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Evaluation of routing policies using an interval-valued TOPSIS approach for the allocation rules

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Abstract

The success of warehouse management in a supply chain widely depends on an efficient and effective retrieve of customer orders, which is known as the picking process. This paper investigates various routing policies of pickers under two different allocation methods of items in a warehouse of fixed layout, and evaluates their performance in terms of the resulting travel distance by means of a simulation approach. The allocation strategies taken into account are the random storage and a multi-criteria approach, called Interval-Value TOPSIS (IV-T), which is expressively proposed in this paper as a new way to solve the storage allocation problem of items in a warehouse. Because of the newness of the approach proposed, an *ad hoc* performance measure is also introduced to evaluate the effectiveness of the IV-T allocation. Results show that the usage of the IV-T approach involves interesting savings in the travel distance compared to the random allocation.

Keywords:

Warehouse management; Picking; Storage allocation; Interval-value TOPSIS; Simulation.

1 Introduction

Warehouse management has undergone major changes in recent years due to the increase in time-reduction competition and the growth in e-commerce. The challenge for researchers and managers is to reduce the cost of warehouse design and management activities. In particular, most of the existing activities are still operated manually, with low or medium technical support. The high amount of human work makes warehouse activities intensive processes with regards to time and cost (Battini et al., 2011). Direct labour carried out in a distribution centre, where the stored products are intended to be shipped to retailers, wholesalers or customers, involves different activities. Shipping and receiving of products, preparing orders according to the received requests, products positioning inside the warehouse and their retrieval or preparation of the load units are examples of such activities. Among the different warehouse processes, order picking is generally recognized as a one of the most expensive, because it tends to be either very labour or capital intensive (Frazelle, 2002). Improving the efficiency of the order picking process plays a fundamental role in reducing warehousing costs and, consequently, supply chain costs (Atmaca & Ozturk, 2013). The order picking process involves the searching, selection and gathering of a defined quantity of products in order to satisfy the customer's request (Rouwenhorst et al., 2000).

In a manual process, it is estimated that picking operations account for more than 55% of the total cost of warehouse operations (Bottani et al., 2015). For this reason, both researchers and logistics managers consider order picking as a promising area for productivity improvement (de Koster et al., 2007). The high cost of picking is mainly due to the fact that pickers spend approximately 50% of the total order picking time in travelling. As the travel time is an increasing function of the travel distance, reducing the travel distance of pickers has an obvious impact on warehouse performance in terms of cost and delivery lead-time, and consequently affects the performance of the whole supply chain (Petersen & Aase, 2004; de Koster et al., 2007; Bottani et al., 2012). Researchers (e.g. Gu et al., 2007 or de Koster et al., 2007) agree that several factors affect the travel distance in a manual order picking system. Among these factors, the overall structure of the warehouse in terms of size and layout (Roodbergen & Vis, 2006) and the presence of narrow aisles, which increase the likelihood of congestion whenever more pickers operate simultaneously in the warehouse, are relevant aspects (Chen et al., 2013). Operational factors include the picking strategy, e.g. order picking vs. batch picking (Le-Duc & de Koster, 2007), the storage assignment policy (Bottani et al., 2012; Micale et al., 2019), the use of zone picking (de Koster et al., 2012) and the routing policy (Kulak et al., 2012). Moreover, it has been proved that 40% of the total investments of warehousing comes from the cost of material handling operations (Yamazaki et al., 2017). An efficient storage location of products is an operating condition that allows for a faster material handling, which in turn increases the speed of delivery and, therefore, the competitiveness of enterprises (Da Silva e al., 2015). The Storage Location Assignment Problem (SLAP) involves placing a set of items in a warehouse in order to reduce material handling costs and improve the space utilization (Kovács, 2011). There are several criteria that may be used to cluster and allocate products in the warehouse, such as cube per order index (Haskett, 1963), turnover (Van Gils et al., 2018), popularity (Manzini et al., 2015), frequency, size, weight, part number, supplier, volume, demand or cost, among others. Moreover, in many cases, these criteria can be conflicting, and therefore the choice of the best place to locate each product becomes a difficult task. Therefore, an integrated and structured approach that allows these different aspects to be taken into account simultaneously is appropriate. Multi-criteria decision-making (MCDM) approaches could provide suitable solutions to this end; thus, the SLAP can be translated into a MCDM problem to take into account more aspects simultaneously (Da Silva e al., 2015; Fontana & Cavalcante, 2014). Studies that directly address the attribution of products to warehouse sites and make use of a multi-criteria approach are still scarce in the literature (Da Silva e al., 2015). For example, Fontana & Nepomuceno (2017) proposed the use of ELECTRE TRI method for establishing the shelf level of each product and the ELECTRE III approach to determine their fixed location in each shelf. In this approach, the authors rank items of each shelf level by placing in the first position the items not allocated in the previous level. A rank procedure able to take into account all the items could improve the allocation efficiency. On the other hand, Da Silva et al. (2015) proposed replacing the cube per order index with the SMARTER and lexicographic methods to rank the items, following the same dynamic of allocation from cube per order index, in a dedicated storage policy. However, the research was developed in 2D warehouses and the extension to 3D space is necessary to represent real cases.

The primary objective of this paper is to propose an alternative MCDM approach, based on interval-value TOPSIS (IV-T), to locate the products in a warehouse. To the best of the authors' knowledge, most of the available literature on SLAP, such as that reviewed above, has considered non-compensatory approaches. The methodological approach proposed in this paper to deal with SLAP allows instead to take into account the inherent multi-criteria nature of the problem by means of a compensatory approach, such as TOPSIS. Among the different possible MCDM methods, TOPSIS has also some unique features, such as that of being particularly suitable for application when ranking a large number of alternatives (as the items handled in a warehouse) due to its simplicity, good computational efficiency and rationality (Roszkowska, 2011). As a second point, the IV-T approach grounds on membership intervals and is, which is a further newness compared to the existing literature; indeed, almost all the existing approached have assumed the input data to be crisp values, thus allowing for a deterministic formulations of the evaluation judgements only. On the contrary, the proposed approach is the first attempt to consider the epistemic uncertainty of Decision Makers (DMs) when expressing the rating of alternatives against criteria. This point takes direct inspiration from real life problems, in which DMs (i.e. warehouse managers) are often requested to express preferences on the basis of uncertain and incomplete data; the use of exact/deterministic numerical values can be inappropriate to capture the ambiguity of concepts related to human knowledge, perception and opinions in these situations. The IV-T allows instead for the scores of alternative to be expressed in interval form, and is expected to effectively deal with the intrinsic uncertainty of DMs in assessing alternatives against criteria.

Overall, the proposed IV-T approach represents a new way for allocating items in a warehouse, with the ultimate aim to decrease the time required for retrieving activities. This approach is compared to the well-known random storage policy, which reflects the situation in which each item can be located randomly in all eligible empty locations. Random storage is selected as baseline scenario because it is a very popular strategy, often requires less space than other storage methods, and results in a homogeneous utilization of all picking locations (Petersen & Schmenner, 1999).

When trying to minimise the picking time, storage allocation decisions need to be coupled with appropriate routing methods or warehouse layout (Bottani et al., 2019a). Indeed, routing and storage allocation policies are strictly related decisions, with significant interactions with one another (Manzini, et al., 2007; Petersen & Schmenner, 1999; Theys et al., 2010; Caron, Marchet, and Perego, 1998; Petersen 1999; Petersen and Aase, 2004). Warehouse layout, especially due to the possible presence of cross-aisles, also has relationships with the storage assignment problem and impacts on the travel distance of pickers (Berglund and Batta, 2012). Hence, after proposing the IV-T approach, the secondary objective of this paper is to test the effectiveness of the new allocation policy when implemented in combination with various routing methods, taking into account the possible usage of cross-aisles in the warehouse. In summary, the following key design factors of picking systems will be evaluated in this paper:

- the items allocation policy;
- the routing policy;
- the usage of the warehouse cross-aisles.

The remainder of the paper is organized as follows. The materials and methods are described in Section 2; this section details, in particular, the methodological approach used to carry out the study, the allocation policy and the picking routing functions. In the same section, an *ad hoc* performance measure is introduced to capture the improvements made by the new items allocation policy. Section 3 shows a numerical application and discusses the main findings. Section 4 evaluates the effectiveness of the IV-T approach using the performance measure introduced in Section 2. Conclusions are finally drawn in Section 5.

2 Materials and methods

The methodological approach followed in this paper consists of different macro-steps as shown in Figure 1. The starting point is the items allocation in the warehouse. As mentioned, this is performed according to a MCDM method, i.e. IV-T approach; related details are proposed in section 2.1. Then, items are assigned to the warehouse locations. The next steps (routing policies, picking list generation and travel distance computation) deal with the simulation of the warehouse activities and in particular of the picking process. Simulation is particularly useful for reproducing various configurations in terms of routing and allocation methods. A software tool developed in Microsoft Excel™ was used to support these steps and to derive the key results in terms of travel distance of pickers. Details about the software tool and scenarios simulated are proposed in section 2.2. Finally, the performance evaluation step deal with the assessment of the proposed MCDM approach; given the peculiarities of this approach, an *ad hoc* performance metric is introduced in section 2.3.

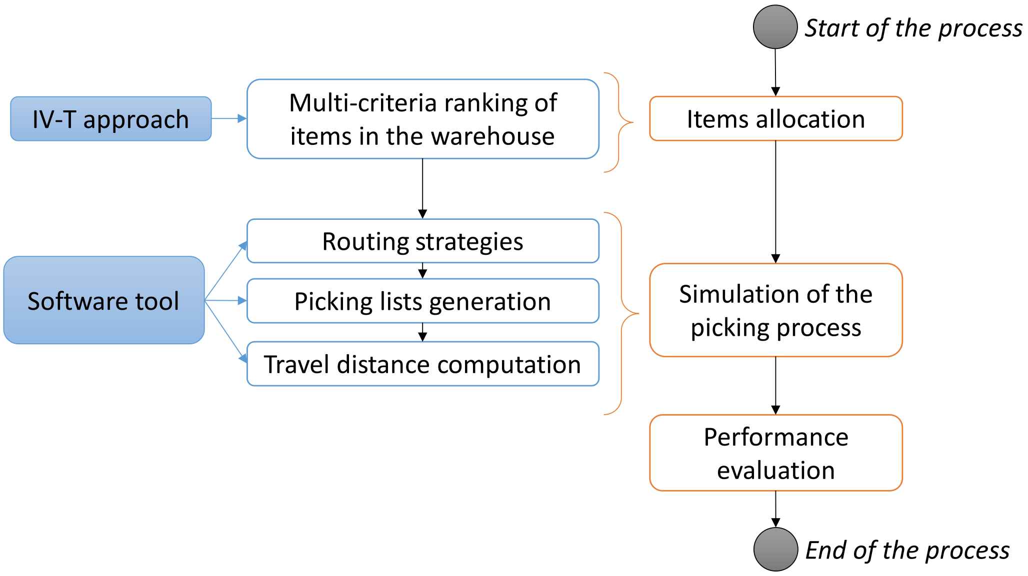

Figure 1: methodological approach.

