JOURNAL OF MODERN SOCIAL SCIENCES Volume 2 Issue 1, 2025 , 56-64
ISSN (P): 3078-4433 | ISSN (O): 3078-4441 Doi:10.71113/jmss.v2i1.158

Adaptive Customization of Electronic Commerce Packaging for Sustainable Business Development

Shenglin Liu[1*], Gongchao Wan[2]

[1]*College of Science and Technology, Ningbo University, Ningbo, Zhejiang, China*
[2]*Graduate School of International, East Asian Studies , Hanyang University, Korea*
*Corresponding author: shenlyn575@gmail.com

Abstract

To address the growing demand for sustainable practices in e-commerce logistics, this research explores the innovative application of the NSGA-II algorithm for customized packaging optimization in distribution. A novel unconstraint mixed-integer linear programming mathematical model was developed and integrated with the NSGA-II algorithm to optimize packaging design dimensions and material properties. The approach emphasizes flexibility, compressibility, and adaptability to achieve an optimal balance between resource efficiency and product protection. Through rigorous simulation experiments, the NSGA-II algorithm demonstrated significant material savings while maintaining packaging integrity, achieving reductions of 1.87% in packaging quantity, 8.97% in volume, and 3.33% in weight. The results underscore the model's alignment with e-commerce objectives of cost reduction and environmental impact minimization, offering a scalable framework for resource-efficient and sustainable distribution packaging solutions.

Keywords : Adaptive Customization, Electronic Commerce, NSGA-II Algorithm, Unconstraint Mixed-integer Linear Programming

Suggested citation : Shenglin Liu, & Wan, G. (2025). Adaptive Customization of Electronic Commerce Packaging for Sustainable Business Development. *Journal of Modern Social Sciences*, 2(1), 56–64. https://doi.org/10.71113/jmss.v2i1.158

Introduction

The rapid expansion of e-commerce has significantly influenced consumer shopping habits and reshaped the global economic landscape. Analysts project that e-commerce market penetration could reach as high as 25% by 2026, underscoring the ongoing shift toward online retail [1]. Between 2015 and 2018, the proportion of online purchases rose from 32% to 43% [2], highlighting this trend. However, the environmental implications of e-commerce, particularly in logistics and packaging, have become increasingly concerning. Research indicates that the last-mile delivery phase of e-commerce operations is a major contributor to carbon emissions and energy consumption [3, 4]. Consequently, there is an urgent need for innovative and sustainable packaging solutions to mitigate the environmental challenges associated with the sector's rapid growth [5]. The rapid expansion of e-commerce and express delivery services has transformed global logistics while introducing significant environmental challenges. In 2017, China alone reported over 40 billion express deliveries, a figure projected to climb to 70 billion annually by 2020 [6]. This dramatic increase in express delivery has resulted in a substantial rise in packaging waste, much of which is non-degradable and improperly managed. Research indicates that packaging materials commonly used in express delivery, such as plastic, polystyrene, and PVC, contribute significantly to municipal solid waste and pose severe environmental risks [7]. Although recycling is crucial to addressing this issue, recovery rates remain alarmingly low, with less than 20% of express packaging materials being recycled in China [8]. This exacerbates pollution, particularly due to over-packaging practices, where excessive amounts of tape, cushioning materials, and oversized containers are used beyond what is necessary to protect products [9]. Without effective interventions, packaging material consumption in China is projected to reach 41.3 million tons by 2025, posing serious threats to environmental sustainability [10]. In response to these challenges, China has introduced the "Fourteen-Five Year Plastic Pollution Control Action Plan," which aims to reduce disposable plastic usage, encourage recyclable packaging, and enhance sustainability within the express delivery industry [11]. Therefore, the urgent need for sustainable packaging solutions and effective regulatory frameworks to mitigate the environmental impacts of the rapidly growing express delivery sector.

In the context of practical e-commerce environments, packaging optimization is of paramount importance. Zhou, in her study, highlights several issues in logistics packaging within the e-commerce sector, including the lack of standardization in packaging design and difficulties in selecting appropriate materials. As the e-commerce market rapidly expands, one of the key challenges lies in making packaging designs more adaptable and environmentally friendly [12]. Subsequently, Zhang analyzed the issue of green logistics packaging in e-commerce, proposing strategies to address it. She emphasized the selection of green materials in packaging design and the optimization of transportation processes to reduce excessive packaging and achieve environmental goals. However, a significant challenge in practical application is finding a balance between the eco-friendly characteristics of packaging materials and constraints related to costs and production limitations [13]. Furthermore, Zhao et al. researched the development of green e-commerce packaging under the "dual carbon" goals in China. They argued that the implementation of green packaging design requires innovation and optimization in the packaging material supply chain. Nevertheless, the procurement of packaging materials and supply chain management remain challenged by high costs and complex logistics [14]. On the international front, Gurumoorthy et al. proposed a packaging type recommendation system for e-commerce shipments, utilizing machine learning algorithms to suggest the most suitable packaging for different products, thus reducing packaging waste during transportation. However, ensuring the feasibility of this system in real-world applications, particularly when dealing with a diverse range of product demands, remains a question that requires further exploration [15]. In addition, Yang et al. examined a machine learning approach to shipping box design. They argued that machine learning algorithms can effectively optimize box sizes and designs, enhancing the utilization of

JOURNAL OF MODERN SOCIAL SCIENCES **Volume 2 Issue 1, 2025 , 56-64**
ISSN (P): 3078-4433 | ISSN (O): 3078-4441 **Doi:10.71113/jmss.v2i1.158**

packaging space and reducing transportation costs. However, the key challenge to the broad applicability of this method lies in overcoming the adaptability issues of the algorithms across various e-commerce platforms [16]. Despite the numerous optimization strategies proposed in existing research, implementing adaptive packaging optimization in practical e-commerce environments still faces considerable challenges. To resolve these issues, it is necessary to integrate additional technological tools and industry experience.

In order to solve the sustainable optimization of e-commerce packaging, Martin et al. developed a location-flexible approach utilizing logical operators to minimize container volume when packing rectangular boxes. This method demonstrates competitive performance compared to traditional Mixed-Integer Programming (MIP) models, efficiently delivering both optimal and feasible solutions [17]. Similarly, Yang et al. proposed a Variable Neighborhood Descent Space-Ordering Algorithm (VND-SOA) integrated with an MIP model to optimize multi-order, multi-box packing. By incorporating constraints, their approach enhances packing efficiency and box size optimization [18]. In addition, Xin et al. emphasized that in container loading, weight limitations are often more restrictive than volume, and proper weight distribution is crucial for maintaining stability during transportation [19]. However, both methods exhibit high computational complexity and extended processing times, which limit their application for rapid packaging optimization within express delivery systems.

