Analysis of grouping tuning parameters in flower-cutting optimization heuristics for efficient space allocation problem with item categorization

Kateryna Czerniachowska[1]

[1]Wroclaw University of Economics and Business, Komandorska St 118/120, 53-345, Wroclaw, Poland

Abstract

This study explores the concepts of computational optimization heuristics for item categorization and allocation on distribution center racks. Properly organizing products on racks in warehouses or distribution centers according to their respective categories is essential for efficient operations. The research proposes the flower-cutting optimization heuristics with 17 tuning parameters. Special attention is given to examining the effect of two grouping tuning parameters on the number of generated product allocations and their implications for space utilization, accessibility, and operational efficiency: implements a grouping strategy where, for each total width, only one product allocation with the maximum total profit is considered; adopts a grouping strategy where, for each total profit and profit ratio, only one product allocation with the minimum total width is selected. The experiment revealed that the implementation of grouping tuning parameters plays a crucial role in substantially reducing computational requirements while preserving the quality of solutions. By narrowing the solution space, these parameters ensure that the heuristics efficiently produce near-optimal allocations. This streamlined approach enhances the practicality of addressing large-scale shelf space allocation challenges, making the heuristics highly applicable to real-world scenarios.

Keywords

Space allocation, optimization heuristics, decision-making/process, item categorization

1. Introduction

Dividing the warehouse shelving into zones for different product categories or types allows for locating products much easier. In this case, for example, household goods, electronics, clothing, etc., can be stored in different areas of the racks, helping order pickers quickly find the products ordered by customers. This also guarantees effective stock management, provides easy access to products, and reduces the possibility of product damage.

We introduce novel flower-cutting optimization heuristics aimed at addressing the challenges identified in the shelf space allocation problem with specific product categorization and additional item types included in the main categories. Our approach incorporates two heuristic variants, each characterized by a unique sorting sequence for allocation prioritization. There were 17 tuning parameters implemented. However, this research mainly focuses on key grouping parameters for tuning: (1) parameter 7, which limits product allocations to one per total width, maximizing total profit. (2) parameter 9, which limits product allocations to one per total profit and profit ratio, minimizing total width. By combining innovative heuristics with parameterized selection strategies, the flower-cutting approach effectively balances complexity and practical applicability, making it a robust tool for solving shelf space allocation challenges.

Earlier research has investigated the development of heuristics for resource allocation problems, highlighting the significance of tuning parameters to optimize the solution process. These parameters are crucial for narrowing the solution space, effectively reducing complexity while maintaining solution quality [1]-[2].

[1]CMIS-2025: Eighth International Workshop on Computer Modeling and Intelligent Systems, May5, 2025, Zaporizhzhia, Ukraine

kateryna.czerniachowska@ue.wroc.pl (K. Czerniachowska)

0000-0002-1808-6020 (K. Czerniachowska)

© 2025 Copyright for this paper by its authors.
Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

CEUR-WS.org/Vol-3988/paper5.pdf

2. Literature review

Assortment planning refers to the process of selecting and managing the range of items that are available for distribution through a supply chain. In distribution centers, effective assortment planning ensures that the right items are stocked in appropriate quantities to meet customer demand while optimizing inventory levels.

For the formulation of assortment planning, the authors [3] employed an exogenous demand model and integer programming. They present a heuristic to tackle larger problems and solve a number of small problems by thorough enumeration to show how assortment and stocking decisions depend on the characteristics of predicted substitution behavior [3].

The researchers [5] introduced the practice of adjusting the store layout and changing the product allocations multiple times each day to match the changing customers' needs at different hours of the day. In this case, the customers can easily find their favorite products in the supermarket.

Online assortment planning requires a strategic approach to digital catalogue management, ensuring a diverse yet manageable range of products that align with consumer preferences and market trends. This often involves sophisticated algorithms and data analysis to continuously refine the product mix, enhancing the online shopping experience and operational efficiency.

Another researcher [6] developed a model that maximizes the revenue of impulse purchases considering the layout of grocery stores and also maximizes customer satisfaction with product allocations with regard to adjacencies of related departments.

Shelf space allocation refers to the process of assigning physical space on store shelves (or within distribution center storage areas) to different products in a way that maximizes profitability, sales, and operational efficiency. This issue becomes increasingly important in distribution centers as they prepare stock for retail stores or direct customers.

The researchers in [7] provided a revised shelf space allocation problem with additions that address more practical scenarios in the retail sector, rationalizing this issue. They developed a combination of heuristics in a 5-phase "Squeaky Wheel" optimization with a local search technique to generate high-quality solutions to the problem [7].

