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Dealing with the Storage Location Assignment Problem with Precedence Constraints

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Abstract

This paper proposes a zero-one quadratic assignment model for dealing with the storage location assignment problem when there are weight constraints. Our analysis shows that operations can be improved using our model. When comparing the strategy currently used in a real-life company with the designed model, we found that the new placement of products allowed a reduction of up to 22% on the picking distance. This saving is higher than that achieved with the creation of density zones, a procedure commonly used to deal with weight constraints, according to the literature.

Keywords: Storage Location Assignment Problem (SLAP), Correlated Policy, Precedence Constraints

Introduction

Retail and wholesale are major sectors of the European economy. Together, they generate 11% of the Europeans' GDP. A third of European companies belong to the retail or wholesale sectors. They are one of the few sectors that are steadily creating employment across Europe (Eurocommerce, 2019).

In the last decade, there has been a growing adoption of e-commerce in these sectors. Published sources indicate that 21.8% of the world's population buys online and that online sales could reach $ 4.8 trillion by 2021 (eMarketer, 2019). This forces companies to be smarter about how they use their warehouses and distribution centres.

In the retail and wholesale sectors, order-picking processes are still characterized by a high share of manual human work. Currently, the worldwide share of automated warehouses is just 5% (DHL, 2018). This low rate is mainly due to the difficulty in replicating human flexibility and motor skills in machines. As a result, order-picking operations represent more than 55% of picking costs of companies and improving efficiency in this area is key for those companies (Grosse & Glock, 2014).

The efficiency of order-picking can be improved in several ways, including assigning products to appropriate storage locations (storage strategy) and determining the appropriate route, and picking orders in batches (batching) (van Gils et al., 2018).

We focus on storage strategy. Recently, research on the storage location assignment problem (SLAP) has started to consider characteristics of real-world warehouse activities such as product characteristics, human factors and precedence constraints.

This paper deals with SLAP with weight constraints. We investigate the influence of a new storage assignment policy on order-picking efficiency. This paper is inspired by a real-word Portuguese food retailer warehouse. We propose a zero-one quadratic assignment model for manual systems warehouses that operate in a stock environment.

The contributions of this paper are threefold. First, we introduce a rich variation of SLAP with weight constraints inspired by the retail industry. Although SLAP has been well researched in the literature, SLAP subject to constraints still needs further consideration (Chabot et al., 2017). Recently, this subject was defined as a gap in the literature by van Gils et al. (2018) and Zûlj et al. (2018).

Second, in existing studies we found, the solutions to weight constraints were creating density zones (Chabot et al., 2017; Diaz, 2016) and/ or limiting the maximum weight per pallet (Glock and Grosse, 2012; Grosse et al., 2014). These strategies might be inefficient for warehouses with a high number of non-uniform products. With density zones, products are placed according to weight and, therefore, the more variations there are in the weight of fast-mover products, the more zones the picker has to visit (that is, the order-picking distance is increased). Furthermore, the capacity constraint is perceived to be insufficient to ensure the physical integrity of the products. For these reasons, this study proposes a new model to deal with the problem in hand. First, we develop an index to measure the similarity of two products in terms of weight and, then, we incorporate that index in a well-known storage-assignment model, suitable for our case.

Third, this study makes available a new technique, which is easy to understand, and which can easily be implemented in practice. In addition, it may be used to improve the performance of many other retail companies.

This paper is organized as follows. First, we present a brief literature review on the topic. Then, we provide the main methodology employed in this study. Subsequently, we detail the case study that inspired this paper and we present the main results. Finally, we give the main conclusion and some ideas for future research.

Literature Review

As the focus of this project is on SLAP, we provide a brief summary of the relevant literature. SLAP concerns the allocation of products into storage locations, with the aim of maximizing order-picking efficiency. This problem is impacted in two main ways, namely: storage capacity and the physical characteristics of products (Reyes et al., 2019).

