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22nd International Conference on Harbor, Maritime and Multimodal Logistic Modeling & Simulation
17th International Multidisciplinary Modeling & Simulation Multiconference

ISSN 2724-0339 ISBN 978-88-85741-46-1 © 2020 The Authors.
DOI: 10.46354/i3m.2020.hms.001

A storage assignment simulation model for optimizing processes in an e-commerce warehouse of a fashion supply chain

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Abstract

The wide spread of e-commerce and in general B2C systems brought new challenges to supply chains which had to reconsider part of their systems whilst maintaining the same goal: a high level of customer satisfaction. One of the main functions affected by these challenges is the logistics activity, including warehouse management and transports. Indeed, they now have to face higher orders at the same time, to manage picks demand in specified periods, to increase journeys for reaching various customers geographically dispersed. Optimization and synchronization are essential. To this end and according to the steps of the Deming Cycle, this paper presents the case of a warehouse located in northern Italy whose storage activity was firstly simulated and then successfully implemented so as to optimize the picking activity and consequently the subsequent processes of the outbound flow. Improvements were assessed through determined key performance indicators, monitored before and after the implementation of the new strategy.

Keywords: Modeling & simulation; warehouse management; product allocation optimization; picking optimization.

1. Introduction

"Your order has been shipped"; "Your order was successfully completed"; "Your order has been processed and is waiting for shipping"; "Order status: confirmed. You will receive a confirmation email in the next few minutes". Probably all the readers of this manuscript have received one of these notifications at least once in their life; and this because probably all the readers have bought something on the web at least once. If you are from China or from United Kingdom, consider that for each 100 euros you spend in your country, 20 transit online (Politecnico di Milano, 2019).

This is e-commerce: buying and selling of information, products and services over an electronic network, mainly the internet (Balasoui, 2015). It is also considered as hierarchically the highest level of business activity carried out by Information and Communication Technologies (ICT) means (Kunesova and Micik, 2015). In other words, the business enters directly in your home; this is the reason why these systems are also referred to as Business to Consumer (B2C).

Four elements are essential in this exchange: a physical person (1) using a physical technological device equipped with an internet connection (2), e.g. a laptop, a tablet or a mobile phone through which this person can access an online platform able to provide the online purchase (3), and buy an information, a service or a product (4); typically, in case of products they are physically somewhere else. That's just from this place that the goods need to be transferred to the address that the customer entered the system, and this apparently simple action requires a complex organization and brought challenges over the last years (and even now) to supply chains and sales systems, and specifically to the logistics activity.

Indeed, in this context everything revolves around logistics for order fulfilling, including warehouse management and transports, which are seen as bottlenecks in e-commerce systems since logistics providers have to deal with large quantities of orders at one time, are required to be highly flexible in processing capacities to meet demands on the occasion of festival or special days, face complex scenarios since suppliers and customers are geographically dispersed (Yu et al., 2020).

Specifically, warehouse operations have to handle small orders, large assortment of items in a batch, limited space and tight delivery schedules (Yang et al., 2020) and according to that for increasing both their effectiveness and efficiency several actions were proposed to optimize processes: from order picking optimization (e.g. Yang et al., 2020 or Zou et al., 2019), to storage allocation strategies (e.g. Krishnamoorthy and Roy, 2019 or van der Gaast et al., 2019), packing and stacking approaches (e.g. Liu et al., 2019) rather than the application of lean management philosophy (e.g. Pal and Rangarajan, 2017).

In this perspective, the present manuscript aims at presenting a case study on the simulation of a new storage allocation strategy of products with subsequent implementation in an e-commerce warehouse located in northern Italy, belonging to a German logistics service provider (anonymous for privacy reasons and referred as Company A). Specifically, the target for the optimization is a strategy for allocating products in the storage locations according to their *velocity* and their *origins* (both defined in the following), so that picking activities and more in general the outbound processes could benefit from a reduced time and a greater number of items processed.

