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MULTI-CRITERIA ASSIGNMENT MODEL TO SOLVE THE STORAGE LOCATION ASSIGNMENT PROBLEM

Marcele Elisa Fontana[*], Juan Carlos Leyva López[**], Cristiano Alexandre Virgínio Cavalcante[***], and Jesús Jaime Solano Noriega[**1]
[*]Universidade Federal de Pernambuco-UFPE. Centro Acadêmico do Agreste – CAA. Rodovia BR 104 - KM 59 - Sítio Juriti - Zona Rural, Caruaru-PE - Brasil - CEP: 55002-970.
[**]Universidad Autónoma de Occidente, Culiacán, Sinaloa, México. Universidad Autónoma de Sinaloa, Culiacán, Sinaloa, México
[***]Universidade Federal de Pernambuco-UFPE. Centro de Tecnologia e Geociencias - CTG. Recife-PE – Brazil.

ABSTRACT
This paper proposes a multi-criteria assignment approach to solve the storage location assignment problem (SLAP), in class-based storage (CBS) policy, to improve the warehouse operations, as well as inventory management. This model considers the ELECTRE III method, a well-known multi-criteria decision aiding (MCDA) method, to construct a medium-sized valued outranking relation, and a multi-objective evolutionary algorithm (MOEA) to exploit the outranking relation to derive a recommendation. The model compares the classes to define their allocation in the warehouse, and it finds a SLAP solution that can be used for inventory management, balancing the operational and tactical factors, allowing considering warehouse manager preferences, client requirements and stock keeping unit (SKU) characteristics simultaneously. The results of the simulated case showed the robustness of the proposed model for improving the order picking system performance.

KEYWORDS: Warehouse management; Picker-to-parts systems; Multi-objective evolutionary algorithms; Multi-criteria decision analysis, ELECTRE III method.

RESUMEN
Este documento propone un enfoque de asignación multicriterio para resolver el problema de asignación de ubicación de almacenamiento, en la política de almacenamiento basado en clases, para mejorar las operaciones del almacén, así como la gestión del inventario. Este modelo considera el método ELECTRE III, un conocido método de ayuda de decisión multicriterio, para construir una relación de superación valorada de tamaño mediano, y un algoritmo evolutivo multiobjetivo para explotar la relación de superación para derivar un recomendación. El modelo compara las clases para definir su asignación en el almacén, y encuentra una solución SLAP que puede usarse para la gestión de inventario, equilibrando los factores operativos y tácticos, lo que permite considerar las preferencias del gerente del almacén, los requisitos del cliente y las características de la unidad de mantenimiento de inventario simultáneamente. Los resultados del caso simulado mostraron la solidez del modelo propuesto para mejorar el rendimiento del sistema de preparación de pedidos.

1. INTRODUCTION

Warehouse managers are usually interested in providing high quality services to their customers at minimum cost. From a tactical, strategic and operational point of view, the main issues concern both the warehouse operations management and the inventory management [17]. In this sense, a crucial warehouse operation is the order picking that means the stock keeping units (SKUs) retrieval from a local of warehouse to satisfy customer orders. For that, many companies use manual picking, or picker-to-parts systems, due to variability in SKUs shape and size, the variability of demand, the seasonality of the SKUs, or the large investment required to automate an order picking system [25].
In this system, the warehouse operations are labour-intensive and/or capital intensive, and their performance affects warehouse productivity and costs, as well as the whole supply chain. Therefore, the operational efficiency in warehouses is crucial to the competence of a Supply Chain (SC) [1]. Therefore, in order to reduce costs and improve the order picking system performance, Petersen and Aase [25] highlighted three types of decision making: (1) how to pick the SKUs, (2) how to route the pickers in the warehouse, and (3) how to store the SKUs.

