ITT due to their high maneuverability and operational flexibility.

ITT systems are typically managed by the port authority, which employs a fleet of self-owned trucks to serve ITT tasks as they arise. ITT tasks are generated in real time, influenced by many stochastic factors, such as vessel arrivals and departures, cargo inspections, and yard congestion. To reduce empty trips and improve truck utilization, the port authority tends to assign an ITT task to an idle self-owned truck located at, or near, the terminal where the container is released. The dispatching strategy adopted is critical to the overall efficiency of the ITT system.

The directional imbalance of ITT demand poses challenges to system management. Certain terminals generate significantly more outbound ITT tasks than inbound ones, or vice versa, leading to truck accumulation at some terminals and shortages at others. As a result, some terminals may experience congestion due to idle trucks, while others suffer from service delays due to truck unavailability. When the number of available self-owned trucks is insufficient, the port authority may outsource part of the tasks to third-party public trucks at a higher price to avoid late delivery.

Existing studies on ITT management mainly focus on optimizing truck operations through flow assignment, vehicle routing, or dispatching methods. While these techniques help improve the utilization of self-owned trucks, the potential of using public trucks as a supplementary transportation resource has received limited attention in the literature. In practice, outsourcing decisions are typically made in a reactive manner, triggered by temporary shortages of self-owned trucks rather than being incorporated into an integrated truck dispatching strategy.

This study proposes a novel truck dispatching strategy for ITT by incorporating demand outsourcing as a proactive decision. The port authority predetermines outsourcing ratios for ITT tasks between different origin–destination (OD) terminal pairs. Each ratio indicates the proportion of tasks assigned to a public truck, with the remaining tasks transported by self-owned trucks. By proactively adjusting task assignments on selected OD pairs, the system can achieve a more balanced spatial distribution and improved utilization of self-owned trucks, thereby reducing total transportation costs. To identify the optimal strategy, an optimization model is developed in which the ITT system is modeled as a closed Jackson network to capture system stochasticity.

The adoption of a closed Jackson network model is motivated by the operational characteristics of the ITT system. Specifically, the self-owned truck fleet functions as a closed-loop resource: trucks circulate exclusively within the port area, continuously performing ITT tasks without entering or exiting the system. The idle time of a truck depends on the stochastic generation rate of new tasks at each terminal. Therefore, we model self-owned trucks as circulating customers and terminals/routes as service nodes. This formulation avoids the explicit modeling of exogenous task arrivals and instead focuses on the internal dynamics of the self-owned truck fleet. It facilitates the analysis of how proactive outsourcing decisions reshape truck flow distributions and enhance system performance. Though queuing networks have been adopted in the analysis of bike-sharing systems [3,4], ride-hailing or taxi systems [5,6], and ITT systems with exogenous demand distributions [7], their application to proactive demand outsourcing remains underexplored. This study integrates outsourcing decisions into the queuing network framework, providing insights into optimizing truck flows under demand imbalance and operational uncertainty.

The rest of this paper is organized as follows. Section 2 reviews related works regarding ITT management. Section 3 introduces the truck dispatching strategy and optimization methods. The proposed model and algorithms are then validated using real-world data from Shanghai Yangshan Port in Section 4. Finally, Section 5 concludes this paper and discusses directions for future research.

2. Literature Review

ITT refers to the movement of cargo among spatially separated areas within a port [1,2]. Research on ITT mainly falls into two categories: strategic system planning and operational decision-making.

At the strategic level, studies focus on infrastructure layout planning, truck fleet configuration, and resource sharing across facilities. Simulation-based evaluation approaches are widely adopted to analyze the performance of ITT systems under various predetermined configurations of terminals, fleets, and transfer facilities [8–11]. In terms of mathematical modeling, Tierney et al. [12] were the first to propose a multi-commodity flow assignment model on a spatiotemporal network, in which the moving and waiting processes of trucks are represented as flow volumes on arcs. This framework has been extended to incorporate inland railway terminals, where train timetables should be jointly considered [13,14], and container warehouses, which involve coordination with third-party public truck operations [15]. Beyond deterministic flow-based models, stochastic models based on queuing theory offer a tool for evaluating the performance of ITT systems under uncertainty. Mishra, Roy, and van Ommeren [7] proposed a queuing network model to quantify key performance measures, like container throughput and vehicle utilization, with respect to fleet size, vehicle type, and dwell point strategies.

ITT management at the operational level mainly concerns truck routing and dispatching decisions. Heilig et al. [16] proposed a customized vehicle routing problem (VRP) model that integrates three objectives, fleet size, total cost, and emissions, and employed a heuristic algorithm to approximate the Pareto frontier. Heilig et al. [17] designed an online platform that activates a built-in VRP model once sufficient ITT tasks have been accumulated. The optimized routing instructions are communicated to truck drivers via a mobile application. Unlike routing models that determine a sequence of locations for each truck to visit, dispatching methods focus on assigning high-frequency and time-sensitive tasks to available trucks in real time, based on the current system state. Adi et al. [18] applied deep reinforcement learning to dynamically dispatch idle trucks among multiple task options, including serving a random container, the nearest container, the most urgent container, or choosing to remain idle. Ji et al. [19] inserted battery charging tasks for electrified ITT trucks into the container transport process. Their algorithm enables real-time decisions on charging time, location, and service sequence, aiming to coordinate container delivery with energy replenishment operations.