2.1 Items allocation

2.1.1 *Interval-Value TOPSIS*

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a MCDM approach developed by Hwang and Yoon (1981) to rank a set of alternatives evaluated according to different criteria. This algorithm is based on the concept that the best alternative has the shortest and farthest geometric distance from the positive and negative ideal solutions respectively. As input, it requires a decision matrix, whose generic element $g_j(a_i)$ represents the evaluation of the alternative a_i with respect to the criterion C_j, and the criteria weights. Often, considering an exact value for the alternative evaluations against criteria is unsuitable because of the uncertainty typical of many real-world problems. Several researchers face this uncertainty considering intervals rather than exact values (Jahanshahloo et al., 2006, 2009; Dymova et al., 2013). In particular, as regards to the TOPSIS method, in Jahanshahloo et al. (2006) an interval extension of the traditional method is described. In the IV-T, the generic element of the interval-valued decision matrix G_{ij} (table 1) represents the interval score of alternative a_i ($i = 1, \dots, I$) according to criterion C_j ($j = 1, \dots, J$):

***G*$_{ij}$**	***C*$_1$**	**…**	***C$_j$***	**…**	***C$_J$***
***a*$_1$**					
…			…		
a$_i$		…	$g_j\left(a_i\right)=\left[\underline{g}_j\left(a_i\right);\overline{g}_j\left(a_i\right)\right]$	…	
…			…		
a$_I$					

Table 1: interval-valued decision matrix.

The relative importance (i.e. weight) of the criteria is denoted as w_j, (j = 1, …, J), with $\sum_{j=1}^{J} w_j = 1$.

Once the decision matrix has been built, it is possible to determine the interval-normalized decision matrix, in which a generic interval-valued element $z_j\left(a_i\right)=\left[\underline{z}_j\left(a_i\right);\overline{z}_j\left(a_i\right)\right]$ is calculated applying the following equations:

$$\underline{z}_j(a_i)=\frac{\underline{g}_j(a_i)}{\left\{\sum_{i=1}^{I}\left[\underline{g}_j(a_i)^2+\overline{g}_j(a_i)^2\right]\right\}^{1/2}} \qquad \forall a_i \mid i=1,2,\ldots,I; \forall j \mid j=1,2,\ldots,J \tag{1}$$

$$\overline{z}_j(a_i)=\frac{\overline{g}_j(a_i)}{\left\{\sum_{i=1}^{I}\left[\underline{g}_j(a_i)^2+\overline{g}_j(a_i)^2\right]\right\}^{1/2}} \qquad \forall a_i \mid i=1,2,\ldots,I; \forall j \mid j=1,2,\ldots,J \tag{2}$$

Multiplying each element of the interval-normalized decision matrix by the weights w_j of the corresponding criteria, the weighted normalized interval decision matrix is obtained. The generic element $u_j\left(a_i\right)=\left[\underline{u}_j\left(a_i\right);\overline{u}_j\left(a_i\right)\right]$ of this matrix is hence calculated by means of equations 3 and 4:

$$\underline{u}_j(a_i)=w_j\cdot\underline{z}_j(a_i) \qquad \forall a_i \mid i=1,2,\ldots,I; \forall j \mid j=1,2,\ldots,J \tag{3}$$

$$\overline{u}_j(a_i)=w_j\cdot\overline{z}_j(a_i) \qquad \forall a_i \mid i=1,2,\ldots,I; \forall j \mid j=1,2,\ldots,J \tag{4}$$

Then, the positive and negative ideal solutions, named Azimuth (A^*) and Nadir (A^-) respectively, can be determined as follow:

$$A^*=\left\{u_1^*,\ldots,u_J^*\right\}=\left\{\left[\max_i\left[\overline{u}_j(a_i)\right] \mid j\in I'\right],\left[\min_i\left[\underline{u}_j(a_i)\right] \mid j\in I''\right]\right\} \tag{5}$$

$$A^{-} = \{u_1^{-},\ldots,u_J^{-}\} = \left\{ \left[\min_i \left[\underline{u_j}(a_i)\right] \mid j \in I' \right], \left[\max_i \left[\overline{u_j}(a_i)\right] \mid j \in I'' \right] \right\} \tag{6}$$

where I' and I'' denote the sets of benefit and cost criteria respectively.

The n-dimensional Euclidean distances S_i^{*} and S_i^{-}, between each alternative and A^{*} and A^{-} respectively, are computed applying equations 7 and 8:

$$S_i^{*} = \left\{ \sum_{j \in I'} \left[\underline{u_j}(a_i) - u_j^{*}\right]^2 + \sum_{j \in I''} \left[\overline{u_j}(a_i) - u_j^{*}\right]^2 \right\}^{1/2} \qquad \forall a_i \mid i = 1,2,\ldots,I \tag{7}$$

$$S_i^{-} = \left\{ \sum_{j \in I'} \left[\overline{u_j}(a_i) - u_j^{-}\right]^2 + \sum_{j \in I''} \left[\underline{u_j}(a_i) - u_j^{-}\right]^2 \right\}^{1/2} \qquad \forall a_i \mid i = 1,2,\ldots,I \tag{8}$$

Knowing these distances allows for the calculation of the Relative Closeness coefficient index RC_i^{*} (eq. 9):

$$RC_i^{*} = \frac{S_i^{-}}{S_i^{-} + S_i^{*}} \qquad 0 \le RC_i^{*} \le 1 \qquad \forall a_i \mid i = 1,2,\ldots,I \tag{9}$$

The ranking of alternatives is finally obtained by ordering them according to descending values of RC_i^{*}.

As the proposed approach is intended to be applied for items allocation, evaluation criteria have been identified on the basis of recent literature on the SLAP (Micale et al., 2019; Fontana and Nepomuceno, 2017; Da Silva et al., 2015; Fontana & Cavalcante, 2014; Accorsi et al., 2012). In particular, the criteria used are:

Space: referring to a specific time interval, this criterion represents the number of storage locations assigned to each Stock Keeping Unit (SKU) of a particular product category;

Demand: it represents the average amount of SKUs of a particular product category in a defined period;

Profitability: it reflects the (relative) importance of each product category in terms of its contribution to the company's profitability;

Popularity: it represents the average number of consumers served by a given product category in a stated timeframe.

In general terms, the allocation problem is solved with the goal of minimizing average distance travelled by the picker to retrieve SKUs; in line with this, the *space* criterion has to be minimized, which implies that SKUs with high scores are to be assigned furthest from the input/output (I/O) point. On the contrary, *demand*, *profitability* and *popularity* criteria have to be maximized, meaning that SKUs with high scores on these criteria are to be located close to the I/O point. Overall, items that rank first on the basis of the IV-T approach have the highest "priority" for decreasing the travel distance; hence, they should be allocated as closest as possible for the I/O point of the warehouse. Following the same line of reasoning, if two different items get the same score according to the IV-T approach (meaning that they rank in the same position), they have the same priority in the definition of their allocation. The real allocation these two items will have in the warehouse will obviously depend on the availability of empty shelves: if there are two available shelves with the same distance from the I/O, the proposed approach will assign these items to the two available shelves. Their specific position in the two shelf is indifferent, because of the symmetry of the items and shelves characteristics. Otherwise, if just one shelf with a given distance from the I/O is available, the two items with the same rank will be allocated consecutively, i.e. one to the available shelf and the second to the next available shelf with the shortest distance from the I/O.

2.2 Simulation of the picking process

According to Harrison et al. (2007), simulation is an effective tool for generating a large set of output values whose distribution is able to characterize the system's behavior, for reproducing stochastic processes and for exploring the consequences of processes that cannot be easily assessed empirically by means of real observations. On the basis of these considerations, simulation is used in this step of the research to reproduce the picking process once the items have been allocated in the warehouse according either to the IV-T logic or the random allocation policy. Using simulation avoids the observation of a real case of implementation of the proposed IV-T logic, and, at the same time, enables the computation of the travel distance of pickers in a warehouse in which items are allocated using the IV-T policy. In this respect, results of the IV-T allocation are used as input for the simulation model. Simulation is also useful to reproduce a stochastic process, such as picking, in which the items to be picked to fill a customer's order vary continuously, due to the stochasticity of demand.

A software tool programmed with Microsoft Excel^{TM} was developed by some of the authors in a previous publication (Bottani et al., 2019b) in the attempt to help warehouse managers in designing picker-to-parts order picking systems. This tool is able to reproduce various design factors of a picking system, including the warehouse layout (in terms of number of aisles and cross-aisles, shape factor and storage capacity) and the routing policies and was used in this study to reproduce the picking process under different design factors and evaluate their effect on the process performance.

2.2.1 Routing policies

Routing strategies are logics that allow determining the most efficient order picking route given the picking list of orders to be fulfilled (Micale et al., 2019). In the attempt to minimise the order picking cost, the route has to be as short as possible. A routing problem can be solved by exact methods or by heuristic algorithms. At the time of writing, the software tool used embodies several routing policies, such as (Petersen, 1997, 1999):

> **S-shape**: Aisles characterized by one or more picking operations are entirely traversed by the picker, while aisles where nothing has to be picked are skipped. After picking the last item, the picker goes back to the I/O station. This policy is very simple to use and particularly suitable for high pick density contexts.
>
> **Return**: The picker enters and leaves the aisles from the same side, and the aisles without picks are not visited. Differently from the S-shape policy, this strategy is generally employed when the picking density is low.

For each of those policies, the software tool supports two alternatives settings, called *simple* and *advanced*. The simple setting reflects the traditional routing policy as described above and in particular, cross-aisles (if present) are not used by the picker. By advanced, instead, it is meant that in both policies, the picker may choose to use a cross-aisle to move to the next aisle where further items are to be picked. Figures 2 and 3 provide examples of the picker routes resulting from the application of these policies, taking into account a picking list of 20 items.

