

**A MIXED ELECTRE TRI - BEST WORST APPROACH TO SOLVE THE
STORAGE LOCATION ASSIGNMENT PROBLEM**

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ABSTRACT

This study provides a multi-criteria model based on the integration of three techniques to solve the storage location assignment problem. The ELECTRE TRI was firstly used to divide the items into three classes previously defined by the decision maker. Successively, correlation analysis and clustering have been performed in order to group, within each class, the items into families based on their similarity. Finally, ELECTRE TRI was used one more time to assign the items to the shelf levels. The proposed model has been applied using real data gathered from a company operating in the footwear industry. Results show that the model is able to help the decision maker in choosing the storage position of any items, avoiding the random storage, and increasing the picking velocity.

KEYWORDS. Storage location assignment problem, Multicriteria methods, Clustering

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1. Introduction

Current warehouses are crucial to provide supply chain efficiency and customer satisfaction. The warehouse system function is composed of a set of related activities: (i) receiving, (ii) storage/warehousing, (iii) order picking (separation of requests), and (iv) expedition [Da Silva et al. 2015]. The high competition and the prospection of new markets ended up transforming these activities into an important strategy to achieve operational efficiency and the ability to serve expanding markets. Order picking constitutes a key operation, considering that an efficient process of retrieving items from warehouse storage locations to quickly satisfy customer orders may become a critical factor of success for the enterprise.

The decision regarding the location where each product will be stored in the warehouse should consider the characteristics of the item (size, weight, volume, etc.) and other aspects, such as popularity, cost, and distance, among others. When all these criteria are considered simultaneously, selecting the best place to locate products becomes a difficult task. In practice, companies usually categorize products into classes.

One of the most adopted approaches to categorizing products into classes is the use of indexes, such as the cube-per-order index (COI), which was proposed by Heskett, in 1693. This index captures the popularity of the item and its storage space condition, which is expressed as the ratio of storage space required (cube) per SKU (Stock Keeping Unit) and the order frequency of the SKU. Once calculated the COI for all SKUs, these are ranked in ascending order of the index. The SKUs with the highest COI are allocated nearest the Input/Output point, aiming to reduce the cost of order picking. However, these indexes aggregate the product characteristics into just one value, and this could be very restrictive especially when conflicting objectives should be considered.

Multicriteria analysis can be a powerful tool for solving the Storage Location Assignment Problem (SLAP), however, studies on this topic are still scarce in the literature [Da Silva et al. 2015]. Some related studies are: Fontana and Cavalcante (2013) proposed a model to construct a storage location assignment system in a warehouse, in which ELECTRE TRI assigns each item or product to class-based storage, according to the decision maker's preferences; the model proposed by Da Silva et al. (2015) combines the SMARTER method with the lexicographic method for ranking products and assigning them to warehouse storage locations; Fontana and Nepomuceno (2017) used a model based on an integration between ELECTRE TRI and ELECTRE III methods, where ELECTRE TRI is used to define the shelf level, whereas ELECTRE III is used to establish a fixed location for each product on the shelf it belongs to; Micale et al. (2019) applied ELECTRE TRI to assign products to shelf levels, combined with TOPSIS that is afterward applied to determine their storage location within every level; in the study by Fontana et al. (2020), ELECTRE III has been used to construct an outranking relation, and, successively, a multi-objective evolutionary algorithm (MOEA) was employed to exploit the outranking relation to derive a recommendation.

In this work, we proposed an approach based on ELECTRE TRI and Best Worst Method (BWM) aiming at helping the decision-maker to solve the SLAP. The BW method was applied to elicit the weights of criteria. The ELECTRE TRI method was applied in two different steps, firstly to assign SKUs to three classes (A, B, C) where each class corresponds to a specific area of the warehouse. Successively the ELECTRE TRI has been applied within each class to assign SKUs to shelf levels, avoiding the random storage.

2. The Proposed Model

The model addresses the storage location assignment process through five phases (Figure 1): (i) definition of warehouse characteristics, SKUs features, and the set of criteria; (ii) division

of SKUs into classes (warehouse zones); (iii) correlation analysis and clustering; (iv) assignation of SKUs to shelves; (v) storage positioning.