Several storage policies may be used to allocate products in warehouses. The most recognized of these are: random, dedicated and class based. In a random storage policy, products are randomly allocated into the available spaces (Petersen, 1997). In a dedicated storage policy, products are allocated to a specific area (De Koster et al., 2007). In a class-based storage policy, products are grouped into categories and inside each category, products are randomly allocated (Petersen & Schmenner, 1999). Within the class-based storage method, it is possible that the correlated storage system will also be used. This policy is based on the idea that products with high values of correlation must be stored close to each other (Frazelle, 2002).

A lot of studies have been designed around the correlated storage policy. These studies propose various clustering techniques (see Bindi et al., 2009; Liu, 2004; Manzini et al., 2012; Rosenwein, 1994) and (meta-) heuristic approaches (see Brynzér and Johansson, 1996; Liu, 2004; Wutthisirisart et al., 2015; Zhang, 2016). However, the studies have often neglected constraints arising in real-world applications.

Order-picking is often subject to constraints. These constraints include requiring certain products to be collected before other products, owing to fragility, shape, size, and preferred unloading sequence (Chabot et al., 2017). Focusing on weight constraints, we found two different approaches that are usually taken: the creation of density zones and maximum capacity.

The creation of density zones is where products are allocated into areas according to their weight. Chabot et al. (2017), for example, propose two mathematical models and develop five heuristic methods to solve the order-picking problem with weight, fragility and category constraints. In this study, products were classified and allocated to a density zone based on their weight. Diaz (2016) develops a two-step heuristic procedure of, first, creating density zones and, second, allocating products within those zones by using the model developed by Liu (2004).

The maximum capacity approach is where the maximum capacity of a pallet, or the number of boxes that can be loaded on top of each other, is limited, based on weight. Glock and Grosse (2012), for example, describe the order-picking system of a U-shape warehouse in a formal model, to examine the impact of different storage assignment policies. In the model, the authors consider the maximum capacity that a batch can carry. Grosse et al. (2014) propose a simulated annealing approach for solving the joint problem of order-batching and order-picking routing. The authors take into consideration the maximum capacity of a batch. Xiao and Zheng (2012) design a correlated storage assignment system with demand dependences to minimize the order-picking distance. The authors also take into consideration the maximum capacity of a batch.

We also found one study that deals with the weight precedent constraint by proposing a new picker-routing (see Žulj et al., 2018).

Having researched the literature, our aim in this paper is to develop an alternative method for SLAP with weight constraints.

Methodology

In this section, we present the methodology employed in this study. First, we provide the problem description, then, the model building concepts and, finally, the model formulation. Given the complexity of the problem in hand and the similarity between our problem and that discussed by Liu (2004), we base our allocation model on his design and we further develop it to incorporate the weight (see the next subsections). We also develop and test a program in C++ to calculate the exact distance travelled by the picker, using the locations given by the designed allocation model.

Problem Description

The problem in hand can be defined as stated below:

Given:

- A set of available slots and a set of products to allocate to those same slots;
- The distance from the start-end point to each one of the slots;
- The distance from one slot to another;
- The warehouse storage capacity expressed in slots;
- The products' similarity;
- The products' demand, in a regular month;
- The products' weight.

Determine:

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

Goal:

- To minimize the total distance travelled by the picker.

Model Building Concepts

Many SLAP studies assume that the warehouse configuration may be modified to accommodate the products. In this study, however, the warehouse configuration as well as the routing policy are assumed to be fixed. This is due to the fixed layout and narrow aisles of our case company.

We focus, instead, on the improvement of the storage assignment policy. We propose the allocation of products based on three criteria: similarity, demand and weight. The similarity is given by the probability of two products appearing together in orders. The higher the probability, the higher the similarity between two products. The demand is given by the probability of one product appearing on orders. The weight criterion is given by the similarity of two products, in terms of weight. In the end, the highest requested products must be placed in the slots that are next to the start-end point; the products with higher similarity must be placed next to each other; and the products of similar weight must be in slots near each other, to avoid risking the physical integrity of the products.