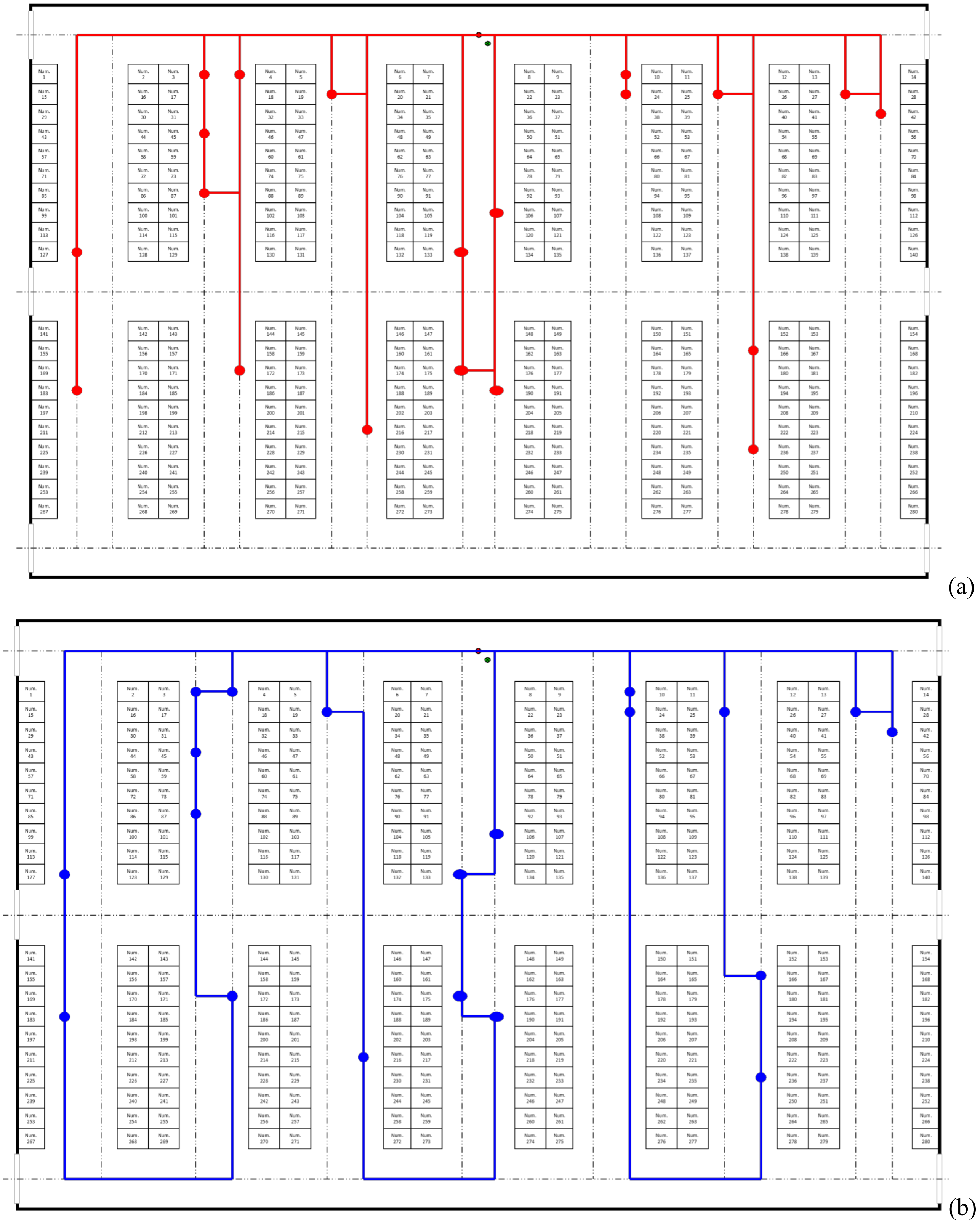

Figure 2. Simple Return (a) and S-shape (b) policies.

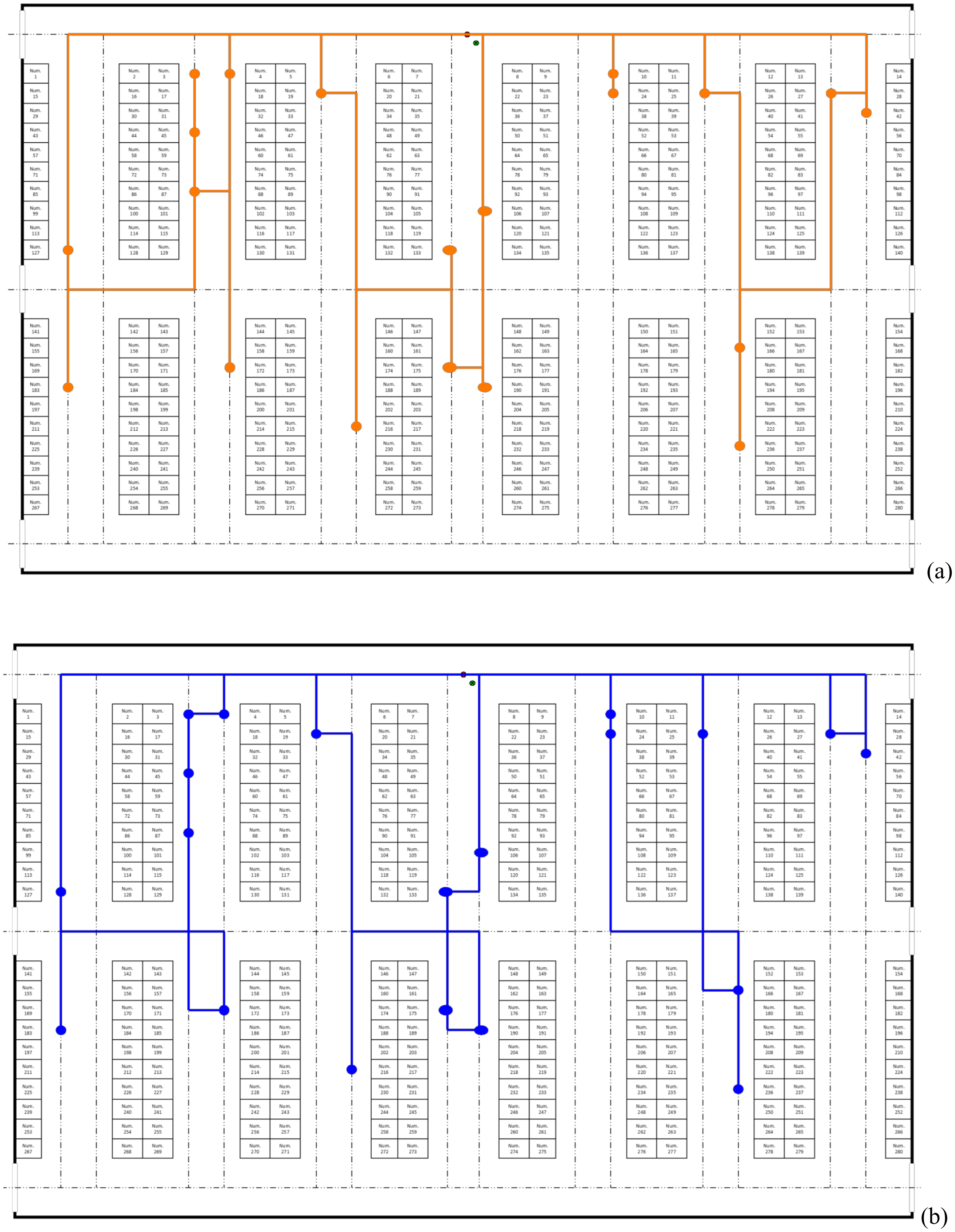

Figure 3. Advanced Return (a) and S-shape (b) policies.

2.2.2 Picking lists

As far as the picking lists are concerned, the software enables the user to generate random picking lists of a given size.

2.2.3 Travel distance computation

As output, the software tool computes the travel distance covered for each picking list, as a function of the routing policy applied. The output is then averaged across all the random picking lists (of given length) generated by the tool, obtaining an average travel distance that is useful to compare the performance of the different routing policies when varying the allocation of items in the warehouse. The software tool creates a digital twin of the warehouse, in which each allocation (and therefore each product to be picked) is described in terms of its spatial coordinates (*x,y*). Starting from randomly generated customer's order and taking into account the routing policy set, the model allows to simulate each movement of the picker during the picking process. Based on these data, the relative distance $d_{i-1,i}$ between product *i-1* and product *i* of the picking list is computed. To determine the total travel distance of a picking list of *n* different products, the partial distances $d_{i-1,i}$ between the various references to be picked are summed up as follows:

$$\text{Travel distance } = \sum_{i=1}^{n+1} d_{i-1,i}$$

where $i = 0$ is the warehouse input depot and $i = n+1$ is the warehouse output depot.

2.3 Efficiency evaluation

When moving from the random to the multi-criteria allocation of items in the warehouse, *ceteris paribus*, it is generally expected that the travel distance of pickers will improve, meaning that the length of the picking tour will decrease. Indeed, under random storage all picking locations have the same probability of being visited, meaning that pick density is equally distributed across the warehouse; this implies that, typically, it is difficult to achieve advantages in terms of length of the picking tours. However, random storage could be effective in some contexts. More precisely, this strategy is useful when the range of products is large compared to the number of locations. As no locations are reserved for products, less space is typically needed to store the items compared to a situation in which the products are assigned to a given pick location (Petersen & Schmenner, 1999), as made when using the multi-criteria allocation proposed in this paper. By the way, space is one of the criteria used for items allocation in the IV-T model. Because of these antithetic aspects, it is paramount to evaluate the efficiency of the multi-criteria allocation model proposed in this study. For making such an evaluation, a two-step procedure has been developed and is detailed below.

2.3.1 Criteria transformation

Numerical values of the criteria for each product should be first normalized for making them comparable; indeed, criteria used in the IV-T approach are quite different in nature and measured with different units. Normalization is simply made by rescaling the numerical values of each product against each criterion in the range [0;1] on the basis of the maximum observed value.

Moreover, it is important to check whether the numerical value of each criterion increases with the increase in the travel distance, meaning that it is directly proportional to the distance travelled, or whether it decreases with the increase in the travel distance, meaning that it is inversely proportional to the distance travelled. When dealing with a minimization problem (as that in this paper), it is probably more effective to make all criteria inversely proportional to the travel distance, so as to ensure that they will minimize it. Looking at the criteria used in the IV-T approach, popularity, demand and profitability all are inversely proportional to the travel distance, while space is the only criterion which is directly proportional to the travel distance (higher space required to a product implies higher travel distance). Numerical values of this criterion are therefore transformed in their complement to one.

