



Identifying critical variables of warehouses performance under highly
seasonal demand using system dynamics

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This Thesis is dedicated to:

This thesis is dedicated to my mother Calixta Isabel, my father Diego José, my brother Howard Diego, my wife Kelly Beatriz and my son Matias.

ABSTRACT

This research aims to identify the variables having the greatest influence on the performance of a warehouse with a picker-to-parts storage system in a scenario of high seasonal demand and products with short- and long-life cycles simultaneously. Systems dynamics and statistical screening were used to address this situation from a systemic point of view. The main results show that the picking percentage and the receipt percentage on pallets are the dominating parameters driving the warehouse's total operating cost. Contrarily, the cross-docking percentage and, the shipment percentage on pallets do not significantly affect the total operating cost. Using the data of a Colombian warehouse as a case study, the best values of the different parameters lead to a total operating cost reduction of 38% compared to the case base scenario; if the effect of the season is eliminated, it decreases to 41%, but if the flow of the season doubles, it decreases by 21%. The reductions in the total operating cost are generated by the reduction of the penalties in each process under the best values of each parameter. By contrast, the receipt percentage on pallets, picking percentage, cross-docking percentage and, shipment percentage, do not affect the fill rate of receipt and shipment within the uncertainty ranges analyzed.

Keywords: Warehouse Operation, Warehouse Performance, Seasonal Products, System Dynamics, Statistical Screening

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1. Introduction

Currently, globalization, the advancement of the world economy, technological development, and the complexity of consumer orders have caused an increase in the demand for transportation and storage services (Karim, 2020). The demand is increasingly changing, with a greater variety of products, smaller orders, and increasingly shorter response times (Binos, Bruno, & Adamopoulos, 2021; Marchet, Melacini, & Perotti, 2015). Warehouses are under constant pressure to increase productivity and precision while reducing costs and improving customer service (Karim, 2020).

In a supply chain (SC), one of the most important nodes is the warehouse (Popovi, 2021; Staudt, Alpan, Di Mascolo, & Rodriguez, 2015). Taking into account that its total operating cost is between 22-24% of total logistics costs (Baker & Canessa, 2009; Havenga et al., 2014). Moreover, 10% of warehouses handle only products on full pallets, while 66% of warehouses handle a mix of pallets, cases, and broken cases (Binos et al., 2021). For instance, in Colombia, on average the logistics cost as a percentage of the sale represents 13.5%, with the costs associated with warehousing being 46.5% of this value (Ministerio de Transporte, 2018).

Although the literature reports that most of the manual warehousing in Western Europe are picker-to-parts systems (van Gils, Ramaekers, Caris, & de Koster, 2018), and they are still the dominant order fulfillment solution worldwide (Yang et al., 2021), researchers have focused on analyzing warehouses with parts-to-picker and automatic systems (de Koster et al., 2007; Yang et al., 2021). In Colombia, for example, to date, there is only one fully automated warehouse.

Even though the future of warehouses is automation, not all warehouses can be automated in a viable way. The high cost of automation, the size of some of them, and the irregular and bulky shapes of the products are among the main barriers to the automation of warehousing operations (Binos et al., 2021; Yang et al., 2021). In a picker-to-parts storage system, the order picker must walk or drive through the aisles of the warehouse to collect the items (Berg & Zijm, 1999), the use of labor is intensive, especially in order picking operations (de Koster et al., 2007; Wang et al., 2019), and it is the most expensive resource of this type of warehouse (Aminoff et al., 2002; Amorim-lop et al., 2020).

Considering the main processes of a warehouse (receipt, storage, order picking, and shipping) (Shah & Khanzode, 2017), the academic literature has mainly focused on the storage and order picking processes (van Gils et al., 2018). According to Gu et al. (2007), these are the processes that have the greatest impact on general operational performance, order picking being the main process in most warehouses (Davarzani & Norrman, 2015; de Koster et al., 2007), and accounting for more than 50% of the total operating cost (Chen, Cheng, Chen, & Chan, 2015; Staudt, Alpan, Di Mascolo, & Rodriguez, 2015). On the other hand, research on the receipt and shipping processes is rather scarce (Davarzani & Norrman, 2015).

In general, the vast majority of scientific articles that analyze warehouse performance address isolated, well-defined problems that can be tackled using analytical tools (Rouwenhorst, B., B. Reuter, V. Stockrahm, G.J. van Houtum, R.J. Mantel, 2000). For instance, the assignment of SKUs (Stock Keeping Unit) to various warehouse departments, the scheduling of inventory movements between departments, the assignment of SKUs to different zones (zoning), and assigning storage locations (SLAP)

within a department/zone (Gu et al., 2007). Moreover, several authors that have studied individual planning problems that affect warehouse performance, conclude that these planning problems are interdependent and mutually affect each other (Shah & Khanzode, 2017; van Gils et al., 2018). According to (Davarzani & Norrman, 2015), most research on warehouse planning problems neglects the dynamism it faces, therefore, optimizing each problem separately can generate a non-optimal solution for overall performance from the global warehouse point of view (van Gils et al., 2018).

In practice, these solutions are difficult to implement because the models are solved with enormous assumptions or limitations (Shah & Khanzode, 2017). Most of the published works are in deterministic conditions, although the business environment contains many uncertainties and risks (Davarzani & Norrman, 2015). This requires a solution that promotes the improvement of the general performance of the warehouse (Shah & Khanzode, 2017), considering, simultaneously, multiple planning problems to face the new challenges of the market (van Gils et al., 2018). This new approach and real-life aspects will make warehouse research more valuable in practice (van Gils et al., 2018).

Likewise, external variables that affect warehouse performance must be analyzed. For instance, (Gu et al., 2007) state that, the flow of material through the warehouse changes dynamically due to the seasonality of demand and the life cycles of the products. According to (de Koster et al., 2007), marketing channels, customer demand patterns, inventory replenishment patterns, and the state of the economy also affect warehouse performance.

In particular, the life cycle of products plays an important role in the management of today's supply chains, where multiple products must be distributed, each with a different life cycle. The simultaneous flow of different types of products causes important challenges in the warehouse, since they use similar resources, and may negatively impact their costs (Guthrie et al., 2017). Furthermore, the seasonality of demand is a very common external factor that affects warehouse performance but is difficult to manage efficiently (Tayal & Sharma, 2014). Seasonality causes fluctuations throughout the year that trigger the hiring of temporary workers (Nikaido et al., 2006), the scheduling of overtime (Takey & Mesquita, 2006), or the rental of more space (Tayal & Sharma, 2014) and increasingly efficient warehouse processes (Cagliano et al., 2011).

Most of the studies have been aimed at improving the performance of the warehouse under an analytical approach. That is, they decompose the warehouse into processes or parts of processes and then study them in detail and under ideal conditions, overlooking a whole-system vision. However, this approach is valid, in principle, for systems with simple relationships, but it is not enough when it comes to complete systems, such as warehouses (Cagliano et al., 2011; Staudt et al., 2015). Furthermore, warehouses present an increasing complexity due to the possible non-linear relationships between their variables that affect their performance (Cagliano et al., 2011; Li, 2016). Therefore, all these previous arguments require that researchers focus their efforts on generating knowledge about the impact of variables on the dynamic behavior of the warehouse, under a systemic approach that allows to better evaluate their performance. It is here, where SD appears as a useful tool. As a very flexible modeling and simulation technique, SD allows the analysis of complex systems (Forrester, 1961), and the design of policies (Greasley, 2005), as well as the understanding of the behavior of output variables and the influence that input parameters have on system performance.

Therefore, the main objective of this thesis is to develop a methodology that considers the warehouse as a system and that determines the degree of impact of a set of selected input variables on its general performance. The warehouse under study will have a picker-to-parts order picking system, under the effect of products with seasonal demand and long-life (line) and short-life (season) cycles. The proposed methodology leverages SD and statistical screening (SS) as the main tools for the analysis. Moreover, real data from a food company will be used as a case study.

2. Literature review

2.1. Warehouse processes and typology

Consistent with Khan, Dweiri, & Chaabane (2016), a warehouse is a node of the SC where raw materials, products in process, or finished goods are stored. Its main processes can be decomposed into reception, storage, order picking, and shipping (J.P. van den Berg, 1999; van Gils et al., 2018). In all processes, decisions are made that affect the general performance of the warehouse, such as the allocation of resources (Reyes et al., 2019). The receipt process consists of assigning docks to vehicles and scheduling and executing unloading activities (Gu et al., 2007). The product is unloaded at the reception docks, quantities are verified and random quality controls are carried out (J.P. van den Berg, 1999). 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). This involves marking the storage unit (for example pallets) and on occasions repackaging (e.g. full pallets or cases) (de Koster et al., 2007; J.P. van den Berg, 1999). Order picking consists of obtaining the correct quantity from the correct references for a given set of sales orders (de Koster et al., 2007). Finally, shipping involves scheduling and assignment of trucks to docks (Gu et al., 2007) and, the orders packing after picking and the loading of trucks (Staudt et al., 2015). The flow of products through all the processes of the warehouse can occur on pallets, cases, or broken cases (de Koster et al., 2007). Additionally, cross-docking is a shipping strategy that involves moving products from the receiving dock to the shipping dock with minimal dwell time between them. Cross-docking can lead to decreases in order cycle time, thus improving the flexibility and responsiveness of the warehouse (Apte & S. Viswanathan, 2010).

According to their level of automation, order picking systems are classified into three types: picker-to-parts systems, parts-to-picker systems, and automatic systems (de Koster et al., 2007; J.P. van den Berg, 1999). In picker-to-parts systems, the order picker walks or drivers an order-pick truck through the aisles of the warehouse to collect the different items (de Koster et al., 2007; J.P. van den Berg, 1999). Parts-to-picker systems are made up of automated storage and retrieval systems (AS / RS), generally using equipment that retrieves one or more load units and brings them to a collection location (de Koster et al., 2007). At this location, the order picker takes the required quantity and then the remaining load is stored again (de Koster et al., 2007). In automatic systems, order picking is carried out at high speed, with non-fragile articles, of uniform shapes and small or medium size (J.P. van den Berg, 1999). Human resources are not used to carry out the processes (de Koster et al., 2007; J.P. van den Berg, 1999).

Picker-to-parts systems have basic variants that include batch picking and discrete picking (order selection) (de Koster et al., 2007; J.P. van den Berg, 1999). Consistent with de Koster et al. (2007), in the case of batch picking, orders from multiple customers are picked up by an order preparer while sorting simultaneously (sort-while-pick) or carried out after the picking process has finished (pick-and-sort). In batch picking, zoning can be

done, which means that a storage area is divided into several parts, each with different order pickers. Zoning can be progressive or synchronized. In progressive zoning, an order picker begins picking and when his part is finished, he delivers it to the next picker who continues the selection. This process is repeated until the different orders are finished in the selection wave. In synchronized zoning, multiple order pickers begin the separation process simultaneously, but each in a different zone. Partial orders are merged after selection. In picker-to-parts systems, the use of labor is intensive, especially in order picking (de Koster et al., 2007; Wang et al., 2019), being the most expensive resource in this type of warehouse (Aminoff et al., 2002; Amorim-lobes et al., 2020).

2.3. Warehouse performance evaluation

To improve warehouse performance, the scientific community has studied the problems facing warehouses. Below is a summary of a selected subset of works that describe the contributions from an analytical approach. According to that considers that the whole is the sum of its parts and that a general explanation is made up of a set of individual explanations (Garbolino et al., 2019).

A seminal literature review on warehouse planning problems (Gu et al., 2007) showed that research on these systems is unbalanced. For example, SLAP (assignment storage locations) represented 32% of the total literature surveyed, while zoning less than 6%. Moreover, these authors also found an imbalance in the treatment of problems that arise in order picking, routing representing 38%, while batching 12%, and sorting just 3% of the total literature surveyed.

Similarly, Davarzani & Norrman (2015), conclude that most of the works consider travel time as the main indicator to optimize when evaluating the order picking process. The authors identified that the most widely used research method is mathematical modeling but without the use of data from real cases (51.9% out of the papers they surveyed used synthetic data). Finally, they state that static information is the main mode of entry for the problems addressed, while the uncertainty of the business environment is generally neglected.