[1] E-mail: marcele.elisa@ufpe.br (Corresponding author)

The third decision is about the storage location assignment problem (SLAP) that allocates SKUs to storage places [27]. Rouwenhorst et al. [26] highlighted three basic storage policies: dedicated, random and class-based. The dedicated storage (DS) policy determines a fixed location for each SKU to be stored, while the random storage (RS) policy assigns the SKUs to any empty space. The class-based storage (CBS) policy aggregates SKUs into classes (as RS) and, then, it defines a fixed place for each class (as DS) [2, 14 and 22]. According to Chan and Chan [5] random and dedicated storage policies are extreme cases of the class-based storage policy, where all SKUs and each SKU represent a class, respectively.
Therefore, assigning the SKUs to proper storage locations is important to minimizing the operating cost [1]. Moreover, it "affects space usage, which is critical for space availability and space costs" [23]. In other words, In SLAP, the main objectives are both minimize the order-picking costs and maximize space utilization [16]. If only the order-picking cost is considered, DS policy may yield the lowest cost; on the other hand, if only space cost is considered, the RS policy will yield the lowest cost solution [22]. In this sense, CBS policy usually shows a balance between the two previous policies.
In order to solve CBS, authors usually propose to use space and/or handling costs in order-picking operation to evaluate the solutions. However, there are many difficulties in determining these costs, and it can result in suboptimal solutions [13]. Moreover, other factors affect the SLAP, such as order picking method, size, and layout of the storage system, material handling system, SKU characteristics, demand trends, turnover rates, space requirements and client’s characteristics [5, 11 and 13]. Therefore, multiples objectives, or criteria, should be considered to solve SLAP, especially in CBS policy, then, the SLAP can be model as a multi-criteria decision problem [15 and 28].
In this sense, some authors [11 and 14] proposed to use the ELECTRE TRI method to CBS formation. ELECTRE TRI is a traditional MCDA method used to solve a multicriteria sorting problem, where the number of classes is pre-fixed and determined by the decision-maker (DM) [4, 8, 10 and 24]. This sorting problematic is very useful when the DM has clarity on the number of classes to assigns the alternatives (in this case, SKUs). However, in SLAP, usually, the DM is not sure about the number of classes, and it becomes more complicated when the number of SKUs is too large. In this sense, other authors [6 and 7] proposed a Clustering-Assignment Problem Model (CAPM) to clustering the SKUs into groups based on item association, and, then, assign the storage locations. However, they considered only a single objective function in each phase. Moreover, they did not consider the decision maker's preferences.
This paper aimed to solve the SLAP, where the class-based storage policy was considered through a multi-criteria approach. The approach used was developed by Leyva et al. [19] and explored in more detail by Leyva et al. [20] in another context. It is a ranking procedure (named RP^2-NSGA-II) based on the hybridization of the reference point method with the non-dominated sorting genetic algorithm (NSGA-II); for grouping alternatives that are indifferent while also separating the classes that are strictly preferred to others or incomparable so that a partial order between them is found.
The contributions of this work are: (1) to establish classes based storage from the characteristics of the SKUs and the managers' preferences; (2) the methodology does not pre-fixed or predetermine the number of classes. It follows from the used methodology; (3) multiple criteria are considered in the modelling of the problem; (4) the proposal does not seek for an optimal storage location, but a solution that balance operational and inventory control concerns, as well as to provide an adequate service level to clients. These concerns together have not yet been explored in the researched literature.
Besides this introduction, this paper was organized as follows: Section 2 presents the methodological background. Section 3 describes the proposed SLA model. Section 4 presents a case. Section 5 reports the discussion of results. Finally, the concluding remarks are made.

2. METHODS OVERVIEW

The outranking approach used for solving the SLAP problem needs two phases: (i) an aggregation phase, where the ELECTRE III method is used to construct an aggregation model of the decision maker’s preferences; and (ii) an exploitation phase, where the RP^2-NSGA-II method exploits this model to derive a recommendation in the form of a partial order of classes of SKUs.

2.1. ELECTRE III method

ELECTRE III method is an outranking method, which seeks to build a valued outranking (binary) relation S_A^σ on a set of alternatives $A = \{a_1, a_2, ... a_n\}$. It incorporates preference p, indifference q, and veto v

thresholds to consider the ill-determination, imprecision, and uncertainty that affect the performance of the alternatives under the decision maker's preferences [3 and 9]. Thus, for each criterion g_h, $h = 1,2, \ldots.m$, the decision-maker preferences are modelled as follows [18]:

$$a_i P_h a_j \ \left(a_i \ is \ strongly \ preferred \ to \ a_j\right) \Leftrightarrow g(a_i) - g\left(a_j\right) > p \tag{1}$$

$$a_i Q_h a_j \ \left(a_i \ is \ weakly \ preferred \ to \ a_j\right) \Leftrightarrow q < g(a_i) - g\left(a_j\right) \leq p \tag{2}$$

$$a_i I_h a_j \ \left(a_i \ is \ indifferent \ to \ a_j; \text{ and } \ a_j \ to \ a_i\right) \Leftrightarrow \left|g(a_i) - g\left(a_j\right)\right| \leq q \tag{3}$$

