A Logistics Loading Optimization Approach Considering Cargo Density Differences

Zhanxu Zhu*

Liaoning University of Engineering and Technology, School of Business Administration, Huludao, Liaoning, 125105, China
*Corresponding author: 804754444@qq.com

Abstract. In logistics loading, the heterogeneity of cargo items in weight and volume leads to inefficient resource utilization. This paper addresses a bin packing problem with dual-capacity constraints. A scalarized single-objective model is proposed to minimize container usage and reduce resource utilization imbalance. An Adaptive Density Matching Heuristic (ADMH) is developed, which categorizes cargo by density deviation and dynamically adjusts the loading strategy based on container capacity and residual space utilization. The proposed method integrates adaptive decision rules to enhance loading efficiency across different demand structures. Numerical experiments show that ADMH improves resource utilization in balanced scenarios and maintains stability under unbalanced conditions, while consistently achieving competitive performance compared with baseline methods. These results demonstrate its effectiveness and robustness for practical less-than-truckload (LTL) operations.

Keywords: Logistics Optimization, Vector Bin Packing, Density Matching, Heuristic Algorithm

1 Introduction

With the rapid development of modern logistics and the expansion of less-than-truckload (LTL) consolidation, issues such as unbalanced weight and volume resource utilization, inefficient loading of heterogeneous cargo items, and high transportation costs have become increasingly prominent. Improving container resource utilization and reducing logistics costs are critical to enhancing operational efficiency and enterprise competitiveness. Consequently, loading optimization under dual-capacity vector bin packing frameworks has become a key research direction in intelligent logistics.

Extensive research has been conducted on vehicle and container loading optimization. For instance, Liang et al [1] proposed a size classification strategy and a hybrid heuristic for highly heterogeneous three-dimensional bin packing. Ma et al [2] designed a packing algorithm considering space utilization and vehicle center of gravity. Yang et al [3] presented a block-merging multi-objective algorithm to improve loading safety and efficiency. Ji et al[4] solved the two-dimensional loading problem for wing-opening trucks with gravity constraints using a hybrid heuristic. Wang et al [5] proposed a branch-and-price algorithm balancing heterogeneous packing costs and penalty con-

L. W. Koon et al. (eds.), *Proceedings of the 2026 7th International Conference on Management Science and Engineering Management (ICMSEM 2026)*, Advances in Economics, Business and Management Research 399,
https://doi.org/10.2991/978-94-6239-758-3_58

straints. Liao et al [6] developed a block-loading hybrid heuristic for large-scale container loading. Yang et al [7] formulated a two-stage packing model solved via column generation and branch-and-bound techniques.

The core objective of this study is to construct a logistics loading optimization model that explicitly considers cargo density differences. Furthermore, the ADMH is developed to minimize the total number of containers used and reduce container resource utilization imbalance in practical LTL scenarios.

2 Problem Description and Modeling

2.1 Description of the Problem

Given a set of heterogeneous cargo items and a fleet of identical containers with strict weight and volume capacities, cargo items must be allocated without violating dual-capacity constraints. Due to significant variance in cargo density, cargo items consume weight and volume resources asymmetrically. Optimizing solely for the number of containers used often leads to inefficient utilization of one resource dimension and premature exhaustion of the other.

Therefore, this study formulates a scalarized weighted-sum single-objective optimization model aiming to minimize both the number of containers used and the resource utilization imbalance, thereby improving overall loading efficiency.

The following assumptions are made:

(1) The number of available containers is sufficient, and all containers are homogeneous;

(2) Each item must satisfy individual weight and volume capacity constraints;

(3) Each cargo item is indivisible and assigned to exactly one container;

(4) Internal geometric packing constraints are not considered.

2.2 Description of Symbols

The symbols used in this paper are explained in Table 1 below:

Table 1. The meaning of symbols

Number	Notation	Meaning
1	S	Set of cargo items, $S = \{1,2,\dots,n\}$
2	K	Set of containers, $K = \{1,2,\dots,m\}$
3	w_i	Weight of item i
4	v_i	Volume of item i
5	Q	Maximum weight capacity of a single container
6	V	Maximum volume capacity of a single container
7	Z	Total number of containers used
8	x_{ik}	A binary variable, $x_{ik} = 1$ if item i is assigned to container k, and 0 otherwise
9	y_k	A binary variable, $y_k = 1$ if container k is used, and 0 otherwise

2.3 Mathematical Model

a) Objective Function

Minimize the number of containers used and container resource utilization imbalance:

$$\min Z = \alpha \frac{\sum y_k}{Z_{max}} + (1 - \alpha)I \tag{1}$$

where the container resource utilization imbalance index is defined as:

$$I = \frac{1}{\sum_{k \in K} y_k} \sum_{k \in K} y_k \cdot \left| \frac{\sum_{i \in S} w_i x_{ik}}{Q} - \frac{\sum_{i \in S} v_i x_{ik}}{V} \right| \tag{2}$$

