# SIMULATION STUDY ON A WAREHOUSE PICKING PROCESS TAKING INTO ACCOUNT A PREDETERMINED ORDER OF FURTHER GOODS LOADING 


#### Abstract

Keywords: Logistics; Order-picking; Simulation; Routing; Warehouse management In this article, the results of a series of selected algorithms used during the picking of goods in a warehouse, assuming the order of stacking goods in transport containers is predetermined, are analysed, simulated and evaluated. The importance of the development of this type of algorithms is the possibility of reducing the waiting time of both transport and goods in order to reduce the total cost of the picking process. Afterwards, the results will be analysed by varying the parameters and evaluating the solutions. The aim is to show the results of various picking algorithms when their subsequent stacking order is predetermined, and to use these to identify relationships and define guidelines that could be used to support the design of similar picking algorithms.


## 1. INTRODUCTION

The warehouses and distribution centres, as well as the quantity and variety of products handled, are growing steadily and rapidly. Logistics companies are increasingly in demand and need to improve their algorithms and solutions.

The competitive advantage of companies implementing solutions and algorithms comes with the responsibility that the strategy can be supported by the logistics operation of the distribution centre. This is where the order picking of the products on the pallets comes into play, as the profile of the products changes from time to time and the way they are placed on the pallets and in the warehouse has to be redesigned. Picking algorithms are also important for warehouses, even if the assortment does not change. Each delivery to a customer must be prepared individually because each customer wants specific goods. This is especially important for warehouses in airports or logistics centres.

[^0]Logistics and picking optimisation projects in warehouses ultimately reduce product waiting times, transport and, in short, costs. Optimisation processes involve concepts, tools and heuristics and operations research models that are coupled to improve and design operations and strategies involved in warehouse logistics management. Environmental logistics is also taken into account, which seeks sustainable policies aimed at reducing the environmental impact of this business's activities.

Finally, we know that achieving a more efficient storage facility follows the precepts of environmental logistics: reducing waste through a global improvement of processes. Therefore, reducing movements within the warehouse thanks to a combination of good storage location management and optimised picking planning is key to approaching environmental logistics.

## 2. ANTECEDENT WORKS

### 2.1. WAREHOUSE CONFIGURATION

The layout of the warehouse in terms of the general type of warehouse considered, racking levels, the number and location of the depot (end zone) and various characteristics of the aisles is a determining factor in improving picking times [1, 2]. Three types of warehouses can be distinguished in terms of their configuration: conventional (with a rectangular shape and parallel and perpendicular aisles), non-conventional (they do not have all their aisles parallel) and general (in which distance matrices are used) [2].

Within the warehouse layout, it is also necessary to define the number and location of the products and the characteristics of the aisles (narrows, that can lead to blocking situations if there are several pickers, or wides) [3].

Finally, regarding the configuration of the warehouse, it must be taken into account whether the racks have one or more levels and, in the latter case, whether the upper levels are for storage and picking or only for storage (and when they go down to the lower level, they can be picked) [4].

### 2.2. STORAGE ASSIGNMENT POLICY

The storage policy refers to the way in which specific points are designated where each product should be placed within the warehouse [4] to achieve high space utilisation and to facilitate efficient material handling [5]. The storage location allocation problem (SLAP) consists of allocating incoming products to storage areas. It aims at reducing material handling costs and improving space utilisation.

There are several ways to allocate products to a certain location within the warehouse $[6,7]$ : as dedicated storage, random storage, nearest open location storage, full-rotation (or rotational) storage or family-based storage.

The concept of class-based warehousing combines the previously mentioned methods. One way of dividing items into classes according to their popularity is the Pareto method, and the ABC classification is based on this rule [8]. The idea is to group products into classes determined by the frequency of demand for the products. The products with the highest turnover are called A items; those belonging to the next category (a lower turnover than A ) are known as B , and so on $[6,7]$. Even if the layout of the picking area is ideal, even if good storage and routing methods are applied, the efficiency of the process will not improve as much. Therefore, the decision on the configuration of the picking area in the warehouse must be carefully considered [1].