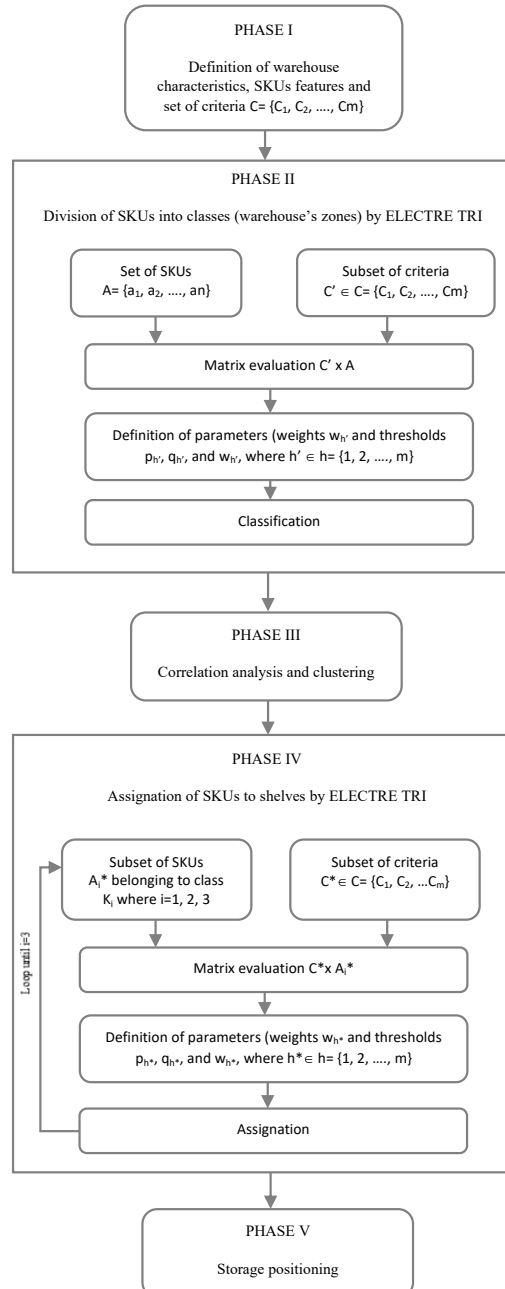


Figure 1: Flowchart of the model

2.1. Definition of warehouse characteristics, SKUs features, and evaluation criteria

The purpose of this phase is to enter the model with all the necessary information on the warehouse and SKUs, to allow the storage location assignment process. In this paper it was assumed that:

- There is a single input/output (I/O) point.
- The unit-load warehouse is the pallet.

- Each pallet contains only one SKU, and it may contain multiple units thereof.
- The size of the unit load varies according to SKU contained.
- The weight of the unit load varies according to SKU contained.
- $A = \{a_1, a_2, \dots, a_n\}$ represents the set of SKUs that must be allocated.
- x represents the row, such that $x = \{1, 2, \dots, X\}$.
- y represents the column or shelf, such that $y = \{1, 2, \dots, Y\}$.
- z represents the shelf level, such that $z = \{1, 2, 3\}$.
- The first shelf level is the biggest in height.

Evaluation criteria considered in the present phase are listed and described in Table 1, according to Fontana et al. (2020), Micale et al. (2019), and Fontana and Cavalcante (2013):

ID	CRITERIA	DESCRIPTION	UM
C ₁	Size	It is related to the density of the products. Products with a high density should be located closer to the I/O point, to avoid bottlenecks while moving them to the shipping area and to allow for faster evasion of customer orders.	m ³ /unit-load
C ₂	Demand	It expresses the average amount of products required over a given time interval. Products characterized by high demand must be located closest to the I/O point.	m ³
C ₃	Popularity	It represents the average number of consumers served by every product category in a specific timeframe. The higher the popularity, the closer to the I/O station the SKU.	Unit
C ₄	Sensitivity	This criterion measures the level of sensitivity that the client presents concerning the service provided, per unit time. The more sensitive the client is, the more attention they should receive, and the faster their orders should be shipped. Therefore, the SKUs with high sensitivity should be assigned closest to the I/O point	(4) much, (3) medium, (2) regular, (1) little, (0) very little
C ₅	Weight	It represents the weight of every unit load. The higher this value, the lower the level where the unit load should be located in the shelves.	kg
C ₆	Profitability	It represents the importance of every product in terms of its contribution to the company's profitability. Products characterized by high values of profitability are to be assigned to lower shelves.	%
C ₇	Picking frequency	It measures the number of times a product is retrieved from the shelves in a given time interval.	Nº/hours

Table 1: Evaluation criteria

2.2. Division of SKUs into classes

In this step, information on products should be raised from a company database, determining, therefore, the set of SKUs $A = \{a_1, a_2, \dots, a_n\}$. Successively, the model must be fed with information on the subset of criteria that should be used, that is, $C' \in C = \{C_1, C_2, \dots, C_m\}$.

