A System Dynamics Model for Warehouse Performance Measurement with Highly Seasonal Demand and with Long and Short Life Products

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Abstract

This paper presents a model that identifies those variables that significantly affect the general performance of a warehouse with picker-to-parts storage systems, considering the dynamic nature of its processes and the possible non-linear relationships between its variables, under the effect of products with seasonal demand and long and short life cycles at the same time. As a methodology, a simulation model was developed under the systems dynamics (SD) paradigm. The main conclusions are that with this type of model it is possible to explain the behavior of the very structure of the warehouse and explain some non-linear relationships between its variables, such as the percentage of receipt on pallets, the percentage of picking and the total operating cost. The total operating cost is significantly affected when the percentage of receipt in full pallets decreases or when the percentage of picking increases. In relation to the percentage of income from full pallets, the imbalance between the receiving capacity in full and non-full pallets, generating accumulation of product to receive and penalization in costs due to delays in unloading (stand by) as the strategy upon receipt, full pallets decrease its percentage. The same happens with the picking percentage, as it increases, the increase in the total operating cost increases exponentially, because the pallets to be sent to customers cannot be processed on time, because there is also an imbalance between the capacity to prepare full and non -complete pallet orders.

keywords: Warehouse Operation, Warehouse Policies, Seasonal Products, Life Cycle, System Dynamics.

1. Introduction

Within the supply chain (SC) one of the most important node is the warehouse (Kusrini, Novendri, & Helia, 2018), which is a fundamental part of the development of logistics activities (Staudt, Alpan, Di Mascolo, & Rodriguez, 2015). Additionally, its operating cost is between 22 and 24% of the total logistics costs (Baker & Canessa, 2009; Havenga, Simpson, De Bod, & Viljoen, 2014). According to the National Logistics Survey (2018), the average logistics cost as a percentage of sales of companies in Colombia represents 13.5%, with the costs associated with warehouses being the most representative (46.5% out of 13.5%). However, although more than 80% of all order picking systems in Western Europe are picker to parts, the academic literature focuses primarily on warehouses with automated storage systems (product-to-picker) and automated storage/retrieval system (AS/RS - no utilization of personnel) (van Gils, Ramaekers, Caris, & de Koster, 2018). In Colombia, for example, to date, there is only one warehouse with an AS/RS.

The processes of a warehouse can be decomposed into several processes: receipt, storage, order picking and shipping. However, academic literature has mainly focused on the second and third processes (van Gils et al., 2018). All processes are conditioned by internal or external variables that affect their performance (de Koster, Le-Duc, & Roodbergen, 2007). Underestimating or ignoring them can lead to the failure of the warehouse operation, which demands a more precise knowledge on how to identify and understand the impact of these variables on the performance of this nodes of the SC (Razik, Radi, & Okar, 2016).

Most of the research aimed at improving the performance of warehouses has focused on studies with an analytical approach, that is, decomposing the warehouse into elementary parts in order to study them in detail and under ideal conditions (no environment); with the corresponding loss of vision of the whole. However, this approach in principle, is valid when the variables involved have simple relationships, but it is not enough when it comes to approaching complex systems, such as warehouses (Cagliano, Demarco, Rafele, & Volpe, 2011; Staudt et al., 2015). In addition, warehouses present an increasing complexity linked to the possible non-linear relationships between the variables that affect their performance (Cagliano et al., 2011; Li, 2016) and it needs researchers to constantly incorporate new information about the environment, dynamic and operational processes associated with their processes (Gu et al., 2007; van Gils et al., 2018). This is, a systemic vision for evaluating their performance. Then, systems dynamics (SD) is considered an useful approach, since it is a modeling and simulation technique that helps to elicit complex systems (Forrester, 1961). Likewise, it provides an understanding of the general behavior of the output variable and the influence of the various input variables on its performance and also guides policy design by simulating different scenarios (Greasley, 2005).

1.1. Objective of the Study

Based on the opportunities described above, this paper's main objective is to create a model under a systemic approach, which identifies those variables that affect the general performance of a warehouse related to the picker-to-parts order-picking system, under the effect of products with seasonal demand and a long and short life cycle. In particular, the effect of the picking percentage and the percentage of product received on pallets on the total operating cost was unveiled.

2. Literature review

2.1. Warehouse processes and typology

A warehouse is basically an intermediate storage point in the supply chain, where raw materials, work in process and finished product are stored (Khan, Dweiri, & Chaabane, 2016). Its processes can be decomposed into reception, storage, order preparation and shipping (Indrawati, Miranda, & Bryan Pratama, 2018; Shah & Khanzode, 2017; van Gils et al., 2018).