A more recent literature review on warehouse planning problems (van Gils et al., 2018), states that the number of articles considering multiple problems of the order picking planning process has increased considerably in the last decade (2008-2017). However, the publications continue to focus on SLAP, batching and routing. According to the authors, the literature has focused heavily on reducing order picking time. They also conclude that there is a need to integrate more planning problems and include real-life features. In a recent literature review on SLAP (Reyes et al., 2019), the authors highlight that this is one of the problems that has received the most attention from the scientific community.

However, although several decision support models have been proposed in the literature to improve warehouse performance, considerable difficulties continue to be found in the application of these models (Gu et al., 2007). In practice, it is difficult to implement such algorithms due to the hard assumptions often made (Moeller, 2011), since they are solved with enormous assumptions or limitations (Shah & Khanzode, 2017). Most of the published investigations are found in deterministic conditions, although the business environment contains many uncertainties and risks (Davarzani & Norrman, 2015). For instance research on order picking systems is subject to a large number of

assumptions to simplify the order picking operations (Davarzani & Norrman, 2015; de Koster et al., 2007; van Gils et al., 2018).

Similarly, Gu et al. (2007), state that there is little evidence of collaboration between the academic research community and industry, and many of the research results are not sufficiently communicated to the industry to have a significant impact on the practice of warehouse operations. Furthermore, according to Carter (2008), the gap between research and practice is generated because the knowledge produced is not relevant to managerial needs or is not adequately transferred (Davarzani & Norrman, 2015). Finally, according to Shah & Khanzode (2017), most academics focus on quantitative research methods and mathematical models without any real case example therefore more simulation-based studies or real case studies are required.

A major drawback in the vast majority of scientific papers is that they address well-defined isolated problems and are typically analytical (Rouwenhorst, B., B. Reuter, V. Stockrahm, G.J. van Houtum, R.J. Mantel, 2000), although there is some research on dynamic planning of warehouse operations (Gu et al., 2007). According to Davarzani & Norrman (2015), most publications about warehouse planning problems neglect the dynamism it faces, therefore, optimizing each problem separately and in a static environment, although several authors have found that all warehouse operational problems are interrelated and mutually affect each other (Shah & Khanzode, 2017), proposing an analysis under a systemic approach. In this context, simulation appears as a valuable tool to evaluate and analyze warehouse performance. In the next section, we focus on SD applied to warehouse modelling and analysis. For the traditional discrete event simulation approach, the interested reader is referred to (Agalinos et al., 2020; Banks, J., Carson II, J. S., Nelson, B. L., & Nicol, 2015).

Consistent with Garbolino et al. (2019), the systemic approach states that phenomena and problems are considered systems. Furthermore, that every system has properties that cannot be reduced to the sum of the properties of its components. According to Durand (2006), the systemic approach is characterized by four main concepts: interaction, comprehensiveness, organization, and complexity (Garbolino et al., 2019). Interaction is related to causality in a system, where the elements that compose it interact with each other. They perform actions on other elements and in turn are subjected to actions of other elements. Completeness means that not everything can be reduced to the sum of its parts. There are specific properties that depend on a subset of the system or the entire system. Organization refers to both the structure and the functioning of the system and suggests, implicitly, a goal. According to Donnadiou and Karsky (2002), the complexity of systems generally suggests that it is difficult to predict the dynamics or evolution of a system (Garbolino et al., 2019). These four main approaches reflect the difficulties of studying, understanding, and acting on complex systems. However, one method to evaluate, diagnose, and understand these types of systems is systemic modeling (Garbolino et al., 2019).

2.4. Warehouse performance evaluation: Simulation

Several works have addressed warehouse planning problems under a systemic approach, using simulation as an analysis method and taking into account that the warehouse is a complex system. Indeed, Cagliano et al. (2011) and Li (2016), the warehouses present an increasing complexity due to the possible non-linear relationships between their variables, which can affect their performance. Furthermore, the use of an analytical

approach, in principle, is not enough when it comes to complex systems, such as warehouses (Cagliano et al., 2011; Razik et al., 2016; Staudt et al., 2015).

According to Wai & Chooi-Leng (2011), the application of SD is being considered one of the best methods to increase competitiveness. It is a suitable methodology for studying complex feedback systems and provides a means of understanding the causes of their behavior. Unlike other simulation methodologies, SD highlights the structural aspects of the system that explain the observed behavior (Bala et al., 2017; Sterman, 2000). This simulation approach has four steps for its implementation: (1) identification of the problem and analysis of the behavior of the key variables, (2) creation of a qualitative or causal diagram, (3) creation of a quantitative model with stocks and flows, and (4) evaluation and analysis of the model (Aracil, 1995). The variables within the model are classified into stocks, flows, and auxiliary variables (Sterman, 2000). Flows indicate the rate of variation of variables as a function of time and stocks are the result of the difference between inputs and outputs (Sterman, 2000).

Under SD, several works have been developed on improving the performance of warehouses. For example, Cagliano et al. (2011), propose an analysis of different supply and personnel allocation policies that affect the dynamics of the general operational performance of the warehouse. In particular, the study suggests that the flexible use of human resources, the outsourcing of some warehouse operations, such as the counting of items in the receipt process, and the sourcing of reliable, but more expensive suppliers, generate total cost savings of the warehouse, reduced inventory and shorter delivery times. Yuan X. & Zhang Q. (2016) developed a system that integrates the warehouse and the distribution process. Through an information exchange mechanism, reduced lead time through active coordination and prediction of the warehouse target inventory, they reduced the average total cost and the possibility of supply shortages, ensuring the quality and speed of delivery, improving buyers' shopping experience. Sadowski, Wojciechowski, & Engelseth (2021) investigate the flexibility of the warehouse in a supply network. The simulation revealed that external changes to the warehouse affect its daily activities and the reorganization of processes. This occurs because the warehouse processes, together, do not necessarily react in the same way to a disturbance of the environment. Chan & Tang (2007), investigate the connections of order demands, expiration dates, and production schedules, to minimize storage time. Zhang & Yi (2013), establish a model of the express logistics distribution system to analyze the behavior of the warehouse by simulating inventory levels. They consider two measures to deal with the difficulties that the warehouse suffers when it is exposed to high levels of demand: incorporating new sorting devices and hiring temporary sorters. Rodrigues, Motlagh, & Rao (2011), developed a simulation model to optimize the space allocation of the different products inside the warehouse, to use space effectively, and improve the efficiency of inventory management. The maximum capacity of the warehouse was the modified input parameter for the different analyzes. Agumas & Jayaprakash (2019), implemented a simulation model to improve the optimal amount of replenishment of expired and out-of-stock products within the warehouse, due to fluctuating market demand. The implementation of the defined strategies generates savings in the total cost of operation, decreases the loss of sale, the cost of the expired product, the maintenance cost, and the order cost.

In general, the literature that addresses warehouses under a systemic approach has identified those variables that affect warehouse performance, but not the degree of impact that each one has on all processes simultaneously, which is, ultimately, the objective of this research.

2.5. Warehouse Performance Measurement

Performance measurement can be defined as the process of quantifying the efficiency and effectiveness of an action or process (Neely et al., 2005). According to Kusrini et al. (2018), there are several methods to classify the metrics that measure the performance of a warehouse. These metrics, in general, have three components that cross the processes of a warehouse, time, space, and cost. Napolitano (2003), affirms that these three components are the three cornerstones by which an efficient and effective warehouse is measured.

We reviewed a total of 17 documents to identify the different metrics for warehouse performance measurement. We found that these metrics can be grouped into the following dimensions: time, quality, cost, productivity, efficiency, safety, customer satisfaction, environment, and flexibility. The dimensions with the greatest presence were quality (32%), time (18%), productivity (16%), cost (15%), and efficiency (15%). However, very few metrics were associated with the environment, customer satisfaction, flexibility, and security. In total, 67 performance indicators were reported and 11 of them represent 39% of the total number of times that they were included in at least one article (see Table 1).

Table 1. Main indicators reported in the literature

Dimensions	Indicator name	No. of articles	Authors
Quality	On-time delivery	9	(Staudt et al., 2015); (Kuo et al., 1999); (Indrawati et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Banomyong & Supatn, 2011); (Gotzamani, 2010); (Chae, 2009); (Buonamico et al., 2017)
Time	Order lead time	8	(Staudt et al., 2015); (Indrawati et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Banomyong & Supatn, 2011); (Gotzamani, 2010); (Chae, 2009); (Kusrini et al., 2018)
Quality	Picking accuracy	8	(Staudt et al., 2015); (Kuo et al., 1999); (Kusrini et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Banomyong & Supatn, 2011); (Buonamico et al., 2017); (Baker & Halim, 2007)
Quality	Physical inventory accuracy	7	(Staudt et al., 2015); (Indrawati et al., 2018); (Sakun Boon-itt, 2018); (Chae, 2009); (Kusrini et al., 2018); (Buonamico et al., 2017); (Baker & Halim, 2007)
Quality	Shipping accuracy	7	(Staudt et al., 2015); (Kusrini et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Banomyong & Supatn, 2011); (Buonamico et al., 2017); (Baker & Halim, 2007)
Productivity	Picking productivity	7	(Staudt et al., 2015); (Kusrini et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Ganesan et al., 2009); (Gu et al., 2007); (Evangelista et al., 2012)
Efficiency	Warehouse utilization	7	(Staudt et al., 2015); (Kuo et al., 1999); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Gu et al., 2007); (Evangelista et al., 2012); (de Koster et al., 2007)
Time	Queuing time	6	(Staudt et al., 2015); (Kusrini et al., 2018); (Sakun Boon-itt, 2018); (Banomyong & Supatn, 2011); (Ganesan et al., 2009); (Chae, 2009)
Cost	Warehousing costs	6	(Staudt et al., 2015); (Indrawati et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Kuo et al., 1999); (Shah & Khanzode, 2017)
Cost	Distribution cost	6	(Staudt et al., 2015); (Kusrini et al., 2018); (Sakun Boon-itt, 2018); (Mascolo et al., 2014); (Banomyong & Supatn, 2011); (Ganesan et al., 2009);
Productivity	Receiving productivity	6	(Staudt et al., 2015); (Kuo et al., 1999); (Kusrini et al., 2018); (Mascolo et al., 2014); (Ganesan et al., 2009); (Evangelista et al., 2012)

However, according to Rouwenhorst, B., B. Reuter, V. Stockrahm, G.J. van Houtum, R.J. Mantel (2000), the trade-offs between costs and operational performance of warehouses will be the subject of future studies. Gu et al. (2007) state that space, labor, and equipment must be allocated among the different warehouse processes to achieve the system requirements in terms of capacity, service level, and minimum cost. In addition, according to Shah & Khanzode (2017), the cost and the level of customer service should be considered as performance metrics that focus on the operational level. van Gils et al. (2018) propose that future research should additionally focus on other performance measures, such as the fill rate, which is rarely used as a performance measure, despite the importance of the quality of customer service. Therefore, to achieve a balance between the reduction of total warehouse costs and customer service, as output variables to measure the general performance of the warehouse, the total operating cost and the fill rate in receipt and shipment were defined as performance measures in this thesis.

In summary, as described above, the literature that seeks to improve warehouse performance has focused on two main processes, developing solutions, in general, for individual and well-defined warehouse planning problems. Most of the investigations have developed an analytical approach, using exact methods, heuristic, and metaheuristic methods. However, some authors have approached the analysis of warehouses under a systemic approach, using SD and identifying variables that affect warehouse performance, but not the degree of impact that each one has on all processes simultaneously.

3. Materials and methods

The proposed methodology aims to determine the degree of simultaneous impact that the selected input parameters have on the general performance of a warehouse with a Picker-to-parts order picking system, under the effect of seasonal demand and products with long- and short-life cycles. The research was divided into two stages, in the first stage, an SD model was developed to represent the system and in the second an SS analysis was performed to determine which variables impact the performance of the warehouse the most.