Once the subset C' of criteria has been selected, DM must raise the matrix evaluation $C' \times A$, and the parameters (that is, the preference threshold p_h , the indifference threshold q_h , and the veto threshold v_h , where $h' \in h = \{1, 2, \dots, m\}$ and m is the total number of criteria. The criteria

that have been considered in this phase are C_1, C_2, C_3 , and C_4 . Therefore, the subset $C' = \{C_1, C_2, C_3, C_4\}$ will be taken into consideration. The DM defines also, the three zones of the warehouse in which the SKUs must be divided, that is, the three classes K_1, K_2, K_3 .

For the weight elicitation, the BWM [Rezaei 2015] will be applied. In this case, the DM defines the most important criterion (best criterion) and the least important criterion (worst criterion) of set C .

Thereafter, the DM defines the preference of the best criterion over all the others using a number between 1 and 9, where number 1 means equal preference between the best criterion and another criterion, while number 9 means the extreme preference of the best criterion over another criterion. The result of this step is the vector Best-to-Others (BO) which would be $P_B = (p_{B1}, p_{B2}, p_{B3}, \dots, p_{Bh'})$, where $h' = \{1, 2, 3, 4\}$, $p_{Bh'}$ indicates the preference of the best criterion B over the criterion h' , and it can be deduced that $p_{BB} = 1$. Equivalently, the DM determines the preference of all criteria over the worst criterion based on a score between 1 and 9. The result, in this case, is the vector Others-to-Worst (OW) which would be $P_W = (p_{1W}, p_{2W}, \dots, p_{h'W})^T$, where $p_{h'W}$ shows the preference of criterion h' over the worst criterion W . It can be deduced that $p_{WW} = 1$.

At this point, the optimal weights ($w_1^*, w_2^*, \dots, w_{h'}^*$) are calculated. The optimal weights of the criteria should satisfy the following requirements: for each pair of $w_B/w_{h'}$ and $w_{h'}/w_W$, the ideal situation is where $w_B/w_{h'} = p_{Bh'}$ and $w_{h'}/w_W = p_{h'W}$. To satisfy these conditions for all h' , it should be minimized the maximum among the set of $\{|w_B - p_{Bh'}w_{h'}|, |w_{h'} - p_{h'W}w_W|\}$, and the problem can be formulated as follows:

$$\begin{aligned} \min \max_{h'} \{ & |w_B - p_{Bh'}w_{h'}|, |w_{h'} - p_{h'W}w_W| \} \\ \text{subject to} & \\ \sum_{h'} w_{h'} = & 1, w_{h'} \geq 0 \quad \forall h' \end{aligned} \quad (1)$$

Problem (1) can be transferred to the following linear programming problem:

$$\begin{aligned} \min \quad & \xi \\ \text{subject to} & \\ |w_B - p_{Bh'}w_{h'}| & \leq \xi \quad \forall h' \\ |w_{h'} - p_{h'W}w_W| & \leq \xi \quad \forall h' \\ \sum_{h'} w_{h'} = & 1, w_{h'} \geq 0 \quad \forall h' \end{aligned} \quad (2)$$

After solving problem (2), the optimal weights ($w_1^*, w_2^*, \dots, w_{h'}^*$), and ξ^* are obtained. Being $h = 4$, the vector of optimal weights will be $(w_1^*, w_2^*, w_3^*, w_4^*)$ which represents the weights of the criteria C_1, C_2, C_3 , and C_4 . ξ^* can be seen as a direct indicator of the comparison system consistency. The closer the value of ξ^* is to zero, the higher the consistency, and consequently, the more reliable the comparison becomes.

At this point the ELECTRE TRI method [Roi 1991], will be applied to sorting the SKUs of the set $A = \{a_1, a_2, \dots, a_n\}$ in the classes belonging to the set $K = (K_1, K_2, K_3)$ previously defined by the DM. Class K_3 is the class closest to the I/O point, class K_2 is the intermediate class, and class K_1 is the class furthest from the I/O point.