Existing studies focus mainly on optimizing the utilization and routing processes of self-owned truck fleets, while the potential of proactive outsourcing strategies involving third-party public trucks has received limited attention. Practical dispatching approaches typically respond reactively to temporary truck shortages rather than integrating outsourcing decisions into a unified scheduling framework in advance. In addition, published models usually assume deterministic demand and truck operation times, which may oversimplify the stochastic nature of ITT operations. To address these gaps, this study proposes a novel truck dispatching framework that incorporates proactive outsourcing ratios as decision variables, enabling more effective spatial and temporal balancing of truck resources, and thus improves the system efficiency.

3. Methodology

3.1. Problem Description

Figure 1 illustrates the advantage of the proposed proactive outsourcing strategy through a simplified example involving three terminals. Initially, five self-owned trucks are available at Terminal A. Under the traditional dispatching strategy, self-owned trucks are prioritized to serve ITT tasks generated at their current terminal, i.e., Terminal A. Consequently, two ITT tasks from Terminal A to C are reactively outsourced to public trucks in Phase 2 due to the unavailability of self-owned trucks. In contrast, the proactive outsourcing strategy assigns two ITT tasks to public trucks in Phase 1, thereby reserving sufficient self-owned trucks for long-distance tasks from Terminal A to B in Phase 2.

Although both strategies require two tasks to be outsourced, the difference in transport distance leads to varying total costs: 275 units under the proactive strategy versus 345 units under the traditional one. This example illustrates the cost-saving potential of proactive outsourcing, which motivates the development of a stochastic optimization model in this study.

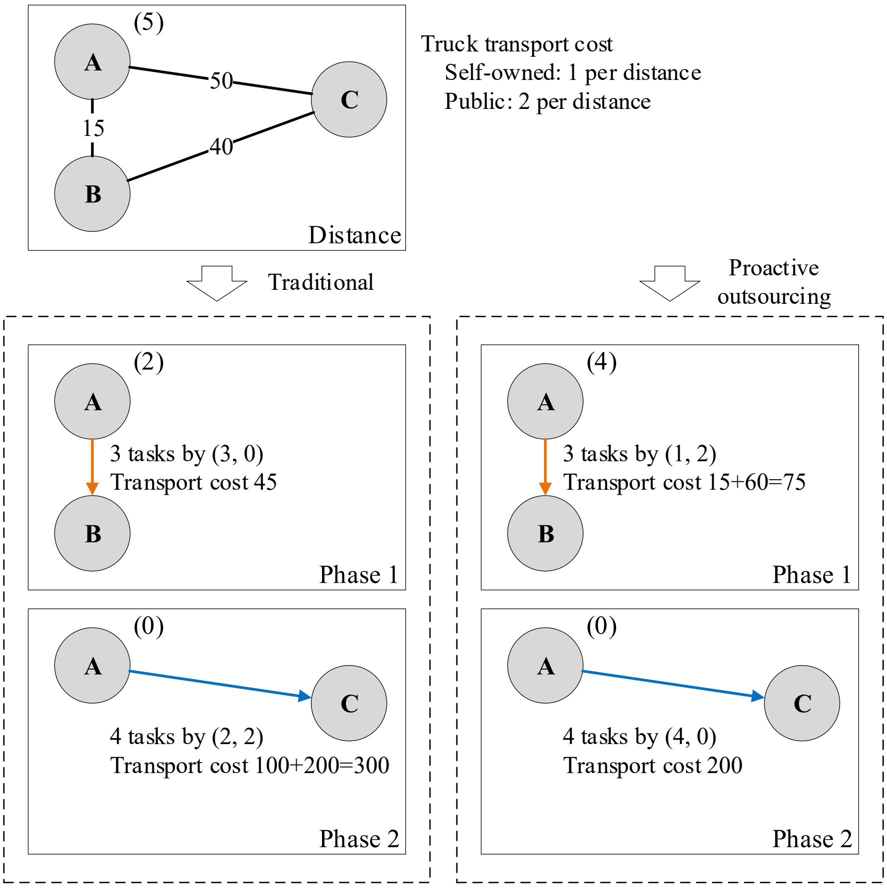

Figure 1. An illustrative example. The first and second numbers in round brackets denote the numbers of self-owned and public trucks, respectively.

We define the sets, parameters, and decision variables in Table 1, where bold symbols denote sets or vectors.