### 2.3. PICKING LIST

In the case of order picking systems, orders are received to form a picking list. This list indicates the products for the order picker to move down the aisles and pick the products from their locations in the warehouse [9]. There are two main types of heuristics that attempt to minimise the total picking effort for a list and are based on the VRP heuristic. The VRP is the vehicle routing problem, where "stops" are assigned to routes and the objective is to minimise the total route distance or time. The two types of heuristics are defined as follows [5].

A seed algorithm initially selects a single seed order in the list. More orders are then added to the list based on a route proximity criterion until no more orders can be added due to a capacity constraint. A savings heuristic starts by assigning each order to a separate list. The algorithm then selects a pair of orders to combine and adds to the list iteratively based on the savings from combining them until no more orders can be combined due to a constraint.

In addition, the order list algorithms can be static or dynamic, i.e. with preparation orders that are triggered continuously or discretely. Information about this can be found in [1], [2], [5] or in [7].

### 2.4. PICKER; ORDER-PICKING SYSTEMS

Order picking systems can be classified as can be found in Fig. 1. Among the systems that employ humans, the first to be found are the picker-to-parts systems. In these, it is the order picker who walks or drives different maintenance equipment through the aisles in order to pick the materials. This is the most common order picking system $[6,7]$. It can be distinguished into two types: low-level picking and high-level picking, depending on whether vertical movements are necessary to reach the products on the racks $[2,6]$.

Parts-to-picker systems include automated storage and retrieval systems. It is also referred to as unit load or end-of-aisle order picking. In this case, it is the goods that are moved to the location of the personnel using automated storage systems [6, 7].

Put systems are based on a process of first picking and then distributing. First, the items have to be retrieved, which is done in such a way that the parts are retrieved with a picker-to-parts system or a parts-to-picker system. Secondly, the carrier with these previously collected units is offered to an order picker who distributes them between the different customers' boxes [6].


Fig. 1. Method programming flowchart. Source: own elaboration on the basis of [6].
In these order picking systems, the human being is the most important element, as the picking of products of different sizes and shapes works best. An issue to consider when picking is done by humans is that employees cannot learn the new routes that exact algorithms set for each change in order lists. Therefore, heuristic algorithms will, in this case, be preferable to exact results [4].

Finally, the main characteristic of automated and robotic systems is the absence of personnel involvement in picking [10].

### 2.5. PICKING POLICY

Picking policies focus on the division of labour among the workers, so that the picking time, according to the order picking list, is as short as possible [11]. There are various approaches to picking policy. Strict order picking is used when orders are quite large and each order can be picked individually, i.e. a single order is picked directly by one worker. Batch picking is used when orders are small.Several orders can be combined in a batch to reduce travel distances by picking a set of orders during a single picking route [6,11]. Thus, a worker is assigned a picking list with more than one number of orders to pick simultaneously in a single trip [2, 12].

In zone picking, the storage area is divided into logical zones so that each picker is assigned to pick only the part of the products on the picking list in that sub-zone. Depending on the picking strategy, zone picking can be further classified into three types. The first are sequential progressive zoning and parallel synchronised zoning, depending on whether orders picked in one zone are passed on to other zones for completion or picked in parallel. And the last is wave picking, where an employee picks large batches of goods continuously, not according to the products on the order
list but according to the items ordered in his zones. Then the orders are prepared according to the goods that have been picked $[6,11]$.

### 2.6. ORDER PICKING ROUTES

The objective of order picking in the warehouse is to sequence the items on the pick list to ensure the best sequence of locations to pick a given set of items [5, 6]. The aim is to minimise the total material moving cost. As the distance to the picked items is proportional to the travel time to pick them, minimising the time means minimising the distances [9] and therefore the total cost. Reducing this length of picking routes will therefore reduce the time it takes a worker to prepare the order.

The characteristics of three general types of algorithms used to solve the order picker routing problem are presented next. Exact algorithms always find an optimal solution (i.e., the shortest route) to an order picker routing problem [2]. This optimal routing procedure minimises the total travel distance and is based on the algorithm presented by Ratliff and Rosenthal in [13]. Heuristics are problem-dependent algorithms that are constructed according to their specifications, with a solution that in most cases is not optimal but similar to algorithms with exact results [2, 4]. That is, heuristic strategies can provide near-optimal routes and are easier to understand [7]. Finally, meta-heuristics are algorithms that provide a set of guidelines or strategies for solving a problem [2].

