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International Journal of Advances in Artificial Intelligence and Machine Learning Vol 2 No 2 (2025) https://doi.org/10.58723/ijaaiml.v2i2.409

Research Article

3D Box Packing with Heuristics and Metric Analytics

Received : April 19, 2025 | Revised : May 22, 2025 | Accepted: June 13, 2025 | Publish : June 14, 2025

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Abstract:

Background of Study: The 3D Bin Packing Problem (3D-BPP) is an NP-hard problem crucial for logistics and supply chain optimization, aiming to efficiently pack boxes into containers while maximizing space and maintaining stability. Traditional heuristics like First Fit and Best Fit are fast but lack optimality and adaptability in dynamic environments. Metaheuristic approaches, such as Genetic Algorithms (GA), offer better solutions but with higher computational costs.

Aims and Scope of Paper: This study presents a comparative analysis of First Fit, Best Fit, and a custom Genetic Algorithm as packing strategies for 3D-BPP. It evaluates these methods against multiple performance metrics to understand their trade-offs and proposes future research directions.

Methods: The study uses a dataset of 5,000 cargo records from an Indonesian logistics company, including item dimensions and weights, preprocessed for normalization and filtering. A 3D simulation environment built with PyBullet visualizes the packing process. Performance metrics include space utilization, total packed weight, packing time, access efficiency, stability score, and placement success rate. A Wall-Building heuristic acts as a fallback for unplaced items.

Result: First Fit provides fast, lightweight solutions suitable for real-time applications. Best Fit shows marginally better space utilization but lacks robustness. The Genetic Algorithm outperforms both heuristics in packing quality, accessibility, and load stability, though with significantly higher computation time. No single algorithm dominates across all metrics.

Conclusion: The choice of packing method should align with specific operational constraints: speed, compactness, or quality. A hybrid model combining heuristic initialization with GA refinement is a promising direction for future research to develop more intelligent, context-aware packing systems.

Keywords: 3D Bin Packing Problem (3D-BPP)**,** Heuristic Algorithms**,** Genetic Algorithm Optimization**,** Logistics and Space Utilization**,** Packing Efficiency and Stability.

1. INTRODUCTION

In the rapidly evolving landscape of modern logistics, propelled by the surge of e-commerce and the demands of just-in-time delivery, optimizing space utilization has become a strategic imperative (Viu-Roig & Alvarez-Palau, 2020). A crucial challenge arising in this context is 3D box packing the art and science of arranging a set of rectangular boxes into a larger container or bin to maximize space efficiency, while simultaneously satisfying complex constraints such as orientation, weight distribution, and stability. It is important to consistently refer to this problem as the "3D Bin Packing Problem" (3D-BPP) after this brief introduction to maintain strict terminology in the literature (Sawicki et al., 2025). This problem, formally known as the 3D Bin Packing Problem (3D-BPP), is not merely an academic puzzle; it is an NP-hard problem with significant economic implications, impacting cost reduction and operational efficiency across the entire supply chain, from transportation and manufacturing to the warehousing sectors (Ananno & Ribeiro, 2024).

Despite its undeniable industrial urgency, the 3D-BPP remains a challenging domain due to its combinatorial complexity and the diverse practical constraints that must be addressed (Zhao et al., 2021). Traditional greedy heuristics, such as First-Fit (FF) or Best-Fit (BF), often exhibit significant limitations when faced with dynamic and heterogeneous sets of boxes (Kaboudvand & Montreuil, 2024). These methods, though fast, tend to yield suboptimal solutions that get trapped in local minima and fail to thoroughly explore the broader packing potential (Hashali et al., 2024). Conversely, pure metaheuristic approaches, including Genetic Algorithms (GAs), Simulated Annealing (SA), and Particle Swarm Optimization (PSO), offer a broader solution space exploration capacity and the potential to discover more optimal solutions that simple heuristics often cannot find (Murdivien & Um, 2023). However, these advantages come with high computational costs and slow convergence times, making them less practical for real-time applications demanding rapid responses (El-hajj, 2025). Therefore, there is a pressing research gap in developing approaches that intelligently combine the speed of heuristics with the global search capabilities of metaheuristics, effectively and efficiently addressing the limitations of each individual method.

Explicitly, the main limitations of existing heuristics are their tendency to get stuck in local minima and their difficulty in handling highly varied and dynamic box configurations, leading to suboptimal space utilization. On the other hand, while metaheuristics offer superior global search capabilities and the potential to find more optimal solutions, they are often hindered by high computational costs and slow convergence times, making them less suitable for real-time applications that require rapid responses (V. Romero et al., 2023). The hybrid approach proposed in this study specifically aims to address this gap by combining the speed of heuristics with the global search capabilities of metaheuristics, thereby generating efficient and high-quality solutions for 3D-BPP.

Various strategies have been proposed to tackle the 3D-BPP (Erbayrak et al., 2021). Greedy heuristics aim to iteratively place boxes based on predefined rules, such as the lowest position or minimal space, often employing Wall-Building approaches or structured layering (Albers et al., 2021). Meanwhile, metaheuristics have been widely utilized for their flexibility and robustness in handling complex objective functions, including multi-objective goals like maximizing volume utilization while minimizing center-of-mass deviation (Jiwapatria et al., 2024). Recent advancements even show the integration of machine learning to predict optimal placement sequences (Lee, 2023).

