Product Allocation Planning with Handling Constraints: A Case Study Analysis

Maria A. M. Trindade[a]*, Paulo S. A. Sousa[b] and Maria R. A. Moreira[c]

[a]Faculdade de Economia, Universidade do Porto, Rua Dr. Roberto Frias, 4200-464 PORTO, Portugal; Católica Porto Business School, Universidade Católica, R. de Diogo Botelho 1327, 4169-005 PORTO, Portugal (matrindade@porto.ucp.pt). ORCID 0000-0001-8284-9291

[b]Faculdade de Economia, Universidade do Porto, Rua Dr. Roberto Frias, 4200-464 PORTO, Portugal (paulus@fep.up.pt);

[c]Faculdade de Economia, Universidade do Porto, Rua Dr. Roberto Frias, 4200-464 PORTO, Portugal; INESC TEC, Rua Dr. Roberto Frias, 4200-465 PORTO, Portugal (mrosario@fep.up.pt)

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The storage policy has a tremendous impact on the efficiency of order-picking operations, which can account for up to 50% of operating costs. The coronavirus pandemic has reinforced the importance of managers making the right operational decisions, namely regarding the definition of the storage policy. It is therefore important to consider handling constraints while making this decision. This article is inspired by a Portuguese retail company and it considers two handling constraints: weight and shape. We define the location of products by using a zero-one quadratic assignment model. In this model, in addition to the demand and similarity, we considered the weight and shape of the products. We used both weight and shape parameters to set products with similar shapes together, placing aside products with odd shapes. Our analysis shows that the inclusion of the shape and weight into the problem improved the current operations. We found that our method allowed for a reduction of up to 24% in the picking distance; a percentage higher than the one that only considers weight constraints. The inclusion of the shape parameter into the study enabled the company to increase the flow and efficiency of the order-picking operations. Thus, it can be an asset for many other warehouses.

Keywords: SLAP; Precedence constraints; Order-picking; Retail; Weight; Shape

1 Introduction

Over the past decades, industrial production has been constantly improving. Globalization has allowed products to be exported to final consumers located in all nations. Markets have grown globally. The technological evolution in the Warehouse Management System has gained the attention of industrial practitioners and researchers. Still, in December 2019, the coronavirus pandemic imposed severe limitations on the movement of people. This fact had, necessarily, an impact on the economic system, as many production firms were closed to reduce possible infections (Ivanov, 2020). The pandemic showed us that it may be overly simplistic to base operational decisions on observable factors. In a few days, companies had to adjust their business to the online market and consequently to the higher number of smaller and more customized orders. This has forced a quick reorganization of the picking operations, to quickly answer to the needs of the costumers (Ivanov, 2020), and has highlighted the importance of managing uncertainties in companies (Hu *et al.*, 2020).

Order-picking operations account for up to 50% of all operating costs. They can be performed by humans or machines. Despite the increasing interest in automated warehouses (Lamballais *et al.*, 2020; Keung *et al.*, 2020), 80% of warehouses are still manually operated (DHL[1] 2019). This high rate is primarily due to the difficulty in replicating human motor skills and flexibility in machines (Grosse *et al.* 2014).

One way of improving order-picking operations is by assigning products to appropriate locations (SLAP). In recent years, SLAP has always been a topic of interest in academia, with several publications in indexed journals (Reyes *et al.*, 2019). Recently, authors in the field have highlighted the importance of considering precedence constraints in SLAP. These constraints require some products to be picked before others due to their weight, shape or size (Matusiak *et al.*, 2015; Chabot *et al.*, 2017). This is especially relevant when approaching multi-product multi-aisle warehouses.

This work is enlivened by a practical case of a manual picking retail warehouse in Northwest Portugal and it deals with SLAP when there are shape constraints and precedence constraints (in this instance concerning weight). We define the location of products by making an adaptation of the zero-one quadratic assignment model, developed by Liu (2004). In this model, in addition to the demand and similarity, we considered the

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[1]"Rethinking Packaging." DHL, 2019, accessed 11 March, 2020, https://www.logistics.dhl/content/dam/dhl/global/core/documents/pdf/glo-core-rethinking-packaging-trend-report.pdf.

weight and shape of the products. We used the weight parameter proposed by Trindade *et al.* (2020) and we put forward a shape parameter to set apart products with odd shapes. This allows for guaranteeing the stability of the pallets during the order-picking course.