The ITT system is modeled as a closed Jackson network, where self-owned trucks circulate among terminals to transport containers. The following assumptions are made to facilitate model formulation:

- Task generation. ITT tasks are generated in real time and follow a Poisson process, which is a standard assumption for modeling randomly occurring tasks driven by independent external factors like vessel arrivals, yard operations, and customs inspection requirements [7]. Each task is associated with a specific OD terminal pair, and the demand is exogenously given.
- Truck dispatching. Upon generation, a task can either be proactively outsourced to a public truck or assigned to a self-owned truck that is idle at the origin terminal. If no self-owned truck is available at the origin terminal, the task must be reactively outsourced. Public trucks are assumed to be always available upon request.
- Truck operations. Each self-owned truck begins idle at a terminal. Once dispatched, it completes a cycle consisting of (1) picking up the container at the origin terminal, (2) transporting it to the destination terminal, and (3) parking and waiting at the destination terminal for the next task.

Table 1. Notations used in the formulation.

Input Sets and Parameters	
$\boldsymbol{T}$	Set of terminals. Let $\mid \boldsymbol{T} \mid$ be the number of terminals.
$\boldsymbol{R}$	Set of routes, each connecting two terminals. Let $\mid \boldsymbol{R} \mid$ be the number of routes.
$\boldsymbol{N}$	Set of nodes, including terminals and routes, i.e., $\boldsymbol{N} = \boldsymbol{T} \cup \boldsymbol{R}$. Let $\mid \boldsymbol{N} \mid$ be the number of nodes.
d_i	Generation rate of ITT tasks originated from terminal i.
r_{ij}	Proportion of ITT tasks from terminal i to j, to the total generation rate d_i.
h_i	Capacity for self-owned trucks at terminal i.
a_r	Road capacity for self-owned trucks on route r.
b_r	Average travel time on route r.
g_{ij}	Transport cost of a self-owned truck from terminal i to j.
e_{ij}	Outsourcing fee of a public truck from terminal i to j.
p_i	Penalty per truck for congestion at terminal i.
M	A large positive integer.
Parameters for the Closed Jackson Network	
γ_{ij}	Proportion of self-owned trucks from node i to j, to the total outflow from node i.
c_i	Number of servers at node i.
μ_i	Service rate for each server at node i.
v_i	Arrival ratio, i.e., proportion of self-owned truck arrival rate at node i to the system throughput.
Intermediate Variables	
$G(q)$	Self-owned truck throughput over the entire system when the fleet size is q.
$\lambda_i(q)$	Average self-owned truck arrival rate into node i when the fleet size is q.
$L_i(q)$	Expected number of self-owned trucks presented at node i when the fleet size is q.
$W_i(q)$	Average waiting time of self-owned trucks at node i when the fleet size is q.
$\pi_i(t,q)$	Probability of t self-owned trucks presented at node i when the fleet size is q.
$\boldsymbol{n}$	State vector of the network, $\boldsymbol{n} = (n_1, \ldots, n_N)$ and n_i is the number of self-owned trucks at node i.
$f_i(t)$	Unnormalized steady-state probability at node i when the number of self-owned trucks is t.
$L(q)$	Normalization constant, which ensures that the sum of the probabilities of all possible states equals 1.
Decision Variables	
s_{ij}	Proportion of outsourced tasks from terminal i to j, to the total generation rate d_i.
F	The fleet size of self-owned trucks.

The closed Jackson network representation of the ITT system is illustrated in Figure 2. The modeling approach is inspired by Vishkaei et al. [20], who adopted the closed Jackson network for analyzing an urban shared bike system. The network consists of two types of nodes: terminal nodes and route nodes. Each terminal node is modeled as a single-server queuing system where self-owned trucks wait in a queue for new tasks, with a service rate equal to the rate of task generation d_i. Each route node represents a direct connection between two terminals and is modeled as a multi-server queuing system, where the service rate for each server corresponds to the travel time. That is,

$$c_i = \begin{cases} 1 & i \in \boldsymbol{T} \\ a_i & i \in \boldsymbol{R} \end{cases} \tag{1}$$

$$\mu_i = \begin{cases} d_i & i \in \boldsymbol{T} \\ 1/b_i & i \in \boldsymbol{R} \end{cases} \tag{2}$$

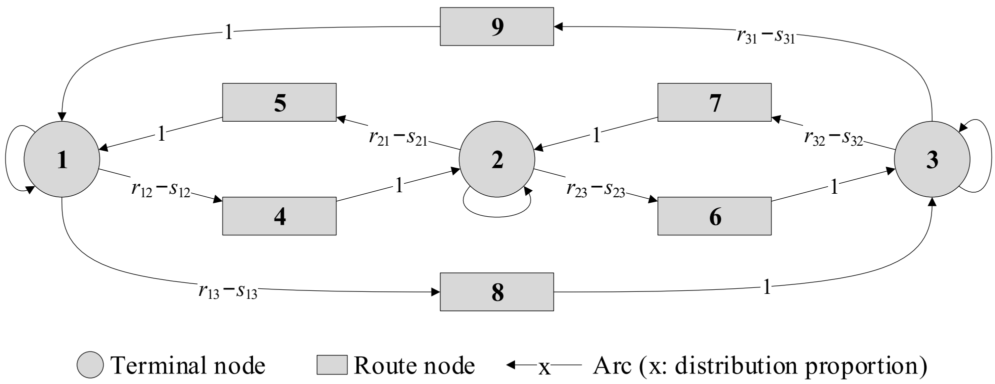

Figure 2. An illustrative closed Jackson network for ITT with three terminals.