3.1. Modelling

3.1.1. Real warehouse description

In Figure 1, there is an aggregated representation of the product flow of the warehouse chosen for the development of this research. The product flow begins in the receipt process when a supplier arrives at the warehouse. The supplier can bring the product on pallets or in boxes according to the supply contract conditions. Generally, the product that arrives on pallets is delivered by an adjacent production plant. If the product arrives in boxes it comes from external suppliers. In the process of receipt, the product is unloaded at the reception docks, where quantities are verified and safety and quality controls are carried out.

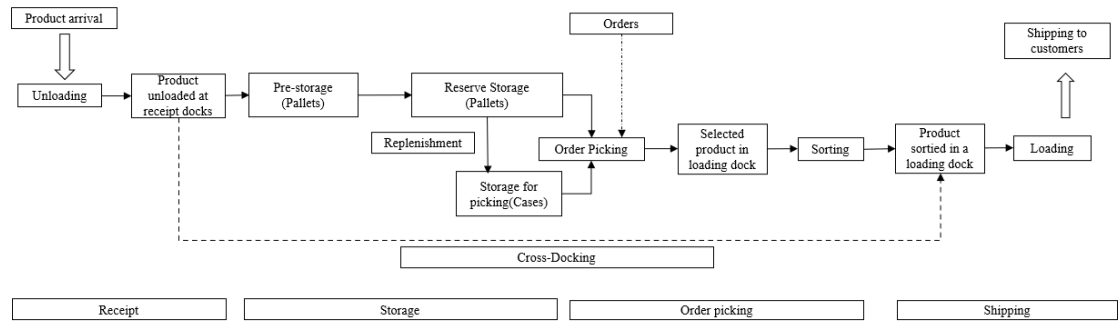


Figure 1. Description of the real warehouse

Once the product is on the receiving docks, the storage process is activated, which is nothing more than moving the different products to a defined area for its storage until it is used to fulfill a customer order. All storage is done on pallets and is divided into two stages. First, inventory from the receiving docks is moved to a location close to where the product will be stored, known as pre-storage. Then a team places each pallet in a reserve storage area (storage at height). From the reserve storage area, replenishment is made to an area called “storage for picking”.

The order picking process is activated with the arrival of the orders. Orders are divided into full pallets and single boxes. Full pallets are selected from reserve storage and the cases from “storage for picking”. There is a resource assigned for each selected path. After the selection of the product, the sorting is carried out (pick-and-sort). The selected and classified product is located in the exit docks (load). Finally, the product that is at the departure docks is loaded into vehicles to be delivered to the different customers. The product can be loaded also on pallets or boxes.

Receiving and shipping process activities such as truck-dock assignment, order-truck assignment, and truck dispatch schedule are not taken into account in this research. The cross-docking strategy is not currently implemented in the warehouse. However, we analyze in our experiments the impact of such a strategy in the performance of the warehouse operations. Each process has an assigned resource that remains fixed throughout the entire simulation period.

To develop the simulation model, the limits of the system and its key variables were defined taking into account 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) and its flow structure (de Koster et al., 2007). However, taking into account that the scope of the investigation only takes into account the typical processes of a warehouse, variables such as the location of the warehouse and possible delays in the arrival of vehicles that affect the occupation of the docks were excluded.

Finally, to illustrate the real store in terms of SD, a causal-loop diagram is presented (Figure 2), which consists of a map showing the causal links between variables. The relationship between two variables can be positive or negative. If the sign at the head of the arrow is +, the relationship is positive, if the sign is -, the relationship is negative. When one the relationship is positive, if one variable increases, the other also increases. It can also mean that if one variable decreases, the other will decrease as well. However, if the relationship is negative, the two variables change inversely. The signs on each arrow only indicate the direction of the effect but not its magnitude. Now when the relationship between the variables creates a closed-loop, a feedback loop is created, which can be a

reinforcing loop (R) or a balancing loop (B). Reinforced loops are a source of growth, while balance loops are a source of balance in the system (Sterman, 2000).

3.1.2. SD equations

In this section, we convert the causal loop diagram into a flow and stock diagram, which represents the causal relationships in terms of stocks, flows, and auxiliary variables (Aracil, 1995). Stocks (levels) and flows (rates) are the basic components of SD modeling. Stocks are the result of the difference between inputs and outputs, they represent the current state of the system. The flows indicate the rate of variation of the variables as a function of time (Sterman, 2000). Table 2-6 summarizes the main variables by process, type of variable, unit of measure, and equation used. The stock-type variables found in Tables 2,3,4,5 and 6 have measurement units Pal/ Δt , where Δt corresponds to the simulation step (1 hour). This is because, conceptually, the available amount of each level variable in a time delta (Δt) has units of measure Pal/h.

Table 2 summarizes the main variables of the receipt process. As the capacity to receive the inventory that arrives from the plant and the different suppliers is divided into two parts, receipt in cases and receipt in pallets, resources are assigned for each type of unloading. In this case, the productivity of receipt in cases is 4.6 times lower than the productivity of receipt in pallets. The receiving rate-pallets is the result of the minimum value between “inventory waiting to be received on pallets”, “receiving productivity-Pallets” and “receipt area available capacity”. Similarly, the "receiving productivity-cases" is calculated. However, the priority on the receipt is for inventory arriving on pallets. The inventory received and available is represented by the variable “Inventory available in receipt docks”. The flow of the different products in the warehouse was configured in a vector where the first position corresponds to line products and the second position to seasonal products {line; season}.

Once inventory is available at the receiving docks, the warehousing process begins. The product has two exit routes, pre-storage, and cross-docking; priority is for cross-docking. The pre-storage rate is the minimum value between the difference of the inventory available at the receiving docks and the cross-docking rate and the available pre-storage productivity. The pre-stored product is transferred to the reserve storage area taking into account the pre-stored available inventory, the available reserve storage capacity, and the productivity of the resource assigned to this activity (“Storage productivity”). To attend to the orders in boxes, the restocking activity is carried out from the reserve storage area to the storage area for picking (“Inventory for picking”). The replenishment rate is the minimum value between the available reserve inventory, the “replenishment productivity” and the inventory available for picking. Table 3 summarizes those explained above.

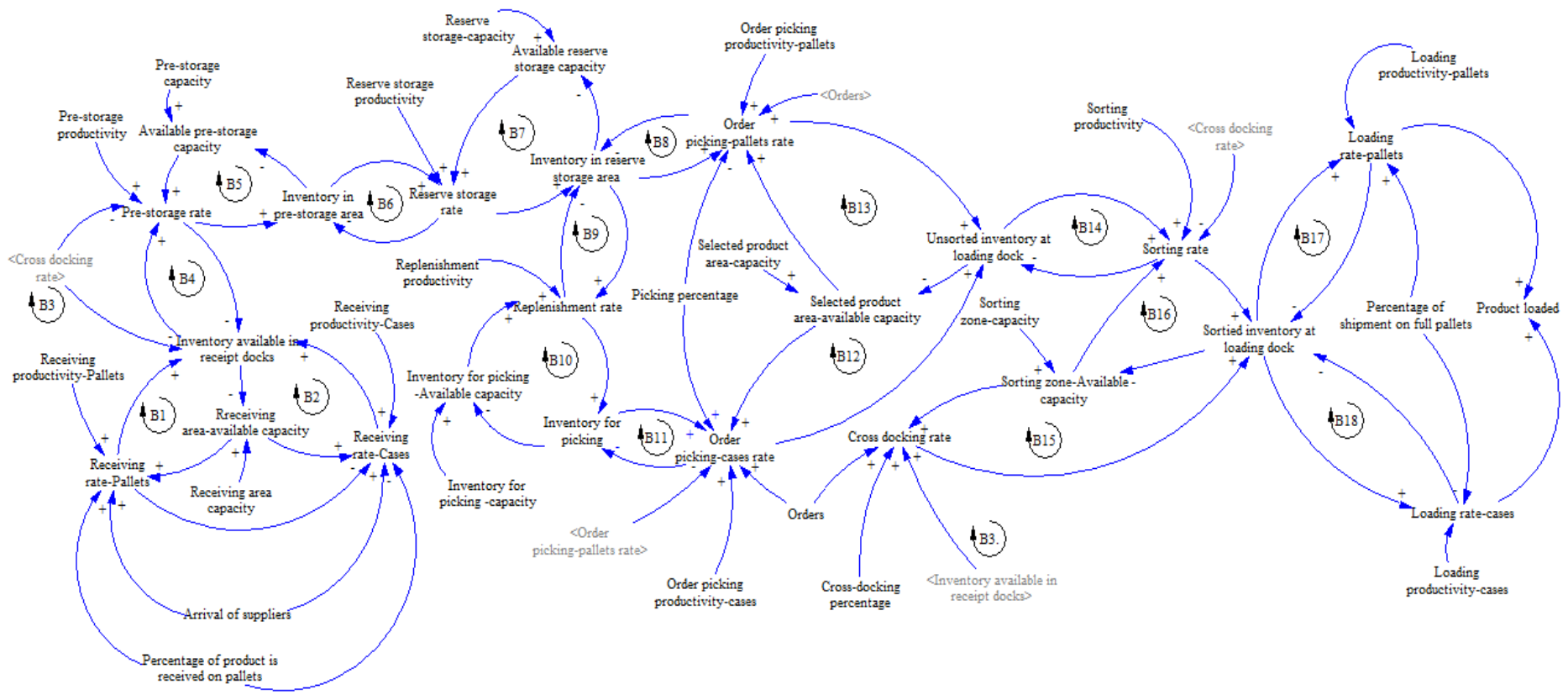


Figure 2. Causal diagram of the real warehouse

Table 2. Main variables and equations of the receipt process

Process	Variable	Unit	Initial operating condition	Equations	Type of variable
Receiving	The arrival rate of suppliers on pallets/cases	Pal/h	External data (Excel)	VECTOR ('Receive line product'; 'Receive seasonal product')	Flow
	Percentage of product is received on pallets	%	100	100%	Constant
	Receiving area capacity	Pal	480	480 <<pal>>	Constant
	Receiving productivity-Cases	Pal/h	39	Number of people assigned to unload cases * Productivity per person-unload in cases	Auxiliary
	Receiving productivity-Pallets	Pal/h	180	Number of people assigned to unload pallets * Productivity per person-unload on pallets	Auxiliary
	Inventory waiting to be received on pallets	Pal	{0;0}	=Arrival rate of suppliers on pallets - Receiving rate-pallets	Stock
	Inventory waiting to be received on cases	Pal	{0;0}	=Arrival rate of suppliers on cases - Receiving rate-cases	Stock
	Receiving rate-pallets	Pal/h	{0;0}	MIN(Inventory waiting to be received on pallets/ Δt ; Receiving productivity-Pallets; Receipt area available capacity/ Δt)	Flow
	Receiving rate-cases	Pal/h	{0;0}	MIN(Inventory waiting to be received on cases/ Δt ; Receiving productivity-cases; Receipt area available capacity/ Δt - Receiving rate-pallets)	Flow
	Inventory available in receipt docks	Pal	{0;0}	=Receiving rate-pallets + Receiving rate - cases - Pre-storage rate - Cross-docking rate	Stock

Table 3. Main variables and equations of the storage process

Process	Variable	Unit	Initial operating condition	Equations	Type of variable
Storage	Pre-storage capacity	Pal	330	330 <<pal>>	Constant
	Reserve storage capacity	Pal	66.150	66.150 <<pal>>	Constant
	Inventory for picking - capacity	Pal	1.350	1.350 <<pal>>	Constant
	Initial reserve inventory	Pal	{34360;0}	= Reserve storage rate - Replenishment rate - Order picking-pallets rate	Stock
	Pre-storage productivity	Pal/h	180	Number of people assigned for pre-storage * Productivity per person-pre-storage	Auxiliary
	Reserve storage productivity	Pal/h	135	Number of people assigned for reserve storage * Productivity per person-reserve storage	Auxiliary
	Replenishment productivity	Pal/h	45	Number of people assigned for replenishment * Productivity per person-replenishment	Auxiliary
	Pre-storage rate	Pal/h	{0;0}	= Min(Product available in receipt docks - Cross-docking rate; Available pre-storage capacity; Pre-storage productivity)	Flow
	Inventory in pre-storage area	Pal	{0;0}	= Pre-storage rate - Reserve storage rate	Stock
	Inventory for picking	Pal	{0;0}	= Replenishment rate - Order picking-cases rate	Stock
	Reserve storage rate	Pal/h	{0;0}	= Min(Inventory in pre-storage area; Available reserve storage capacity; reserve storage productivity)	Flow
Replenishment rate	Pal/h	{0;0}	= Min(Inventory in reserve storage; Available Inventory for picking -capacity; Replenishment productivity)	Flow	

Table 4 shows the equations to model the order picking process. At this time, the inventory is stored and available to fulfil customer orders. Customer orders are processed from the reserve storage area (pallets) and from the storage area for picking (cases). The proportion is defined by the picking percentage. The pallet order picking rate is the result

of the minimum value between the proportion of pallet orders pending to be processed, the reserve inventory, the pallet order picking productivity and the available capacity in the selected product area. Similarly, the case order picking rate results from the minimum value between the proportion of case orders pending to be processed, the inventory for picking, the case order picking productivity, and the available capacity in the selected product area. The order picking rate in pallets has priority over the order picking rate in cases when placing the product in the selected product area. Another strategy to process orders on pallets is cross-docking, for this is taking into account the inventory available in the receiving docks, the pre-storage productivity, and the availability of space in the loading docks. Cross-docking takes precedence over the pallet order picking rate.