2.3.2 Computation of the key performance indicator

Once criteria have been transformed into usable values, a synthesis index can be computed. This is called *multi-attribute work* (*MAW*) because it takes into account all the different attributes considered in the items allocation in a computational procedure which has analogies with that of the physical work. The idea is, in fact, to multiply each segment of a picking tour by the numerical values of each criterion in that specific part of the picking tour, and then summing up on the whole set of segments of the tour and of the criteria. This kind of computation returns an estimate of the "energy" (work) spent in completing the picking tour. High values of *MAW* thus indicate that more energy has been spent to carry out the picking list; lower values of *MAW* therefore denote better performance of the picking process and are generally to be preferred.

The following set of formulae details the computation:

$$MAW_{space} = \sum_{i=1}^{n+1} d_{i-1,i}\, F_{space,i} \tag{10}$$

$$MAW_{demand} = \sum_{i=1}^{n+1} d_{i-1,i}\, F_{demand,i} \tag{11}$$

$$MAW_{profitability} = \sum_{i=1}^{n+1} d_{i-1,i}\, F_{profitabiliy,i} \tag{12}$$

$$MAW_{popularity} = \sum_{i=1}^{n+1} d_{i-1,i}\, F_{popularity,i} \tag{13}$$

$$MAW = MAW_{space} + MAW_{demand} + MAW_{profitability} + MAW_{popularity} \tag{14}$$

In the above formulae, $d_{i-1,i}$ reflects the length of a generic trait of the picking tour (with $i = 1, \ldots n+1$ if the picking list includes n items) and $F_{criterion,i}$ the normalized value of each criterion for item i.

As highlighted by the formulae, determining the MAW requires knowing the length of each trait of the picking tour, which was, once again, obtained by means of the software tool used to support the study.

3 Numerical application

3.1 Warehouse settings

As a numerical application to test the proposed approach, a rectangular shape 2-block warehouse is considered. The warehouse has 7 parallel aisles of 3 m width where the different SKUs are located on both sides (Figure 4). The number of bays and racks is 10 and 28 respectively for a total number of picking locations (assuming low level picking) equal to 280. The I/O depot is located at the center of the upper side of the warehouse and 60 product categories are considered. A manual picker-to-part system is assumed. Under these assumptions, storage locations close to the I/O point are favored in terms of distance (Chan and Chan, 2011).

Storage locations = 280	Side *x* of pallet = 1.25 m
Width = 38.5 m	Side *y* of pallet = 1 m
Length = 29 m	Aisle width = 3 m
Area = 1116.5 m^2	Number of bays = 10
Shape factor = 1.327	Number of racks = 20

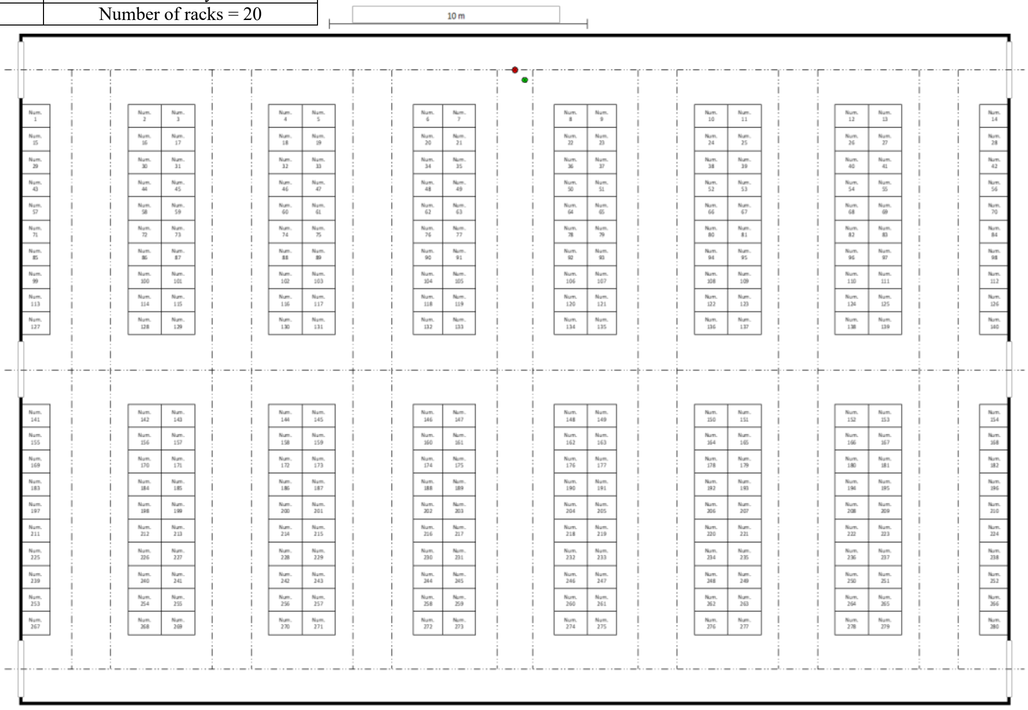

Figure 4. Warehouse layout.

3.2 Products characteristics

The product characteristics, in terms of the scores against the four criteria considered, were at first randomly generated in a crisp way, according to the procedure detailed below:

- the scores of the *space* criterion were generated as a random integer numbers in the range [1;10];
- the scores of the *demand* criterion were randomly generated as integer numbers in intervals of different widths and orders of magnitude (e.g. [1;5], [1,200; 2,300], etc.);
- the scores of the *profitability* criterion were generated using a random continuous variable in the interval [0;1];
- the scores of the *popularity* criterion were generated by a random integer number in the range [100; 500].

These values were subsequently converted into intervals considering an error factor of 5%. For example, let us suppose that for a generic item A_i, the score of the demand criterion was 219 SKU, randomly generated in the range [200; 300]. Then, the interval used in the IV-T approach has been obtained adding and subtracting ± 5% (208-230). The same procedure was applied for the profitability criterion whose value is 14% randomly extracted in the range [0-1] while the corresponding interval was (13%-15%). For the popularity criterion the value is 106 clients randomly extracted in the range [100-500], while the corresponding interval was (101-111). Finally, regarding the space criterion, the value of 5 SKU has been randomly generated in the range [1-10] respecting the constraint on the maximum availability of the warehouse places (280). In this case the corresponding interval degenerated (5-5), in order to comply with the abovementioned constraint. The decision matrix used in the IV-T approach has been reported in Appendix (table 6). In relation to the criteria weights, a sensitivity analysis was conducted according to the data reported in Table 2.

	Criteria weights			
	Space	**Demand**	**Profitability**	**Popularity**
Scenario 0 (S_0)	0.250	0.250	0.250	0.250
Scenario 1 (S_1)	0.274	0.242	0.242	0.242
Scenario 2 (S_2)	0.242	0.274	0.242	0.242
Scenario 3 (S_3)	0.242	0.242	0.274	0.242
Scenario 4 (S_4)	0.242	0.242	0.242	0.274
Scenario 5 (S_5)	0.226	0.258	0.258	0.258
Scenario 6 (S_6)	0.258	0.226	0.258	0.258
Scenario 7 (S_7)	0.258	0.258	0.226	0.258
Scenario 8 (S_8)	0.258	0.258	0.258	0.226

Table 2: Criteria weights for different scenarios.

The rankings resulting with the different criteria weights are also shown in Appendix (Table 7). In general, the ranking of a product can vary depending on the weights set for the criteria, although of a very limited number of positions; in addition, it can also be seen from Table 7 that products that rank in the top three and last three positions remain unchanged across the scenarios, which suggests a limited dependency of the ranking from the criteria weights. This is an important point, as the criteria weights typically depend on the particular implementation context and on the decision maker expectations; the proposed approach is therefore sufficiently robust in this respect. On the basis of these considerations, in the present paper only one representative scenario (i.e. S_0) was considered for the implementation. This is also in line with the primary aim of the paper, which is to show a methodological approach for items ranking and allocation.

3.3 *Simulation settings*

3.3.1 *Items allocation*

The allocation of items in the warehouse has been carried out by applying the IV-T approach detailed in section 2.1.1, with randomly generated product data as explained in the previous sub-section. To implement the IV-T approach, the definition of criteria weights is also necessary; in this example, they were set at 0.25 for each criterion. We recall that this setting will be compared to a baseline scenario in which items are allocated using the random storage policy; therefore, 2 allocation policies are taken into account in the evaluation.

3.3.2 *Routing policies*

The routing policies taken into account in the evaluation are both the S-shape and return policies, in their simple and advanced variants, generating 4 routing policies overall.

3.3.3 *Picking lists*

The length of the picking lists was varied in the range [2,100], evaluating 11 different sizes of the picking list. The upper limit of the list length is higher than the total number of different items (i.e. 60) available in the picking locations and therefore under some circumstances, the same product can be picked in more than one location. This implicitly means that the simulation also takes into account the situation in which the amount of a product stored in a picking location runs out after the pick, which forces the picker to move to another location in which the same product is available, to complete the picking task.

3.4 *Results and discussion*

By combining the number of picking list sizes (11), allocation strategies (2) and routing policies (4), 104 scenarios were obtained and evaluated in total. For each scenario, 10,000 random picking lists were generated using the Microsoft Excel^{TM} simulation model mentioned previously. Results, in terms of the travel distance, were averaged on the whole set of picking lists.

For each scenario, Table 3 shows the travel distance of pickers [meters].

Picking mission		**Random**				**IV-TOPSIS**			
Visited locations	**Visited locations / Total locations**	**Return S [m]**	**Return Adv [m]**	**S-Shape S [m]**	**S-Shape Adv [m]**	**Return S [m]**	**Return Adv [m]**	**S-Shape S [m]**	**S-Shape Adv [m]**
2	0.7%	71.86	62.09	77.50	62.09	65.24	57.61	75.73	57.61
5	1.8%	140.55	110.91	144.31	109.26	128.47	105.63	141.68	103.99
10	3.6%	212.43	167.15	203.60	160.88	195.40	160.71	201.59	154.40
15	5.4%	258.69	210.03	233.16	195.65	238.20	201.89	230.24	186.93
20	7.1%	289.17	244.86	250.95	221.77	267.71	234.89	246.80	211.01
25	8.9%	311.50	273.18	262.93	241.51	291.02	262.28	258.79	230.70
30	10.7%	327.49	295.78	271.97	256.45	306.93	283.61	267.16	245.28
40	14.3%	349.89	329.67	285.47	277.62	330.98	316.06	280.46	267.78
50	17.9%	362.82	350.37	295.52	291.56	346.26	336.79	290.62	283.40
75	26.8%	380.81	377.39	317.39	316.75	368.31	365.48	312.73	311.25
100	35.7%	389.60	388.77	337.34	337.25	380.24	379.51	333.64	333.42

Table 3. Comparison of IV-T and random allocation method in terms of picking distance.