Model Formulation

The procedure has two parts. First, as in Liu (2004), this work formulates the problem as a zero-one quadratic assignment model that gives the location of the products by using: the products' similarity, demand and weight; the relative distance between the slots; and the relative distance to the start-end point. Then, this work calculates the exact distance travelled by the picker through a program design in C++ language for this purpose, using the locations given by the allocation model. The assignment model uses the set of indexes, parameters, and variables, that are presented in the following.

Indices

i – product *i* (*k* is also an index for products)
j – slot *j* (*l* is also an index for the slots)

Parameters

d_{jl} – travel distance between slot *j* and slot *l*
f_i – frequency with which product *i* appears on the orders – see Equation 1

Equation (1):
$f_i = \frac{n_i}{N}$, where n_i – number of orders in which product i appears and N – 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 start-end point to slot *j*
ys_{ik} – similarity between products *i* and *k*, in terms of demand pattern – see Equation 2

Equation (2):
$ys_{ik} = \frac{n_{ik}}{N}$, where n_{ik} – number of orders in which product i and k appear together

yw_{ik} – similarity between products *i* and *k*, in terms of weight – see Equation 3

Equation (3):
$yw_{ik} = 1 - \frac{|w_{i-}w_k|}{max\ (|w_i|,|w_k|)}$, where w_i – weight of product i and w_k – weight of product k

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

Mathematical Formulation
Given the indices, parameters, and variables presented, the generic model design is formulated as follows.

Equation (4):
$$Minimise\ \frac{1}{2}\sum_{i=1}^{A}\sum_{j=1}^{P}\sum_{k=1}^{A}\sum_{l=1}^{P} f_i ys_{ik} yw_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^{A}\sum_{j=1}^{P} f_i rs_j x_{ij}$$

Subject to:

Equation (5):
$$\sum_{i=1}^{A} x_{ij} = 1 \qquad \forall j = 1, \dots, P$$

Equation (6):
$$\sum_{j=1}^{P} x_{ij} = sn_i \qquad \forall i = 1, \dots, A$$

Equation (7):
$$x_{ij} = 0,1 \qquad \forall i = 1, \dots, A \quad \forall j = 1, \dots, P$$

Where:

Equation (8):
$$\sum_{i=1}^{A} sn_i \leq P$$

Equation (9):
$$A \leq P$$

The objective function (Equation 4) gives the expected distance necessary to perform the order-picking operation. If a product *i* is allocated to slot *j*, it takes rs_j kilometres (km) to come from the start-end point to slot *j*. f_i provides the likelihood that an operator picks product *i* for an order. The second part of the equation, given by the product of f_i *and* $rs_j x_{ij}$, defines the expected distance required to go from the start-end point to slot *j*. It is assumed that a picker can travel from slot *j* to slot *l* during the picking trip. ys_{ik} provides the likelihood that an operator picks both products *i* and *k* for an order. yw_{ik} provides the similarity of weight between products *i* and *k*. The product of f_i *and* $ys_{ik} yw_{ik} d_{jl} x_{ij} x_{kl}$ denotes the expected distance from slot *j* to slot *l*. The sum of all the parcels results in the total expected travel distance by the picker.

Equation (5) guarantees that only one product *i* is assigned to slot *j*. Equation (6) assures that the number of slots assigned to product *i* equals sn_i. Equation (7) constricts the binary variable values to zero or one. Equation (8) ensures that the number of slots needed by the product does not exceed the number of available slots. Finally, Equation (9) ensures that the number of products does not exceed the number of available slots.

Note that the objective function proposed uses approximated probabilities instead of exact values. Nevertheless, probabilities were also used in other successful approaches such as Diaz (2016), Kovács (2011) and Kutzelnigg (2011); therefore, although it is an approximation, it is still suitable for practical use.

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. We focus on the non-food stock section of the non-perishables warehouse. The current layout consists of a closed area, divided into several aisles that are assigned to different categories of products such as car tools, lights, cooking equipment and so on. Pickers perform a conventional manual picking operation within a one-way s-shape route. The company has a picker-to-parts system with low-level picking. During the process, the pickers are guided by a voice speaking system that tells them the location of the products. The picking guide is generated by the company management system, which already divides the orders according to the typology (food, non-food and drinks). There are pickers exclusively allocated to the non-food area.