In the literature, SLAP with shape constraints and precedence constraints (in this instance concerning weight) has not received much attention (van Gils *et al.*, 2018; Zûlj *et al.*, 2018). We only found one study that considered both constraints, a study performed by Fontana and Nepomuceno (2016). In this study, the authors considered the weight for the vertical allocation of the products and, the volume of the products for horizontal allocation. Still, this study did not ensure that heavy products are picked first. Thus, the main contribution of this paper is to close this gap by including shape and weight precedence constraints in the design of the storage assignment policy. This is particularly relevant for warehouses with a high number of non-uniform products (in terms of shape and weight) to ensure the physical integrity of the goods.

The rest of this paper is organized as follows. Section 2 represents the literature review. Section 3 provides the methodology. Section 4 describes our case study. Section 5 presents the results. Section 6 presents the experimental design and Section 7 provides the theoretical and managerial implications. Lastly, Section 8 gives the main conclusions and some suggestions for future research.

2 Literature Review

SLAP assigns inventory items received to available locations, following certain standards while meeting pre-defined objectives. The three most common objectives are the improvement of the general operational efficiency (De Koster *et al.*, 2007), the minimization of storage costs (Petersen, 1999) and the minimization of the picking distance (Liu, 2004; Rosenwein, 1994). The commitment to green supply chain practices has also been increasingly considered (Khalafi *et al*., 2020).

There are several storage allocation policies for incoming items, this includes random, dedicated, and class-based policies. Random storage randomly assigns products to empty locations. It has the advantage of allowing better use of the space (De Koster *et al.,* 2007). Dedicated storage provides a fixed location for each product. It has the advantage of improving efficiency and reducing costs (De Koster *et al.,* 2007). Class-based storage combines the storage methods mentioned above. It classifies products into several categories, each one with a fixed zone and, within those zones, products are assigned randomly (De Koster *et al.,* 2007).

In recent research, it is possible to find a variety of clustering approaches that have been built on class-based policies, particularly on correlated storage policy (a policy that stores together products that are highly correlated to each other). For example, Bindi *et al.* (2009) designed a new clustering similarity index to measure the level of correlation between the products. Lee *et al.* (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 *et al.* (2012) suggested a two-stage clustering-assignment model. Foremost, the authors have drawn item-association indexes and then, applied assignment techniques to locate the groups of clusters. Brynzér and Johansson (1996) proposed a storage assignment strategy based on the product structure. Keung *et al.* (2020) investigated the application of cyber-physical systems, in automated warehouses, considering the order correlation of the products. Kofler *et al.* (2015) put forward an extension of the dynamic ABC approach to generate more robust assignments that are suitable for warehouses with several changes in the demand pattern. Liu (2004), Rosenwein (1994) and Wutthisirisart *et al.* (2015) developed heuristic and optimization models to group products according to their demand patterns. Manzini *et al.* (2012) proposed different storage assignment rules, based on the application of hierarchical clustering algorithms, that are backed by an ISO-time function. Yu *et al.* (2015) produced an algorithm that can be applied for finding the optimal number and boundaries of storage classes in warehouses that implement a class-based storage assignment policy.

Nevertheless, in prior research, constraints arising from real warehouses were often neglected (van Gils *et al.,* 2018, Žulj *et al.* 2018). In the studies that we found, that take shape constraints into account, most authors used the volume as a proxy for the shape of the product and used one of two approaches: Definition of the product´s location based on its volume (see Larco *et al*., 2016; Da Silva *et al.,* 2015; Karimi *et al.,* 2017; Yener *et al.*, 2019) and /or limitation of the number of products that can be picked, based on their volume (see Alfares and Turnadi, 2018). For instance, Larco *et al*. (2016) put forward a two-phase heuristic procedure for SLAP, in manual order-picking warehouses, in which the products with the lowest volume were placed next to the I/O point. Da Silva *et al.* (2015) offered a multicultural model for ranking and assigning the products to storage locations considering simultaneously the product population, the product turnover and the product volume. Yener *et al.* (2019) used mixed-integer linear programming for hazardous materials; this model considers the volume of the goods to find the space required for its allocation. Finally, Alfares and Turnadi (2018) introduced a general mixed-integer programming model and two heuristic methods for a multi-product lot-sizing problem. The authors looked at the volume of the products to assure that the volume of the boxes that are collected does not exceed the capacity of the transport vehicles. We also found some studies that have included the ordering cost, order quantity, reorder level and lead time into the problem (Gholami-Qadikolaei & Mirzazadeh, 2013) as well as the perishability of the products (Mishra & Singh, 2011; Chellappan &

Natarajan, 2011) and the replenishment level per slot (Lamballais *et al.*, 2020). None of the mentioned studies have considered weight precedence constraints.