Figure 5 shows the travel distance of pickers as a function of the routing policy applied and the length of the picking list, in the baseline scenario of random allocation of items. By comparing these outcomes with those obtained applying the IV-T policy (Figure 6), it is immediate to see that this latter policy generates savings in the travel distance for all the routing policies considered. In general terms, the significant difference observed in the picking distance generated by the IV- T allocation and the random allocation is an indirect measure of the effectiveness of the proposed approach. Indeed, this difference is the obvious consequence of the improved allocation generated by the whole set of factors taken into account in the IV-T logic. Nonetheless, it could be argued that the demand is one of the main reasons for that significant difference. Indeed, in the case example a non-uniform demand was modelled; accordingly, the IV-T approach tends to allocate higher rotating references in the warehouse areas close to the I/O depot, so that the operators will cover shorter distances during the picking process. The random allocation policy, instead, grounds on different (and simpler) logics which do not aim at optimizing the position of an item in the warehouse, and as a consequence, has no potentials for minimising the picking tour.

Figures 5 and 6 also show some common trends. For instance, a general outcome is that S-shape policy (either in its simple or advanced version) performs better than the return policy, regardless of the picking list size. This result has been previously demonstrated by Petersen (1997) in random storage contexts, considering different sizes of the order picking list; by this study, the same performance is confirmed when the IV-T allocation policy is applied.

Moreover, regardless of the allocation policy adopted, the best results are in general obtained using the advanced S-shape routing. We recall that the layout of the warehouse is fixed, i.e. a 2-block warehouse; therefore, the difference between the simple and advanced configurations of the routing policies reflects the usage of (just) one cross-aisle. From Figures 5 and 6 it is easy to see that the difference between the advanced and simple configurations of the return and S-shape routing policies tends to disappear when the size of the picking list is either very low or very high. This result indicates that the usage of the cross-aisle does not generate benefits in these scenario. Indeed, if the number of items to be picked is very low or very high, the picker route becomes almost obliged and there is less room for improving it with the usage of cross-aisles (and more in general, with the application of specific routing policies or allocation strategies). In a random storage environment, Vaughan & Petersen (1999) have demonstrated that using cross-aisle generally decreases the travel time of pickers compared to a scenario in which cross-aisle are absent or not used; however, the savings in the travel distance depends on the length of the picking list. These findings are confirmed also in the case the IV-T allocation policy is applied.

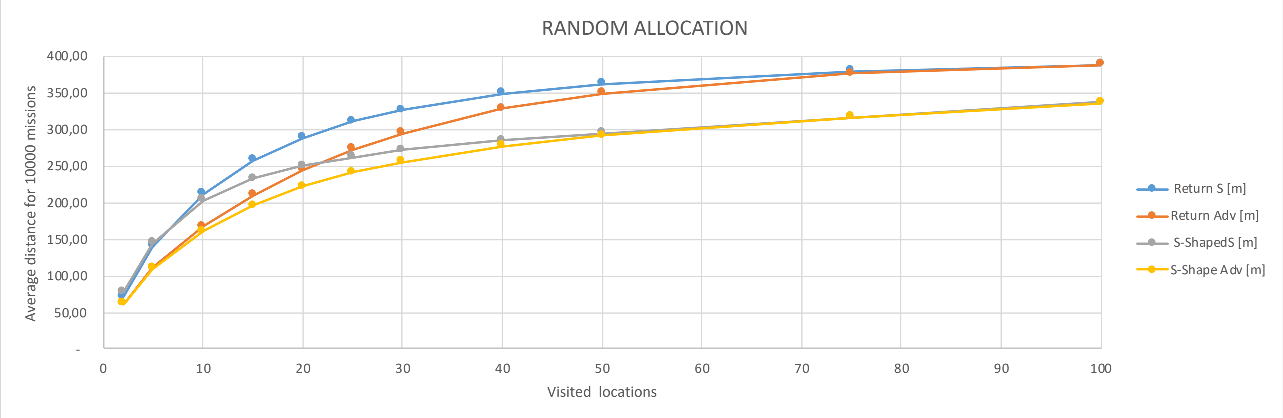

Figure 5: Comparison of picking policies using random allocation.

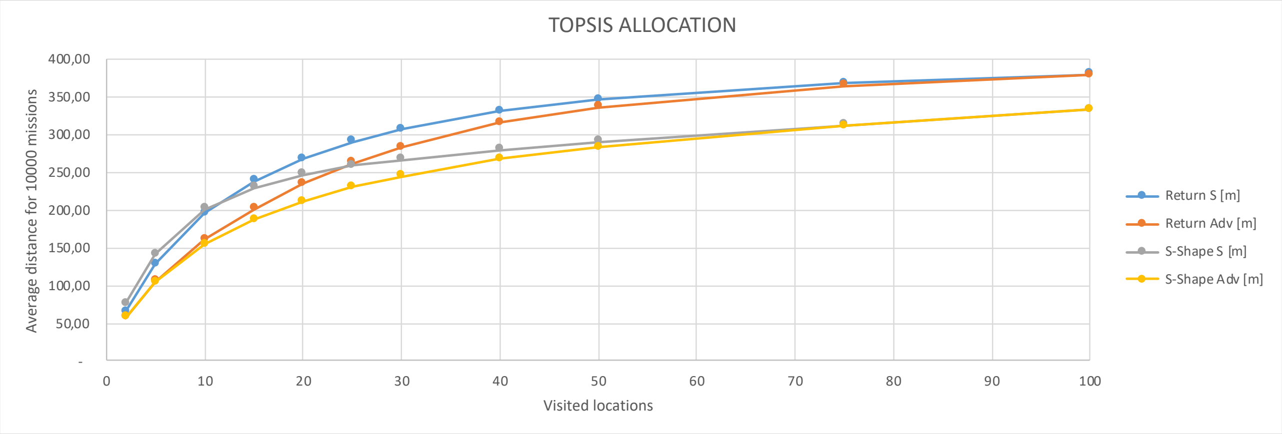

Figure 6: Comparison of picking policies using IV-T allocation

Figure 7 combines the findings in Figures 5 and 6 and details the improvement that can be obtained when using the IV-T allocation. From this figure it can be seen that the maximum saving in the travel distance is reached with the simple return policy, while the minimum reduction is given by the simple S-shape policy. The logical consideration is that the simple S-shape policy does not benefit from being associated to any particular allocation strategy. This finding is reasonable, as in S-shape routing the picker always has to cover the whole aisle length, regardless of the number of items to be picked in that aisle; hence, benefits from a particular allocation strategy are likely to be limited.

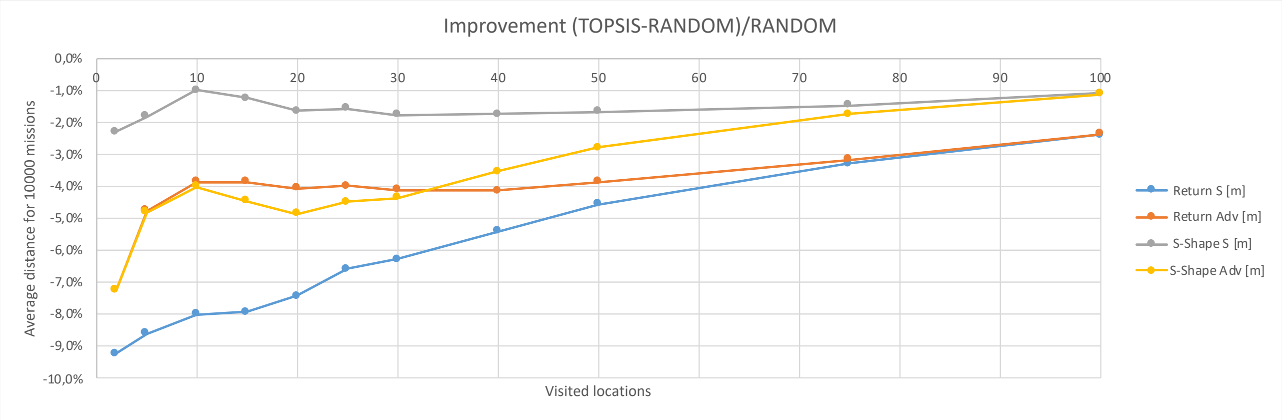

Figure 7: Improvement obtained using the IV-T allocation.

Figure 8 instead deepens the benefits resulting from the usage of the cross-aisle by providing a detailed comparison of the travel distance obtained using the advanced routing policies to that resulting from the usage of the simple routing policies. Results confirm that the usage of the cross-aisle does not generate benefits when the number of visited locations is either very small or very large. As a matter of fact, in neither situation the picking tour can be truly optimized by applying a specific routing strategy. Overall, the minimum travel distance is obtained by combining the advanced S-shape routing with the IV-T allocation rule; such combination allows for reducing the length of the picking tour of more than 4% when considering picking lists up to 30 items (with reflect 10.7% of the warehouse locations). It is also interesting to note that the maximum benefit is achieved when picking 7 items, which could be the typical length for a picking list in an e-commerce environment.

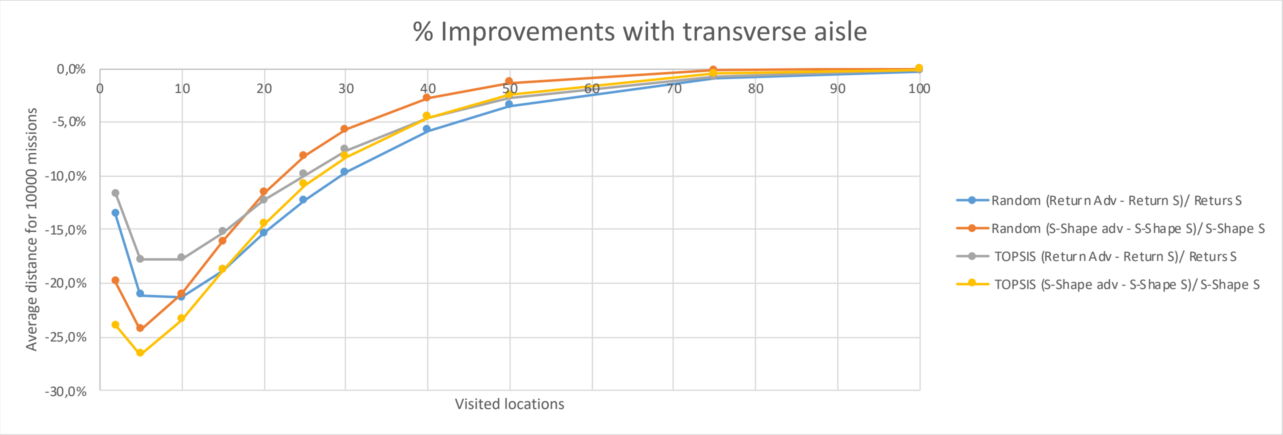

Figure 8: Improvement obtained using the cross-aisle.