Although marketing factors' elasticity can be fixed beforehand with known values, the demand function can readily accommodate them. The theory regarding self-service grocery retail stores posits that product demand is influenced by the extent of display exposure. It is hypothesized that this promotional structure can alter consumers' brand preferences [7]-[9]. Thus, in the demand function, only the product's direct spatial elasticity is often taken into account. Several strategies were given to solve the linear model [10]-[11].

This behavior reflects aggregated substitution effects, influencing overall demand patterns rather than just individual customer experiences at the store. Consequently, the initial assortment decision must account for potential substitution to accurately forecast demand and optimize inventory levels.

Metaheuristics are problem-solving techniques that aim to find approximate solutions to complex optimization problems, particularly when exact methods are impractical. These methods are often used to tackle large-scale, difficult problems by exploring various strategies and approaches to find near-optimal solutions efficiently.

The researches in [12] provided a comprehensive overview of meta-heuristic methods. Among the many types of metaheuristics are greedy random adaptive search procedures, neural networks, constraint logic programming, natural evolutionary computation, non-monotonic search strategies, space-search techniques, simulated annealing, tabu search, threshold algorithms and their hybrids, and neural networks [12].

The researches in [13] proposed to use a genetic algorithm to improve the retail shelf-space configuration instead of a heuristic approach, building on the genetic algorithm shelf-space research stream [13]-[16]. The suggested meta-heuristic technique has the following benefits: (1) it involves less computational work; and (2) managers can apply the solution obtained directly to the retail shelf space.

The researcher in [16] used a population-based solution or genetic algorithm and concluded that a metaheuristic outperformed a heuristic approach. On the other hand, the simulation makes the assumption that the product profit is independent of the horizontal shelf location inside a shelf section [16].

The researcher in [17] in their research grounded on the work of [16]. The researcher in [17] presented a hyperheuristic approach, such as a fast variant of the variable neighbourhood search and the reduced variable neighbourhood search. A commonly reduced variable neighbourhood search is beneficial when a local search is extremely costly. If random points are chosen from the current's nearby solutions and no descent is performed, the reduced variable neighbourhood search method is achieved [17].

The research [18] emphasized the principles and aims of space management in retailing, paying specific attention to space management activities at the category, segment, and brand levels. The goal was to assist retailers in navigating the retailer-imposed category management.

These advancements in metaheuristic techniques highlight the growing interest and potential of these methods in optimizing complex problems, including retail shelf-space allocation. By incorporating genetic algorithms and hyperheuristics, researchers have been able to enhance the effectiveness and efficiency of solution methods, reducing the computational burden and providing more practical, implementable results for managers. This progression in metaheuristic application allows for more refined, cost-effective approaches to shelf-space configuration, offering valuable insights for the retail industry.

Both assortment planning and shelf space allocation are critical in ensuring that a distribution centre operates efficiently and that products are delivered to the right place at the right time. Proper assortment planning helps ensure that distribution centres are stocked with the right products, while effective shelf space allocation maximizes the visibility and sales potential of those products. Together, they contribute to a smoother flow of goods, better customer satisfaction, and improved profitability across the supply chain.

3. Problem statement

The research focuses on the shelf space allocation problem (SSAP) in distribution centres and retail stores, analyzing the benefits of vertical and horizontal categorization for item (product) display. Vertical categorization enhances visibility, customer experience, and space utilization, while horizontal categorization increases exposure, navigation, and the promotion of key products. Combining both strategies improves customer experience and brand visibility. Products can be categorized by their specific attributes, like weight or perishability, and need to be stored appropriately to avoid risks like contamination or confusion. Clear categorization, product orientation, and rack dividers aid the organization. Retail managers must also consider historical sales data for better stock management and forecasting.

The goal of the SSAP under investigation is to maximize profit or product movement. To achieve this, retailers must determine the shelf placement for each product based on its vertical and horizontal categorization. Vertical and horizontal categorizations guide the most effective placement strategy to minimize retrieval times, ensuring products are positioned for maximum accessibility and operational efficiency. This includes deciding how many stock-keeping units (SKUs) to assign per shelf, the product orientation (front, side, or top), and addressing various constraints such as shelf, product, multi-shelf, and category-specific limitations.

The criterion of the SSAP is to maximize the profit of each SKU placed on each shelf. The core constraints related to SSAP can be explained as follows.

The shelf constraints: each product must fit within the shelf's length, height, and depth, ensuring the product's dimensions are compatible with the available shelf space.

The product constraints. Products must be placed on the shelf. There is a specified range for the number of SKUs allowed for each product on the shelf. Each product must have a designated orientation (front, side, or top), and only one orientation can be applied per product. Products requiring separate storage must be placed on different shelves. Incompatible products should not be placed next to each other, but if marked compatible, they must be stored together on the same shelf. The placement of products must align with their respective SKUs.

The multi-shelf constraints. Products can be placed on a specific number of shelves, with a defined minimum and maximum number of shelves allowed. There are storage limits when a product is distributed across multiple shelves, and the shelves should be placed near one another for efficient access.