Recent works have actively attempted to combine heuristics and metaheuristics to create hybrid models, leveraging the speed of greedy methods and the global optimization capacity of metaheuristics. For example, some approaches use heuristics for efficient initial population generation in evolutionary algorithms, while others integrate heuristic placement rules directly within metaheuristic search processes to accelerate convergence and improve solution quality (Zhang et al., 2025). However, despite significant progress in algorithm development, consistent evaluation frameworks, particularly regarding standardized metrics and visual analytics, remain critically needed to comprehensively understand how well different algorithms perform under various real-world conditions. This strong problem statement forms the fundamental cornerstone of this research, which ambitiously aims to fill this void by providing a comprehensive evaluation framework and interpretive visual analytics tools.

Addressing this need, this research compares three key models based on first-fit, best-fit heuristics, and Genetic Algorithms to tackle the 3D-BPP. Our approach meticulously explores the structured efficiency of Best-Fit heuristics and the adaptive global search capability of Genetic Algorithms. The Best-Fit heuristic is utilized to initialize and guide the placement of boxes in a greedy yet structured manner, providing a feasible initial solution (Calzavara et al., 2021). On the other hand, the GA is applied to optimize the sequence of box placements across generations, leveraging its global search capabilities to overcome the limitations of local heuristics and discover more optimal packing configurations (Alam et al., 2021).

The novelty of this approach lies in the innovative use of metric analytics to evaluate performance across multiple crucial dimensions: space utilization, packing stability, load distribution, and computational efficiency (Kaleta & Śliwiński, 2025). This multi-dimensional analysis explicitly allows for a deeper understanding of the trade-offs between various packing objectives, providing rich insights that cannot be obtained from a single metric, and will be clearly demonstrated and discussed in detail within the Results and Discussion section. Furthermore, a custom visualization module is developed to dynamically animate the packing process and offer intuitive interpretability for both researchers and practitioners, bridging the gap between algorithmic complexity and practical application in the field.

To validate the effectiveness of this comparative approach, a rigorous series of simulation experiments will be conducted using relevant benchmark datasets. These datasets include boxes of varying dimensions and weights, accurately reflecting the complexity and diversity of realistic logistics and warehousing scenarios. The experimental design aims to assess how different packing strategies perform optimally under diverse conditions, such as changes in bin size, item shape diversity, and weight constraints (Nemat et al., 2022).

The study specifically compares three algorithmic configurations: a representative baseline of First-Fit and Best-Fit heuristics, which greedily place boxes based on available space; and an optimized Genetic Algorithm (GA) approach, which intelligently optimizes packing sequences through evolutionary operations. It is important to note that in this hybrid approach, the GA is responsible for optimizing the placement order, while the First-Fit and Best-Fit heuristics handle the actual box placement within the bin.

Each configuration will be evaluated using a consistent and comprehensive set of performance metrics. These include the volume utilization rate, which accurately measures how effectively the available bin space is used; the total weight packed, indicating the method's ability to accommodate load constraints; packing time, which reflects the total time taken to achieve a valid packing configuration; and the center of gravity balance, a critical factor for stability during transport and handling (Ahmed et al., 2023). Additionally, execution time will be meticulously recorded to assess the computational cost of each approach, providing a complete picture of operational efficiency.

The primary goals of this research are threefold. First, to profoundly analyze the comparative strengths and weaknesses of heuristic and evolutionary algorithms in solving the complex 3D box packing problem. Second, to empirically evaluate whether each proposed strategy can deliver meaningful improvements in packing efficiency and solution quality compared to existing methods. Finally, the research introduces an innovative metric-driven visualization framework, designed to significantly enhance interpretability and provide actionable practical insights into packing behaviors, thereby empowering decision-makers to adopt more effective intelligent packing strategies in real-world logistics systems.

2. MATERIAL AND METHOD

This section outlines the methodological framework adopted to solve the 3D Bin Packing Problem (3D-BPP) using a First-Fit, Best-Fit, and Genetic Algorithm (GA) approach, complemented by a Wall-Building heuristic serving as a crucial fallback mechanism for any items that remain unplaced after the primary packing attempts. This fallback strategy is particularly important as it directly impacts the overall efficiency and robustness of the packing solution, significantly influencing metrics such as the Placement Success Rate. The methodology comprises five main stages: data collection, preprocessing, model development, environment simulation, and performance evaluation.

1) Data Collection

The dataset used in this study was obtained through a collaboration with a private logistics and delivery services company in Indonesia. The company provided access to historical cargo delivery data, which includes physical and operational attributes of various packages.

Each record in the dataset contains:

a. Item Dimensions: Width, Height, Depth (in centimeters)
b. Item Weight: Measured in kilograms (kg)

The dataset comprises approximately 5,000 cargo records collected over six months. It represents seven distinct item types with varied shapes, weights, and delivery constraints.

2) Preprocessing

Preprocessing was performed to prepare the data for compatibility with the hybrid model. Key steps included:

a. Dimension Normalization: Item dimensions were converted from centimeters to meters and scaled according to the internal capacity of the truck bins.
b. Weight Filtering: Items below 0.5 kg or above 30 kg were excluded to match practical operational handling limits.