These preference relations allow the creation of a valued outranking relation S_A^{σ} that is characterized by an outranking degree $\sigma\left(a_i, a_j\right) \in [0,1]$ that is related to each ordered pair $(a_i, a_j) \in A \times A$. Thus $\sigma\left(a_i, a_j\right)$ gives meaning to the credibility degree of the argument "a_i is at least as good as a_j", denoted as $a_i S_A a_j$, as defined in Eq.4.

$$\sigma\left(a_i, a_j\right) = \begin{cases} c\left(a_i, a_j\right), & if \quad d_h\left(a_i, a_j\right) \leq c\left(a_i, a_j\right) \ \ \forall h \\ c\left(a_i, a_j\right) \ \prod_{h \in H(a_i, a_j)} \frac{1 - d_h\left(a_i, a_j\right)}{1 - c\left(a_i, a_j\right)} & \end{cases} \tag{4}$$

$$c(a_i, a_j) = \frac{1}{W} \sum_{h=1}^{m} w_h c_{h(a_i, a_j)} \tag{5}$$

$$c_h\left(a_i, a_j\right) = \begin{cases} 1, & if \quad g_h(a_i) + q_h \geq g_h\left(a_j\right) \\ 0, & if \quad g_h(a_i) + p_h \leq g_h\left(a_j\right) \ \ , h = 1,2, \ldots.m \\ \frac{p_h + g_h(a_i) - g_h\left(a_j\right)}{p_h - q_h}, & otherwise \end{cases} \tag{6}$$

$$d_h\left(a_i, a_j\right) = \begin{cases} 0, & if \quad g_h(a_i) + p_h \geq g_h\left(a_j\right) \\ 1, & if \quad g_h(a_i) + v_h \leq g_h\left(a_j\right) \ , \ \ h = 1,2, \ldots.m \\ \frac{g_h\left(a_j\right) - g_h(a_i) - p_h}{v_h - p_h}, & otherwise \end{cases} \tag{7}$$

Where:
w_h is the weight of criterion h, and $w = \sum_{h=1}^{m} w_h = 1$;
$c(a_i, a_j)$ is concordance index;
$d_h\left(a_i, a_j\right)$ is discordance index;
$H(a_i, a_j)$ is the set of criteria such that $d_h\left(a_i, a_j\right) > c(a_i, a_j)$.

2.2. The RP^2-NSGA-II Algorithm

Once the valued outranking relation S_A^{σ} is built, the issue is to rank the set of alternatives based on the information contained in S_A^{σ}. Thus, a Multiobjective Evolutionary Algorithm (MOEA), called RP^2-NSGA-II [20], was used. The output of this MOEA is a partial order of classes of alternatives $O_{P_k(A)}^{*}$.

When a multiobjective problem is solved, typically, there is no single solution; instead, a set of non-dominated solutions is obtained. Each non-dominated solution of that set represents a ranking of alternatives. Nevertheless, the set of solutions, known as the Pareto Front, could contain a lot of non-dominated solutions. Thus, RP^2-NSGA-II was selected because it uses a strategy to find the Region of Interest (ROI) in the Pareto Front. This ROI can be seen as a restricted Pareto Front with non-dominated solutions, which are according to the decision-maker preferences.

Let λ be a cut value, $(0 \leq \lambda \leq 1)$, associated with S_A^{σ}. For each cut level λ, a crisp outranking relation S_A^{λ} over S_A^{σ} might be induced, where if $\sigma(a_i, a_j) \geq \lambda$, it means that "$a_i$ is at least as good as a_j with credibility level λ" is true ($a_i S_A^\lambda a_j$;) otherwise, it is false ($a_i \neg S_A^\lambda a_j$.) A crisp relation S_A^λ induces a preference structure in the sense of that defined in [21], with the following preference relations:

$$\text{Indifference } (I_A) \quad a_i I_A a_j \leftrightarrow a_i S_A^\lambda a_j \wedge a_j S_A^\lambda a_i \tag{8}$$