The category constraint. Shelf and product compatibility must align according to their category tags. A minimum size for product categories must be maintained if products from the category are placed on a shelf. Products within the same category should be evenly distributed across shelves to maintain balance and organization.

The decision variables constrains. The placement of each product on the shelf. The number of SKUs allocated to that product. The product orientation (front, side, or top) while placing it on the shelf.

4. Flower-cutting heuristics for the SSAP

We introduce novel flower-cutting heuristics that aim to address the challenges of solving SSAPs efficiently by systematically reducing the solution space while retaining high-quality results. The methodology involves two heuristic variants, each with a unique approach to sorting and selecting product allocations. Here's a summarized breakdown of the process.

The core concepts are shelf allocation, and product orientation and key metrics.

The shelf allocation and product orientation: products on shelves are assigned positions (front-facing, side-facing, top-facing) or do not place on the shelf at all. Each shelf allocation sequence encodes the placement and orientation of products.

The key metrics: total profit is the sum of profits from all shelves. Total width is the maximum cumulative width of products in a category. Profit ratio is the profit relative to space usage, excluding empty shelf space.

To decide a problem we use a heuristic workflow.

Problem definition and objectives: define SSAP constraints, profit maximization criteria, and success metrics such as accuracy (profit ratio), estimate the number of solutions, and computational time.

Simplified problem structure: products are allocated within categories individually before being combined across categories, i.e. prepare the parts of the solution for each single category.

Iterative optimization: parameters are adjusted to refine the solution set, focusing on reducing computational effort while preserving near-optimal results.

We state following Implementation highlights. The “flower garden” analogy visualizes the solution space. Each “flower” represents a potential solution. “Clearings” are profitable regions of the solution space. The “basket size” represents the number of solutions to be generated, which is the termination criteria. Parameters guide the selection of flowers (solutions) to focus on the most profitable options.

The optimization process should take into account following aspects. Initial heuristics are tested and evaluated against benchmarks, with parameters fine-tuned to balance solution quality and computational efficiency. Through iterations, the algorithm narrows down solutions using predefined rules, systematically eliminating near-duplicate or suboptimal configurations. A stopping criterion (e.g., basket capacity) ensures the process halts when acceptable resource utilization is achieved.

Tuning parameter roles: parameters of flower clearing forming: 1-4, parameters of moving along the selected flower clearings: 5-10, parameters of the interval between cut flowers on the selected clearings: 11-14, parameters of the flowers to be cut: 15-17.

Let consider the tuning parameter description.

Parameter 1 (focus on the maximum category width before forming product allocations). It limits the category width for product allocations, ensuring that the other categories can achieve high-value configurations.

Parameters 2 and 3 (focus on the number of products that can be placed on the shelf before forming product allocations). They form the number of product allocations per category, excluding low-value product allocations, which could appear in future steps.

Parameter 4 (focus on the profitable groups of products to be placed on the shelf). It establishes base filters for allowable product combinations on each shelf. It ensures only viable initial configurations are considered, reducing unnecessary allocations.

Parameters 5, 6 (focus on the category width threshold after forming product allocations). They cap the number of product allocations per category, focusing on the most promising options within each.

Parameter 8 (focus on the sorting order limiting the number of product allocations on the shelf). It defines the sequence for sorting product allocations, prioritizing based on category width ↑, category profit ↓ (for heuristics H1) and category profit ↓, category width ↑ (for heuristics H2).

Parameter 10 (focus on the sorting order limiting the number of product allocations in the category). It defines the sequence for sorting product allocations, prioritizing based profit ↓, profit ratio ↓(for heuristics H1) and profit ratio ↓, profit ↓(for heuristics H2).

Parameter 11(focus on the product allocation diversity control on the shelf). It ensures that a predefined diversity threshold is met across product allocations formed on the shelf.

Parameter 13 (focus on the product allocation diversity control on the category). It ensures that a predefined diversity threshold is met across product allocations formed on the category.

Parameters 12, 14 (focus on limiting the product allocation after applying parameters 11, 13). They prevent over-consolidation by maintaining a definite number of product allocation options, which is essential for scenarios requiring flexibility in shelf configuration. They enable the fine-tuning of priorities based on profitability for specific product allocations.

Parameters 15, 16 (focus on the category-based profit limits). They process the product on shelves as clusters based on profit similarity. They focus optimization efforts on clusters with the highest potential impact, eliminating the low-profit product allocations.

Parameter 17 (focus on the lower bound of accepted total profit). It establishes the minimum profit for the solution to qualify, ensuring the profitability of the result.

Let consider the tuning grouping parameter roles and impact.

