Warehouse Management Optimization Using A Sorting-Based Slotting Approach

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Abstract:

Purpose: Slotting is one of the main operations in warehouse management. It is based on the efficient allocation of slots for stock-keeping units (SKUs). Order picking and slotting represent a high percentage of total logistics costs; therefore, improving these activities leads to significant savings in overall performance. This paper aims to develop an allocation model integrating SKUs physical variables, warehousing design and operation (dimensions, layout, material handling equipment), and heterogeneous product demand.

Design/methodology/approach: The modeling methodology considers two phases. First, an integer linear programming model for warehousing spaces assignment for SKUs considering priority and required orders is developed. Then, the total operation times using different strategies are calculated.

Findings: The effectiveness of the model was verified through simulation using historical data. The results showed that the best performance in the total time of the slotting operation is achieved by using the ABC as a criterion for the classification of the SKUs and by sequentially assigning the row, level, column, and section.

Practical implications: This approach can be adapted to different industrial sectors and serves as a basis for more robust models regarding the number of constraints or the incorporation of additional warehouse operating parameters.

Originality/value: The most important contribution of this work is the development of an adaptable methodology to changes in the operation to improve the efficiency of storage management through slotting. Future work includes other objective functions of sustainable operations and uncertainty treatment techniques.

Keywords: linear programming model, picking strategies analysis, storage location assignment problem, SKU sorting methods, warehouse optimization methods

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1. Introduction

Warehousing Management aims to achieve the best performance and control in all operations and processes of a warehouse (Kovács, 2011; Montanari, Micale, Bottani, Volpi & La Scalia, 2021; Ribeiro, Jacquillat, Antunes, Odoni & Pita, 2018). Business decisions set the parameters and constraints for a warehouse and define some behavior and policies about the performance (Ai-Min & Jia, 2011; Manzini, Bozer & Heragu, 2015; Yafei, Qingming & Peng, 2018).

Slotting and picking are the most relevant warehousing activities. Slotting refers to how to assign the Stock-keeping Units (SKUs) by a specific priority. Picking refers to those strategies to collect the orders according to quantity, distances, travel times, picking conditions, and other constraints (Accorsi, Manzini & Maranesi, 2014; Zhong, Giannikas, Merino, McFarlane, Cheng & Shao, 2022; Zunic, Hodzic, Hasic, Skrobo, Besirevic & Donko, 2017).

Two classic slotting methodologies are known in practice: (i) ABC classification and (ii) Cube per Order Index (COI). These methodologies set priority to SKUs according to popularity and bulk material, respectively (Duque-Jaramillo, Cuellar-Molina & Cogollo-Flórez, 2020; Schuur, 2015). Each SKU needs different attention and slotting strategy (Chu, Liang & Liao, 2008).

Otherwise, there are several ways to study the picking strategies. The heuristics methods are the most common (Battista, Fumi, Laura & Schiraldi, 2014; Bustillo, Menéndez, Pardo & Duarte, 2016; Cano, 2019; Cano, Correa, Gómez & Cortés, 2019; Guerriero, Pisacane & Rende, 2015; Sukhov, Batsyn & Terentev, 2014; Zhang, Nishi, Turner, Oga & Li, 2016). This problem depends on the constraints and assumptions from each warehouse. The organizational structure sets the constraints on the operative and tactic decisions levels. For example, the order picking may be performed by using a picker-to-part or a part-to-picker method (Boysen & Stephan, 2013; Manzini et al., 2015). The warehousing management must define the strategies about methods, tools, configuration, and the constraints to develop the picking strategy (Kim & Smith, 2011).

This paper works on the lack of studies considering integration between picking and slotting strategies to reduce total operation times that significantly affect warehouse performance. The integration of these strategies has not been widely studied and could improve the performance of warehouse management.

This paper aims to propose a warehousing management model considering the requirements given by a study case. Another purpose is to introduce a tool that can support the implementation of warehouse management strategies using correlated methods between slotting and picking to improve the performance and work around all the warehouse behavior.

This paper is organized as follows: Section 2 presents a research background. Section 3 presents the research framework and methodology proposal referring to a mixed-integer linear model with a two-phase algorithm to solve it. Section 4 presents the proposed model formulation including assumptions, parameters, decision variables, and constraints. Section 5 exhibits the model application relating to a study case. Finally, in section 6, the analysis and results discussion are presented.

2. Research Background

Some researchers and practitioners have studied and proposed warehouse management techniques to improve and optimize warehouse performance. Some previous work had focused on two main factors: (i) spaces assignment and (ii) picking strategies (Duque-Jaramillo et al., 2020; Zhang, 2016; Zhong et al., 2022). For the space assignment, some authors based on the Product Allocation Problem (PAP). PAP consists on to locate the SKUs inside the warehouse slots by reducing cost, operation time, and used slots and increasing the service level (Lorenc, Kuźnar & Lerher, 2021; Lorenc & Lerher, 2020; Scheffler, Wesselink & Buscher, 2021).

In this topic, Millstein, Yang and Li (2014) developed a model to improve the quality and efficiency of the inventory grouping. The model optimized the number of groups and SKUs assignment according to service level. The authors developed a support decision-making tool that offset the service level inventory cost and more decision factors.