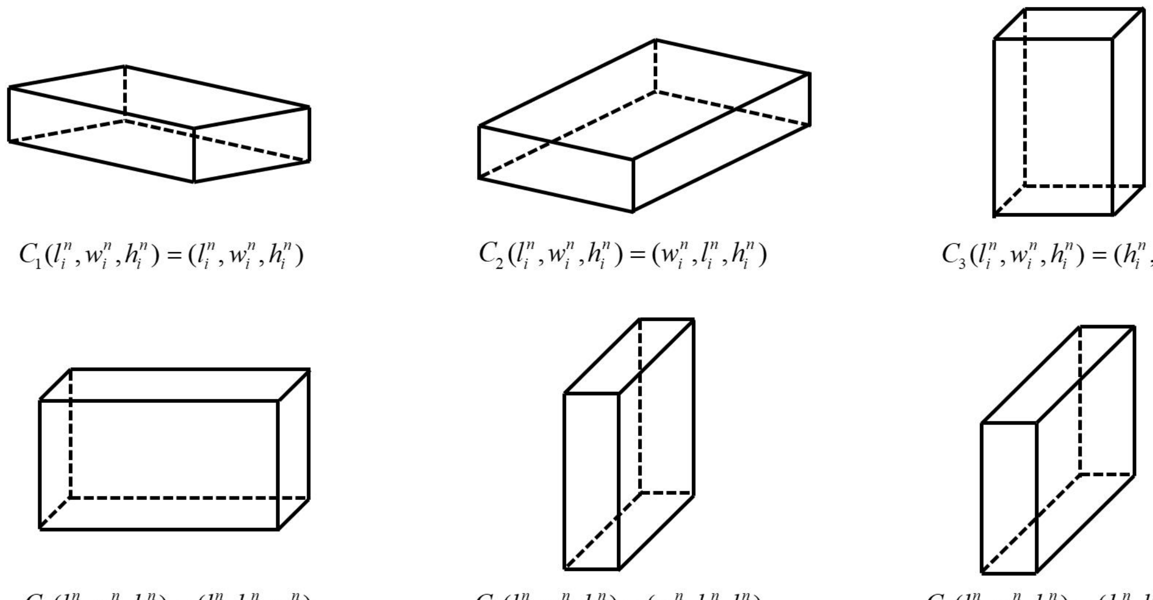
To overcome these challenges, Fang et al. introduced a Sequence-Transfer-based Particle Swarm Optimization (ST-PSO) algorithm, which employs transfer learning and adaptive adjustment strategies to improve packing efficiency, minimize waste, and reduce processing times. This approach has demonstrated significant potential in industrial applications [20]. Furthermore, Zhang et al. through a multi-objective genetic optimization algorithm, offer a novel perspective on packaging solutions by balancing cost and spatial utilization efficiency [21]. Then, Kucukyilmaz and Kiziloz proposed a Cooperative Parallel Grouping Genetic Algorithm (IPGGA), which leverages an island model to enhance solution quality and computational efficiency. By optimizing migration strategies and diversification techniques, IPGGA outperforms traditional genetic algorithms, delivering superior performance in complex packing scenarios [22].

However, these methods primarily focus on improving packing efficiency without explicitly addressing waste reduction in packaging materials. In response to the rapid growth of express delivery volumes and the sustainability demands of e-commerce development, this study proposes an innovative three-dimensional packaging optimization mathematical model. By applying the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), the model aims to optimize packaging, reduce material usage, and enhance the sustainability of e-commerce practices.

The remainder of this paper is organized as follows. Section 2 introduces the unconstraint mixed-integer linear programming model developed in this research and explains the operational mechanisms of this approach. Section 3 describes the construction and objectives of the NSGA-II model. Section 5 and 6 presents the experimental results of the proposed model and methodology, concludes the research.

Methodology

The 3D packing problem for express delivery is an NP-hard problem. To optimize packaging utilization in logistics, this research assumes that the length, width, and height of items can be interchanged freely. For any item that cannot fit into the packaging material in any orientation, it is excluded from consideration. Consequently, each item can be packed in six possible orientations, as illustrated in Figure 1.



$C_1(l_i^n, w_i^n, h_i^n) = (l_i^n, w_i^n, h_i^n)$ $C_2(l_i^n, w_i^n, h_i^n) = (w_i^n, l_i^n, h_i^n)$ $C_3(l_i^n, w_i^n, h_i^n) = (h_i^n, w_i^n, l_i^n)$

$C_4(l_i^n, w_i^n, h_i^n) = (l_i^n, h_i^n, w_i^n)$ $C_5(l_i^n, w_i^n, h_i^n) = (w_i^n, h_i^n, l_i^n)$ $C_6(l_i^n, w_i^n, h_i^n) = (h_i^n, l_i^n, w_i^n)$

Figure 1: Packing Methods in Different Orientations.

It is known that the majority of express deliveries utilize box and bag packaging; therefore, this research establishes distinct loading mathematical models of unconstraint mixed-integer linear programming [23] for both box and bag packaging methods.

Box Loading Model

Before initiating the packaging model, several assumptions must be established:

1） All items within orders are assumed to be rectangular in shape, with the exception of irregularly shaped items.

2） Each order may consist of multiple items; however, the packaging process will not combine items from separate orders.

3） Items within the same order are assumed to be non-overlapping in spatial arrangement.

Requirements for box packaging:

$$l_i^n \le l_{\max}^{T_j} \quad T \in \{1\}, \forall j = 1, 2, \ldots, 5, \tag{1}$$

$$w_i^n \le w_{\max}^{T_j} \quad T \in \{1\}, \forall j = 1, 2, \ldots, 5, \tag{2}$$

$$h_i^n \le h_{\max}^{T_j} \quad T \in \{1\}, \forall j = 1, 2, \ldots, 5, \tag{3}$$

ISSN (P): 3078-4433 | ISSN (O): 3078-4441 Doi:10.71113/jmss.v2i1.158

where, i denote the i-th order, n represent the n-th item within the i-th order, and T=1 indicate packaging by means of a box, while T=2 corresponds to packaging via a bag. The index j specifies the j-th package of the designated packaging type.

