# Improvement in inventory control and products layout in a multiclient warehouse

## The Torrestir Logistics case study

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## Abstract

Warehouses play a crucial role in supply chains. Its management must be rigorous to reach the increasingly demanding levels of customers. When this is the case, warehouses can provide lower transportation costs, reduce delivery times, and minimize the effects of demand uncertainty, among other advantages. Torrestir Logística is a Portuguese logistics and storage services provider that owns a 25.000 m$^2$ warehouse in Azambuja. This warehouse is multiclient, and it provides services to more than 25 clients. The company's managers have realized that high operating costs have become a problem. To overcome these high costs, they consider that the solution should focus on two critical factors: inventory control; and the layout of the products in the storage areas. So, this work's main objective is to improve the inventory control process for a particular customer by implementing a cycle counting methodology and other strategies to improve the location of items, such as family grouping, ABC analysis, and demand correlation analysis.

Concerning the cycle counting methodology, it was possible to calculate an initial Inventory Record Accuracy (IRA) of 88% for the customer under study. The possible causes for this low value were studied to eliminate them and increase the IRA to values close to 100% and decrease the operational costs. The results also showed the layout changes resulted in a 33% reduction in time per unit in picking. This reduction can generate an annual saving of around 4.200 euros in the customer's operations alone. These results show that the objectives have been achieved. It is predictable that, if the company implements the same measures for other customers, the savings will be even more significant.

**Key word:** Inventory control; Cycle counting; Family grouping; ABC Analysis; Demand correlation analysis.

## 1. Introduction

In supply chains, optimization has proved to be essential for the competitiveness of companies. The competition in the market and the increasing demand from customers, who expect speed and quality at the lowest cost (Hompel & Schmidt, 2007) requires continuous improvement in the design and operation of production-distribution networks, which in turn, requires a higher performance of warehouses (Gu et al., 2007). The challenges for storage systems, which represent between 20 and 30 percent of a company's total logistics costs (Richards, 2018), are increasing, inventory control must be more rigorous, response time shorter and product variety greater (Gu et al., 2007). These factors have led many companies to pass on their logistics and warehousing services to third parties, taking advantage of their expertise, technology and cheaper labour (Maltz & Dehoratius, 2004).

The warehouse under study belongs to a Portuguese Third-Party Logistics (3PL), Torrestir Logística (TorresLog), and has about 25,000 m$^2$. This warehouse is multiclient and serves more than 25 companies from completely different business areas, dimensions and requirements. It is TorresLog's responsibility to manage the operations of the warehouse in order to meet the requirements of customers, receiving and sending material according to their needs. In this context, the operation of the warehouse becomes something complex and must be managed in a rigorous way so that it is possible to take its maximum profitability. To achieve this, it is necessary to have a great control over operational costs, which warehouse managers consider to have been at very high levels, becoming a problem.

With the implementation of measures aimed to improving inventory control processes and warehouse layout (more specifically the location of items), developed in this case study, it is intended to achieve the objective of contributing positively to the resolution of the problem faced by the company, the high operating costs. To improve inventory control and thus increase the accuracy of records, a cycle counting methodology is implemented, contrary to the usual annual counting performed by the company. Regarding product layout, several methodologies are implemented, specifically family grouping, ABC analysis and demand correlation analysis.

Section 2 of this document contextualizes the case study and section 3 presents a review of the literature on the methodologies to be implemented. Sections 4 and 5 present the interventions made in the warehouse and their results. Finally, in section 6 the main conclusions and recommendations for future work are discussed.

## 2. Presentation of the case study

In a 3PL company like TorresLog, the operational costs have a great influence on all the warehouse management. These costs cause a decrease in the profitability of the warehouse, which corresponds, in this case, to the value that the client pays for a certain area less the cost of that occupied area. The costs corresponding to these areas (where the operational costs correspond to a large percentage) are the factor that can make profitability vary the most, with two main scenarios. On the one hand, if the costs are high, the company's profitability will be low, which may take away capacity for new investments or to remain competitive with the competitors. On the other hand, if costs are low profitability may be higher and therefore there will be more capacity for new investments, but there will also be more capacity to lower prices to customers and thus remain more competitive with the competitors. With the objective of reducing these costs, the company managers understand that there are two processes that can be improved: the inventory control; and the location of the items in the storage areas.

In order to test the impact of the measures in the warehouse, a client was chosen for intervention. If the implemented measures prove to be beneficial, the objective is to implement them in the remaining clients. The client chosen for the intervention was Client X (so named due to data confidentiality issues). This client is a company dedicated to importing and distributing pet food brands in Portugal, namely cats and dogs. Client X is present in stores throughout the country and in the warehouse under study are stored all the products to be distributed in Portugal, amounting to 200 SKUs. The decision to choose this client was based on the fact it was an important but medium sized client and because there was an acknowledgement that neither the inventory control was satisfactory, nor the location measures of the products were generating benefits to the operation.

