

Improving Order-picking Operations with Precedence Constraints through Efficient Storage Location Assignment: Evidence from a Retail Company

Maria A. M. Trindade¹, Paulo S. A. Sousa², Maria R. A. Moreira³



¹Faculty of Economics, University of Porto, Rua Dr. Roberto Frias, 4200-464 Porto, Portugal; Católica Porto Business School, Universidade Católica, Rua de Diogo Botelho, 4169-005 Porto, Portugal (malicemoreirat@gmail.com) ORCID [0000-0001-8284-9291](https://orcid.org/0000-0001-8284-9291); ²Faculty of Economics, University of Porto, Rua Dr. Roberto Frias, 4200-464 Porto, Portugal (paulus@fep.up.pt) ORCID [0000-0002-0578-1593](https://orcid.org/0000-0002-0578-1593); ³Faculty of Economics, University of Porto, Rua Dr. Roberto Frias, 4200-464 Porto, Portugal; INESC TEC-Institute for Systems and Computer Engineering, Technology and Science, Faculty of Engineering campus, Rua Dr. Roberto Frias, Building I, 4200-465 Porto, Portugal (mrosario@fep.up.pt) ORCID [0000-0003-4439-6230](https://orcid.org/0000-0003-4439-6230)

Abstract

This paper is inspired by a manual picking retail company where shape and weight constraints affect the order-picking process. We proposed an alternative clustering similarity index that considers the similarity, the weight and the shape of products. This similarity index was further incorporated in a storage allocation heuristic procedure to set the location of the products. We test the procedure in a retail company that supplies over 191 stores, in Northern Portugal. When comparing the strategy currently used in the company with this procedure, we found out that our approach enabled a reduction of up to 40% on the picking distance; a percentage of improvement that is 32% higher than the one achieved by applying the Jaccard index, a similarity index commonly used in the literature. This allows warehouses to save time and work faster.

Author Keywords. Storage Location Assignment Problem, Correlated Policy, Precedence Constraints, Weight Constraints, Shape Constraints.

Type: Research Article

 Open Access  Peer Reviewed  CC BY

1. Introduction

The retail sector is an important part of the world economy. It serves over a billion times a day as the link between producers and consumers. According to information provided by eMarketer (2019)¹, the global retail market is expected to reach \$26 trillion in 2020; with e-commerce accounting for 16.1% of global retail sales.

In March 2020, according to Digital Commerce (2020)², online sales in Europe increased by 52% (compared to the same period in the previous year). The number of online shoppers has increased by 8.8% since the COVID-19 pandemic began. Thus, as reinforced by studies on the area, retail companies need to be prepared to face new situations and quickly adapt their warehouses to respond efficiently to customers' needs, during these times (Ivanov 2020).

¹eMarketer. 2019. "Global Ecommerce 2019". Accessed March 20, 2020. <https://www.emarketer.com/content/global-ecommerce-2019>.

²Digital Commerce. 2020. "How the Coronavirus Is Affecting Online Retailers". Accessed March 20, 2020. <https://www.digitalcommerce360.com/2020/03/12/coronavirus-affects-online-retailers/>.

Order-picking (OP) operations are primary elements of any retail's supply chain. Since 1984, the Storage Education and Research Council have identified the OP activity as the primary field of opportunity for the storage industry. OP can be performed by humans or machines. However, even with the various advantages that warehouse automation offers, 80% of warehouses are still manually operated (DHL 2018)³. This high rate is primarily ascribable to the difficulty in replicating human motor skills and flexibility in machines (Grosse, Glock, and Ballester-Ripoll 2014). Studies carried out by Tompkins et al. (2010) and Henn et al. (2010) evidence that OP represents 55–60% of the total operating costs. Therefore, improving OP activities is key for retail companies. One of the ways of improving OP operations is by assigning products to appropriate storage locations. The Storage Location Assignment Problem (SLAP) has got considerable attention from academia, having more than seventy publications in journals of high impact and academic relevance, from 2005 to 2017 (Reyes, Solano-Charris, and Montoya-Torres 2019). The academic research about SLAP has recently begun to reflect the real characteristics of products to meet the needs of real warehouses. In this context, relevant authors in the field highlighted the importance of considering precedence restrictions to collect some products before others due to weight, fragility, shape or size restrictions (Matusiak et al. 2014; Chabot et al. 2017). Some studies have also emphasized the importance of ensuring product stability on pallets. According to Abdou and El-Masry (2000), the products must be stable during the OP process, to guarantee the flow of the operation and the physical integrity of the goods.

This work is inspired by a practical case of a manual picking retail warehouse in Northwest Portugal. We further developed the method proposed by Trindade, Sousa, and Rosário (2020a) to incorporate a new clustering similarity index to deal with SLAP when there are weight precedence constraints (picking heavy products before light ones) and shape constraints. We use the volume of products as a proxy of the handling complexities brought by the shape, as Larco et al. (2017). These are relevant constraints to ensure the stability of the pallets during OP course.

The developed procedure is suitable for warehouses with a high level of non-uniform products (in terms of shape and weight), operating in a stock environment and it incorporates five criteria that were identified in the literature:

- The products' similarity,
- The products' demand,
- The products' weight,
- The products' shape and
- The distance travelled by the picker to pick the products.

Although SLAP, in general, has been fairly well researched in the literature, SLAP with shape constraints and precedence constraints (in this instance concerning weight) has not had much consideration (van Gils et al. 2018; Žulj et al. 2018). We only found one study that considers both constraints. Fontana and Nepomuceno (2017) consider the weight, for the vertical allocation of the products (heaviest products were placed in the lower racks) and, the volume of the products, for horizontal allocation (high volume products were placed far from the

³DHL. 2019. "Rethinking packaging". Accessed March 11, 2020.
<https://www.logistics.dhl/content/dam/dhl/global/core/documents/pdf/glo-core-rethinking-packaging-trend-report.pdf>.

Input/Output (I/O) point). Still, this strategy may not be appropriate for warehouses with a high number of non-uniform products since it does not ensure that heavy products are picked in the first place.

This paper aims to overcome this gap by answering to the question:

- “How to set a storage policy in companies with high variability (in terms of shape and weight) within their fast moving products, attending to both weight and shape precedence constraints?”

The main theoretical contribution of this paper is the development of an alternative similarity index, called Composite Index (CI), that considers the similarity, weight and shape of products. First, we develop and test the CI. Second, we incorporate CI into a two-phase heuristic storage allocation procedure of first clustering and then weight-ordering to set the allocation of the products (procedure developed by [Trindade, Sousa, and Rosário \(2020a\)](#)). This method allows us to group the products with similar characteristics together and to make sure that the precedence constraint of picking heavy products before light ones was met.

Moreover, by doing so, we make available a new technique that may be used to improve the performance of many other retail companies. We also show that the developed technique performs well for SLAP with weight and shape constraints, when there are high product-weight and product-shape variability.