The receipt process consists of assigning docks to vehicles and scheduling and executing unloading activities (Gu et al., 2007). Storage is defined as the movement of materials from the unloading area to the place defined for it (Johnson & McGinnis, 2011; L.-R.Yang & Jieh-Haur Chen, 2012). Order picking consists of listing customer orders (Staudt et al., 2015) and shipping comprises assigning vehicles to docks, packing orders, and loading vehicles (Gu et al., 2007).

According to their level of automation, we can distinguish three types of storage systems: manual storage systems (picker-to-parts systems), automated storage systems (parts-to-picker systems) and automatic storage systems (de Koster et al., 2007; J.P. van den Berg, 1999). A storage system refers to the combination of equipment and operational policies that are used in an item storage / retrieval environment (J.P. van den Berg, 1999). In the manual storage system (picker-to-product systems), what is the type of warehouse that is studied in this research, the operator drives a vehicle along the storage sites in search of the product (J.P. van den Berg, 1999).

2.2. Warehouse Performance Measurement

Performance measurement can be defined as the process of quantifying the efficiency and effectiveness of an action or process (Neely, Gregory, & Platts, 2005). There are several methods to classify metrics for measuring the performance of a warehouse (Kusrini et al., 2018). A literature review of papers dedicated to warehouse measurement and analysis were conducted, a total of 23 papers were reviewed and when going into the details of each classification they can be grouped into the following dimensions: time, quality, cost, productivity, efficiency, safety, customer satisfaction, environment, and flexibility. Figure 1 shows that the dimensions with the highest presence in the literature were quality, time, productivity, cost, and efficiency (32, 18, 16, 15 and

15%, respectively). However, very few metrics were associated with the dimensions of environment, customer satisfaction, flexibility, and safety.

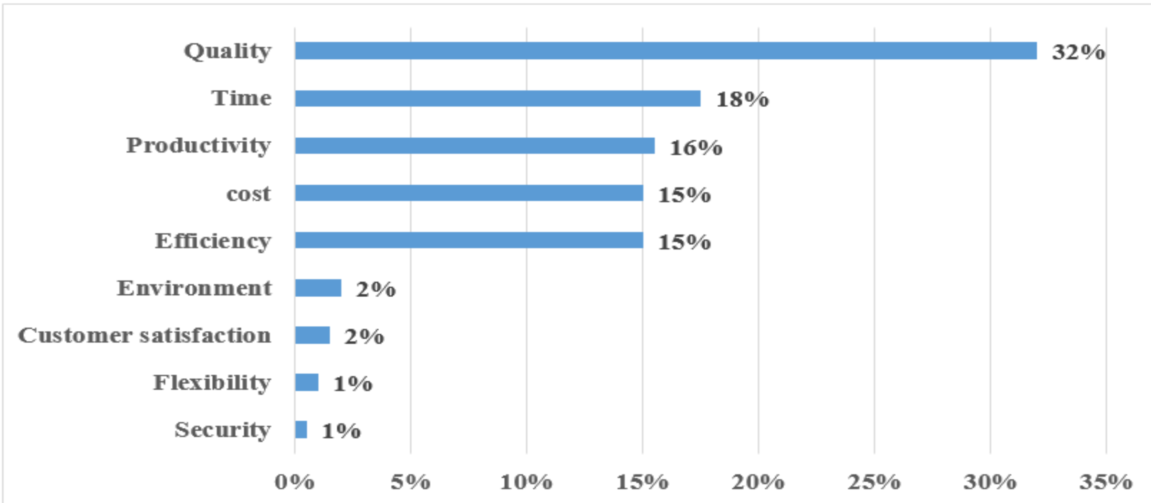

Figure 1. Dimensions to measure warehouse performance.

Considering all the dimensions of the studies cited in this research, a total of 67 indicators were reported and 11 of them represent 39% of the total number of times they were included in at least an article (Figure 2). The metrics with the highest inclusion correspond to the dimensions with the highest presence in the papers.