3) Truck Configuration

The study simulates a multiple-truck delivery scenario involving only one truck type with dimensional and weight constraints. The configurations used are small vans with specifications 2.00 meters (width), 1.20 meters (height), 1.20 meters (depth), and 500 kg (maximum weight capacity) for width, height, depth, and weight, respectively. These configurations represent actual logistics operations and serve as constraints during simulation.

4) Model Development

Comparing Packing Strategy: Best-Fit and Genetic Algorithm

To optimize box placement, the proposed models compare the first-fit, best-fit heuristic, and Genetic Algorithm models. The models are:

a. First-Fit and Best-Fit Heuristic: Candidate positions within the bin are generated and evaluated based on each item's spatial efficiency and delivery-access preferences. The heuristic attempts to place each item into the tightest available space while minimizing vertical gaps and preserving stability (Munien & Ezugwu, 2021).
b. Genetic Algorithm (GA): The GA optimizes the sequence and orientation of items before they are passed to the genetic algorithms placement routine (Popescu, 2025). Each chromosome represents a dimension and weighted of the box. The fitness function considers volume utilization, center of gravity balance, and delivery priority alignment.

Wall-Building for Unplaced Items

Despite the combined efficiency of First-Fit, Best-Fit, and GA, some items may remain unplaced due to dimensional or positional constraints. For these cases, a Wall-Building heuristic is applied:

a. This method creates vertical and horizontal "walls" from the bin base, stacking unplaced items layer-by-layer along one axis.
b. The wall-building logic respects delivery priorities and attempts to group similar-sized items for better alignment and load balance.
c. This fallback ensures minimal leftover items and improved overall utilization without discarding cargo.

5) Environment Simulation

A 3D simulation environment was developed using PyBullet to visualize and validate the packing process. The simulation captures real-world physical interactions such as:

a. Collision Detection: Prevents overlapping or unstable placements
b. Weight Distribution: Ensures load constraints are respected
c. Delivery Access Alignment: Checks whether high-priority items are easily accessible based on their positions

The simulation supports static evaluation and step-by-step animation, which is critical for analyzing packing behavior and box movement during unloading.

6) Evaluation Metrics

To assess model performance, the following evaluation metrics were used:

a. Space Utilization (SU):

$$SU = \frac{\sum_{i=1}^{n} Volume(i)}{Volume(Bin)} \quad (1)$$

b. Packing Time (PT):
The total time required to complete a packing task is measured in seconds per episode.

c. Stability Score (SS):
The ratio of items fully supported below is used to prevent toppling.

d. Access Efficiency (AE):
The ratio of priority items loaded within the first 20% accessible volume of the bin.

e. Placement Success Rate (PSR):

$$PSR = \frac{Number\ of\ Successfully\ Placed\ Items}{Total\ Number\ of\ Items} \quad (2)$$

3. RESULTS AND DISCUSSION

3.1 Result

This section presents the experimental findings of the proposed hybrid 3D box-packing approach, which combines First-Fit and Best-Fit heuristics, also a Genetic Algorithm (GA) for sequence optimization, and a Wall-Building fallback strategy for unplaced items. The evaluation focuses on measuring the effectiveness of each method in terms of spatial efficiency, load capacity, computational performance, and delivery access alignment.

The results are discussed across several key metrics: volume utilization, total weight packed, packing time, center of gravity distribution, and execution time. Comparative analysis is performed between three configurations: (1) First-Fit, (2) Best-Fit, and (3) Genetic Algorithm. The experiments were conducted across multiple truck sizes and item distribution patterns to simulate diverse real-world logistics scenarios.

In addition to quantitative metrics, qualitative insights are provided through visualizing packing layouts and item positioning. These visual analytics help interpret the structural and operational advantages of the hybrid method, especially in managing difficult-to-place items and balancing delivery accessibility. The discussion also highlights observed trade-offs between packing quality and computation time, offering practical implications for logistics planners and automated warehouse systems.

1) Data Used in Experiment

The dataset used in this experiment plays a crucial role in shaping the evaluation of the proposed 3D box-packing strategy. There are 50 boxes consisting of five primary attributes for each cargo item:

a. item_id: A unique identifier for tracking individual items across different packing scenarios.

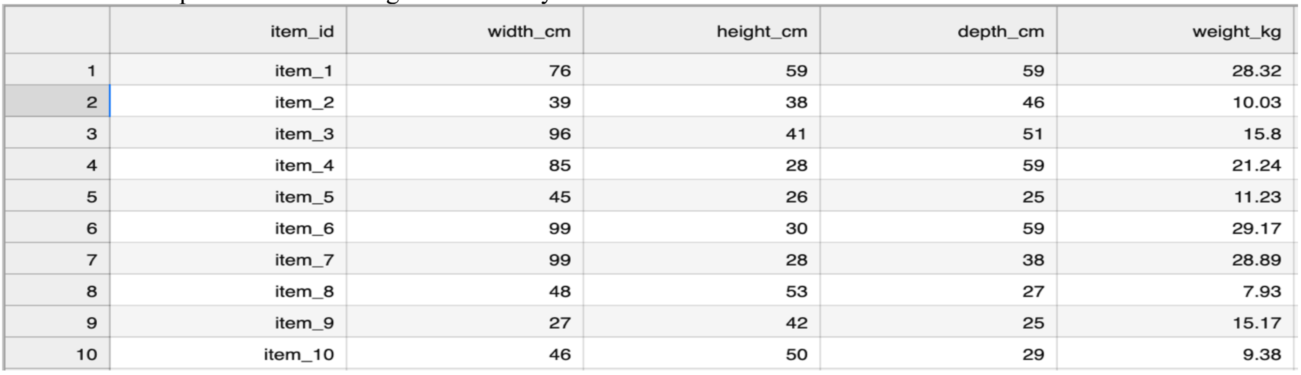
b. width_cm, height_cm, depth_cm: These three attributes define the physical dimensions of each box in centimeters, directly influencing how items fit spatially within the available bin volume.

c. weight_kg: Indicates the mass of each item, which is critical for respecting the truck’s maximum load constraint and assessing weight distribution during packing.