The distribution proportions of self-owned trucks among nodes γ_{ij} are generated according to the modified flow distributions among terminals (i.e., $r_{ij} - s_{ij}$). These values can be calculated either manually or through automated scripts [20], based on the connectivity among terminals and their associated routes. For example, in Figure 2, terminal 1 is connected to terminal 2 via route 4; thus $\gamma_{14} = r_{12} - s_{12}$ and $\gamma_{42} = 1$.

The arrival ratios v_i are obtained by solving the flow conservation constraints defined in Equation (3), which consist of $|\boldsymbol{N}|$ variables and $|\boldsymbol{N}|$ equations, with one equation being linearly dependent. Therefore, an additional Equation (4) is introduced to ensure the uniqueness of the solution by normalizing the total throughput of truck flows in the system to one.

$$v_i = \sum_{j \in \boldsymbol{N}} v_j \gamma_{ji} \quad i \in \boldsymbol{N} \tag{3}$$

$$\sum_{i \in \boldsymbol{N}} v_i = 1 \tag{4}$$

Without outsourcing, self-owned trucks are dispatched directly in response to task generation. The demand outsourcing strategy proactively adjusts the dispatching rate of self-owned trucks across OD pairs, thereby altering the truck flow distribution in the network.

3.2. Model Formulation

Based on the closed Jackson network, this study proposes an optimization model to determine the proactive outsourcing ratio s_{ij} for each OD pair, as well as the appropriate fleet size for self-owned trucks. From the perspective of the port authority, the objective is to minimize the total ITT cost, including the following:

1. Operating cost of self-owned trucks;
2. Reactive outsourcing cost, when no self-owned truck is available at the origin terminal and the task must be assigned to a public truck with a higher fee;
3. Proactive outsourcing cost, incurred for tasks intentionally assigned to public trucks based on the optimized outsourcing rate;
4. Penalty cost for terminal congestion, i.e., when the number of self-owned trucks at a terminal exceeds the capacity.

The mathematical formulation is presented as follows:

$$\begin{aligned} \text{minimize} & \sum_{i \in \boldsymbol{T}} \sum_{j \in \boldsymbol{T}} g_{ij} \cdot d_i \cdot \left(R_{ij} - s_{ij}\right) \cdot \sum_{t=1}^{M} \pi_i(t, Q) \\ & + \sum_{i \in \boldsymbol{T}} \sum_{j \in \boldsymbol{T}} e_{ij} \cdot d_i \cdot \left(R_{ij} - s_{ij}\right) \cdot \pi_i(0, Q) \\ & + \sum_{i \in \boldsymbol{T}} \sum_{j \in \boldsymbol{T}} e_{ij} \cdot d_i \cdot s_{ij} \\ & + \sum_{i \in \boldsymbol{T}} \sum_{t=h_i+1}^{M} p_i \cdot (t - h_i) \cdot \pi_i(t, Q) \end{aligned} \tag{5}$$

s.t.

$$F \leq \sum_{i \in \boldsymbol{T}} h_i \tag{6}$$

$$s_{ij} \leq R_{ij} \quad i, j \in \boldsymbol{T} \tag{7}$$

$$s_{ij} \geq 0 \quad i, j \in \boldsymbol{T} \tag{8}$$

$$F \in \boldsymbol{Z}_+ \tag{9}$$

The objective Function (5) captures the four components of the total ITT cost, where $\pi_i(t,Q)$ denotes the probability that t self-owned trucks are available at terminal i, given a total fleet size Q. The detailed computation of $\pi_i(t,Q)$ is introduced in Section 3.3.1. Constraint (6) ensures that the total number of self-owned trucks does not exceed the aggregated capacity across all terminals. Constraint (7) defines the feasible domain of the number of outsourcing tasks. Constraints (8) and (9) define types for decision variables.

3.3. Solution Method

This section first introduces the computation method of $\pi_i(t,Q)$, given the necessary parameters of the queuing systems (e.g., arrival and service rates). Then a heuristic algorithm is adopted for solving the optimization model.