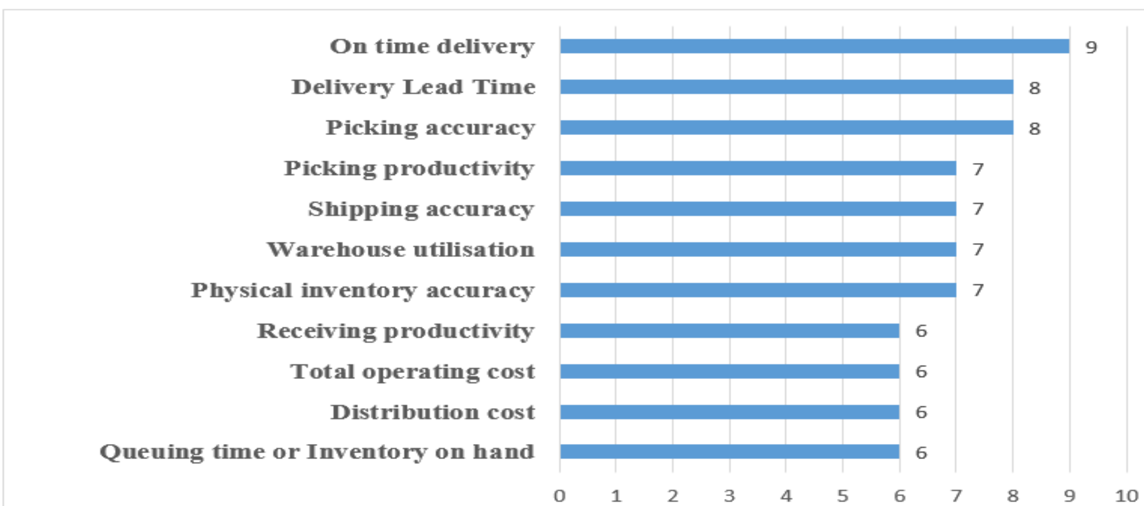

Figure 2. Main indicators for warehouse performance measurement

2.3.System Dynamics

In the modeling process of the warehouse we resort to the SD methodology , which is a tool that allows the modeling of systems in a more aggregated form and in terms of the inputs required by the simulation model (Sterman, 2000). Unlike other simulation methodology, SD focuses on highlighting the structural aspects of the system that explain the observed behavior (Bala, Arshad, & Noh, 2017; Sterman, 2000). This type of model has four steps for its development: (1) identification of the problem and analysis of the behavior of key variables, (2) creation of a qualitative or causal diagram, (3) creation of a quantitative model with stocks and flows as is main components (known also as Forrester diagram) and (4) evaluation and analysis of the model. (Aracil, 1995).

The variables within the model are classified into stocks, flows and auxiliary variables. In addition, constants are included in the model. The flows indicate the rate of change of the variables as a function of time and the stocks are the result of the difference between the inflow and outflows.

3. Materials and methods

This section explains in detail the steps and results of the construction of the SD simulation model. To develop the simulation model that measures the performance of a warehouse, a local warehouse with a picker-to-part system from a Colombian company in the food sector are used (Table 1 presents the relevant data). The simulation step chosen was in hours and the time horizon of one year. The modeling was performed using the computer program Powersim Studio 10.

Identification of the problem and analysis of the behavior of key input variables. Table 1 details the system variables, which were established according to the main processes of a warehouse: receiving, storing, order picking and shipping, (Rouwenhorst et al., 2000; Staudt et al., 2015; van Gils et al., 2018). Table 1 also introduces the input variables whose impact on the warehouse performance will be considered by the SD modelling.

In addition, the total operating cost of the warehouse and the fill rate related to the number of pallets received or shipped to customers during the simulation period were defined as output variables. However, although the evaluation of performance at the operational level is mainly based on non-financial indicators (Staudt et al., 2015), such as the fill rate, the total cost of operation is one of the most important metrics in measuring the performance of a warehouse, so it was included in this study.

Qualitative or causal diagram. In the second step, the qualitative or causal diagram of the system has to be created, which is nothing more than a diagram of influences showing the basic relationships between variables describing the feedback structure that causes the problem (Sterman, 2000). Figure 3 depicts the description of a warehouse according to (de Koster et al., 2007).

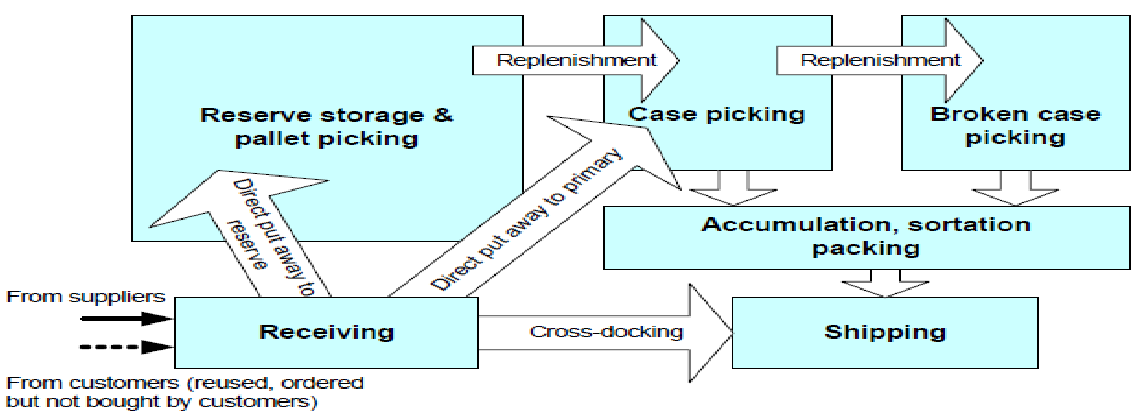

Figure 3. Typical warehouse functions and flows. Adapted from (de Koster et al., 2007).