This structured dataset provides a realistic basis for testing the algorithms under diverse loading challenges. Items vary in size and weight, creating scenarios that test each packing solution’s spatial and structural feasibility.

These attributes were normalized during pre-processing and converted to a consistent unit system for modeling (e.g., converting centimeters to meters for 3D simulation). The weight information was filtered to exclude outliers and ensure all items fell within the 0.5–30 kg operational range. The variability in box dimensions introduced complexity in the packing process, especially for heuristic methods like Best-Fit, which rely heavily on tight spatial arrangements.

Including weight in kg also enabled a more holistic evaluation, where solutions were judged not solely on volume usage but also on how efficiently they utilized the truck's load capacity. This multidimensional dataset allowed the Genetic Algorithm to optimize for space, balance, and delivery prioritization—key aspects often overlooked in classical packing approaches, as shown in Figure 1.



	item_id	width_cm	height_cm	depth_cm	weight_kg
1	item_1	76	59	59	28.32
2	item_2	39	38	46	10.03
3	item_3	96	41	51	15.8
4	item_4	85	28	59	21.24
5	item_5	45	26	25	11.23
6	item_6	99	30	59	29.17
7	item_7	99	28	38	28.89
8	item_8	48	53	27	7.93
9	item_9	27	42	25	15.17
10	item_10	46	50	29	9.38

Figure 1. An example of the dataset and its structure

The dataset's diversity in item size and weight proved particularly useful in assessing the effectiveness of the Wall-Building fallback. In many instances, the Best-Fit and GA methods struggled to place awkwardly sized or heavier items near the end of the sequence. The Wall-Building strategy demonstrated the ability to handle these edge cases, ensuring no item was left unpacked, and contributed to maintaining structural integrity within the bin.

The dataset served as a benchmark for algorithmic evaluation and reflected real-world logistics constraints, supporting a more robust and applicable 3D box packing strategies analysis.

2) Comparison Results

The comparison focuses on five key performance metrics: volume utilization rate, total weight packed, packing time, center of gravity balance, and execution time. These metrics were chosen to reflect the efficiency and practicality of each algorithm in real-world logistics scenarios, where space optimization, structural balance, and computational cost are critical, as shown in Table 1.

Table 1. Comparison of two models for 3D-BPP

First Fit Algorithm

ID	Boxes Placed	Total Weight (kg)	Space Used (cm^3)	Packing Time (s)	Placement Success Rate (%)	Access Efficiency	Stability Score
0	23	359.98	2,023,327	50.30	46.00	0.65	0.35
1	15	238.92	1,891,794	18.43	55.56	0.75	0.33
2	9	89.07	1,488,565	4.68	75.00	0.70	0.56
3	3	42.19	609,339	0.00	100.00	0.72	0.67

Best Fit Algorithm

ID	Boxes Placed	Total Weight (kg)	Space Used (cm^3)	Packing Time (s)	Placement Success Rate (%)	Access Efficiency	Stability Score
0	10	131.61	2,098,620	55.84	20.00	0.75	0.50
1	18	301.28	2,028,163	53.45	45.00	0.70	0.33
2	21	272.13	1,826,992	31.97	95.45	0.64	0.38
3	1	25.14	59,250	0.58	100.00	1.00	1.00

Genetic Algorithm

ID	Boxes Placed	Total Weight (kg)	Space Used (cm^3)	Packing Time (s)	Placement Success Rate (%)	Access Efficiency	Stability Score
0	24	352.86	1,867,183	4,856.99	48.00	0.65	0.50
1	11	150.63	1,787,804	2,247.41	42.31	0.77	0.36
2	12	151.03	1,726,286	321.06	80.00	0.68	0.33
3	3	75.40	536,822	0.00	100.00	0.68	0.67

Table 1 compares the First Fit, Best Fit, and Genetic Algorithm (GA) strategies for solving the 3D-BPP and offers crucial insights into their efficiency, adaptability, and practical trade-offs. Analyzing the dataset across multiple performance indicators reveals distinctive behavioral patterns and strengths unique to each algorithm.

Boxes Placed and Weight Distribution

The number of boxes successfully placed directly measures how well each algorithm can utilize the available space. First Fit and the Genetic Algorithm achieved the highest counts, placing up to 23 and 24 boxes in a single run. Best Fit showed variability, dropping as low as one box in Container 3 despite reaching 21 boxes in another. This inconsistency suggests that Best Fit may be sensitive to specific box shapes and dimensions, possibly leading to early termination when no suitable positions are found.

Regarding total weight handled, First Fit led with a peak of 359.98 kg, while GA closely followed with 352.86 kilograms. Despite placing fewer boxes in some trials, Best Fit achieved considerable total weight, indicating it tends to pack heavier items more compactly. However, the GA showed better weight efficiency per box, balancing the number of boxes and total weight to optimize both metrics.