$$\text{Preference positive } (P_A^+) \; a_i P_A^+ a_j \leftrightarrow a_i S_A^\lambda a_j \wedge a_j \neg \; S_A^\lambda a_i \tag{9}$$

$$\text{Preference negative } (P_A^-) \quad a_i P_A^- a_j \leftrightarrow a_i \neg \; S_A^\lambda a_j \wedge a_j S_A^\lambda a_i \qquad 10)$$

$$\text{Incomparability } (R_A) \quad a_i R_A a_j \leftrightarrow a_i \neg \; S_A^\lambda a_j \wedge a_j \neg \; S_A^\lambda a_i \tag{11}$$

Taking into account the previous preference relations, a nested family of crisp outranking relations can be constructed and defined from S_A^σ as follows: $S_A^\lambda = \{(a_i, a_j) \in AxA : S_A^\lambda(a_i, a_j) \geq \lambda\}, \lambda \in [\lambda_0, 1]$; where λ_0 is a minimum value for λ. These crisp outranking relations represent the cut levels (λ-cuts) in S_A^σ, where the cut level λ is the minimum value of S_A^σ for which $a_i S_A^\lambda a_j$ is true. Every single S_A^λ is generated through different cut levels λ over a valued outranking relation S_A^σ.

In the ranking problematic, indifferent alternatives are grouped; in doing so, the classes of alternatives are formed. On the other hand, alternatives that are not indifferent to each other are separated (assigned to different classes).

Let $P_k(A) = \{C_1, C_2, \ldots, C_k\}$ be a partition of set A in k classes of alternatives. When comparing a pair of classes $C_r, C_q \in P_k(A)$, the most frequent relation by comparing alternatives of C_r with alternatives of C_q is taken as a preference relation among them, i.e., I_A, P_A^+, P_A^-, R_A. Once the relations between classes are determined, a partial order of classes of alternatives $O^*_{P_k(A)}$ is obtained.

As mentioned, the multicriteria ranking problem of a set of alternatives could be addressed as a multiobjective optimization problem. In the following, the objectives and the model to be solved by RP^2-NSGA-II are presented.

2.2.1. Maximum Cut Level Objective

Each potential solution is associated with a λ-cut representing the level of credibility for the crisp outranking relation S_A^λ. Then, it is desirable to have potential solutions with a credibility level λ close to 1. This indicates a high credibility level of the obtained ranking through the decoded procedure included in RP^2-NSGA-II. The name of this objective is the *Maximum Cut Level Objective*.

2.2.2. MinCut Objective

This objective is based on the idea that the alternatives in a class should be indifferent among themselves. Using this property, the *MinCut* objective works by *maximizing* the indifference of the alternatives inside the classes. Here, it penalizes the pairs of alternatives that lie within a class but are not indifferent. This objective function is minimized in the respective multiobjective optimization problem. This objective is called the *MinCut objective*.

2.2.3. Minimum pair-wise preference disagreement objective

The quality of a crisp outranking relation $O^*_{P_k(A)}$ should be judged according to the number of discrepancies and concordances with S_A^σ and the crisp outranking relation S_A^λ. Thus, it is necessary to have a function that counts the number of pair-wise preference disagreements. This is a function n_V that quantifies the number of preference between the alternatives in the crisp outranking relation S_A^λ that are inconsistent in the sense of $O^*_{P_k(A)}$. This function is called the *minimum pair-wise preference disagreement objective*.

2.2.4. The Model

Based on the previous objectives, the exploitation of a valued outranking relation for the multicriteria ranking problem can be modelled as the following multiobjective optimization problem:

$$Min\big(Min\ Cut(\tilde{p})\big), Min\big(n_V(\tilde{p})\big), Max\big(\lambda(\tilde{p})\big) \tag{12}$$

subject to:

$$\tilde{p} \in \Omega \tag{13}$$

$$\lambda \in [0,1], \quad \lambda \geq \lambda_0 \tag{14}$$

Where:
Ω is the set of partial orders of alternatives of *A;*
$\tilde{p}$ is a partial order of classes of alternatives;
λ_0 is a minimum level of credibility;

To sum up, RP[2]-NSGA-II tries to find a partial order of classes of alternatives $O^*_{P_k(A)}$ from a valued outranking relation S^σ_A in which the number of inconsistencies among $O^*_{P_k(A)}$ and the preferences of the decision-maker S^σ_A are minimized. This partial order constitutes a recommendation for a decision-maker. For more details, see [20].