2.3. Correlation analysis and clustering

Once sorted the SKUs in the different classes previously established (K_1, K_2, K_3), in each class, they must be grouped based on their similarity degree. The similarity degree depends on the extent to which different SKUs are generally requested jointly on multiple picking orders. The idea is, to highlight the similar SKUs in order to stock them near each other (correlated storage) [Bindi and Marzini 2007], and, consequently, reduce the picking time. To perform this task, firstly it is necessary to establish a method to measure the SKUs similarity. Successively, based on this measure it is necessary to group similar SKUs through a process named clustering [Bindi and Ferrari 2007].

The correlation analysis consists of 3 steps: (1) creation of the incidence matrix; (2) calculation of similarity indexes; (3) creation of similarity matrix. The incidence matrix is a

Boolean matrix, which has the picking orders per row and the codes of the SKUs involved per column. On the intersection between row and column, the matrix has the value 1 when the item is present in that order, the value 0 otherwise. Once obtained the incidence matrix, the similarity indexes should be calculated, that represent the degree of similarity between the various SKUs. Different types of similarity indexes exist in the literature, and all of them combine in a different way 4 common parameters, that can be obtained from the incidence matrix.

Let i and j be two generical SKUs, the following parameters are considered:

- a = number of picking orders in which both i and j are present.
- b = number of picking orders in which only j is present.
- c = number of picking orders in which only i is present.
- d = number of picking orders in which neither i nor j is present

Among the similarity indexes present in the literature, in this paper, the Jaccard coefficient, proposed by McAuley (1972), has been employed. The mathematic formulation of this coefficient is the following: $S_{ij} = \frac{a}{a+b+c}$ with $0 \leq S_{ij} \leq 1$. S_{ij} represents, therefore, represents the degree of similarity of two SKUs, i and j .

At this point, the similarity matrix should be built. This matrix has the SKUs per row and per column, and each cell contains the correspondent S_{ij} value. Thereafter, the clustering step begins, in order to group the SKUs into families.

In order to do it, in this work the Single Linkage (SLINK) algorithm has been adopted, which is composed of the following steps [Manzini et al. 2004]:

- i. Begin with the disjoint clustering having a level $L(0) = 0$ and sequence number $m = 0$.
- ii. Find the most similar pair of clusters in the current clustering, say pair $(r), (s)$, according to $d[(r), (s)] = \min d[(i,j)]$ where the minimum is over all pairs of clusters in the current clustering
- iii. Increment the sequence number: $m = m + 1$. Merge clusters r and s into a single cluster to form the next clustering m . set the level of this clustering to $L(m) = d[(r), (s)]$
- iv. Update the similarity matrix D , by deleting the rows and columns corresponding to clusters r and s and adding a row and column corresponding to the newly formed cluster. The similarity between the new clusters denoted (r,s) and the old cluster (k) is defined as $d[(r,s), k] = \min \{d[(k), (r)], d[(k), (s)]\}$
- v. If all objects are in one cluster, then stop. Else, go to step 2.

The result of the clustering process can be visualized through a dendrogram, which shows the sequence in which clusters were merged and the distance at which each merge took place. The dendrogram shows which SKUs can be considered similar and consequently stored near each other on the shelves. Figure 2 shows a dendrogram with the products a, b, c, d, e, f, g, and h. Fixing the cutting level at $\lambda = 0.52$, two clusters will be formed ($d-e$) and ($g-h$). The cluster ($d-e$) has the highest value of similarity coefficient (~ 0.65). The products a, b, and f cannot be grouped.

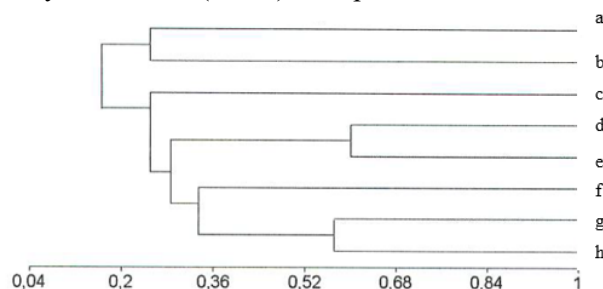


Figure 2: Dendrogram of the clustering process

Taking into consideration the above dendrogram, the SKUs (*d-e*) must be stored near each other, as well as the SKUs (*g-h*), while the SKUs *a*, *b*, and *f* can be stored randomly.