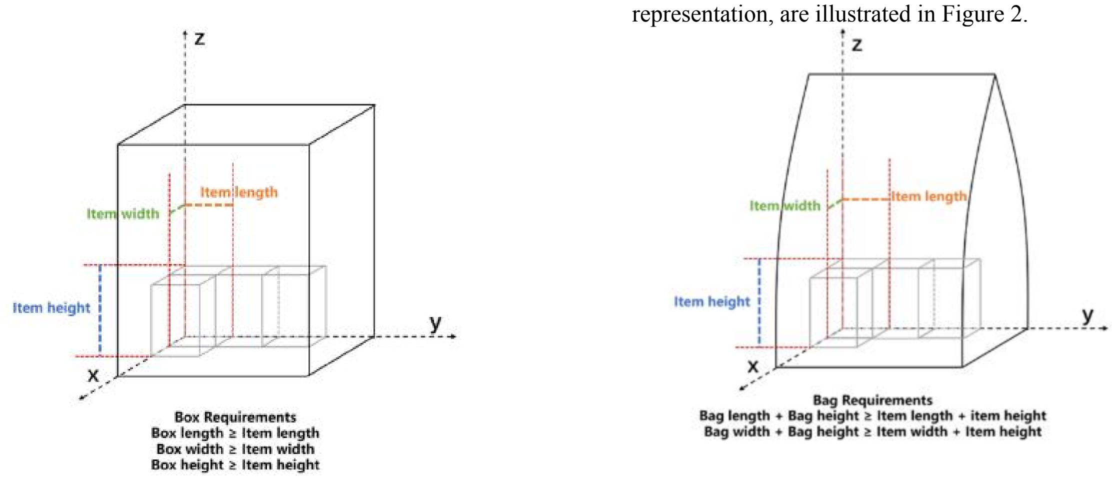
Bag Loading Model

Requirements for box packaging:

$$l_i^n + h_i^n \le l_{\max}^{T_j} + h_{\max}^{T_j} \quad T \in \{2\}, \forall j = 1, 2, \ldots, 4, \tag{4}$$

$$w_i^n + h_i^n \le w_{\max}^{T_j} + h_{\max}^{T_j} \quad T \in \{2\}, \forall j = 1, 2, \ldots, 4, \tag{5}$$

The specific packaging requirements, along with a schematic representation, are illustrated in Figure 2.



(a) Box Requirements *(b) Bag Requirements*

Figure 2: Packaging Requirements and Schematic.

Decision Variables

d_q is a 0-1 variable, where $d_q = 1$ indicates that the current order has selected a specific packaging q, and $d_q = 0$ indicates that it has not been selected. By summing the quantity of d, the total required packaging amount for this order can be deter-mined. Since a single order may utilize multiple types of packaging, the total quantity of packaging used, denoted as D, is the summation of the packaging quantities across all orders.

$$D = \sum_{q=1}^{n} d_q \quad d_q \in \{0,1\}, \forall q = 1, 2, \ldots, n, \tag{6}$$

In summary, the model for the overall packaging decision is as follows:

$$D = \sum_{q=1}^{n} d_q$$

$$s.t. \begin{cases} d_q = \begin{cases} 1 & \text{if} Con_1 \text{or} Con_2 \text{or} \ldots \text{or} Con_5 \\ 0 & \text{otherwise} \end{cases} \\ Con_1 = l_i^n \le l_{\max}^{T_j} \quad T \in \{1\}, \forall j = 1, 2, \ldots, 5 \\ Con_2 = w_i^n \le w_{\max}^{T_j} \quad T \in \{1\}, \forall j = 1, 2, \ldots, 5 \\ Con_3 = h_i^n \le h_{\max}^{T_j} \quad T \in \{1\}, \forall j = 1, 2, \ldots, 5 \\ Con_4 = l_i^n + h_i^n \le l_{\max}^{T_j} + h_{\max}^{T_j} \quad T \in \{2\}, \forall j = 1, 2, \ldots, 4 \\ Con_5 = w_i^n + h_i^n \le w_{\max}^{T_j} + h_{\max}^{T_j} \quad T \in \{2\}, \forall j = 1, 2, \ldots, 4 \end{cases} \tag{7}$$

Objective Function

To enhance the sustainability of e-commerce, minimizing the use of packaging materials in the shipping process is of paramount importance. Accordingly, the objective function of this research is:

To minimize the quantity of packaging:

$$f_1(x) = D, \tag{8}$$

To minimize the overall volume of packaging:

$$f_2(x) = \sum_{T=1, j=1}^{a,b} D^{T_j} V_{T_j}, \tag{9}$$

where, a denote the index of packaging type T, b represents the index of packaging within this type, and V_{T_j} signify the volume of the specified packaging.

To minimize the total weight of packaging:

$$f_3(x) = \sum_{T=1, j=1}^{a,b} D^{T_j} W_{T_j}, \tag{10}$$

where, W_{T_j} signify the weight of the specified packaging.

The limits of a and b are determined by the packaging type T:

$$T_j = \begin{cases} a = 2 & b = j \in \{1,2,3,4\} \\ a = 1 & b = j \in \{1,2,3,4,5\} \end{cases}, \tag{11}$$

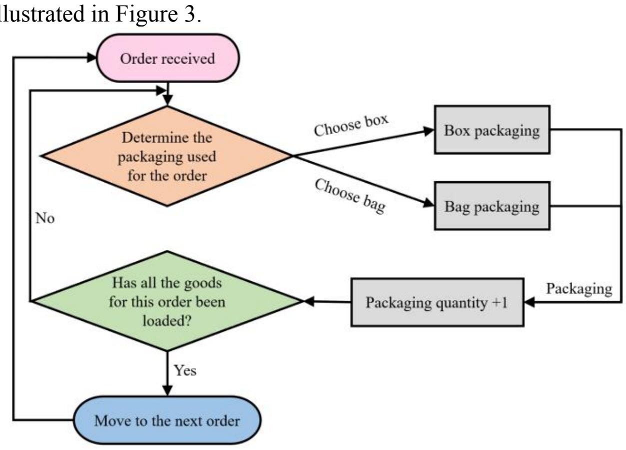
Total objective:

$$\min_x \; F(x) = \left(f_1(x), f_2(x), f_3(x) \right), \tag{12}$$

Through the application of the above model, material savings can be maximized, thereby protecting the environment by preventing waste of both materials and space.

Total process

The complete operational process of the parcel packaging is illustrated in Figure 3.



ISSN (P): 3078-4433 | ISSN (O): 3078-4441 Doi:10.71113/jmss.v2i1.158

Figure 3: Item Packaging Process.

NSGA-II Optimization Algorithm

Packaging size optimization represents a continuous data optimization process. To enhance the precision of multi-objective optimization for packaging dimensions, this research utilizes the NSGA-II Optimization Algorithm, enabling efficient and effective solution identification.

Traditional Genetic Algorithms (GA) comprise three core operations: reproduction, crossover, and mutation [24]. The Non-Dominated Sorting Genetic Algorithm (NSGA) adapts these foundational principles into a sophisticated multi-objective optimization methodology [25]. In this research, apply NSGA-II [26], an advanced version of NSGA that incorporates an elitist mechanism. Through the integration of elitism and a crowding-distance comparison operator, NSGA-II addresses the limitations of arbitrarily assigned sharing parameters, enabling solutions within the approximate Pareto front to achieve an even distribution across the entire Pareto optimal set, thereby ensuring diversity within the population and an expanded search space.