This paper is organized as follows. Section 2 presents the literature review. Section 3 details the warehouse and of the problem in hands. Section 4 describes the proposed method and Section 5 gives the results of the application of the method in a real case. Section 6 presents four experimental designs and Section 7 provides the main conclusions, insights and some hints for future research.

2. Literature Review

OP operations are essential for the effective management of a warehouse. Increasing the efficiency of OP processes allows reducing storage costs and, consequently, the costs of the supply chain. One of the ways to improve OP processes is through an efficient allocation of products. An efficient organization of the products allows products to be moved quickly, within the warehouse, which increases the speed of delivery and, consequently, the competitiveness of the company. Many properties of products have been well-thought to support the assignment decisions, including popularity, volume and turnover ([Petersen, Siu, and Heiser 2005](#)). Given the complexity of SLAP, [Frazelle and Sharp \(1989\)](#) had classified it as an NP-hard, in 1989.

The literature presents some storage assignment policies for SLAP that can be classified in one of the following categories: random, dedicated and class-based storage. In a random storage policy, each product is randomly assigned to the available spaces. In a dedicated storage policy, each product is designated to a specific storage zone, according to predefined criteria. In class-based policy, products are grouped into categories and each category is delegated to a dedicated storage area. Within class-based storage, there is a correlated storage policy that allocates products with a high level of correlation close to each other ([Bindi et al. 2009](#)).

2.1. Correlated storage assignment policy

In recent research, it is possible to find out a variety of clustering and (meta-) heuristic approaches built on correlated storage assignment policy. [Bindi et al. \(2009\)](#), for instance, suggest a clustering similarity index to assess the degree of correlation between products; the performance of the proposed index is compared with the Jaccard Index (JI), a very common

clustering similarity index that was developed by Paul Jaccard, in 1901. Lee, Chung, and Yoon (2020) put forward a correlated and traffic balanced two-phase storage assignment of first clustering and assignment, to minimize the travel time and picking delays. Chuang, Lee, and Lai (2012) propose a two-stage clustering-assignment model. First, the authors draw item-association indexes and then, apply assignment techniques to locate the groups of clusters. Brynzér and Johansson (1996) suggest a storage assignment strategy based on the product structure. Kofler et al. (2015) put forward an extension of the dynamic ABC approach developed by Pierre et al. (2003) to generate more robust assignments that are suitable for warehouses with frequent demand pattern changes. Liu (2004), Rosenwein (1994) and Wutthisirisart, Noble, and Chang (2015) develop heuristic and optimization models to group products according to their demand patterns. Manzini et al. (2012) propose different storage assignment rules, based on the application of hierarchical clustering algorithms, supported by an ISO-time mapping of the storage area. Yu, de Koster, and Guo (2015) develop an algorithm for determining the optimal number and boundaries of storage classes in warehouses that use a class-based storage assignment policy.

2.2. SLAP with shape constraints

However, in prior research, constraints arising from real-world warehouses were often neglected (van Gils et al. 2018; Žulj et al. 2018). In the studies that we have found addressing shape constraints, most authors used volume as a proxy for the shape of a product. By volume we mean the 3-dimensional space a product takes up. Volume is incorporated in order-picking problems to set the product's location in two ways. High volume products are placed further away from the I/O point (Larco et al. 2017) or products are stored in slots that have a storage capacity equal to or greater than their volume (da Silva, Vasconcelos, and Cavalcante 2015; Yener et al. 2019). Larco et al. (2017), for instance, put forward a two-phase heuristic for SLAP for manual OP warehouses, aiming to minimize the pickers' discomfort and cycle time. In this method, the products with the lowest volume were placed next to the I/O point. da Silva, Vasconcelos, and Cavalcante (2015), propose a multicriteria model for ranking and assigning the products to storage locations considering simultaneously three criteria: the product population (number of customers served by a product), the product turnover and the product volume. The volume of the product reflected the space needed for product allocation. Yener et al. (2019) use mixed-integer linear programming for a hazardous materials' SLAP. This model also considers the volume of the product to determine the storage space needed. We have also found some studies regarding the pallet loading action, for instance, Abdou and El-Masry (2000), propose a new pallet loading technique for boxes of different dimensions, considering the base dimensions and the height. Li et al. (2018) propose a stacking method for an OP system that combines two-dimensional and three-dimensional vision. Additionally, we found some studies about the similarity of the shapes of the products (Sun 2000; Tsai and Su 2009) and the size and the shape of the shelves (Zou et al. 2017). None of the mentioned studies considered weight precedence constraints.

2.3. SLAP with weight constraints

When looking for the precedence constraint of picking heavy products before light ones, it is possible to find two different approaches. There is the creation of density zones, where products are allocated to zones, according to their weight. Within those zones, products are distributed by demand criteria – the highest demand products are placed in the aisle nearest from the I/O point (Battini et al. 2015; Chabot et al. 2017; Diaz 2016). Then, there is the approach of limiting the number of boxes that can be loaded on top of each other (Glock and

Grosse 2012; Grosse, Glock, and Ballester-Ripoll 2014; Xiao and Zheng 2012). Focusing on the density zone strategy, Battini et al. (2015) present a joint method of storage assignment and travel distance estimation, to evaluate a manual picker-to-parts OP system. The developed method is appropriate for different levels of detail (macro, aisle and location level), allowing some flexibility within each area to establish some rules regarding the positioning of the products, which can encompass the weight of the products, in a form of density zones. Chabot et al. (2017) propose two distinct mathematical models, solved by a branch-and-cut algorithm, and five heuristic methods to deal with OP problems when there are weight, fragility and category constraints. In these methods, products were classified in terms of weight (i.e., products were classified as fragile if the weight is between 1–10 kg). Diaz (2016) develops a heuristic procedure based on quadratic integer programming to generate a solution that considers customer demand and order-clustering. A simulation model is used to investigate the effects of creating and implementing these solutions in conjunction with a density zone strategy. Additionally, Trindade, Sousa, and Rosário (2020a) propose a two-phase heuristic procedure of first, clustering and then, weight-ordering that incorporate the products' similarity, demand and weight, in the allocation procedure. In another study (Trindade, Moreira, and Sousa 2020), we introduce a zero-one quadratic assignment model for dealing with the storage location assignment problem when there are weight constraints. None of the mentioned studies consider shape constraints.

2.4. SLAP with both shape and weight constraints

Focusing on both weight and shape constraints, we were able to find one study. Fontana and Nepomuceno (2017) propose a multi-criteria decision model to perform the product classification and to solve the SLAP in a multi-layer warehouse. The authors use the ELECTRE TRI method to define the shelf level for each product. The model considers several criteria simultaneously, namely frequency, size, weight, demand and cost. The weight is used for the vertical allocation of the products (heaviest products were placed in the lower racks) and the volume of the products for horizontal allocation (high volume products were placed away from the I/O point). Still, this strategy may not be appropriate for warehouses with a high number of non-uniform products since it does not ensure that heavy products are picked in the first place. We also found a study of Bennekrouf, Boudahri, and Sarib (2011), who present a mixed-integer linear programming model to help companies in designing reverse logistic operations. In this study, both weight and volume are considered, but not as a constraint; both parameters were used as criteria for the estimation of the operational costs.