To prepare an order, a picker may travel through the aisles of a warehouse following different routes. In practice, the problem of assigning routes to order pickers in a warehouse is mainly solved by using simple heuristics [6, 7]. Below we describe the five main heuristic methods for defining picking routes.

The S-shaped tactic is one of the simplest strategies. The employee moves between the shelves in a defined manner, starts at the beginning of an aisle and does not move to the next aisle until he has picked all the goods in that aisle, leaving the aisle at the other end [4, 7]. It only enters those aisles where there are references to be picked during the route and travels along them completely. From the last aisle visited, the order picker returns to the depot $[6,7]$.

The next strategy is the return tactic. The picker enters and exits an aisle from the same transverse front aisle, moves to the last item on the pick list in that aisle, and only enters aisles that contain references to be picked [4, 7]. Once the order picker has picked the last item, he returns to the front end of the aisle and continues to the next aisle with the same rule [2].

The third tactic is the mid-point strategy. The warehouse is divided into two zones and the operator moves along the front cross aisle to the centre of the warehouse (the midpoint) to pick the picks from the front half, which is the margin of zone 1. Products from zone 2 are picked from the back cross aisle. The order picker goes to the back half through the last aisle he visits [4, 6]. The picker enters and exits each aisle
from the same cross aisle [2]. Therefore, the order picker takes a return route from the front cross aisle to the middle point and a return route from the back aisle [7].

The largest gap strategy is similar to the mid-point strategy, except that the preparer travels down each aisle to the largest gap within an aisle, which is the part of the aisle that the order picker does not pass through. As in the case of the mid-point strategy, the order picker first completes the front part of the warehouse and then moves to the back part to pick the requested items there [2].

The composite routing strategy combines the best features of the S-shaped and return strategies but is more complex to implement [7]. Aisles with picks are either fully traversed or entered and exited at the same end. However, for each corridor visited, the choice depends on the heuristic that gives the shortest travel distance to retrieve the furthest requested items from two adjacent aisles [2].

### 2.7. MAIN CONTRIBUTION

With all the information gathered, a series of algorithms that meet different design requirements are designed and, with them, the effectiveness of using or not using a predetermined order of subsequent loads to build our picking list is simulated, analysed and evaluated. In this way, the designed algorithms will order the picking lists according to standard return and S-shaped tactics (as detailed in the previous section). In addition, the same algorithms will also be modified to pick the products according to their location but prioritising the picking in the order of the layers of the subsequent palletisation. In other words, in the methods called in the paper "layered methods", first the heaviest items from layer 1 will be picked, then those from layer 2 and finally the lightest ones from layer 3. In other words, knowledge is presented that helps to discern in which cases it is more convenient to consider the order of subsequent loads to pick our products and in which cases it would be inconvenient or unnecessary to take it into account.

## 3. DESCRIPTION OF THE PROBLEM AND ASSUMPTIONS

### 3.1. DESCRIPTION OF THE WAREHOUSE

In the simulated warehouse are stored the goods that will be sent to the company's intermediaries or final customers. This warehouse is rectangular and has parallel aisles of equal length. It is therefore a block-type warehouse [9] with narrow aisles (lateral movement within an aisle is not taken into account, as this is minimal).

The warehouse has an assortment of 120 different items (material indices) which are stored in 120 different locations. The boxes are placed in rows, side by side, connected by longer sides [1]. The racks have several levels, but we only take into
account the lower level, at floor level, from which picking takes place. The replenishment of the lower level is considered to be automatic and instantaneous, and there is never an out-of-stock situation. We can also collect on the same order list, and even consecutively, the same goods twice $[4,11]$.

The main aisles have a width of 2 metres and a length of 15 m . The width of the cross aisles, which separate the rows where goods can be picked, is 1.2 m . As it has been said in the previous section, long side aisles do not work well because they do not allow for quick aisle changes, so the length of these aisles may not exceed 5 m .

### 3.2. ALLOCATION AND PICKING POLICY

A strategy for storage policy is followed. As discussed and explained in [1], each good has its own location in the warehouse, a specific and unique place assigned to it within a single aisle. For this, the most important thing is that the products with the fastest turnover times have the shortest distances to the finishing area, so that the total route distance and picking times will decrease [4]. It has also been seen in [1] that ABC classification gives the best results with in-aisle storage, for this it is used the ABC classification and also store the goods according to dimensions.