Figures 9 and 10 provide examples of the items allocation obtained using the IV-T policy (right part of the figures) and the random allocation policy (left part of the figures), in the case of a long picking lists (100 items) or a short one (25 items). Only for visualization purpose, the S-shape advanced policy is depicted in these figures; however, the goal is to provide a comparison of the allocation strategies, and therefore the focus in on the distribution of the picking locations in the warehouse. To this end, one can see that in general, the IV-T policy allows concentrating the picking locations close to the I/O zone (i.e., in the first block of the warehouse) compared to the random policy. However, in the case of 100 items in the picking list, this is less evident, as many items always have to be picked in the second block of the warehouse, which is farther from the I/O depot. Moreover, the high number of items in the picking list also causes the cross-aisle not to be used to change aisle, as this would not allow reducing the length of the picking tour. If the number of locations visited is lower (Figure 10), the cross-aisle is instead used in both allocation policies, with consequent savings in the travel distance.

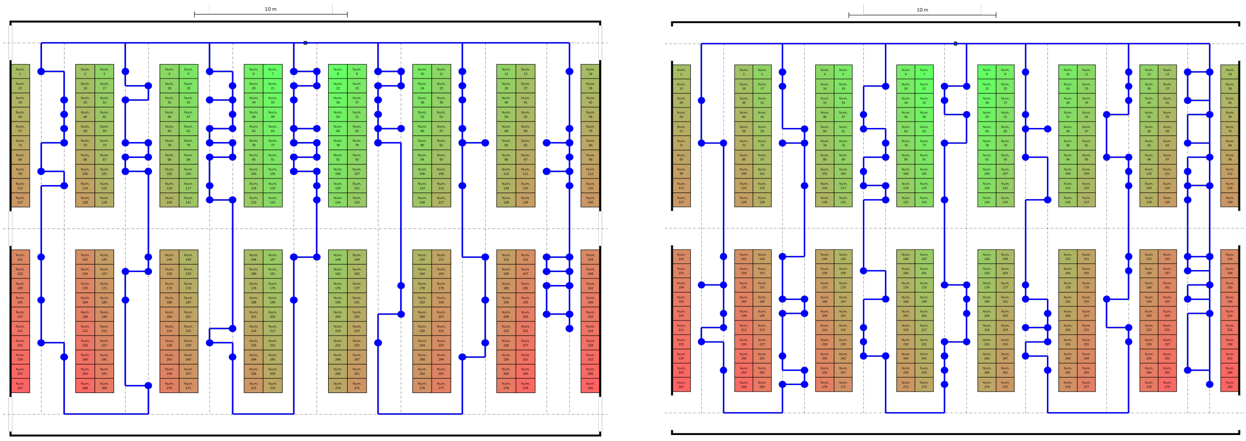

Figure 9: Random versus IV-T allocation policy (picking list size: 100 items).

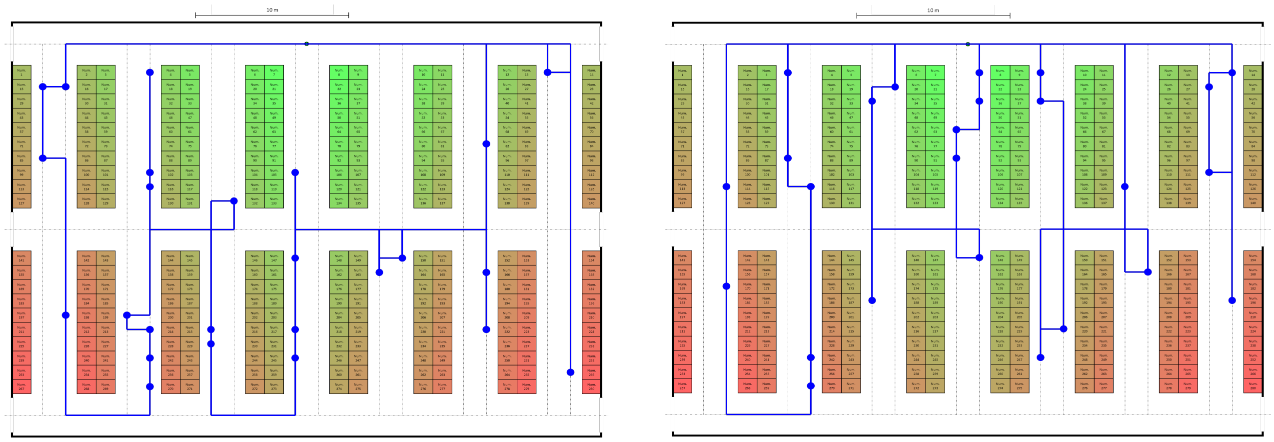

Figure 10: Random versus IV-T allocation policy (picking list size: 25 items).

3.5 *Efficiency evaluation*

To evaluate the efficiency of the proposed IV-T allocation policy, the performance of the products against the criteria were transformed as described in section 2.3 and the set of equations 10-14 was applied to the normalized values to compute the *MAW*.

Tables 4 and 5 report the detailed evaluation of the *MAW* (total and with its partial contributions) and the total picking distance as a function of the routing policy, the item allocation strategy and the length of the picking list, taking the average values on the 10,000 random picking lists. Figure 11 provides a graphical comparison of the *MAW* and distance values for the random and IV-T policy, as a function of the length of the picking list and of the routing policy.

		Return		**Return-adv**		**S-Shape**		**S-Shape adv**	
Items in the picking list	**KPI**	**Random**	**IV - T**	**Random**	**IV - T**	**Random**	**IV - T**	**Random**	**IV - T**
2	MAW	142.07	125.33	122.78	110.79	153.47	147.09	122.66	110.72
	MAW-Demand	*29.00*	*24.62*	*25.01*	*21.82*	*31.52*	*28.99*	*24.96*	*21.81*
	MAW-Popularity	*42.48*	*37.26*	*36.55*	*32.82*	*45.35*	*43.50*	*36.56*	*32.82*
	MAW-Profitability	*40.22*	*35.96*	*34.92*	*31.75*	*43.63*	*42.20*	*34.89*	*31.76*
	MAW-Space	*30.37*	*27.49*	*26.30*	*24.39*	*32.97*	*32.40*	*26.25*	*24.33*
5	MAW	275.95	246.61	218.55	202.54	284.21	274.51	215.53	199.88
	MAW-Demand	*55.47*	*47.53*	*44.11*	*38.98*	*57.39*	*53.42*	*43.46*	*38.85*
	MAW-Popularity	*82.62*	*73.10*	*65.23*	*59.54*	*83.98*	*81.24*	*64.04*	*58.91*
	MAW-Profitability	*78.49*	*71.46*	*62.46*	*58.80*	*81.37*	*79.12*	*61.78*	*57.73*
	MAW-Space	*59.37*	*54.52*	*46.75*	*45.22*	*61.47*	*60.72*	*46.25*	*44.39*
10	MAW	414.96	373.54	328.64	307.18	400.05	388.62	317.06	295.85
	MAW-Demand	*82.60*	*71.26*	*65.60*	*58.51*	*80.17*	*75.46*	*63.43*	*57.34*
	MAW-Popularity	*124.18*	*110.13*	*98.26*	*89.95*	*118.07*	*114.90*	*94.04*	*86.81*
	MAW-Profitability	*118.85*	*109.31*	*94.62*	*90.20*	*115.56*	*112.31*	*91.63*	*86.09*
	MAW-Space	*89.34*	*82.85*	*70.17*	*68.52*	*86.26*	*85.95*	*67.96*	*65.61*
15	MAW	504.64	454.88	412.42	385.98	457.85	442.05	385.75	357.47
	MAW-Demand	*100.49*	*86.59*	*82.12*	*73.46*	*91.78*	*86.45*	*77.20*	*69.90*
	MAW-Popularity	*151.29*	*133.73*	*123.68*	*113.02*	*135.03*	*129.83*	*114.36*	*104.56*
	MAW-Profitability	*144.94*	*133.63*	*119.06*	*113.73*	*132.46*	*127.71*	*111.73*	*103.97*
	MAW-Space	*107.92*	*100.94*	*87.56*	*85.77*	*98.59*	*98.06*	*82.45*	*79.04*
20	MAW	564.82	511.31	481.10	449.79	492.82	471.32	437.53	401.95
	MAW-Demand	*111.74*	*97.08*	*94.98*	*85.40*	*98.43*	*92.29*	*87.34*	*78.67*
	MAW-Popularity	*169.79*	*150.36*	*144.68*	*132.00*	*145.80*	*137.77*	*130.17*	*117.24*