Huang, Wang, Batta and Nagi (2014) introduced an integrated two phases model for slot selection and space determination with products carried from supplier to warehouse and stored for an indeterminate time. The objective was to reduce the inbound and outbound transportation costs as well as the total cost of operation,

including the location and variable costs. The authors mentioned that the picking and slotting problem is closely related to the warehouse selection and sizing problem.

Zhang et al. (2016) pointed out an application in the real world where the challenge was to search free slots for products and manage them. They developed an integrated strategy that combined PAP with the capacitated lot-sizing using COI rule allocation based on priority. This was achieved by formulating an integer linear programming model to optimize the total cost of production, setup storage, handling, and reserving places.

Alqahtani (2023) developed an analytical hierarchical process model to solve the storage allocation and assignment problem using COI as the ABC analysis criterion. The storage area was partitioned according to the class-based policy. However, SKUs were randomly assigned within a class. Zhang, Shang, Alawneh, Yang and Nishi (2021) proposed a joint production planning and randomized storage strategy to increase space utilization by using IoT systems. The model minimized the total cost of both operations by determining the production quantity, inventory level, and storage assignments. However, the class-based storage assignment policy was not considered.

Yiğit and Esnaf (2021) proposed a technique to sort the inventory combining ABC analysis, a fuzzy C-Mean cluster algorithm and analytic hierarchical process for a multicriteria inventory classification. The authors considered most companies used ABC inventory classification, but they pointed out as a weakness the use of popularity as single criterion. The model included nominal and non-nominal variables like the criticality factor and average unit cost.

Yan, Zhang, Liu, Lv, Zhang and Li (2021) presented a multi-objective algorithm combining an NSGA II genetic algorithm and an ABC method for neighborhood search to optimize warehouse schedule considering aisle switching time. The model aimed to minimize the total competition time and total delay penalty. This work was based on an automated warehouse and did not use the COI classification in its algorithms.

Silva, Roodbergen, Coelho and Darvish (2022) proposed a methodology to predict the optimal size of an ABC warehouse product allocation. They considered warehouse layout, demand characteristics, and storage and routing policies. To solve the problem, they used machine learning models and demonstrate a performance increase by comparing ABC with random storage. The authors explored a PAP but just considered ABC as the unique slotting methodology and no routing optimization.

The picking strategies cover the methodologies to prepare the order including the routing methods to reduce operation times (Bustillo et al., 2016; Cano, 2019; Guo, Wu, Shen, Starner, Baumann & Gilliland, 2015). Zhang (2016) mentioned several solutions for correlated storage assignment strategy. The author developed some picking strategies using picker-to-parts methods in a warehouse section. These strategies were based on the correlation between SKUs and search the best results in warehouse operation. This approach could help to reduce travel distances for order pickers and improve the efficiency of the picking process.

Yener and Yazgan (2019) performed a literature review and proposed a mixed-integer quadratic model considering variables like consumption, capacity, and travel distances. They focused on three issues: (i) the effectiveness of warehouse design (ii) picking assignment zones and (iii) order picking process aiming to reduce the picking time.

Yuan, Li, Wang, Dou and Pan (2021) introduced a slotting methodology for zone-based robotic picking distribution systems. The authors included the mathematical formulation to solve the slotting problem but, due to the problem complexity they developed a four phases hybrid heuristic. One of them included correlated items picking analysis according to SKUs correlation.

Boysen and Stephan, (2013) analyzed a PAP under a pick-by-order policy. The objective was to allocate the SKUs making the least possible picker effort. The authors also designed a multiple-aisle warehouse configuration. This configuration could change aisle parameters allowing a more complex analysis. They stated that the picking and slotting strategies combination is a critical factor in warehouse operations due to it can have a significant impact on picking efficiency and order accuracy.

Schuur (2015) described some cases where COI classification was not the best decision. However, the COI strategy could be combined with a wave picking strategy to improve the overall performance of the warehouse. He also stated that there were other slotting strategies that could be combined with picking strategies.

An approach for warehouse management and design systems was introduced by Manzini et al. (2015). It involved demand patterns with SKUs lifetimes. The authors formulated a mixed-integer linear model based on costs and used two policies (picker-to-part and part-to-picker) with SKUs assignment using the lifetime as a popularity criterion. They concluded there were several different ways to combine picking and slotting depending on the characteristics of the warehouse operation.

Guerriero et al. (2015) presented a mathematical model for multi-level PAP. The objective was to reduce the inventory delivery times and logistic costs and guarantee the service level by combining slotting and picking strategies. The problem was represented using mixed-integer linear programming and compatibility constraints according to product classification. The solution was found with an iterated local search-based heuristic and cluster-based heuristic.

Kuo, Kuo, Chen and Zulvia (2016) developed a methodology to zone warehouses and allocate space (synchronized zone order picking) based on logistics management policies combining picking and slotting strategies. Their goal was to reduce cost, travel distances, and lead times and increase customer satisfaction and warehouse utilization. To solve these problems, they used Particle Swarm Optimization metaheuristics and genetic algorithms.

Kung and Liao (2017) developed a PAP solution methodology to maximize the result based on the demand behavior and minimize the impact on marginal benefit with a non-linear model focusing on the problem of competitive facility location with network effects. Pferschy and Schauer (2018) developed a methodology to work with non-standard warehouses structure. They used a heuristic solution algorithm based on a fair graph model considering the order batching and grouping them for picking.