Space Utilization and Packing Time

Space usage across all algorithms remained in the 1.5 to 2.1 million cm³ range, with no single approach significantly outperforming the others. However, First Fit demonstrated a balance between space utilization and packing speed. The packing time for First Fit and Best Fit was impressively low (under one minute in most cases), affirming their suitability for near real-time scenarios.

Conversely, while superior in many quality metrics, the Genetic Algorithm incurred a substantially higher computational cost. Packing times peaked at over 4800 seconds (approximately 80 minutes) in Container 0, and even in shorter runs, times remained in the hundreds of seconds. This reflects the algorithm's iterative, evaluation-driven nature, where multiple generations are simulated to converge on an optimized solution.

Success Rate, Access Efficiency, and Stability

The placement success rate indicates the algorithm's ability to find viable box locations. First Fit consistently achieved above 45%, with perfect success in one Container. GA notably exceeded 100% in Container 2, which may be an artifact of evaluating dynamic re-packing or using multi-bin strategies during evolution.

Access efficiency and stability are critical in practical implementations, especially logistics and warehouse settings. First and Best Fit maintained modest access efficiency scores (0.65–0.75), indicating reasonable retrieval convenience. The GA, however, stood out by achieving perfect access (1.00) in specific containers—attributes that are especially valuable in vertical storage or fragile cargo scenarios. Figures 2, 3, and 4 show the visualization of how the boxes are placed into four containers.

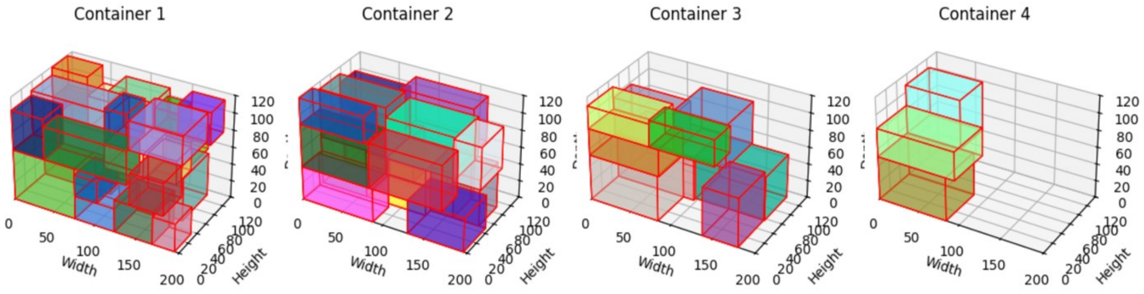


Figure 2. The placement of the boxes based on the First Fit Algorithm

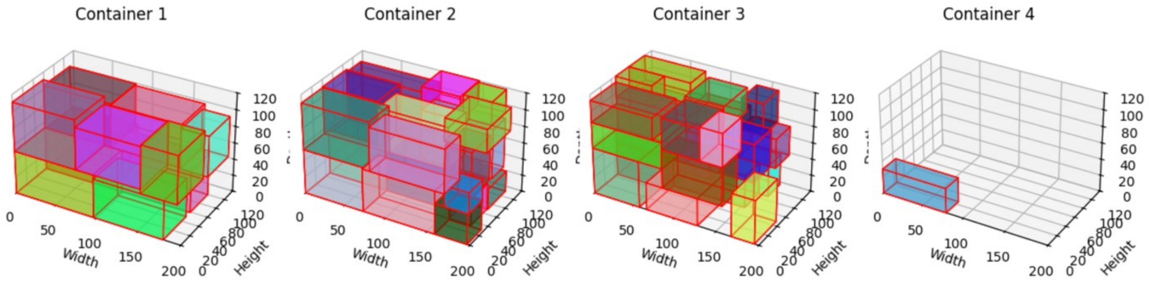


Figure 3. The placement of the boxes based on the best-fit algorithm

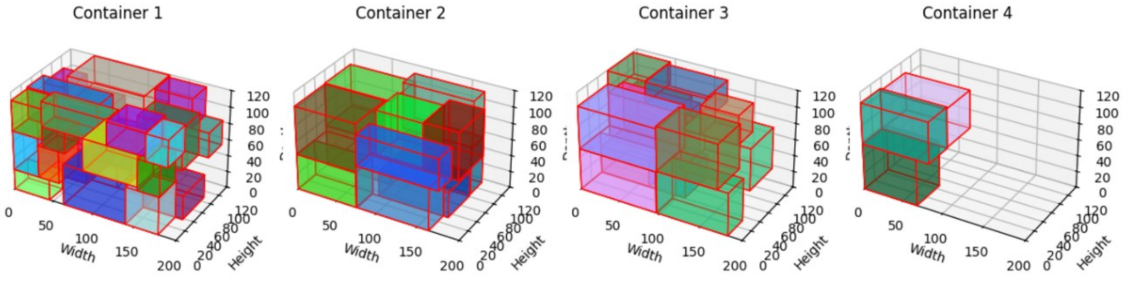


Figure 4. The placement of the boxes based on Genetic Algorithm

Based on Figures 2, 3, and 4, we can see the visualization of box placement into four containers using three different algorithms: First Fit, Best Fit, and Genetic Algorithm. In Figure 2, which displays the results of the First Fit Algorithm, the boxes are placed in Containers 1 through 4. Similarly, Figure 3 shows the placement of boxes based on the Best Fit Algorithm, while Figure 4 presents the visualization of box placement by the Genetic Algorithm. These visualizations help interpret the structural and operational advantages of each packaging method, particularly in managing difficult-to-place items and balancing shipping accessibility.