Stocks and flows structure. In the third step, the quantitative model was created with its respective mathematical equations. The modeling process was carried out by representing the system variables identified in the previous step in terms of constants, stocks and flows (Table 1 and Figure 4), where flows are denoted as valves (pre-storage rate or storage rate) and stocks as rectangles (pre-storage area or inventory) (Aracil, 1995). Constants are represented by diamonds.

Table 1. Variables and base scenario that describe the warehouse under a DS approach.

Process	Variable	Base scenario	Observations	Type of variable
Receiving	Product entry on pallets	Information in hours	Line and season product	Flow
	Percentage of product is received on pallets	99%		Constant
	Receiving area capacity	400 pallets		Constant
	Product waiting to be received full pallet	Pallets		Stock
	Product waiting to be received non full pallet	Pallets		Stock
	Receiving productivity- non full pallet	19,5 Pallet/hour-labour	2 people in the process. Receiving case for case	Auxiliary
	Receiving productivity-full pallet	30 pal/hours-labour	2 people in the process	Auxiliary
	Receiving rate	Pallets/hour	Result of several variables	Flow
Storage	Pre-storage productivity	60 pal/hours-labour	3 people in the process	Auxiliary
	Storage productivity	45 pal/hours-labour	3 people in the process	Auxiliary
	Pre-storage capacity	330 pallets		Constant
	Product in pre-storage area	Pallets		Stock
	Storage capacity	67.500 pallets		Constant
	Stored pallets	Pallets		Stock
	Pre-storage rate	Pallets/hours	Result of several variables	Flow
	Storage rate	Pallets/hour	Result of several variables	Flow
Order Picking	Product output on pallets	Information in hours	Line and season product	Flow
	Order picking area capacity	750 pallets		Constant
	Picking productivity-full pallet	30 Pallets/hours-labour	3 people in the process	Auxiliary
	Picking productivity-non full pallet	10,5 Pallets/hours-labour	3 people in the process	Auxiliary
	Picking percentage	10%		Constant
	Order waiting to be order picking- full pallet	Pallets		Stock
	Order waiting to be order picking- non full pallet	Pallets		Stock
	Order picking rate on full pallets	Pallets/hour	Result of several variables	Flow
	Total order picking rate	Pallets/hours	Result of several variables	Flow
	Order picking rate- non full pallet	Pallets/hours	Result of several variables	Flow
Sorting	Sorting productivity	45 pal/hours-labour	4 people in the process	Auxiliary
	Sorting rate		Result of several variables	Flow
Shipping	Shipping productivity	15 pal/hours-labour	10 people in the process	Auxiliary
	Shipping rate- non full pallet	Pallets	Result of several variables	Flow

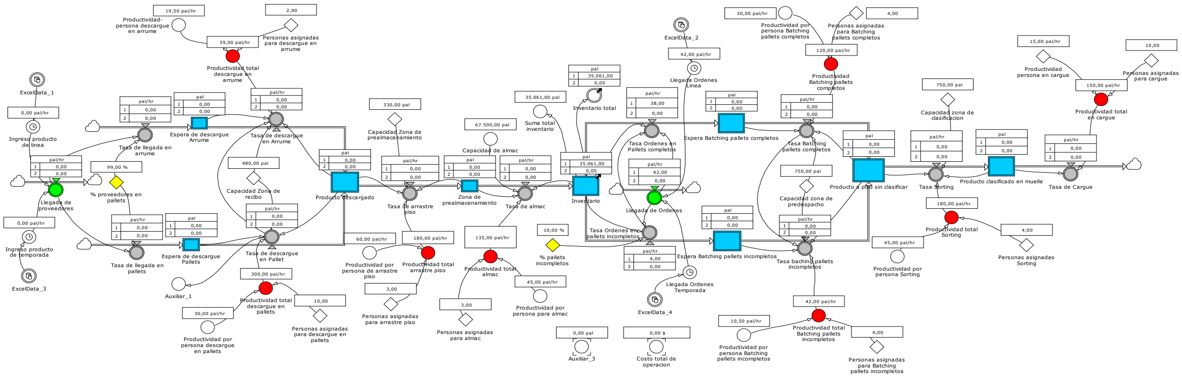

Figure 4. Stocks and flows diagram of the warehouse simulation model.