Here, Z_{max} denotes an upper bound on the number of containers used, and α is a weighting parameter balancing container minimization and resource utilization imbalance. The normalization ensures comparability in scale, while α controls the trade-off within a scalarized single-objective optimization framework.

b) Constraints

Weight constraint:

$$\sum_{i \in S} w_i x_{ik} \leq Q y_k, \forall k \in K \tag{3}$$

Volume constraint:

$$\sum_{i \in S} v_i x_{ik} \leq V y_k, \forall k \in K \tag{4}$$

Assignment constraint:

$$\sum_{k \in K} x_{ik} = 1, \forall i \in S \tag{5}$$

Binary decision variables:

$$x_{ik} \in \{0,1\}, y_k \in \{0,1\}, \forall i \in S, \forall k \in K \tag{6}$$

c) Model Explanation

Equation (1) defines a composite objective that jointly minimizes the number of containers used and the imbalance between weight and volume utilization. Equation (2) quantifies the imbalance of each container by measuring the deviation between normalized weight and volume usage. Equations (3) and (4) ensure that the weight and volume constraints are satisfied for each container. Equation (5) guarantees that each cargo item is assigned to exactly one container, and Equation (6) defines the binary decision variables.

3 Heuristic Algorithm Based on Density Matching

3.1 Density Classification

To capture the resource consumption characteristics of cargo items, the density of each cargo item and the ideal state of a container are defined as:

$$\rho_i = \frac{w_i}{v_i}, \quad \rho_0 = \frac{Q}{V} \tag{7}$$

Where ρ_0 represents the theoretical optimal density, defined as the equilibrium ratio Q/V, corresponding to the state where weight and volume capacities are jointly saturated. This ratio serves as a benchmark for evaluating deviations in heterogeneous cargo item distributions.

To measure density deviation rigorously, a normalized form $\Delta\rho_i = (\rho_i - \rho_0)/\rho_0$ is introduced for each cargo item. Based on a predefined deviation threshold $\varepsilon \in (0,1)$, cargo items are classified into three categories: (1) medium-density ($|\Delta\rho_i| \leq \varepsilon$), indicating the density is close to the theoretical optimal; (2) high-density($\Delta\rho_i > \varepsilon$), meaning the density significantly exceeds ρ_0; and (3) low-density ($\Delta\rho_i < -\varepsilon$), meaning the density is significantly lower than ρ_0.

This classification enables a complementary matching strategy that improves resource coordination. In this study, the threshold ε is selected through a sensitivity-based calibration. Candidate values in [0.05, 0.30] are tested, and ε = 0.10–0.20 is adopted to ensure stable performance across different scenarios.

3.2 Dynamic Density Matching Mechanism

During the iterative loading process, the remaining resource density of the current container is defined as:

$$\rho_{res} = \frac{Q_{res}}{V_{res}} \tag{8}$$

Based on this dynamic value, an adaptive selection mechanism is applied: (1) If $\rho_{res} > \rho_0$, the container has relatively more remaining weight capacity but limited volume, thus high-density items are prioritized; (2) If $\rho_{res} < \rho_0$, the container has excess volume but limited weight, prioritizing low-density items; (3) Otherwise, medium-density items are selected. If the target density group is empty, a fallback greedy strategy is applied to maintain feasibility. This mechanism dynamically promotes the balance between weight and volume utilization, strictly aligning with the objective defined in the mathematical model.

3.3 Algorithm Procedure

The ADMH procedure is summarized as follows: Step 1. Compute item densities and classify cargo into density sets. Step 2. Initialize container set and activate the first container. Step 3. Compute ρ_{res} and select items according to the density matching rule. Step 4. Update residual capacities; if no feasible item exists, close the current container and open a new one. Step 5. Repeat Steps 3–4 until all items are assigned.

4 Simulation Example Analysis

4.1 Experimental Setup and Data Description

To evaluate the performance of the proposed ADMH, computational experiments were conducted on synthetically generated heterogeneous cargo item datasets. Two problem scales were considered: a medium-scale instance with $N = 400$ and a large-scale instance with $N = 1600$. Two density distributions were adopted to represent different levels of resource heterogeneity: a balanced density distribution (50–50) and a skewed density distribution (70–30).

The proposed ADMH was compared with three baseline strategies: Randomized packing heuristic, Volume-based greedy, and First-Fit Decreasing (FFD). The evaluation metrics included the number of containers used, container resource utilization, container resource utilization imbalance (I), and the composite objective value (Z).

4.2 Analysis of Operational Results

The experimental results under different problem scales and density distributions are summarized in Table 2.