Table 4. Main variables and equations of the order picking process

Process	Variable	Unit	Initial operating condition	Equations	Type of variable
	Arrival of orders	Pal/h	External data (Excel)	VECTOR ('Arrival Line Orders'; 'Arrival Season Orders')	Flow
	Picking percentage	%	10	10%	Constant
	Cross-docking percentage	%	0	0%	Constant
	Selected product area capacity	Pal	750	$750 \llcorner \text{pal} \gg$	Constant
	Order picking productivity-pallets	Pal/h	120	Number of people assigned for order picking-pallet * Productivity per person-order picking-pallets	Auxiliary
	Order picking productivity-cases	Pal/h	42	Number of people assigned for order picking-cases * Productivity per person-order picking-cases	Auxiliary
	Order picking-pallets rate	Pal/h	{0;0}	$= \text{Min}(\text{Inventory in reserve storage}/\Delta t; \text{Order waiting to be order picking-pallet}/\Delta t; \text{Available capacity selected product area}/\Delta t; \text{Order picking productivity-pallets})$	Flow
Order Picking	Order picking-cases rate	Pal/h	{0;0}	$= \text{Min}(\text{Inventory for picking}/\Delta t; \text{Order waiting to be order picking-cases}/\Delta t; \text{Available capacity selected product area}/\Delta t - \text{Order picking-pallets rate}/\Delta t; \text{Order picking productivity-cases})$	Flow
	Order waiting–Cross-docking	Pal	{0;0}	$= (\text{Arrival of orders} * \text{Cross-docking percentage}) - \text{Cross docking rate}$	Stock
	Cross docking rate	Pal/h	{0;0}	$\text{Min}(\text{Order waiting–Cross-docking}/\Delta t; \text{Product available in receipt docks}/\Delta t; \text{Pre-storage productivity})$	Flow
	Order waiting to be order picking-pallet	Pal	{0;0}	$= (\text{Arrival of orders} - \text{Cross-docking rate}) * \text{Picking percentage} - \text{Order picking-pallets rate}$	Stock
	Order waiting to be order picking-cases	Pal	{0;0}	$= (\text{Arrival of orders} - \text{Cross-docking rate}) * (1 - \text{Picking percentage}) - \text{Order picking-cases rate}$	Stock
	Unsorted inventory at loading dock	Pal	{0;0}	$= \text{Order picking-pallets rate} + \text{Order picking-cases rate} - \text{Sorting rate}$	Stock

After finishing the order selection, the inventory is sorted. The sorting rate is the result of the minimum value between the selected orders, the available capacity in the loading bays, and the sorting productivity (see Table 5).

Table 5. Main variables and equations of the sorting process

Process	Variable	Unit	Initial operating condition	Equations	Type of variable
Sorting	Sorting productivity	Pal/h	180	Number of people assigned to sorting * Productivity per person sorting	Auxiliary
	Sorting zone-capacity	Pal	750	750 <<pal>>	Constant
	Sorting rate	Pal/h	{0;0}	MIN (Unsorted inventory at loading dock/ Δt ; Sorting productivity; Available loading dock capacity/ Δt)	Flow
	Percentage of shipment on full pallets	%	1	1%	Constant
	Sortied inventory at loading dock	Pal	{0;0}	= Sorting rate - Loading rate-pallets - Loading rate-cases	Stock

Finally, once the product is available and classified at the loading docks, it is loaded into the vehicles for later delivery to customers. The proportion of loading on pallets is defined by “Shipment percentage on full pallets”.

Table 6. Main variables and equations of the shipping process

Process	Variable	Unit	Initial operating condition	Equations	Type of variable
Shipping	Shipment percentage on pallets	%	1%	1%	Constant
	Loading productivity-pallets	Pal/h	120	Number of people assigned to load on pallets* Productivity per person-load on pallets	Auxiliary
	Loading productivity-cases	Pal/h	150	Number of people assigned to load on cases* Productivity per person-load on cases	Auxiliary
	Loading rate-pallets	Pal/h	{0;0}	MIN ((Sortied inventory at loading dock/ Δt * Percentage of shipment on full pallets); Loading productivity-pallets)	Flow
	Loading rate-cases	Pal/h	{0;0}	MIN ((Sortied inventory at loading dock/ Δt *(1- Percentage of shipment on full pallets)); Loading productivity-cases)	Flow
	Product loaded	Pal	{0;0}	= Loading rate-pallets + Loading rate-cases	Flow

3.1.3. Performance measures

To measure the fill rate of receipt, fill rate of shipment, and total operating cost, the following equations were used:

$$\text{Fill rate receipt} = \frac{\text{Pallets received per hour (Simulation)}}{\text{Pallets received per hour (Real)}} * 100 \quad (1)$$

$$\text{Fill rate shipment} = \frac{\text{Pallets shipped per hour (Simulation)}}{\text{Pallets shipped per hour (Real)}} * 100 \quad (2)$$

$$\text{Total operating cost} = \text{Receipt cost} + \text{Storage cost} + \text{Order picking cost} + \text{Shipping cost} \quad (3)$$

To calculate the total cost of each process, receipt, storage, order picking, and shipping, the number of pallets that pass through each one is multiplied by the unit cost of processing. Each process has a different cost according to the number of people assigned, the salary earned, and productivity. However, if this total cost calculated in each simulation step is less than the minimum cost per hour in a particular process, this is replaced by the minimum.

The cost of replenishment was not considered in the calculation of the total operating cost, since the replenishment is not the responsibility of the actual warehouse and does not affect its costs. Each component of the total operating cost is calculated on the basis of labor and does not include infrastructure costs (operation under roof), since they are relatively independent of the infrastructure and do not generate distortions in the behavior of the output variables of the model. Now, the only exception would be with the percentage of cross-docking, since the increase in the value of this parameter should compress the infrastructure of the warehouse, but since the warehouse is already built and its structure is not modifiable, it has no impact on the full operating cost. Therefore, the conclusions of this research are not valid for strategic planning, but for tactical planning.

Continuing with the calculation of the total operating cost, when the pallets that are waiting to be processed in one hour and a particular process exceed a defined threshold (decision rules) the model generates a penalty cost. It is an alert that indicates that the process is out of control at that time and therefore those conditions are penalized. Table 7 shows the decision rules defined for each process, which were validated according to the operating conditions of the case study warehouse. In practice, these penalties would correspond to overtime or hiring temporary workers to keep a given process under control.

Table 7. Decision rules in each warehouse process to define cost penalty

Process	Decision rules
Receiving	If the difference between the total of products to be received in any one hour is greater than the capacity of the pre-receipt area, a cost penalty is generated. The difference between these two variables is multiplied by the unit processing cost and a wage increase factor
Storage	If the inventory in the pre-storage area is greater than the total storage productivity, a cost penalty is generated. The difference between these two variables is multiplied by for the unit cost of the process and a wage increase factor
Order Picking	If the total number of pallets waiting to be processed (order picking + cross-docking) is greater than the maximum delay allowed, a cost penalty is generated. The difference between these two variables is multiplied by for the unit cost of the process and a wage increase factor
Sorting	If the difference between the total of products to sorting in any one hour is greater than the 48% of the capacity of the sorting area, a cost penalty is generated. The difference between these two variables is multiplied by the unit processing cost and a wage increase factor
Shipping	If the total number of pallets waiting to be loaded is greater than twice the productivity of this process, a cost penalty is generated. The difference between these two variables is multiplied by for the unit cost of the process and a wage increase factor

3.1.4. Simulation reporting

The proposed SD simulation model has been implemented using Powersim Studio 10, Euler integration with a one-hour step and a time horizon of one year, using a bank calendar.

3.1.5. Model verification and validation

Initially, each equation within the model was reviewed to verify dimensional consistency without the inclusion of arbitrary scale factors that have no meaning in the real world. This verification was made with the alerts that the Powersim software generated when the dimensions of one or more elements of each equation were not consistent. As the model was being built, the software displayed these alerts visually.

In addition, extreme conditions and conservation of physical laws were evaluated in the receipt and shipment process. In the first scenario, the total number of pallets to receive was zero and it was expected that the total available inventory would quickly fall to zero and would not be negative. In the second scenario, the total number of pallets to

be sent to customers was zero. In this case, the total available inventory would grow rapidly until it reaches the total storage capacity. In turn, the received pallets, at that moment, would reach zero since there is no storage capacity available for their respective reception. In both cases the results were consistent.

In addition, for the validation of the SD model, the procedure by Senge (1980) and Sterman (2000) was implemented using Theil inequalities to determine if the model can reproduce the observed data. This test decomposes the mean square error (MSE) in terms of the bias (UM), unequal variance (US), and unequal covariance (UC) as proposed by (Sterman, 1984).

The behavior validation was carried out using the inventory level of line and seasonal products. Table 8 shows the results of the Theil test and the statistical analysis between the real (R) and simulated (S) data. The results illustrate that the model accurately recreates the behavior of these two state variables.

Table 8. Summary of statistics to evaluate the fit of the simulated vs real data

Indicator	Seasonal product	Line product
Simulated mean (X_S)	4.006	42.212
Real mean (X_A)	4.012	41.951
Simulated standard deviation (S_S)	4.592	3.251
Real standard deviation (S_R)	4.476	3.230
Correlation coefficient (R)	0,994	0,856
R ² coefficient	0,988	0,732
Mean absolute percent error (MAPE)	11,13%	3,52%
Mean square error (MSE)	255.541	8.618
UM-unequal bias	0,02%	2,19%
US-unequal variance	5,28%	0,01%
UC-unequal covariance	94,70%	97,79%

Considering the results of Table 8, most of the MSE is concentrated in UC, while UM and US are relatively small. This indicates that the simulated and real values do not coincide, but the model can capture the average value and the dominant trends (Sterman, 1984). However, as the UC value is large, it indicates that the model does not capture some type of noise or cyclical data. This type of error is not systematic and is not considered as a criterion to reject the validity of the model (Sterman, 1984). Figures 4 and 5 show a comparison between the real and simulated inventory levels for the two products.