3.3.1. Mean Value Analysis Method

Consider a closed Jackson network with $|\boldsymbol{N}|$ nodes, where Q customers (i.e., self-owned trucks) circulate within the system. The service rate for each server at node i is μ_i, and the number of servers is c_i. After leaving node i, a truck transitions to node j with probability γ_{ij}. The steady-state probabilities of the system have a product form:

$$\pi(\boldsymbol{n}) = \frac{1}{L(Q)} \prod_{i \in \boldsymbol{N}} f_i(n_i) \tag{10}$$

where $\boldsymbol{n} = (n_1, \ldots, n_N)$ is the state vector (n_i is the number of trucks at node i). The $f_i(n_i)$ is the unnormalized steady-state probability at node i:

$$f_i(n_i) = \begin{cases} \frac{(\lambda_i/\mu_i)^{n_i}}{n_i!} & n_i \leq c_i \\ \frac{(\lambda_i/\mu_i)^{n_i}}{c_i! c_i^{n_i - c_i}} & n_i > c_i \end{cases} \tag{11}$$

Here, $\lambda_i = v_i G(q)$, where $G(q)$ is the system throughput and v_i is the arrival ratio of node i that satisfies $v_i = \sum_{j \in \boldsymbol{N}} v_j \gamma_{ji}$.

$\pi_i(t,Q)$ is the sum of the probabilities of all possible states when t is fixed in the system state $\boldsymbol{n} = (n_1, \ldots, n_N)$. Substituting the steady-state probabilities of the system formula, we obtain the following calculation formula:

$$\pi_i(t, Q) = \frac{1}{L(Q)} \sum_{\boldsymbol{n}: n_i = t, \sum_{j \in \boldsymbol{N}} n_j = Q} \prod_{j \in \boldsymbol{N}} f_j(n_j) \tag{12}$$

where $L(Q)$ is a normalization constant, calculated as follows:

$$L(Q) = \sum_{\boldsymbol{n}: \sum_{i \in \boldsymbol{N}} n_i = Q} \prod_{j \in \boldsymbol{N}} f_j(n_j) \tag{13}$$

To calculate $L(Q)$, it is necessary to traverse all states of the system, which involves a huge number of computation processes. Therefore, we adopt the mean value analysis (MVA) method, which is recognized as an efficient recursive algorithm. It can directly calculate probabilities such as $\pi_i(t,q)$ and network performance metrics, thereby effectively avoiding the high computational cost of the normalization constant $L(Q)$.

The MVA method starts by assuming zero self-owned trucks in the network. When a new truck is added, the algorithm updates state indicators (i.e., queue lengths, waiting times, and arrival rates) based on the service parameters (e.g., service rates and flow distributions) and the results from the previous iteration. The MVA method iterates over the number of self-owned trucks in the system. The computational procedure is presented in Table 2.

Table 2. Pseudocode of the MVA method.

Input: presented number of self-owned trucks t, given the fleet size q. $t \leq q$. Output: probability $\pi_i(t,q)$.
for $i = 1 : \lvert \boldsymbol{N} \rvert$ $L_i(0) = 0$ $W_i(0) = 0$ $\pi_i(0,0) = 1$ end for for $m = 1$:q for $i =$:$\lvert \boldsymbol{N} \rvert$ $W_i(m) = \frac{1}{\mu_i c_i}\left(1 + L_i(m-1) + \sum_{k=0}^{c_i-1}(c_i - 1 - k)\pi_i(k, m-1)\right)$ $G(m) = \frac{m}{\sum_{i \in N} v_i W_i(m)}$ $\lambda_i(m) = v_i G(m)$ $L_i(m) = \lambda_i(m) W_i(m)$ for $t = 1$:m $\pi_i(t,m) = \frac{\lambda_i(m)}{\mu_i \min(t, c_i)} \pi_i(t-1, q-1)$ end for end for end for

3.3.2. Differential Evolution Algorithm

This study adopts the well-known modified differential evolution (DE) algorithm [21] to solve the proposed model. As a population-based metaheuristic, DE is known for its simplicity and effectiveness in handling complex and non-differentiable objective functions. In the proposed model, the objective Function (5) includes the term $\pi_i(\cdot)$, which is evaluated through the MVA method described in Section 3.3.1.

As illustrated in Figure 3, the algorithm iteratively improves a population of candidate solutions by applying mutation, crossover, and selection operators through evolutionary processes. Each candidate solution is encoded as a vector of decision variables, including the fleet size q and proactive outsourcing rates s_{ij} ($i \neq j$), that is, a solution x = [q, s_{12}, s_{13}, … s_{ij}, …$s_{T,T-1}$]. The algorithm terminates when (1) the number of iterations exceeds a predefined maximum threshold or (2) the objective value does not improve over a specified number of consecutive generations. The exogenous parameters for the algorithm are presented in Table 3.