Wang, Zhang and Fan (2020) developed a storage location assignment mechanism by exploiting data characteristics from item orders seeking to minimize the total travel distance. They generated different instances with ABC classification that allow for improving the picking performance by a data-based approach. Although the authors considered classification methodologies advantageous, they did not consider them a strategy to solve the problem.

Pacheco, Møller-Clausen and Bumann (2023) indicated the pros of ABC classification for reducing operational waste in distribution warehouses. The authors integrated three conceptual modeling tools and a quantitative tool based on successive correlation vectors and matrices. The ABC classification provided a structure for allocations and reduced the waste on transportation during the picking process. The work did not use other classification methodologies, such as COI, to demonstrate waste reduction.

Fontana and Nepomuceno (2017) proposed a multi-criteria decision model for classifying the products and solving the storage location assignment problem in a multi-layer warehouse. The model assigned a fixed location for each product considering several criteria, such as the demand level and the decision-maker preferences. Due to the above, the model goal was optimizing the slotting or picking operations, and it was not possible to obtain and compare the total times of picking orders.

Wang, Man, Zhao, Zhang and Zhao (2022) proposed a storage assignment optimization model using Adaptive Genetic Algorithm in order to reduce goods movement and travel distance and improve order-picking efficiency. The model addressed the robotic mobile fulfillment systems problem in a warehouse with a fishbone rack layout. The model considered the working distance and aisle balance but did not consider the correlation between orders on storage assignment.

Mirzaei, Zaerpour and de Koster (2021) considered product affinity as a relevant variable for improving warehousing management, assigning multiple correlated products to the same inventory cluster, and reducing retrieval time. They proposed an integrated cluster allocation (ICA) policy based on both product turnover and affinity. Although the model could reduce the total retrieval time compared to class-based policies, this was true when applied to robotic mobile fulfillment systems.

Viveros, González, Mena, Kristjanpoller and Robledo (2021) developed a mathematical programming model to minimize the total travel distance addressing the multi-level storage locations assignment problem for SKU pallets. They proposed a sequential decomposition method of the problem whose solution depends on the storage location type, the storage strategy, the number of SKUs, and the warehouse size. However, the model was applicable in warehouses where it was possible to vary the height and the size.

Most of the authors proposed models to provide a solution in specific cases considering the reduction of operating costs and focusing on one of the two activities that significantly affect warehouse performance. But a smaller number of them worked with combined slotting and picking strategies. Integrating slotting and picking strategies could improve picking efficiency and reduce errors and costs. However, there is not enough research on this integration, and some possible barriers to performing this integration are related to data accuracy, the flexibility of the slotting strategies, and the trained force (Khullar, 2021).

Silva, Coelho, Darvish and Renaud (2020) jointly analyzed storage location and order-picking problems by considering four routing policies. The proposed metaheuristic worked efficiently for small instances and improved traditional solutions for large warehouses and picking operations. The results of this work highlighted the importance of jointly analyzing picking and slotting problems. The SKUs allocation policy should be periodically updated according to the seasonality of sales, the products expiration date, among other factors.

Optimization problem	Proposed technique	Objective function	Authors
Space assignment	Grouping SKUs	Service level and cost	Millstein et al. (2014)
	Slot selection and space determination	Operation cost	Huang et al. (2014)
	COI lot-sizing	Total cost	Zhang et al. (2016)
	Randomized storage strategy	Total cost	Zhang et al. (2021)
	Fuzzy ABC sorting inventory	Average unit cost	Yiğit and Esnaf (2021)
	ABC product allocation	Transportation time	Silva et al. (2022)
	COI storage allocation	Response time	Alqahtani (2023)
Picking strategies	COI and wave picking	Overall performance	Schuur (2015)
	Picker-to-parts and COI method	Travel distances	Zhang (2016)
	Layout and Order picking process	Picking time	Yener and Yazgan (2019)
	NSGA II and ABC	Total competition time	Yan et al. (2021)
	COI zone-based robotic picking	Travel distances	Yuan et al. (2021)
	ABC picking process	Waste on transportation	Pacheco et al. (2023)
Space assignment and Picking strategies	PAP and Pick-by-order policy	Picker effort	Boysen and Stephan (2013)
	SKUs lifetimes and Picker-to-part and part-to-picker	Total cost	Manzini et al. (2015)
	PAP and Multi-level configuration	Delivery time	Guerriero et al. (2015)
	Zone warehouse and Order picking	Cost, distance, and lead time	Kuo et al. (2016)
	PAP and Demand behavior	Marginal benefit	Kung and Liao (2017)
	PAP and Multi-criteria decision model	Picking time	Fontana and Nepomuceno (2017)
	Warehouse structure and Order batching and group picking	Total cost	Pferschy and Schauer (2018)
	ABC-PAP and the robotic mobile fulfillment systems	Total travel distance	Wang et al. (2020)
	Integrated cluster allocation and Product turnover and affinity	Retrieval time	Mirzaei et al. (2021)
	PAP and Sequential decomposition method	Travel distance	Viveros et al. (2021)
	PAP and Aisle balance	Goods movements	Wang et al. (2022)