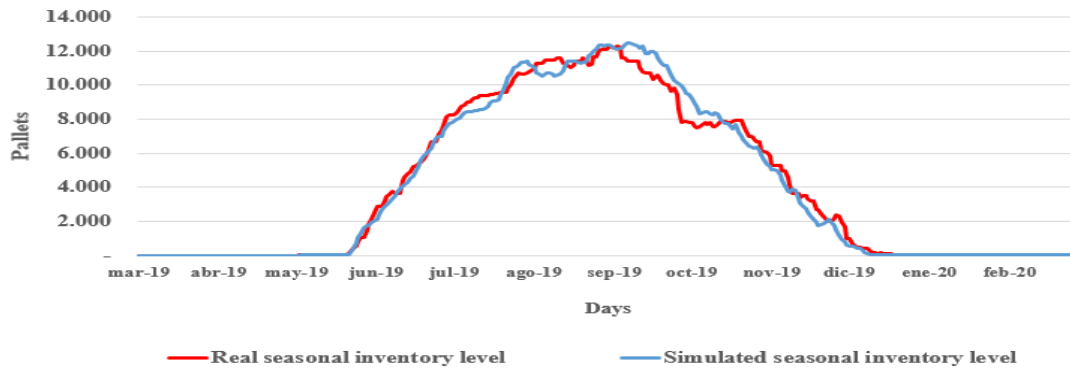


Figure 3. Real vs. simulated seasonal inventory level comparison

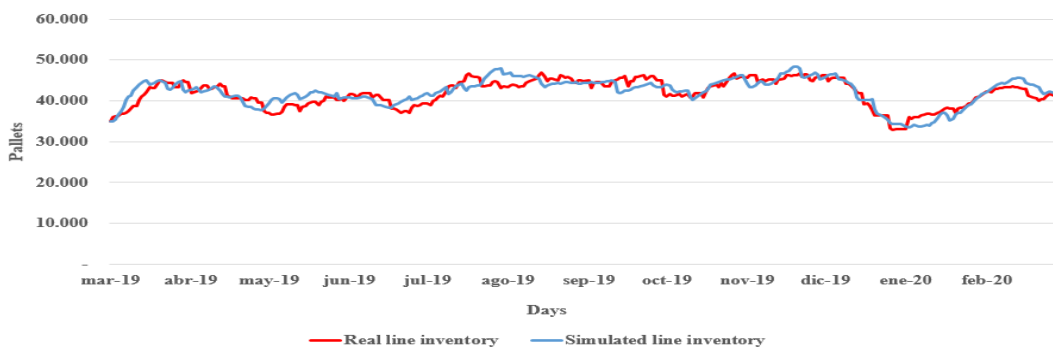


Figure 4. Comparison of the real vs simulated line inventory level.

3.2. Statistical screening

Simulation models under the SD approach focus on the identification of feedback mechanisms within a system to provide explanations of its behavior. These mechanisms are used for policy design (Sterman, 2000). However, a preliminary step in the development of these policies is the identification of parameters and high leverage structures that influence the behavior of the system, that is, the ability of the input parameters of the model to impact its output variables, a method which is known as statistical screening (SS) (Taylor et al., 2010).

SS allows a modeler to test multiple model input parameters simultaneously and analyze the impacts at each time step within the simulation process (Taylor et al., 2010). Calculates the correlation coefficients for each simulation step and each of the defined input parameters, delivering as a result, a time series of said coefficients within the simulation period (Taylor et al., 2010).

To develop SS, the four parameters discussed above and the two output variables already mentioned were included in the analysis. Step by step is shown in Figure 5. The detail of the step-by-step can be found in (Taylor et al., 2010).

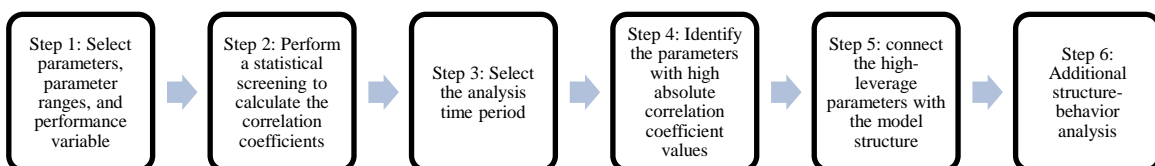


Figure 5. Step by step statistical screening

In the first step, the uncertainty ranges were empirically calculated by modifying from five to five points, in a range from 0 to 100, each input parameter, running the model, and calculating the total operating cost, and the receipt, and shipping fill rate. For the uncertainty range of picking percentage, cross-docking percentage, and percentage of shipment in full pallets, the minimum value of the total operating cost was taken as a basis and symmetric range was defined at this value. For the percentage of receipt on full pallets, a range between 60-100% was defined because it makes sense for the reality of the case-study warehouse process. Finally, the combination of these parameters and variables was analyzed in three scenarios: Current product mix (line and season), eliminating the effect of the season, and doubling the season effect. In the three scenarios, the total product flow was maintained, only the proportions were changed according to the analysis. Table 9 summarizes the uncertainty ranges for the four input parameters of the model that were used to analyze the total operating cost and the receipt and shipping fill rate.

Table 9. Output variables, input parameters, and their uncertainty ranges.

Input parameters	Ranges of uncertainty	Output variables
Receipt percentage on pallets	Uniform (60-100%)	Fill rate of receipt (%)
Picking percentage	Uniform (0-50%)	Fill rate shipment (%)
Cross-docking percentage	Uniform (0-40%)	Total operating cost (\$)
Shipment percentage on pallets	Uniform (1-60%)	

In the second step, 50 runs were made to calculate the correlation coefficients for each parameter, for each simulation step, and each output variable. With this information, the values obtained were plotted to visualize the effect of each parameter on the output variables throughout the simulation horizon. For each run, a random value of the parameter analyzed at that moment was generated and the data was plotted for an initial visual analysis. A graph of the total operating cost of the warehouse was created with the 200 simulations to identify the behavior of this output variable against the changes in each parameter. Then, graphs of the correlation coefficient of the total operating cost of the warehouse against each parameter separately were generated, to identify if any of them dominates the dynamics of the system.

In the third step, an uncertainty range was not defined within the one already established in step 1, because the behavior of the total operating cost was of exponential growth throughout the simulation period, but in the fourth step, the parameters that most influenced the total operating cost and the fill rate of receipt and shipment were identified, considering the values of greater proximity to -1 and 1.

Then, in the fifth step, the model structures that are connected to the parameters with the greatest impact on the output variables were identified. In the case of total operating cost, the formula was disaggregated into its different components (see equation 3) and the evolution of each of them was plotted throughout the simulation period, identifying which warehouse process was driving the increase in this variable and the associated structure. Finally, in a sixth step, these structures were analyzed to explain the behavior of the output variables.

Followed by the SS analysis, policies were defined to reduce the total operating cost and maximize the fill rate of receipt and shipment in the three scenarios listed above. For the development of this analysis, the value of each parameter that minimized or

maximized the value of these two output variables was taken into account. Then, a simulation was run for each combination.

4. Results and discussion

Figure 6 presents the results of the runs to analyze the behavior of the total operating cost for each parameter. This figure shows that the total operating cost has an exponential growth throughout the simulation period and that the order picking process dominates the behavior of this output variable. The receipt percentage on pallets is the second most important parameter in the growth of the total operating cost. The cross-docking percentage and the shipment percentage on pallets do not affect significantly the total operating cost of the warehouse.

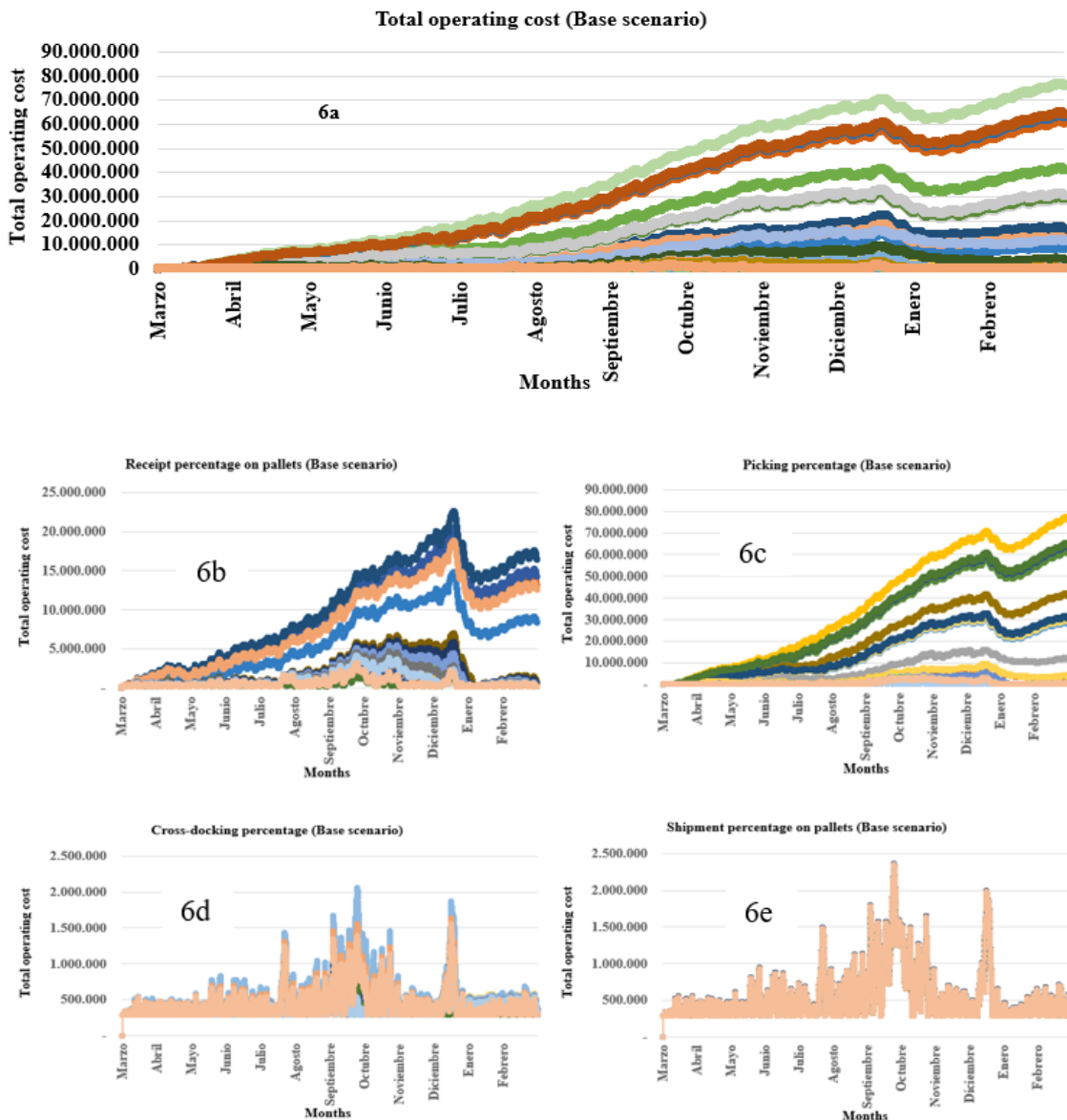


Figure 6. Total operating cost for the 200 simulations and per parameter. Each line corresponds to a run of the model.

Likewise, Figure 7 presents the time series with the correlation coefficients between the total operating cost and the four aforementioned parameters. This figure

illustrates the type of association that exists between this output variable and each parameter.

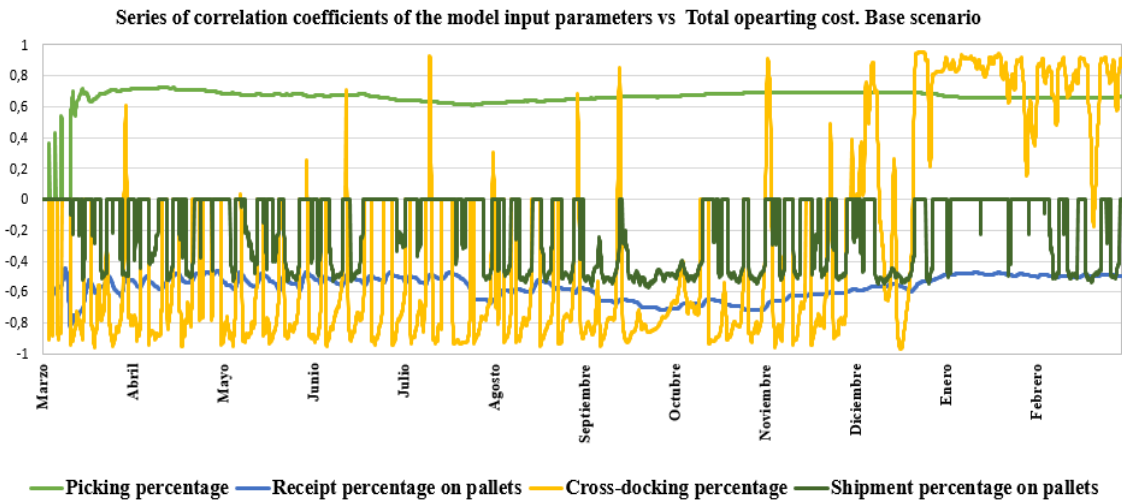


Figure 7. Series of correlation coefficients of the model input parameters vs Total operating cost.