### *2.1. Inventory control*

TorresLog currently has an inventory control plan that is not allowing to minimize inaccuracies. These inaccuracies in the inventory increase the company's operating costs, which has a negative impact on the warehouse's profitability. Some of the costs may come from stock breakdowns or storage locations that are occupied with excess product, often consequences of discrepancies between the actual physical stock and what is inserted in the system, but also from " penalties " applied by the client. Warehouse managers believe that the reason these values do not match is essentially due to human error, however this is an analysis that is deepened in section 4.2.

The inventory control system through the annual inventory counts is not allowing to find the causes of the errors accurately, so that afterwards it is possible to correct them. In order to find new solutions for the annual inventory counts, in this case a cycle counting methodology is implemented, and the results are analysed in order to see if there are improvements in operational costs.

### *2.2. Product allocation*

When items are allocated so that operations (mainly picking) perform better, companies can improve the overall efficiency of their warehouses. In the case of TorresLog there are hundreds of orders to satisfy per day and therefore warehouse managers believe that an improvement in the location of items in order to decrease picking operation times can have a very significant positive impact on operations. Since it is intended that these improvements cause a decrease in picking time, the risk of not satisfying all the orders expected for a given day would be lower, and there may still be the possibility of redistributing the operators to other activities. Since picking operations correspond to about 50 percent of total operational costs (Le-Duc & De Koster, 2005), it is believed that the implementation of methodologies that improve product location, so that travel time is shorter, will have a very significant impact on these costs.

## 3. Literature review

### *3.1. Cycle counting*

According to Brooks & Wilson (2007), the inventory remains one of the most important parts of the production, distribution and retail structures. The authors argue that the management of this critical resource begins with the creation and maintenance of accurate inventory records. Amjed & Harrison (2013) affirm that the inventory count is one of the most essential operations in a warehouse, being important for the management of inventory levels, for the correct location of products, to ensure the supply of seasonal products, for the control of thefts and losses or for balance sheets in the event of accidents or catastrophes.

REM (1999) presents cycle counting, an inventory control process, as a technique that segments the inventory, establishing a calendar for when products should be counted throughout the year, so that, when the period of one year pass all SKUs have been counted at least once (still, in general, they are counted several times). This is one of the most effective methods to solve inventory problems and obtain a high inventory record accuracy (the number of correct counts to be divided by the total number of counts (Muller, 2011)), to levels of 97% or higher (REM, 1999). Since this is a counting method with cycles of less than a year, it is possible to discover discrepancies shortly after its occurrence, unlike what happens with annual counts,

According to REM (1999) cycle counting has several benefits, especially when compared to annual counting. These benefits are:

- few errors in the identification of SKUs;
- great ability to identify and correct errors in the records;
- warehouse operation does not have to be suspended;
- need for fewer employees and they are more experienced;
- systematic improvement of the processes that give rise to errors.

Muller (2011) presents several ways to implement cycle counting, however, he argues that not all of them adjust equally to different companies. Therefore, in each case, the method that best fits should be implemented, with the following being presented by the author:

- Control group.
- Location audit.
- Random selection.
- Diminishing population.
- Product categories.
- ABC classification.

Rossetti et al. (2007), Gumrukcu et al. (2008), Wijffels et al. (2016) and Mahtamtama et al. (2018) adapt some of these methodologies to the reality they have studied and developed new approaches to cycle counting.

In order to increase the accuracy of the inventory through cycle counting, it is necessary to understand what causes possible problems in accuracy. Cause and effect diagrams (Ishikawa Diagram or Fishbone Diagram) are a particularly effective method to help find the root causes of problems (Slack et al., 2018). Andersen & Fagerhaug (2006) present in detail this methodology that was implemented by Gupta & Garg (2014) and Kuendee (2017) to solve problems in inventory.

### *3.2. Products location*

The efficiency of the picking operations depends very much on the storage policy used, i.e., where the products are located inside the warehouse (Le-Duc & De Koster, 2005). The theories of item location indicate where a particular item or category of items should be physically positioned in order to improve this efficiency (Muller, 2011). Putting the most popular products in terms of order frequency in the most accessible locations of the warehouses, or those with a high combined order frequency in nearby locations, are strategies that will contribute to the reduction of travel distances and thus improve the efficiency of operations (Richards, 2014). There are several methodologies for this purpose, including family grouping, demand correlation analysis and ABC analysis.

The family grouping approach consists of storing items with similar characteristics together. Theoretically, similar characteristics will cause these items to be received, stored, collected and shipped together (Muller, 2011).

According to Frazelle (2002) the demand correlation profile indicates the affinity of demand between individual items or between families of items. A high affinity indicates that certain SKUs tend to be ordered together. By studying the activity profile of the items through the demand correlation profile, SKUs are grouped in pairs and are classified based on how often each pair appears in the orders (Frazelle, 2002). Often the perception assumed about the high or low frequency of each pair becomes wrong and ineffective. This uncertainty happens because warehouses often deal with a multitude of SKUs, order patterns, suppliers and decisions, which makes it difficult to form a reliable intuition about logistics operations (Frazelle, 2002). This is why several authors such as Zhang et al. (2019) and Lang et al. (2020) have developed algorithms that have enabled them to achieve effective results.