	MAW-Profitability	*162.80*	*150.48*	*139.12*	*132.83*	*141.85*	*136.46*	*125.98*	*117.14*
	MAW-Space	*120.49*	*113.39*	*102.32*	*99.56*	*106.73*	*104.79*	*94.04*	*88.91*
25	MAW	607.34	556.12	535.38	502.84	516.10	491.29	475.78	437.32
	MAW-Demand	*119.44*	*105.63*	*104.97*	*95.64*	*102.73*	*96.22*	*94.63*	*85.76*
	MAW-Popularity	*183.28*	*163.68*	*161.74*	*147.88*	*153.64*	*143.21*	*142.46*	*127.21*
	MAW-Profitability	*175.56*	*164.08*	*155.03*	*148.55*	*147.84*	*142.39*	*136.25*	*127.40*
	MAW-Space	*129.06*	*122.72*	*113.63*	*110.77*	*111.88*	*109.46*	*102.44*	*96.95*
30	MAW	638.99	588.40	579.98	545.26	534.15	506.22	505.15	464.35
	MAW-Demand	*124.82*	*111.43*	*112.99*	*103.39*	*106.08*	*99.06*	*100.29*	*90.94*
	MAW-Popularity	*193.10*	*173.37*	*175.40*	*160.59*	*159.34*	*146.93*	*151.46*	*134.57*
	MAW-Profitability	*185.69*	*174.41*	*168.69*	*161.82*	*152.78*	*147.51*	*144.37*	*135.89*
	MAW-Space	*135.38*	*129.18*	*122.90*	*119.45*	*115.95*	*112.72*	*109.02*	*102.95*
40	MAW	683.58	635.77	646.03	608.64	559.49	527.46	544.96	503.37
	MAW-Demand	*131.85*	*121.06*	*124.25*	*115.89*	*110.41*	*103.12*	*107.48*	*98.48*
	MAW-Popularity	*207.39*	*187.82*	*196.20*	*179.84*	*168.04*	*152.13*	*164.27*	*145.15*
	MAW-Profitability	*199.79*	*188.36*	*188.68*	*180.45*	*159.34*	*154.21*	*155.13*	*147.52*
	MAW-Space	*144.55*	*138.52*	*136.90*	*132.46*	*121.70*	*118.00*	*118.08*	*112.22*
50	MAW	709.12	666.33	686.18	649.13	577.92	544.03	570.57	530.40
	MAW-Demand	*134.85*	*126.91*	*130.33*	*123.58*	*113.08*	*106.20*	*111.62*	*103.59*
	MAW-Popularity	*215.87*	*197.61*	*209.05*	*192.57*	*173.99*	*156.42*	*172.12*	*152.48*
	MAW-Profitability	*208.73*	*198.02*	*201.59*	*192.95*	*164.86*	*159.81*	*162.68*	*155.99*
	MAW-Space	*149.66*	*143.79*	*145.22*	*140.03*	*126.00*	*121.60*	*124.16*	*118.36*
75	MAW	744.25	711.97	738.23	706.78	616.82	581.53	615.66	578.68
	MAW-Demand	*138.36*	*136.00*	*137.24*	*134.84*	*118.35*	*113.23*	*118.13*	*112.68*
	MAW-Popularity	*228.54*	*212.08*	*226.77*	*210.61*	*186.81*	*166.60*	*186.54*	*165.81*
	MAW-Profitability	*220.83*	*212.76*	*218.71*	*211.23*	*176.37*	*172.40*	*176.02*	*171.58*
	MAW-Space	*156.52*	*151.14*	*155.51*	*150.10*	*135.29*	*129.30*	*134.97*	*128.61*
100	MAW	760.83	736.65	759.42	736.65	652.41	619.39	652.25	618.95
	MAW-Demand	*137.87*	*140.49*	*137.65*	*140.49*	*121.78*	*120.49*	*121.75*	*120.40*
	MAW-Popularity	*236.15*	*219.91*	*235.75*	*219.91*	*198.48*	*178.23*	*198.44*	*178.12*
	MAW-Profitability	*227.15*	*221.96*	*226.58*	*221.96*	*187.72*	*184.24*	*187.67*	*184.11*
	MAW-Space	*159.64*	*154.28*	*159.43*	*154.28*	*144.42*	*136.43*	*144.38*	*136.33*

Table 4: Numerical values MAW as a function of allocation method, routing policy and size of the picking list.

		Return		**Return-adv**		**S-Shape**		**S-Shape adv**	
Items in the picking list	**KPI**	**Random**	**IV - T**	**Random**	**IV - T**	**Random**	**IV - T**	**Random**	**IV - T**
2	Distance [m]	71.86	65.24	62.09	57.61	77.50	75.73	62.09	57.61
5	Distance [m]	140.55	128.47	110.91	105.63	144.31	141.68	109.26	103.99
10	Distance [m]	212.43	195.40	167.15	160.71	203.52	201.50	160.79	154.31
15	Distance [m]	258.69	238.20	210.03	201.89	233.16	230.24	195.65	186.93
20	Distance [m]	289.17	267.71	244.86	234.89	250.95	246.80	221.77	211.01
25	Distance [m]	311.50	291.02	273.18	262.28	262.93	258.79	241.51	230.70
30	Distance [m]	327.49	306.93	295.78	283.61	271.97	267.16	256.45	245.28
40	Distance [m]	349.89	330.98	329.67	316.06	285.47	280.46	277.62	267.78
50	Distance [m]	362.82	346.26	350.37	336.79	295.52	290.62	291.56	283.40
75	Distance [m]	380.81	368.31	377.39	365.48	317.39	312.73	316.75	311.25
100	Distance [m]	389.60	380.24	388.77	380.24	337.34	333.64	337.25	333.42

Table 5: Numerical values of distance as a function of allocation method, routing policy and size of the picking list.

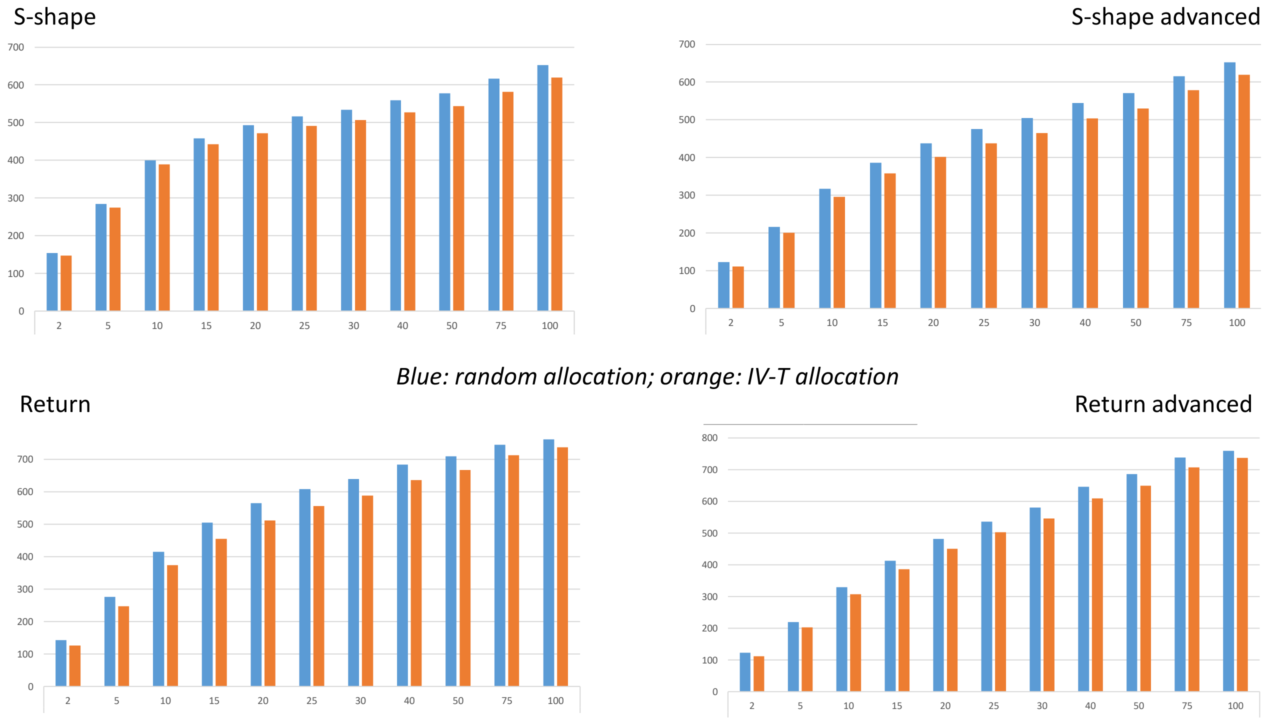

Figure 11: comparison of MAW values for random vs. IV-T allocation policies.

Looking at Tables 4 and 5 it is easy to see that the *MAW* aggregate values and the distance values show a similar trend. This result is reasonable and could be partially expected, since the longer the picking tour, the greater the energy required to carry out the picking process. From Figure 11 it can also be seen that the MAW values obtained when using the IV-T allocation are always lower than those returned by the random allocation, which confirms the effectiveness of the approach proposed in optimizing the items allocation. At the same time, looking at the single *MAW* contributions, the general trend that emerges is that almost all these contributions are lower when using the IV-T allocation compared to the random allocation, which means an improvement of the system's performance against all the criteria taken into consideration. It is also evident from Table 3 that the reduced *MAW* in the IV-T allocation is mainly due to the significantly lower score against the popularity criterion (*MAW-popularity*) compared to the random allocation. This result suggests that compared to the random allocation, the IV-T procedure is particularly effective in defining an allocation of items which takes into account the number of consumers served by a given product.

4 Conclusions and future research

The order picking process is recognized as one of the most critical warehouse activities, because of its direct impact on the customer satisfaction; therefore, carrying out this process in a quick and accurate way is crucial for the company's success. In the attempt to improve the productivity of the order picking process, this paper has proposed a new allocation strategy of items in the warehouse.

The proposed allocation method, called IV-T, grounds on a multi-criteria approach, i.e. the well-known TOPSIS, in which four criteria are taken into consideration for determining the position of an item in the warehouse. The effectiveness of the proposed approach was evaluated by means of a numerical example, referring to a warehouse with 280 storage locations, in which both the random and the IV-T allocation strategies were used for product allocation. Four routing strategies were then simulated with picking list of variable length (from 2 to 100 items), obtaining 104 scenarios. The total picking distance was used to evaluate the performance of the picking process under the different scenarios; moreover, a specific index, called MAW, was introduced to expressively evaluate the effectiveness of the IV-T allocation procedure.

The results obtained lead to the conclusion that the proposed allocation procedure is effective in improving the efficiency of the picking process under all scenarios considered. From a practical perspective, the decrease in the travel distance is particularly appreciable for picking lists of medium length (up to 30 items) and can be enhanced if the IV-T allocation policy is coupled with the advanced S-shape routing strategy. Again from a practical point of view, the proposed IV-T allocation is easy to implement. Indeed, it requires data about some product characteristics which are typically known to any warehouse manager. The computational procedure is easy as well and can be implemented in common spreadsheets, which makes the approach suitable for a practical usage in many real contexts. From a scientific point of view, this study contributes to the literature in several ways. First, the proposed IV-T procedure is new in its idea of combining various criteria for determining the allocation of items on the basis of a compensatory approach. Second, the analyses carried out in this paper evaluate the effectiveness of this new allocation policy in conjunction with different routing methods. The related results allow to extend or confirm some of the findings available in literature in the context of random storage to the case of the IV-T allocation procedure.