This process should be performed in each class K_h ($h = 1, 2, 3$) at the end of which all the SKUs will be grouped into families based on their similarity. Successively, it will be necessary to select the shelves levels on which to store them.

2.4. Assignment of products to shelves

Let A_i^* be the generical subset of SKUs of $A = \{a_1, a_2, \dots, a_n\}$, that was assigned to generical class K_i ($i = 1, 2, 3$). The criteria used in this phase of the model, to assign each SKU to a specific shelf level z_l ($l = 1, 2, 3$) are C_5 , C_6 , and C_7 which have been summarized in Table 1.

At this point, the decision-maker provides the evaluation matrix $A_i^* \times C^*$, where $C^* = \{C_5, C_6, C_7\}$ and the parameters p_h^* , q_h^* , and v_h^* . Moreover, in order to elicit the weights, he defines the best criterion and the worst criterion, and at this point, the BW method will be performed as in phase II of the model. The BWM provides the following vector of optimal weights (w_5^* , w_6^* , w_7^*) corresponding to the criteria C_5 , C_6 , and C_7 . Thereafter, the ELECTRE TRI method will be applied in order to sort the SKUs belonging to the set A_i^* in the shelves presents in the class K_i , ($i=1,2,3$). The ELECTRE TRI will be applied three times, one for each class, in order to assign within each class, the shelf level for each SKU.

2.5. Storage positioning

Once all SKUs have been assigned to a specific shelf level, it is necessary to locate them in the rows, comparing the available space with the demand and considering that similar SKUs must be stored near each other according to the information provided by the clustering process performed in phase III. Moreover, regarding the storage priority, the SKUs that must be stocked first, are they belonging to the clusters with the highest value of the coefficient of similarity. For instance, according to the dendrogram in Figure 3, the cluster with the products (*d-e*) will be stored firstly because it has the highest value of similarity coefficient (~ 0.65), successively the cluster with the products (*g-h*) will be stored. The other products will be located randomly.

3. Application of the model

3.1 Definition of warehouse and SKUs features

Let $A = \{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9\}$ be the set of SKUs with the following characteristics (Table 2):

Product	Popularity (unit)	Size (m3)	Demand (m3)	Sensitivity	Weight (kg)	Profitability (%)	Picking frequency (n° visit/hour)
a1	16	0,5	10	4	75	20	0,46
a2	16	0,75	15	2	78	10	0,44
a3	24	0,4	8	4	80	10	1,1
a4	24	0,6	12	3	130	5	0,64
a5	16	1,5	30	3	40	15	0,11
a6	20	1,2	24	1	115	5	0,16
a7	12	0,65	13	2	60	20	0,33
a8	16	0,45	9	1	80	5	0,8
a9	8	0,5	10	3	120	10	0,22

Table 2: SKUs features

Let's be considered a warehouse with the following characteristics (Figure 3).

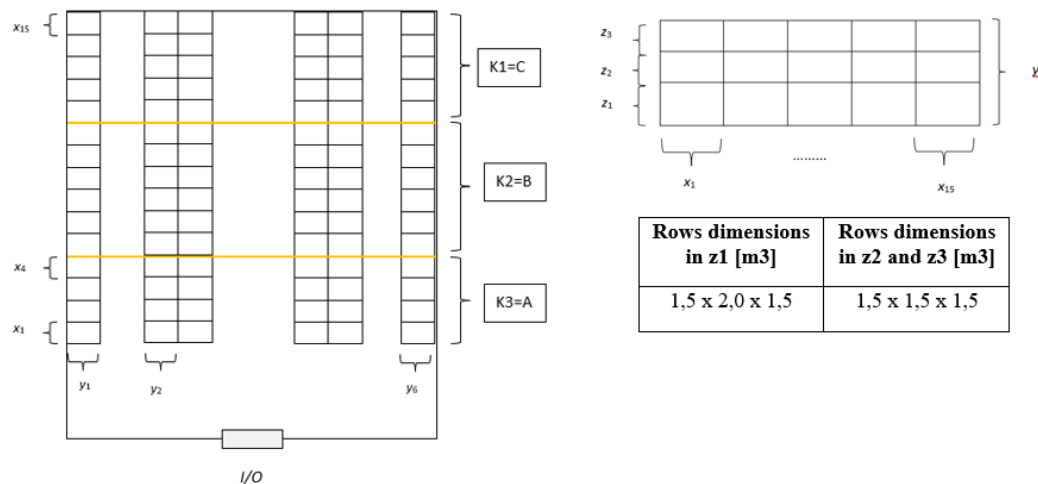


Figure 3: Warehouse layout and shelves disposition.