The categorisation of products through ABC analysis is based on the classic "Pareto Law" which holds that within a given population approximately 20% of things have 80% of the total "value" and the other 80% have only 20% of the value (Emmet, 2005). Therefore, the idea is to concentrate time and the best resources on the important 20 per cent, the "vital few" (Richards, 2014). The "value" can be defined according to various criteria, the most correct being, in a warehouse environment, the order frequency. Richards (2014) and several other authors relate the Pareto Law to the ABC categorisation. According to the author, Class A items correspond to approximately 20% of the total and 80% of the demand, Class B items to the following 35% which correspond to approximately 15% of the demand and Class C items to the last 45% and only 5% of the demand.

## 4. Cycle counting implementation

In order to reduce inventory differences (difference between the physical inventory and the inventory in the system), reduce the costs associated with them and increase customer confidence, a cycle counting methodology was implemented in the warehouse under study. To choose the best methodology to implement, three important factors had to be considered. These factors were:

- Customer characteristics – Client X has 224 different items stored in the warehouse under study, 215 of which are in picking locations (at ground level).
- Time available for counts – Availability to do counts was ten weeks, but only nine were considered to leave a buffer week. However, there was only one day a week available to count, that is, 9 days of counting.
- Characteristics of each methodology – The various methodologies presented in section 3, suggested by Muller (2011) were analysed in order to understand which one best

fits the reality under study. The control group methodology did not fit the case, since it was intended to count all items at ground level and not just a sample. The size of the client area did not justify the implementation of the location audit methodology. Nor was it justified to separate products by categories, and the time available did not make it feasible to implement cycle counting through ABC analysis.

Considering the characteristics of the client, the time available for counting and the characteristics of each counting methodology, it was concluded that the most appropriate is to implement a combination of the random selection method and the diminishing population method. These methods consist of randomly counting all items only once, until all are counted.

In order to carry out the counts some important considerations had to be taken into account:

- Only counts the picking locations (at ground level), since the remaining items had only been moved in the reception operation and were stored in the replenishment locations without being changed. Therefore, it is trusted that there was no opportunity for deviations in the inventory records. This decision was also helped by the fact that if all the locations were counted (picking and replenishment) more equipment and more labour were needed, which was not available.
- Count all the picking locations where each SKU was, thus confirming that the location was the correct one and increasing the efficiency of the process, since nothing remained to be counted. An item can be in several picking locations when there are returns or when it is ordered by specific batches. This meant that more locations were counted than different SKUs.

To calculate the number of items to be counted per day, the nine days available for counting, the fact that only one cycle was carried out and the 215 items with picking locations were considered, resulting in 24 items to be counted per day. Although the number of items obtained was 24, and since this is an acceptable number, it was decided to count 25 items, leaving a margin on the last day. This decision was related to the possibility of new SKUs arriving, creating a possibility for them to be counted on the last day. If this happened, it was guaranteed that in the end all items would be counted once.

The distribution over the days of counting was done randomly, thus ensuring that all items were treated equally, with no differences in demand or cost, for example. For each day, a list was created with relevant information corresponding to each SKU in order to make the counts faster and more accurate. This list included the location, reference, description, batch and expiry date of each product. The quantity of each SKU registered in the system was not entered in the list, as it was decided that the counting would be done "blindly", in order to avoid counting errors by knowing the quantity that was supposed to be in each location.

### *4.1. Results*

With the aim of determining the results, over the weeks of counting, the percentage of accuracy was calculated for each week by applying the formula of the Inventory Record Accuracy. As can be seen in Table 1 in almost every week the accuracy obtained was less than 90%, that is, in the 25 counts there were at least three items where the physical inventory and the inventory in the system did not match. These values per week resulted in an overall IRA of 88%, which corresponds to 189 accurate counts out of a total of 215 items counted. In the 26 items with stock differences there were both cases where there were excess physical units in stock and the opposite, lack of units in physical stock.

Table 1 - Cycle counting results

| Days | Availability | Sample | Accurate counts | Accuracy |
|---|---|---|---|---|
| **Day 1** | 215 | 25 | 21 | 84% |
| **Day 2** | 190 | 25 | 21 | 84% |
| **Day 3** | 165 | 25 | 21 | 84% |
| **Day 4** | 140 | 25 | 22 | 88% |
| **Day 5** | 115 | 25 | 23 | 92% |
| **Day 6** | 90 | 25 | 24 | 96% |
| **Day 7** | 65 | 25 | 22 | 88% |
| **Day 8** | 40 | 25 | 20 | 80% |
| **Day 9** | 15 | 15 | 15 | 100% |
| **Total** | | 215 | 189 | 88% |

### *4.2. Causes for low inventory accuracy*

Taking into account the results of the IRA, an assessment was made of the possible causes that were giving rise to such low inventory accuracy. For this, a brainstorming session was held with various elements of the warehouse management and operations, so that various perspectives could be considered. This analysis is very important in order to find out the root causes of the problem and to take measures to combat and eliminate these causes.

An Ishikawa diagram was created and filled in as ideas were shared. In order to fill in the diagram, six categories were considered which could contain causes for errors. The categories considered were:

- manpower;
- the management of operations;
- operational equipment;
- the warehouse management system;
- errors originating from the customer;
- and the product itself.