Focusing on both weight and shape constraints, we were able to find one study from Fontana and Nepomuceno (2016). The authors proposed a multi-criteria decision model to perform the product classification and to solve the SLAP in a multi-layer warehouse. The writers used the ELECTRE TRI method to determine the shelf level for each product. The model looks at several criteria simultaneously, namely frequency, size, weight, demand and price. The weight is employed for the vertical allocation of the products (heaviest products stay in the lower racks) and the volume of the products for horizontal allocation (high volume products were placed farther from the I/O point). Still, this strategy may not be appropriate for warehouses with non-uniform products (in terms of weight) since it does not consider the precedence constraint of picking heavy products in the first place.

Taking into consideration the reviewed literature, this paper differs from former research in its problem structure and resolution techniques. In prior research, few authors have considered both shape and weight constraints and the ones that did so did not ensure that heavy products were picked in the first place. This work offers a storage assignment policy in which the location of products is settled by adjusting a zero-one quadratic assignment model, developed by Liu (2004). In this model, in addition to the demand and similarity, we considered the weight and shape of the products. We developed a shape parameter to set apart products with odd shapes and we incorporated that into the problem, contributing to close the gap in the literature. The following section details the methodology.

3 Materials and Methods

In this section, we present the methodology employed in this study. Many studies assume that the warehouse configuration may be changed to hold the goods. In this work, however, the warehouse configuration is assumed to be fixed. This is due to the fixed layout of most of the retail warehouses. Likewise, we did not change the routing and batching policies. Since the batch policy is difficult to implement when there are small orders; a reality that is gaining weight with the growth of e-commerce (Lamballais *et al.*, 2020; Keung *et al.*, 2020) and the routing policy is hard to apply when there are products with non-uniform sizes. Once, in this situation, there is a higher probability of miscalculating the route (Fontana and Nepromuceno, 2016). For these reasons, we focus, instead, on improving the storage assignment police. Next, we provide the methodological framework behind the proposed model (exhibited in Figure 1) and we detail the procedures adopted at each stage.

[Figure 1 near here]

3.1. *First Phase: Data Analysis*

In the first phase, we extract the dimensions of the warehouse and we make a data analysis of the products (in terms of demand, similarity, and weight) to build both similarity and weight parameters.

3.1.1. Similarity parameter

First, based on the orders of a regular month, we build a matrix with the similarity of the products in terms of demand pattern. The process can be described as follows:

1. Design an incidence matrix, based on the products ordered per order. The incidence matrix only presents 0-1 values (1 - If a product appears on an order; 0 – otherwise).
2. Design the similarity matrix, based on the probability of two products appearing together, in the same order – see Equation 1.

Equation (1):

$ys_{ik} = \frac{n_{ik}}{N}$, where n_{ik} is the number of orders in which product *i* and *k* appear together.

3.1.2. Weight parameter

Then, based on information about the weight of the products, we build a matrix with the similarity of the products in terms of weight, using the measure proposed by Trindade *et al.* (2020). – see Equation 2.

Equation (2):

$yw_{ik} = 1 - \frac{|w_{i-}w_k|}{max\ (w_i,w_k)}$, where w_i is the weight of product *i* and w_k is the weight of product *k.*

These data (similarity and weight matrixes) were further incorporated into the model that would be presented at the third phase. We used R-Studio 1.2.5019 to perform this operation.

3.2. *Second Phase: Creation of the Shape Parameter*

Product shape has been quite explored in other areas, such as marketing (Ziaei *et al.*, 2020), but in operations, it has been largely overlooked. In the literature, -is difficult to find a measure of the similarity of two products shapes based on data that can be easily obtained from companies. Therefore, in the second phase, we propose an original problem-oriented shape parameter, that measures the level of similarity between the shape of two products and supports storage location assignment activity in an order picking system. For this purpose, we use the volume as a proxy of the shape (as Larco *et al*, 2016). By volume we mean, the amount of space an item occupies.

The proposed shape parameter evaluates the similarity of two products shape by using the relative difference between the shape of two products, in terms of the maximum value. – see Equation 3.

Equation (3):

$yv_{ik} = 1 - \frac{|v_{i} - v_{k}|}{max\ (v_i, v_k)}$, where v_i is the volume of product *i* and v_k is the volume of product *k*.

The use of relative differences is widely used in a great many disciplines e.g. genetics, medical science, data mining and mathematics (see Törnqvist *et al*., 1985, Trindade *et al.*, 2020). The proposed parameter allows the values to range from 0 when two products are ‘completely dissimilar’ to 1 when they are ‘fully similar’; which is in line with the other parameters of the storage assignment model (presented at first phase). The performance of the ‘proposed’ shape parameter has been compared with alternative ways of calculating the shape parameter (see Section 6).