Parameter 7 (focus on maximum total profit per total width). It limits product allocations by considering only one product allocation for each total width, selecting the one with the maximum total profit. It balances computational efficiency and solution diversity. It enables heuristics for faster solution generation while maintaining near-optimal results.

Parameter 9 (focus on minimum total width per profit and profit ratio). It limits product allocations by considering only one product allocation for each combination of total profit and profit ratio, selecting the one with the minimum total width. It is particularly effective in accelerating convergence for larger problem instances. It significantly minimizes the solution space, allowing for efficient handling of large-scale problems.

Results and deployment. The heuristics demonstrate scalability, handling larger instances while maintaining solution diversity. The tuning parameters allow us to achieve significant reductions in solution space without sacrificing profitability. Final heuristics are validated documented, and could be integrated into retail space management systems.

Figure 1 depicts the flower garden analogy, focusing on the specific flower patches where the gardener (representing the heuristic) selects and cuts flowers, symbolizing potential solutions. In the real solution space, multiple flower patches may be chosen, each defined by unique characteristics.

The selection process begins with identifying a threshold height above which flowers are deemed suitable for cutting and placing in the basket. Within each selected patch, only certain flowers are cut and spaced apart by intervals that reflect the heuristic criteria. These intervals, along with the height thresholds and the patch widths, vary between patches, emphasizing the diversity of potential solutions. Flowers in unselected patches are ignored, even if their heights surpass the thresholds of other patches, focusing the effort on promising areas.

The objective is to prioritize patches with the largest and most profitable flowers, ensuring no valuable patch is overlooked. The gardener's task is unconcerned with the distances between patches; instead, the focus remains on harvesting the most profitable flowers within the chosen patches.

The algorithm's computational time mirrors the gardener's efficiency, relying solely on the time spent assessing and cutting flowers in the selected patches while disregarding unselected patches. This visualization underscores the heuristic's ability to streamline the solution space, concentrating only on areas with the highest potential for optimal outcomes.

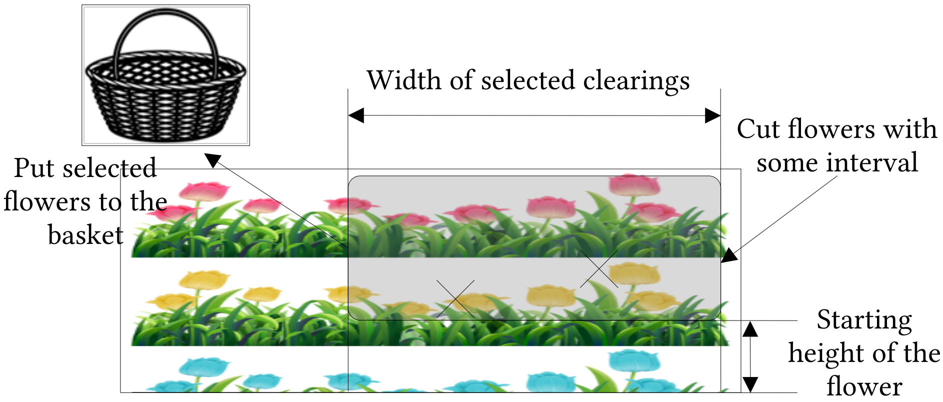

Figure 1: Looking for patches to cut flowers and cutting flowers with some intervals

5. Experiment

The study evaluates the performance of two heuristics (H1 and H2) across a range of test scenarios with varying product counts (10, 15, 20, 25, and 30) and shelf widths (250, 375, 500, 625, and 750). The performance of the developed heuristics for solving the SSAP was evaluated through experiments comparing their solutions to the optimal results from the CPLEX solver.

The study focused on the best-performing parameter configurations, identified through systematic tuning, to ensure high-quality solutions. Key metrics such as solution quality, computational time, and proximity to optimality were analyzed. The results provide insights into the efficiency of the heuristics and their potential for improving shelf space management in complex scenarios.

The computer parameters were: processor: AMD Ryzen 5 1600 Six-Core Processor 3.20 GHz, system type: 64-bit Operation System, x64-based processor,. RAM: 16 GB, operation system: MS Windows 10.

Table 1 presents the average performance of the developed heuristics. Across all test scenarios, heuristic H1 consistently achieved near-optimal profit ratios, averaging 99.85%, with computation times ranging from 0.05 to 5.60 minutes. Heuristic H2 displayed slightly higher computation times, ranging from 0.05 to 7.01 minutes, but similar profit ratios, averaging 99.86%. The CPLEX solver was effective for smaller cases, with times as low as 0.36 seconds, but scaled less efficiently; its maximum computation time was 6.48 seconds.