The first general impression was that errors occurred due to counting errors in picking by the operator, however it was concluded that there were many other causes that could result in errors and should be considered. As possible causes arose, they were added to the diagram in the category to which they belong. This visual illustration facilitated the detection of other possible causes of errors and made it easier to see which errors were most likely, and consequently where improvement actions should be focused. In Figure 1 it is possible to see in detail the whole diagram developed. The categories that proved to be the most critical because they have the most possible causes of errors, were the operations and the manpower, which is natural since they have a more direct interference with the product.

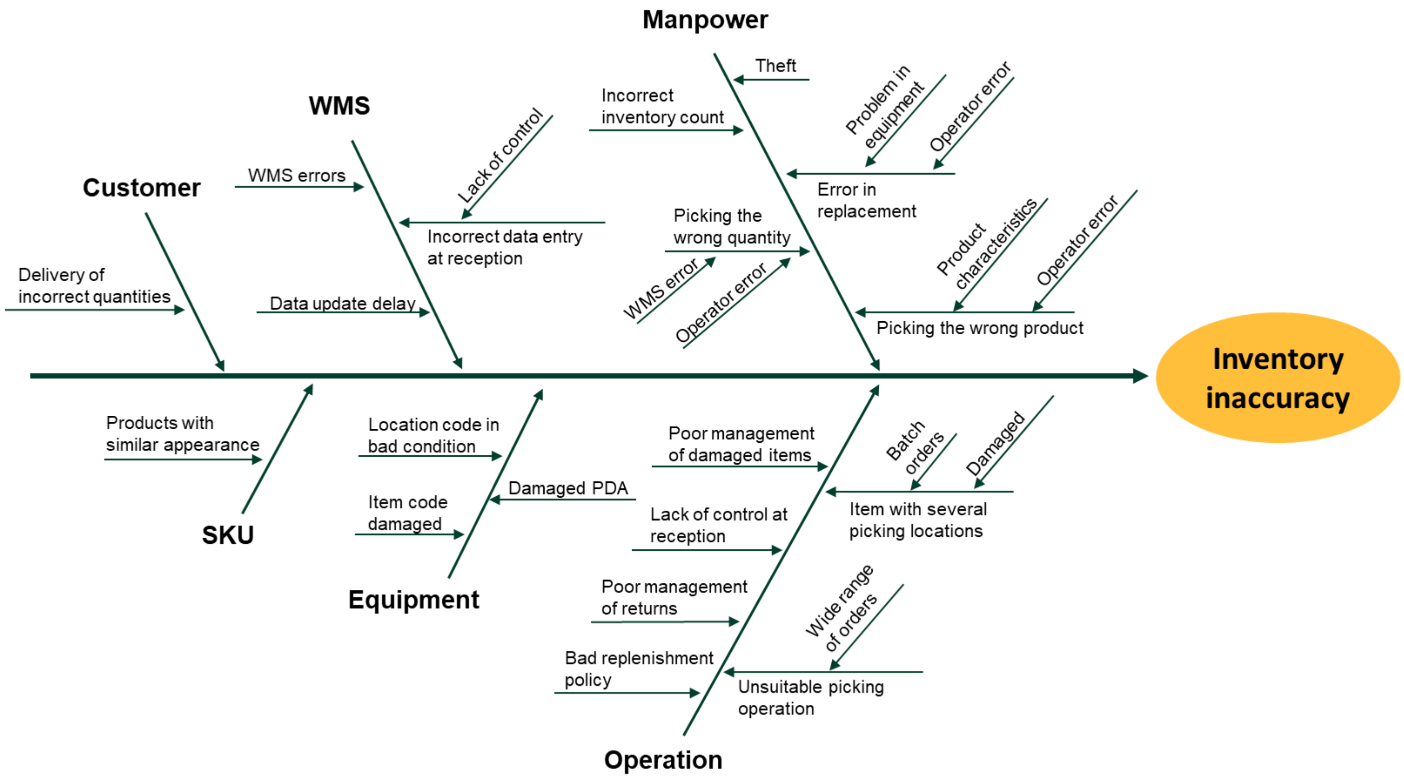


Figure 1 - Ishikawa diagram

## 5. Layout improvement

As already mentioned, one of the causes for the problem of high operational costs that the company faces is the lack of efficiency in locating the items in the storage area. This lack of efficiency can greatly increase picking times, which have a direct relationship with operating costs. It was then realised that the implementation of measures aimed at improving the locations of each item, within the area destined for each customer, could contribute in a positive way to solving the problem.

For a good analysis and understanding of the company and customer routines, and for the implementation of measures to be based on realistic data, it was necessary, at an early stage, to spend some time for learning and setting with the WMS used in the warehouse, so that it would then be easier to collect and analyse various types of data. It was necessary to collect data such as orders history, product locations, product history, among others.

### *5.1. ABC analysis*

In order to carry out an ABC analysis adapted to the practical reality of the operations and the characteristics of the items, it was necessary to monitor the daily processes of the operations related to the client under study. Through this monitoring, as well as historical data, it was possible to understand the behaviour of each SKU and thereby make an ABC analysis as real as possible.