Fast non-dominated sorting algorithm

In the NSGA, the computational complexity of the non-dominated sorting procedure exhibits a notable distinction. The conventional non-dominated sorting method operates with a computational complexity of mN^3 , whereas the NSGA-II employs a more efficient fast non-dominated sorting approach, reducing the complexity to mN^3 . Below, a detailed exposition of the computational steps and complexity associated with these two methodologies is presented.

Complexity of the Standard Non-dominated Sorting Algorithm

For a multi-objective optimization problem characterized by m objectives and a population size of *N*, the traditional non-dominated sorting method necessitates pair-wise comparisons between each individual and every other individual to ascertain dominance relationships. Consequently, the total number of comparisons scales as mN^3 .In order to identify all non-dominated solutions (those comprising the first front of non-dominated solutions), the algorithm iteratively assigns individuals to different dominance levels. This recursive procedure is applied across multiple layers until each solution is classified into a specific rank, with the maximum number of ranks capped by *N*. Consequently, the overall complexity of this approach escalates to mN^3 .

Complexity of the Fast Non-dominated Sorting Algorithm

The fast non-dominated sorting algorithm, as implemented in NSGA-II, optimizes computational efficiency, reducing the complexity to mN^2 . The following steps encapsulate the core operations:

1） Identification of the First Non-dominated Front: The algorithm initially segregates all solutions that are not dominated by any other solutions into a set, denoted as Z_1 .

2） Updating Dominance Relationships: For each individual within Z_1 , the algorithm identifies the subset of solutions it dominates, termed as *S*. Subsequently, for each solution in *S*, it decrements a count that reflects the number of other solutions by which it is dominated. If this count reaches zero—indicating that the solution is no longer dominated by any other solutions—it is assigned to the subsequent non-dominated set, Z_2 .

3） Recursive Layering: This recursive sorting process continues for each newly identified non-dominated front, iterating until all solutions are assigned to a non-dominated layer. Since each layer is constructed based solely on direct dominance relationships within that layer, the complexity of the entire process remains confined to mN^2 .

The aforementioned steps effectively circumvent redundant comparisons inherent in traditional non-dominated sorting methods, thereby significantly reducing computational complexity.

Crowding Comparison Operator

Determination of Congestion

To maintain population diversity, a strategy of "crowding degree" comparison has been introduced. The crowding degree reflects the density of an individual’s relative position within the population, determined by assessing the distribution of surrounding individuals. Figure 4 illustrates the calculation of crowding degree: individuals with greater distances from others are considered to have a higher crowding degree, indicating sparsity in their vicinity, whereas individuals with smaller distances are assigned a lower crowding degree, signifying a dense arrangement of nearby individuals.

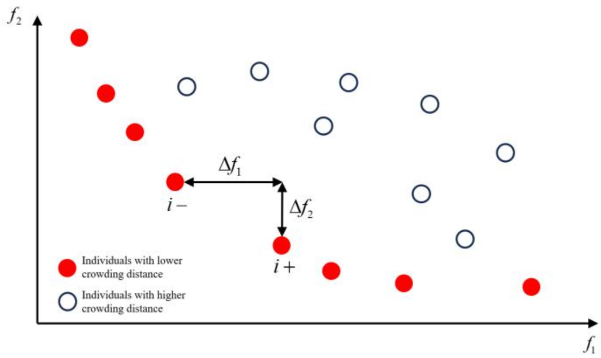


Figure 4: The Crowding Degree of i.

In the process of non-dominated sorting selection, calculating the crowding degree is a crucial step in ensuring population diversity. The calculation procedure is as follows:

1） For each non-dominated front, the crowding degree of boundary individuals is set to infinity to ensure that boundary solutions are not eliminated.

2） For each objective function, individuals within the population are sorted. For the sorted population, the crowding degree of the two boundary individuals is also set to infinity to protect the boundary solutions from elimination.

3） For each non-boundary individual, the crowding degree is computed according to the specified formula.

$$i_d = \sum_{j=1}^{m} \left(\left| f_j^{i+1} - f_j^{i-1} \right| \right), \tag{13}$$

Where, i_d denotes the crowding degree of individual *i*, f_j^{i+1} represents the value of the individual ranked one level higher than *i* in the *j*-th objective function, and f_j^{i-1} is the value of the individual ranked one level lower than *i* in the *j*-th objective function.

The magnitude of the crowding degree depends on the complexity of the ranking process. In the most extreme scenario, where all individuals belong to the same non-dominated front, the computational complexity of calculating crowding degree becomes $mN \log N$, where *N* is the population size and *m* represents the number of objective functions.

ISSN (P): 3078-4433 | ISSN (O): 3078-4441 Doi:10.71113/jmss.v2i1.158

Crowding Comparison Criteria

After completing the fast non-dominated sorting and crowding degree calculation, each individual in the population is endowed with two attributes: non-domination rank r and crowding degree i_d . Based on these attributes, a crowding-comparison criterion can be defined, enabling the assessment of relative quality between two individuals during population selection.

1） If an individual belongs to a lower non-domination rank, meaning its rank r_{rank} is less than the rank j_{rank} of another individual, the individual with the lower rank is prioritized.

2） If two individuals reside in the same non-domination rank, $r_{\text{rank}} = j_{\text{rank}}$, then the individual with the greater crowding degree, $i_d > j_d$, is selected.

These criteria ensure the selection of higher-quality solutions within the population: individuals with lower non-domination ranks (indicating better solution quality) are prioritized, and if ranks are equal, those with greater crowding degrees are favored to maintain population diversity and prevent excessive solution clustering.

Elite Strategy

The NSGA-II algorithm employs an elite strategy to effectively prevent the loss of high-quality individuals. This approach involves merging all individuals from both the parent and offspring populations, followed by a non-dominated sorting process to ensure the preservation of superior individuals from the parent generation. The specific execution steps of this elite strategy are illustrated in Figure 5.

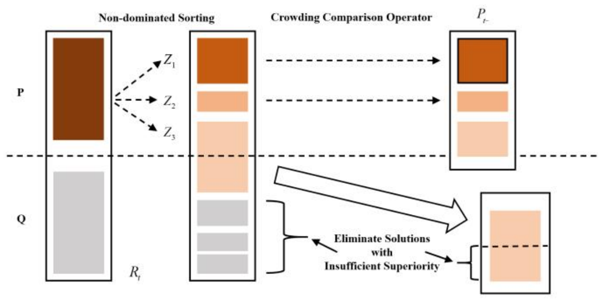


Figure 5: Elite Strategy Process.