Taking into consideration the reviewed literature, our aim, in this paper, is to improve the OP for retail warehouses with a high share of non-uniform products (in terms of weight and shape). This study differs from previous research in its problem structure and solution techniques. In prior research, only a few authors have considered both constraints. The ones who did so, did not ensure that heavy products are picked first, which is important to ensure the physical integrity of the goods. This study proposes a new clustering similarity index that was further incorporated in a heuristic procedure to deal with SLAP when there are shape and weight constraints. Our similarity index contributes to closing this gap by joining together the products with similar weight, shape and demand pattern. The next section details the methodology.

3. Problem Description

In this section, we supply information about the problem in hands. We provide a description of the warehouse and the main problem assumptions.

In retail companies, it is oftentimes hard to establish batching or routing policies. For this reason, we focus, instead, on improving the storage allocation policy. The batch policy is difficult to implement when there are small orders; a reality that is gaining weight with the increase of online sales, in the retail industry. The routing policy is difficult to apply when there are products with varying sizes. This is easily justified by the higher probability of route miscalculation in when there are a lot of non-uniform products (the designed route can be insufficient to gather all the goods of one order). Also, the fixed layout of most warehouses, with narrow aisles (as in the case company) can restrict the application of these policies.

3.1. Warehouse description and problem assumptions

This paper is inspired by a practical case of a manual warehouse for retail products that supply over 191 stores, in Northern Portugal. The warehouse is currently organized as four sub-warehouses: non-perishables, fish, codfish, and fruit and vegetables. We only address the layout of the non-perishables warehouse. The non-perishables warehouse is currently divided into the JIT zone and stock zone. The stock part of the warehouse is divided into food (area AL), non-food (area NA) and drinks (area BE) (see Figure 1).

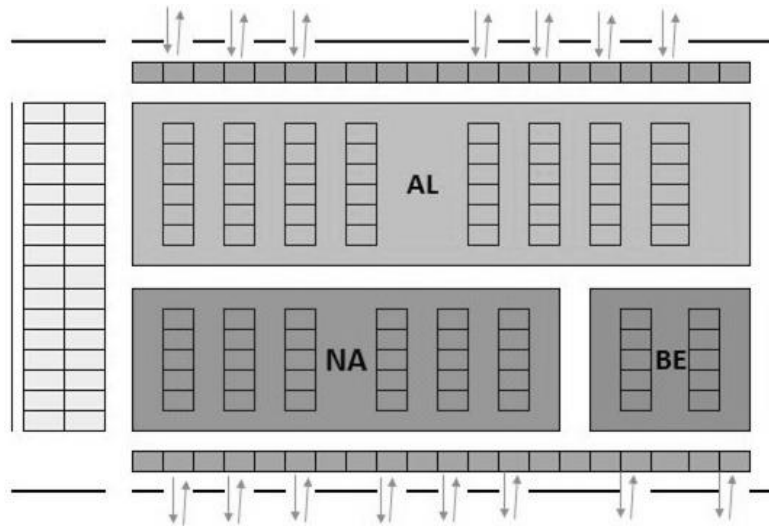


Figure 1: Non- Perishable Warehouse layout scheme – Stock Zone

We focus on the non-food stock zone (the NA area in Figure 1). In this zone, the products are currently organized by families, as happens in stores. So, in each aisle, there is a different family, for instance: car tools, clothes, hair products and so on. The aisles are organized in descending order of the families' weight. The storage capacity is equal to 1440 slots. Each slot dimension is equal to 60cm x 80cm x 197cm.

The company has a conventional, manual OP using low-level picking. The picker starts the OP operation with two empty pallets and travels through the warehouse in an S-shape route with one direction only. Orders are fulfilled one at a time and products are collected according to the sequence given by the voice-speaking system. During the process, the picker retrieves products on both sides of the aisles (taking a zigzag course). In stock operations, there are pickers allocated to each section of the warehouse (one for the food, one for non-food and one for the drinks section).

3.2. Problem description

The storage location assignment problem in hands can be defined as follows:

Given:

- A set of available slots,

- A set of products,
- The distance from one slot to another,
- The distance from the I/O point to each one of the slots,
- The products' similarity,
- The products' demand,
- The products' shape,
- The products' weight, and
- The warehouse storage capacity (expressed in slots).

Determine:

- The assignment of the products within the warehouse available spaces.

Goal:

- To minimize the total distance travelled by the picker.

This problem can be theoretically formulated as a zero-one quadratic assignment model (as defined by [Trindade, Sousa, and Rosário \(2020b\)](#)). The assignment model uses the set of indices, parameters, and variables, that are now presented.

Indices:

i – product i (k is also an index for products).

j – slot j (i is also an index for the slots).

Parameters:

d_{ji} – travel distance between slot j and slot i .

f_i – frequency with which product i appears on the orders.

A – number of products to be allocated.

P – number of existing slots.

sn_i – storage necessities for product i .

rs_j – relative distance from the I/O point to slot j .

ys_{ik} – similarity between products i and k , in terms of orders (products that are frequently bought together).

yw_{ik} – similarity between products i and k , in terms of weight.

yv_{ik} – similarity between products i and k , in terms of shape.

Variables:

x_{ij} – (a binary variable) with 1 if the product i is assigned to slot j , and 0 otherwise.

Considering the indices, parameters, and variables presented above, the generic model design can be defined as follows (see [Equation \(1\)](#)).

$$\text{Minimize } \frac{1}{2} \sum_{i=1}^A \sum_{j=1}^P \sum_{k=1}^A \sum_{l=1}^P f_i y s_{ik} y w_{ik} y v_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^A \sum_{j=1}^P f_i r s_j x_{ij} \quad (1)$$

Subject to:

$$\sum_{i=1}^A x_{ij} = 1 \quad \forall j = 1, \dots, P \quad (2)$$

$$\sum_{j=1}^P x_{ij} = sn_i \quad \forall i = 1, \dots, A \quad (3)$$

$$x_{ij} = 0,1 \quad \forall i = 1, \dots, A \quad \forall j = 1, \dots, P \quad (4)$$

Where:

$$\sum_{i=1}^A sn_i \leq P \quad (5)$$

$$A \leq P \quad (6)$$

Equation (1) represents the theoretical model, that describes the problem in hands. The first part, given by the product of f_i (the likelihood that an operator picks product i for an order) and $\gamma_{sik} \gamma_{wik} \gamma_{vik} d_{jl} x_{ij} x_{kl}$ aims to reduce the distance covered by the picker within the slots and to assign products with similar weight, volume and demand patterns close to each other, simultaneously. The second part of the equation, given by the product of f_i and $r_{sj} x_{ij}$, defines the expected distance required to travel from the I/O point to slot j . It is assumed that a picker can travel from slot j to slot l .