Indeed, a correct and specific location of the inventory together with accuracy, great capacity, automated storage/retrieval and appropriate forecasting is listed among the top five warehouse considerations for the fashion context (Mullin, 2017).

Contents are organized as follows: the section below, namely 2, presents a brief overview of the company in question, including the actual warehouse layout and organization. Section 3 outlines the methodology followed, while section 4 deals with the detailing of all the steps implemented to reach the implementation of the simulated configuration. Conclusion and future directions are discussed in section 5.

2. The Context

2.1. Overview of the Company

Company A represents a Westphalian group leader in Europe, specialized in planning and managing complex logistics solutions worldwide. It owns 160 branches within 15 countries, counting 2.7 million square meters of warehouses, where 15.000 employees work. Fashion, healthcare, manufacturing, consumables and tires are the main goods traded.

Three warehouses are located in northern Italy, whose core business is within the fashion context. Specifically, in the warehouse subject of the case study which was built in 2015 with an area of 20.000 square meters, only goods from a specific e-commerce fashion player (Company B, for convenience) headquartered in Berlin are managed, to quickly reach the Italian market and the South of Europe. This player manages an online platform since 2008 in which women, men and children clothes and accessories are sold, with a Free-of Charge return within 100 days. Both renown brands (around 2,000) and its private label are traded. Their focus is on the continuous improvement of the online shopping experience for the customer, as well as the service provided: everything is customer oriented and this approach led to reach 28 million consumers in 2018, 14% more than the previous year, providing 5.4 billion in revenue (data source: Company B).

2.2. Warehouse Layout and Operations

The warehouse to be modeled can handle around 5,000,000 products and is structured as shown in Figure 1.

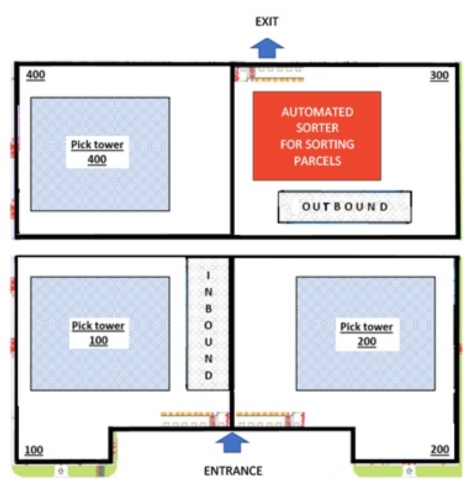

Figure 1. Warehouse Layout.

There are four similar cells (called 100, 200, 300 and 400), separated by two orthogonal walls; three of these cells host the so-called Pick Towers (i.e. PT 100, PT 200, PT 400), shelves dedicated to the storage of goods. Each tower has three storage levels: ground (indicated as 100 for PT 100, 200 for PT 200 and 400 for PT 400), middle (101 for PT 100, 201 for PT 200 and 401 for PT 400) and upper level (102 for PT 100, 202 for PT 200 and 402 for PT 400).

Within the 100 cell there is an area where packaging materials are stored and 384 pallet spaces; adjacent, there is a *goods-in area* (420 m^2) composed of 11 loading docks for receiving products. Longitudinally to the wall, there are 42 workstations for the receiving process (referred as Inbound in Figure 1).

In cell 200 there is a *goods-in area* as well with the same amount of loading docks, exclusively dedicated to the "customer returns" and, additionally, 144 pallet locations. Cell 300 is the only cell with no storage. Indeed, packing, sorting and shipping activities take place here.

PT 400 owns the rows dedicated to the Warehouse Mixed Order (WMO), occurring when an order is made of different order lines, which correspond to items stored in different places and different warehouses which have to be collected before being packed.

What happens in this warehouse can be easily divided into two main activities: the *Inbound* process, dealing with receiving and storage operations, and the *Outbound* process, including activities needed for order and shipping fulfillment (e.g. picking, packing, sorting etc.).