3.2 Division of SKUs into classes

Let $C' \times A$ be the following evaluation matrix, where $C' = \{C_1, C_2, C_3, C_4\}$ (Table 3):

Product	Popularity	Size	Demand	Sensitivity
a1	16	0,5	10	4
a2	16	0,75	15	2
a3	24	0,4	8	4
a4	24	0,6	12	3
a5	16	1,5	30	3
a6	20	1,2	24	1
a7	12	0,65	13	2
a8	16	0,45	9	1
a9	8	0,5	10	3

Table 3: Evaluation matrix $C' \times A$

Let's suppose that the DM has chosen the following parameters (Table 4).

Product	Popularity	Size	Demand	Sensitivity
q	5	0,15	4,5	1
p	7	0,3	9	2
v	10	0,5	20	3
b2	20	0,75	15	3
b1	16	0,5	10	2

Table 4: Parameters established by the decision-maker

After this, the BW method will be performed to determine the vector of optimal weights. The DM decided that Popularity is the most important criterion, while Sensitivity is the less important one. The DM provided, also, the vector $P_B = (1, 2, 6, 5)$ and the vector $P_W = (8, 8, 7, 1)^T$. In light of this decision the BW method provided the following results: $w^* = \{0.47; 0.36; 0.12; 0.05\}$.

At this point, all information is available to perform the ELECTRE TRI method aiming at sorting all SKUs into the three classes *A*, *B*, *C*. The solution provided by the software is shown in Table 5:

Alternative	Pessimist	Optimist
a1	C	B
a2	B	A
a3	B	B
a4	B	A
a5	A	A
a6	A	A
a7	C	B
a8	C	B
a9	C	C

Table 5: Assignment of SKUs to classes

In this case, the DM decided to select the optimistic solution to encourage the SKUs placement in zone A as much as possible. At this point, all the SKUs in each category must be clustered in families based on their similarity indexes, that is, phase III of the model begins.

3.3 Correlation analysis and clustering

In this step, we have a group of SKUs in each zone of the warehouse. For each of these groups, correlation analysis and clustering should be undertaken. Let's start with the group belonging to class A, that is $A^*_1 = \{a_2, a_4, a_5, a_6\}$. The incidence matrix is the following (Table 6):

	a2	a4	a5	a6
ORDER 1	1	1	1	0
ORDER 2	0	0	0	1
ORDER 3	1	1	0	1
ORDER 4	0	1	1	1
ORDER 5	1	0	0	0
ORDER 6	1	1	1	0
ORDER 7	0	1	1	1
ORDER 8	0	1	0	1

Table 6: Incidence matrix

With the information provided by the incidence matrix, the similarity indexes will be calculated for each couple of items using the Jaccard coefficient, and the following similarity matrix will be derived (Table 7):

	a2	a4	a5	a6
a2	1	0,428	0,333	0,125
a4	0,428	1	0,666	0,571
a5	0,333	0,666	1	0,285
a6	0,125	0,571	0,285	1

Table 7: Similarity matrix

At this point the SLINK algorithm will be applied and, in the end, the following clusters will be derived (Table 8):

CLUSTER	SIMILARITY COEFFICIENT
a4 - a5 - a6	0,571
a2	0,428

Table 8: Clusters of SKUs in class A

3.4 Assignment of SKUs to shelf levels

Based on Table 8, the SKUs a4, a5, and a6 must be stored near each other. At this point, ELECTRE TRI can be applied to determine in which shelf levels should be stored the SKUs belonging to the set $A^*_I = \{a_2, a_4, a_5, a_6\}$. In this case, the following evaluation matrix can be derived (Table 9).