Equation (2) guarantees that only one product i is assigned to slot j . Equation (3) assures that the number of slots assigned to product i equals sn_i . Equation (4) constricts the binary variable values to zero or one. Equation (5) ensures that the number of slots required by the product does not exceed the number of available slots. Finally, Equation (6) ensures that the number of products does not exceed the number of available slots.

4. Solution Method

Figure 2 shows the methodological framework of this paper, that was prompted by the work of Bindi et al. (2009). First, we develop an alternative similarity index to measure the similarities between products in terms of orders' similarity, shape and weight. Second, we incorporate that index into a two-phase heuristic procedure, developed by Trindade, Sousa, and Rosário (2020a), of first clustering and then, weight-ordering to determine the location of the products. The next subsections detail each sage.

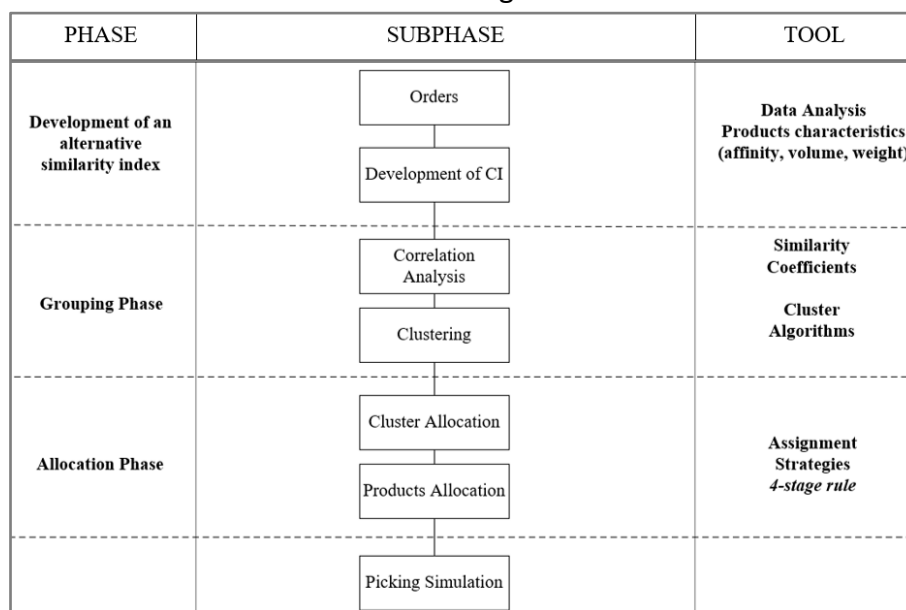


Figure 2: Methodologic Framework

4.1. Phase 1. Development of an alternative similarity index

In this stage, we suggest an original problem-oriented index, denominated as composite index (CI), that measures similarities between products in terms of orders' similarity, shape and weight and that supports the storage location assignment decision. In the proposed CI, the similarity parameter is given by the probability of two products appear together in the orders – Equation (7) –; the shape parameter is given by one minus the relative difference between the volumes of two products (we use the volume as a proxy of the shape, as proposed by Larco et al. (2017) – Equation (8) – and the weight parameter is given by one minus the relative difference between the weights of two products – Equation (9). All parameters run in the same direction: the higher the value, the higher the similarities between two products. Also, each of the parameters set an associated weight: α – weight associated with the weight parameter –, β – weight associated with the shape parameter –, and θ – weight associated with the similarity parameter –. The developed CI draws on the set of parameters that are now presented.

Parameters

ys_{ik} – similarity between products i and k , in terms of orders (products that are frequently bought together) – see Equation (7).

$$ys_{ik} = \frac{n_{ik}}{N} \quad 0 < ys_{ik} < 1 \quad (7)$$

n_{ik} is the number of orders in which product i and k appear together, and N is the total number of orders

yv_{ik} – similarity between products i and k , in terms of volume as a proxy for shape – see Equation (8).

$$yv_{ik} = 1 - \frac{|v_i - v_k|}{\max(v_i, v_k)}, \quad 0 < yv_{ik} < 1 \quad (1)$$

v_i is the volume of product i and v_k is the volume of product k

yw_{ik} – similarity between products i and k , in terms of weight – see Equation (9).

$$yw_{ik} = 1 - \frac{|w_i - w_k|}{\max(w_i, w_k)}, \quad 0 < yw_{ik} < 1 \quad (2)$$

w_i is the weight of product i and w_k is the weight of product k

Given the indices, parameters, and variables presented, CI is formulated as follows (see Equation (10)):

$$CI = \left| \frac{\alpha \left[1 - \frac{|w_i - w_k|}{\max(w_i, w_k)} \right] + \beta \left[1 - \frac{|v_i - v_k|}{\max(v_i, v_k)} \right] + \theta \left[\frac{n_{ik}}{N} \right]}{(\alpha + \beta + \theta)} \right| \Leftrightarrow CI = \left| \frac{\alpha yw_{ik} + \beta yv_{ik} + \theta ys_{ik}}{(\alpha + \beta + \theta)} \right| \quad (3)$$

After building the composite index, we incorporate it into a heuristic procedure developed by Trindade, Sousa, and Rosário (2020a). The heuristic consists of two consecutive processes: the grouping phase and the allocation phase (phases 2 and 3 in Figure 2, respectively), which are, now, briefly detailed. This technique already takes into account the precedence constraint of picking heavy products before light ones for choosing the location of products.

4.2. Phase 2. Grouping phase

The grouping phase consists of the formation of the clusters, taking into consideration the shape, the weight, and similarities between products. This phase can be summed up in two steps:

- Step 1. Perform a correlation analysis: Build a similarity matrix using CI.
- Step 2. Cluster the products to ensure that highly correlated products are assigned to the same zone. We use one of the most popular clustering algorithms, the nearest neighbor (see [Andendelfer and Blashfield 1994](#)).

