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OPTIMIZATION BASED ON FLOWER CUTTING HEURISTICS FOR SPACE ALLOCATION PROBLEM

Czerniachowska K. S. – PhD, Lecturer, Department of Process Management, Wroclaw University of Economics and Business, Wroclaw, Poland.

Subbotin S. A. – Dr. Sc., Professor, Head of the Department of Software Tools, National University "Zaporizhzhia Polytechnic", Zaporizhzhia, Ukraine.

ABSTRACT

Context. This research discusses the shelf space allocation problem with vertical and horizontal product categorization, which also includes the products of general and brand assortment as well as products with different storage conditions stored on different shelves and incompatible products stored on the same shelf but no nearby.

Objective. The goal is to maximize the profit, product movement, or sales after allocating products on store shelves, defining the shelf for the product and the number of stock-keeping units it has.

Method. The research proposes the two variants of heuristics with different sorting rules inside utilized as an approach to solving the retail shelf space allocation problem with horizontal and vertical product categorization. It also covers the application of 13 developed steering parameters dedicated to instances of different sizes, which allows to obtain cost-effective solutions of high quality.

Results. The results obtained by heuristics were compared to the optimal solutions given by the commercial CPLEX solver. The effectiveness of the proposed heuristics and the suitability of the control settings were demonstrated by their ability to significantly reduce the number of possible solutions while still achieving the desired outcomes. Both heuristics consistently produced solutions with a quality surpassing 99.80% for heuristic H1 and 99.98% for heuristic H2. Heuristics H1 found 12 optimal solutions, and heuristics H2 found 14 optimal solutions among 15 test instances – highlighting their reliability and efficiency.

Conclusions. The specifics of the investigated model can be used by supermarkets, apparel stores, and electronics retailers. By following the explained heuristics stages and the methods of parameter adjustments, the distributor can systematically develop, refine, and deploy a heuristic algorithm that effectively addresses the shelf space allocation problems at hand while being robust and scalable.

KEYWORDS: heuristics, shelf space allocation, knapsack problem, decision-making/process.

ABBREVIATIONS

SSAP is a shelf space allocation problem;
SKU is a stock-keeping unit.

NOMENCLATURE

S is a total number of shelves;
P is a total number of products;
K is a total number of categories;
T is a total number of tags;
i, a, b are shelf indexes;
j, c, d are product indexes;
k is a category index;
t is a tag index;
r is an orientation index.

Parameters of the shelf i:

s_i^l is a shelf length;

s_i^h is a shelf height;

s_i^d is a shelf depth;

s_{ti}^g is a shelf binary tag t.

Parameters of the product j:

p_j^w is a product width;

p_j^h is a product height;

p_j^d is a product depth;

p_j^u is a product unit movement/profit;

p_{tj}^t is a product tag t;

p_j^k is a product category;

p_j^s is a group of products for separate storage (not on the same shelf);

p_j^n is a group of incompatible products (must be allocated on the same shelf but not side by side);

p_{jr}^o is a product orientation binary parameter;

$f_j^{\min}, f_j^{\max}$ are minimum and maximum numbers of SKUs;

$s_j^{\min}, s_j^{\max}$ are minimum and maximum numbers of shelves for allocation of the product;

p_j^l is a limitation of the product in the warehouse;

Additional product parameters expressions:

p_{jr}^w is a product width considering orientation;

p_{jr}^d is a product depth considering orientation;

p_{jr}^h is a product height considering orientation;

Parameters of the category k:

c_k^m is a minimum category size as a percentage of the shelf length;

c_k^t is a category size tolerance between shelves in the category as a percentage of the shelf length.

Parameters of the tag t:

b_t^n is a tag type;

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b_{tij}^{t} is a product to shelf compatibility tag;

x_{ijr} is a product placement binary variable;

f_{ijr} is a number of SKUs of the product j on the shelf i on orientation r.

INTRODUCTION

The retailer SSAP involves determining how to optimally distribute available shelf space across different products in a retail environment. The problem is often critical to improving product visibility, sales, and customer satisfaction, as shelf space directly influences purchase behaviour. When considering vertical and horizontal product categorization, this problem becomes more complex and requires strategic decision-making. In this research, we investigate the SSAP with simultaneous vertical and horizontal categorization.

Vertical categorization refers to how products are arranged within each category (i.e., the layout of products in a column or row vertically on the shelf). This could involve stacking products on shelves based on brand, price range, size, or sales frequency, where products within the same category are placed in a vertical alignment. Example: On a shelf dedicated to soft drinks, Coca-Cola might be placed above Pepsi, with smaller bottles at the top and larger ones at the bottom.

Horizontal categorization refers to how different product categories are distributed across the entire shelf space, where each category (such as beverages, snacks, cleaning products, etc.) gets a designated portion of the shelf. Products within each category are then placed horizontally within their allotted space. Example: One horizontal section of the shelf could be dedicated to beverages, another to snacks, and another to cleaning supplies.

Both the retailer and the consumer can gain a number of important advantages from the obvious horizontal and vertical grouping of general assortment and high-end brands on store shelves. The purchasing experience is more efficient, well-organized, and straightforward thanks to these classifications. These are the main advantages:

1. Enhanced shopping experience.

Effortless navigation: Based on their requirements, tastes, or budgets, customers can find products with ease. Customers can more easily locate particular product classes, including “general” or “luxury” items, thanks to horizontal and vertical categorization, without becoming overwhelmed by a sloppy display.

Clear product segmentation: Grouping products logically helps shoppers understand what’s available and where to look for what they need, making their shopping experience more enjoyable and less stressful.

2. Helpful comparison.

Fast price and feature comparison: Customers may quickly compare various goods based on features, quality, or price by grouping premium brands and general selection into areas that are clearly defined. Customers can compare similar products within their price range, for example, by distinguishing brands with lower and higher prices.

Evident visual indications for decision-making: By placing premium brands at eye level or on higher shelves, for example, visual cues can gently nudge consumers toward more expensive items, while more accessible displays of less expensive items can aid in their decision-making.

3. Increased sales and conversion rates.

Up-selling and cross-selling opportunities: Clear distinctions between general assortment and expensive brands enable upselling opportunities. Shoppers interested in a mid-tier product might be persuaded to consider a more expensive version once they see the differences in product quality or features.

Impulse purchases: When expensive brands are clearly separated but still prominently displayed, customers may be enticed to make purchases they hadn’t initially planned for, especially if they perceive the products to be of higher quality or status.

4. A higher level of brand awareness.

Premium brand setting up: Clearly positioned vertically or horizontally at eye level or in high-traffic locations is advantageous for premium or luxury companies. This raises its profile and strengthens the brand’s exclusivity and prestige, setting it apart from the more generic collection items.

Tactical shelf placement: Brands may make sure that their items are positioned in high-visibility areas where they are more likely to be discovered and, consequently, increase the likelihood of purchase by employing vertical or horizontal categorization.

5. Better stock management.

Streamlined inventory control: Categorizing products into clear sections makes it easier for retailers to manage stock levels and ensure that shelves are adequately stocked. Retailers can identify popular price segments and adjust their inventory accordingly, reducing the chances of stockouts or overstocking.

Efficient restocking and display management: With a categorized system, store employees can quickly identify which products need to be restocked or repositioned, improving operational efficiency and ensuring a consistently appealing display.

6. Optimized space utilization.

Effective shelf management: Categorizing products effectively maximizes shelf space by ensuring products are grouped logically based on their characteristics. It reduces clutter and prevents overcrowding of certain product types, making the best use of available retail space.

Customized layouts: Retailers can experiment with different layouts of horizontal and vertical categorization to optimize space based on customer traffic flow and product demand.

7. Better customer targeting.

Appealing to different demographics: By clearly categorizing products, retailers can cater to a broader range of

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customers, from budget-conscious shoppers to those looking for luxury items. The layout helps customers quickly identify products that match their buying intentions and budget, which can lead to higher satisfaction and loyalty.

Tailored marketing and promotions: Retailers can use shelf categorization to target specific customer segments with tailored promotions or discounts for specific product groups. For example, a store could highlight premium brands with exclusive offers or bundle general assortment items together to offer value deals.