3. MULTI-CRITERIA RANKING MODEL TO SOLVE SLAP

The SLAP was formulated as a multi-criteria ranking problem. The steps of the model can be summed up in Figure 1.

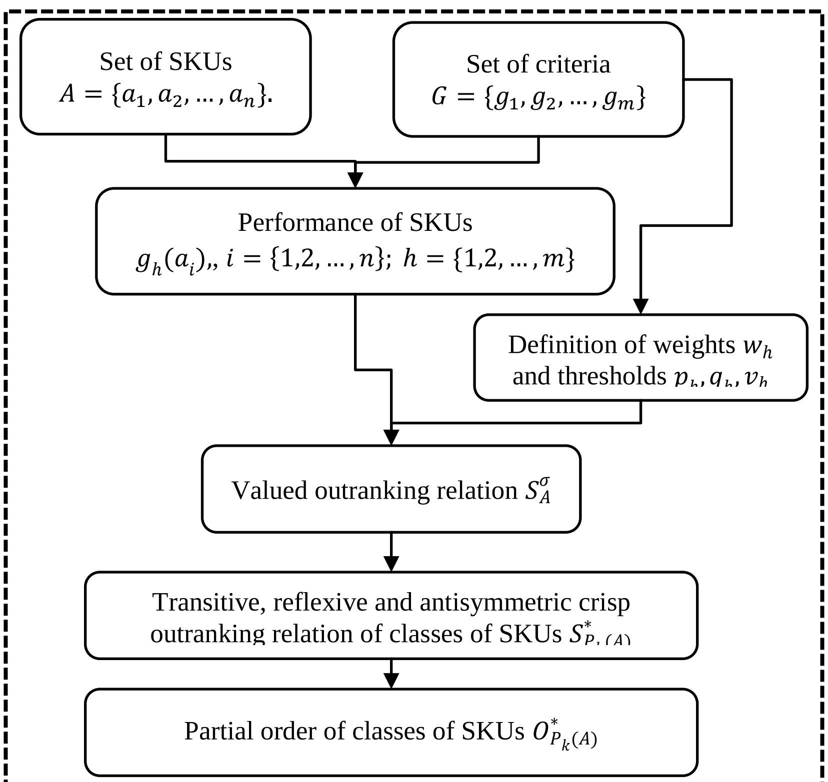


Fig.1. General Scheme of the model to solve SLAP

In this model, some points were assumed, such as:

1. All variables and parameters are known and measurable;

2. The characteristics of each SKU are independent of each other and do not change during the planning horizon considered;
3. There are enough spaces, or storage locations, for all SKUs.

The first step of the model requires the definition of set of SKU and criteria. After that, the performance of all the SKUs on all criteria is defined. In addition, some parameters need to be elicited from the decision-maker, such as the weight and thresholds of criteria. Thus, a valued outranking relation is obtained by ELECTRE III method. After that, from RP^2-NSGA-II Algorithm generates a transitive, reflexive and antisymmetric crisp outranking relation of classes of SKUs. This procedure groups alternatives that are indifferent and separates the classes that are strictly preferred to others or incomparable so that a partial order between them is found.

4. RESULTS

Let us consider u shelves, where each space (s) is represented by a coordinate (x, y). All aisles r are the same size. The assignment rule is the across aisle, i.e., according to the direction indicated by the arrows, as shown in Figure 2.