Fashion products are particularly difficult to efficiently manage in a warehouse as they have high demand variability, with a short shelf-life and very little replenishment (Pedrielli et al., 2016); for these reasons, products are actually stored according to their *velocity* and their *origin*. The term velocity represents the average time they occupy their location (from their storage to their pick). Three types of velocity are considered: A (3, 6 or 9 days), B (12 days), C (>12 days). Typically, there are five different origins of the received goods to which a determined velocity corresponds, as well as a specific location. Table 1 below, useful for understanding the new storage approach developed, details the different inflows, their description, their velocity, their average days of stay, and finally their actual locations in the Picking Towers. The number in brackets in Velocity column refers to the number of days, while the number of the Storage Location indicates their level within the Picking Towers.

There are two different type of orders: Customer Orders (CO) from private clients who buy from the online platform, and Non-Customer Orders (NCO), basically inverse replenishment to German hubs. On 600,000 items leaving each week, 86% is CO and the remaining 14% is NCO. A further subdivision of CO is on Single Orders (SO), made of one item and Multi Orders (MO), made, of course, of more order lines; regarding NCO, instead, we find orders for simple Transfer, or for Replenishment of other hubs.

Table 1. Characteristics of the Products Received.

Category	Description	Velocity	Storage Location
Pre-Processed Returns (3PL)	Customer returns to other warehouses already processed elsewhere (algorithmic assignment to other warehouses)	A (6)	100, 201, 400, 401, 402
New Goods (NG)	New products (both from external brands and from Private Label)	B - C (for Private Label products)	101, 202
Replenishment (REP)	Products coming from German hubs according to demand forecasting	A (9)	100
Italian Customer Returns (CR)	Returns from Italian customers	A (6)	200
Warehouse Mixed Orders (WMO)	Products belonging to mixed orders, coming for being merged with the rest of the order	A (3)	400

The last essential information is that there are three different batch modes for picking, whose characteristics are resumed in Table 2 below.

Table 2. Characteristics of the batching modes.

Batching mode	Picking characteristics	Average Time
Zone	Only at one level of a PT, the most productive, high density	1 h
Module	Two or more levels of the same PT	2 h
First in first out (FIFO)	More levels, more PTs, the less productive, low density	4 h

3. Methodology

This work consists in the analysis of the different input flows with the aim to determine and implement a storage strategy able to let the picking process (manually carried out) and therefore the Outbound process of the whole warehouse to be optimized. The Deming cycle (Johnson, 2002) was selected as tool for examining the processes and defining actions to be undertaken, which is a different procedure than those found in the existing literature dealing with warehouse optimization. It consists of four steps, namely Plan (1), Do (2), Check (3) and Act (4), and for this reason it is also abbreviated to the acronym PDCA. According to our case, for each step the following actions were recognized, in accordance with the management of the company and their specific requests and available tools:

1. PLAN: current model (AS IS) analysis;

    - Data mining from the Warehouse Management System (WMS);
    - Development of an Excel tool for the analysis of the input flows;
    - Current Key Performance Indicators (KPIs) analysis;
    - Batch analysis;

    Data were collected from September to December 2019.

2. DO: design of the simulated TO BE model for the storage;
3. CHECK: implementation and testing of the TO BE model, carried out in January 2020;
4. ACT: assessment of the TO BE model and benchmark with the previous model (AS IS).

Note that for constraints on the length of the paper, only the more relevant outcomes will be below detailed.

4. Model Development

4.1. Step 1: Plan

The development of the model begins with the data mining for assessing the current situation.

The aim is to deepen the average storage of products in terms of time according to their origin by comparing data from the Inbound and Outbound processes.

Specifically, four weeks were selected for the Inbound process (receiving activity), whose data will be benchmarked with data from seven weeks for the Outbound process (picking activity). A total of 6,000,000 records from the receiving was analyzed, and 11,000,000 records from picking.

Because of the constraints about the length of the paper, this part will not be detailed, as well as the development of the Excel tool; only essential results for understanding will be depicted.

Overall, around 740,000 items enter each week, including: 525,000 3PL, 70,000 NG, 45,000 REP, 65,000 CR, 35,000 WMO.