Figure 7 shows that the picking percentage has a positive and stable association with the total operating cost during the entire simulation period with an average correlation of 0.67 and a small deviation of 0.03. Besides, considering the behavior of the total operating cost in figures 6 and 7, the interest focuses on understanding the reason why the percentage of picking makes the total operating cost grows exponentially throughout the simulation period. An initial explanation is that the picking percentage is structurally connected with the efficient operation of a warehouse, and the greater the need to process pallets through this causal route increases the number of pallets waiting and affecting also the picking rate. This in turn affects the number of pallets waiting through a balancing loop (B11), generating penalties that exponentially increase the order picking process cost and at the same time the total operating cost. This penalty appears, when the difference between the number of pallets waiting and the picking rate is greater than the threshold defined for the generation of costly penalties. This identifies this causal path as the dominant structure for the total operating cost in the chosen time frame. These results are in line with Razik et al. (2016), that point out that one of the main success factors for improving the performance of a warehouse is the correct management of the picking process (policy). Similarly, Aminoff et al. (2002) conclude that the picking process is the one with the highest cost within the warehouse (24%) and that the general performance of this link is strongly related to this process, especially with the order structure and the efficiency of the productivity of the same.

Conversely, the percentage of receipt on full pallets has a negative association with the total operating cost throughout the simulation period, with a mean of -0.57 and a deviation of 0.07. Moreover, as shown in Figure 7, during most of the seasonal period (July-November), the negative association strengthens by 9%, going to 0.62 with a similar deviation of 0.06. The higher the value of this parameter, the lower the total operating cost, being 100% the one that generates the minimum of this output variable (see Figure 8). Connecting this parameter with the structure of the model, we can identify that, as its value increases, the greater the need to process pallets through this causal route (balancing loop B1), increasing the wait for full pallets to be received, which could generate penalties

that exponentially increase the cost of receipt and at the same time, the total operating cost. However, 94.5% of the time, the productivity of receipt on full pallets is greater than the product arrival flow and allows the level of pallets waiting not to exceed the penalty rule within this process. This behavior implies that no penalties have been generated in this process and therefore the total operating cost remains controlled (B1). On the other hand, the productivity of receipt in non-full pallets is lower than the receipt flow 86.1% of the time, generating penalties that do affect the receipt cost and the total operating cost. This result is in line with Cagliano et al. (2011), that state the negative association between the percentage of receipt on pallets and the total operating cost. This percentage can be increased through the flexible use of resources, the subcontracting of item counts, and the supply of reliable suppliers, encouraging receipt on complete pallets and from certified suppliers.

Similarly, the relationship between the cross-docking percentage and the total operating cost is negative in 58% of the simulation period, with a mean of 0.77 and a deviation of 0.17 (March-November). The negative association occurs because the higher the percentage of cross-docking, the lower the pre-storage rate, directly impacting the flow and level of the pre-storage area, which in turn affects the storage rate, thus reducing the inventory level and consequently the total cost of this process (lower product flow through this causal route, B4-B7). In addition, the higher the percentage of cross-docking, the less need for order picking, reducing the flow of this causal route and consequently the total operating cost (B8-B13). In both causal routes, the sorting rate is decreased, since the product arrives sorted at the loading docks (B14). Similar results are found in the research by Johnson & McGinnis (2011), where the authors highlight the positive effect on warehouse performance with the increase in the percentage of cross-docking, which implies a decrease in the total operating cost.

However, in this same period, there is evidence of the absence of linear association (correlation coefficients with zero value). This scenario occurs when the total operating cost, in a particular hour, does not exceed the minimum operating cost of this process due to the lack of product flow. In this case, regardless of the value of each parameter, the value of the output variable will be the same, the minimum cost per hour of the process.

In the last three simulated months, the association changes direction and becomes positive, with a mean of 0.72 and a deviation of 0.24 (see Figure 7). The positive association of the last three months is given by the same design of the model when separating the flow of the line and season product. In this case, as the waiting need for cross-docking contains seasonal products and the receipt of this type of product has already ended, it generates penalties that increase the total operating cost. For values of this parameter between 10-40%, the total operating cost does not change significantly, below 10% it increases significantly.

Likewise, the analysis of the percentage of shipment on full pallets reveals that during 45% of the simulated period it has a negative association with the total operating cost, with a mean of -0.45 and a deviation of 0.09, but the remaining 55% does not present a linear association with this variable. The explanation is the same as that given in cross-docking. Throughout the uncertainty range of this parameter, the total operating cost does not change significantly, it is almost constant. Connecting this parameter with the structure of the model of Figure 2, we identify that, the higher the percentage of shipment on full pallets, the higher the shipping rate on full pallet, which affects the number of

pallets available for loading through a balancing loop (B17). The shipping rate on full pallet directly affects the number of products sent to customers. However, as the shipping productivity on full pallets is similar to the shipping productivity on non-full pallets and each one of them is greater than the product flow pending loading, it does not significantly affect the total operating cost or the latter is not sensitive to changes in the values of this parameter (without association).

Finally, Figure 8 shows that the total operating cost decreases when the percentage of the product received on pallets with a value of 100%, picking percentage varies between 10-30%, the cross-docking percentage between 15-30%, and the percentage of shipment on full pallets between 20-45%. Additionally, shows the behavior of the receipt and delivery fill rate for changes in the uncertainty ranges of each input parameter analyzed. After the SS analysis, unlike the total operating cost, these two output variables did not show significant associations with the input parameters throughout the simulation period. However, the only parameter that affects these two output variables to some extent is the percentage of picking, between 45-50%, extreme values in the uncertainty range evaluated.

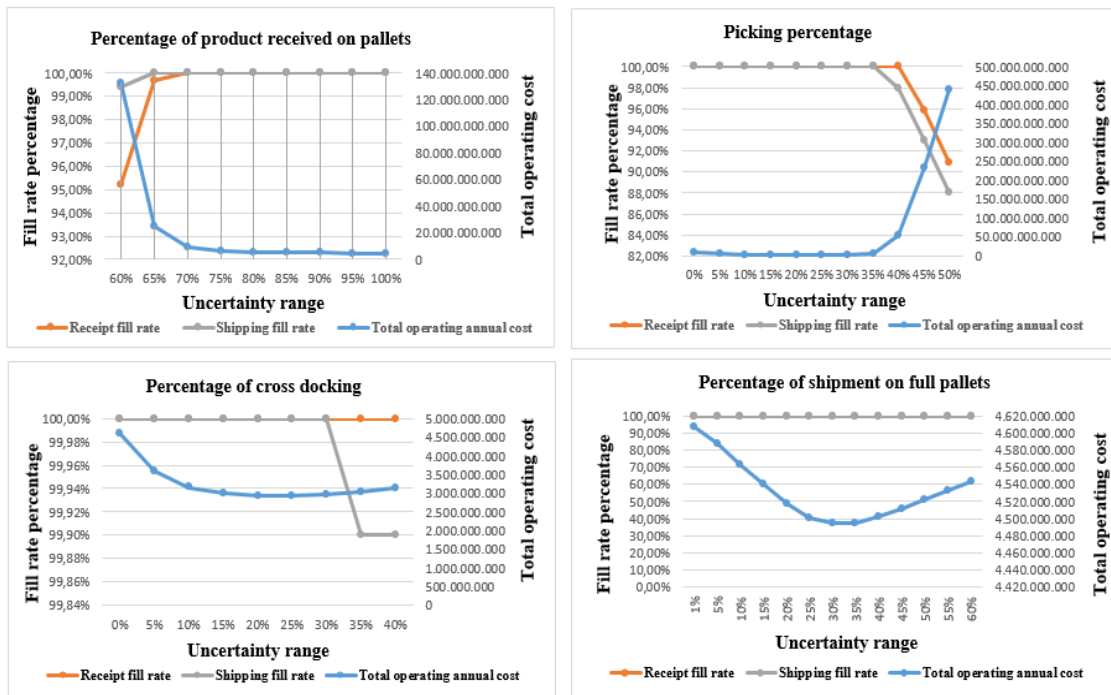


Figure 8. The behavior of the output variables vs uncertainty range of each input parameter was analyzed.

4.1. Sensitivity analysis

In a final analysis, we evaluate the behavior of the system under extreme but probable scenarios. The former eliminates the short-life cycle product flow, whereas the latter one duplicates it. Figures 9a and 9b show the behavior of the total operating cost for the warehouse and that of each parameter under these two scenarios, respectively.

Comparing figures 9a and 9b show that, in general, the behavior of the total operating cost of the warehouse is the same, but with different effects within the period

that includes the season (May-November). In particular, between September and December, in the scenario where the flow of the season is doubled, the total operating cost increases. Similarly, when the effect of the season is eliminated, it is evident that the total operating cost decreases between September and December concerning the current operating conditions of the warehouse.

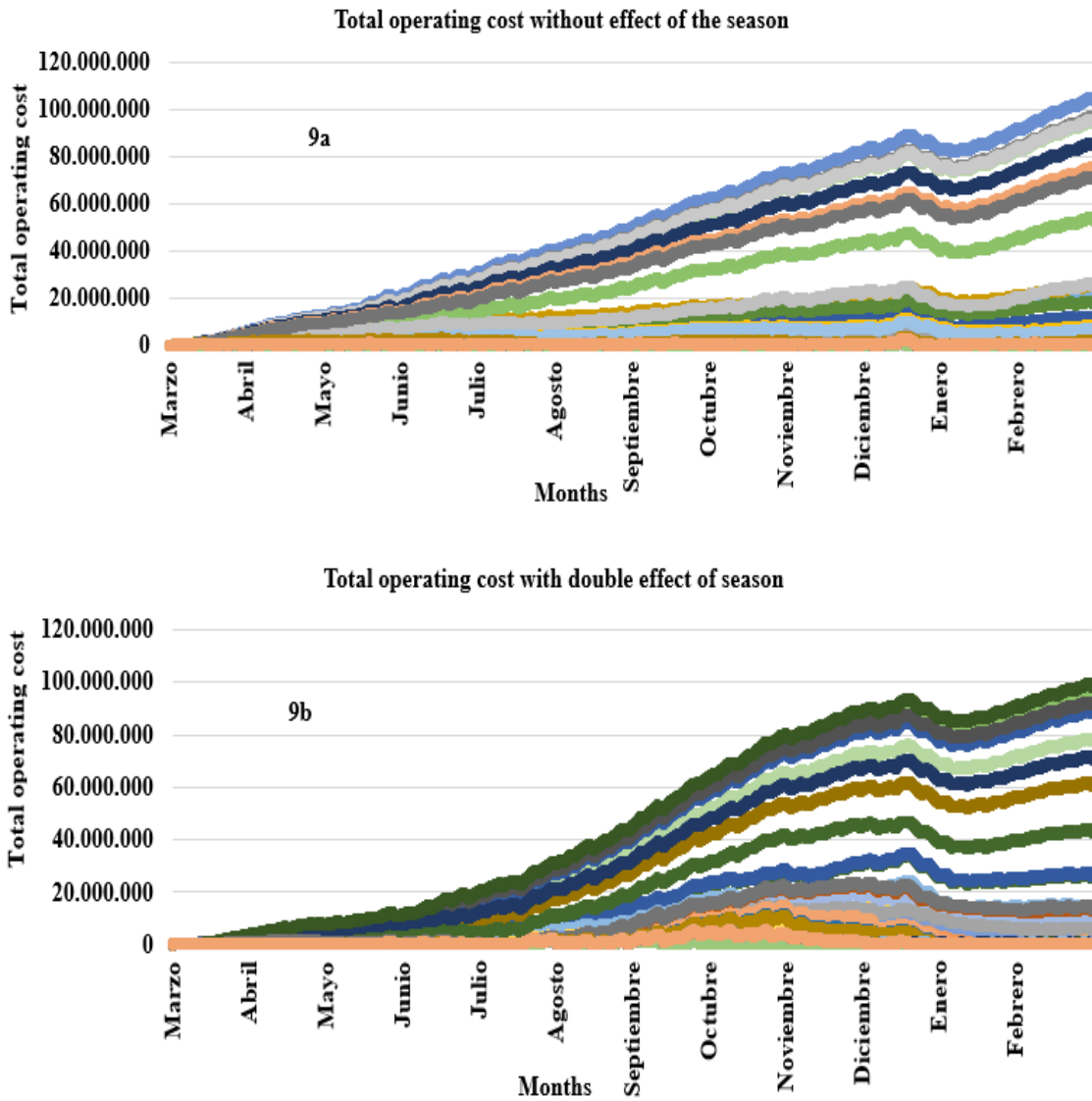


Figure 9. The total operating cost of the warehouse. Evaluation of the effect of eliminating the season or duplicating it.