Even though the relative differences have been effectively used in a great many disciplines and studies. This is, to the authors best knowledge, the first time relative differences have been used in the design of a shape parameter suited to be integrated in a model that supports the storage location assignment decision and that uses the actual data of the company (real volume of the products).

3.3. *Third Phase: Appling Storage Assignment Problem*

In the third phase, given the complexity of the problem at hand and the similarity between our problem and that discussed by Liu (2004), we base our allocation procedure on the model presented by Liu and we further develop it to incorporate the weight and shape parameters. We formulate the problem as a zero-one quadratic assignment model, to set the position of the products by using: the similarity of the products, demand, shape and weight as well as the distance travelled by the picker (data already treated in the previous stages). 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_{jl} – travel distance between slot *j* and slot *i*.

f_i – frequency with which product *i* appears on the orders – see Equation 4.

Equation (4):

$f_i = \frac{n_i}{N}$, where n_i is the number of orders in which product *i* appears and N is the number of 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 demand pattern is given by the probability of two products appearing together on the same order (as in Liu, 2004 and Diaz, 2016)– see Equation 1.

yw_{ik} – similarity between products *i* and *k*, in terms of weight, proposed by Trindade *et al.* (2020) – see Equation 2.

yv_{ik} – similarity between products *i* and *k*, in terms of shape – see Equation 3.

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.

Equation (5):

$$Minimise\ \frac{1}{2}\sum_{i=1}^{A}\sum_{j=1}^{P}\sum_{k=1}^{A}\sum_{l=1}^{P} f_i ys_{ik} yw_{ik} yv_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^{A}\sum_{j=1}^{P} f_i rs_j x_{ij}$$

Subject to:

Equation (6):

$$\sum_{i=1}^{A} x_{ij} = 1 \qquad \forall j = 1, \dots, P$$

Equation (7):

$$\sum_{j=1}^{P} x_{ij} = sn_i \qquad \forall i = 1, \dots, A$$

Equation (8):

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

Where:

Equation (9):

$\sum_{i=1}^{A} sn_i \leq P$

Equation (10):

$A \leq P$

Equation (5) represents our model. The first part, given by-product of f_i (the likelihood that an operator picks product *i* for an order) and $ys_{ik}yw_{ik}yv_{ik}d_{jl}x_{ij}x_{kl}$, 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 rs_jx_{ij}, defines the expected distance required to travel from the I/O point to slot *j*. It is presumed that a picker can travel from slot *j* to slot *l*.

Equation (6) guarantees that only one product *i* is assigned to slot *j*. Equation (7) assures that the number of slots assigned to product *i* equals sn_i. Equation (8) constricts the binary variable values to zero or one. Equation (9) ensures that the number of slots required by the product does not surpass the number of available slots. Finally, Equation (10) ensures that the number of products does not surpass the number of available slots.

The objective function proposed uses approximated probabilities instead of precise values. However, the probabilities have also been applied in other successful approaches such as Diaz (2016), Kovács (2011) and Kutzelnigg (2011); thus, although it is an approximation, it is suitable for this purpose.

3.4. *Fourth Phase: Run the Locations*

At the fourth phase, we develop and validate a program in C++ language in Visual Studio, to calculate the exact distance travelled by the picker, using the locations given by the designed allocation model. This allows us to get the exact distance travelled by the picker.

4 Case Study

This paper is inspired by a real-life case of a manual warehouse for a company that supplies retail products to over 191 stores, in Northern Portugal.

The company has a conventional, manual picking operation using low-level picking. Products ready for collection are on low-level racks. There are higher racks above that are used for storage. The warehouse configuration is showed at Figure 2.

[Figure 2 near here]

The warehouse is composed of multiple aisles and storage locations are distributed on both sides of each aisle. We assume that one type of item occupies exactly one storage location and that one storage location holds only one type of item – Single deep racks (as Zhang *et al.*, 2019 and Xiao and Zheng, 2009).

In this warehouse, pickers perform a conventional manual picking operation within a one-way s-shape route. During the procedure, the pickers are guided by a voice speaking system that tells them the location of the goods. The picking guide is generated by the company management system, which already divides the orders according to the typology (food, non-food and drinks).

Since the warehouse is two-dimensional and different types of items are placed in different locations, travel distance will be incurred by moving from one item to the next item. We also assume that the replenishment cost is disregarded, since the cost is minimal compared with the cost of order-picking due to bulk replenishment (as Zhang *et al.*, 2019).