Results

This section covers the application of different assignment methods for our case study. SLAP was proved to be a non-deterministic polynomial-time hard (NP-hard) problem (Frazelle & Sharp, 1989). The study company has, on average, 11033 orders per day and up to 400 products per order. For this reason, the optimal solution cannot be obtained for large solution spaces. Thus, the problem is solved by using as a sample the orders of one store, in a regular month. We test two different scenarios:

- Diaz’s method (density zones strategy) – First, we distribute products into density zones, according to weight. Then, within those zones, we sort products according to the demand and similarity criteria (following Liu’s model) – see Diaz (2016).
- New model (scenario designed for this paper) – We allocate products based on the combination of similarity, demand and weight 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 at 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 a reduction on the picking distance of up to 22%.

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

	Diaz’s method	**New model**	**Current situation**
Distance (km/month)	24.40	19.68	25.50
% of improvement	4.31%	22.82%	–

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 0.22 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 2 (down limit: 2.83 | upper limit: 2.90).

Table 2 – Savings obtained in the different scenarios

Savings	**Diaz's method**	**New model**
Distance reduction (km/ month)	1.10	5.82
Distance reduction (km/day)	0.04	0.22
Reduction in daily hours of operation (h)	0.02	0.11
Potential reduction of pickers (nº of pickers)	0.003	0.015
Potential reduction of pickers – $C.I._{0.01,95\%}$	0.49 – 0.65	2.83 – 2.90

Note 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 in the warehouse management system used by the company. The employees would also have to adapt to a different work environment. In addition, these results refer to the specific case study to which the proposed approach has been applied. They should not be generalized.

Experimental Design

We create three experimental designs (of 2x3, 7x3, and 2x3, respectively) to test different ways of calculating the similarity of two products in terms of weight – weight parameter (Experiment I and II) and to test an alternative way of integrating the weight of products in the model (Experiment III).

In Experiment I, we test the use of the non-normalized weight parameter $-yw_{ik}$–, in three ways (yw_{ik}, yw_{ik}^2 and $\sqrt{yw_{ik}}$) for two different indexes. These indexes already return a number between 0 and 1; the number in line with the values of the demand and similarity parameters. Results are presented in Table 3. Cases in which it is not possible to get a solution are marked with a line.

Table 3 – Experiment I

Relative difference indexes	yw_{ik}	$\sqrt{yw_{ik}}$	yw_{ik}^2
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{(w_i + w_k)/2}$	19.68	19.68	-
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{\max(\lvert w_i \rvert, \lvert w_k \rvert)}$	19.68	19.68	-

In Experiment II, we examine the use of a normalized weight parameter $-yw_{ik}^*$ –, in three ways (yw_{ik}^*, yw_{ik}^{2*} and $\sqrt{yw_{ik}^*}$), for seven indexes. In this experiment, all the relative difference indexes are normalized through Min-Max algorithm to ensure that the index returns a value between 0 and 1 (see Equation 10). Results are presented in Table 4. Situations in which it is not possible to get a solution are marked with a line.

Equation (10):

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

Table 4 – Experiment II

Relative difference indexes	yw_{ik}^{*}	$\sqrt{yw_{ik}^{*}}$	yw_{ik}^{2*}
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{\lvert w_k \rvert}$	19.68	19.68	19.68
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{(w_i + w_k)/2}$	19.68	19.68	-
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{\sqrt{w_k w_i}}$	19.68	19.68	19.68
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{[1/2 \text{ x } (w_i^{-1} + w_k^{-1})]^{-1}}$	19.68	19.68	19.68
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{\min(\lvert w_i \rvert, \lvert w_k \rvert)}$	19.68	19.68	19.68
$yw_{ik} = 1 - \frac{\lvert w_i - w_k \rvert}{\max(\lvert w_i \rvert, \lvert w_k \rvert)}$	19.68	19.68	-
$yw_{ik} = 1 - log_e\left(\frac{w_i}{w_k}\right)$	19.68	19.68	19.68

In Experiment III, we assess an alternative approach that includes the introduction of the normalized weight of a product – $w_i *$ –rather than the similarity of two products in terms of weight, in the zero-one quadratic assignment model (Equation 4). The weight is normalized through Min-Max algorithm (see Equation 11).