8. Consistent branding and store identity.

Clear brand identity: Categorization ensures that each brand or product category is consistently presented in alignment with its image. For example, expensive brands might be placed in more elegant, sophisticated sections, while more budget-friendly brands could be organized in straightforward, no-frills sections. This enhances the overall atmosphere of the store and reinforces the store's identity.

Brand loyalty: Over time, customers will associate specific areas of the store with their favourite products or brands, leading to stronger brand loyalty. A consistent categorization system helps reinforce this connection by making it easier for customers to find their preferred brands quickly.

9. Competitive advantage.

Differentiation in the marketplace: A well-organized store with clear categorization of general assortment and premium products can set a retailer apart from competitors. It creates a more seamless and pleasant shopping experience, which can attract customers and positive word-of-mouth referrals.

Customer satisfaction: By providing customers with a clear, organized, and easy-to-navigate shopping environment, retailers can increase customer satisfaction, which ultimately drives higher retention rates and repeat business.

The main goal in solving the retailer SSAP is to optimize profits, sales or product movement while maintaining a balanced and accessible store layout. Retailers aim to:

– maximize product visibility: products that drive sales should be easily visible and accessible, which can lead to strategic vertical and horizontal placement;

– increase sales efficiency: allocating more shelf space to high-demand or high-margin items can increase the sales of those products while avoiding overstocking less popular items;

– enhance customer experience: a well-organized shelf helps customers find what they need quickly, increasing the likelihood of a purchase. Clear categorization and logical product positioning are keys to a satisfying shopping experience;

– minimize space wastage: proper categorization can avoid the underuse of space (e.g., leaving gaps on a shelf that could be used for additional products).

The object of study is the retailer shelf space allocation problem with simultaneous horizontal and vertical product categorization on the shelves. This problem can be framed as a linear programming or integer programming optimization problem. The objective function typically seeks to maximize sales, product movement or profit, subject to constraints related to shelf space availability, product demand, product compatibility (i.e., products that should be grouped together), product size and packaging.

The subject of study is the heuristics algorithms for maximizing profits or product movement when allocating products on the shelves and specifying the number of SKUs for each one. Some approaches to solving the problem include heuristic algorithms (such as genetic algorithms, simulated annealing, or greedy methods) for approximating optimal solutions and data-driven methods, where historical sales data and customer behaviour are used to inform decisions about product placement and space allocation.

The purpose of the work is to increase the speed and quality of solution generation by developing heuristics and introducing the tuning parameters which significantly reduce the solution space without violating the quality of the solution obtained.

1 PROBLEM STATEMENT

The model proposed in this study contrasts with the vertical product categorization models outlined in [1–3], which emphasize the need for separate storage of products on different shelves and the allocation of incompatible items on either the same or different shelves. Unlike these previous models [1–3], the current approach integrates a more flexible method of product arrangement, allowing for better optimization of shelf space. This model also considers the dynamic relationships between products, such as complementary separate storage and incompatible goods, to enhance sales and customer satisfaction. By refining how products are grouped and allocated, retailers can improve operational efficiency and increase consumer purchase behaviour.

The criteria function of the SSAP can be formulated as follows:

$$\max \sum_{i=1}^{S} \sum_{j=1}^{P} \sum_{r=0}^{2} p_j^u f_{ijr}, \tag{1}$$

Subject to:

$$\forall (i)[\sum_{j=1}^{P} \sum_{r=0}^{2} p_{jr}^w f_{ijr} \le s_i^w], \tag{2}$$

$$\forall (i,r,j : p_{jr}^h > s_i^h)[f_{ijr} = 0], \tag{3}$$

$$\forall (i,r,j : p_{jr}^d > s_i^d)[f_{ijr} = 0], \tag{4}$$

$$\forall (i,j,r)[x_{ijr} \le f_{ijr} \le f_j^{\max}], \tag{5}$$

$$\forall (i,j)[f_j^{\min} x_{ijr} \le \sum_{r=0}^{2} f_{ijr} \le f_j^{\max} x_{ijr}], \tag{6}$$

$$\forall (i,j,r)[x_{ijr} \le p_j^o], \tag{7}$$

$$\forall (i,j)[\sum_{r=0}^{2} x_{ijr} \le 1], \tag{8}$$

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$$\begin{gathered}\forall(i)\forall(c,d: p_c^s = p_d^s, \\ c \neq d,\ c,d = 1,...,P) \\ [\sum_{r=0}^{2} x_{icr} + \sum_{r=0}^{2} x_{idr} \leq 1]\end{gathered}, \tag{9}$$

$$\begin{gathered}\forall(i)\forall(a,b: p_a^n = p_b^n,\ a,b = 1,...,P) \\ [\sum_{r=0}^{2} x_{iar} = \sum_{r=0}^{2} x_{ibr}]\end{gathered}, \tag{10}$$

$$\begin{gathered}\forall(k,i,c) \\ [\sum_{\substack{j=1, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} x_{ijr} - \sum_{\substack{j=1, \\ p_j^n = c, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} x_{ijr} \geq \\ \geq \sum_{\substack{j=1, \\ p_j^n = c, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} x_{ijr} - 1]\end{gathered}, \tag{11}$$

$$\forall(i,j,r)[\frac{s_i^w x_{ijr}}{p_{jr}^w} \geq f_{ijr}], \tag{12}$$

$$\forall(j)[s_j^{\min} \leq \sum_{i=1}^{S} \sum_{r=0}^{2} x_{ijr} \leq s_j^{\max}], \tag{13}$$

$$\forall(j)[\sum_{i=1}^{S} \sum_{r=0}^{2} f_{ijr} \leq p_j^l], \tag{14}$$

$$\begin{gathered}\forall(j)\forall(a,b: |a-b| \neq 1 \wedge a < b, \\ a,b = 1,...,S)\forall(r)[x_{ajr} + x_{bjr} \leq 1]\end{gathered}, \tag{15}$$

$$\forall(i,j)[\prod_{t=1}^{T} b_{tij}^t \geq \sum_{r=0}^{2} x_{ijr}], \tag{16}$$

$$\begin{gathered}\forall(i,k)[(\sum_{\substack{j=1, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} p_{jr}^w f_{ijr} \geq \left[s_i^l \cdot c_k^m\right]) \vee \\ \vee(\sum_{\substack{j=1, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} f_{ijr} = 0)]\end{gathered}, \tag{17}$$

$$\begin{gathered}\forall(k)[\max_{i=1,...,S}(\sum_{\substack{j=1, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} p_{jr}^w f_{ijr}) - \\ - \min_{i=1,...,S}(\sum_{\substack{j=1, \\ p_j^k = k}}^{P} \sum_{r=0}^{2} p_{jr}^w f_{ijr}) \leq \left[\max_{i=1,...,S}(s_i^l) \cdot c_k^t\right]]\end{gathered}, \tag{18}$$

Decision variables:

$$\forall(i,j,r)[x_{ijr} \in \{0,1\}], \tag{19}$$

$$\forall(i,j,r)[f_{ijr} = \{f_j^{\min} ... f_j^{\max}\}], \tag{20}$$

The constraints signify the following. (2) – the total product width is within the shelf length. (3) – the product height must fit the shelf height. (4) – the product depth must fit the shelf depth. (5) – the product is placed on the shelf. (6) – minimum and maximum number of product SKUs must be within the limits. (7) – specific orientation (front, side, top) is possible for the product. (8) – only one specific orientation is possible is possible for the product. (9) –if products are required to be stored separately, they must be placed on different shelves. (10) – if products are marked as incompatible, they must be placed on the same shelf. (11) – if products are marked as incompatible products, they must not be placed nearby. (12) – product on-the-shelf placement and SKU relationships. (13) – minimum and maximum number of shelves on which the product may be placed. (14) – product storage limit if the product is placed on multiple shelves. (15) – if the product is placed on multiple shelves, the shelves must be allocated nearby. (16) – tags compatibility for the shelves and products must be satisfied. (17) – minimum category size if the products from the category are placed on the shelf must be satisfied. (18) – category size tolerance, i.e., products from the category, must possibly be evenly distributed on the shelves within the category.

There are two decision variables. (19) – the product is placed on the shelf. (20) – the number of product SKUs.