In the NSGA-II algorithm, the newly generated population Q_t from generation t is first combined with the parent population P_t to form a unified set R_t of size 2N. Subsequently, R_t undergoes a non-dominated sorting process, producing multiple hierarchical non-dominated sets, and calculating the crowding distance for each individual. Since R_t includes all individuals from both the parent and offspring populations, it effectively safeguards the elite individuals from the parent generation. Starting from the highest-priority non-dominated set, the algorithm incrementally transfers all individuals in this set to the new parent population P_{t+1} for the next generation. If the number of individuals in P_{t+1} remains below N, the next non-dominated set is added sequentially until the population size approaches N.

If, after adding a certain non-dominated front, the number of individuals in P_{t+1} exceeds N, only a subset of individuals from this front is selected to ensure that the final count of individuals in P_{t+1} precisely equals N. During this selection process, the crowding distance comparison operator is employed to determine which individuals to retain, with preference given to those exhibiting larger crowding distances, thereby preserving population diversity. Specifically, the top $\{\text{num}(Z_i) - (\text{num}(P_{t+1}) - N)\}$ individuals with the highest crowding distances are chosen from this non-dominated set, so that the total number of individuals in P_{t+1} reaches N. Subsequently, the processes of selection, crossover, and mutation are applied to generate a new offspring population Q_{t+1} .

The overall computational complexity of the NSGA-II algorithm is mN^2 , with the non-dominated sorting process constituting the primary factor influencing the algorithm's efficiency. During execution, it requires only a single non-dominated sorting operation on the population of size 2N, thereby eliminating the need for repeated sorting. Once the N individuals required for P_{t+1} are identified, the sorting process can be terminated. By employing the crowding distance comparison operator, NSGA-II effectively maintains diversity among non-dominated solutions, thereby achieving a more efficient distribution control.

NSGA-II Process

By employing the aforementioned strategy, the NSGA-II algorithm will proceed in accordance with the operations delineated in the flow presented in Figure 6, continuing iteratively until the termination criteria of the program are satisfied.

ISSN (P): 3078-4433 | ISSN (O): 3078-4441
Doi:10.71113/jmss.v2i1.158

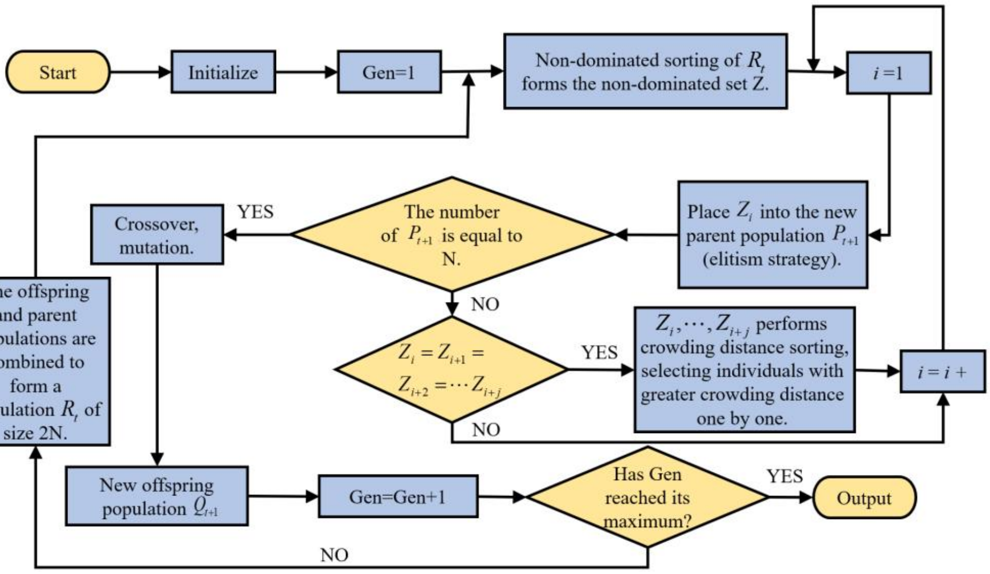


Figure 6: NSGA-II Operation Process.

Experiment and Analysis

Data Source

The dataset for this research is derived from the 2023 Third Yan gtze River Delta University Mathematical Modeling Competition, Problem A—Optimization of E-commerce Parcel Packaging. These files provide essential data to support the analysis of packaging res ource utilization and its environmental impact in the logistics sec-to r. (Data source: https://www.saikr.com/c/nd/12413)

The packaging data file details various common packaging mater ials, including bags and boxes, with specifications such as name, ty pe, dimensions (length, width, height), and weight. This informatio n reflects the actual materials employed in the e-commerce delivery process. Detailed data are presented in Table 1.

Table 1: Packaging Data.

Consumables Name	Types	Length	Width	Height	Weight
No. 1 bag	Bag	250	190	1	10
No. 2 bag	Bag	300	250	1	8
No. 3 bag	Bag	400	330	1	15
No. 4 bag	Bag	450	420	1	23
No. 1 carton	Carton	165	120	55	45
No. 2 carton	Carton	200	140	70	67
No. 3 carton	Carton	200	150	150	103
No. 4 carton	Carton	270	200	90	132
No. 5 carton	Carton	300	200	170	179

The order data file details the dimensions (length, width, and height) and quantities of items within various orders. These sample data emulate the diverse range of goods requiring delivery in e-commerce transactions, encompassing items of varying specifications and quantities. Descriptive statistics for the order data are presented in Table 2.

Table 2: Order Data.

Total Quantity of Orders	Average Length of Items	Average Width of Items	Average Height of Items	Total Quantity of Items
10001	224.1807	154.3641	64.9015	25837

This research analyzes the aforementioned data to conduct simulation modeling of parcel packaging use and optimization within an e-commerce context. The objective is to reflect common issues and demands encountered in the practical operations of e-commerce logistics.

Environment Configuration

The hardware configuration of the simulation experiment in this research is de-tailed in Table 3.

Table 3: Computer Configuration.

Configuration	Version
CPU model	Intel i7-11800H
Operating system	Windows 10 Pro
System memory	16.0 GB
GPU model	NVIDIA RTX-3060
GPU memory	13.9GB
Code environment	Python 3.9

All simulation experiments were conducted in the Python 3.9 environment, mainly relying on the following module (See Table 4):

Table 4: Environment Configuration.

Module	Version
Pandas	2.1.1
Numpy	1.26.0

Through the above experimental environment, three-dimensional loading and packaging optimization can be simulated, simulating the optimization and decision-making in a real e-commerce environment.

Data Preprocessing

ISSN (P): 3078-4433 | ISSN (O): 3078-4441 Doi:10.71113/jmss.v2i1.158

Data preprocessing is crucial prior to conducting experiments. In this research, a greedy algorithm is employed to simulate the packing process, leveraging its high efficiency to swiftly identify orders that cannot be packaged. These orders are subsequently excluded from the experiments, with their some of the order ID listed in Table 5 and total order ID in the appendix.

Table 5: The Order ID for The Part of The Items That Cannot Be Packaged.