Having in consideration the characteristics of each item, it was concluded that it was advantageous to create two families of products. The separation was based on the weight of each item and will contribute to the balance and conservation of the items on the pallet, with the heaviest (and largest) items being picked first. The families created were:

- Big bags - the Big bags families include all items weighing 4.5 kg or more (17; 11.4; 6; 5; and 4.5 kg). For these items, which have higher weights and dimensions, the picking locations are at ground level and the items are placed on full American type pallets.
- Small bags - from the small bags' family are all the items with weight below 4.5 kg (2; 1.8; and 0.34 kg, bags and cans of wet food, among other items). In the case of this family, due to the small size of the products, most of them are placed inside boxes and in shelves, in order to make the best possible use of the space. However, some of the items with the highest ordering rate are placed in floor picking locations on full Euro type pallets.

Taking both families into account, an ABC analysis was made for each family's items. For both families, orders were analysed over a one-year period, from 14 October 2019 to 14 October 2020, thus considering 5,835 orders. The division of the items into A, B or C was made considering the cumulative percentage of items and the percentage of demand, separately. The following considerations were considered for these two studies:

- For the division based on the cumulative percentage of demand the following was considered: up to 80% of demand the items are class A, the following 15% class B and the last 5% class C; however, this division did not prove useful, since the quantity resulting from class A items was much higher than the others.
- For the study making the division based on the accumulated percentage of items, this division was made considering the following: the first 20% of items are class A, 20% to 55% class B and 55% to 100% class C. This was the division considered in the implementations made in the warehouse, for both families. Table 2 presents an extract from the ABC analysis and shows this division for the small bags' family.

Table 2 - Example of ABC analysis for the "small bags" family, with the items arranged in descending order by demand values

| Line no. | Prod. Ref. | Annual demand | % cum. line no. | % cum. demand | ABC |
|---|---|---|---|---|---|
| 1 | **ACH111** | 1267 | 0.59% | 3.13% | A |
| 2 | **ACH104** | 943 | 1.18% | 5.47% | A |
| 3 | **NMA1101** | 830 | 1.78% | 7.52% | A |
| … | **…** | … | … | … | … |
| 33 | **NMA201** | 456 | 19.53% | 51.60% | A |
| 35 | **NMA1306** | 426 | 20.71% | 53.76% | B |
| … | **…** | … | … | … | … |
| 92 | **ORD207** | 130 | 54.44% | 91.28% | B |
| 94 | **ORT512** | 127 | 55.62% | 91.91% | C |
| … | **…** | … | … | … | … |
| 167 | **ACP006** | 1 | 98.82% | 100.00% | C |
| 168 | **ACP007** | 1 | 99.41% | 100.00% | C |
| 169 | **ACP003** | 1 | 100.00% | 100.00% | C |

Although the rule originally suggested by Pareto, which states that 20% of the products correspond to 80% of the demand, did not occur, this analysis still proved to be important for both families. In the graph of Figure 2 it can be seen that for the family "Small bags" the items of class A correspond to more than 50% of the demand and adding the items of class B the demand exceeds 90%, values that are still quite significant. It is also possible to see from the graph why the values of demand were not chosen for the class division: by separating the items of class A at 80% of demand, the percentage of items of that class would be very high. For the "Big bags" family the values obtained are similar, even if lower, the class A items correspond to 46% of the demand and adding the class B items together correspond to 82% of the demand.

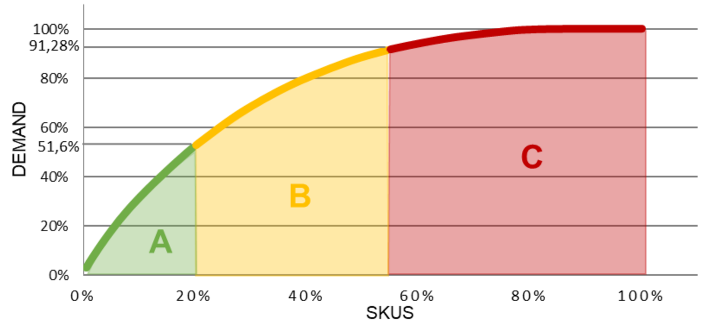


Figure 2 - Graph of the ABC analysis for the "Small bags" family

Table 3 presents the results of the analyses of both families. For the Big Bags family 70 items were considered, of which 14 were class A, 24 class B and 32 class C. For the small bags family 169 items were considered, of which 33 are class A, 59 class B and 77 class C.

Table 3 - Results of the ABC analysis

| | Big bags | | | Small bags | | |
|---|---|---|---|---|---|---|
| | SKUs | SKUs % | Demand % | SKUs | SKUs % | Demand % |
| **A** | 14 | 20% | 45.65% | 33 | 20% | 51.6% |
| **B** | 24 | 35% | 36.43% | 59 | 35% | 39.68% |
| **C** | 32 | 45% | 17.92% | 77 | 45% | 8.72% |
| **Total** | 70 | 100% | 100% | 169 | 100% | 100% |

### *5.2. Demand correlation analysis*

Consumer behaviour is a very important factor when storing items. By studying this behaviour, it is possible to adapt warehouse operations to make them more efficient. Through the study of the demand correlation it is possible to check if there are items that tend to be ordered together. Doing this analysis and if this tendency occurs in two or more items, it can be advantageous to store them in nearby locations, thus reducing the distance travelled in picking.