Validation and analysis of the model. To validate the model, we implemented the validation procedures proposed by Forrester and Senge (1980) and Sterman (2000). The validation tests the model considering its structure, behavior, and policies. To verify if the model is able of reproducing observed date we use the Theil´s inequalities test. This tests provides a percentage decomposition of the mean square error (MSE) in terms of the bias (UM), unequal variance (US) and unequal covariance (UC) as proposed by (Sterman, 1984). The validation was carried out based on the main processes and variables of a warehouse, which are widely known in the literature (Rouwenhorst et al., 2000; Staudt et al., 2015; van Gils et al., 2018).

The behavior validation was done on two output variables measured in pallets, which represent the state of the system at a given moment. They are the inventory level of line product (long cycle) and the inventory level of seasonal product (short cycle). Table 2, shows the results of the general goodness of fit test (Theil method) and the statistical analysis between the real (A) and simulated (S) results. These results illustrate that the model accurately recreates the behavior of the inventory level in the warehouse for the two types of product.

Table 2. Summary of statistics to evaluate the fit of the simulated vs real data

Indicator	**Seasonal product**	**Line product**
Simulated mean (X_S)	4337	41584
Real mean (X_A)	4012	41951
Simulated standard deviation (S_S)	4831	4474
Actual standard deviation (S_A)	4482	3.235
Correlation coefficient (R)	0.991	0.853
R^2 coefficient	0.981	0.728
Mean absolute percent error (MAPE)	19.6%	4.7%
Mean square error (MSE)	633409	5887016
Root Mean Square Error (RMSE)	796	2426
UM	16.70%	2.28%
US	19.26%	26.08%
UC	64.27%	72.07%

For the two cases, line and seasonal product, most of the MSE is concentrated in the unequal covariance (UC), while the bias (MU) and unequal variance (US) values are relatively small. This indicates that the point-by-point values of the simulated and real series do not coincide, although the model is able to capture the average value and the dominant trends (Sterman, 1984). In addition, as the value of the unequal covariance (UC) is large, it indicates the presence of noise or cyclical data not captured by the model, however, this type of error is not systematic and is not considered a criterion to reject its validity (Sterman, 1984). Figures 5 and 6 show a comparison between the real and simulated inventory levels for the two products (seasonal and line) depicting how well the model represents the behavior of the two output variables chosen for this analysis. Moreover, as Table 2 shows the coefficient of correlation is relatively high, with values above 85% in both products, showing that the behavior of this variables is well captured by the proposed SD model.