Binary variables could have the following values.

$$r = \begin{Bmatrix} 0, \text{ for front orientation} \\ 1, \text{ for side orientation} \\ 2, \text{ for top orientation} \end{Bmatrix};$$

$$s_{ti}^g = \begin{Bmatrix} 1, \text{ if shelf } i \text{ is tagged} \\ 0, \quad \text{otherwise} \end{Bmatrix};$$

$$p_{jr}^o = \begin{Bmatrix} 1, \text{ if specific orientation is available} \\ 0, \quad \text{otherwise} \end{Bmatrix};$$

$$p_{jr}^w = \begin{Bmatrix} p_j^w, \text{ if } r = 0, \text{ width for front orientation} \\ p_j^d, \text{ if } r = 1, \text{ depth for side orientation} \\ p_j^h, \text{ if } r = 2, \text{ height for top orientation} \end{Bmatrix};$$

$$p_{jr}^d = \begin{Bmatrix} p_j^d, \text{ if } r = 0, \text{ depth for front orientation} \\ p_j^w, \text{ if } r = 1, \text{ width for side orientation} \\ p_j^w, \text{ if } r = 2, \text{ width for top orientation} \end{Bmatrix};$$

$$p_{jr}^h = \begin{Bmatrix} p_j^h, \text{ if } r = 0, \text{ height for front orientation} \\ p_j^h, \text{ if } r = 1, \text{ height for side orientation} \\ p_j^d, \text{ if } r = 2, \text{ depth for top orientation} \end{Bmatrix};$$

$$b_{tij}^t = \begin{Bmatrix} 1, \text{ if } s_{ti}^t = p_{tj}^t \wedge b_t^n = \{H\} \\ 0, \quad \text{otherwise} \end{Bmatrix},$$ – for the horizontal, e.g. brand products level shelves;

$$b_{tij}^t = \begin{Bmatrix} \min(p_{tj}^t; 1) \wedge b_t^n = \{V^+\} \\ 1, \text{ if } p_{tj}^t = 1 \wedge s_{ti}^t = p_{tj}^t \wedge b_t^n = \{H^+\} \\ 0, \text{ if } p_{tj}^t = 1 \wedge s_{ti}^t \neq p_{tj}^t \wedge b_t^n = \{H^+\} \\ 1, \text{ if } p_{tj}^t = 0 \wedge b_t^n = \{H^+\} \end{Bmatrix},$$ – for the horizontal and vertical, e.g. general assortment shelves.

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Binary product placement decision variable could have the following values.

$$x_{ijr} = \begin{cases} 1, \text{ if product } j \text{ is placed on shelf } i \\ \quad \text{on orientation } r \\ 0, \text{ otherwise} \end{cases}$$

2 REVIEW OF THE LITERATURE

Merchandising and retail literature discussed retail layout by shelf space management, which aims to identify the most profitable range of products and their resulting placement and space distribution on shelves. By analyzing consumer behaviour and purchasing patterns, researchers have identified that the strategic placement of products, considering factors such as visibility and accessibility, can significantly influence consumer decisions and ultimately drive higher revenue. Empirical research, such as [4] and [5] demonstrated that product exposure has a major impact on revenue and is contingent on the shelf location. The placement of products within prime shelf locations, such as eye-level or end-cap displays, can increase product exposure and lead to higher purchase rates, underscoring the critical role of shelf space allocation in retail profitability. Nevertheless, most models neglect to account for position visibility instead of focusing on product demand, space elasticity and cross-elasticity, and inventory management [6–10].

Some retailing research focuses on maximizing the visibility of products on shelves to encourage impulse buying, recognizing that consumer purchases can be strongly influenced by immediate, unplanned decisions [4–5, 11–13]. By strategically placing high-margin or attention-grabbing items in easily accessible and highly visible areas, retailers can create environments that prompt spontaneous purchases. This approach often involves techniques such as placing products near checkout counters, at eye level, or within frequent customer pathways to trigger impulse buying behaviours, ultimately boosting sales and enhancing store profitability.

There are some principles for marketing managers regarding the impulse purchase likelihood among different product categories with different customers' adjacency preferences. Locating the fish aisle next to the fruit and vegetables aisle would allow consumers to spend much time in the fruit aisle during the planning of their fish orders. The garment aisle and the cosmetics aisle should lay close together for female customers. Complementary packaged food aisles and lentils/oil aisles should lie next to each other [14].

A product's value has always been determined by the direct revenues it generates. However, rather than existing in isolation, products impact one another's sales. A large-scale product network is formed when products are frequently provided as a group of web pages connected by suggestion hyperlinks in e-commerce environments [15]. This relationship can be particularly seen in retail shelf space allocation, where products are often placed together based on complementary purchasing behaviour or category relevance. For instance, in brick-and-mortar stores, similar or complementary products are grouped to increase the likelihood of impulse buying and cross-selling, while in e-commerce environments, a product's value can also be influenced by its proximity to related items, as seen through suggestion hyperlinks or "customers also bought" recommendations. The dynamic nature of product networks, where products influence each other's visibility and purchase probability, emphasizes the importance of strategically allocating shelf space, both in physical stores and online, to maximize overall sales and optimize consumer purchasing patterns.

The goal for every retail store is to identify the most significant differences between substitutable and complementary products which will influence customers' buying behaviour or purchase decisions. Substitutable products are those that can be easily replaced by alternatives, and their placement on shelves should be strategically positioned to highlight price or quality comparisons, driving consumers toward their preferred choice. In contrast, complementary products are those that are often purchased together, and their placement near each other encourages bundling or cross-selling, which can increase the overall value of the transaction. By carefully analyzing these differences, retailers can make informed decisions about shelf space allocation, ultimately enhancing the shopping experience and maximizing sales opportunities.

Under the overall store layout, it is important to decide which types of products can be positioned next to each other. This is where the concepts of space distribution and space layout are interconnected. A store layout would provide the buyer with logic while allowing the retailer to accomplish his/her own goals in terms of introducing the store to customers to as much of the merchandise variety as possible and increasing the importance of each customer's purchase [16].

In [17] the authors conducted research that examined the relationship between consumer preferences for specific product brands and future product demand. They focused on how these preferences influenced decisions regarding the allocation of shelf space in retail stores. Their study suggested that retailers should consider consumer brand choice as a key factor when determining the optimal amount of shelf space for different products. This was critical for ensuring that high-demand products were readily available and visible to consumers, potentially leading to increased sales [17]. Later, another authors in [18] introduced an improved model that built upon work in [17] by incorporating the cost effect. Their model addressed the need for a more balanced approach, taking into account not only consumer demand but also the costs associated with stocking and displaying various products on store shelves [18].

However, for the buying association between items, customer behaviours/patterns for product-to-shelf assignment issues should be considered. When shopping in a supermarket, the customer walks through the store's aisles, pauses at some locations, explores his or her considerations, and selects the best choices. This process continues until the entire shopping trip is completed [19].

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Merchandising and retail shelf space studies emphasize the importance of efficient shelf space management to enhance product visibility and optimize sales performance [20–23].

3 MATERIALS AND METHODS

In the given research, we introduce novel flower-cutting heuristics aimed at addressing the difficulties identified in the retail SSAP studies we analyzed. Our approach includes two distinct heuristic variants, each characterized by a particular sorting sequence for allocation. These variants offer different methods for prioritizing the allocation process, allowing for greater flexibility in handling various problem scenarios. By incorporating these innovative sorting strategies, our methodology enhances the efficiency and effectiveness of flower-cutting heuristics solutions, contributing to improved outcomes in SSAP-related challenges. The two heuristics present alternative ways to optimize the process based on differing allocation priorities, ensuring better adaptability to different sets of constraints.

A series of numbers, which we call in the research as the shelf allocation, indicates whether a product is put on the shelf or not. One can arrange items on the shelf in one of three ways: top-facing (0/3), side-facing (0/2) or front-facing (0/1). Products are oriented on the shelf according to the coding system. When the value is zero, the product is not put on the shelf. A series of numbers, which we call in the research as the product allocation, indicates how many SKUs are placed on the shelf.

The following step-by-step instructions outline the general structure of the new flower-cutting heuristic, highlighting how tuning and sorting strategies can influence the shelf and product allocation process and lead to an efficient solution for the investigated SSAP problem.

Stage 1. Problem initialization. Define the SSAP by categorization, including the number of shelves, products, and product categories to which these products belong. Set up any constraints and requirements for the allocation on the shelves. Establish success indicators.