As seen in [9], when the order arrival rate increases, it is better to work with a static order scenario (SOP). It developed strict discrete order picking [11] from the order picking policy approaches seen in section 2.6 , in which a single employee is assigned to pick an order. As only one operator is working, there will be no blocking situation [4].

### 3.3. MEANS OF TRANSPORT AND END ZONE

All movements are carried out by one employee with a single handling device to place the products while picking them up. This vehicle has limited space available for transporting goods and that limits the weight capacity. Therefore, with a single picking route, it can pick and transport more than one item from the shelves to a finishing area. But also, if an order requires more goods than the vehicle can handle, picking will be done in several trips, adding up the total distances to and from the route [11].

As mentioned, there will be a weight limitation on the total weight of boxes picked up on each route. However, with regard to the boxes, boxes weighing more than 25 kg are not taken into account, as it would not make sense to manually pick and organise the pallets.

The employee, as mentioned above, carries the goods from the warehouse to the end zone. This finishing area is adjacent to the place where the pallets are loaded and the goods are temporarily stored, waiting to leave the warehouse or go beyond the limits of our warehouse.

The goods are transported from the finishing area to their next destination on pallets. The layout of the pallets takes into account the weight of the goods placed on a pallet and its dimensions. Thus, the arrangement involves the sequence in which the goods are stacked (i.e. the first layer is dedicated to heavier goods, the second to lighter ones, etc.).

Due to the subsequent palletisation of the goods, three different ranges of weight are considered, in kg , of our goods: 20-25 kg boxes (layer 1), $10-19 \mathrm{~kg}$ boxes (layer $2)$ and $5-9 \mathrm{~kg}$ boxes (layer 3 ).

### 3.4. SCIENTIFIC PROBLEM

The transport of the goods to the finishing area, their loading onto a pallet, as well as the process of relocation of the goods waiting to be placed on a higher layer on the pallet, generates costs (proportional to the mass of the goods transported and loaded as well as proportional to the length of the transport and of the goods' movements during loading/relocation) expressed by $€ /($ tonne $\cdot \mathrm{km})$. Also, the waiting cost is taken into account;, each specific item on the collection lists has one ( $€ / \mathrm{min}$ ).

The total waiting cost of a picking list is calculated by considering the waiting time for each item from the time an item is collected until the end of the collection list. This time is multiplied by the waiting cost of that particular item, and summed up to get the total waiting cost of the list. Waiting costs for items increase as the item's weight decreases. Thus, the later the lighter items (those in layer 3, which will go on top of everything in the palletisation) are picked up and transported to the end point, the lower the waiting cost will be. The objective is to determine whether picking in the same order in which the pallet is prepared will result in greater cost savings.

The scientific problem is: how to organise the picking process in the warehouse in order to obtain the best (cheapest) solutions, i.e. the cheapest transport and the goods correctly arranged on a pallet.

## 4. PROGRAMME MODELLING

The following is a flowchart (Fig. 2) of how the model will be programmed from data to result collection.

It starts by generating the data of all the products in the warehouse (the location, the weight of the goods, the layer in which they will be placed on the subsequent pallet, etc.) and the picking time data. Then this product data is passed to picking lists of different lengths or numbers of products. The following table (Tab. 1) shows the most important values for the configuration of the warehouse and the goods.

One of the generated lists is taken and sorted to calculate the route according to the corresponding algorithm. Once the route has been calculated, the route distances,
route times and waiting times of the products are obtained. Finally, all the results are collected and analysed.