In terms of performance consistency, both heuristics (H1 and H2) consistently achieve high-profit ratios, with most values at or near 100%. This indicates their effectiveness in maximizing profit regardless of the number of products or shelf width. When talking about the efficiency of heuristics, it can be observed that H1 generally has faster computation times than H2. As the number of products and shelf width increase, computation times for both heuristics and CPLEX increase, although CPLEX exhibits significant variation in computation time.

Table 1
The average performance of the developed heuristics

Products	Average profit ratio of H1	Average profit ratio of H2	Average time of H1 [min]	Average time of H2 [min]	Average time of CPLEX [s]
10	100.00%	100.00%	0.33	0.33	0.52
15	99.96%	99.96%	0.78	1.52	0.75
20	99.99%	100.00%	3.21	4.39	1.07
25	99.85%	99.87%	2.92	3.87	1.79
30	99.43%	99.45%	2.52	2.81	3.68

The next phase of the experiment focuses on evaluating the impact of grouping tuning parameters. Parameter 7 prioritizes generating a single product allocation for each total width that maximizes the total profit among the available options. Parameter 9, on the other hand, focuses on generating a single product allocation for each total profit and profit ratio that minimizes the total width among the available options.

Table 2 displays the number of product allocations (the number of SKUs put on the shelf) that correspond to the number of generated shelf allocations if the product is put on the shelf). The number of product allocations is presented after applying the initial product allocation parameters 1-4 and the minimum and maximum width parameters (parameters 5 and 6). So, there is not a complete solution space, but there is already a reduced one. Although this is not the entire number of potential solutions, it is clear that even after reduction, there are still a lot of product allocations that need to be examined. These product allocations will be used to determine the ultimate solution.

The numbers of shelf allocations for 10, 15, 20, 25, and 30 product sets varied from 3 to 6, from 3 to 36, from 3 to 79, from 4 to 106, and from 4 to 119 for each product set, respectively. The numbers of product allocations for 10, 15, 20, 25, and 30 product sets varied from 24 to 2 879, from 54 to 23 609, from 42 to 57 289, from 48 to 728 143, and from 65 to 87 881 for each product set respectively. Despite the fact that the presented numbers of product allocations are calculated after the reduction solution space parameters, we can’t check all of them; therefore, further reduction solution space is still needed.

Table 2
Numbers of generated shelf allocations and product allocations in heuristics H1, H2

Products	Shelf width	Number of shelf allocations				Number of product allocations			
		Shelf 1	Shelf 2	Shelf 3	Shelf 4	Shelf 1	Shelf 2	Shelf 3	Shelf 4
10	250	4	6	4	6	24	145	140	80
	375	4	6	4	6	26	414	426	279
	500	4	6	4	6	30	950	956	688
	625	3	6	4	6	28	1 782	1 771	1 359
	750	3	6	4	6	26	2 870	2 879	2 361
15	250	3	36	17	24	57	271	791	120
	375	3	35	17	24	76	1 480	3 241	397
	500	3	35	17	24	54	3 213	5 454	681
	625	3	35	17	23	84	4 708	13 510	949
	750	3	34	17	23	88	9 480	23 609	1 695
20	250	3	68	62	48	66	1 524	6 377	3 346
	375	3	79	69	59	90	7 312	29 609	14 350
	500	3	35	30	24	109	2 855	9 802	5 628
	625	3	35	30	24	42	5 913	14 682	7 860
	750	3	35	30	24	50	44 254	57 289	23 794
25	250	4	84	63	62	48	1 385	6 931	1 035
	375	4	106	69	74	48	3 040	19 743	2 378
	500	4	79	61	59	71	8 860	43 337	5 237
	625	4	82	61	62	74	23 257	148 586	15 541
	750	4	64	50	53	65	83 946	728 143	25 577
30	250	5	119	105	91	65	1 550	1 885	2 167
	375	4	58	38	48	75	4 762	3 447	752
	500	4	59	24	38	110	5 639	5 834	8 879
	625	4	51	31	38	83	10 105	7 789	15 989
	750	4	71	24	45	120	11 500	87 881	6 521

Table 3 presents the number of product allocations after applying grouping parameter 7 to all instances except the smallest 10 product sets. The values in Table 3 could be compared to the values in Table 2. Therefore, the product allocations given here are also achieved after applying all previous reducing space parameters, i.e. the initial product allocation parameters 1-4 and the minimum and maximum width parameters (parameters 5 and 6). The number of product allocations that will be processed after applying parameter 7 is limited by parameter 8. The amount of checked product allocations limited by the parameter 8 was shown in Table 2.

Table 3 shows how much the solution space was reduced with the help of parameter 7. So, on average, the number of product allocations on each shelf was 56, 1 937, 870, 1 139. These numbers varied from 22 to 117 for the 1st shelf, 661 to 3 512 for the 2nd shelf, 110 to 1 692 for the 3rd shelf, 252 to 2 216 for the 4th shelf.