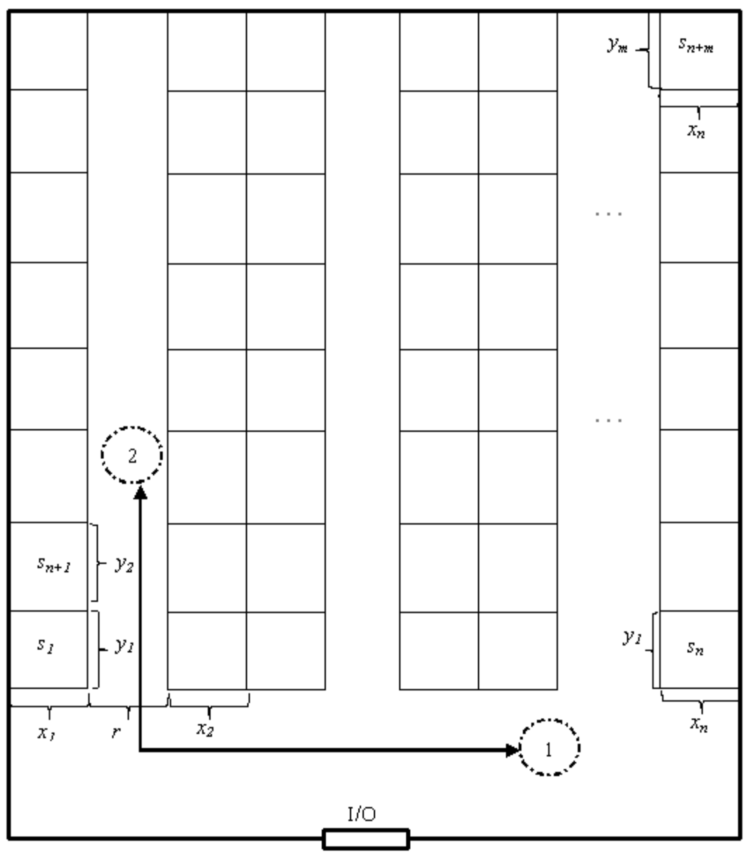


Fig.2. Warehouse layout considered
Source: Adapted from [12] and [13].

Moreover, 50 SKUs were generated randomly. The criteria considered were based on [11], as follows:

- Popularity(g_1): it is defined as the number of storage/retrieval operations for an SKU per unit time. This information directly influences on the travel distance. For this reason, the most popular SKUs should be assigned closest to the I/O (in/out), i.e., in this criterion, it is desired to maximize. Here discrete values were randomly generated between 1 and 1000 units.
- Maximum inventory(g_2): it is defined as the maximum warehouse space (s) reserved for an SKU, or class, per unit time. Large reserved spaces for an SKU, or class, at the front of the warehouse, tend to worsen access to other SKUs. Thus, the lowest required space SKUs should be assigned closest to

the I/O, i.e., in this criterion, it is desired to minimize. Here discrete values were randomly generated between 1 and 100 m^2.

- Profit(g_3): it is defined as the percentage of profitability (%) related to its given cost per each SKU per unit of time. Since the SLAP influences the variable costs of the warehouse, these were not considered in the definition of the profitability of the SKUs. For inventory management purposes, the most profitability SKUs should be more visible and, therefore, assigned closest to I/O, i.e., in this criterion, it is desired to maximize. In turn, this location favours the least displacement and, consequently, lower cost. Therefore, there is a tendency to improve the profitability of the most important SKUs for the company. Here continuous values were randomly generated between 0 and 100 percent (%), except zero.
- Sensitivity(g_4): This criterion measures the level of sensitivity that the client presents concerning the service provided, per unit time. The more sensitive the client(s) is (are), the more attention they should receive, i.e., the faster their orders should be shipped, so that there is no repentance of the purchase and/or the loss of future purchases. Thus, those SKUs, or classes that show the highest sensitivity should be assigned closest to the I/O, i.e., in this criterion, it is desired to maximize. The DM will evaluate this criterion observing the regular clients for each SKU. A nominal scale is suggested, which can measure customer sensitivity, such as (1) Not measurable or Very Low; (2) Low; (3) Medium; (4) High; (5) Very High. Discrete values between 1 and 5 were randomly generated.

The performance matrix and the required parameters are shown in Table 1.