Fig. 2. Method programming flowchart. Source: own elaboration.
Tab. 1. Warehouse data values. Source: own elaboration

| № of aisles |  |  | 6 |
| :---: | :---: | :---: | :---: |
| No. of items in each aisle |  |  | 20 |
| Distance between aisles [m] |  |  | 2,5 |
| Distance between items (same aisle) [m] |  |  | 0,5 |
| Distance from aisle to rack (1st item) [m] |  |  | 1 |
| Maximum aisle coordinate (j) [m] |  |  | 6,5 |
| Pallet layer | Max. Weight | Min weight |  |
| 1 | 20 | 25 |  |
| 2 | 10 | 19 |  |
| 3 | 5 | 9 |  |

## 5. RESULTS AND DISCUSSION

For the simulations, 3 variables were taken into account: the limitation of the weight that can be picked on each picking route, the ABC distribution of the picking list and the number of items in the picking list. In each set of simulations (except the first one), one of these variables is fixed. Below (Tab. 2) is a summary table of the variations carried out in each set of simulations. The cells marked are the values that remain fixed in each set of simulations. Also, the ABC classification data shown in the subsequent Figures are represented on the X -axis of their graphs as follows (Tab. 2) i.e. $\mathrm{ABC}=50 / 30 / 20$ is $50 \%$ of the products in the picking list are A products, $30 \%$ are B items and $20 \%$ are C items.

The results obtained for each routing method are: Distance (m), Distance with mass ( $\mathrm{m} \cdot \mathrm{kg}$ ), Time (min), Transport costs (Euros) and Waiting cost (Euros). For all figures, the legend is as follows (Fig. 3):

$$
\longrightarrow \text { S Shape } \rightarrow-\text { Return tactic } \quad \rightarrow-S \text { shape with layers } \rightarrow \text { Return tactic with layers }
$$

Fig. 3. Warehouse data values. Source: own elaboration.
Tab. 2. Summary table restrictions in the sets of simulations and the representation of the ABC classification values on the X -axis. Source: own elaboration

| SET | No of items | A | B | C | Max weight |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 50 | 70 | 20 | 10 | 100 |
| 2 | 50 | 70 | 20 | 10 | 50 |
| 3 | 50 | 70 | 20 | 10 | 150 |
| 4 | 20 | 70 | 20 | 10 | 100 |
| 5 | 90 | 70 | 20 | 10 | 100 |
| 6 | 50 | 50 | 30 | 20 | 100 |
| 7 | 50 | 80 | 15 | 5 | 100 |


| ABC classification | X-axis representation |
| :---: | :---: |
| $50 / 30 / 20$ | 1 |
| $55 / 25 / 20$ | 2 |
| $55 / 30 / 15$ | 3 |
| $60 / 25 / 15$ | 4 |
| $60 / 30 / 10$ | 5 |
| $65 / 20 / 15$ | 6 |
| $65 / 25 / 10$ | 7 |
| $70 / 20 / 10$ | 8 |
| $75 / 15 / 10$ | 9 |
| $80 / 10 / 10$ | 10 |
| $80 / 15 / 5$ | 11 |

In the following Fig. 4, it can be seen the results concerning the first set of simulations. In the first set (Fig. 4, first column), it is noticed how the travelled distance decreases as the maximum weight that can be carried on each route increases, which is normal considering that the more weight on each route, the fewer routes are necessary to collect a complete list. The same happens with the time and cost of waiting.


Fig. 4. Maximum weight, ABC and number of items variation graphs for set 1 (Fixed values change between 50 products list with a maximum picking mass of 100 kg in one route, with the distribution $70 \% \mathrm{~A}, 20 \% \mathrm{~B}$ and $10 \% \mathrm{C}$. Source: own elaboration.

It can be seen that the transport costs increase with the maximum weight, and the increase is more important in the layered methods. This is because of the accumulation of much more mass and distance on the routes, and this is reflected in this result. As you can see, it will be similar in the rest of the results, the distance, time and transport costs are lower in the methods that do not take into account the subsequent palletisation, but the cost of waiting for the products is lower in the layered methods.

In the same set of results (Fig. 4, middle column), it is analysed how the ABC variation of the products in the list gives, in all cases, decreasing trends, i.e. it is best to have as many A items in our lists as possible, as this way distances, time and costs will be reduced, which is logical since these items are closer to the end zone. Again, it can be seen that the methods without layers have better results when it comes to distance, time and transport cost, and the methods with layers have better results when it comes to waiting cost.

Finally, in this set (Fig. 4, last column), and as expected, as the number of products in the list grows, so do distances, times and costs. Waiting time grows with a trend that would like to be exponential while time and distance grow in a proportional way. Both in distance and, above all, in transport costs, this change is more important for the layered methods as they grow faster than the methods that do not consider the subsequent order of palletisation, and the opposite happens in the waiting times.