4.3. Phase 3. Allocation phase

The allocation phase consists of a four-stage procedure that was developed by [Trindade, Sousa, and Rosário \(2020a\)](#) to integrate and consider the weight precedence constraint. The procedure can be described as follows:

- Step 1. Perform an ABC analysis of the products, based on the quantity ordered.
- Step 2. Categorize clusters from the ABC classification and average demand for its products.
- Step 3. Allocate clusters into the available areas, giving priority to the ones that have a higher average demand. That is, first, place the cluster with higher average demand and a higher percentage of fast mover products, in the area closest to the I/O point.
- Step 4. Allocate products, within clusters, based on their weight and demand. Inside each cluster, products are sorted in descending order of weight. Where products weigh the same, the product' demand comes into effect (see pseudo-code in [Algorithm 1](#)).

```
While (ArticleCODE <= Max (ArticleCODE))
  If ( $w_i > w_k$ )
    Allocate product i first
  Else If ( $ca = 1$ ) && ( $w_i = w_k$ ) && ( $d_i < d_k$ )
    Allocate product i first
  Else if ( $ca = 2$ ) && ( $w_i = w_k$ ) && ( $d_i >= d_k$ )
    Allocate product i first
  Else
    Allocate product k first
End While.
```

Algorithm 1: Pseudo-code for the products allocation decision. Where: ArticleCODE – SKU of the product; w_i – Weight of product i ; w_k – Weight of product k ; d_i – Demand of product i ; d_k – Demand of product k ; ca – Cluster a , where $a = 1$ means cluster positioned at the right side of the I/O point and $a = 2$ means cluster positioned on the left side of the I/O point

In the end, the entire procedure was replicated for the use of the JI as a similarity index, instead of the developed index (CI), so that we could compare the results. Note that, in both situations, pickers must be allocated to a specific cluster zone (zoning) to ensure that heaviest products are placed at the bottom of the pallet.

5. Application to the Real Case

This section covers the application of the process, described at the methodology, to our case company. We used as a performance measure, the distance travelled by the picker; performance measure commonly used in the literature ([Reyes, Solano-Charris, and Montoya-Torres 2019](#)). The distance travelled by the picker is given by the sum of the picking and shipping distance. The picking distance is given by the distance travelled by the pickers within the aisles, while collecting the products. The shipping distance is given by the sum of the distance travelled from the I/O point to the first aisle and the distance travelled from the last aisle to the I/O point. To compute the distance, we designed and ran a program at Visual Studio 2017 (C++ language).

Operational management involves understanding interactions between many factors and using the understanding to achieve a balance between conflicting goals (Jain 2004). For this reason, we set three scenarios in which we emphasize a specific parameter to analyze the trade-off of valuing more one characteristic of the products (in comparison with the others), in terms of the distance travelled by the picker. The designed scenarios are described as follows:

- Normal scenario: Equal weight for each one of the parameters: $\alpha = \beta = \theta = 1$.
- Focus on Weight scenario: Giving a higher importance to weight: $\alpha = 2$ and $\beta = \theta = 1$.
- Focus on Shape: Giving a higher importance to shape: $\beta = 2$ and $\alpha = \theta = 1$.
- Focus on Similarity: Giving a higher importance to similarity: $\alpha = \beta = 1$ and $\theta = 2$.
- Jaccard scenario: Applying JI instead of CI on the grouping phase.

Table 1 is an extract of the results obtained for three clusters. The option for three clusters was based on the information provided by the application of the *Nb Clust package (R-studio)*. This package provides 30 indices for determining the best number of clusters for a dataset. We compared the results with the initial situation of the company; a scenario in which the total distance travelled by the picker equals to 3549 kilometers.

Scenario	Percentage of Improvement
Normal	14%
Focus on weight	20%
Focus on shape	17%
Focus on similarity	13%
Jaccard	11%

Table 1: Comparison of the results obtained in the different scenarios (Distance in km/month)

The results achieved with the CI are better in all scenarios. The application of the CI allows, in the best scenario (focus on weight), the reduction of more than 300 km per month, in the total distance travelled by the picker, in comparison with the application of the JI. These results confirm the importance of considering constraints resulting from characteristics of the products (in real operations) when setting the storage policy, as highlighted by the literature.

Table 2 presents the potential savings of the best-case scenario (focus on weight). The generic travelled distance (km/month) can be converted into a cost (€/month). Considering that new allocation of products, in this scenario, enables a reduction of the distance travelled of approximately 710 km/month. As the warehouse operates 26 days a month and the picking machines move at an average speed of 2 km, operations can be diluted up to 28 hours per day. This reduction leads to the conclusion that it is possible to keep the same warehouse activity level with one employee less (if each employee works on average 7.5 hours/day).

Savings	Best-case scenario
Distance reduction (km/month)	710
Distance reduction (km/day)	27
Reduction in daily hours of operation (h)	14
Potential reduction of pickers (nº of pickers)	1

Table 2: Potential Savings in the best-case scenario

Note that, the implementation of the layout obtained in each of the new scenarios might create future costs, arising from the changes in the location of products and modifications in the warehouse management system used by the company and employees adapting to a different work environment.

6. Computational Experiment

In this section, we carry out four experimental designs (of 2x10, 11x6, 1x7, 1x7) to name the most vital factors affecting the design method. The method is tested for:

- A list of randomly generated orders,
- Different numbers of clusters,
- Changes in the weight ascribed to each of the parameters, and
- Different ways of computing the proposed similarity index - CI.

In the four experimental designs, the results are compared with the current scenario of the company and the number of clusters is given by the application of the *Nb Clust package* (except for the second experimental design in which we set the number of clusters).

6.1. Experimental design 1. Random orders

In the first experimental design, to test the robustness of the procedure, we run the heuristic for ten different samples in which the frequency with which each product appears on the orders was randomly generated from a Gaussian Random Number Generator. Random.org⁴ allows generating random numbers from a normal distribution. The randomness comes from atmospheric noise. The procedure is tested for the application of CI and JI. Table 3 provides the results.

	1	2	3	4	5	6	7	8	9	10
% Improvement CI	20%	38%	38%	38%	38%	39%	38%	39%	38%	38%
% Improvement JI	16%	33%	29%	30%	30%	28%	28%	29%	30%	30%

Table 3: Results of Experimental Design 1

The results indicate the overall savings may be even higher and can go up to 39%. Also, for all scenarios, the percentages of improvement achieved with CI are better than the ones achieved with JI.

6.2. Experimental design 2. Changing the weight of the parameters and the number of clusters

In the second experimental design, we analyze the impact of giving greater importance to each one of the weight parameters of the CI (see Equation (10)); we tested the results for six additional scenarios (in addition to the four already defined), in which we emphasize even more a specific parameter to evaluate the trade-off of highly valuing one of the characteristics of the products. Also, we analyze the impact of changing the number of clusters; we tested the results for six different numbers of clusters (2, 3, 4, 6, 8 and 10 clusters) to check the impact of changing the number of clusters.

- Higher focus on Weight: Giving higher importance to weight: $\alpha=10$ and $\beta=\theta=1$.
- Higher focus on Shape: Giving higher importance to shape: $\beta=10$ and $\alpha=\theta=1$.
- Higher focus on Similarity: Giving higher importance to similarity: $\theta=10$ and $\alpha=\beta=1$.
- Extra focus on Weight: Giving higher importance to weight: $\alpha=20$ and $\beta=\theta=1$.
- Extra focus on Shape: Giving higher importance to shape: $\beta=20$ and $\alpha=\theta=1$.

⁴"RANDOM.ORG: True Random Number Service". Accessed December 13, 2020. <https://www.random.org>.

- Extra focus on Similarity: Giving higher importance to similarity: $\theta=20$ and $\alpha=\beta=1$.