Equation (11):
$$w_i^{*} = 1 - \frac{w_i - min(w_i)}{max(w_i) - min(w_i)}$$

We test the solution for w_i, w_i^2,$\sqrt{w_i}$. Results are presented in Table 5.

Table 5 – Experiment III

Alternative approach for the objective function (Equation 4)	w_i^{*}	w_i^{2*}	$\sqrt{w_i^{*}}$
$Min\ \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{P}\sum_{k=1}^{K}\sum_{l=1}^{P} f_i ys_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^{K}\sum_{j=1}^{P} f_i w_i rs_j x_{ij}$	19.63	19.63	19.63

In this experiment, we also assess the simultaneous use of $w_i$and w_{ik}. For this purpose, we use the initial w_{ik} (Equation 3). We test the solution for w_i, w_i^2,$\sqrt{w_i}$. Results are presented in Table 6.

Table 6 – Experiment III

Alternative approach for the objective function (Equation 4)	w_i^{*}	w_i^{2*}	$\sqrt{w_i^{*}}$
$Min\ \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{P}\sum_{k=1}^{K}\sum_{l=1}^{P} f_i ys_{ik} yw_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^{K}\sum_{j=1}^{P} f_i w_i rs_j x_{ij}$	19.68	19.68	19.68

The use of different ways of calculating the weight parameter does not impact the solution. The percentage of improvement is the same in all the alternatives explored in Experiment I and Experiment II. Nevertheless, the use of the normalized weight of the product (based on Equation 11) shows a small improvement on the distance travelled – when compared to the use of the similarity of two products in terms of weight. However, this improvement is not significant (equivalent to 0.2%).

In addition to the three experiments, we run the model for the samples of three more stores to see if there are significant differences between the percentages of improvement achieved. We also test the procedure on a random sample in which the frequency is generated from a Gaussian distribution with atmospheric noise (see Table 7).

Table 7 – Comparison of the results obtained with different samples

Components	**Store 1**	**Store 2**	**Store 3**	**Store 4**	**Random**
New model – Distance (km/month)	19.68	6.28	8.74	3.63	19.68
Current situation – Distance (km/month)	25.50	7.98	12.07	5.04	25.98
% of improvement	22.82%	23.35%	27.59%	27.98%	24.25%

The percentages of improvement are even higher in the samples of the other stores. Results indicate that the overall saving could go up to 28%.

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 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. Second, on the empirical side, the results show that the proposed model is effective in improving overall warehouse operating efficiency. 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 the location of items within the aisle to be changed without damaging the results. The model can be further extended to allow the allocation of new products that were not initially considered.

Conclusion

This paper is inspired by a real-life case of a manual order-picking retail warehouse, with a high number of non-uniform products, where the product weight 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 weight in the allocation system of the products.

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 a reduction of up to 22% on the picking distance. This percentage is 18% higher than that achieved using density zones, an approach commonly employed to address the storage location assignment problem.

Our analysis shows that the designed model improves current operations in several respects. Warehouse managers can avoid the strict strategy of sorting products by weight and they can reduce the picker travel distance for completing customer orders.

Future studies can further investigate the effects of using the new model. This could include applying it in different kinds of warehouses, such as those with different picking methods and/or layouts (for example, warehouses with a U-shape or fishbone configuration). There is also the potential to incorporate in the method a different routing and/or batching method. Furthermore, there is potential to include a model of the classification of products to investigate its impact on productivity. Another suggestion is to apply the model to different kinds of companies to research the results obtained.

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