Table 1. Main contributions to warehouse management optimization

Table 1 summarizes the main contributions to warehouse management optimization previously mentioned, highlighting the optimization problem (space assignment and picking strategies, individually and jointly), the proposed technique, the optimization objective function, and the authors. The joint management of slotting and picking is important because the two processes are interrelated and complement each other to improve efficiency and productivity in logistics systems. Some of the main reasons for combining slotting and picking are to optimize workflow, reduce picking times, minimize picking and storage costs, and improve picking accuracy (Echeverria-Garcia, Espinoza-Alarcon & Quiroz-Flores, 2022). There is no single best combination of picking and slotting, as the optimal solution depends on the specifics of the warehouse and the order profile. However, the use of ABC classification and COI has not been widely studied and could improve the standardization of picking and slotting strategies, considering bulk conditions.

3. Methodology

This methodology is based on a two-phase algorithm. The first phase manages classic slotting strategies for warehousing management by assigning priority to each SKU. Also, it is supported in an integer linear programming model for warehousing spaces assignment for the SKUs considering priority and required orders. The second phase calculates the strategies total operation time for the selected periods.

ABC classification and Cube per Order Index (COI) were the selected methodologies for priority classification. The assignment strategies were based on an adaptation of the Traveling Salesman Problem (TSP) and establishing six different slot assignment sequences (SAS). The TSP aimed to assign each SKU to the empty slot with the lower travel time and the SAS defined different path patterns (Khalil, Li, Wang & Khan, 2016; Nalivajevs & Karapetyan, 2019). Moreover, the following conditions were considered:

1. The warehouse was divided into sections, rows, columns, and levels. A section is each of the areas into which a warehouse is divided according to the storage or handling requirements of the products. A row is the set of rack locations arranged horizontally along the aisles. A column is a set of spaces arranged one above the other in a row. The level number corresponds to the increasing order of the vertically available spaces in a column. There were twenty-four alternatives to organize the sequence in which the spaces will be assigned under a structured order, changing the section, row, column, and level (Table 2).

2. There were six paths in the tridimensional perspective. The calculated travel times were measured considering Manhattan distances.

3. Only evaluated the sequences and paths that gave priority to the exit of the warehouse and/or reduce traveled distances, considering the warehouse structure. It depends on some factors like: *(i)* the vehicle speed is faster when is empty and *(ii)* the location of the entry and exit gates.

SAS	First step	Second step	Third step	Fourth step
SAS 1	Row	Column	Level	Section
SAS 2	Row	Level	Column	Section
SAS 3	Column	Row	Level	Section
SAS 4	Column	Level	Row	Section
SAS 5	Level	Row	Column	Section
SAS 6	Level	Column	Row	Section

Table 2. Slots assignment sequence (SAS)

The modeling methodology is in Figure 1. The inputs include internal factors from company decisions referred to the warehouse design configuration and external factors associated with product characteristics. Since the proposed model is applied to different operational warehouse parameters, a two-phase approach is used. The first phase focuses on defining the operational strategies regarding priority methods, space requirements, and slot allocation.

This phase establishes the warehouse conditions for the problem formulation and each specific application case. The second phase focuses on measuring and analyzing the different allocation strategies and their contribution to improving the picking activity. The model outputs are the times for the different allocation strategies in each analysis period.

4. Model Characteristics

The model was applied in the distribution center of a baked and packaged food company in the city of Medellin (Colombia), with 22,204 slots. The assumptions, notations, definitions, mathematical formulation, and constraints are presented in this section.

4.1. Model Assumptions

The following assumptions were established to apply this model:

1. The demand of each SKU is known for each period (months).
2. The SKUs do not need special warehousing conditions.
3. The slot sizes are homogeneous.
4. Any pallet can be stored in any slot.
5. The dimensions and weights of the pallets are similar.
6. The warehouse layout is known.
7. The picking orders are made in pallets.
8. The vehicle loading and unloading times are not considered.