Stage 2. Allocation principles. Preparing the garden: set up the necessary input parameters to define the garden, which represents a complex solution space. In this metaphor, flowers of varying heights and bud sizes, along with different flower densities in different areas, symbolize diverse solutions to explore. Each flower represents a potential solution, and the gardener must prepare to navigate this environment for effective problem-solving. Identifying flower clearings: create solutions focusing on specific areas of the garden. It selects clearings that are most likely to yield optimal results based on predefined criteria. By narrowing the search area, the heuristic improves efficiency. Inside the selected clearing, many flowers may grow, so the gardener must establish rules to focus only on certain flowers, further narrowing the solution space. Picking the flowers: Solutions are generated using specific criteria, sorting order, and interval parameters for a systematic approach. The proposed method, like a gardener, selects flowers from the chosen clearings, leaving others to grow according to defined parameters to improve accuracy and efficiency.

Stage 3. Allocation parameters. The Gardener's movement path length optimizes the distance travelled by the gardener, aiming to gather the most high-quality flowers while reducing unnecessary movement. Target flower height sets the minimum height for flowers to be picked, focusing on taller, more profitable blooms. Target flower spacing interval controls the distance between cut flowers in a patch, ensuring the gardener skips some flowers to avoid cutting too many in the same area, optimizing the selection of high-value flowers. Gardener's basket size limits the number of flowers picked in one trip, emphasizing quality over quantity by prioritizing the largest, most valuable flowers.

Stage 4. Parameters of performance tuning.

Parameters of flower clearing cultivation. Parameter 1 – the minimum number of products that can be allocated on the shelf while generating product allocations. Parameter 2 – the maximum number of products that can be allocated on the shelf while generating product allocations. Parameter 3 – the set of profitable groups of products to be allocated on the shelf.

Parameters for travelling through the chosen flower clearings. Parameter 4 – the minimum category width after forming product allocations. Parameter 5 – the maximum category width after forming product allocations. Parameter 6 – if the grouping option (for each total width, only 1 product allocation with the maximum total profit) is generated. Parameter 7 – the maximum number of product allocations on the shelf according to the sorting order. Parameter 8 – the maximum number of product allocations of the category prioritized according to the variant of profitability.

For these paremeters we define sortung rules.

Sorting rule 7.1: category width ↑, category profit ↓ – this prioritizes narrower product allocations that give high profit.

Sorting rule 7.2: category profit ↓, category width ↑ – this prioritizes profitable product allocations that allocate less shelf space.

Sorting rule 8.1: profit ↓, profit ratio ↓. Sorting rule 8.2: profit ratio ↓, profit ↓.

Parameters for the interval between cut flowers on the chosen clearings. Parameter 9 – the interval of taking the product allocations on the shelf after taking all product allocations according to parameter 7. Parameter 10 – the maximum number of product allocations on the shelf created with the interval parameter 9, the sorting rule is the same as in parameter 7. Parameter 11 – the interval of taking the product allocations of the category after taking all product allocations according to parameter 8. Parameter 12 – the maximum number of product allocations of the category created with the interval parameter 11; the sorting rule is the same as in parameter 8.

Parameter of the flowers to be selected to the gardener's basket. Parameter 13 – the minimum profit for each category.

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Stage 5. Constraint checking and adjustment. After each allocation step, verify if the allocation adheres to all provided constraints. Do not generate allocations with violation of constraints required to be re-allocated or adjusted to maintain feasibility (generate only appropriate product allocations checking constraints in earlier steps).

Stage 6. Optimization step. The selection approach continuously refines solutions by not focusing on similar ones and cutting only the flowers that meet the value criteria. It maximizes profitability while optimizing resource use, reducing the gardener's time and preventing the basket from being overfilled. If applicable, apply a tuning or improvement of input parameters to fine-tune the generation of product allocations and re-run the solution-obtaining procedure from the beginning.

Stage 7. Termination criteria. The algorithm terminates once all products have been allocated on the shelves, all constraints have been satisfied and the gardener basket is filled up with a set of high-quality flowers (solutions).

Stage 8. Final allocation output. Return the final allocation plan – the biggest flower from the gardener's basket – which includes the optimal or near-optimal allocation of products along the shelves based on the chosen heuristic variant.

The flower garden scenario is depicted in Figure 1, with particular attention paid to the flower clearing where flowers – which stand in for possible solutions – are growing. In the actual solution space, there could be more than one number of the garden's chosen parts of the garden to be explored. Above a certain initial height threshold, flowers are cut and arranged in the basket, defining the flower clearing. Like in the actual world, not all of the flowers in this particular clearing have been cut; instead, there is some space between them. Depending on the clearing, there may be variations in the height thresholds, widths, and flower intervals. Even if flowers in other clearings are higher than the thresholds of the chosen clearing, they are not taken into consideration. Therefore, the selection of appropriate clearings steered by the tuning parameters is needed. Finding and choosing the clearings with the largest blooms is the goal, making sure that no lucrative clearing is missed. The gardener's duty is unaffected by the distances between the chosen flower clearings. Only the chosen clearings where the gardener cuts flowers are used to determine how long it takes the algorithm to generate and choose solutions to be verified.

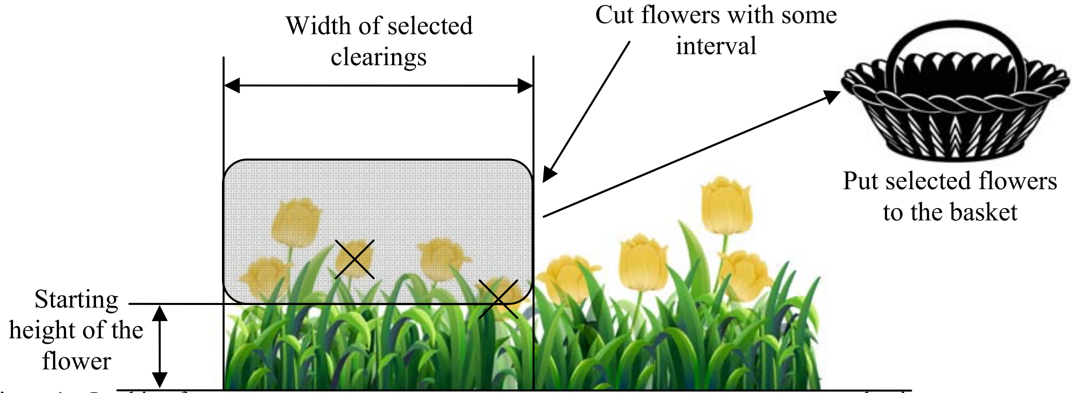

Figure 1 – Looking for clearings to pick flowers and picking flowers with intervals on the clearing

4 EXPERIMENTS

The computer program implementing the proposed heuristics was developed. The experiment was conducted on a personal computer with the following technical characteristics. 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: Windows 10

There were three sets of products prepared. In each set, there were 10, 15, 20 products that needed to be placed on four shelf racks measured by different lengths of shelf: 250, 375, 500, 625, and 750 cm. The products in each set differed with the range of parameters such as dimensions, including height, depth, width, and movement/profit.

In order to define distinct category areas for product distribution on the rack, two vertical category partitions were made for product sets. Making the best use of shelf space by efficiently arranging the products within the categories in the rack was the aim of this problem.

The experimental design incorporated a range of retail constraints, allowing for a comprehensive analysis of the heuristics' performance under varied conditions. Through the use of different testing scenarios, the study highlighted the adaptability of the heuristics when dealing with fluctuating parameters and complex problem settings. By varying the input data across multiple test cases, the experiments provided critical data on the heuristics' efficiency, shedding light on their strengths and areas for improvement.

The testing methodology was meticulously crafted to ensure that the heuristics could be evaluated against both small-scale and large-scale problems, providing a well-rounded assessment. The integration of diverse configurations into the experiment enabled a deep dive into the heuristics' behaviour, ensuring their relevance and applicability to a wide range of practical shelf space allocation problems.

Table 1 illustrates the heuristic settings used in the test examples experiment. For small instances with 10 prod-

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ucts, one parameter was applied. To reduce the solution space, all 13 parameters were used for larger instances (20 products). Medium instances with 15 products utilized 10 parameters. Both heuristic strategies employed the same input parameters to minimize the solution space.