The average storage of the products according to each origin is shown in the following graph (Figure 2):

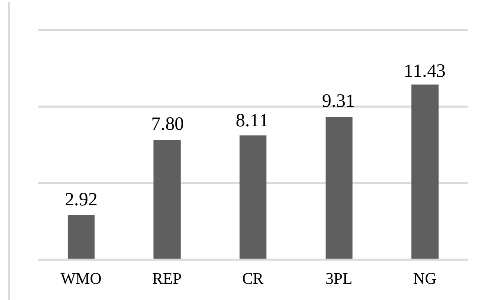

Figure 2. Average Storage [days] of Products according to their Origin.

Note that pre-processed Returns correspond to the 71% of goods arriving at the warehouse; this means that around 71% of the goods in the warehouse stay there around 9 days.

Additionally, for each storage level of each Picking Tower the average storage (again in days) for the whole period in question (September-December) was identified, and it is depicted in the following graph (Figure 3):

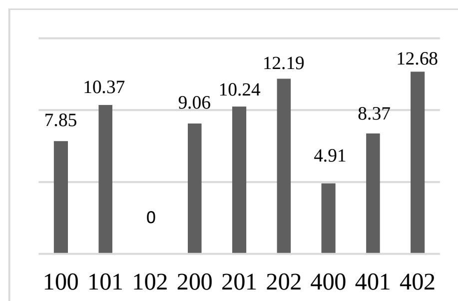

Figure 3. Average Storage [days] for each of the three storage levels of the three Picking Towers.

As expected, the lowest values are recorded at the ground levels.

As far as the KPIs and quality indicators (QI) intended to be monitored during the four months under observation and improved, they are detailed below:

Storage Productivity: it is measured through the units per hour (UPH) processed, and in our case this value corresponds to approximately 800, constant trend, right under the target (set at 900 UPH). The QI, instead, refers to one of the problems which may occur related to this activity, namely a mismatch between the physical and virtual inventory; according to that, it corresponds to the percentage of the remaining virtual inventory (i.e. percentage of Klarfalle, that is how Company A calls the remaining virtual stock; in German, it means "question to be clarified"). The value, obtained through a simple arithmetic mean of the single monthly values, equals 0.15 approximately; note that it was recorded an upward trend, probably due to the Black Friday or Christmas festivities, that generated more orders and accordingly more seasonal beginner workers, not so careful.

Picking Productivity: it is again measured in UPH, it is definitely below the target (set at 350 UPH), and it counts around 225 UPH. From a quality perspective, instead, the accuracy is defined according to the % of item not found during the picking operation, named Not on Stock (NOS), and it corresponds to 0.28 (growing trend for the same reasons of the Klarfalle's increase).

% of FIFO batch for Multi Customer Orders: FIFO batch is the most onerous in terms of time and complexity, and according to that there is the will to improve it. This percentage is around 44.5 on outgoing volumes (value obtained as average of the single data on the four months under observation, specifically 54% in September, 40 in October and 42 in both November and December).

Further interesting outcomes achievable through the aforementioned data mining and analysis useful for the assessment of the TO BE model, are the *efficiency* of goods, i.e. percentage of received goods which is converted into orders from a customer, and the opposite *inefficiency*, i.e. those products entering the warehouse and not leaving as customer's orders. These percentages are shown in Figure 4. Dark grey refers to efficiency, light grey color to inefficiency.

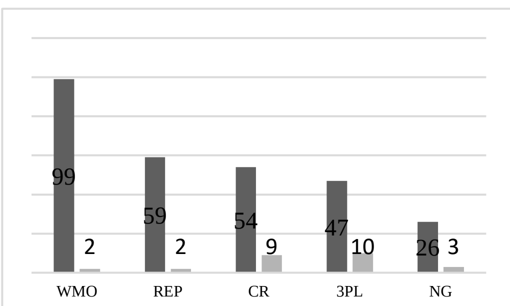

Figure 4. Efficiency (dark grey) and inefficiency (light grey) of the goods.