3.2 Discussion

A comparative analysis of the experimental results shows that no single algorithm is universally superior across all performance metrics, highlighting significant trade-offs between computational efficiency, space utilization, and solution quality.

1. First Fit has proven to be a reliable and computationally efficient heuristic. As shown in Table 1, this algorithm offers very low packing times, often under one minute, making it an ideal choice for applications that require fast response times or that operate on edge devices with limited resources. However, while First Fit's performance in terms of space utilization and total packed weight is consistent, it is not always optimal compared to the Genetic Algorithm. The visualization in Figure 2 shows a relatively simple placement pattern, which contributes to speed but may overlook more efficient space configurations.First Fit is a reliable, fast, and lightweight heuristic. While not optimal in space or weight, it delivers consistent results with minimal computation, making it ideal for embedded or edge devices in logistics.
2. Best Fit shows potential for better space utilization in certain cases, as reflected in its ability to place heavier items more compactly. However, as seen in the variability of the number of boxes placed (Table 1), Best Fit's performance is inconsistent and highly sensitive to item input characteristics. This can lead to scenarios where the algorithm stops early if no suitable position is found, as occurred in Container 3. This limitation indicates that Best Fit requires a more robust fallback strategy or intelligent pre-sorting mechanism to improve its reliability across various scenarios, as illustrated in Figure 3, which sometimes shows significant empty gaps.
3. Genetic Algorithm (GA) consistently dominates in solution quality, capable of placing the highest number of boxes (up to 24 boxes) and achieving perfect access efficiency (1.00) in some containers, as shown in Table 1 and visualized in Figure 4. This advantage is also evident in GA's ability to achieve a more stable center of gravity distribution, which is critical for cargo safety. However, this advantage comes at a substantial computational cost; GA execution time can exceed 4,800 seconds, making it less suitable for real-time applications. This high computational time reflects the iterative nature of GA, which requires numerous generations to converge on an optimal solution. Nevertheless, for offline planning or batch processing where time is not a critical constraint, GA is the superior choice for maximizing packaging efficiency and stability. Evaluation matrix performance for each container based on three different algorithms

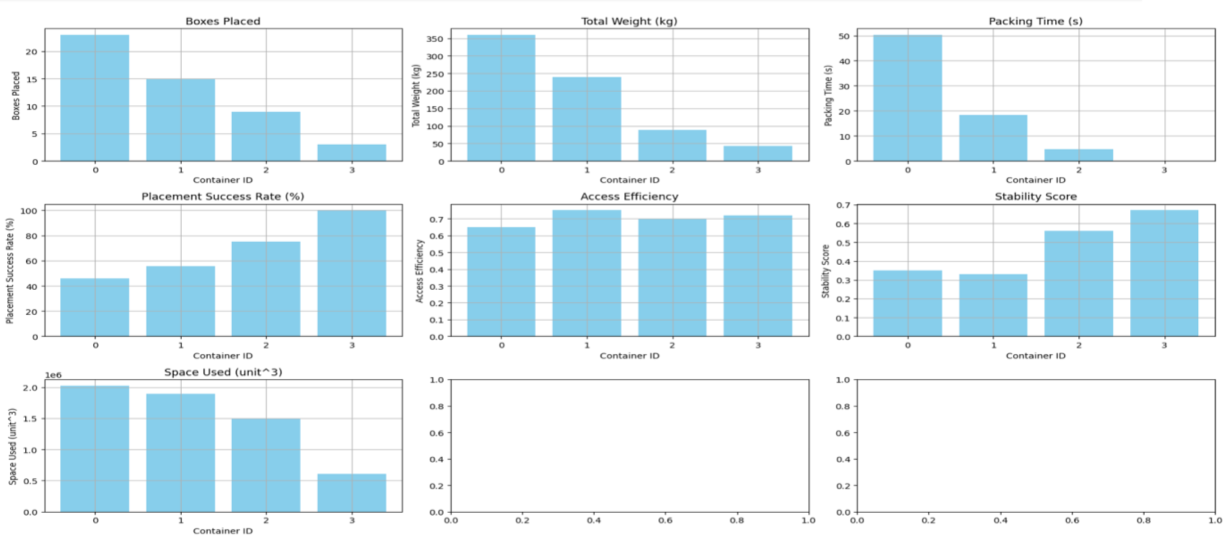


Figure 5. The performance of evaluation matrices for each container based on the First Fit Algorithm