Table 3
Numbers of product allocations after applying grouping parameter 7 in heuristics H1, H2

Products	Shelf width	Shelf 1	Shelf 2	Shelf 3	Shelf 4
15	250	35	661	110	252
	375	40	1 393	262	673
	500	26	1 196	257	624
	625	36	1 425	381	764
	750	38	1 651	459	884
20	250	22	1 458	938	697
	375	38	1 964	1 322	1 185
	500	52	1 242	915	790
	625	40	1 325	955	915
	750	48	1 528	1 113	991
25	250	48	2 544	751	917
	375	48	3 512	1 266	1 546
	500	71	3 278	1 544	2 131
	625	74	3 046	1 692	2 216
	750	65	2 739	1 362	1 972
30	250	63	1 382	1 374	1 184
	375	72	1 667	485	1 098
	500	106	2 040	753	1 115
	625	81	1 634	741	1 226
	750	117	3 054	720	1 592
Minimum		22	661	110	252
Average		56	1 937	870	1 139
Maximum		117	3 512	1 692	2 216

Following the application of grouping parameter 9, the number of created product allocations (the number of SKUs put on the shelf) is displayed in Table 4. Only large test instances of 25 and 30-product sets were subject to this parameter. The values attained were used for subsequent actions.

Even though Table 3 shows nearly equal numbers of product allocations on the shelves for 15-20 and 25-30 product sets, the issue arises when the new category (25-30 product sets) is added, making the reduction grouping parameter 9 necessary. Not every product allocation obtained after grouping is used for subsequent phases. Parameter 10 sets a limit on how many product allocations can be handled following the application of parameter 9.For medium (15-20 product sets) instances parameter 10 was utilized without the use of parameter 9. For small (10 product sets) instances, parameters 9 and 10 were not used.

It could be observed that for the 1st category for 25-product set on the 250 cm shelves, the number of product allocations was reduced from 1 074 107to 742 after applying this parameter. For most of these 3-category instances, the number of product allocations has been significantly reduced from millions and thousands to thousands and hundreds, which is a forward-looking improvement of the main algorithm. The procedure for looking for further solutions is streamlined, and efficiency is increased by this modification.

Table 4
Numbers of product allocations before and after applying grouping parameter 9 in heuristics H1, H2

Products	Shelf width	Before grouping			After grouping		
		Category 1	Category 2	Category 3	Category 1	Category 2	Category 3
10	250	703	680	-	-	-	-
	375	3 057	908	-	-	-	-
	500	3 478	2 580	-	-	-	-
	625	3 852	296	-	-	-	-
	750	394	440	-	-	-	-
15	250	17 047	12 318	-	-	-	-
	375	168 557	41 100	-	-	-	-
	500	11 086	583	-	-	-	-
	625	53 101	7 488	-	-	-	-
	750	98 474	18 904	-	-	-	-
20	250	2 397	25 749	-	-	-	-
	375	3 536	1 100	-	-	-	-
	500	34 906	44 365	-	-	-	-
	625	12 145	59 414	-	-	-	-
	750	6 021	17 989	-	-	-	-
25	250	1 074 107	4 571	4 464	742	656	492
	375	437 455	186 094	3 119	748	681	691
	500	128 524	10 056	45 370	474	443	998
	625	147 050	22 473	102 114	422	455	616
	750	130 019	11 815	4 391	340	314	391
30	250	371 902	898	2 727	1 082	308	359
	375	408 315	42 091	11 362	1 507	2 383	592
	500	246 462	21 360	4 780	2 465	2 590	547
	625	22 925	26 699	5 021	659	1 581	547
	750	20 036	702	15 679	640	402	1 355
Minimum		394	296	2 727	340	308	359
Average		136 222	22 427	19 903	908	981	659
Maximum		1 074 107	186 094	102 114	2 465	2 590	1 355

6. Discussion

As a result of conducted experiments we obtain following observations.

The reduction in solution space. Both grouping parameters (7 and 9) significantly reduce the number of generated product allocations, which directly minimizes the solution space, enhancing computational efficiency. Parameter 7: By focusing on maximizing the total profit for each total width, the number of product allocations was drastically reduced across all shelf widths. For instance, at the 3rd shelf for 25 products and a shelf width of 750 cm, the number of product allocations decreased from 728 143 to 1 362. Parameter 9: Targeting the minimum total width for each total profit and profit ratio resulted in a substantial reduction in the solution space. For example, at 25 products and a shelf width of 250, the number of product allocations in Category 1 dropped from 1 074 107 to 742, Category 2 from 4 571 to 656, and Category 3 from 4 464 to 492.