By comparing Figure 2 and Figure 4, it appears that there is a perfect inverse correlation between the velocity and the efficiency; for instance, the WMO is the most high-rotation class having velocity A, to which corresponds a very high efficiency. Same reasoning for products having low rotation and consequently higher velocity, e.g. NG class, which are the less efficient as well. It follows that in the new model those categories having low average storage and high efficiency should have priority and convenience for the picking activity.

The last preliminary analysis to be carried out is the batch analysis. One again, only outcomes in terms of time dedicated to each batch mode are presented for all four months (listed in Table 3).

Table 3. Time [hours] spent for batching according to the three modes and the type of order.

Batching mode	CO		NCO	
	Single	Multi	Transfer	REP
Zone	0.76	0.73	0.17	0.31
Module	0.77	1.83	0.13	0.14
FIFO	1.20	3.53	-	-

According to the abovementioned results, the following goals to be reached after the implementation of the TO BE configuration were set:

1. Reach the target of the UPH for both receiving and picking;
2. Lower below 40 the FIFO batch for multi customer orders;
3. Reduce the average storage at least for the ground level (as the aim is to allocate here high-rotation products).

4.2. Step 2: Do

The new simulated storage strategy was developed according to what emerged from the Plan stage. Three solutions were proposed to this end; only the selected one is detailed here, imposing that the ground level of the warehouse will be dedicated to products having velocity A.

The following assumptions were taken into account:

- Each level of each tower is divided into 4 blocks, and each of them can host 100,000 items;
- level 102 is not included;
- The whole NG class has velocity C.

In the light of the volumes resulting from the Plan phase and of a precautionary overestimate, WMO will need 1 block, REP 2 blocks, CR 2.5, REP around 22.5 and finally NG 3 blocks.

According to their relative velocity, they were allocated as shown in Figure 5 for the ground level, Figure 6 for the medium level and Figure 7 for the upper level.

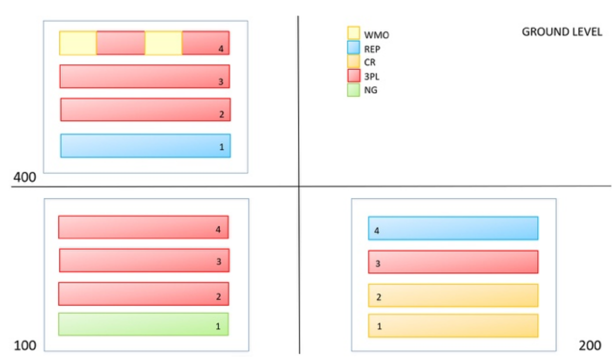

Figure 5. Ground Level storage allocation.

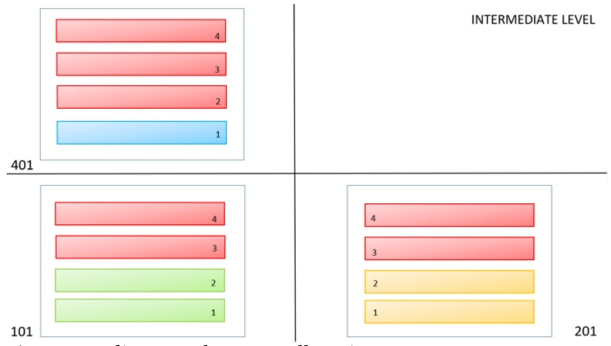

Figure 6. Intermediate Level storage allocation.

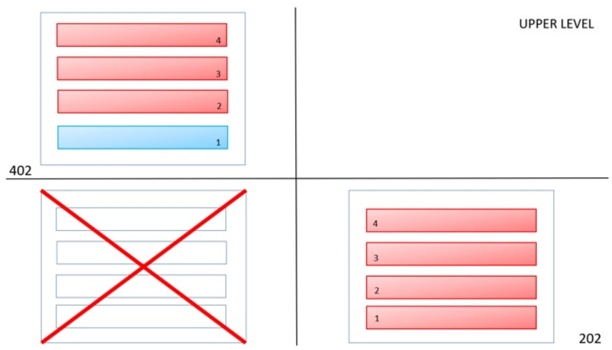

Figure 7. Upper Level storage allocation.