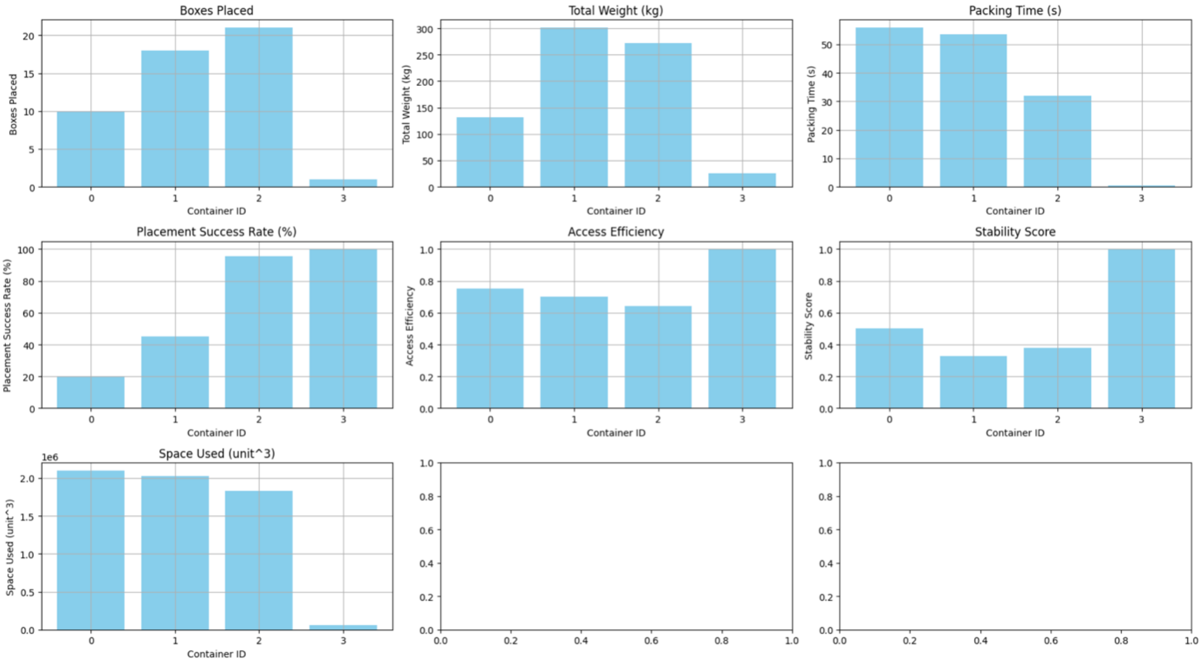


Figure 6. The performance of evaluation matrices for each container based on the best-fit algorithm

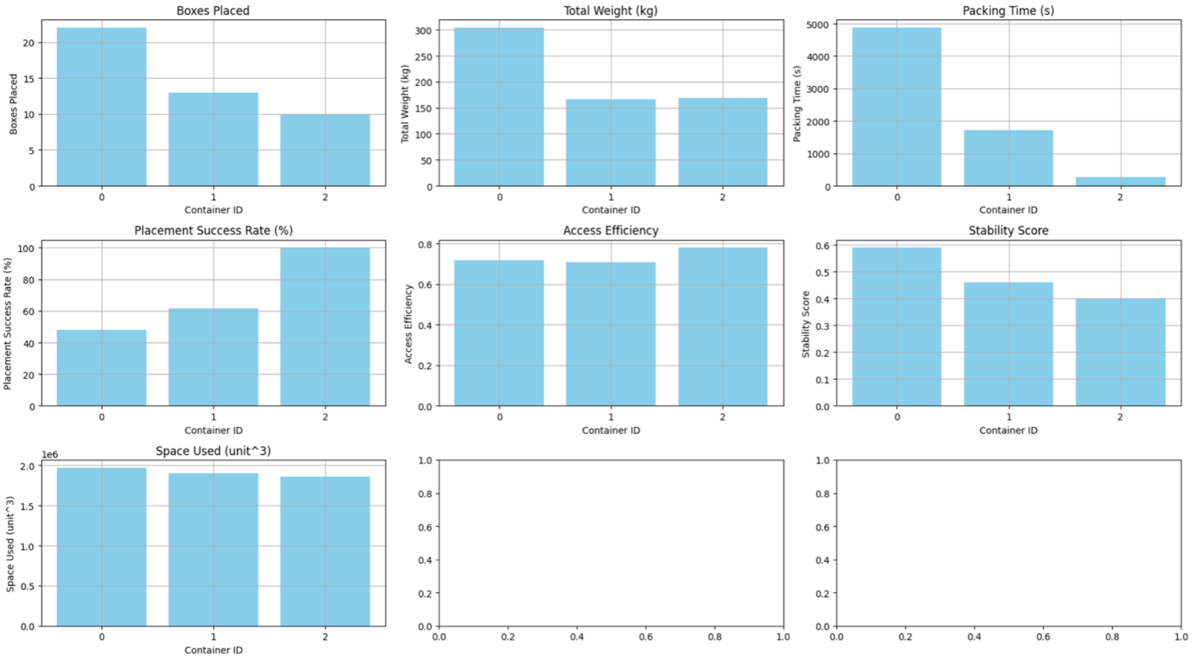


Figure 7. The performance of evaluation matrices for each container based on the Genetic Algorithm

Overall, the performance of the evaluation matrix presented in Figures 5, 6, and 7 reinforces this pattern. First Fit excels in speed, Best Fit has potential for spatial efficiency but is prone to inconsistencies, and Genetic Algorithm provides the highest-quality solutions at a significant computational cost. Algorithm selection should be guided by specific operational constraints: First Fit for speed and simplicity, Best Fit for compactness (provided it is stable), and Genetic Algorithm for maximum quality and optimization.