Order Quantity
11,13,14,17,19,28,29,31,35,39, …, 5118,5119,5125

By excluding orders that cannot be packaged, the usability of the data is significantly enhanced, thereby substantially improving the accuracy of the experiments.

Results Analysis

The optimization of packaging dimensions is inherently stochastic; thus, considering practical operations, this study implements a customized approach to dimension optimization. The dimensions are constrained within a specified range to ensure both manufacturability and ease of modification. The specific constraints are as follows:

$$0.95 l^{T_j} \le l^{T_j} \le 1.05 l^{T_j} , \tag{14}$$

$$0.95 w^{T_j} \le w^{T_j} \le 1.05 w^{T_j} , \tag{15}$$

$$0.95 h^{T_j} \le h^{T_j} \le 1.05 h^{T_j} , \tag{16}$$

These customized constraints ensure that the optimized packaging dimensions are not only feasible for production and easy to modify but also tailored to maximize material efficiency and minimize environmental impact. By applying customized dimensional limits, this approach accommodates the unique requirements of the production process, ensuring that optimized solutions are practical and sustainable, rather than generic. This tailored method is central to achieving both operational feasibility and significant material savings.

The parameter settings are critical to the performance of NSGA-II; to ensure experimental reproducibility, the parameters employed in this study are presented in Table 6.

Table 6: Algorithm Parameters.

Algorithm Parameters	
Mutation Probability	0.1
Crossover Probability	0.9
Population Size	200
Iterations	200

The following section will present a customized optimization experiment for packaging using NSGA-II.

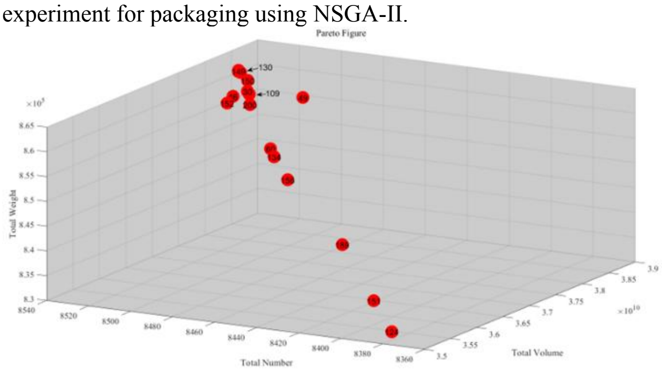


Figure 7: Pareto Chart of Solutions.

Figure 7 illustrates the distribution of various categories in terms of overall impact, with the three axes representing "Total Volume," "Total Weight," and "Total Number." The red points in the figure correspond to individual solutions, distributed in three-dimensional space according to their impact levels. Upon close observation, some solutions exhibit relatively low values across these metrics, indicating a high de-gree of optimization, with Solution 124 standing out as achieving the lowest values in all aspects. This study will employ Solution 124 to conduct a comparative analysis with the original solution, examining the extent of packaging material savings achieved through customized optimization of packaging dimensions.

A comparison of packaging dimensions before and after optimization is shown in Table 7.

Table 7: Comparison Before and After Optimizing Size.

	Original Size			**Optimized Size**		
Consumables Name	**Length**	**Width**	**Height**	**Length**	**Width**	**Height**
No. 1 bag	250	190	1	245.77	197.70	1.00
No. 2 bag	300	250	1	310.96	259.51	1.01
No. 3 bag	400	330	1	393.29	325.73	0.99
No. 4 bag	450	420	1	470.84	432.95	0.99
No. 1 carton	165	120	55	165.74	116.28	55.54
No. 2 carton	200	140	70	202.47	138.82	68.12
No. 3 carton	200	150	150	191.91	151.16	152.89
No. 4 carton	270	200	90	281.53	192.72	92.65
No. 5 carton	300	200	170	289.63	195.58	161.96

Table 7 presents a comparison of the original and optimized dimensions for various consumables of packaging. The optimized sizes show minor adjustments in length, width, and height, demonstrating the effectiveness of this research method in refining the dimensions to achieve material efficiency while retaining functional integrity. This optimization exemplifies the capability of our method to balance size reduction with precision, enhancing overall resource utilization.

The effects of packaging optimization are compared in Table 8.

Table 8: Comparison of Optimization Effects Before and After.

	Before Optimization	**After Optimization**	**Difference ratio**
Total Quantity	8537	8377.00	**-1.87%**
Total Volume	38514830500	3506088 2472.23	**-8.97%**
Total Weight	860996	832356.00	**-3.33%**

Table 8 summarizes the overall impact of this research optimization approach, showing significant reductions in total quantity (-1.87%), total volume (-8.97%), and total weight (-3.33%) after optimization. These results highlight the strength of our method in achieving substantial savings in resource usage, reinforcing its potential in contributing to sustainable practices in e-commerce.

In summary, the findings emphasize the pivotal role of adaptive customization in advancing sustainable business practices within the e-commerce industry. By implementing the tailored packaging dimension approach proposed in this study, significant reductions were achieved in material usage, including volume, weight, and raw materials, thereby enhancing resource efficiency. This method aligns seamlessly with the sustainability goals critical to the growth of e-commerce, offering a scalable and practical solution for minimizing environmental impact. The adaptability and effectiveness demonstrated by this approach reinforce its value as a key strategy for fostering sustainable development in digital commerce.

Conclusion

This research rigorously evaluates and validates a novel method for customized packaging design optimization tailored to e-commerce applications, making significant contributions to resource efficiency in this domain. The details are as follows: (1) It introduces an innovative optimization approach that employs dimension-based customization strategies, accounting for material flexibility, compressibility, and adaptability, thereby opening new avenues for packaging optimization in e-commerce. (2) The method demonstrates a marked improvement in resource utilization efficiency, with experimental results revealing a 1.87% reduction in total packaging quantity, an 8.97% reduction in volume, and a 3.33% reduction in weight, underscoring its exceptional performance in enhancing resource efficiency. (3) This method supports sustainable development and advances the transition to a circular economy within the e-commerce sector, enabling companies to proactively ad-dress resource consumption challenges while minimizing costs and environmental impact. (4) Finally, it provides a practical demonstration of advanced optimization technologies in real-world applications, showcasing their potential to achieve precise material reductions and setting a benchmark for resource-efficient digital commerce practices.

In conclusion, the insights provided by this research demonstrate the capacity of advanced optimization techniques to achieve targeted material reductions, offering practical applications for digital commerce and representing a critical step toward more sustainable and resource-conscious e-commerce operations.

Acknowledgments

I would like to show our greatest appreciation to anonymous reviewers, editor and those who have helped to contribute to this paper writing.

Funding

This research was funded by the China Undergraduate Innovation and Entrepreneurship Training Program Grant (Grant No. 202413277015).

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The original contributions presented in the research are included in the article, further inquiries can be directed to the corresponding author.