Table 1 – The set of parameters used in the test instances

Tuning parameter	Number of products		
	10	15	20
Parameter 1	–	–	●
Parameter 2	–	–	●
Parameter 3	–	–	●
Parameter 4	–	●	●
Parameter 5	–	●	●
Parameter 6	–	●	●
Parameter 7	–	●	●
Parameter 8	–	●	●
Parameter 9	–	●	●
Parameter 10	–	●	●
Parameter 11	–	●	●
Parameter 12	–	●	●
Parameter 13	●	●	●

5 RESULTS

Table 2 compares the performance of two newly introduced heuristics, H1 and H2, with the best results achieved by the commercial CPLEX solver. This comparison spans multiple test cases and focuses on the profit ratio, which indicates the proportion of profit generated by the heuristics relative to the optimal profit determined by CPLEX. For each heuristic and test case, the profit ratio was calculated to assess how closely the heuristics approximated the optimal solutions.

The analysis provides valuable insights into the effectiveness of the heuristics in solving the problem. By examining the profit ratio across different test cases, the evaluation shows how well H1 and H2 perform compared to the commercial solver. This approach offers a clear measure of the heuristics' performance in real-world applications. Additionally, the table presents the solution time for each heuristic test case, offering a comprehensive view of both the efficiency and accuracy of the methods.

Table 3 illustrates the impact of adding parameters 7–12 to reduce the solution space. For the smallest example (a set of 10 products), an assessment of product allocations without parameters, these parameters were provided and all produced product allocations were evaluated. Therefore, there is no information about them in this table. The percentages in Table 2 illustrate the ratio between the evaluated solutions and those that were obtained following the application of the prior reduction parameters. This implies that just a portion of the solutions were evaluated even after the solution space reduction parameters were applied.

Parameter 6 (the grouping option) was applied to 15 and 20 product sets instances except for the smallest 10 products one, after which parameter 7 was applied also to these two product sets. After all product allocations on the shelf specified by parameter 7 were taken, the interval of taking the product allocations on the shelf (parameter 9) was set to 2, and a number of product allocations specified by parameter 10 were taken. The number of product allocations taken with interval (parameter 10) was significantly less compared to the previous number of product allocations (parameter 7) because the quality of them is lower.

Table 3 also illustrates the impact of reducing the solution space by utilizing category parameters 8, 12. After all product allocations generated for the category specified by parameter 8 were taken, the interval of taking the product allocations for the category (parameter 11) was set to 2, and a number of product allocations specified by parameter 12 were taken. The number of product allocations taken with interval (parameter 12) was significantly less compared to the previous number of product allocations (parameter 8) because the quality of them is lower.

Table 4 describes the values chosen for reduction parameters 4 and 5, which represent the minimum and maximum category widths once product allocations are formed.

After determining the potential product allocations on each shelf, the average category width may be calculated. Even though the precise product allocations that will be selected for the final solution are unknown, they still enable the estimation of category width and profit.

Parameter 4, which determines the minimum category width after product allocations are formed, has one value set. This value is compared to the average category width of the product allocations and the shelf width to ensure accuracy.

A percentage of the shelf width is used to represent parameter 5, or the maximum category width. Additionally, it contrasted with the average shelf width and category width of the product allocations. The mentioned parameters were not applied to the 10-product instances, therefore there is no information about them in Table 4.

Table 4 also shows the results of determining values for the category profit parameter 13. All instances used this parameter for reducing the solution space.

Table 5 displays the number of product allocations and solutions generated by heuristics H1 and H2. These allocations yielded solutions or product allocations that satisfy all criteria.

Constraint violations, however, can make it impossible to develop a solution if insufficient product allocations are looked at. When the option with the largest overall profit was selected from the group of possibilities, the main goal was accomplished. Because of the specific criteria used in each heuristic, heuristics H1 and H2 yield different numbers of solutions even though they use the same steering settings. The number of product allocations employed in both techniques was the same.

The total number of shelf allocations in a general case is $(r+1)^{PS} = 4^{PS}$.

The number 4 signifies the various ways a product can be allocated: (1) not displayed on the shelf, (2) displayed on the shelf facing forward, (3) displayed on the shelf sideways, and (4) displayed on the shelf from the top.

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Table 2 – Performance of the developed heuristics

Products	Shelf width	Profit ratio of H1	Profit ratio of H2	Time of H1, minutes	Time of H2, minutes	Time of CPLEX, s
10	250	100.00%	100.00%	0.06	0.08	0.44
	375	100.00%	100.00%	0.11	0.17	0.59
	500	100.00%	100.00%	1.51	1.49	0.45
	625	100.00%	100.00%	0.60	0.56	0.78
	750	100.00%	100.00%	0.58	0.60	0.36
15	250	100.00%	99.98%	0.48	3.28	0.56
	375	99.80%	100.00%	1.15	18.74	0.75
	500	100.00%	100.00%	1.01	17.74	0.86
	625	100.00%	100.00%	1.57	1.40	0.78
	750	100.00%	100.00%	1.65	1.65	0.81
20	250	99.94%	100.00%	0.67	0.66	1.08
	375	100.00%	100.00%	1.85	1.86	1.38
	500	100.00%	100.00%	1.33	1.54	0.84
	625	99.88%	100.00%	1.27	1.27	1.20
	750	100.00%	100.00%	2.93	4.36	0.86
Minimum		99.80%	99.98%	0.06	0.08	0.36
Average		99.97%	100.00%	1.12	3.69	0.78
Maximum		100.00%	100.00%	2.93	18.74	1.38

Table 3 – The usage of the maximum number of product allocations on the shelf (Parameters 7, 10) and for the category (Parameters 8, 12) for heuristics H1 and H2

		Checked allocations on shelves (parameter 7)			Checked allocations on shelves with intervals (parameter 10)			Checked allocations for categories (parameter 8)		Checked allocations for categories with interval (parameter 12)	
Prod-ucts	Shelf width	Shelf 2	Shelf 3	Shelf 4	Shelf 2	Shelf 3	Shelf 4	Category 1	Category 2	Category 1	Category 2
15	250	57.37%	100.00%	100.00%	1.25%	10.03%	2.58%	2.74%	22.59%	0.34%	2.82%
	375	10.00%	80.24%	20.67%	0.42%	3.66%	0.81%	6.37%	21.26%	0.29%	0.97%
	500	3.76%	32.97%	7.25%	0.18%	1.65%	0.34%	6.12%	37.71%	0.51%	3.14%
	625	2.75%	24.82%	5.10%	0.09%	0.85%	0.17%	13.18%	100.00%	0.94%	
	750	1.88%	16.92%	3.36%	1.02%	1.67%	3.08%	7.11%	37.03%	0.51%	2.64%
20	250	10.25%	13.35%	27.73%	0.16%	0.26%	0.36%	100.00%	46.60%		1.94%
	375	1.57%	1.85%	2.55%	0.40%	0.69%	1.16%	100.00%	100.00%		
	500	3.98%	6.88%	11.63%	0.07%	0.17%	0.09%	20.06%	67.04%	1.43%	2.79%
	625	0.72%	1.71%	0.90%	0.01%	0.03%	0.01%	100.00%	31.80%		1.77%
	750	0.11%	0.31%	0.14%	1.25%	10.03%	2.58%	100.00%	74.37%		7.44%
Minimum		0.11%	0.31%	0.14%	0.01%	0.03%	0.01%	2.74%	21.26%	0.29%	0.97%
Average		39.49%	51.94%	45.29%	0.93%	2.11%	0.96%	63.71%	69.23%	0.67%	2.94%
Maximum		100.00%	100.00%	100.00%	5.74%	10.03%	3.08%	100.00%	100.00%	1.43%	7.44%

Table 4 – The usage of the minimum and maximum width after forming product allocations (parameters 4 and 5) and usage of the minimum category profit (parameter 13)