4.2. Notations and Definitions

The notation definitions, index parameter sets and decision variables for this model are defined as follows.
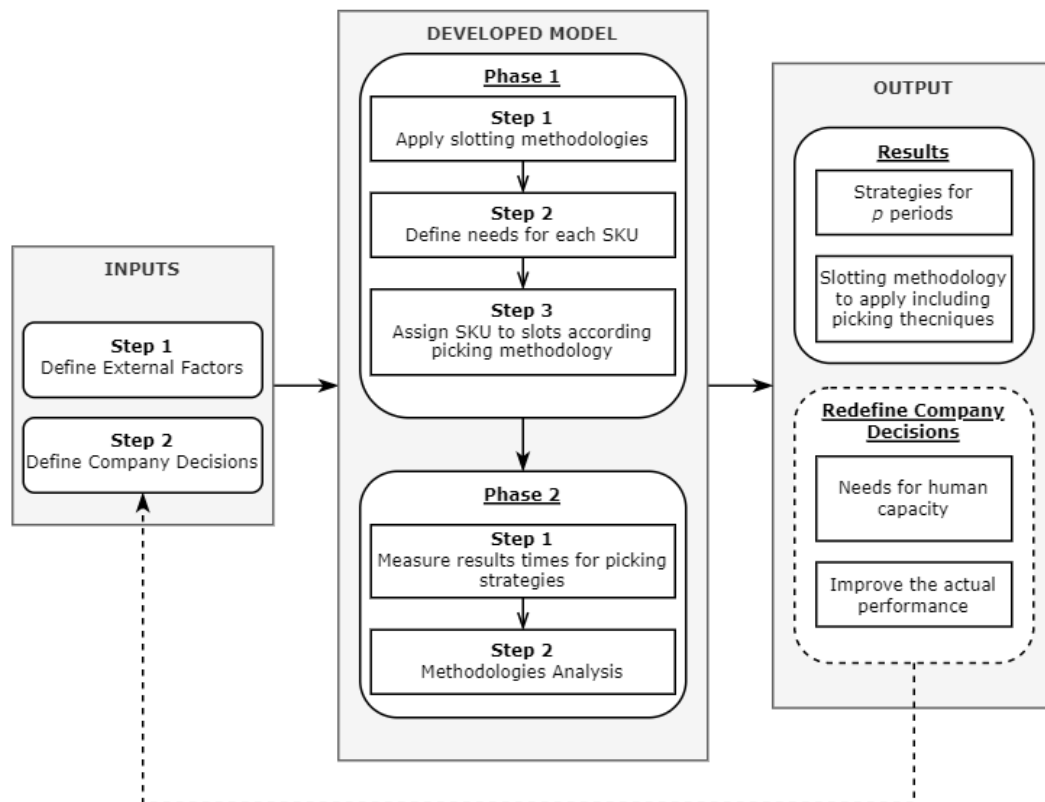

Figure 1. Proposed model structure

Index

p, s, r, c, l, i: index for periods, sections, rows, columns, and levels, and item, respectively.

Parameters

Table 3 presents the input parameters to define the warehouse conditions and configurations.

Symbol	Meaning
wwl	Warehouse width length
wdl	Warehouse depth length
mhwl	Main hall width length
hswl	Hall between sections width length
hrwl	Hall between rows width length
ssdl	Single shelving depth length
dsdl	Double shelving depth length
swl	Shelving width length
avswl	Average vehicle speed without load
avsl	Average vehicle speed with load
pq, sq, rq, cq, lq	Periods, sections, rows, columns, and levels quantities, respectively
tsku$_p$	Total SKU in the period p
d$_r$	Distance to row r
d$_s$	Distance to section s
d$_c$	Distance to column c
dctlif$_l$	Lifting time from the floor to level l
tlow$_l$	Lowering time from the level l to the floor

Table 3. Model parameters configuration

Sets

Table 4 shows the sets for defining the objective function limits for summations.

Set	Configuration
PER	*Periods, PER = {1, 2, …, pq}*
ITEM$_p$	*Item in period p, ITEM$_p$ = {1, 2, …, tsku$_p$}*
SEC	*Sections, SEC = {1, 2, …, sq}*
ROW	*Rows, ROW = {1, 2, …, rq}*
COL	*Columns, COL = {1, 2, …, cq}*
LEV	*Levels, LEV = {1, 2, …, lq}*

Table 4. Sets and limits.

Decisions Variables

There are two decision variables: B_{isrcl} for slot assignment (1) and Q_{isrcl} for quantity assignment times (2):

$$B_{isrcl} = \begin{cases} 1 \ if \ item \ i \ is \ assigned \ to \ the \ slot \ srcl \\ 0 \ in \ other \ case \end{cases} \tag{1}$$

$$Q_{isrcl} = \begin{cases} \geq 1 \ if \ B_{isrcl} = 1 \\ 0 \ in \ other \ case \end{cases} \tag{2}$$

4.3. Mathematical Formulation

The objective function (3) minimizes the strategies times ST_p for each period p. Equation (4) calculates each ST_p according to the parameters sets and decision variables. Also, Equations (5), (6) and (7) calculate the distances for row (d_r), column (d_c), and section (d_s).

$$Min \sum_{p=1}^{pq} ST_p \tag{3}$$

$$ST_p = \sum_{i=1}^{tsku_p} \sum_{s=1}^{sq} \sum_{r=1}^{rq} \sum_{c=1}^{cq} \sum_{l=1}^{lq} [avswl \times (d_r + d_c + d_s + wwl) + tlif_l + tlow_l \\ + avsl \times (wwl - d_r + d_c + d_s)] \times B_{isrcl} \times Q_{isrcl} \tag{4}$$

$$d_r = ssdl + \left[round.\,up \left(\frac{r}{2} \right) \times hrwl \right] + \left[(round.\,up \left(\frac{r}{2} \right) - 1) \times dsdl \right] \tag{5}$$

$$d_c = c \times swl \tag{6}$$

$$d_s = mhwl + (s - 1) \times (hswl + c \times swl) \tag{7}$$

4.4. Model Constraints

The following constraint sets were defined: Eq. (8) defines the type of decision variables. Equation (9) defines the upper limits for periods total, SKUs, sections, rows, columns, and levels indexes. Equation (10) defines the maximum spaces that can be assigned. Equation (11) indicates the total assigned SKUs in period p. Equation (12) refers to the combination of total assigned SKUs regarding total spaces. Equation (13) defines that the total SKUs in period p are less or equal to the maximum warehousing capacity. Finally, Equations (14), (15), and (16) limit the distance to the rows, sections, and columns, respectively.