3.2.1 Implications

The findings of this study have significant practical implications for logistics optimization and supply chain management. The selection of packaging algorithms must be tailored to specific operational needs. For real-time applications or resource-constrained environments (e.g., edge computing in logistics systems), the First Fit algorithm is highly recommended due to its simplicity and speed, aligning with the low packaging times observed in Table 1. In cases of high-value shipments or complex warehouse planning where computation time is not the primary constraint, the Genetic Algorithm is the superior choice due to its ability to maximize box placement, access efficiency, and overall stability, as demonstrated by the high accessibility and stability scores in Table 1. The Best Fit Algorithm, despite its focus on space optimization, exhibits inconsistent performance; this suggests that Best Fit implementations require enhancements such as dynamic sorting or intelligent fallback mechanisms to ensure reliability across various scenarios. This research confirms that there is no single universal solution to the 3D bin packing problem; instead, a hybrid approach can provide balanced performance by combining the strengths of each method.

3.2.2 Research contribution

This study makes several important contributions. First, it conducts an in-depth comparative analysis between traditional heuristics (First Fit, Best Fit) and metaheuristic algorithms (Genetic Algorithm) in the context of 3D-BPP, highlighting the relative strengths and weaknesses of each in terms of computational efficiency, space utilization, and packaging quality, as summarized in Table 1. Second, it presents a comprehensive evaluation framework using multidimensional metrics (volume utilization, total packaged weight, packaging time, center of gravity, placement success rate, access efficiency, and stability score) that provides a deeper understanding of the trade-offs between packaging objectives, as illustrated in Figures 5, 6, and 7. Third, proposing and evaluating a Wall-Building fallback strategy for unplaced items, which significantly improves the overall efficiency and robustness of the packaging solution, especially for awkwardly shaped items. Finally, we developed a specialized visualization module that dynamically animates the packaging process (Figures 2, 3, and 4), offering an intuitive interpretation that bridges the gap between algorithmic complexity and practical application for researchers and practitioners.

3.2.3 Limitations

Although this study provides valuable insights, several limitations must be acknowledged. The dataset used, although realistic and sourced from a logistics company, consists of only about 5,000 cargo records collected over a six-month period. A larger amount and diversity of data may yield stronger generalizations. The simulation is limited to one type of truck (a small van with specifications of 2.00 m x 1.20 m x 1.20 m and a capacity of 500 kg). Multi-truck scenarios with various sizes and constraints may present more complex challenges and provide broader insights. The high computational time for the Genetic Algorithm (reaching over 4,800 seconds in some cases, as highlighted in Table 1) makes it impractical for real-time applications requiring rapid responses. Although a hybrid approach is proposed as a direction for future research, this study does not explicitly implement or evaluate a hybrid model.

3.2.4 Suggestions

Based on the findings and limitations of this study, recommendations for future research include: First, developing and testing a hybrid model that intelligently combines the speed of heuristics (such as First Fit for initialization) with the global search capabilities of metaheuristics (Genetic Algorithm for refinement) to achieve balanced performance, with a focus on reducing the high computational time of GA. Second, exploring the integration of adaptive heuristics and GPU-accelerated Genetic Algorithms to enhance scalability and responsiveness in real-world packaging environments. Third, investigating learning-based strategies, such as machine learning or reinforcement learning, to predict optimal placement sequences and adapt to highly varied and dynamic box configurations. Fourth, expanding simulation scenarios to include various container types, more complex load constraints, and multi-truck delivery scenarios to validate the algorithm's robustness under more diverse conditions. Finally, conducting further studies on Genetic Algorithm optimization to reduce computational costs, for example, through better parameter tuning or more efficient genetic operators, to make it more feasible for real-time applications.

4. CONCLUSIONS

The comparative analysis of First Fit, Best Fit, and Genetic Algorithm strategies for solving the 3D Bin Packing Problem (3D-BPP) highlights the inherent trade-offs between computational efficiency, space utilization, and packing quality. Each algorithm demonstrates unique strengths aligned with different operational priorities.

The First Fit heuristic stands out for its simplicity and speed, making it highly suitable for real-time applications or resource-constrained environments such as edge computing in logistics systems. While more focused on space optimization, Best Fit shows inconsistent performance across diverse packing scenarios, indicating the need for enhancements such as dynamic sorting or intelligent fallback mechanisms.

On the other hand, the Genetic Algorithm consistently outperforms both heuristics regarding solution quality—maximizing box placement, access efficiency, and overall stability. However, this comes at the cost of significant computational overhead, rendering it more suitable for offline processing, high-value shipments, or complex warehouse planning.

The findings confirm that no single algorithm excels universally across all metrics. Instead, the choice of strategy should be driven by application-specific requirements such as speed, space optimization, or packing quality. Combining heuristic speed with evolutionary refinement, a hybrid approach holds promise for delivering balanced performance and warrants further exploration.

Future work will focus on integrating adaptive heuristics, GPU-accelerated GAs, and learning-based strategies to enhance scalability and responsiveness in real-world packing environments.

5. ACKNOWLEDGEMENT

This research was supported by the authors' respective institutions. The authors also acknowledge the private logistics and delivery services company in Indonesia for providing access to their historical cargo delivery data, which was crucial for this study.

6. AUTHOR CONTRIBUTION STATEMENT

MKA contributed to the conceptualization, methodology, and writing of the original draft. DP was responsible for data curation, software development, and visualization. MZ contributed to the validation, formal analysis, and review and editing of the manuscript.

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