Products	Shelf width	Minimum width of the category compared to the average category width of product allocations (parameter 4)		Minimum width of the category compared to the shelf width (parameter 4)		Maximum width of the category compared to the average category width of product allocations (parameter 5)		Maximum width of the category compared to the shelf width (parameter 5)		Minimum profit of the category compared to the average category profit of product allocations (parameter 13)	
		Cat. 1	Cat. 2	Cat. 1	Cat. 2	Cat. 1	Cat. 2	Cat. 1	Cat. 2	Cat. 1	Cat. 2
10	250	–	–	–	–	–	–	–	–	107%	31%
	375	–	–	–	–	–	–	–	–	87%	108%
	500	–	–	–	–	–	–	–	–	80%	80%
	625	–	–	–	–	–	–	–	–	73%	108%
	750	–	–	–	–	–	–	–	–	98%	92%
15	250	80%	47%	44%	26%	124%	95%	68%	52%	141%	61%
	375	83%	63%	45%	35%	112%	107%	61%	59%	131%	87%
	500	78%	73%	43%	40%	93%	106%	51%	58%	112%	102%
	625	111%	44%	61%	24%	138%	70%	75%	38%	149%	73%
	750	110%	61%	60%	33%	125%	77%	68%	42%	143%	74%
20	250	96%	46%	54%	26%	129%	79%	72%	44%	165%	24%
	375	106%	53%	59%	29%	135%	70%	75%	39%	158%	31%
	500	116%	52%	62%	28%	134%	75%	72%	40%	164%	37%
	625	119%	58%	62%	30%	138%	76%	72%	40%	165%	43%
	750	102%	83%	52%	43%	117%	92%	60%	47%	150%	62%
Minimum		78%	44%	43%	24%	93%	70%	51%	38%	73%	24%
Average		100%	58%	54%	31%	150%	124%	78%	64%	128%	67%
Maximum		119%	83%	62%	43%	212%	212%	100%	100%	165%	108%

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Table 5 – Numbers of generated product allocations and solutions in heuristics H1, H2

Products	Shelf width	Number of generated product allocations to be checked	Number of solutions H1	Number of solutions H2
10	250	$6.17 \cdot 10^5$	$5.96 \cdot 10^4$	$5.96 \cdot 10^4$
	375	$3.67 \cdot 10^6$	$9.31 \cdot 10^4$	$9.31 \cdot 10^4$
	500	$9.59 \cdot 10^6$	$1.31 \cdot 10^6$	$1.31 \cdot 10^6$
	625	$2.51 \cdot 10^6$	$5.18 \cdot 10^5$	$5.18 \cdot 10^5$
	750	$5.27 \cdot 10^5$	$5.20 \cdot 10^5$	$5.20 \cdot 10^5$
15	250	$2.58 \cdot 10^9$	$2.10 \cdot 10^2$	$1.49 \cdot 10^6$
	375	$8.93 \cdot 10^9$	$6.64 \cdot 10^2$	$1.06 \cdot 10^7$
	500	$1.56 \cdot 10^9$	$3.51 \cdot 10^5$	$1.02 \cdot 10^7$
	625	$3.10 \cdot 10^8$	$7.31 \cdot 10^4$	$7.70 \cdot 10^4$
	750	$1.86 \cdot 10^9$	$1.15 \cdot 10^4$	$4.81 \cdot 10^4$
20	250	$2.12 \cdot 10^7$	$1.80 \cdot 10^1$	$3.05 \cdot 10^2$
	375	$2.86 \cdot 10^7$	$1.00 \cdot 10^2$	$1.00 \cdot 10^2$
	500	$6.25 \cdot 10^8$	$3.60 \cdot 10^3$	$1.14 \cdot 10^5$
	625	$2.23 \cdot 10^7$	$2.00 \cdot 10^0$	$2.70 \cdot 10^3$
	750	$2.71 \cdot 10^6$	$9.29 \cdot 10^4$	$1.20 \cdot 10^5$
Minimum		$5.27 \cdot 10^5$	$2.00 \cdot 10^0$	$1.00 \cdot 10^2$
Average		$1.06 \cdot 10^9$	$2.02 \cdot 10^5$	$1.67 \cdot 10^6$
Maximum		$8.93 \cdot 10^9$	$1.31 \cdot 10^6$	$1.06 \cdot 10^7$

Each product has the option to be placed in only one among the available orientations based on the product package. The total number of product allocation possibilities for any set of products can be determined using formula

$$\prod_{j=1}^{P} (f_j^{\max} - f_j^{\min} + 1)^S \ .$$

Additionally, this calculation accounts for every potential positioning choice for each product. Therefore, as the number of products increases, the number of possible allocations grows.

Table 6 displays the number of possible shelf and product allocations in the general scenario, which corresponds to the entire solution space as calculated by the previously given equations. However, Table 5 shows a significant difference between the number of shelf and product allocations produced by heuristics H1 and H2.

Table 6 – Numbers of all possible shelf and product allocations in the general case

Products	Number of shelf allocations	Number of product allocations
10	$1.21 \cdot 10^{24}$	$1.10 \cdot 10^{52}$
15	$1.33 \cdot 10^{36}$	$1.15 \cdot 10^{78}$
20	$1.46 \cdot 10^{48}$	$1.21 \cdot 10^{104}$

This illustrates how employing heuristic rules with steering parameters is both very valid and useful. These instinctive rules are very logical and useful for directing decision-making. They are strong problem-solving tools that use logical thinking and real-world insights to successfully negotiate challenging situations. They are effective problem-solving tools that successfully navigate difficult circumstances by applying reasoned reasoning and practical insights.

6 DISCUSSION

The proposed flower-picking heuristics provides the following key advantages.

– enhanced problem handling. The heuristic's category-based approach enables it to tackle complex problems more efficiently by focusing on relevant groups of items, reducing the complexity compared to individual item processing. This method allows for better optimization of space and resources in retail stores or other structured environments;

– customizable parameter settings. The pre-solution investigation allows the heuristic to customize its parameter settings based on the problem's specific characteristics. This adaptability ensures that the heuristic can perform well across a variety of problem types, improving its generalization potential;

– adaptive input parameters improving through iteration. The iterative tuning of parameters means that the heuristic can evolve and improve as it interacts with the problem. This dynamic changing of input parameters process helps it better navigate the solution space or changes in the problem's structure, making it more robust and flexible in the long term;

– optimization of termination logic. The heuristic's termination condition is tailored to the problem's needs rather than being based on arbitrary iteration limits. Integrating various tuning parameters ensures that the algorithm concludes only when a sufficient number of viable solutions have been identified, preventing unnecessary computations and promoting more efficient problem-solving;

– cost-effectiveness. Due to its ability to focus only on the most relevant parts of the solution space and its flexibility in parameter adjustment, the heuristic reduces the need for extensive computational resources, making it a more cost-effective solution for large-scale problems;

– increased accuracy. By refining parameters through iteration and pre-solution investigation, the heuristic is able to deliver more accurate and effective solutions. This increases its reliability, especially in complex scenarios with multiple interacting variables;

– greater adaptability to real-world problems. The combination of category-based optimization, iterative adjustments, and flexible termination criteria allows the heuristic to adapt to real-world scenarios where problems may evolve or require a more tailored solution approach over time. This makes the method particularly suitable for dynamic environments like inventory management, logistics, or warehouse design;

– efficient resource utilization. By intelligently narrowing down the solution space and stopping once a satisfactory set of solutions has been found, the heuristic optimizes the use of computational and time resources, ensuring that solutions are reached in a timely and resource-efficient manner.

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CONCLUSIONS

In this study, we investigate a model for the retail SSAP that incorporates both vertical and horizontal product categorization on the shelves. The model accounts for key constraints such as the need to store certain products on different shelves due to safety concerns, odour issues, or potential chemical reactions. Additionally, it considers the importance of not placing products from the same category side by side if they could cause confusion for customers or pickers. The model allows for flexibility in the division between vertical categories, which can be either rigid or more adaptable based on the store's specific layout and product types. Furthermore, it designates specific shelf levels for both brand-specific and general assortment products, ensuring efficient space usage and product organization. This approach optimizes both accessibility and safety, ultimately enhancing the customer experience while maintaining effective inventory management.

The retailer SSAP with vertical and horizontal categorization is commonly used in supermarkets (managing aisles with multiple product categories such as fresh food, canned goods, cleaning products, etc), apparel stores (Allocating space across different clothing categories, sizes, and brands), and electronics retailers (organizing shelves for various gadgets, accessories, and brands).