Table 4 provides the results.

Scenario	2 Clusters	3 Clusters	4 Clusters	6 Clusters	8 Clusters	10 Clusters
Normal	19%	14%	18%	12%	5%	-12%
Focus on weight	19%	20%	18%	13%	1%	0%
Focus on shape	21%	17%	16%	18%	-1%	-13%
Focus on similarity	19%	13%	18%	13%	4%	-5%
Higher focus on weight	13%	10%	10%	8%	0%	-1%
Higher focus on shape	14%	12%	8%	12%	-1%	-2%
Higher focus on similarity	25%	30%	26%	28%	26%	24%
Extra focus on weight	19%	15%	15%	12%	0%	0%
Extra focus on shape	24%	17%	11%	11%	0%	-13%
Extra focus on similarity	37%	43%	42%	42%	42%	40%
Jaccard	15%	11%	11%	14%	6%	6%
Average	20%	18%	18%	17%	7%	2%

Table 4: Results of Experimental Design 2

The results indicate that, giving a higher weight to the similarity parameter, in our case company, the percentages of improvement can be even higher and may go up to 43%. Globally, CI continues to better percentages of improvement, in comparison with the JI. The percentages of improvement achieved by JI still very small when compared to other solutions. Also, it is possible to see that two clusters generally lead to better results.

Note that, the higher percentage achieved by a greater focus on the similarity leads to better results because fast movers, in this situation, stay together (in the same group), in an area that is located close to the I/O point. However, in the *Extra focus on the similarity* scenario, similarity vastly overlaps with weight and shape factors, which can lead to greater difficulties in the OP flow, that is, it may require greater work on the stability of the pallets since the shape parameter ends being neglected (weight is still considered in the heuristic procedure).

6.3. Experimental design 3. Changing the way of calculating yw_{ik}

In the third experimental design, we analyze the impact of changing the way of calculating yw_{ik} (in the CI). yw_{ik} is an index that measures the similarity of two products in terms of weight, based on the relative difference. In the formulation of this parameter, we use the relative difference in terms of the maximum value, one of the most common measures (Haber, Lampoltshammer, and Mayr 2017). However, this is not the only way to do it. For this reason, we test the use of seven alternative relative difference indexes (presented in Table 5) to calculate the weight parameter. The weight parameter was normalized using the Min-Max algorithm to ensure that, like the other parameters, it is a value between 0 and 1 (see Equation (11)).

$$yw_{ik}^* = 1 - \frac{yw_{ik} - \min(yw_{ik})}{\max(yw_{ik}) - \min(yw_{ik})} \quad (4)$$

Table 5 presents the results of the application of the different indexes in the CI and consequently on the procedure. The indexes were selected based on the study performed by Törnqvist, Vartia, and Vartia (1985) about the measurement of relative differences.

	Relative Difference Indexes	% of improvement
I1	$yw_{ik} = 1 - \frac{ w_i - w_k }{ w_k }$	17%
I2	$yw_{ik} = 1 - \frac{ w_i - w_k }{(w_i + w_k)/2}$	18%
I3	$yw_{ik} = 1 - \frac{ w_i - w_k }{\sqrt{w_k w_i}}$	17%
I4	$yw_{ik} = 1 - \frac{ w_i - w_k }{[1/2 \times (w_i^{-1} + w_k^{-1})]^{-1}}$	17%
I5	$yw_{ik} = 1 - \frac{ w_i - w_k }{\min(w_i, w_k)}$	17%
I6	$yw_{ik} = 1 - \frac{ w_i - w_k }{\max(w_i, w_k)}$	14%
I7	$yw_{ik} = 1 - \log_e \left(\frac{w_i}{w_k} \right)$	17%

Table 5: Results of Experimental Design 3

The results indicate that the calculation of the weight parameter, using the standardized I2 index, can lead to a percentage of improvement that is 4% higher than the one achieved with the initial formula. In any case, according to a Kruskal-Wallis test performed on *IBM SPSS Statistics 26*, changes in the weight parameter do not have a significant impact on the results (p-value = 0.423).

6.4. Experimental design 4. Changing the way of calculating yvik

In the fourth experiment design, we examine the impact of modifying the way of calculating yvik, in the CI. yvik is an index that trials the similarity of two products in terms of shape, based on the relative difference. In the design of this parameter, we use the relative difference in terms of the maximum value, one of the most usual measures (Haber, Lampoltshammer, and Mayr 2017). However, this is not the only way to do it. For this reason, we assess the use of seven alternative relative difference indexes (presented in Table 6) to calculate the shape parameter. In whole cases, the shape parameter was normalized, using the Min-Max algorithm, to ensure that, like the other parameters, it is a value between 0 and 1 (see Equation (12)).

$$yv_{ik}^* = 1 - \frac{yv_{ik} - \min(yv_{ik})}{\max(yv_{ik}) - \min(yv_{ik})} \tag{5}$$

Table 6 shows the results of the application of the different indexes in the CI and consequently on the process. The indexes were selected based on the study performed by Törnqvist, Vartia, and Vartia (1985) about the measurement of relative differences.

The results show that the calculation of the shape parameter, applying the standardized I2 index, can lead to a percentage of improvement that is 5% higher than the one achieved with the formula initially proposed. In any case, according to a Kruskal-Wallis test performed on *IBM SPSS Statistics 26*, changes in the shape parameter does not have a significant impact on the results (p-value = 0.423).

	Relative Difference Indexes	% of improvement
I1	$yv_{ik} = 1 - \frac{ v_i - v_k }{ v_k }$	15%
I2	$yv_{ik} = 1 - \frac{ v_i - v_k }{(v_i + v_k)/2}$	19%
I3	$yv_{ik} = 1 - \frac{ v_i - v_k }{\sqrt{v_k v_i}}$	15%
I4	$yv_{ik} = 1 - \frac{ v_i - v_k }{[1/2 \times (v_i^{-1} + v_k^{-1})]^{-1}}$	15%
I5	$yv_{ik} = 1 - \frac{ v_i - v_k }{\min(v_i, v_k)}$	15%
I6	$yv_{ik} = 1 - \frac{ v_i - v_k }{\max(v_i, v_k)}$	14%
I7	$yv_{ik} = 1 - \log_e \left(\frac{v_i}{v_k} \right)$	18%

Table 6: Results of Experimental Design 4

7. Conclusion

This paper is inspired by a practical case of a manual OP retail warehouse, with a high percentage of non-uniform products (in terms of shapes and weights), where the item weight influences the sequence of the OP operations. A characteristic that is very common among retail warehouses but that it is often neglected in the literature. This paper aims to fulfil this gap by putting forward a method that allows assigning products considering both shape and weight constraints.

We have built an alternative similarity index (CI) to measure the similarities between products in terms of the orders' similarity, shape and weight and incorporated that index into a two-phase heuristic procedure, developed by [Trindade, Sousa, and Rosário \(2020a\)](#), to determine the location of the products. We have made the method intuitive, and easy to implement in a real-world environment.