5 Results

This section covers the application of the assignment method for our case study. SLAP has proved to be a non-deterministic polynomial-time hard (NP-hard) problem (Frazelle and Sharp, 1989). The study company has, on average, 11,033 orders per day and up to 400 products per order. The optimal solution cannot be achieved for large solution spaces thus, the problem is solved by using as a sample the orders of one store, in a regular month. We examine three different scenarios:

- Shape model (SM) - We allocate products based on the volume, following the algorithm applied by Larco *et al.* (2016) and Fontana and Nepromuceno (2016); this implies that products with higher volume are placed farther from the I/O point.
- Weight model (WM) – We allocate products based on the weight, following the procedure developed by Trindade *et al. (*2020) this implies that products with higher weight are placed farther from the I/O point.
- Shape and Weight model (SWM) – We allocate products based on the combination of similarity, demand, weight and shape criteria, following the model presented in the methodology section of this paper.

For the computation of the results, we run the model in DOcplexcloud – a cloud with a 10-core processor and 60 GB RAM. The model was developed at ILOG Cplex Optimization Studio 12.9. The stop time was 3600s. The calculation of the exact order-picking distance was performed in Visual Studio 15.9 (C++ language).

Table 1 is an extract of the results obtained in the three scenarios. When comparing the current strategy of the company with the new model, it was found that the new placement of products allowed for a reduction in the picking distance of up to 24%; a percentage that is higher than the one achieved with the existing models in the literature.

[Table 1 near here]

The generic travelled distance (km/month) can be converted at a cost (€/month), quantifying the necessary number of pickers in the system. Table 2 shows the potential savings in each of the scenarios (in comparison to the current scenario of the case company). The allocation of the products in the new model scenario enables a reduction of the distance travelled monthly of 6 km. As the warehouse operates 26 days a month and the picking machines used in the warehouse move at an average speed of 2 km per hour, operations can be reduced up to 0.24 hours a day. This reduction leads to the conclusion that it is possible to maintain the same warehouse activity level, fulfilling the orders of one store, with 0.02 employees less (if each employee works on average 7.5 hours per day). Extrapolating this data for the 191 stores, within a 95% confidence interval, the potential reduction of pickers goes up to 3 (down limit: 3.02 | upper limit: 3.09); which represents a saving of one more picker per month (when compared to the other strategies).

[Table 2 near here]

A final remark that the implementation of the layout required for each of the scenarios might create costs arising from the changes in the location of the products and the warehouse management system. The employees would also have to adjust to a different environment.

6 Experimental Design

In this section, we present five experiments. We create three experimental designs (of 2x3, 7x3, and 1x3, respectively) to test different ways of calculating the similarity of two products in terms of shape – shape parameter (Experiment I and II) and to test an alternative way of integrating the shape of products in the model (Experiment III) and we create two additional experimental designs (of 5x1 and 4x1) to test the robustness of the model. We run the model for five additional stores (Experiment IV) and four random samples (Experiment V).

6.1. *Experiment I and II: Testing the use of an alternative shape parameter.*

In the methodology section, we propose a shape parameter based on the relative difference between the shape of two products, in terms of the maximum value. However, there are other ways of measuring it. Therefore, in Experiment I and II, we test the use of alternative shape parameters (parameters based on another relative difference indexes) in the model. The difference between Experiment I and II is that the relative indexes presented in Experiment II do not return values from 0 to 1 (values in line with the other parameters in the model). So, in Experiment II, we normalize the indexes. In the next subsections, we provide more details.

6.1.1. *Experiment I*

In Experiment I, we test alternative ways of calculating the shape parameter. We examine the use of the non-normalized shape parameter – yv_{ik}–, in three ways (yv_{ik}, yv_{ik}^2 and $\sqrt{yv_{ik}}$) for two different relative difference indexes. These indexes already return a number between 0 and 1; the number in line with the values of the demand and similarity parameters. We run the model for the alternative shape parameters. Results are presented in Table 3.

[Table 3 near here]

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 (α = 1.000).

6.1.2. *Experiment II*

In Experiment II, we examine the use of a normalized shape parameter –yv_{ik}^* –, in three ways (yv_{ik}^*, yv_{ik}^{2*} and $\sqrt{yv_{ik}^*}$), for seven indexes. In this experiment, all the relative difference indexes are normalized through the Min-Max algorithm to ensure that the index returns a value between 0 and 1 (see Equation 10). We run the model for the normalized shape parameters. Results are presented in Table 4.

The indexes were selected based on the study performed by Törnqvist *et al. (*1985) about the measurement of relative differences.

Equation (10):

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

[Table 4 near here]

The results show that the calculation of the shape parameter, applying the standardized I7 index, can lead to a percentage of improvement that is 0.27% 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 ($\alpha = 0.423$).