A further important point to mention is that the subject of this paper is relatively new and scientific literature offers a very limited number of approaches to solve the SLAP for 2D warehouses. However, none of the methods available in literature can be directly compared to the approach proposed in this paper, either because of their inherently different nature (non-compensatory vs. compensatory) or because they make use of different evaluation criteria or assumptions. This lack of direct comparisons with published studies could be seen as a limitation of the proposed work, although it has been partially overcome by the definition of an *ad hoc* set of measures for evaluating the effectiveness of the IV-T approach.

Starting from this work, some interesting future research directions can be outlined. An interesting future research activity concerns the application of the IV-T procedure to different warehouse layouts. In line with the fact that this study aimed at providing a proof-of-concept of the new allocation procedure, a fixed warehouse layout has been taken into account for the application of the IV-T allocation. However, the warehouse layout has implications on picker routing and items allocation; therefore, evaluating different layouts could be important to substantiate the results obtained in this study. As a second point, items with different demand values (e.g., fast moving vs. slow moving items, or items with seasonal demand trend) could be taken into account in the application of the IV-T allocation, to check whether the proposed approach is effective in determining an allocation that well captures this specific item characteristic.

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Appendix

Product categories	Space	Demand	Profitability	Popularity
A1	[5; 5]	[208; 230]	[0.13; 0.15]	[101; 111]
A2	[6; 6]	[62; 68]	[0.19; 0.21]	[103; 113]
A3	[8; 8]	[38; 42]	[0.73; 0.80]	[158; 174]
A4	[2; 2]	[249; 275]	[0.86; 0.95]	[459; 500]
A5	[2; 2]	[1218; 1346]	[0.59; 0.65]	[366; 404]
A6	[7; 7]	[7; 7]	[0.94; 1.00]	[181; 200]
A7	[10; 10]	[592; 654]	[0.84; 0.92]	[439; 485]
A8	[5; 5]	[422; 450]	[0.50; 0.55]	[430; 476]
A9	[2; 2]	[108; 120]	[0.17, 0.19]	[391; 433]
A10	[7; 7]	[54; 60]	[0.22; 0.24]	[185; 205]
A11	[3; 3]	[306; 327]	[0.75; 0.83]	[439; 485]
A12	[3; 3]	[829; 917]	[0.59; 0.66]	[449; 497]
A13	[8; 8]	[849; 939]	[0.71; 0.79]	[106; 118]
A14	[3; 3]	[1,201; 1,327]	[0.52; 0.58]	[355; 393]
A15	[3; 3]	[862; 952]	[0.58; 0.64]	[103; 113]
A16	[2; 2]	[509; 563]	[0.84; 0.93]	[371; 410]
A17	[6; 6]	[126; 140]	[0.66; 0.73]	[237; 261]
A18	[5; 5]	[247; 273]	[0.66; 0.72]	[344; 380]
A19	[2; 2]	[28; 30]	[0.76; 0.84]	[393; 435]
A20	[2; 2]	[53; 59]	[0.90; 1.00]	[371; 411]
A21	[2; 2]	[199; 219]	[0.14; 0.16]	[116; 128]
A22	[5; 5]	[72; 80]	[0.91; 1.00]	[295; 327]
A23	[9; 9]	[597; 659]	[0.92; 1.00]	[469; 500]

A24	[2; 2]	[139; 153]	[0.02; 0.02]	[100; 108]
A25	[3; 3]	[280; 310]	[0.50; 0.56]	[439; 485]
A26	[4; 4]	[40; 42]	[0.69; 0.76]	[344; 380]
A27	[3; 3]	[85; 93	[0.61; 0.68]	[429; 475]
A28	[4; 4]	[85; 93]	[0.13; 015]	[425; 469]
A29	[4; 4]	[150; 166]	[0.88; 0.97]	[473; 500]
A30	[5; 5]	[1,447; 1,599]	[0.68; 0.75]	[162; 179]
A31	[5; 5]	[1,002; 1,108]	[0.07; 0.07]	[102; 112]
A32	[10; 10]	[281; 295]	[0.82; 0.90]	[428; 473]
A33	[9; 9]	[295; 326]	[0.67; 0.74]	[473; 500]
A34	[5; 5]	[1,198; 1,300]	[0.55; 0.61]	[225; 249]
A35	[7; 7]	[653; 721]	[0.25; 0.28]	[239; 265]
A36	[4; 4]	[204; 226]	[0.57; 0.63]	[153; 169]
A37	[7; 7]	[189; 209]	[0.55; 0.60]	[305; 337]
A38	[5; 5]	[248; 274]	[0.64; 0.71]	[100; 107]
A39	[3; 3]	[76; 84]	[0.53; 0.58]	[146; 162]
A40	[6; 6]	[237; 261]	[0.43; 0.48]	[208; 230]
A41	[5; 5]	[1,024; 1,132]	[0.14; 0.15]	[160; 176]
A42	[3; 3]	[1,258; 1,390]	[0.82; 0.90]	[280; 310]
A43	[3; 3]	[47; 51]	[0.24; 0.26]	[199; 219]
A44	[5; 5]	[23; 25]	[0.73; 0.81]	[392; 434]
A45	[10; 10]	[1,632; 1,720]	[0.07; 0.08]	[219; 242]
A46	[2; 2]	[430; 462]	[0.43; 0.47]	[453; 500]
A47	[2; 2]	[102; 112]	[0.90; 0.99]	[455; 500]
A48	[2; 2]	[537; 593]	[0.31; 0.35]	[271; 299]
A49	[4; 4]	[1,394; 1,540]	[0.72; 0.79]	[290; 320]
A50	[5; 5]	[190; 210]	[0.45; 0.50]	[201; 223]
A51	[3; 3]	[135; 149]	[0.29; 0.32]	[242; 268]
A52	[10; 10]	[452; 490]	[0.68; 0.75]	[371; 410]
A53	[9; 9]	[1,424; 1,574]	[0.55; 0.61]	[273; 301]
A54	[3; 3]	[225; 249]	[0.52; 0.58]	[260; 288]
A55	[5; 5]	[202; 224]	[0.67; 0.74]	[312; 344]
A56	[5; 5]	[333, 369]	[0.41; 0.45]	[155; 171]
A57	[2; 2]	[155; 171]	[0.63; 0.70]	[167; 185]
A58	[2; 2]	[8; 8]	[0.50; 0.55]	[400; 442]
A59	[4; 4]	[607; 671]	[0.59; 0,65]	[403; 445]

A60	[3; 3]	[210; 228]	[0.65; 0.72]	[330; 364]

Table 6: Decision matrix for the IV-T approach.

S_0	**S_1**	**S_2**	**S_3**	**S_4**	**S_5**	**S_6**	**S_7**	**S_8**
A49	A49	A49	A49	A49	A49	A49	A49	A49
A42	A42	A42	A42	A42	A42	A42	A42	A42
A5	A5	A5	A5	A5	A5	A5	A5	A5
A14	A14	A30	A14	A14	A14	A14	A14	A30
A30	A30	A14	A30	A30	A30	A30	A30	A14
A34	A12	A34	A34	A12	A53	A12	A34	A34
A12	A34	A53	A12	A34	A34	A34	A12	A53
A53	A53	A12	A53	A53	A12	A16	A53	A12
A16	A16	A45	A16	A16	A45	A53	A45	A16
A45	A15	A15	A15	A45	A16	A4	A16	A15
A15	A59	A16	A4	A59	A15	A59	A15	A45
A59	A4	A59	A59	A4	A59	A15	A59	A59
A4	A45	A41	A45	A15	A23	A11	A4	A4
A23	A46	A4	A23	A23	A4	A47	A41	A41
A11	A11	A23	A47	A46	A11	A46	A46	A23
A46	A47	A31	A11	A11	A41	A23	A11	A11
A47	A41	A46	A46	A47	A7	A45	A23	A46
A41	A23	A13	A29	A29	A47	A29	A47	A47
A29	A20	A11	A20	A41	A46	A20	A31	A13
A20	A29	A47	A7	A7	A13	A19	A48	A31
A7	A48	A7	A13	A20	A29	A25	A29	A20
A13	A25	A48	A41	A25	A20	A7	A20	A29
A48	A19	A29	A19	A48	A31	A48	A13	A48
A31	A31	A20	A25	A19	A48	A41	A7	A7
A25	A13	A25	A48	A8	A25	A8	A25	A19
A19	A7	A8	A8	A13	A8	A60	A8	A25
A8	A8	A19	A31	A31	A19	A27	A19	A8
A60	A60	A60	A60	A27	A60	A13	A60	A60
A27	A27	A27	A27	A60	A27	A58	A27	A27
A58	A58	A58	A22	A58	A22	A22	A58	A57
A22	A57	A22	A18	A22	A32	A31	A57	A22
A18	A22	A18	A58	A18	A18	A18	A18	A58

A57	A54	A57	A57	A32	A33	A57	A54	A18
A54	A18	A32	A32	A44	A58	A44	A9	A54
A44	A9	A54	A44	A33	A52	A26	A22	A26
A26	A26	A52	A26	A57	A44	A54	A26	A44
A32	A44	A33	A55	A26	A57	A55	A44	A55
A55	A55	A44	A54	A54	A26	A32	A32	A32
A33	A32	A26	A33	A9	A55	A9	A55	A9
A9	A33	A35	A52	A55	A54	A33	A33	A52
A52	A52	A55	A9	A52	A9	A52	A52	A33
A35	A36	A9	A6	A35	A35	A36	A35	A35
A36	A39	A36	A36	A28	A6	A39	A28	A36
A39	A21	A38	A38	A36	A36	A6	A36	A39
A6	A51	A39	A39	A6	A38	A28	A39	A38
A38	A35	A6	A35	A39	A28	A38	A21	A6
A28	A28	A28	A17	A38	A39	A51	A51	A21
A51	A38	A21	A28	A51	A17	A17	A38	A51
A21	A6	A51	A51	A17	A51	A35	A24	A17
A17	A24	A17	A21	A21	A37	A21	A6	A28
A56	A17	A56	A37	A37	A21	A37	A17	A56
A24	A56	A24	A56	A56	A56	A56	A56	A24
A37	A43	A37	A50	A24	A50	A24	A43	A50
A50	A50	A50	A3	A50	A3	A43	A37	A43
A43	A37	A43	A24	A43	A24	A50	A50	A37
A40	A40	A40	A43	A40	A43	A40	A40	A40
A3	A3	A3	A40	A3	A40	A3	A3	A3
A1	A1	A1	A1	A1	A1	A1	A1	A1
A2	A2	A2	A2	A2	A2	A2	A2	A2
A10	A10	A10	A10	A10	A10	A10	A10	A10

Table 7: Ranking obtained with different criteria weights (scenarios S_0-S_8).