In a numerical study, we have compared our strategy to the one currently applied in the case company. We have found that the new placement of products allowed for a reduction of up to 40% in picking distance. This percentage is 32% higher than the one reached with the JI; similarity index commonly used in the literature, highlighting the importance of considering the characteristics of the goods of real OP operations into SLAP.

This research has valuable theoretical and managerial implications. First, theoretically, this article puts forward an effective storage allocation solution which considers two relevant real-world constraints: shape constraints and weight precedence constraints (pickers must collect heavy products first). Additionally, we put forward a new similarity index that allows to group products with similar shape, demand patterns and weight; improving the stability of the pallet and the flow of OP operations. The developed index presented better results than JI, a similarity index commonly used in the literature; stressing the importance of considering constraints resulting from real operations, as cited by [van Gils et al. \(2018\)](#) and [Žulj et al. \(2018\)](#).

Second, on the empirical side, the results indicate that our method is effective in improving OP activities. Therefore, this method can be an important tool in the development of the storage allocation policy for many other retail warehouses. The proposed strategy allows warehouses to save time and operate faster and allows managers to have more flexibility in the products allocation procedure: operational managers can modify the weight of the

parameters in the developed similarity index (CI) so that products are grouped according to the specifics of each company. Besides, operation managers can modify the location of products, inside the aisles, without decreasing the percentage of improvement.

The main limitations detected in this paper are the constraints brought by the fixed layout of the company warehouse. Other operations that could potentially improve OP operations were not considered, for example, the routing method, batching operations and pallet construction procedure. These were not the object of our study because it was not practicable to change current procedures for the time being, in the company under study.

Future studies can, therefore, investigate the effect of applying the heuristic method to a different kind of warehouse; for example, in a warehouse that has a different OP method. In that respect, there is also the potential to comprise, in the heuristic, a routing problem, by trying to combine this process with a different routing method, for instance, the largest gap routing strategy. Furthermore, there is potential in including a model of classification of products to examine the impact on productivity. Other suggestions include designing a model to optimally attribute the weight of each parameter in the developed similarity index (CI).

References

- Abdou, G., and M. El-Masry. 2000. "Three-dimensional random stacking of weakly heterogeneous palletization with demand requirements and stability measures". *International Journal of Production Research* 38, no. 14 (september): 3149-63. <https://doi.org/10.1080/002075400418199>.
- Andendelfer, M. S., and R. K. Blashfield. 1994. *Cluster analysis: Quantitative applications in the social science series*. London: Sage.
- Battini, D., M. Calzavara, A. Persona, and F. Sgarbossa. 2015. "Order picking system design: The storage assignment and travel distance estimation (SA&TDE) joint method". *International Journal of Production Research* 53, no. 4 (february): 1077-93. <https://doi.org/10.1080/00207543.2014.944282>.
- Bennekrouf, M., F. Boudahri, and Z. Sarib. 2011. "Optimal design of two levels reverse logistic supply chain by considering the uncertain quantity of collected multi-products". Paper presented at the 4th International Conference on Logistics, LOGISTIQUA'2011, Hammamet, Tunisia, 31 May through 3 June 2011. <https://doi.org/10.1109/LOGISTIQUA.2011.5939433>.
- Bindi, F., R. Manzini, A. Pareschi, and A. Regattieri. 2009. "Similarity-based storage allocation rules in an order picking system: an application to the food service industry". *International Journal of Logistics-Research and Applications* 12, no. 4: 233-47. <https://doi.org/10.1080/13675560903075943>.
- Brynzér, H., and M. I. Johansson. 1996. "Storage location assignment: Using the product structure to reduce order picking times". *International Journal of Production Economics* 46-47 (december): 595-603. [https://doi.org/10.1016/0925-5273\(94\)00091-3](https://doi.org/10.1016/0925-5273(94)00091-3).
- Chabot, T., R. Lahyani, L. C. Coelho, and J. Renaud. 2017. "Order picking problems under weight, fragility and category constraints". *International Journal of Production Research* 55, no. 21 (november): 6361-79. <https://doi.org/10.1080/00207543.2016.1251625>.
- Chuang, Y. F., H. T. Lee, and Y. C. Lai. 2012. "Item-associated cluster assignment model on storage allocation problems". *Computers & Industrial Engineering* 63, no. 4 (december): 1171-77. <https://doi.org/10.1016/j.cie.2012.06.021>.
- da Silva, D. D., N. V. C. de Vasconcelos, and C. A. V. Cavalcante. 2015. "Multicriteria Decision Model to Support the Assignment of Storage Location of Products in a Warehouse".

- Mathematical Problems in Engineering* 2015: Article number 481950. <https://doi.org/10.1155/2015/481950>.
- Diaz, R. 2016. "Using dynamic demand information and zoning for the storage of non-uniform density stock keeping units". *International Journal of Production Research* 54, no. 8 (april): 2487-98. <https://doi.org/10.1080/00207543.2015.1106605>.
- Fontana, M. E., and V. S. Nepomuceno. 2017. "Multi-criteria approach for products classification and their storage location assignment". *International Journal of Advanced Manufacturing Technology* 88, no. 9-12 (february): 3205-16. <https://doi.org/10.1007/s00170-016-9040-3>.
- Frazelle, E. A., and G. P. Sharp. 1989. "Correlated assignment strategy can improve any order-picking operation". *Industrial Engineering* 21, no. 4 (april): 33-37.
- Glock, C. H., and E. H. Grosse. 2012. "Storage policies and order picking strategies in U-shaped order-picking systems with a movable base". *International Journal of Production Research* 50, no. 16 (august): 4344-57. <https://doi.org/10.1080/00207543.2011.588621>.
- Grosse, E. H., C. H. Glock, and R. Ballester-Ripoll. 2014. "A simulated annealing approach for the joint order batching and order picker routing problem with weight restrictions". *International Journal of Operations and Quantitative Management* 20, no. 2 (june): 65-83. <http://www.ijqom.org/v20no2.asp>.
- Haber, P., T. J. Lampoltshammer, and M. Mayr, eds. 2017. *Data science—Analytics and applications*. Springer. <https://doi.org/10.1007/978-3-658-19287-7>.
- Henn, S., S. Koch, K. F. Doerner, C. Strauss, and G. Wäscher. 2010. "Metaheuristics for the order batching problem in manual order picking systems". *Business Research* 3, no. 1 (may): 82-105. <https://doi.org/10.1007/BF03342717>.
- Ivanov, D. 2020. "Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case". *Transportation Research Part E: Logistics and Transportation Review* 136 (april): Article number 101922. <https://doi.org/10.1016/j.tre.2020.101922>.
- Jain, S. 2004. "Supply chain management tradeoffs analysis". In *Proceedings of the 2004 Winter Simulation Conference*, 1358-64. <https://doi.org/10.1109/WSC.2004.1371472>.
- Kofler, M., A. Beham, S. Wagner, and M. Affenzeller. 2015. "Robust storage assignment in warehouses with correlated demand". In *Computational Intelligence and Efficiency in Engineering Systems*, 415-28. https://doi.org/10.1007/978-3-319-15720-7_29.
- Larco, J. A., R. de Koster, K. J. Roodbergen, and J. Dul. 2017. "Managing warehouse efficiency and worker discomfort through enhanced storage assignment decisions". *International Journal of Production Research* 55, no. 21 (november): 6407-22. <https://doi.org/10.1080/00207543.2016.1165880>.
- Lee, I. G., S. H. Chung, and S. W. Yoon. 2020. "Two-stage storage assignment to minimize travel time and congestion for warehouse order picking operations". *Computers & Industrial Engineering* 139: Article number 106129. <https://doi.org/10.1016/j.cie.2019.106129>.
- Li, D., S. Liu, X. Jiang, and G. Chen. 2018. "Stacking objects picking system based on structured light". Paper presented at the 2018 International Conference on Information, Cybernetics, and Computational Social Systems, ICCSS 2018, Hangzhou, China, August 2018. <https://doi.org/10.1109/ICSS.2018.8572394>.