This analysis has been applied to the case under study and has been allied to the ABC analysis done previously. In order to reduce the computational effort, only class A items from both families were considered, as they have a greater importance in the functioning of the warehouse. For the same reason, six-month orders were also considered, and not a year as in the ABC analysis, which means that 2,698 orders were considered.

In the demand correlation analysis, contrary to what was done in the ABC analysis, the class A items of the "big bags" and "small bags" were joined to check if there was any correlation between items from both families. By combining the 47 items into pairs (resulting from the joining of the families) and making all possible combinations, 1,081 combinations of pairs were obtained. With the help of the Excel software's Pivot Tables it was possible to check how many times each pair appeared in the total of the orders and thus calculate the frequency with which each item was ordered with that of the respective pair. In Table 4 are some of these combinations and their results. In the absence of any optimal rule, all pairs where both SKUs had a joint demand of 45% or more with the other SKU were considered as important pairs for joint storage, and there were 18 pairs that met this criterion. An important point to note is that all pairs with high frequencies were composed of SKUs from the "Small bags" family, pairs composed only of SKUs from the "Big bags" family and combining SKUs from both families did not obtain relevant values. Interpreting Table 4, for the first pair, the pair frequency for SKU 1 is 67%, which means that 67% of the times this SKU is ordered SKU 2 is also. On the other hand, 72% of the times that SKU 2 is ordered, so is SKU 1.

Table 4 Example of demand correlation analysis

| | | Amount of orders | | | Pair freq. | |
|---|---|---|---|---|---|---|
| **SKU 1** | **SKU 2** | **SKU 1** | **SKU 2** | **Par** | **SKU 1** | **SKU 2** |
| NMA1200 | NMA1202 | 262 | 244 | 176 | 67% | 72% |
| NMA1202 | NMA1203 | 244 | 322 | 161 | 66% | 50% |
| NMA1200 | NMA1203 | 262 | 322 | 169 | 65% | 52% |
| NMA1201 | NMA1203 | 315 | 322 | 203 | 64% | 63% |
| NMA1200 | NMA1201 | 262 | 315 | 166 | 63% | 53% |
| NMA105 | NMA106 | 277 | 247 | 167 | 60% | 68% |
| NMA1100 | NMA1101 | 387 | 393 | 233 | 60% | 59% |
| NMA1102 | NMA1103 | 298 | 287 | 175 | 59% | 61% |
| ACH101 | ACH111 | 412 | 658 | 237 | 58% | 36% |

### *5.3. Layout change*

After the ABC analysis was completed, the layout of the area corresponding to Customer X was filled according to the class of the item that occupied each picking location. As it is possible to see in Figure 3 this layout does not present any kind of optimization. Class A, B, or C items are mixed and there are many empty spaces in important locations.

Taking into account the state of this warehouse area, a layout change proposal was made. This proposal was based on the separation into families, the respective ABC analyses and the demand correlation analysis. For this change there were some aspects to be taken into consideration, such as the U-shaped layout of the warehouse (the entry docks are the same as the exit docks) and the fact that the operation ends near the place where it starts. In a meeting at which the proposal was presented, the necessary adjustments were discussed and finally the layout presented in Figure 4 was achieved.

In the new layout (Figure 4) the big bag family occupies the entire rows 41 and 42, up to rack 12. The small bag family is all placed in rows 43 and 44, also up to rack 12. Some of the class C items from both families were not assigned picking location on level 1. This decision was due to the fact that these items are ordered very few times a year and for that reason it is not justified to be in a floor level location. These changes have allowed half of corridors 43 and 44 to be left free and the company can dispose of them for other purposes.