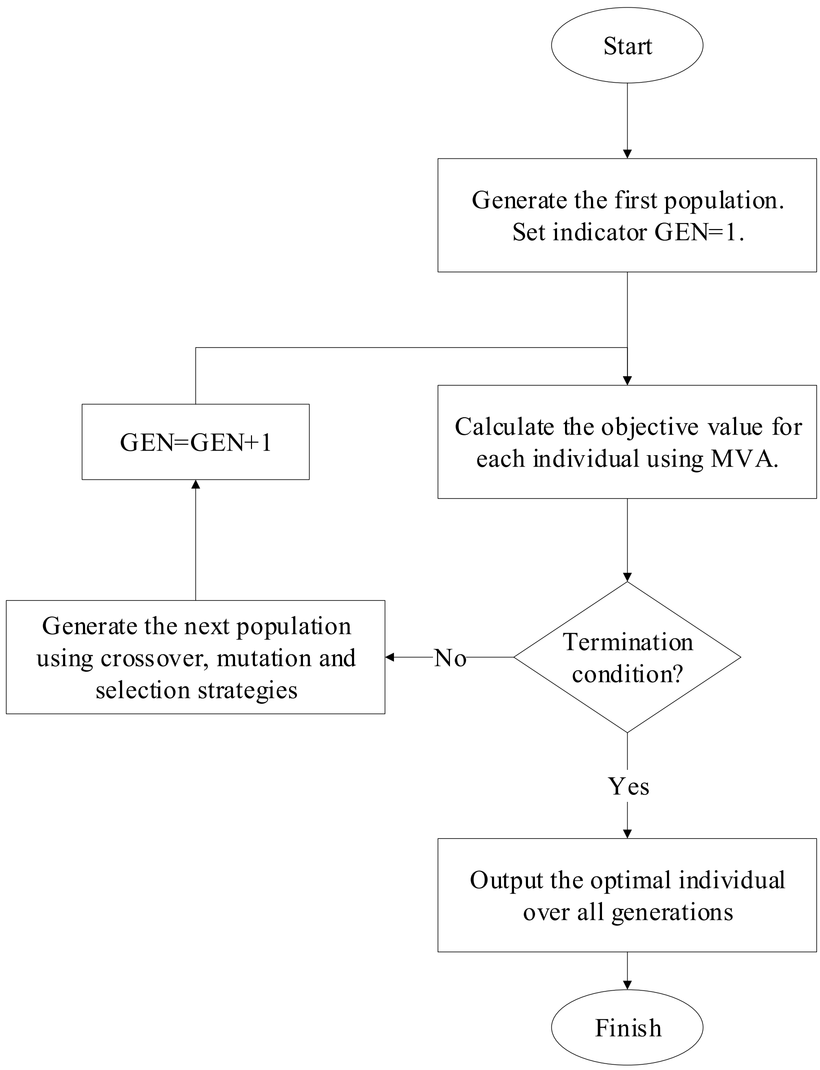

Figure 3. Flowchart of the DE algorithm.

Table 3. Parameters for the DE algorithm.

Parameter	Value
Population size	20
Variant scaling factor	0.5
Crossover fraction	0.75
Maximum generations	2000
Maximum generations without improvement	200

3.4. Implementation in Practice

Although the proposed model is designed for strategic planning by determining the optimal fleet size and outsourcing task amount, it can also support real-time operational management. Here, we provide a rule-based implementation method for illustration. For each newly generated ITT task with OD terminal pair (i, j), the port authority refers to the planned outsourcing proportion s_{ij} and calculates the probability s_{ij}/r_{ij}, with which the task is immediately outsourced to a public truck, even if idle self-owned trucks are available. This allows the system to reserve self-owned trucks for future tasks that may yield higher utility. If no self-owned truck is available, the task is reactively outsourced.

4. Case Study

4.1. Case Setup

The proposed methodology is evaluated numerically based on the real-world case of Shanghai Yangshan Port. As shown in Figure 4, the study area includes four terminals: three deep-sea terminals located on the islands and one inland terminal in the hinterland. Average travel times between terminals and container handling times at terminals are estimated using operational data provided by the port authority.

Figure 4. Study area: Shanghai Yangshan Port.

Table 4 presents the container transportation demand between terminals. The travel times and self-owned truck transport costs are reported in Table 5. Outsourcing costs of public trucks are set to 1.9 times those of self-owned trucks. The port authority currently operates a fleet of around 300 self-owned trucks to handle ITT tasks and aims to determine the optimal outsourcing strategy and fleet size for daily operation. The congestion thresholds for terminals T0 to T3 are set to 30, 30, 25, and 25, respectively, based on the available parking spaces at each terminal.

Table 4. Container transport demand between terminals (containers/h).

Origin	Destination				Generation
	T0	T1	T2	T3	
T0	0	188	165	181	534
T1	121	0	70	81	272
T2	149	96	0	92	337
T3	119	73	66	0	258

Table 5. Travel times (min) and self-owned truck transport costs (CNY) between terminals.