Now interesting results from the next sets presented in Tab. 2 will be compared. For example, in the case of light routes, set 2 of Tab. 2, when the maximum weight is only 50 kg , the results of the distance graphs have similar results for the normal S-shaped method and the palletised return method (Fig. 5, left graph), which makes sense because for the same list it will have to make a greater number of routes to pick all the items as our weight limitation is lower. The results are also less satisfactory for the cost and time results. In the number of items variable graph (Fig. 5, middle graph) it can be seen again that the results for time, when performing such a large number of routes for a list, are very close, not different methods.


Fig. 5. ABC (left) and number of items (middle graph) variation graphs for set 2 (Fixed value: maximum picking mass of 50 kg in one route) and ABC variation graph for set 3 (right) (Fixed value: maximum picking mass of 150 kg in one route). Source: own elaboration.

Now the other extreme, heavy routes Fig. 5 right (set 3 of Tab. 2), which have better results for distance, time and waiting costs, but when it comes to transport
costs, especially in the case of layered algorithms, they skyrocket. This is because a lot of distance and mass is accumulated on the routes, making transporting the items heavier and more costly.

As expected, at the routes of short lists (Fig. 6, left column, set 4 of Tab. 2), the results with lists with fewer items are better than with long lists. The graphs behave similarly to the set 1 graphs. Long list (Fig. 6, right column) routes also behave in a similar way. In this case, as the number of items to be collected is greater, so are the distances, times and costs.


Fig. 6. Maximum weight variation graphs for sets 4 and 5 (Fixed values: 20 products list for set 4 on the left and 90 product list for set 5 on the right). Source: own elaboration.

Finally, in the last two sets (sets 6 and 7 of Tab. 2), it can be seen how the results vary while keeping the ABC configuration of the picking list constant. It is interesting to see how the graphs are practically the same in the standard case (set 1 ) and in these ones. Taking a look at the axes, the lists with fewer A items (Fig. 7, left column, set 6 of Tab. 2) are shifted upwards, which is normal since, as said before, these lists should pick more products farther away from the end zone. With respect to the changes in distance and time, the changes in time and waiting cost are less significant. Similarly for the lists with more A items (Fig. 7 right column, set 7 of Tab. 2),
these are shifted downwards, and again, the results are very similar for time, transport cost and waiting cost.


Fig. 7. Maximum weight variation graphs for sets 6 and 7 (Fixed values: the distribution $50 \%$ A, $30 \% \mathrm{~B}$ and $20 \%$ C for set 6 on the left and distribution $80 \% \mathrm{~A}, 15 \%$ B and $5 \% \mathrm{C}$ product list for set 7 on the right). Source: own elaboration.

## 6. SUMMARY OF RESULTS

Summarising, considering that the proposed results of the "layered" algorithms are those that assume that the posterior order of stacking goods in transport containers is predetermined, in general, the return method (without taking into account the layers) gives the best results in terms of total distance travelled. The S-shaped method gives better results in terms of total collection time and transport costs (except for light routes in set 2, Fig. 5, left and middle graphs). On the other hand, it is the methods that do take into account the subsequent order of palletisation of the products that give the lowest waiting costs, especially the S -shaped layer method.

## 7. CONCLUSION

It would be necessary to evaluate what interest or weight we give to the different costs derived from the transport and waiting time of the goods. In cases where transport costs within the warehouse are low, it would be much more beneficial to apply a routing method that takes into account the subsequent palletisation order. This would be especially true in the case of short picking lists (Fig. 6, left column).

On the other hand, when the total picking routes are very long (Fig. 6, right column, set 5 of Tab. 2) and the transport costs increase and far exceed the waiting costs, it would not make sense to take the subsequent palletisation order into account, because it would only further increase picking distances and picking times.

Finally, before starting the development of a warehouse project, it is important to have a good pre-design. That is, take into account the products, the way of sorting them, the methods used for picking, and a pre-analysis of how to save on these picks, which will be the best algorithm. And as for future lines of research, the size of the warehouse in general could be varied, to see, in that case, how the model behaves and to have information on the results of the simulations for large and small warehouses.

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