- Liu, C.-M. 2004. "Optimal storage layout and order picking for warehousing". *International Journal of Operations Research* 1, no. 1: 37-46. http://www.orstw.org.tw/ijor/6_volume1_no1.html.
- Manzini, R., F. Bindi, E. Ferrari, and A. Pareschi. 2012. "Correlated storage assignment and iso-time mapping adopting tri-later stackers. A case study from tile industry". In *Warehousing in the global supply chain: Advanced models, tools and applications for storage systems*, 373-96. Springer. https://doi.org/10.1007/978-1-4471-2274-6_14.
- Matusiak, M., R. de Koster, L. Kroon, and J. Saarinen. 2014. "A fast simulated annealing method for batching precedence-constrained customer orders in a warehouse". *European Journal of Operational Research* 236, no. 3 (august): 968-77. <https://doi.org/10.1016/j.ejor.2013.06.001>.
- Petersen, C. G., C. Siu, and D. R. Heiser. 2005. "Improving order picking performance utilizing slotting and golden zone storage". *International Journal of Operations & Production Management* 25, no. 9-10: 997-1012. <https://doi.org/10.1108/01443570510619491>.
- Pierre, B., B. Vannieuwenhuysse, D. Dominanta, and H. Van Dessel. 2003. "Dynamic ABC storage policy in erratic demands environments". *Jurnal Teknik Industri* 5, no. 1 (june): 1-12. <https://doi.org/10.9744/jti.5.1.pp.%201-12>.
- Reyes, J. J. R., E. L. Solano-Charris, and J. R. Montoya-Torres. 2019. "The storage location assignment problem: A literature review". *International Journal of Industrial Engineering Computations* 10, no. 2 (april): 199-224. <https://doi.org/10.5267/j.ijiec.2018.8.001>.
- Rosenwein, M. B. 1994. "An application of cluster-analysis to the problem of locating items within a warehouse". *IIE Transactions (Institute of Industrial Engineers)* 26, no. 1 (january): 101-03. <https://doi.org/10.1080/07408179408966588>.
- Sun, T. L. 2000. "Shape similarity assessment of polyhedral parts based on boundary models". *International Journal of Production Research* 38, no. 18 (december): 4655-70. <https://doi.org/10.1080/00207540050205569>.
- Trindade, M., P. Sousa, and M. Rosário. 2020a. "Solving storage location assignment problem in a real-world warehouse". Paper presented in EurOMA Doctoral Seminar, University of Warwick, UK, June 2020.
- Trindade, M., P. Sousa, and M. Rosário. 2020b. "Defining a storage policy when there are handling constraints: A case study analysis". In *EBES 32nd Conference Proceedings*, 1357-74. Istanbul: EBES.
- Trindade, M., R. Moreira, and P. Sousa. 2020. "Dealing with storage location assignment problem with precedence constraints". Paper presented at the 27th EurOMA Conference, University of Warwick, UK, June 2020.
- Tompkins, J. A., J. A. White, Y. A. Bozer, and J. M. A. Tanchoco. 2010. *Facilities planning*. 4th ed. John Wiley & Sons.
- Törnqvist, L., P. Vartia, and Y. O. Vartia. 1985. "How should relative changes be measured". *American Statistician* 39, no. 1 (february): 43-46. <https://doi.org/10.2307/2683905>.
- Tsai, D. M., and Y. J. Su. 2009. "Non-referential, self-compared shape defect inspection for bond pads with deformed shapes". *International Journal of Production Research* 47, no. 5 (january): 1225-44. <https://doi.org/10.1080/00207540701549590>.
- van Gils, T., K. Ramaekers, A. Caris, and R. B. M. de Koster. 2018. "Designing efficient order picking systems by combining planning problems: State-of-the-art classification and

- review". *European Journal of Operational Research* 267, no. 1 (may): 1-15. <https://doi.org/10.1016/j.ejor.2017.09.002>.
- Wutthisirisart, P., J. S. Noble, and C. A. Chang. 2015. "A two-phased heuristic for relation-based item location". *Computers & Industrial Engineering* 82 (april): 94-102. <https://doi.org/10.1016/j.cie.2015.01.020>.
- Xiao, J., and L. Zheng. 2012. "Correlated storage assignment to minimize zone visits for BOM picking". *International Journal of Advanced Manufacturing Technology* 61, no. 5-8 (july): 797-807. <https://doi.org/10.1007/s00170-011-3740-5>.
- Yener, F., S. Kir, S. E. Comert, and H. R. Yazgan. 2019. "Class based storage with mixed integer linear programming approach for hazardous materials storage". *Acta Physica Polonica A* 135, no. 4: 678-80. <https://doi.org/10.12693/APhysPolA.135.678>.
- Yu, Y., R. B. M. de Koster, and X. Guo. 2015. "Class-based storage with a finite number of items: Using more classes is not always better". *Production and Operations Management* 24, no. 8 (august): 1235-47. <https://doi.org/10.1111/poms.12334>.
- Zou, B. P., Y. M. Gong, X. H. Xu, and Z. Yuan. 2017. "Assignment rules in robotic mobile fulfilment systems for online retailers". *International Journal of Production Research* 55, no. 20 (october): 6175-92. <https://doi.org/10.1080/00207543.2017.1331050>.
- Žulj, I., C. H. Glock, E. H. Grosse, and M. Schneider. 2018. "Picker routing and storage-assignment strategies for precedence-constrained order picking". *Computers & Industrial Engineering* 123 (september): 338-47. <https://doi.org/10.1016/j.cie.2018.06.015>.

Acknowledgements

We gratefully acknowledge the assistance of the blinded reviewers, who reviewed the manuscript. They helped to improve the quality of the paper.