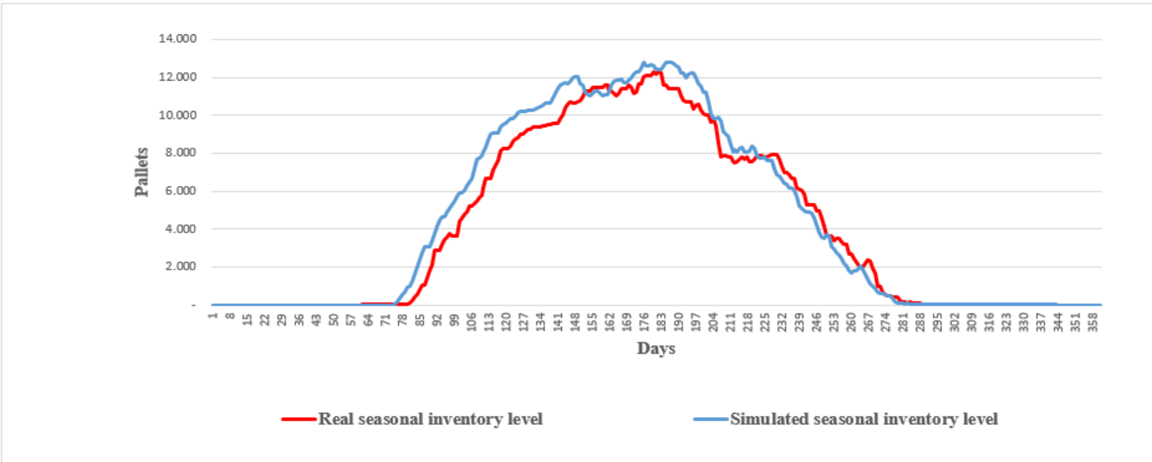

Figure 5. Real vs. simulated seasonal inventory level comparison

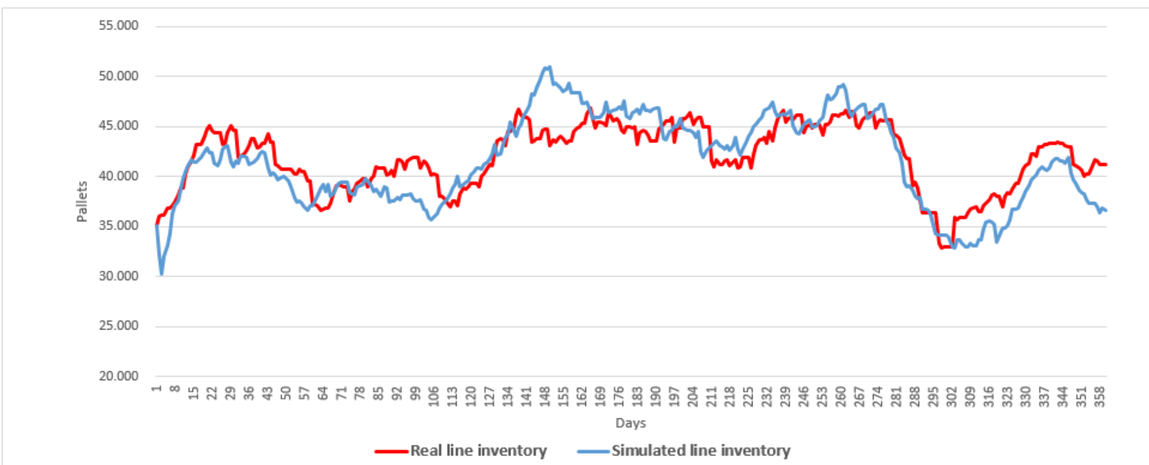

Figure 6. Comparison of the real vs simulated line inventory level.

S*cenario evaluation.* A base scenario was defined with the historical information of one year of warehouse operations. The following strategies were simulated: 1) Modification of the percentage of receipt on pallets from 0% to 100% with increments of 5 points; 2) Modification of the picking percentage from 0% to 100% with increments of 5 points. The two previous strategies sought to evaluate the behavior of the total cost of operation of the warehouse. In the first one, the pallet receipt percentage variable, as its name indicates, is associated with the receipt process and it was expected that the higher the magnitude, the higher the productivity within this process. In the second, the variable to be modified was the picking percentage within the order preparation process, which is equivalent to the percentage of orders to be processed on non-full pallets. Here, it was expected that the lower the picking percentage, the higher the productivity within this process.

The percentage of picking in a warehouse with manual storage systems (picker-to-parts systems), increases the complexity and use of resources in the picking process, this being the most expensive among all the processes within the warehouse, with more than 60% of all operating costs (Gu et al., 2007; Staudt et al., 2015). Regarding the percentage of receipt in full pallets, the reasoning is similar to that of the picking percentage, taking into account that, although it is not part of one of the most expensive processes, it does have a direct effect on the others, since, if product is not received, there is no way to execute the other processes or reprocesses within these.

4. Results and Discussion

The behavior of the total operating cost of the warehouse was evaluated by modifying the percentage of product that enters on full pallets and the percentage of (non-full pallet) picking. Figures 7 and 8 illustrate how the total cost of operation does not vary significantly between 70 and 100% of product entry on pallets (around 2%). However, for values lower than 70% it grows substantially, but almost constantly.

The significant increase in the total operating cost decreasing the entry of full pallets to the warehouse, which increases the percentage of receipt in non-full pallets, is due to the accumulation of pallets pending to receive in this process and the corresponding penalty for the delay (stand by). This accumulation and delay in the receipt, becomes more critical as the percentage of receipt of full pallets decreases, considering that its capacity is 7.6 times greater than that of the receipt of not full pallets.