The generation of near-optimal results. Despite the reduction in solution space, both parameters retained the heuristics' ability to generate solutions close to the optimal, as demonstrated earlier in their high-profit ratios. Parameter 7: Ensures near-optimal results by prioritizing the maximum profit allocation for each shelf width, maintaining the quality of solutions while drastically reducing complexity. Parameter 9: Focuses on minimizing total width for specific profit categories for each total profit and profit ratio, aligning with the goal of achieving efficient space utilization without compromising profitability.

The grouping tuning parameters. The number of product allocations after applying Parameter 7 was reduced by approximately 60–90% in most cases while preserving diversity across profit categories. Parameter 9 achieved reductions of up to 95% in certain scenarios, particularly in high-complexity instances like 30 products or large shelf widths, enabling faster solution convergence.

The effectiveness across problem scenarios. The grouping tuning parameters demonstrated scalability across varying problem sizes (e.g., 10–30 products) and shelf widths (250–750). This confirms their adaptability and robustness in handling different complexities inherent in the SSAP.

The overall impact of grouping tuning parameters. The application of grouping tuning parameters (7 and 9) is instrumental in significantly reducing computational demands while maintaining solution quality. This allows the heuristics to remain effective in generating near-optimal allocations with a fraction of the original solution space. These parameters enable a more practical approach to solving large-scale SSAP problems, making them suitable for real-world applications.

7. Conclusion

In this research, concepts of item categorization and allocation on the warehouse racks are considered. It’s critical to arrange items on warehouse or distribution centre racks according to the correct categories. The investigated SSAP approach allows organizing the racks simultaneously vertically and horizontally according to the category or product type. The proposed model deals with shelf space optimization by appropriately arranging product categories maximizing the gained profit or movement of the products to make the most of available shelf space while adhering to the following categories of constraints: shelf, product, multi-shelves, and category constraints. It makes it possible to efficiently distribute shelf space in a way that optimizes operational effectiveness and guarantees the integrity of the stored goods by combining these constraints. Furthermore, our approach extends beyond traditional shelf allocation methods by considering the diverse needs of different products. Therefore, in the developed model, we include two types of such products: (1) incompatible products, which must not be placed one next to the other on the same shelf, and (2) products requiring separate storage, which must not be placed on the same shelf.

In order to optimize space usage and uphold safety regulations in the warehouse setting, decisions on shelf structure, spacing, and weight distribution can also be made based on the products’ heterogeneous character. Some products have a specific packaging shape, size or stocking possibilities, which may determine how best to place them and which orientation is better. If there is a grouping of products by category on the shelf, then it is advisable to display the products so that their name or main element is visible at first glance of the picker at this category on the rack. In this research, we use three orientations of the product on the shelf: front, side, and top.

In this research, we propose flower-picking heuristics with tuning parameters to deal with the described SSAP. Performance metrics include the profit ratio, computation times for the heuristics, and the computation time for the CPLEX solver, which serves as a benchmark for exact solutions.

The profit ratios remain consistently high across all scenarios, with averages near 99.85% for H1 and 99.86% for H2. Computation times show significant variability, with H1 taking up to 5.60 minutes and H2 taking up to 7.01 minutes in the worst case. The fastest computation time was 0.05 minutes for both heuristics.

Comparing the heuristics performance with CPLEX, it could be observed that the CPLEX solver is faster in small-scale scenarios but does not scale as efficiently with an increasing number of products or shelf width. The heuristics are more practical for larger problem sizes due to their ability to deliver optimal or near-optimal solutions in a shorter time frame.

The study also investigates the impact of two grouping tuning parameters on the number of generated product allocations and their influence on space utilization, accessibility, and operational efficiency. Parameter 7 represents a strategy that considers only one product allocation with the maximum total profit for each total width. Parameter 9 represents a strategy that selects only one product allocation with the minimum total width for each total profit and profit ratio.

The use of grouping tuning parameters results in fewer product allocations. These reductions of solution space, coupled with the maintenance of solution quality, underscore the value of grouping as an efficient strategy for tackling the investigated SSAP.

Applying Parameter 7 reduced the number of product allocations by approximately 60–90% in most cases while maintaining diversity across profit categories. Parameter 9 achieved reductions of up to 95%, especially in high-complexity scenarios such as instances with 30 products or large shelf widths, significantly accelerating solution convergence.

There are several ways in which future research can enhance its effectiveness. Firstly, it is real-time optimization in dynamic environments: Future studies could focus on optimizing product allocation in environments that are constantly changing, such as warehouses with high product turnover or seasonal demand fluctuations. This would involve developing heuristics that adjust automatically based on real-time data, such as stock levels, order frequency, or product shelf-life. Secondly, it is a multi-objective optimization. Research could explore models that balance multiple objectives, such as reducing operational costs, improving product accessibility, and maximizing profitability. This would involve developing complex heuristics or hybrid algorithms that can handle conflicting goals efficiently.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

[1] Czerniachowska, Kateryna. "Mushroom Picking Heuristics Framework for Knapsack-like Problems of Resource Allocation." Scientific Journal of Bielsko-Biala School of Finance and Law 28.3 (2024): 42–59. doi:10.19192/wsfip.sj3.2024.6.