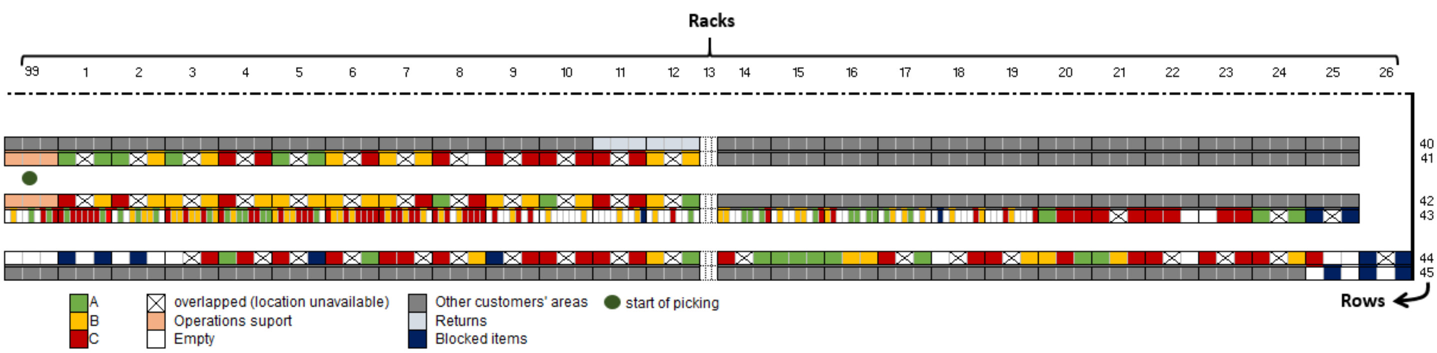


Figure 3 - Organization of the Client X area before the layout changes

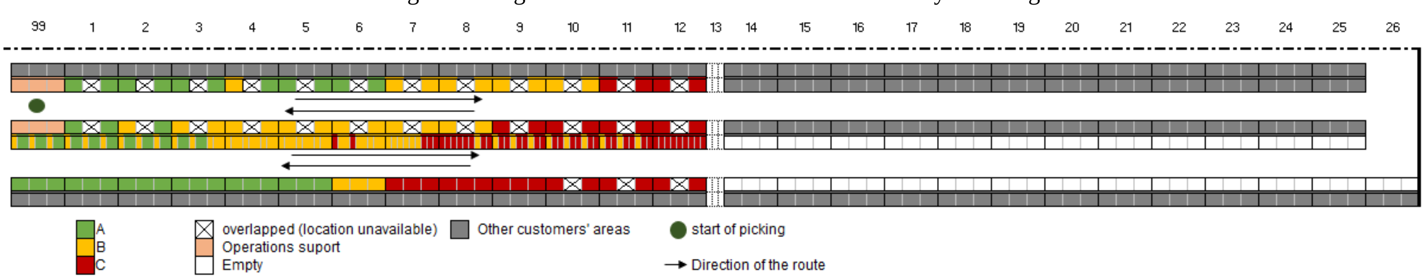


Figure 4 - Organization of the Client X area after the layout changes

*5.4. Results*

In order to reach concrete conclusions on the changes implemented in the layout, the picking times before and after these changes were studied and compared. To give the data some validity it was necessary to impose some restrictions on the orders to be considered. These restrictions were:

- not to consider orders that filled more than one pallet because this will cause interruptions in the picking for the change of pallet;
- not to consider operations that needed replenishment - it also forced the interruption of the operation;
- not to consider other operations that would otherwise be stopped.

The time counts were extended over two phases, before the layout changes and after the changes, and results were calculated for each phase, so that a comparison could then be made between the two.

**First phase**

The first phase of time collection consisted in collecting the times before the layout improvements. At this stage, a total of 111 order times were considered. From the histogram of Figure 5 it can be seen that most picking operations took between two and 9.7 minutes, however there is some variety of values. This variety is considered acceptable as there is a great diversity in the type of orders. About 70% of the orders had up to 13 different SKUs, but the remaining 30% had a wide variety in the quantity of SKUs, going up to 37. For the units per order the biggest trend was orders up to 14 items, corresponding to about 50% of the total orders, and for the rest there were orders with up to 74 units. At this stage, the orders considered resulted in an average of 1.7 units per SKU.

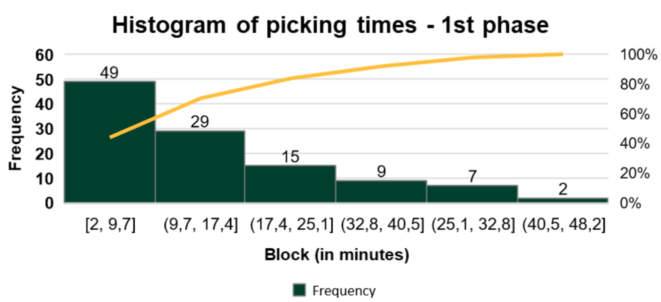


Figure 5 - Histogram of order times considered in the first phase of time collection

**Second phase**

The second phase of time collection consisted in collecting picking times after changes were made to improve the location of the items. In this phase 88 times were considered. This number is smaller than the one registered in the first phase, being explained by the fact that the time period for collecting times was slightly smaller. At this stage the picking times per order were considerably different from the first stage, however no direct comparisons can be made between the total times of the operations of the two phases, because the behaviour of the orders was different. As can be seen in Figure 6, at this stage more than 50% of orders take up to 6.4 minutes, and there was some time diversity from there, which was also natural due to the differences between orders. At this stage more than 50% of the orders had up to eight items, and there were orders with more than 40 SKUs. In relation to units, more than half of the orders had up to 15 units and the average per SKU was 1.8 units.

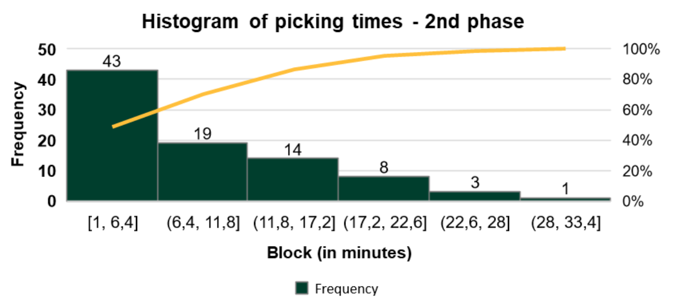


Figure 6 - Histogram of order times considered in the second phase of time collection

**Comparison of the two phases**

After the results of the two time collection phases have been calculated, it is possible to make comparisons to see what impact the changes in product layout have had on the picking operation.