$$B_{isrcl} = \ binary \ variable; \ Q_{isrcl} = integer \ variable \tag{8}$$

$$p \leq pq; \ i \leq tsku_p; s \leq sq; r \leq rq; c \leq cq; l \leq lq \tag{9}$$

$$\sum_{isrcl} B_{isrcl} \leq rq \times cq \times lq \tag{10}$$

$$\sum_{isrcl} Q_{isrcl} = tsku_p \tag{11}$$

$$\sum_{isrcl} B_{isrcl} \times Q_{isrcl} = tsku_p \tag{12}$$

$$If \ tsku_p \leq rq \times cq \times lq \ ; Q_{isrcl} \leq 1 \tag{13}$$

$$d_r \leq wwl \tag{14}$$

$$d_s \leq wdl \tag{15}$$

$$d_c \leq wdl \tag{16}$$

4.5. Application Software and Algorithm

The model was applied using Microsoft Excel© and written in Visual Basic for Application (VBA). The algorithm used to solve the integer linear programming problem of warehousing space assignment is as follows:

a) Step 1: Define input parameters (Table 3).

b) Step 2: Define demand for each period (Table 4).

c) Step 3: Classify each SKU ($ITEM_p$) under ABC and COI classification methodologies for each period.

d) Step 4: Calculate slot needs for each SKU in the period under each classification methodology.

e) Step 5: Assign one by one SKU to free slots under SAS (Table 2).

f) Step 6: Calculate the time for each SKU and the total time for the strategy, for each period under each classification and each SAS.

g) Step 7: Compare the strategies in each period and get the best solution.

5. Model Application in a Real Case

Model application with real data is presented in this section, by setting the warehouse and vehicle characteristics and the orders selection criteria.

5.1. The Warehouse Configuration

Table 5 shows the warehouse configuration and dimensions. The warehouse layout is shown in Figure 2.

Characteristic	Quantity
Sections per warehouse *(sq)*	2
Rows per section *(rq)*	24
Columns per row *(cq)*	66
Level per Column *(lq)*	7
Total slots	22176
Warehouse width *(wwl)*	72 m
Warehouse depth *(wdl)*	190 m
Main hall width *(mhwl)*	7 m
Hall between sections width *(hswl)*	5 m
Hall between rows width *(hrwl)*	1.5 m
Single shelving depth *(ssdl)*	1.3 m
Double shelving depth *(dsdl)*	2.6 m
Shelving width *(swl)*	1.2 m

Table 5. Warehouse configuration and dimensions

The orders are selected considering the SAS from Table 2 and the following conditions:

• The section is the last factor to change. The warehouse entry and exit doors are on the same axis, which is perpendicular to the section changes direction. Hence, section one must be assigned before section two.

- The rows assignment is from the nearest to the doors to the farthest, according to route conditions shown in Figure 2 (orange and green lines) and the forklift speed.
- The columns assignment is in ascending order (1 to 66). Items with higher priority must be allocated near the entry or exit doors.
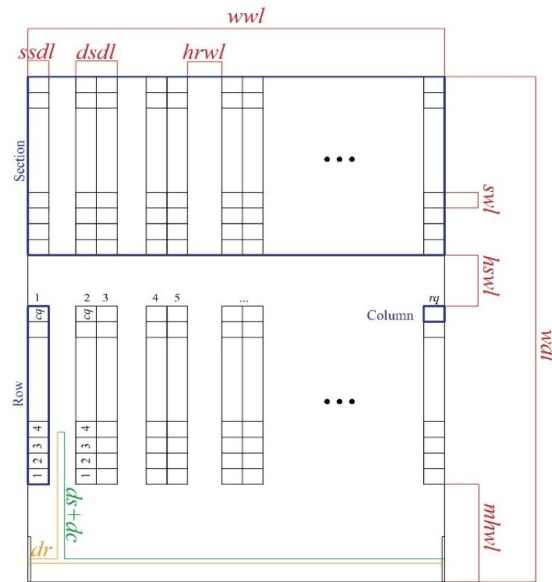- The levels assignment is from bottom to top. Items with higher priority must be allocated near the floor.

Figure 2. Warehouse layout

5.2. The Vehicles

Table 6 shows the vehicle characteristics used in this study case. There is only one forklift type with one pallet capacity.

Characteristic	Speed (meters/second)
Average vehicle speed without load (*avswl*)	3.611
Average vehicle speed with load (*avsl*)	3.056

Table 6. Vehicle characteristics

6. Results Analysis

The application was made considering two periods in one year (semester 1 and semester 2) and the SKUs demand behavior (stational and regular). Table 7 shows the ABC classification per semester. The total SKUs increases from 224 to 286, because of stational demand behavior.

	Semester 1	Semester 2
Total SKUs	224	286
Category A	50	79
Category B	68	89
Category C	106	118

Table 7. ABC Classification per semester

6.1. Classification Methodologies Comparison

Classification methodologies comparison is made by matching ABC and COI by position in the priority list. Table 8 exhibits this comparison for the two semesters. Only 30 SKUs are in the same position (13.39%) in semester 1. In semester two, there is less coincidence (9.79%), although the total SKUs are higher.