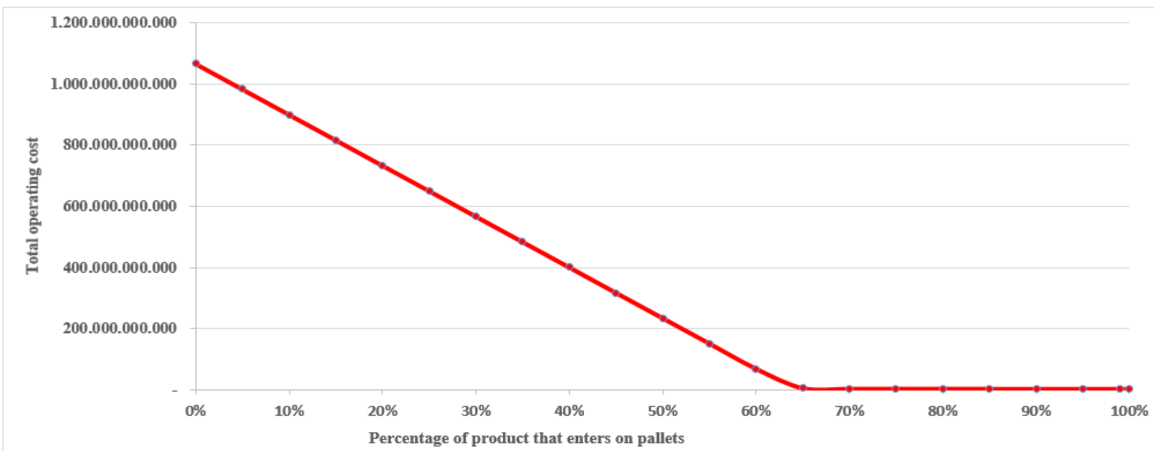

Figure 7. Comparative graph of the total operating cost vs percentage of receipt on pallets. Range 0-100%.

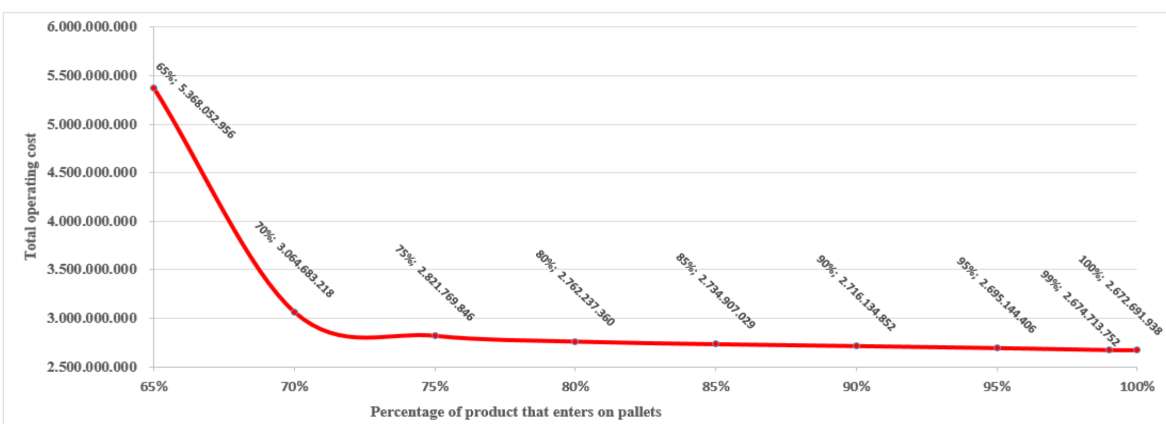

Figure 8. Comparative graph of the total operating cost vs percentage of receipt on pallets (Zoom between 65-100%)

Similarly, in Figure 9 and 10, a similar behavior is observed between the total operating cost and the picking percentage, where this first variable does not vary significantly when the picking percentage is between 15-30%. However, for picking percentage values lower or higher than this range, the total operating cost increases, presenting considerable growth levels with values higher than 40%. The significant increase in the total operating cost, increasing the percentage of picking in the order preparation process, is due to the accumulation of pending pallets to be processed in this process and the corresponding penalty charge for the delay (plus overtime of the operating personnel). This accumulation and delay, becomes more critical as the percentage of receipt of full pallets increases, considering that its capacity is 2.9 times greater than the preparation of orders in full pallets.