Regarding the composition of the orders there was a slight difference between the two phases. In the second phase the orders considered resulted in an average of 1.46 fewer items and 0.8 fewer units per order. This is not a significant difference, but it is natural that, in terms of time of the operation, the second phase resulted in a lower average, taking on average 5.1 minutes less. However, if the time values are seen to the SKU, and especially to the unit, it is possible to see with certainty that there has been a reduction in the overall time of operations, caused by the changes made. Per SKU the reduction was 19 seconds, that is, 27% less time, and per unit it was 14 seconds, which is equivalent to 33% less time. In

Table 5 it is possible to see the comparison of the two phases values.

Table 5 - Comparison of the results of the two time collection phases

| | | 1st phase | 2nd phase | Difference | Difference % |
|---|---|---|---|---|---|
| Averages per order | SKUs | 11.7 | 10.3 | -1.46 | **-12%** |
| | Units | 19.7 | 18.9 | -0.80 | **-4%** |
| | Time (min) | 14.1 | 9.0 | -5.1 | **-36%** |
| | Time (s) | 846 | 543 | -304 | **-36%** |
| Average time per SKU (s) | | 72 | 53 | -19 | **-27%** |
| Average time per unit (s) | | 43 | 29 | -14 | **-33%** |

With this reduction in picking time, it was possible to predict a possible saving in the costs of the operation. For these calculations, the average picking time per unit was used, as it is the most reliable for comparison due to the differences in the quantity of items per order and units per item. The following data were used for the calculation of the savings: 14 seconds saved per unit in picking; average of 19 units per order; cost per hour of an operator equal to 9.50 euros. Taking these data into account, the values of possible savings have been calculated and are presented in Table 6. For this calculation a weekly average of 110 orders per week was also considered. The changes made in the layout have resulted in potential weekly savings of 80 euros, which can be as much as 4.156 euros per year, considering 52 weeks per year.

Table 6 - Savings in costs

| | Week | Year* |
|---|---|---|
| Orders | 110 | 5720 |
| Saved time (hours) | 8.4 | 437.4 |
| Savings | **80 €** | **4,156 €** |
| *Considered 52 weeks per year | | |

## 6. Conclusions

Given the problem presented by the company, the proposed objective for the case study was to implement actions that would contribute to solve the problem of high operational costs in the warehouse. To achieve these objectives, an intervention was made in the inventory control processes and in the location of the products, meeting the interests of the company's managers.

Regarding inventory control, a cycle counting methodology was developed, the inventory record accuracy metric was implemented and possible causes of error were checked by means of a causeeffect diagram. With these methodologies it was possible to ascertain that the IRA of Customer X is 88% as well as the possible causes for this low value. Since data from other years relating to costs due to inventory differences have not been released, it can still be concluded that, if measures are taken to minimize the causes of inventory differences, thus making it possible to increase IRA to values close to 100%, high cost savings can be generated.

Regarding the layout of the locations of the items, the lack of organisation was visible. There were many locations with no item allocation, many items in several locations, and no concern with allocating the products with the highest order rate to the locations closest to the dispatch area. To improve this by assigning new locations to the items, a separation of items in two families was made, considering their weights, an ABC Analysis was performed for each family and a demand correlation analysis was also made. Through the implemented measures an improvement of 33% in the average picking time per unit has been achieved. The changes made allowed an average saving in picking of 14 seconds per unit, which gave rise to a potential saving in costs of 80 euros per month, up to 4,156 euros per year.

With the results obtained, both with the implementation of the new counting model and the new layout, it can be concluded that the objective of the case study has been achieved.

For the company to further improve its processes, it is recommended that implement the methodologies developed in this case study for the remaining warehouse customers, both in terms of inventory control as well as the location of the products. Considering that only a very small part of the warehouse has been worked on, it is believed that these measures may have a much greater impact when applied to all customers, or at least to those to which they are adaptable.

To improve inventory control procedures the following work is also suggested:

- Insisting on employee training to reduce the probability of picking errors.
- Create a replenishment count sheet so that when the operator goes to replenish, he enters the date and quantity of units that are in the respective location, and compares it with the system values, thus detecting divergences.
- Create an incentive for employees if a certain percentage is reached in the IRA.
- Implement the cycle count according to the ABC analysis (Muller, 2011) after the IRA values are at stable and acceptable levels.

To reduce picking times, the following work is also suggested:

- Calculate the turnover rate of the items in the picking locations, in order to understand which items can be placed in locations divided into smaller compartments (those with a lower turnover rate).
- Implement a minimum stock system in the picking locations to avoid so many stops in the operation due to lack of items to collect.
- Review the picking strategy and test the implementation of cluster picking, in order to reduce the number of routes and consequently decrease the total picking time (Aboelfotoh et al., 2019).
- Review the picking method and test the implementation of Voice picking, thus avoiding the use of PDA, which proves to be an obstacle in the operation, and increasing productivity (Wong, 2016).
- Create productivity incentives for employees.

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