Conflict of interest

The authors declare no conflicts of interest.

Appendix

The total order ID for the items that cannot be packaged is as follows:

Order ID
11,13,14,17,19,28,29,31,35,39,44,47,48,53,55,63,66,67,70,73,81,8
6,90,101,102,105,118,127,133,134,141,150,155,157,163,168,169,1
71,174,176,177,179,182,189,190,191,193,204,208,212,216,219,22
2,223,231,234,235,238,258,259,263,277,278,279,281,282,284,287,
290,291,292,297,305,306,312,315,316,317,320,321,329,332,334,3
38,340,344,345,348,350,356,357,359,363,364,365,370,371,372,38
0,381,382,389,391,392,398,399,400,401,402,403,406,410,412,413,
415,416,421,422,424,429,442,444,447,449,461,466,468,473,479,4
85,489,493,498,504,505,509,511,514,515,522,523,526,527,529,53
1,536,537,538,543,544,545,549,551,553,555,563,565,573,579,580,
582,583,586,588,592,596,598,600,602,606,618,622,624,625,628,6
30,649,654,655,656,664,665,667,668,672,674,685,687,688,693,69
4,695,702,706,709,711,712,713,714,724,726,728,732,739,745,746,
748,753,760,761,765,766,771,782,783,787,792,796,802,803,811,8
20,825,828,832,833,839,843,847,848,860,861,868,874,877,878,88
1,883,884,885,886,887,892,899,906,909,910,911,917,929,933,937,
960,964,970,972,973,975,977,978,979,986,1000,1001,1003,1007,1
010,1013,1021,1022,1023,1034,1035,1054,1066,1081,1088,1090,1
099,1106,1120,1123,1133,1140,1142,1143,1154,1164,1165,1166,1
169,1172,1174,1183,1184,1195,1199,1205,1206,1207,1209,1210,1
217,1228,1235,1237,1238,1242,1248,1249,1269,1291,1294,1300,1
302,1305,1307,1309,1312,1316,1325,1328,1329,1333,1335,1337,1
341,1342,1346,1355,1356,1360,1366,1391,1396,1397,1406,1410,1
415,1416,1417,1422,1435,1470,1472,1474,1482,1495,1499,1506,1
511,1513,1524,1534,1555,1556,1562,1564,1569,1572,1576,1579,1
582,1594,1599,1613,1614,1620,1623,1642,1643,1654,1655,1656,1
660,1661,1667,1670,1677,1684,1697,1698,1702,1703,1706,1707,1
710,1724,1726,1729,1736,1739,1741,1749,1754,1759,1761,1763,1
772,1781,1785,1790,1793,1814,1829,1840,1842,1844,1846,1850,1
852,1860,1861,1862,1863,1865,1866,1870,1872,1878,1883,1895,1
897,1901,1902,1903,1904,1905,1911,1913,1914,1924,1925,1930,1
931,1932,1937,1938,1939,1944,1947,1953,1959,1961,1963,1964,1
968,1969,1976,1978,1981,1995,2002,2005,2014,2026,2027,2035,2
046,2052,2057,2058,2060,2061,2062,2068,2073,2077,2080,2081,2
082,2084,2087,2100,2111,2115,2116,2117,2119,2120,2125,2126,2
134,2135,2141,2151,2156,2160,2161,2164,2165,2166,2170,2172,2
173,2175,2176,2179,2180,2181,2183,2188,2193,2195,2198,2199,2
202,2205,2208,2214,2219,2229,2241,2256,2257,2258,2264,2265,2
271,2272,2274,2277,2282,2285,2290,2296,2300,2303,2304,2308,2
311,2316,2321,2322,2326,2328,2338,2340,2342,2350,2351,2353,2
361,2364,2370,2373,2380,2381,2386,2387,2404,2406,2407,2411,2
414,2417,2419,2421,2424,2427,2428,2432,2433,2435,2436,2439,2
442,2444,2445,2447,2451,2454,2455,2457,2458,2460,2475,2476,2
477,2483,2484,2502,2507,2509,2512,2514,2519,2521,2523,2524,2
530,2532,2551,2554,2556,2559,2562,2575,2577,2582,2594,2596,2
613,2618,2619,2620,2624,2625,2632,2633,2637,2641,2642,2643,2
653,2663,2665,2670,2672,2677,2679,2681,2682,2683,2684,2688,2
693,2708,2712,2716,2719,2720,2724,2726,2727,2735,2737,2738,2
739,2747,2753,2756,2763,2768,2770,2781,2783,2785,2786,2788,2
790,2800,2802,2816,2821,2822,2831,2834,2835,2844,2858,2866,2
867,2870,2872,2876,2882,2885,2909,2918,2919,2924,2928,2933,2
945,2957,2965,2966,2967,2972,2976,2985,2992,2993,2998,3009,3
012,3016,3032,3034,3036,3041,3043,3050,3053,3059,3060,3064,3
067,3069,3070,3077,3080,3083,3090,3100,3108,3111,3118,3120,3
121,3126,3127,3134,3137,3140,3141,3145,3147,3152,3156,3158,3
161,3165,3172,3173,3174,3179,3182,3183,3203,3211,3215,3220,3
223,3228,3229,3236,3237,3240,3254,3270,3275,3278,3279,3282,3
289,3301,3302,3306,3313,3316,3318,3320,3323,3325,3329,3330,3
336,3337,3338,3340,3346,3347,3353,3354,3355,3356,3359,3371,3
378,3384,3385,3386,3387,3393,3394,3396,3400,3402,3407,3412,3
417,3421,3425,3427,3428,3436,3438,3441,3444,3445,3453,3454,3
455,3457,3459,3474,3475,3479,3481,3482,3484,3497,3501,3502,3
514,3519,3523,3525,3526,3527,3528,3543,3546,3547,3550,3554,3
556,3557,3563,3566,3571,3572,3574,3575,3578,3584,3587,3589,3
606,3614,3615,3620,3623,3638,3640,3644,3646,3650,3656,3662,3
673,3674,3676,3688,3692,3699,3704,3714,3718,3726,3727,3732,3
751,3769,3772,3773,3776,3781,3784,3794,3802,3805,3806,3812,3
813,3814,3815,3816,3817,3819,3830,3836,3850,3855,3863,3865,3
868,3870,3873,3874,3876,3878,3886,3891,3892,3905,3923,3924,3
925,3928,3930,3938,3956,3962,3967,3969,3970,3972,3983,3984,3
985,3990,3991,3995,3996,4001,4004,4008,4010,4017,4021,4026,4
033,4040,4044,4051,4056,4062,4069,4080,4093,4094,4097,4106,4
108,4110,4111,4112,4113,4114,4118,4122,4139,4146,4162,4163,4
165,4181,4184,4185,4188,4191,4193,4197,4200,4211,4212,4220,4
234,4236,4240,4242,4250,4251,4257,4258,4269,4274,4275,4279,4