Origin	**Destination**			
	T0	**T1**	**T2**	**T3**
T0	0, 0	47.0, 136.9	49.0, 143.1	49.0, 156.0
T1	47.0, 143.9	0, 0	6.7, 33.2	3.4, 46.0
T2	49.0, 153.6	6.7, 36.6	0, 0	4.3, 13.2
T3	49.0, 166.1	3.4, 49.2	4.3, 12.5	0, 0

4.2. Results and Discussion

The results are summarized in Table 6, which compares the system performance under three scenarios:

- Benchmark: Reactive outsourcing. The fleet size of self-owned trucks is fixed at its current value (i.e., 300 trucks). ITT tasks may be outsourced reactively but proactive outsourcing is not allowed.
- Alternative: Proactive outsourcing with fixed fleet size. The fleet size remains fixed, while the proactive outsourcing proportions are optimized.
- Proposed: Proactive outsourcing with variable fleet size. Both the fleet size and outsourcing rates are jointly optimized using the proposed model and algorithm.

Table 6. Results of the proposed strategy compared with two alternatives.

	Benchmark	**Alternative**	**Proposed**
Objective: total cost	196,918.1	183,402.1 (−6.9%)	177,645.9 (−9.8%)
- self-owned trucks	115,644.6	128,005.6	128,829.5
- reactive outsourcing	73,704.2	3973.5	25,083.6
- proactive outsourcing	/	45,255.9	22,514.5
- congestion penalty	7569.3	6167.1	1218.3
Fleet size	300	300	107
Outsourcing ratios s_{ij}/r_{ij}			
- T0 to T1	/	45.9%	34.3%
- T0 to T2	/	2.9%	/
- T0 to T3	/	26.0%	/
- T1 to T0	/	/	/
- T1 to T2	/	25.6%	/
- T1 to T3	/	16.3%	/
- T2 to T0	/	/	/
- T2 to T1	/	29.3%	/
- T1 to T3	/	50.5%	70.5%
- T3 to T0	/	/	/
- T3 to T1	/	/	/
- T3 to T2	/	19.7%	/

Note: Percentages in brackets indicate the change from the Benchmark scenario. "/" means proactive outsourcing is not applicable.

As shown in the table, the Proposed strategy achieves the lowest total cost among all three scenarios. Compared to the Benchmark, it reduces total system cost by 9.8%, mainly through a reduction in the reactive outsourcing cost. The Alternative scenario achieves partial improvements by reallocating transport demand more efficiently via outsourcing, but its performance is limited by the fixed fleet size.

The results highlight the efficiency of joint optimization of outsourcing ratios and fleet size. The Proposed scenario operates a smaller self-owned truck fleet than the Alternative scenario, yet achieves a lower overall cost. This outcome stems from the structural assumptions of the closed Jackson network model—specifically, all self-owned trucks must circulate continuously within the system, and no vehicles can be reserved outside the network. In the Alternative scenario, although outsourcing decisions are optimized, the large fleet size leads to suboptimal internal circulation. Some self-owned trucks may accumulate at low-demand terminals, while high-demand terminals experience truck shortage, leading to increased congestion and reactive outsourcing costs. By contrast, the Proposed strategy flexibly decreases the fleet size, allowing the system to mitigate internal imbalance and concentrate outsourcing activities on critical OD pairs. As a result, only two OD pairs are partially (i.e., 34.3% and 70.5%, respectively) outsourced to public trucks in the Proposed scenario, compared to eight in the Alternative one.

Figure 5 further investigates the sensitivity of operational cost components to fleet size. When the fleet size is below 107, the total transport cost decreases as more self-owned trucks become available to handle ITT tasks that were previously outsourced to public trucks. This shift results in a moderate increase in the cost associated with self-owned truck operations, but a larger reduction in outsourcing costs. When the fleet size exceeds 107, the costs for both self-owned and outsourced trucks tend to remain stable. However, the increasing number of circulating trucks within the system raises the likelihood of terminal congestion. As a result, congestion penalties increase the total system cost beyond the optimal level.

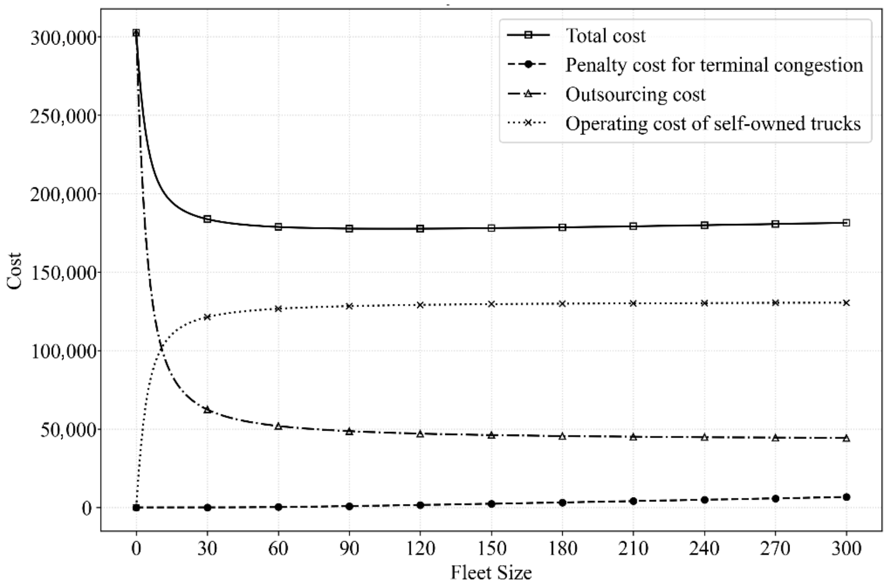

Figure 5. Operation costs with respect to the fleet size.