Table 1. Matrix evaluation: Criteria *vs.* SKUs and required parameters

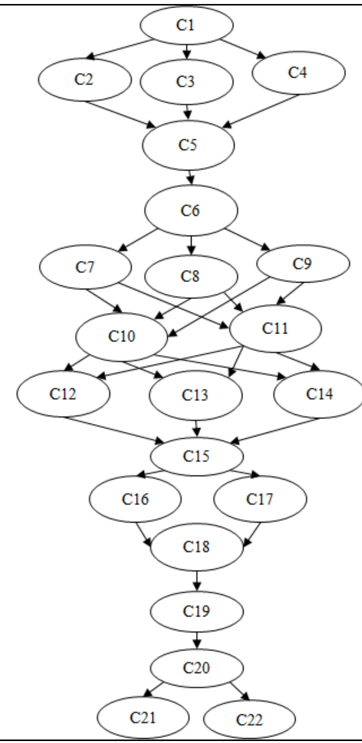
SKUs	g_1	g_2	g_3	g_4	**SKUs**	g_1	g_2	g_3	g_4
01	50	6.00	70	5	26	670	5.15	100	3
02	675	0.60	33	2	27	255	14.90	41	2
03	260	1.90	19	4	28	730	5.48	30	4
04	350	1.43	100	5	29	590	7.63	65	5
05	120	5.42	10	4	30	60	76.67	15	5
06	560	1.43	55	1	31	420	11.67	85	3
07	950	0.84	68	5	32	315	16.19	25	3
08	800	1.13	20	1	33	280	18.93	86	2
09	450	2.56	90	4	34	550	9.82	15	4
10	540	2.41	25	2	35	350	16.00	92	1
11	100	13.50	5	3	36	840	7.14	34	2
12	230	6.09	80	2	37	710	8.59	4	2
13	55	28.18	75	3	38	290	21.38	100	5
14	900	1.89	30	1	39	380	17.11	65	4
15	35	51.43	76	2	40	130	50.00	50	3
16	680	2.94	15	5	41	370	18.11	10	5
17	190	11.05	53	3	42	915	7.65	5	1
18	790	2.85	76	4	43	90	82.22	26	3
19	80	28.75	63	4	44	650	12.31	45	4
20	700	3.29	54	5	45	230	35.65	53	3
21	855	2.87	20	3	46	730	11.64	60	5
22	980	2.65	2	5	47	810	10.49	21	5
23	420	6.90	47	1	48	970	9.28	46	3
24	130	23.08	30	4	49	95	97.89	92	2
25	60	52.50	95	1	50	145	62.00	32	2
Parameters	g_1	g_2	g_3	g_4	**Parameters**	g_1	g_2	g_3	g_4
q	50	3	8	1	v	350	25	40	3
p	100	8	16	1	w	0.2	0.2	0.3	0.3

Source: Adapted from [11].

The assignment of the SKUs into classes and the allocation in the warehouse can be seen in Table 2.

Note, in Table 2, that some classes were indifferent, i.e., the model did not pre-fixed the allocation in the warehouse. In this way, in the literature, the cube-per-order index (COI) is commonly used to define the allocation order. COI makes a trade-off between the required space and popularity, and this can lead to sub-optimal allocations [22]. Thus, it was decided to verify the popularity and space criteria separately, establishing two possible solutions. Only two inversions of the order were noticed, as they were highlighted in Table 2.

Table 2. Class-based policy (CBP) assignments and their allocation in warehouse

Popularity (g_1)	Max Inventory (g_2)	SKUs	Relation
C01	C01	07 and 18	
C02	C02	04	
C03	C03	09	
C04	C04	26	
C05	C05	20	
C06	C06	48	
C07	C07	14	
C08	C08	29	
C09	C09	46	
C10	C11	02, 06, 08, 10, 16, 21, 22, 23, 28, 34, 36, 44 and 47	
C11	C10	01, 31, 38 and 39	
C12	C12	42	
C13	C13	12, 33 and 35	
C14	C14	25	
C15	C15	37	
C16	C17	13, 15 and 19	
C17	C16	49	
C18	C18	03, 05, 17, 24, 27, 32, 40, 41 and 45	
C19	C19	30	
C20	C20	11	
C21	C21	50	
C22	C22	43	

5. DISCUSSION

The main managerial implication of this work is to relate SLAP decisions to warehousing operational and inventory management criteria. This allows warehouse operating gains not to overlap with the service level offered to the customers. This aspect will be more easily noticed by those companies that have concise customer service lead time.

Moreover, the results should be compared with other possible solutions to check their robustness. Thus, four new solutions were generated: (1) DS policy assignment by the COI, (2) RS policy, (3) CBS policy based on ABC analysis by 80/20 rule (three classes) from criterion g_3, and (4) CBS policy based on ABC curve from criterion g_4 (five classes). The travel distance and the required space were calculated and reported in Table 3. Regarding the travel distance, the dynamics reported by [22] was used. For that, six shelves($x = 6$), a storage space size equal to $1m^2$ and $r = 1m$ were considered.