ISSN (P): 3078-4433 | ISSN (O): 3078-4441 Doi:10.71113/jmss.v2i1.158

280,4284,4293,4297,4299,4303,4310,4317,4320,4324,4325,4328,4
335,4340,4343,4347,4349,4354,4356,4359,4360,4369,4374,4379,4
386,4387,4392,4407,4409,4434,4440,4444,4459,4460,4462,4468,4
484,4490,4493,4502,4509,4516,4522,4530,4536,4546,4555,4580,4
595,4608,4614,4615,4616,4621,4628,4629,4631,4636,4638,4645,4
656,4660,4663,4671,4678,4679,4684,4699,4701,4708,4714,4723,4
725,4735,4738,4743,4748,4751,4754,4763,4766,4781,4803,4812,4
813,4816,4820,4829,4830,4834,4836,4839,4852,4855,4857,4859,4
862,4869,4870,4874,4887,4891,4898,4900,4919,4925,4926,4927,4
931,4935,4939,4940,4952,4955,4963,4979,4985,4990,4994,5017,5
022,5023,5027,5031,5032,5036,5037,5047,5051,5055,5058,5066,5
077,5078,5086,5090,5096,5118,5119,5125

References

[1] Escursell, S., Llorach-Massana, P., & Roncero, M. B. (2021). Sustainability in e-commerce packaging: A review. Journal of cleaner production, 280, 124314.

[2] Zhou, L., Wang, X., Ni, L., & Lin, Y. (2016). Location-routing problem with simultaneous home delivery and customer's pickup for city distribution of online shopping purchases. Sustainability, 8(8), 828.

[3] Pålsson, H., Pettersson, F., & Hiselius, L. W. (2017). Energy consumption in e-commerce versus conventional trade channels-Insights into packaging, the last mile, unsold products and product returns. Journal of cleaner production, 164, 765-778.

[4] Rizet, C., Cornélis, E., Browne, M., & Léonardi, J. (2010). GHG emissions of supply chains from different retail systems in Europe. Procedia-Social and Behavioral Sciences, 2(3), 6154-6164.

[5] Lu, S., Yang, L., Liu, W., & Jia, L. (2020). User preference for electronic commerce overpackaging solutions: Implications for cleaner production. Journal of Cleaner Production, 258, 120936.

[6] Duan, H., Song, G., Qu, S., Dong, X., & Xu, M. (2019). Post-consumer packaging waste from express delivery in China. Resources, Conservation and Recycling, 144, 137-143.

[7] Rochman, C. M., Browne, M. A., Halpern, B. S., Hentschel, B. T., Hoh, E., Karapanagioti, H. K., ... & Thompson, R. C. (2013). Classify plastic waste as hazardous. Nature, 494(7436), 169-171.

[8] Fan, W., Xu, M., Dong, X., & Wei, H. (2017). Considerable environmental impact of the rapid development of China's express delivery industry. Resources, Conservation and Recycling, 126, 174-176.

[9] Pinos, J., Hahladakis, J. N., & Chen, H. (2022). Why is the generation of packaging waste from express deliveries a major problem?. Science of The Total Environment, 830, 154759.

[10] Duan, H., Song, G., Qu, S., Dong, X., & Xu, M. (2019). Post-consumer packaging waste from express delivery in China. Resources, Conservation and Recycling, 144, 137-143.

[11] Chen, Y., Awasthi, A. K., Wei, F., Tan, Q., & Li, J. (2021). Single-use plastics: Production, usage, disposal, and adverse impacts. Science of the total environment, 752, 141772.

[12] Rong Zhou. (2017). Discussion on the development and problems of logistics packaging under e-commerce environment. Finance and Management, 1(1), 123-124.

[13] Zhang Juan. (2024). Problems and countermeasures of green logistics packaging based on e-commerce. E-Commerce Letters, 13, 5812.

[14] Zhao Lin, & Guo Zhiwen. (2022). Research on the development of green express packaging of e-commerce in my country under the goal of "dual carbon". Sustainable Development, 12, 931.

[15] Gurumoorthy, K. S., Sanyal, S., & Chaoji, V. (2020). Think out of the package: Recommending package types for e-commerce shipments. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases (pp. 290-305). Cham: Springer International Publishing.

[16] Yang, G., & Mu, C. (2020). A machine learning approach to shipping box design. In Intelligent Systems and Applications: Proceedings of the 2019 Intelligent Systems Conference (IntelliSys) Volume 1 (pp. 402-407). Springer International Publishing.

[17] Martin, M., de Queiroz, T. A., & Morabito, R. (2024). Solving the three-dimensional open-dimension rectangular packing problem: A constraint programming model. Computers & Operations Research, 167, 106651.

[18] Yang, J., Liu, H., Liang, K., Zhou, L., & Zhao, J. (2024). Variable neighborhood genetic algorithm for multi-order multi-bin open packing optimization. Applied Soft Computing, 163, 111890.

[19] Xin, J., Meng, C., D'Ariano, A., Wang, D., & Negenborn, R. R. (2021). Mixed-integer nonlinear programming for energy-efficient container handling: Formulation and customized genetic algorithm. IEEE Transactions on Intelligent Transportation Systems, 23(8), 10542-10555.

[20] Fang, J., Rao, Y., Liu, P., & Zhao, X. (2021). Sequence transfer-based particle swarm optimization algorithm for irregular packing problems. IEEE Access, 9, 131223-131235.

[21] Zhang, C., & Zhai, Y. (2021). Air container loading based on improved genetic algorithm. Journal of Beijing University of Aeronautics and Astronautics, 47(7), 1345-1352.

[22] Kucukyilmaz, T., & Kiziloz, H. E. (2018). Cooperative parallel grouping genetic algorithm for the one-dimensional bin packing problem. Computers & Industrial Engineering, 125, 157-170.

[23] Berahas, A. S., Xie, M., & Zhou, B. (2025). A Sequential Quadratic Programming Method With High-Probability Complexity Bounds for Nonlinear Equality-Constrained Stochastic Optimization. SIAM Journal on Optimization, 35(1), 240-269.

[24] Alhijawi, B., & Awajan, A. (2024). Genetic algorithms: Theory, genetic operators, solutions, and applications. Evolutionary Intelligence, 17(3), 1245-1256.

[25] Bagchi, T. P., & Bagchi, T. P. (1999). The nondominated sorting genetic algorithm: NSGA. Multiobjective Scheduling by Genetic Algorithms, 171-202.

[26] Yin, Q., Wu, G., Sun, G., & Gu, Y. (2025). Multi-objective orbital maneuver optimization of multi-satellite using an adaptive feedback learning NSGA-II. Swarm and Evolutionary Computation, 93, 101835.