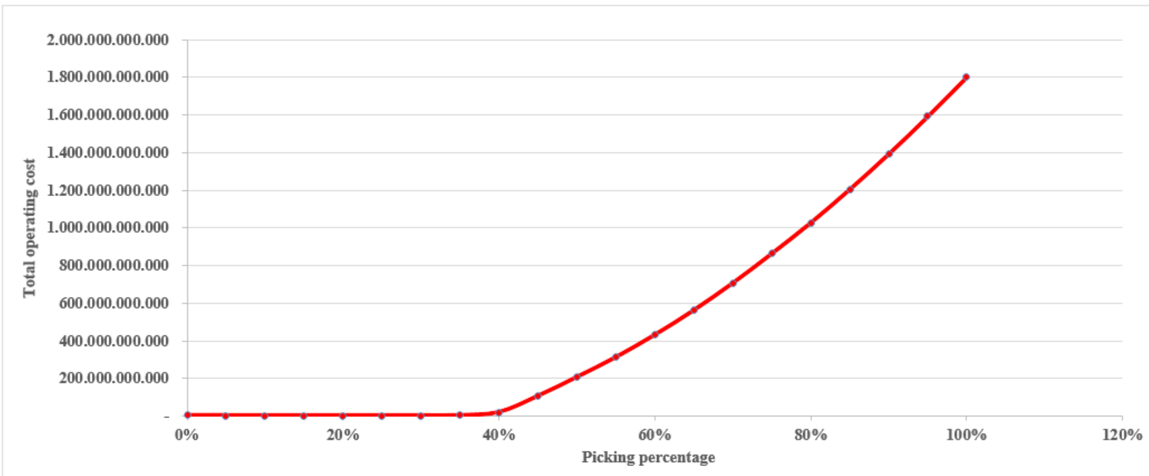

Figure 9. Comparative graph of total operating cost vs percentage of picking. (Range 0-100%).

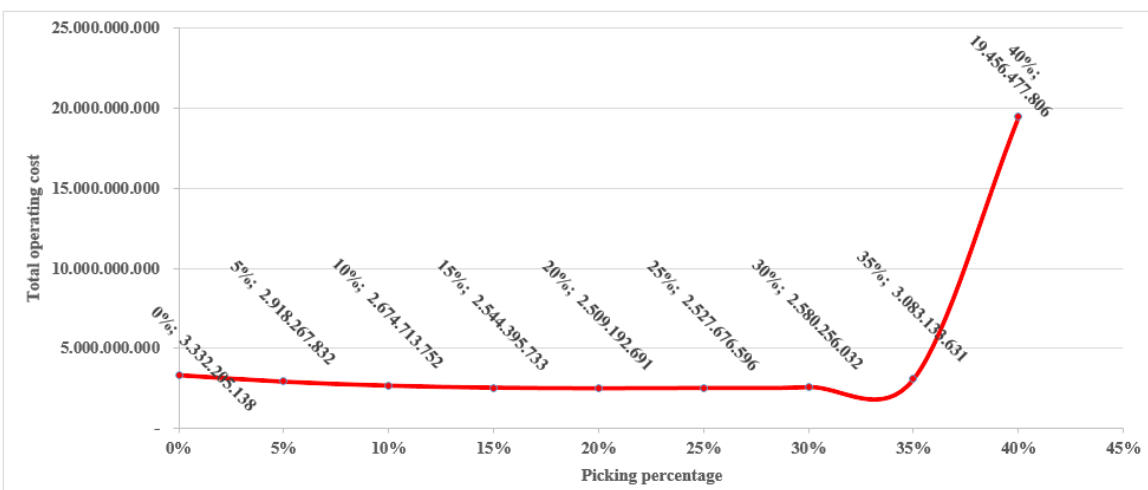

Figure 10. Comparative graph of total operating cost vs percentage of picking (0-40%)

It was expected that, as the percentage of entry on pallets increased or the percentage of picking decreased, the total operating cost would decrease its value. However, the result shows that, among the variables that are part of a warehouse with picker-to-parts order-picking systems, there are always not necessarily linear relationships. Moreover, both figures exhibit a critical value, above this value the behavior of the operating cost is affected, whereas below this value the system is insensitive to the modification of these variables.

5. Conclusion

In this work we present a system dynamics model of a warehouse with picker-to-parts system that represent a major portion of warehouse operations in practice. Using this model, we identified that among the variables that are part of such type of warehouse there are always not necessarily linear relationships, this is the case between the percentage of product that enters the warehouse on full pallets, the percentage of picking and the total operating cost.

The reasons are associated with the imbalance between the receiving capacity in full and non-full pallets, the first being 7.6 times greater, generating accumulation of product to receive and penalization in costs due to delays in unloading (stand by) as the strategy upon receipt full pallets decrease its percentage. The same happens with the picking percentage, as it increases, the increase in the total operating cost increases exponentially, because the pallets to be sent to customers cannot be processed on time, using a greater number of hours to make the same job due to delay; considering that, the imbalance between the capacity to prepare full and non-full pallet orders also influences, with their ratio being 2.9 times.

Future work will analyze the relationship between the total cost of operation and other variables, such as the capacity of the reception area, the capacity of the area of preparation of orders or storage and the inclusion of the availability of vehicles and delays in their arrivals, as well such as staff turnover between processes and its effect on performance.

For example, the lack of availability of vehicles or the delay in their arrival could increase the level of inventory since it would affect the continuous output of product and could increase the total operating cost, considering that more man-hours would be needed to make the same work. Also, if operating personnel are trained to do various tasks within the warehouse, the total operating cost could decrease because personnel could move between processes to level product flows.

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