Table 3. Travel distance and required space for each solution

Policy	Distance (*meters*)	Space (unit = *1x1 m*)
CBS – Popularity – g_1	1,067,695.96	907
CBS – Space – g_2	1,218,495.75	907
DS - COI	695,006.73	918
RS	3,365,226.67	896
ABC – profit - g_3	3,967,127.75	897

ABC – client - g_4	3,023,893.84	898

Note that the DS policy resulted in a shorter travel distance than the RS policy, but used a more significant number of spaces. The ABC solutions privileged the criteria considered for managing inventory, and, as the RS policy, their performance in terms of travel distance was worse. These results were expected, according to the literature, which demonstrates the coherence of the values. In this sense, the proposed model, in both criteria, returned new intermediate values. Thus, the final decision should take into account the costs associated.

Also, the behaviour of CBS and DS solutions regarding the criteria g_3 and g_4 should be studied, because criteria g_3 and g_4 are linked to inventory management, as shown in Table 4.

Table 4. CBS and DS policies regarding the criteria g_3 and g_4

ABC – profit – g_3						
SKUs	**DS - COI**		**CBS - g_1**		**CBS - g_2**	
	Class/Rank	*Average distance*	*Class*	*Average distance*	*Class*	*Average distance*
04	C09	3.00	C04	2.50	C02	1.17
09	C13	5.17	C03	1.83	C03	1.83
12	C27	24.21	C13	34.00	C13	34.00
25	C46	96.92	C14	41.92	C14	41.92
26	C16	7.17	C02	1.17	C04	2.50
31	C28	25.83	C11	24.41	C10	13.24
33	C36	45.61	C13	34.00	C13	34.00
35	C31	32.19	C13	34.00	C13	34.00
38	C37	49.00	C11	24.41	C10	13.24
49	C48	123.34	C17	74.17	C16	56.00
ABC – client – g_4						
SKUs	**DS - COI**		**CBS - g_1**		**CBS - g_2**	
	Class/Rank	*Average distance*	*Class*	*Average distance*	*Class*	*Average distance*
1	C38	51.33	C11	24.41	C10	13.24
4	C09	3.00	C04	2.50	C02	1.17
7	C01	0.50	C01	0.50	C01	0.50
16	C10	3.50	C10	14.08	C11	23.59
20	C12	4.50	C05	2.75	C05	2.75
22	C06	1.50	C10	14.08	C11	23.59
29	C21	14.13	C09	7.88	C08	6.17
30	C49	137.92	C19	118.25	C19	118.25
38	C37	49.00	C11	24.41	C10	13.24
41	C32	35.08	C18	97.08	C18	97.08
46	C23	17.67	C08	6.17	C09	7.88
47	C22	15.77	C10	14.08	C11	23.59

Considering the first class from both ABC solutions, the model was more efficient than DS policy in 80% of SKUs in the criterion g_3 and 75% and 66.67% for CBS - g_1 and CBS - g_2, respectively, in the criterion g_4. Also, SKU-04 and SKU-38 are the Pareto front optimum considering the g_3 and g_4 criteria simultaneously. The proposed model better allocated both.

6. CONCLUSION

SLAP is a real multi-criteria decision problem, where at least two criteria are in contradiction. SLAP solved solely by operational performance or by managerial performance may not be the right choice for the warehouse manager. Thus, the proposed model was able to balance these approaches and provide a more significant overall performance.

Besides, the simulated case, by alternatives randomly generated, worked with the worst possible case, thus demonstrating the robustness of the proposed model. The results proved that the proposed model could deal very well with the subjectivity inherent to the problem, especially when there is a combination of SLAP with inventory management.
Moreover, one of the significant advantages of the algorithm used was the class-based formation and ranking of classes of SKUs without the need to predefine the number of classes, as occurs in many classification methods. This proposal must to be applying in a real case to confirm its robustness, and it is leaved as future work opportunity. In this work, the generated solution (CBS) was compared with other traditional solutions (DS, RS and CBS based on the ABC curve). However, this result can also be compared to solutions from others class formation algorithms reported in the literature, and it is also considered an opportunity for future work.

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