The behavior of each parameter is also affected by the greater flow of short life cycle product, but the percentage of picking and the percentage of receipt on full pallets are still the dominant parameters in the behavior of the system (see Figure 10).

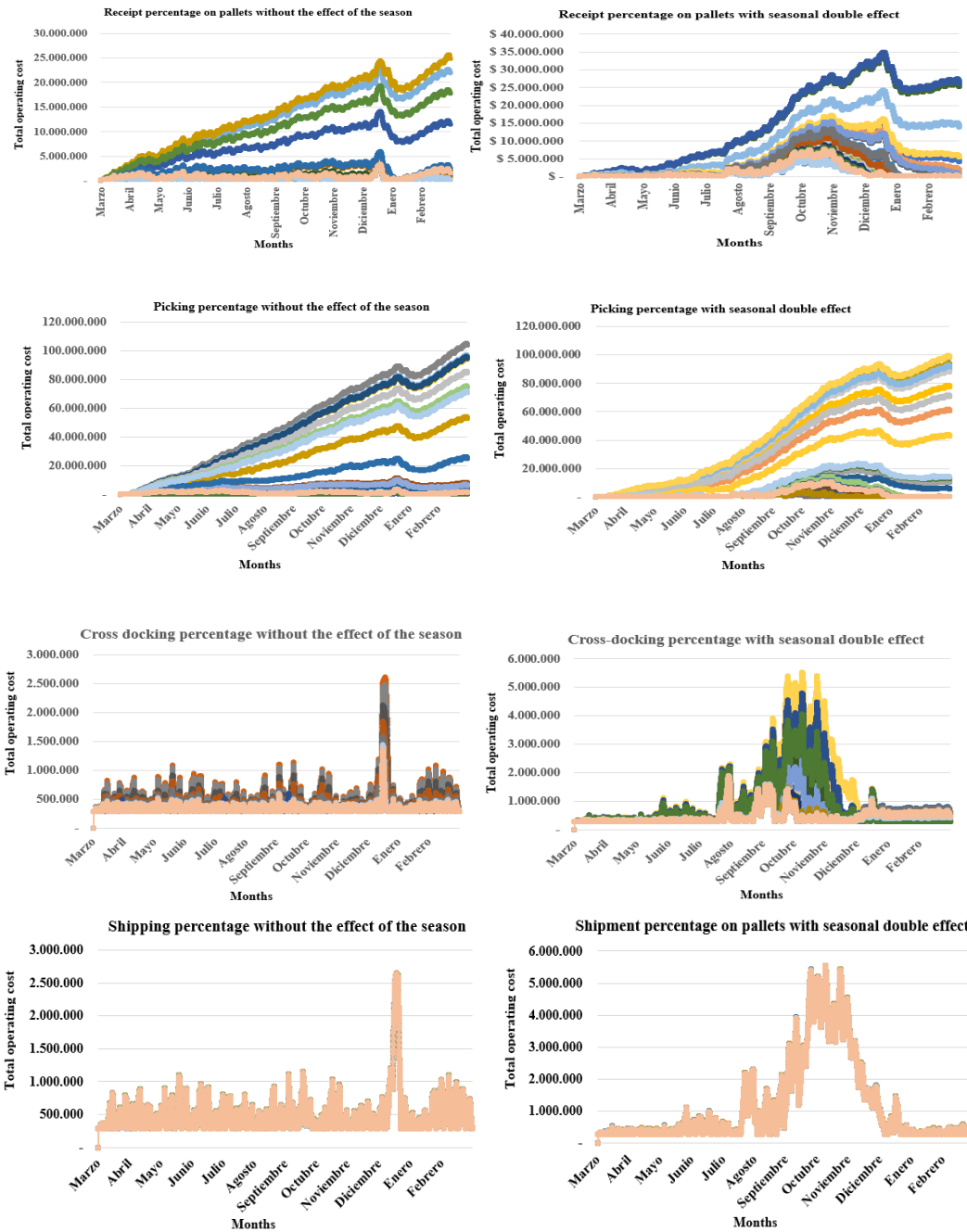


Figure 10. The total operating cost of the warehouse and per process. Evaluation of the effect of eliminating the season or duplicating it.

Figure 11, shows that the intensity of the association between the picking percentage and the total operating cost remains almost constant with or without the effect of the season, but it does show the effect of eliminating or doubling the flow of seasonal products in the other parameters.

Figure 11a shows that the behavior of the percentage of the product received on full pallets without the effect of the season, makes it almost constant throughout the simulation period, but with the double effect of the season, the intensity of the association becomes stronger in the negative direction, favoring the decrease of the total operating cost during the period that includes the season. In this case, the productivity of receipt on

full pallets is greater than the product arrival flow 93.5% of the time, which allows the level of pallets waiting not to exceed the penalty rule within this process, reducing the penalties that increase its cost and therefore the total operating cost.

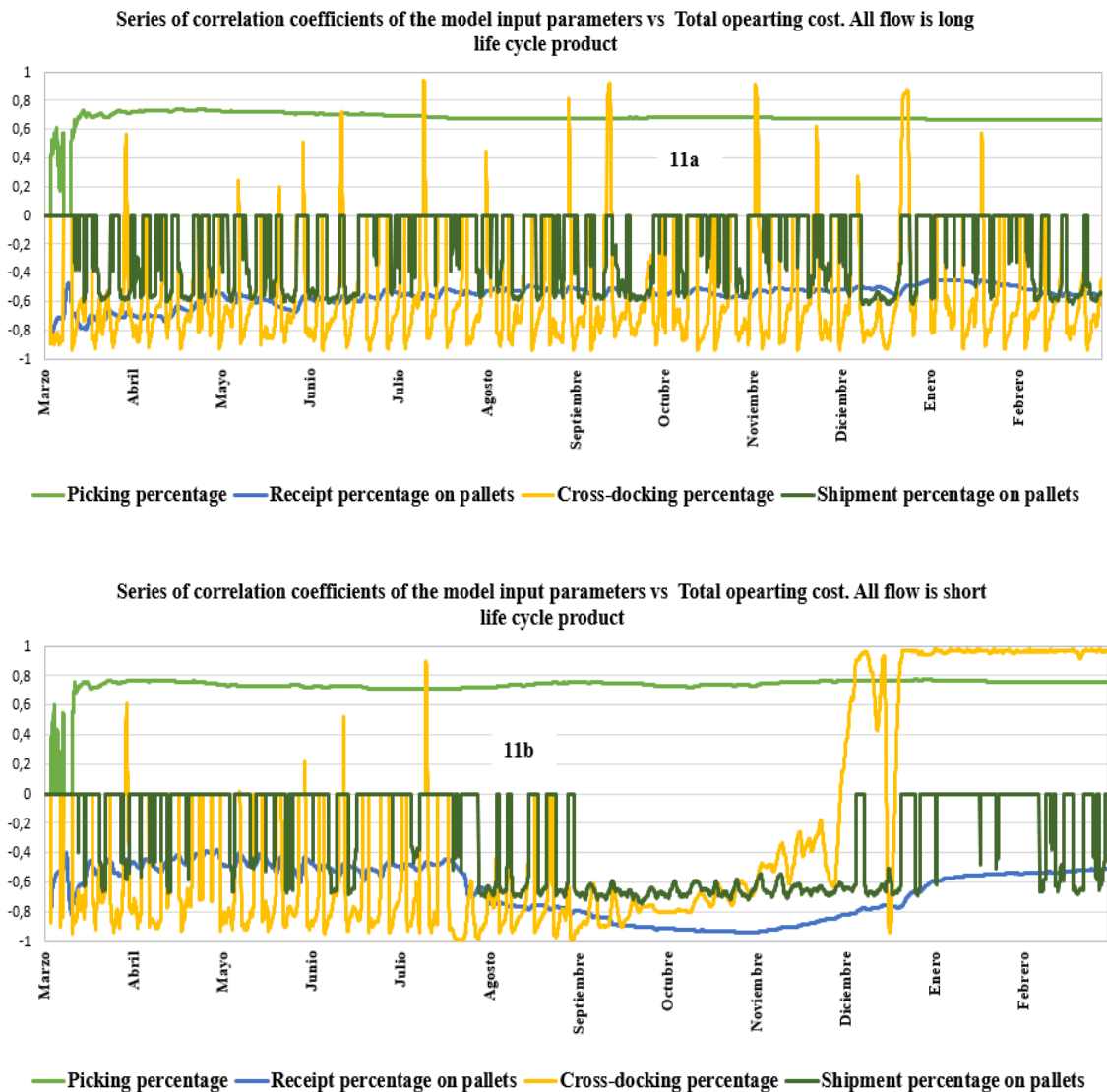


Figure 11. Series of the correlation coefficients of the model input parameters and the Total operating cost. Scenario eliminating the season (a) or duplicating it (b).

Figure 12 compares the base scenario, without the effect of the season and doubling its effect, for the two parameters with the greatest degree of impact on the total operating cost, picking percentage and receipt percentage on pallets. The increase in seasonal flow has a greater effect on the strength of the linear association between receipt percentage on pallets and total operating cost than on picking percentage and total operating cost.

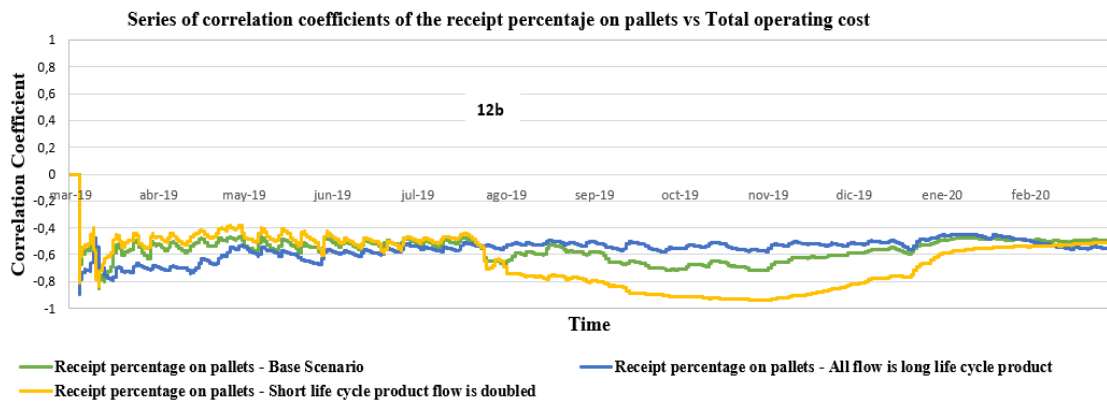
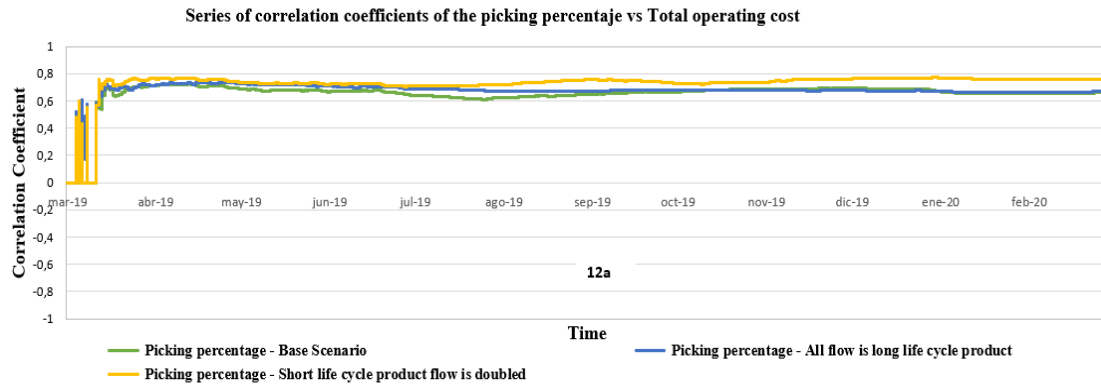


Figure 12. Series of the correlation coefficients of the most effect parameters in the total operating cost. Base scenario, scenario eliminating the season (a) or duplicating it (b).