The retailer SSAP, with vertical and horizontal categorization, focuses on optimizing the arrangement of products on the shelves in a way that maximizes sales, ensures product visibility, improves the shopping experience, and minimizes space wastage. It involves balancing product demand, accessibility, and the overall store layout strategy.

The scientific novelty of the obtained results lies in the development of two variants of new heuristics called flower-cutting heuristics that provide innovative solutions to complex problems within the retail store. These heuristics introduce novel approaches for optimizing products on the shelves. Unlike previous methods, the new heuristics take into account multiple dynamic factors and could be steered by the set of parameters appropriate for instances of different sizes. Additionally, the heuristics offer greater flexibility and adaptability, allowing for adjustments based on real-time data and changing store conditions. This advancement represents a significant step forward in improving the efficiency of product placement strategies in retail environments. Furthermore, the heuristics demonstrate improved performance in terms of both operational efficiency and customer satisfaction, offering a valuable contribution to the field of retail optimization.

The practical significance of the results lies in the development of heuristics called the flower-cutting heuristics and 13 steering parameters, which allow a quick search of the solution space and obtain high-quality results, along with the execution of experiments to assess the properties of the modelled SSAP. These experimental findings provide valuable insights, making it possible to recommend the proposed indicators for practical use in real-world scenarios.

Prospects for further research are to study the applicability of the SSAP model and the heuristics for various store sizes and product types, accommodating future growth and changes in the retail environment. In other words, future research in this area could explore several promising directions to further enhance the efficiency and effectiveness of retail store SSAP models. One potential direction is the integration of advanced machine learning and artificial intelligence techniques to dynamically adjust product categorization and shelf allocation based on real-time data, such as customer purchasing behaviour, stock levels, and demand patterns. Another area of exploration could be the development of more sophisticated algorithms for optimizing product placement that consider not only physical constraints but also factors such as shelf visibility, accessibility, and customer preferences.

REFERENCES

1. Czerniachowska K. A genetic algorithm for the retail shelf space allocation problem with virtual segments, *OPSEARCH,* 2022, Vol. 59, № 1, pp. 364–412. DOI: 10.1007/s12597-021-00551-3.
2. Czerniachowska K., Lutoslawski K., Fojcik M. Heuristics for shelf space allocation problem with vertical and horizontal product categorization, *Procedia Computer Science,* 2022, Vol. 207, pp. 195–204. DOI: 10.1016/j.procs.2022.09.052.
3. Czerniachowska K. The Method of Finding High-Runner Products in the Assortment, *Informatyka w zarządzaniu,* 2023, pp. 52–65. DOI: 10.15611/2023.51.0.03.
4. Drèze X., Hoch S. J., Purk M. E. Shelf management and space elasticity, *Journal of Retailing,* 1994, Vol. 70, № 4, pp. 301–326. DOI: 10.1016/0022-4359(94)90002-7.
5. Chandon P., Hutchinson J. W., Bradlow E. T. et al. Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase, *Journal of Marketing,* 2009, Vol. 73, № 6, pp. 1–17. DOI: 10.1509/jmkg.73.6.1.
6. Hwang H., Choi B., Lee M. J. A model for shelf space allocation and inventory control considering location and inventory level effects on demand, *International Journal of Production Economics*, 2005, Vol. 97, № 2, pp. 185–195. DOI: 10.1016/j.ijpe.2004.07.003.
7. Hariga M. A. Al-Ahmari A., Mohamed A. R. A. A joint optimisation model for inventory replenishment, product assortment, shelf space and display area allocation decisions, *European Journal of Operational Research,* 2007,Vol. 181, № 1, pp. 239–251. DOI: 10.1016/j.ejor.2006.06.025.
8. Hwang H., Choi B., Lee G. A genetic algorithm approach to an integrated problem of shelf space design and item allocation, *Computers and Industrial Engineering*, 2009, Vol. 56, № 3, pp. 809–820. DOI: 10.1016/j.cie.2008.09.012.
9. Hübner A. H., Kuhn H. Retail category management: State-of-the-art review of quantitative research and software applications in assortment and shelf space management, *Omega,* 2012, Vol. 40, № 2, pp. 199–209. DOI: 10.1016/j.omega.2011.05.008.
10. Irion J., Lu J. C., Al-Khayyal F. et al. //A piecewise linearization framework for retail shelf space management models, *European Journal of Operational Research*, 2012, Vol. 222, № 1. DOI: 10.1016/j.ejor.2012.04.021.

DOI 10.15588/1607-3274-2025-2-17

11. Botsali A. R., Peters B. A. A network based layout design model for retail stores, *Industrial Engineering Conference*, Atlanta, GA, 2005.
12. Zhang W., Rajaram K. Managing limited retail space for basic products: Space sharing vs. space dedication, *European Journal of Operational Research,* 2017, Vol. 263, № 3, pp. 768–781. DOI: 10.1016/j.ejor.2017.05.045.
13. Flamand T., Ghoniem A., Maddah B. Promoting impulse buying by allocating retail shelf space to grouped product categories, *Journal of the Operational Research Society,* 2016, Vol. 67, № 7, pp. 953–969. DOI: 10.1057/jors.2015.120.
14. Ozcan T., Esnaf S. A Discrete Constrained Optimization Using Genetic Algorithms for A Bookstore Layout, *International Journal of Computational Intelligence Systems,* 2013, Vol. 6, № 2. DOI: 10.1080/18756891.2013.768447.
15. Oestreicher-Singer G., Libai B., Sivan L. et al. The network value of products, *Journal of Marketing*, 2013, Vol. 77, № 3, pp. 1–14. DOI: 10.1509/jm.11.0400.
16. Varley R. Retail product management: Buying and merchandising.Routledge, 2005, Second edition. DOI: 10.4324/9780203358603.
17. Anderson E. E., Amato H. N. Mathematical model for simultaneously determining the optimal brand-collection and display-area allocation, *Operations Research,* 1974, Vol. 22, № 1. DOI: 10.1287/opre.22.1.13.
18. Hansen P., Heinsbroek H. Product selection and space allocation in supermarkets, *European Journal of Operational Research,* 1979, Vol. 3, № 6, pp. 474–484. DOI: 10.1016/0377-2217(79)90030-4.
19. Tsai C.-Y., Huang S.-H. Integrating Product Association Rules and Customer Moving Sequential Patterns for Product-to-Shelf Optimization, *International Journal of Machine Learning and Computing,* 2015, Vol. 5, № 5, pp. 344–352. DOI: 10.7763/ijmlc.2015.v5.532.
20. Czerniachowska K., Subbotin S. Merchandising rules for shelf space allocation with product categorization and vertical positioning, *Informatyka Ekonomiczna,* 2021, Vol. 2021, № 4, pp. 34–59. DOI: 10.15611/ie.2021.1.02.
21. Kpossa M. R., Lick E. Visual merchandising of pastries in foodscapes: The influence of plate colours on consumers' flavour expectations and perceptions, *Journal of Retailing and Consumer Services*, 2020, Vol. 52. DOI: 10.1016/j.jretconser.2018.10.001.
22. Czerniachowska K. Merchandising rules for shelf space allocation with horizontal and vertical positions, *Informatyka Ekonomiczna,* 2021, Vol. 2021, № 4, pp. 9–33. DOI: 10.15611/ie.2021.1.01.
23. Ali Soomro D. Y., Abbas Kaimkhani S., Iqbal J. Effect of Visual Merchandising Elements of Retail Store on Consumer Attention, *Journal of Business Strategies,* 2017, Vol. 11, № 1. DOI: 10.29270/jbs.11.1(17).002.

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ОПТИМІЗАЦІЯ НА ОСНОВІ ЕВРИСТИКИ ЗБИРАННЯ КВІТІВ ДЛЯ ПРОБЛЕМИ РОЗПОДІЛУ ПРОСТОРУ

Черняховська К. С. – доктор філософії, викладач кафедри управління процесами Вроцлавського університету економіки і бізнесу, Вроцлав, Польща.

Субботін С. О. – д-р техн. наук, професор, завідувач кафедри програмних засобів Національного університету «Запорізька політехніка», Запоріжжя, Україна.