Product	Weight (kg)	Profitability (%)	Picking frequency (n° visit/hour)
a2	78	10	0,44
a4	130	5	0,64
a5	40	15	0,11
a6	115	5	0,16
q	5	2	0,5
p	10	4	0,1
v	20	5	0,2
b2	115	10	0,44
b1	40	5	0,11
w	0,33	0,09	0,58

Table 9: Evaluation matrix

In this case, the DM defined all the parameters (q, p, v, b1, b2) and the elicitation of the weights have been carried out through the BW method. Finally, the solution proposed by ELECTRE TRI is the following (Table 10):

Alternative	Pessimist	Optimist
a2	Z2	Z2
a4	Z2	Z1
a5	Z2	Z1
a6	Z2	Z2

Table 10: Assignment of items to shelf levels

3.5 Storage positioning

In this case, the DM decided to select the optimist rule because is the most equilibrate choice. By virtue of this, and considering that a4, a5, and a6 must be stored near each other, a possible storage solution can be the following (Figure 4) (Tables 11):

SKU	Shelf level	Demand [m3]	Rows required [demand/row dimension]
a2	z2	15	5
a4	z1	12	3
a5	z1	30	7
a6	z2	24	8

Table 11: Determination of required space

According to Table 11, the rows required in z1 are 10, the rows required in z2 are 13, and the rows required in z3 are 0. By virtue of this, the required columns in sector A are 4.

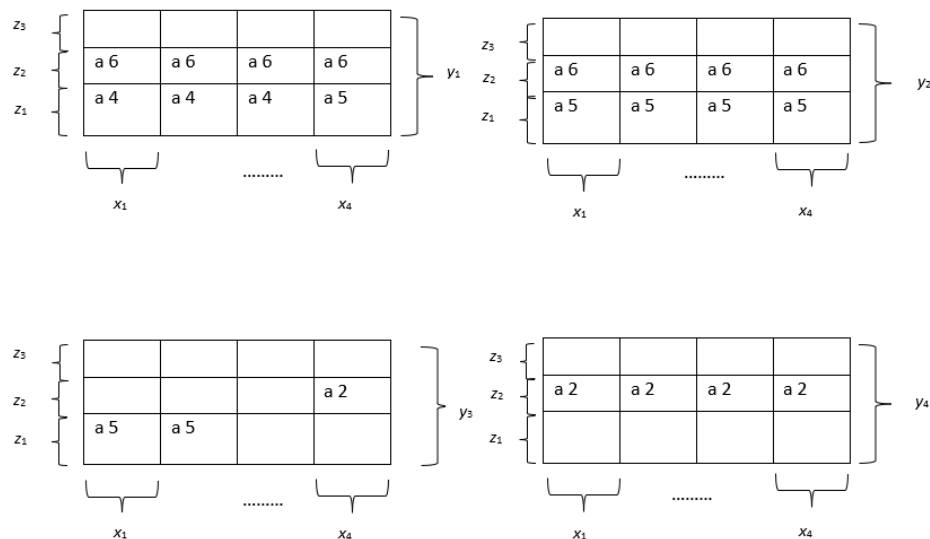


Figure 4: Assignment of SKUs to shelf levels

The same process should be carried out in class B, while in class C there is only an SKU, therefore it can be stored in a random way (that is at any level of any shelf).

4. Final remarks

This paper proposed the use of a multi-criteria model based on the combination of three methods (ELECTRE TRI, BW, and clustering analysis) to solve the SLAP. The results show that the model is able to provide the DM with an efficient decision support to solve in a quick manner the storage location assignment problem.

ELECTRE TRI, seems to provide extremely balanced solutions in both sorting the SKUs in classes and assigning them to the shelf levels. This is probably due either to the use of the BW method in eliciting the weights or to the use of real data gathered for a real company. In fact, in light of the outcomes obtained, it seems that the BW method allows for reducing the errors of subjectivity related to a direct weight's elicitation, while the use of real data allows to obtain non-strongly conflicting alternatives (Optimistic and Pessimistic). In addition, the results show that the use of the correlation analysis and clustering can have a positive effect on the solution of the SLAP, because, by grouping the SKU's based on their similarity degree, it allows to avoid the random storage as far as possible, therefore, this can reduce the travel distance, and, consequently, the picking time [Bindi and Marzini 2007].

The main limitation of this model lies in the previous definition of criteria. Indeed, in many situations, the DM might not agree with them. Therefore, as a suggestion for future research,

we propose the use of criteria chosen directly by the DM. Successively, the results could be compared with what has been obtained in this work.

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