Furthermore, the three groups of the ABC classification are compared with the COI classification considering the total SKUs that are in the same location in both methodologies (Table 9). There are high coincidence percentages between categories, the lowest is for category B in semester 1 (92.13%), and the highest is for category C in semester 1 (98.11%).

	Semester 1	Semester 2
Total SKUs	224	286
Coincidence quantity	30	28
Coincidence Percent	13.39%	9.79%

Table 8. Classification coincidence per position

Category	Semester 1			Semester 2		
	Total SKUs	Coincident SKUs	Coincidence %	Total SKUs	Coincident SKUs	Coincidence %
A	50	47	94.00%	79	76	96.20%
B	68	63	92.65%	89	82	92.13%
C	106	104	98.11%	118	114	96.61%

Table 9. Classification coincidence per location

6.2. Time Results Analysis

The times were calculated by applying the mathematical model and compared in seven different scenarios regarding the SAS. We run the model 30 times, and Table 10 shows the summary for the time results (in hours) for semester 1 and semester 2, including all the SAS. For both semesters the best order to assign the slots is the proposed model because it is the nearest strategy to the TSP classification travel time used as a benchmark time.

SAS	ABC time (hours)				COI time (hours)			
	Semester 1		Semester 2		Semester 1		Semester 2	
	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ
TSP	18372.20	7.61	29052.33	7.35	18335.01	7.70	29107.97	7.57
SAS 1	19371.97	8.10	30172.64	8.56	19323.83	7.39	30384.12	12.60
SAS 2	18432.71	7.23	29152.04	11.92	18401.79	6.57	29233.06	10.86
SAS 3	19896.88	10.05	30943.27	10.58	19939.74	11.23	30989.04	8.56
SAS 4	20060.29	7.94	31130.85	12.66	20099.62	8.71	31174.79	13.87
SAS 5	18442.88	8.47	29159.45	9.18	18403.25	9.47	29218.06	8.60
SAS 6	20152.23	10.55	31074.66	14.73	20063.51	10.75	31134.38	15.96

Table 10. Time results per semester

In that sense, for established orders the best two configuration assignments are the SAS 2 and the SAS 5, getting an operation time near to the TSP. These two SAS change the columns and section factors in the last positions. Only the first and second step changes varying the rows and the columns.

6.3. Times per Item and Cumulative Times

Figure 3 and Figure 4 present the results of cumulative times for semester two with ABC and COI classification for all SAS, respectively. It is noted that the TSP, SAS 2 and SAS 5 lines are close because these strategies behavior are similar. Moreover, the cumulative line slopes are related to the ABC classification.
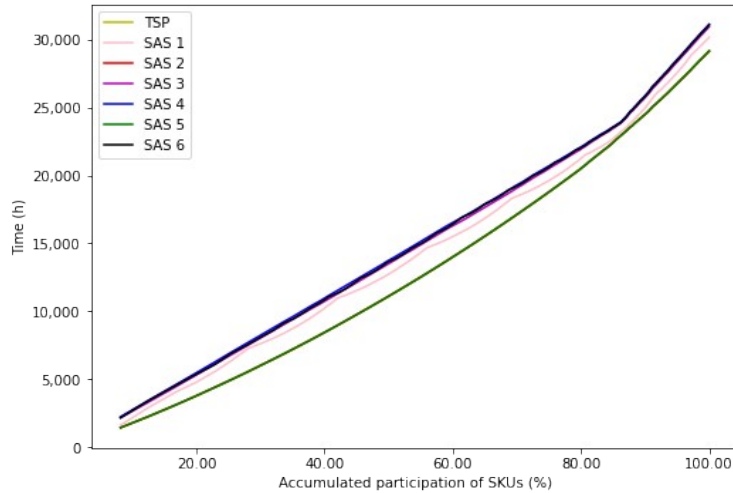

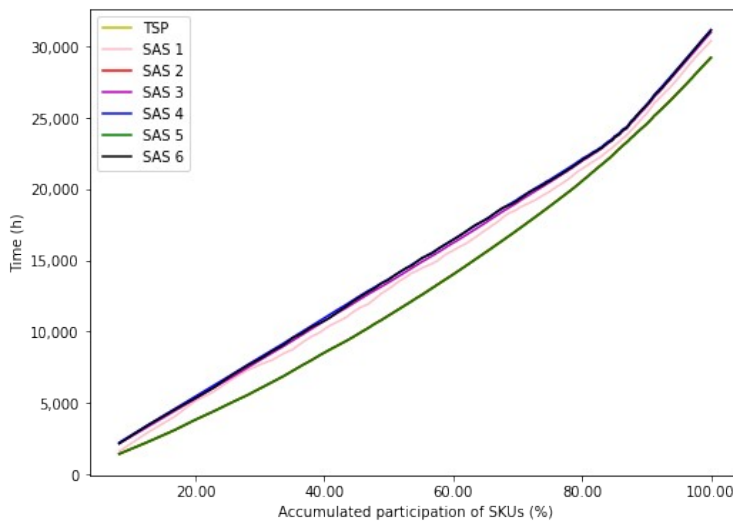Figure 3. Cumulative times for ABC – SAS semester two

Figure 4. Cumulative times for COI – SAS semester two

The times for the B-class SKUs are higher than A-class SKUs because the assigned slots are nearer to entry and exit doors, but there are a lot of pallets that increase the final time. Regarding the C-class SKUs, the travel times are lower, but longer than A-class SKUs travel times. For this reason, the quantity and participation are quite significant in final times results strategies involving the location.