6.2. ***Experiment III: Testing an alternative way of integrating the shape in the model.***

In Experiment III, we assess an alternative approach in which the shape parameter is given by the normalized volume of a product (instead of the similarity of two products volume – Equation 3). The volume of a product is normalized through the Min-Max algorithm to ensure that it returns a value between 0 and 1 (see Equation 11) - value that is in line with the other parameters in the model (Equation 5).

Equation (11):

$v_i^* = 1 - \frac{v_i - min(v_i)}{max(v_i) - min(v_i)}$, where v_i^* is the normalized volume of product *i*.

We run the model for v_i, v_i^2,$\sqrt{v_i}$. Results are presented in Table 5. Cases in which it was not possible to get a solution are marked with a line.

According to a Kruskal-Wallis test performed on *IBM SPSS Statistics 26*, the use of the normalized shape of a product rather than the similarity of two products in terms of shape does not have a significant impact on the results ($\alpha = 1.000$).

6.3. ***Experiment IV: Testing the procedure in different stores.***

In Experiment IV, we run the model for the samples of four more stores to see the impact on percentages of improvement achieved (see Table 6).

[Table 6 near here]

The percentages of improvement for the other stores were even higher than the ones achieved for the store under study. Results indicate that the overall savings could go up to 40%.

6.4. *Experiment V: Testing the procedure in random samples.*

In Experiment V, we run the procedure for four random samples in which the frequency is generated from a Gaussian distribution with atmospheric noise, to see the impact on the percentage of improvement achieved (see table 7). This allowed us to test the effectiveness of the method outside the case study.

[Table 7 near here]

In the random samples, the percentages of improvement are higher (in comparison to the store understudy) and results indicate that the overall savings could go up to 33%.

7 Theoretical and Managerial Implications

This section highlights the implications of the present study for theory as well as for practice. First, theoretically, a new model is purposed for dealing with SLAP where there are shape and weight constraints. The developed model is of potential interest for warehouses that store a high percentage of non-uniform products and that want to avoid sorting strategies. The model may be combined with the modelling of the situation where the slots are empty and should be replenished (replenishment operations) and may be further extended to incorporate a different routing or batching method.

Second, on the empirical side, the results show that the proposed model is effective in improving overall warehouse operating efficiency, with the percentage of improvement going up to 40%. Third, the developed model can potentially help operational managers, in different industries, in the development of a storage assignment policy, allowing them to save time and operate in a faster way. Also, the new model allows for the location of items within the aisle to be changed without damaging the results. The model can be further extended to allow for the allocation of new products that were not initially considered. Moreover, the model has the potential to be applied in warehouses with non-traditional layouts (such as inverted-v, fishbone, flying-v and chevron), since the location of a product is always defined based on the jointly combination of the products frequency, shape, weight, and on the distance travelled by the picker (from and to the I/O point), independently of the distribution of the aisles.

Conclusion

This paper was inspired by a real-life case of a warehouse, in the retail sector, with manual order-picking operations, with a high number of non-uniform products, where the product shape influences the sequence of order-picking operations. In the literature, real-world constraints are often neglected. This study further develops the model developed by Liu (2004) to integrate the shape constraints in the allocation procedure. These constraints are extremely relevant for warehouses that have a high number of non-uniform products (in terms of shape and weight); since they are crucial to ensure the physical integrity of the goods.

We developed a shape parameter that uses easily accessible data (real volume of the products), to support the storage location assignment decision. This parameter allows for companies to set apart products with odd shapes (such as clotheslines and grills) - products that can compromise the flow of the order-picking operations.

In a numerical study, we compare our model to the current strategy applied by the company under study. Our findings show that the new placement of products allows for a reduction of up to 24% on the picking distance. This percentage was even higher, when applied to random samples (outside the case company), indicating that the overall savings could go up to 33%.

Our analysis shows that the consideration of the shape parameter in the model improves current operations in several aspects. Warehouse managers can avoid the strict strategy of sorting products by weight/shape; strategy usually presented in the literature. Also, consideration of the shape allows managers to improve the order picking flow and the stability of the pallets, which results in a smaller number of incidents during the fulfilment of the orders. These advantages are even higher as the variety of the shape of the products increases.

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

Future research projects should quantify the impact of the proposed method by using metrics that reflect contributions of the warehouse performance viewed from the green supply chain perspective (see Khalafi *et al.,* 2020). The model can also be adapted for other contexts. Since this research has been focused on a Portuguese retail warehouse, it would be interesting to test the model, in other countries and/or industries. Future studies can also further investigate the effects of using the storage assignment model. This could include applying it to different kinds of warehouses, such as those with different picking, routing or batching methods or with a non-traditional layout. Furthermore, there is potential to include a model of the classification of products to investigate its impact on productivity.