Table 2. Optimization results of different algorithms under representative scales

Scale (N)	Distribution	Random (C/U/I/Z)	Volume (C/U/I/Z)	FFD (C/U/I/Z)	Density (Proposed) (C/U/I/Z)
400	50-50	22.40/91.18/0.107/23.47	27.80/73.56/0.464/32.44	22.00/92.79/0.056/22.56	**21.80/93.67/0.041/22.21**
400	70-30	**29.20/69.84**/0.545/**34.65**	33.20/61.45/0.708/40.28	29.60/68.90/0.544/35.04	29.60/68.90/**0.542**/35.02
1600	50-50	89.00/91.82/0.116/90.16	111.60/73.23/0.493/116.53	88.00/92.86/0.074/88.74	**85.20/95.91/0.031/85.51**
1600	70-30	**116.40/70.17/0.544/121.84**	132.80/61.51/0.710/139.90	117.40/69.57/0.548/122.88	117.80/69.34/**0.544**/123.25

Note: C, U, I, and Z denote the number of containers, utilization rate (%), imbalance metric, and objective value, respectively; N denotes the problem scale.

From Table 2, two key observations are drawn:

(1) Balanced density distributions: Under the 50–50 setting, the proposed ADMH consistently outperforms all benchmark methods across both problem scales. For N = 1600, it achieves the lowest number of containers (85.20), the highest utilization (95.91%), and the smallest imbalance (0.031), demonstrating superior efficiency in coordinating weight and volume resources. In contrast, FFD and Volume-based methods

exhibit higher imbalance values, indicating their limited capability in handling multi-dimensional resource constraints.

(2) Skewed density distributions: Under the 70–30 setting, the performance of all methods deteriorates due to increased heterogeneity in cargo density. The Volume-based method suffers from severe resource fragmentation, while FFD shows reduced efficiency due to its static sorting mechanism. The proposed ADMH maintains relatively stable performance, with comparable container usage and imbalance levels to other heuristics, indicating its robustness under skewed and more challenging conditions.

4.3 Sensitivity analysis

To evaluate the impact of the density deviation threshold ε, representative parameter settings are selected and summarized in Table 3.

Table 3. Sensitivity analysis under representative parameter settings

ε	Cont (400)	Util (400)	Imb (400)	Z (400)	Cont (1600)	Util (1600)	Imb (1600)	Z (1600)
0.05	22.00	92.65	0.044	22.44	85.00	95.82	0.035	85.35
0.10	22.00	92.65	0.040	22.40	85.00	96.07	0.035	85.35
0.30	22.00	92.55	0.042	22.42	85.00	95.82	0.033	85.33

Note: Cont, Util, Imb, and Z denote number of containers, utilization rate, imbalance, and objective value; values in parentheses indicate problem size (N = 400, 1600).

Table 3 reports the results under representative values of the density deviation threshold ε. It can be observed that the number of containers remains unchanged across all parameter settings for both problem scales, while utilization varies only marginally. The influence of ε is mainly reflected in the imbalance metric, where slight improvements are observed at $\varepsilon = 0.10$ for $N = 400$ and $\varepsilon = 0.30$ for $N = 1600$. However, these differences have negligible impact on the overall objective value. Overall, the results indicate that the proposed method is robust to parameter selection and maintains stable performance without requiring fine parameter tuning.

5 Conclusion

This study addresses a bi-objective two-dimensional vector bin packing prob-lem—aiming to minimize both container usage and resource imbalance—by formu-lating a scalarized single-objective mathematical model. The proposed ADMH solves the model. Experimental results demonstrate it improves container resource utilization and reduces cost in balanced cargo distributions, while remaining robust under skewed scenarios. In terms of scalability, framework can be extended to three-dimensional bin packing by incorporating geometric dimensions of cargo items. It can also be adapted to practical operational constraints, including stacking stability constraints, center-of-gravity balance requirements, and unloading sequence restrictions. Overall, ADMH achieves a good trade-off between solution quality and computational efficiency, making it a reliable decision-support tool for less-than-truckload logistics operations.

References

1. LIANG Zhixin, WANG Zhiwei. Enterprise logistics bin packing problem with large differences in cargo size[J]. Journal of Chongqing University.
2. MA Ying et al. 3D bin packing algorithm for solving logistics bin packing problem[J]. Science Technology and Engineering, 2025, 25(27): 11692-11704.
3. YANG Xin, LI Ming. Multi-objective optimization algorithm for 3D bin packing based on block merging strategy[J]. Packaging Engineering, 2025, 46(01): 193-202.
4. JI Jialu, WANG Haodong, JI Shengzhong, TANG Limin. Research on two-dimensional loading problem of wing-body trucks considering center-of-gravity constraints[J]. Systems Engineering — Theory & Practice, 2024, 44(10): 3451-3466.
5. WANG Sirui, WANG Lin, LIU Rui, ZENG Yurong. Research on heterogeneous cargo bin packing problem based on branch-and-price algorithm[J]. Systems Engineering — Theory & Practice, 2023, 43(10): 3040-3057.
6. LIAO Yunfeng, SHAN Hongtao, SONG Wanqing. Container loading optimization based on hybrid heuristic algorithm[J]. Manufacturing Automation, 2023, 45(05): 118-123.
7. YANG Yubing, YANG Songpo. Two-stage quadratic bin packing problem based on column generation and branch-and-bound algorithm[J]. Computer Integrated Manufacturing Systems, 2025, 31(01): 341-354.