6.4. Slotting Strategies Difference

This section presents the analysis of time differences between ABC and COI slotting methodologies considering the best results for the second semester. The differences are calculated by subtracting the ABC from the COI times. Figure 5 shows the time differences (hours) for the three best strategies considering the accumulated participation of the ABC classification. The points that are up from the zero line indicate that COI time is higher than ABC. Analogy, the points below the zero line indicate that the ABC time is higher than COI.
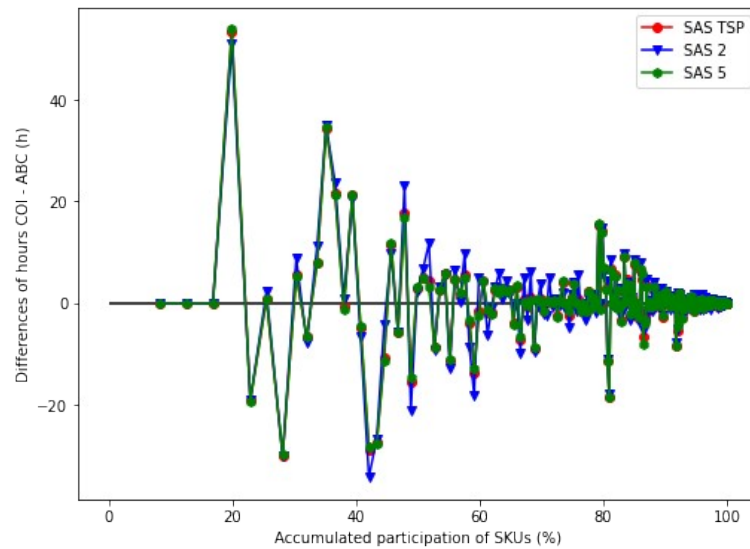
Figure 5. Differences between COI-ABC times for each SKU in semester 2

It is possible that for the first SKUs in the priority list, there is no time difference between the two classification strategies because the SKUs are in the same location for both strategies. A difference in positions in the priority list implies a time difference between the two strategies, and it is probable that this difference persists for the next SKUs. The difference magnitude is determined by participation position on the priority list and location. The differences between ABC and COI are higher until 80% of the accumulated participation of SKUs is reached (i.e., for A and B classes).

The time differences between ABC and COI strategies in SAS 2 are mostly higher (points of the yellow line above and below the zero line). However, this does not have a major impact on the cumulative time because the positive values are balanced out. However, it can be a critical factor if SKU demand is dynamic and/or most of the SKUs are A or B class.

7. Conclusions

This paper presented an allocation model integrating SKUs physical variables, warehousing design, and operation (dimensions, layout, material handling equipment), and heterogeneous product demand. The study assumed that there was no policy for slotting allocation and therefore had no benchmark for results. The implementation of the strategy could serve as a basis to formulate improvements in performance in warehousing management. The joint application of sorting-based slotting and picking models with priority lists can be helpful when each SKU has different behavior. This condition could generate priority lists for products that require more attention in the supply chain.

Traditional allocation strategies achieve adequate fulfillment of warehouse management objectives, but there are differences and variations between priority lists, implying different times for each SKU. Theoretically, COI performs better when the volume and frequency of orders are heterogeneous, while ABC works better with homogeneous products and material handling equipment. Although the COI strategy is not one of the grouping strategies, it can work if there is a greater difference between locations in a group. However, it is necessary to consider storage constraints to stock SKUs according to their classification.

According to the results, the optimal strategy to reduce distances according to the priority lists is the TSP adaptation for both periods. The two best SAS are SAS 2 and SAS 5. This result is due to the fact that the entry and exit doors are on the same axis, and the assignment must be made from the closest slots to the entry or exit doors with higher priority SKUs to the furthest slots with lower priority SKUs. It is necessary to evaluate more than one alternative. In this case, SAS 2 is too close to TSP matching, and depending on the warehouse handling equipment, this decision will affect real-world performance.

In this study, the times are cumulative, and the strategy is evaluated in the total operation time. For each SKU there is a time difference between strategies due to its position in the priority list. A proper strategy evaluation must take into account the cumulative number of SKUs in the analysis period.

The main contribution of this work is the development of an adaptable methodology to operational changes to improve storage management efficiency using slotting. This methodology can be adapted to other industries. Although this work has been validated on a specific case, it can also be adapted to changes in current warehouse operation parameters, becoming a basis for developing more robust models with different constraints or variables sets. The approach proposed in this paper contributes to the state of the art in warehouse optimization, specifically to the need for models that integrate multiple slotting and picking techniques with a solid academic foundation and application in real-world logistics operations.

Future work includes considering other objective functions of sustainable operations (economic, social, and environmental) and incorporating uncertainty treatment techniques. This study could be extended in several aspects, aiming to generalize the studied problem, considering the warehouse design, including new technology and equipment used in picking and slotting activities, using data analysis, and new modeling techniques.

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