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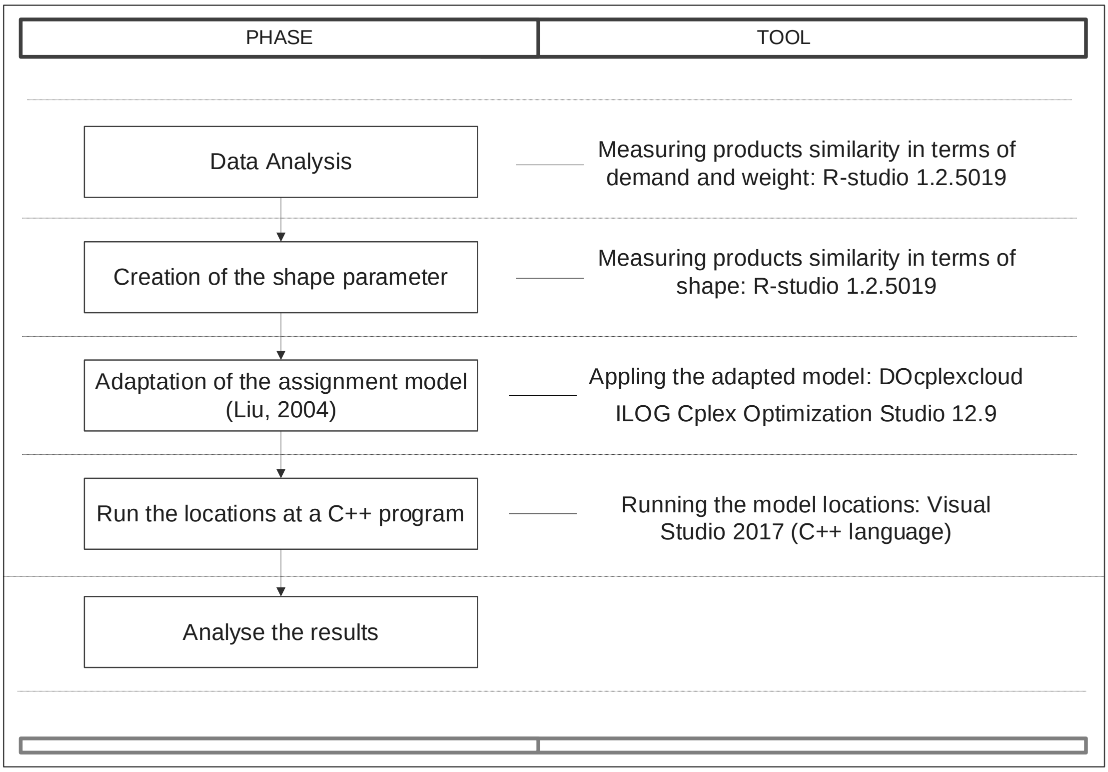
Product Allocation Planning with Handling Constraints: A Case Study Analysis

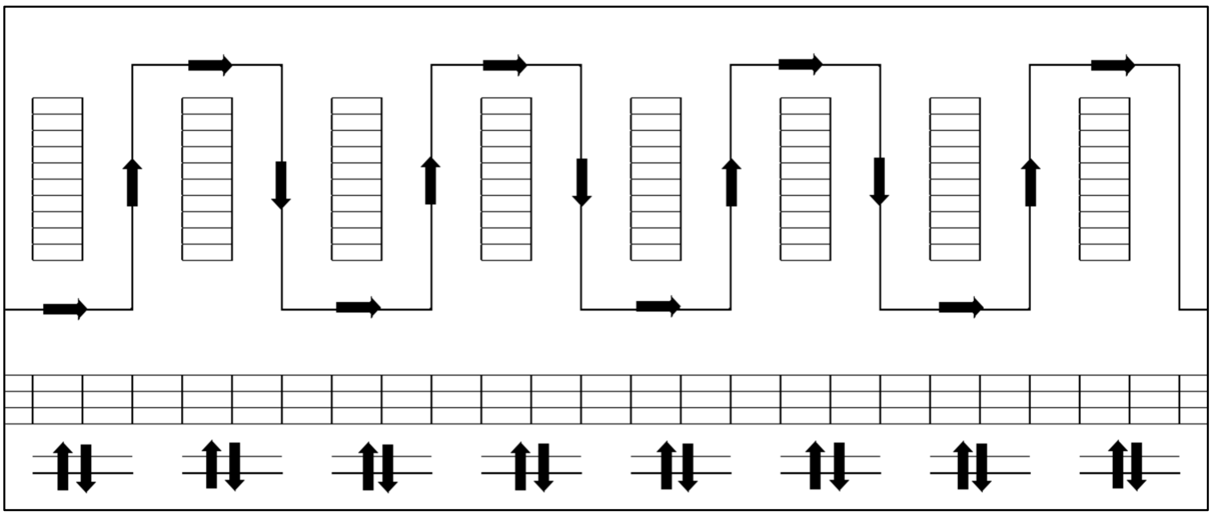
List of Figures

Figure 1 - Methodological Framework



Source: authors

Figure 2 – Warehouse Layout



Adapted from the company report.