АНОТАЦІЯ

Актуальність. Досліджується проблема розподілу простору на полицях з наявною вертикальною та горизонтальною категоризацією продуктів, які також включають продукти загального асортименту та брендового асортименту. Окрім того, в моделі наявні також продукти з різними вимаганнями щодо умов зберігання, котрі повинні зберігатися на різних полицях, а також несумісні продукти, котрі повинні зберігаються на одній полиці, але не поруч.

Мета роботи полягає в тому, щоб максимізувати прибуток, товарний рух або продажі після розміщення продуктів на полицях магазину, визначивши полицю для продукту та кількість його складських одиниць.

Метод. У дослідженні запропоновано два варіанти евристики з різними правилами сортування всередині, які використовуються як підхід до вирішення проблеми розподілу простору на полицях я наявною видимою горизонтальною та вертикальною категоризацією продуктів. Дослідження також охоплює застосування 13 розроблених параметрів управління евристиками, призначених для екземплярів різних розмірів, що дозволяє отримати економічно ефективне рішення високої якості.

Результати отримані за допомогою евристик, порівнювали з оптимальними рішеннями, опрацьованими комерційним вирішувачем CPLEX. Ефективність запропонованих евристик і придатність параметрів управління було продемонстровано їхньою здатністю значно зменшити простір пошукувань, при цьому досягаючи бажаних результатів. Обидві евристики послідовно створювали рішення з якістю, що перевищувала 99.80% для евристики H1 і 99.98% для евристики H2. Евристика H1 знайшла 12 оптимальних рішень, а евристика H2 знайшла аж 14 оптимальних рішень з 15 екземплярів тестування, підкреслюючи їх надійність і ефективність.

Висновки. Особливості досліджуваної моделі можуть використовувати супермаркети, магазини одягу, роздрібні торговці електроніки. Дотримуючись описаних етапів створення евристики та методів коригування параметрів, дистриб'ютор може систематично розробляти, уточнювати та розгортати евристичний алгоритм, який ефективно вирішує поточні проблеми розподілу на полицях, будучи надійним і масштабованим.

КЛЮЧОВІ СЛОВА: евристика, розподіл місця на полицях, проблема рюкзака, процес прийняття рішень.

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ЛІТЕРАТУРА

1. Czerniachowska K. A genetic algorithm for the retail shelf space allocation problem with virtual segments / K. Czerniachowska // OPSEARCH. – 2022. – Vol. 59, № 1. – P. 364–412. DOI: 10.1007/s12597-021-00551-3.
2. Czerniachowska K. Heuristics for shelf space allocation problem with vertical and horizontal product categorization / K. Czerniachowska, K. Lutoslawski, M. Fojcik // Procedia Computer Science. – 2022. – Vol. 207. – P. 195–204. DOI: 10.1016/j.procs.2022.09.052.
3. Czerniachowska K. The Method of Finding High-Runner Products in the Assortment / K. Czerniachowska // Informatyka w zarządzaniu. – 2023. – P. 52–65. DOI: 10.15611/2023.51.0.03.
4. Drèze X. Shelf management and space elasticity / X. Drèze, S. J. Hoch, M. E. Purk // Journal of Retailing. – 1994. – Vol. 70, № 4. – P. 301–326. DOI: 10.1016/0022-4359(94)90002-7.
5. Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase / [P. Chandon, J. W. Hutchinson, E. T. Bradlow et al.] // Journal of Marketing. – 2009. – Vol. 73, № 6. – P. 1–17. DOI: 10.1509/jmkg.73.6.1.
6. Hwang H. A model for shelf space allocation and inventory control considering location and inventory level effects on demand / H. Hwang, B. Choi, M. J. Lee // International Journal of Production Economics. – 2005. – Vol. 97, № 2. – P. 185–195. DOI: 10.1016/j.ijpe.2004.07.003.
7. Hariga M. A. A joint optimisation model for inventory replenishment, product assortment, shelf space and display area allocation decisions / M. A. Hariga, A. Al-Ahmari, A. R. A. Mohamed // European Journal of Operational Research. – 2007. – Vol. 181, № 1. – P. 239–251. DOI: 10.1016/j.ejor.2006.06.025.
8. Hwang H. A genetic algorithm approach to an integrated problem of shelf space design and item allocation / H. Hwang, B. Choi, G. Lee // Computers and Industrial Engineering. – 2009. – Vol. 56, № 3. – P. 809–820. DOI: 10.1016/j.cie.2008.09.012.
9. Hübner A. H. Retail category management: State-of-the-art review of quantitative research and software applications in assortment and shelf space management / A. H. Hübner, H. Kuhn // Omega. – 2012. – Vol. 40, № 2. – P. 199–209. DOI: 10.1016/j.omega.2011.05.008.
10. A piecewise linearization framework for retail shelf space management models / [J. Irion, J. C. Lu, F. Al-Khayyal et al.] // European Journal of Operational Research. – 2012. – Vol. 222, № 1. DOI: 10.1016/j.ejor.2012.04.021.
11. Botsali A. R. A network based layout design model for retail stores / A. R. Botsali, B. A. Peters // Industrial Engineering Conference, Atlanta, GA. – 2005.
12. Zhang W. Managing limited retail space for basic products: Space sharing vs. space dedication / W. Zhang, K. Rajaram // European Journal of Operational Research. – 2017. – Vol. 263, № 3. – P. 768–781. DOI: 10.1016/j.ejor.2017.05.045.
13. Flamand T. Promoting impulse buying by allocating retail shelf space to grouped product categories / T. Flamand, A. Ghoniem, B. Maddah // Journal of the Operational Research Society. – 2016. – Vol. 67, № 7. – P. 953–969. DOI: 10.1057/jors.2015.120.
14. Ozcan T. A Discrete Constrained Optimization Using Genetic Algorithms for A Bookstore Layout / T. Ozcan, S. Esnaf // International Journal of Computational Intelligence Systems. – 2013. – Vol. 6, № 2. DOI: 10.1080/18756891.2013.768447.
15. The network value of products / [G. Oestreicher-Singer, B. Libai, L. Sivan et al.] // Journal of Marketing. – 2013. – Vol. 77, № 3. – P. 1–14. DOI: 10.1509/jm.11.0400.
16. Varley R. Retail product management: Buying and merchandising. / R. Varley. – Routledge, 2005. – Second edition. DOI: 10.4324/9780203358603.
17. Anderson E. E. Mathematical model for simultaneously determining the optimal brand-collection and display-area allocation / E. E. Anderson, H. N. Amato // Operations Research. – 1974. – Vol. 22, № 1. DOI: 10.1287/opre.22.1.13.
18. Hansen P. Product selection and space allocation in supermarkets / P. Hansen, H. Heinsbroek // European Journal of Operational Research. – 1979. – Vol. 3, № 6. – P. 474–484. DOI: 10.1016/0377-2217(79)90030-4.
19. Tsai C.-Y. Integrating Product Association Rules and Customer Moving Sequential Patterns for Product-to-Shelf Optimization / C.-Y. Tsai, S.-H. Huang // International Journal of Machine Learning and Computing. – 2015. – Vol. 5, № 5. – P. 344–352. DOI: 10.7763/ijmlc.2015.v5.532.
20. Czerniachowska K. Merchandising rules for shelf space allocation with product categorization and vertical positioning / K. Czerniachowska, S. Subbotin // Informatyka Ekonomiczna. – 2021. – Vol. 2021, № 4. – P. 34–59. DOI: 10.15611/ie.2021.1.02.
21. Kpossa M. R. Visual merchandising of pastries in foodscapes: The influence of plate colours on consumers' flavour expectations and perceptions / M. R. Kpossa, E. Lick // Journal of Retailing and Consumer Services. – 2020. – Vol. 52. DOI: 10.1016/j.jretconser.2018.10.001.
22. Czerniachowska K. Merchandising rules for shelf space allocation with horizontal and vertical positions / K. Czerniachowska // Informatyka Ekonomiczna. – 2021. – Vol. 2021, № 4. – P. 9–33. DOI: 10.15611/ie.2021.1.01.
23. Ali Soomro D. Y. Effect of Visual Merchandising Elements of Retail Store on Consumer Attention / D. Y. Ali Soomro, S. Abbas Kaimkhani, J. Iqbal // Journal of Business Strategies. – 2017. – Vol. 11, № 1. DOI: 10.29270/jbs.11.1(17).002.

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