Figure 6 presents the utilization of each terminal with respect to fleet size, where utilization is defined as the probability that at least one self-owned truck is present at the terminal. In general, terminal utilization increases with fleet size until reaching a saturation level. When the fleet size is small, expanding the fleet effectively reduces the risk of truck unavailability at terminals, thereby lowering the likelihood of reactive outsourcing. However, once the fleet size exceeds a certain threshold, terminals begin operating at full capacity, and further fleet expansion leads to truck accumulation and congestion. Notably, the inland terminal T0 presents a lower saturated utilization (82.3%) compared to the three island terminals T1–T3 (average 99.3%). This difference is driven by the longer travel distance between T0 and the island terminals, as well as the directional imbalance in container flows across the Donghai Bridge.

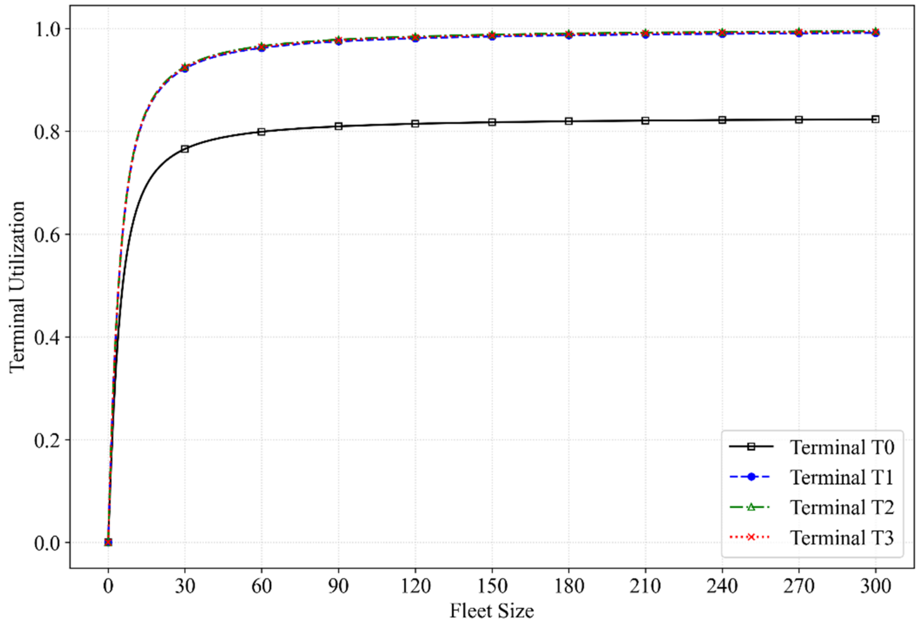

Figure 6. Terminal utilizations with respect to the fleet size.

5. Conclusions and Future Research

This paper proposes a truck dispatching strategy that integrates proactive task outsourcing for ITT in large ports, aiming to address the stochastic and imbalanced nature of ITT demand. The ITT system is modeled as a closed Jackson network, where terminals and routes are treated as service nodes and self-owned trucks as customers. A stochastic optimization model is formulated to jointly determine the optimal outsourcing ratios for OD pairs and the required fleet size of self-owned trucks, with the objective of minimizing the total system cost. The model accounts for both proactive and reactive outsourcing activities. The model is efficiently solved using a heuristic algorithm integrated with the MVA method.

The results demonstrate that incorporating proactive outsourcing decisions into the dispatching strategy can significantly reduce the total system cost, with a reduction of 9.8% observed in the presented case. By optimizing the outsourcing ratios across OD pairs, more self-owned trucks can be reserved for high-demand routes. In addition, the experiments highlight the importance of joint optimization of the fleet size and outsourcing ratios. An appropriately sized self-owned fleet helps ensure high truck utilization while avoiding both congestion and shortage.

For future research, several directions are worth exploring. First, developing a semi-open queuing network model for the ITT system may better capture the interaction between container flows and truck dispatching. However, such a model would require more detailed representations of task arrivals and truck movements, significantly increasing modeling complexity. Second, relaxing the assumption of Poisson arrivals could improve the model's applicability to a wider range of demand scenarios. Finally, incorporating truck reallocation or planned pauses after completing tasks may further enhance system flexibility and operational performance.

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