Product Allocation Planning with Handling Constraints: A Case Study Analysis

List of Tables

Table 1 – Comparison of the results obtained in the three scenarios

	SM	WM	SWM	Current situation
Distance (km/month)	19.68	19.68	19.38	25.50
% of improvement	22.82%	22.82%	23.97%	–

Source: authors

Table 2 – Savings obtained in the different scenarios

Savings	SM	WM	SWM
Distance reduction (km/ month)	5.82	5.82	6.11
Distance reduction (km/day)	0.22	0.22	0.24
Reduction in daily hours of operation (h)	0.11	0.11	0.12
Potential reduction of pickers (nº of pickers)	0.015	0.015	0.016
Potential reduction of pickers – C.I. 95%	2.83 – 2.90	2.83 – 2.90	3.02-3.09

Source: authors

Table 3 – Experiment I – Percentages of Improvement

	Relative difference indexes	yv_{ik}	$\sqrt{yv_{ik}}$	yv_{ik}^2
I1	$yv_{ik} = 1 - \frac{\lvert v_i - v_k \rvert}{(v_i + v_k)/2}$	23.97%	22.82%	22.82%
I2	$yv_{ik} = 1 - \frac{\lvert v_i - v_k \rvert}{\max(v_i, v_k)}$	23.97%	23.97%	22.82%

Source: authors

Table 4 – Experiment II – Percentages of Improvement

	Relative difference indexes	$\boldsymbol{yv_{ik}^{*}}$	$\sqrt{\boldsymbol{yv_{ik}^{*}}}$	$\boldsymbol{yv_{ik}^{2*}}$
I1	$yv_{ik} = \frac{\lvert v_{i-}v_k \rvert}{\lvert v_k \rvert}$	23.97%	23.97%	23.97%
I2	$yv_{ik} = \frac{\lvert v_{i-}v_k \rvert}{(v_{i+}v_k)/2}$	23.97%	23.97%	22.82%
I3	$yv_{ik} = \frac{\lvert v_{i-}v_k \rvert}{\sqrt{v_k v_i}}$	23.97%	23.97%	23.97%
I4	$yv_{ik} = \frac{\lvert v_{i-}v_k \rvert}{\left[1/2 \text{ x } (v_i^{-1}+v_k^{-1})\right]^{-1}}$	23.97%	23.97%	23.97%
I5	$yv_{ik} = \frac{\lvert v_{i-}v_k \rvert}{\min(v_{i,}v_k)}$	23.97%	23.97%	23.97%
I6	$yv_{ik} = \frac{\lvert v_{i-}v_k \rvert}{\max(v_{i,}v_k)}$	23.97%	22.82%	23.97%
I7	$yv_{ik} = log_e\left(\frac{v_i}{v_k}\right)$	24.20%	22.82%	23.97%

Source: authors

Table 5 – Experiment III – Percentages of Improvement

An alternative approach for the objective function (Equation 5)	v_i^{*}	v_i^{2*}	$\sqrt{v_i^{*}}$
$Min\ \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{P}\sum_{k=1}^{K}\sum_{l=1}^{P} f_i ys_{ik} yw_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^{K}\sum_{j=1}^{P} f_i v_i rs_j x_{ij}$	22.82%	-	-

Source: authors

Table 6 – Comparison of the results obtained with different stores

Components	**Store 1**	**Store 2**	**Store 3**	**Store 4**	**Store 5**
SWM – Distance (km/month)	19.38	6.57	8.46	3.63	19.68
% of improvement SM	23.97%	40.21%	29.89%	39.90%	24.25%
Current situation – Distance (km/month)	25.50	10.98	12.07	6.04	25.98

Source: authors

Table 7 - Comparison of the results obtained with random samples

Components	**Rand 1**	**Rand 2**	**Rand 3**	**Rand 4**
SWM – Distance (km/month)	2606.45	2633.62	2629.80	2534.39
% of improvement SM	32.75%	33.04%	30.15%	33.48%
Current situation – Distance (km/month)	3875.70	3933.19	3765.16	3809.77

Source: authors