Finally, regarding the fill rate of receipt and shipment under the two scenarios that were analyzed, again, the result showed insignificant relationships throughout the simulation period under the different changes in the uncertainty ranges. Similarly, the only parameter that affects these two output variables to any degree is the percentage of picking, between 45-50%. Figure 13 and 14 shows the values that show this behavior.

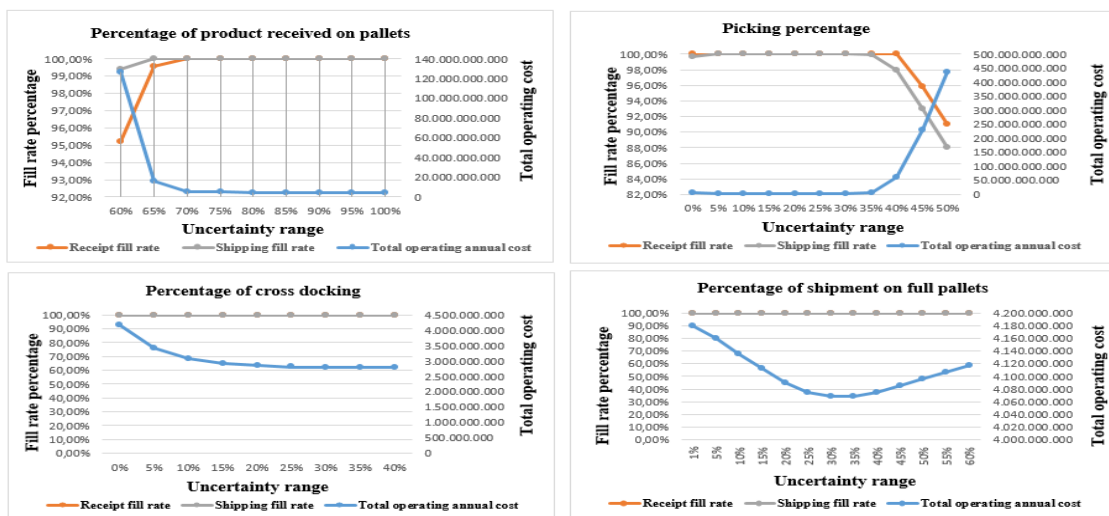


Figure 13. The behavior of the output variables vs uncertainty range of each input parameter was analyzed. Without the effect of the season.

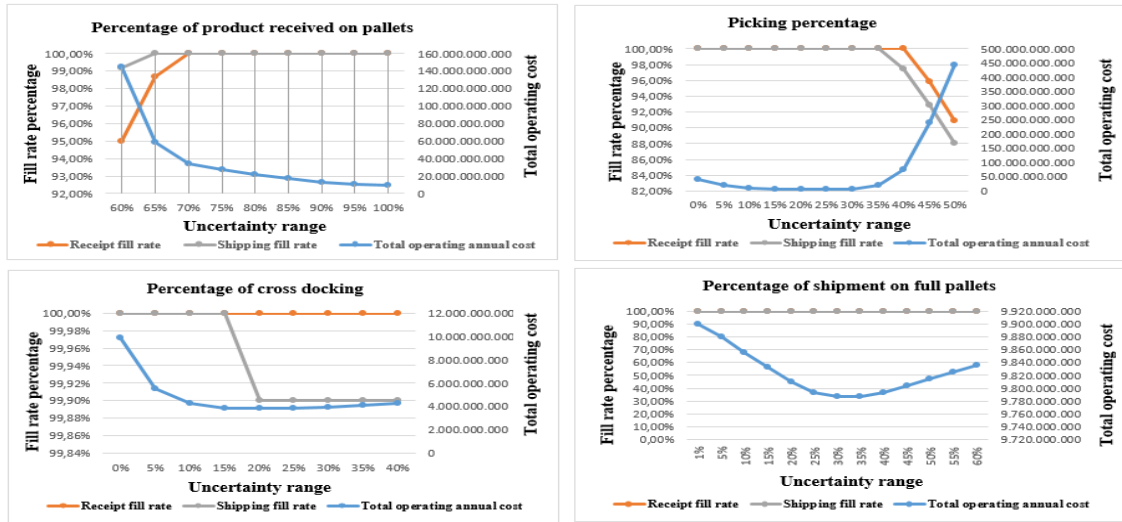


Figure 14. The behavior of the output variables vs uncertainty range of each input parameter was analyzed. Duplicate effect of the season.

4.2. Policy design

Finally, after completing the analysis, we perform a run of the SD model to analyze the behavior of the system under good values of the operating parameters identified thanks to the SS analysis. Table 9 shows the values of the input parameters to the model with which the warehouse must operate under current conditions to reduce the total operating cost without affecting the receipt and shipping fill rate. This table also shows the values of these parameters under the without-season scenario and doubling-the-season scenario. The values chosen were those that minimized the total operating cost within the range of uncertainty as illustrated in Figures 8, 13, and 14.

With the current line and season product mix, a run was made with these values and the total operating cost was decreased, from \$ 4,607,735,413 to \$ 2,846,822,572, representing a 38% decrease. Now, if the effect of the season is eliminated, the decrease in the total operating cost is 41% over the base scenario, but when its effect is doubled, it decreases by only 21%. In all the analyzed scenarios, the receipt and delivery fill rate were not affected.

Table 10. Values of the input parameters to the model with which the warehouse must operate to reduce the total operating cost.

Parameter	Value of each parameter			
	Current warehouse state	Best value	All flow is long life cycle product	Short life cycle product flow is doubled
Receipt percentage on pallets	100%	100%	100%	100%
Picking percentage	10%	25%	25%	25%
Cross-docking percentage	0%	20%	35%	20%
Shipment percentage on pallets	1%	30%	30%	35%
Total operating cost	4.607.735.413	2.846.822.572	2.718.555.158	3.648.753.161
Receipt fill rate	100%	100%	100%	100%
Shipment fill rate	100%	100%	100%	99,9%

4.3. Model limitations

From the SS application point of view, the uncertainty ranges chosen to analyze the performance of the warehouse can bias the results (Taylor et al., 2010). In this case, they were defined empirically. Alternatively, analytical methods can be used to determine them, but without neglecting the validity in the daily operation of the warehouse.

Other limitations of SS were identified by Ford & Flynn (2005). The authors observed that the correlation coefficients may not recognize a high influence parameter when the influence pattern is not linear in the uncertainty range. Furthermore, the value of each parameter analyzed is fixed throughout the simulation period, a very strong assumption that is not really in practice.

Finally, the chosen input parameters, which are well known in real operations, cannot always be 100% controlled. The complexity of the orders in the case of the picking percentage or the restrictions of the production and/or transport plants in relation to the receipt percentage on pallets could affect the control that the warehouse has over these parameters. However, knowing the behavior and impact of the picking percentage, a parameter with the greatest influence on the total operating cost, helps to understand how the warehouse's performance would be if I have new clients with more complex operations.

5. Conclusions and future research opportunities

This document discusses the application of SD and SS in the identification and degree of impact of variables that affect the performance of a warehouse under the effect of seasonal demand and short- and long-life cycle products. SD is a valuable analysis tool not only for strategic evaluations but also for decision-making aimed at improving warehouse operational performance. It could also be concluded that, despite the limitations of SS, it is a method that allows a better understanding of the simulation model and the identification of potential leverage structures that dominate the behavior of the system.

In particular, the results found in the baseline scenario show that the picking percentage is the input parameter with the greatest influence on the total operating cost, followed by the receipt percentage on pallets. By contrast, the cross-docking percentage and the shipment percentage on pallets are not part of the dominant causal path of the total operating cost.

Within the sensitivity analysis that was carried out, eliminating the effect of the season or doubling it, show that the behavior of the total operating cost does not change significantly, but the percentage of picking and the percentage of receipt in full pallets are still the parameters that dominate the dynamics of this output variable. The correlation and behavior between the picking percentage and the total operating cost are almost constant between these two scenarios when compared against the baseline scenario. This result indicates that the flow of short-life cycle products does not have a major effect on the relationship between these two variables. However, the receipt percentage on pallets is affected by this change within the seasonal period. Finally, for the fill rate of receipt and shipment, the result showed that they are not affected throughout the simulation period under the different changes in the uncertainty ranges.

The analysis of the effect of these four variables leads to an ideal operating scenario, where the total operating cost can be reduced if the picking percentage varies

between 10-30%, the cross-docking percentage between 15-30%, the shipment percentage on pallets between 20-45% and the receipt percentage on pallets with a value of 100%. In particular, the total operating cost decreases 38% compared to the base scenario, if the picking percentage is 25%, the cross-docking percentage is 20%, the shipment percentage on pallets is 30%, and the receipt percentage on pallets with a value of 100%. However, despite the limitations of SS, it is a method that allows a better understanding of the simulation model and the efficient identification of potential leverage structures that dominate, in this case, the general performance of the warehouse.

The main limitation of this research comes from the design of the simulation model, productivity in the different warehouse processes was modeled as an exogenous variable throughout the time horizon, which could affect the dynamics of warehouse performance. Under this choice, these productivities are not affected by the possible absenteeism of the personnel, the rotation of this resource and its impact on the efficiency of the processes due to the learning curve they need, as well as the complexity of the orders in terms of their structure (SKU number, quantities, weight, volume). In addition, the model does not present delays between order release, order picking, and vehicle availability, which could significantly affect the outbound flow, increasing total operating cost and, affecting the fill rate. On the other hand, the model does not pose the need for external storage if the capacity is used at 100%. In addition, analyze parameters that are 100% controlled by the warehouse, such as order picking by order or by batches, the size of the batch to be separated, the dynamic assignment of personnel within the warehouse (multivalence) or simultaneously modify the parameters chosen to evaluate the performance of the warehouse, could potentiate the results found in this research. These would be options to motivate researchers to pursue new challenges that help improve the systemic understanding of warehouse performance.

Academic contributions

Conference paper

Diego Ramirez-Malule, Juan Sebastián Jaén-Posada, Juan G. Villegas. *A System Dynamics Model for Warehouse Performance Measurement with Highly Seasonal Demand and with Long and Short Life Products*. The 2nd South American International Conference on Industrial Engineering and Operations Management Sao Paulo, Brazil, April 5-8, 2021, Hosts: IFSP and Facens University.

Oral Presentations

Diego Ramirez-Malule, Juan Sebastián Jaén-Posada, Juan G. Villegas. *A System Dynamics Model for Warehouse Performance Measurement with Highly Seasonal Demand and with Long and Short Life Products*. The 2nd South American International Conference on Industrial Engineering and Operations Management Sao Paulo, Brazil, April 5-8, 2021, Hosts: IFSP and Facens University.

Award

Diego Ramirez-Malule, Juan Sebastián Jaén-Posada, Juan G. Villegas. *A System Dynamics Model for Warehouse Performance Measurement with Highly Seasonal Demand and with Long and Short Life Products*. *The second place of the graduate student paper competition*. The 2nd South American International Conference on Industrial Engineering and Operations Management Sao Paulo, Brazil, April 5-8, 2021, Hosts: IFSP and Facens University.

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