[2] Czerniachowska, Kateryna, and Philippe Krajsic. "Grass Cutter Heuristics for Knapsack-Like Problems of Resource Allocation." In Emerging Challenges in Intelligent Management Information Systems, edited by Marcin Hernes, Jarosław Wątrybski, and Artur Rot, 212–223. Cham: Springer Nature Switzerland, 2024.

[3] Smith, Stephen A., and Narendra Agrawal. "Management of Multi-Item Retail Inventory Systems with Demand Substitution." Operations Research 48.1 (2000): 50–64. doi:10.1287/opre.48.1.50.12443.

[4] Lim, Andrew, Zhang, Qian, Rodrigues, Brian; "A Heuristic for Shelf Space Decision Support in the Retail Industry." In AMCIS 2002 Proceedings, 30, 2002.

[5] Lee, Hau L., and Seungjin Whang. "Demand chain excellence." Supply Chain, Management Review (March/April), 40–46. 2001.

[6] Ozgormus, Elif, and Alice E. Smith. "A Data-Driven Approach to Grocery Store Block Layout." Computers and Industrial Engineering 139 (2020). https://doi.org/10.1016/j.cie.2018.12.009.

[7] Dijk, Albert van, Harald J. van Heerde, Peter S.H. Leeflang, and Dick R. Wittink. "Similarity-Based Spatial Methods to Estimate Shelf Space Elasticities." Quantitative Marketing and Economics 2.3 (2004): 257–277. doi:10.1023/b:qmec.0000037079.73934.a2.

[8] Kim, Gwang, and Ilkyeong Moon. "Integrated Planning for Product Selection, Shelf-Space Allocation, and Replenishment Decision with Elasticity and Positioning Effects." Journal of Retailing and Consumer Services 58 (2021): 102274. doi:10.1016/j.jretconser.2020.102274.

[9] Reyes, Pedro M., and Gregory V. Frazier. "Initial Shelf Space Considerations at New Grocery Stores: An Allocation Problem With Product Switching and Substitution." The International Entrepreneurship and Management Journal 1.2 (2005): 183–202. doi:10.1007/s11365-005-1128-4.

[10] Lim, Andrew, Brian Rodrigues, and Xingwen Zhang. "Metaheuristics with Local Search Techniques for Retail Shelf-Space Optimization." Management Science 50, no. 1 (2004): 117–131. doi:10.1287/mnsc.1030.0165.

[11] Yang, Ming Hsien. "Efficient Algorithm to Allocate Shelf Space." European Journal of Operational Research 131.1 (2001): 107–118. doi:10.1016/S0377-2217(99)00448-8.

[12] Osman, Ibrahim H., and Gilbert Laporte. "Metaheuristics: A Bibliography." Annals of Operations Research 63 (1996): 513–623. doi:10.1007/bf02125421.

[13] Hansen, Jared M., Sumit Raut, and Sanjeev Swami. "Retail Shelf Allocation: A Comparative Analysis of Heuristic and Meta-Heuristic Approaches." Journal of Retailing 86.1 (2010): 94–105. doi:10.1016/j.jretai.2010.01.004.
[14] Esparcia-Alcбzar, Anna I., Lidia Lluch-Revert, Ken C. Sharman, Josй Miguel Albarracнn-Guillem, and Marta E. Palmer-Gato. "Towards an Evolutionary Tool for the Allocation of Supermarket Shelf Space." In GECCO 2006 - Genetic and Evolutionary Computation Conference, 2: 1653–1660, 2006. doi:10.1145/1143997.1144269.
[15] Hwang, Hark, Bum Choi, and Min Jin Lee. "A Model for Shelf Space Allocation and Inventory Control Considering Location and Inventory Level Effects on Demand." International Journal of Production Economics 97.2 (2005): 185–195. doi:10.1016/j.ijpe.2004.07.003.
[16] Urban, Timothy L. "An Inventory-Theoretic Approach to Product Assortment and Shelf-Space Allocation." Journal of Retailing 74.1 (1998): 15–35. doi:10.1016/S0022-4359(99)80086-4.
[17] Yu, Vincent F., Renan Maglasang, and Yu Chung Tsao. "A Reduced Variable Neighborhood Search-Based Hyperheuristic for the Shelf Space Allocation Problem." Computers and Industrial Engineering 143 (2020). doi:10.1016/j.cie.2020.106420.
[18] Dujak, Davor, Marina Kresoja, and Jelena Franjkovic. "Space Management in Category Management - a Comparative Analysis of Retailers." Strategic Management, May (2016): 409–24.