Specifically:

- WMO items position is retained in level 400, block 4 (yellow color in Figure 5);
- REP owns a total of 4 blocks: one at level 400, one at level 200, one at levels 401 and 402 (blue color in Figures 5, 6 and 7);
- CR (orange color in Figures 5 and 6) owns two blocks at level 200 and two at level 201;
- NG (green color in Figures 5 and 6), having low rotation, has one block in level 100 and two at level 101;
- The remaining blocks are dedicated to 3PL items, including the available part of the area dedicated to WMO (red colored in the three figures above).

Clearly, the buffers position was taken into account in the modelling, as well as picking conditions and fill rate; in other words, this is not a pure theoretical model since it also considers practical issues. Indeed, also the fact that we deal with a preexisting warehouse was considered: it is not possible to entirely empty it, and changes can only be done when operations are running.

4.3. Step 3: Check

This stage corresponds to the real implementation of the allocation model simulated, which took place from January 13th to 19th 2020, all shifts of a workday. Preliminarily, the week before tests signage was added to indicate the different blocks so that workers could become familiar, and the team was trained to the new allocation strategy.

4.4. Step 4: Act

The assessment of the TO BE model is here carried out starting from KPIs results from the AS IS configuration.

As far as the KPI relating to the Inbound process, the storage productivity trend is shown in the following Figure 8, with an average of 740 items stored per hour, a little bit under average and below the target. But this is probably due to the physiological time the employees need for adaptation to the new working conditions.

Figure 8. Storage UPH trend.

That week, instead, the average *Klarfalle*[1] was at 0.17%; an infinitesimal deviation from the value in the AS IS model, but nonetheless an improvement considering that the two previous weeks it got 0.19 and 0.23.

Since the picking activity takes into account also the average storage of products and affects also the subsequent weeks, its time span for the assessment is longer; results are depicted below (Figure 9):

Figure 9. Picking UPH trend.

The performance is improving and has a positive influence on the following workdays, allowing to even exceed the target set. NOS as well overall got a positive

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[1] Following the terminology of the company, this term is used here to denote the problematic situations observed during the process.

score: that week it corresponded to 0.31%, despite the 0.28 from the AS IS model, but the following weeks, after a little adjustment ranged from 0.33 to 0.30.

There has been an improvement in terms of percentage of FIFO batch for Multi CO; indeed, it lowered to 39% (from 44.5%), satisfying the third goal listed in section 4.1. It can be excluded that this decrease is attributable to an increase of volumes, since they were steady.

The last item examined concerned the timing of batch. Table 4 below, to be compared with the previous Table 3, illustrates outcomes.

Table 4: Time [hours] spent for Batch according to the three modes and the type of order after the TO BE model implementation.

Batch Mode	CO		NCO	
	Single	Multi	Transfer	REP
Zone	0.66	0.75	0.29	0.25
Module	-	1.87	0.13	0.23
FIFO	-	2.85	-	-

The best result is obtained for the FIFO mode, which is also the more critical and according to that the most satisfactory result.

5. Conclusions

The simulation of a new model for allocating products in a warehouse managing e-commerce orders and its implementation were presented in the present manuscript, with the purpose of optimizing processes in terms of determined KPIs analyzed before and after the implementation of the model. According to the short period, the model promises to be positive and valid; indeed, outcomes are overall satisfactory and improved compared to the previous values.

Among the main limitations, surely the testing period was too small. Despite that, highlighted problems and main issues emerged during that week will constitute the starting point for what it is considered from the authors an additional step to the original Deming Cycle: its reiteration after having properly modified the model according to test, that is what is indented to be done in the future. A longer testing phase is scheduled.

Moreover, the average storage in terms of time according to both the origin of products and the storage levels should be calculated so that it can be compared to that presented in section 4.1.

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