Determining optimal inventory positions in an urban network

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Abstract

Supply chain networks are becoming increasingly complex due to the aggressive growth of multiple digital trends, like the rise of e-commerce and the increased customer expectations, which have been enhanced through the pandemic over the last few years. Therefore, this study proposes a model to develop an inventory optimization strategy for a multi-tier supply chain case study in the US market, considering the supply and demand variability for local and international distribution. First, different approaches from the theoretical perspective are analyzed, from traditional inventory management to the new end-to-end perspectives. After that, details of the methodology will be explained, considering the statistical benefits of demand pooling. Finally, real numbers from a case study are applied to the methodology to measure the solution's impact, followed by the conclusions found from the study.

Keywords: Inventory, optimization, planning, network, multi-tier, *urban logistics*

<u>The following content must be between 7500 and 10000 words plus tables, charts, and figures.</u>

1. Introduction

Changes in the world economy have significantly variated competitive standards across industries and their supply chains. The fiercer competition between brands and suppliers, fluctuating market demand, and increasing consumer requirements due to an intense rate of urbanization has raised the expected service level standards. Moreover, this is only the beginning. According to projections, between 2011 and 2050, the world's population living in urban areas is expected to increase by more than 70% to 6.25 billion people (Kamal-Chaoui & Sanchez-Reaza, 2012; United Nations, 2012), playing the leading role within the emerging countries in Asia, Africa, and Latin America and the Caribbean (Biswas et al., 2018). Industries have become more competitive in world markets, bringing greater complexity to distribution networks.

This dynamic reality gives Supply Chain networks a strategic role in organizations since they cover all their supply, production, distribution, and sale facilities (Martel & Klibi, 2016), strategic decisions related to implementing production points, distributions, or sales across the network are highly relevant since they involve significant investments with long-term impacts. Thus, as complex as they can get, it becomes a priority for every company to optimize the network's performance in terms of cost and the value added to the commercial activities to fulfill the strategic goals (Martel & Klibi, 2016).

However, having an optimal network is just one part of the problem. To fulfill customer expectations, it is also highly necessary to consider how much inventory is needed to maximize the value of the company's operations. Depending on the industry and the company's strategic objectives, defining the correct inventory amount to meet the demand is important. To pursue high service levels, it is necessary to have enough inventory available, but in an increasingly urbanized market, overstocking can have profound consequences. According to Das et al. (2021), overstocking causes potential waste of perishable items and can become a real problem in space-constrained, small-format, urban stores or warehouses. These constraints limit the company's ability to grow and successfully operate to attend to customers, becoming equally harmful as the stock is out.

Shapiro (2009) explains that network optimization models often ignore inventory deployment decisions, associated costs, and replenishment rates. However, in industries where the decisions on cycle and safety stock deployment can have high financial impacts, it is essential to have the inventory variable added to the optimization model.

As mentioned earlier, the need for a more resilient Supply Chain Network has been raised, as Wladawsky-Berger (2020) commented. In addition, Wladawsky-Berger (2020) also stated that: “Many companies in emerging economies had found themselves with a complex multi-tier network design, often generated by an aggressively growing e-commerce channel among other accelerated existing trends like AI adoption or automation." Even when traditional single-tier inventory policy is applied in most cases because of its simplicity (Ying Liu, 2013), this approach can create essential consequences related to service level and increased costs, as stated below (Simchi-Levi et al., 2000):

- Excess of inventory in the form of redundant safety stock.
- Low customer service level and brand image harm even while adequate inventory exists in the whole network.
- Some locations experience stockout, while supply between tiers occurs without significant deviation.
- Increased inaccurate demand forecasting on every tier.

This study proposes a model to develop an inventory optimization strategy for a multi-tier supply chain in a medium to large emerging country, considering the supply and demand variability for local and international distribution. Specifically, the goals of this research are (1) to propose a multi-tier inventory model that companies may use to optimize their post-pandemic inventory policy, (2) to put that model to test with actual data, and (3) to prove the potential economic impact it could have on the entire network.

Therefore, the following question will be answered:

- Where should the inventory be located, and how much should be kept on each node to achieve the desired service level on a previously optimized network model to fulfill the company's objectives with the minimum cost?

2. Literature review

Adding inventory decisions to facility location decision-making models in supply-chain networks (SCN) can potentially achieve significant economic gains at the cost of more complex models to solve.

> “SCN design problems are difficult to solve comprehensively largely because of the complexity of the huge number of options to consider and evaluate. For this reason, it is essential to use an optimization model to develop good designs. Given the magnitude of the problem, it can also be extremely difficult to find the optimal solution for the optimization model. Consequently, most SCN design models address only a subset of identified issues, and they focus on subnetworks that consider only one or two echelons (or stages) of global SCNs. These simplified models typically rely on several approximations (in the representation of relevant revenues and costs, among others), overlook some important decisions, and neglect some aspects of reality (e.g., dynamics, uncertainty).” (Martel and Klibi, 2016, p.245)

In this sense, it is essential to look at the classical models discussed in the literature on inventory positioning in urban networks regardless of the factors adding more complexity to the models, such as the scope of the decisions to make, the number and disparity of products, the objectives to optimize, the constraints to consider or the uncertainties of the business environment.

This section is divided into four topics that briefly overview the three main models identified and urban networks. The first two topics focus on isolated models for both network location and inventory optimization. At the same time, the third part presents some integration alternatives between the two types of models and some of their limitations. In addition, the fourth section will talk about urban distribution networks.

a. Facility Location Models

Locating facilities along a supply chain is an important decision that gives shape, structure, and conformity to the logistical system. Location problems typically fall into a limited number of categories that cover: the nature of the overriding factors, the number of facilities, the level of data aggregation, and the time horizon.

In this way, several ways exist to classify location models. Daskin (2008) presents that the problems are divided according to the space used to model the problem in analytic, continuous, networked, and discrete models. Analytical models can be solved through calculation or simple techniques, and it usually assumes that demands are distributed continuously throughout the service region. Continuous models typically take that demands arise only at discrete points, and a location (X, Y) is searched for anywhere in the plan. Network location problems are considered a representation in decision trees, where demands arise only on nodes in the network. Finally, there are discrete problems, which may or may not use distances, which may be arbitrary, and costs.

On the other hand, according to Martel and Klibi (2016), it is important to identify the complexity of the optimization model considering the reach of the decision to make, which can be oriented to:

- Considering site-selection decisions and assuming predetermined flows (pure location)
- Finding the mission, every facility should assume a fixed facilities location (pure allocation)
- The combination of the previous cases is a more complex problem that might even include supplier selection, market restrictions, or capacity flexibility.

In this particular case, the starting point of the analysis will be based on a previously optimized network based on a pure location problem, assuming flows are already defined as a result of the previous company's work and assigned to the closest warehouses. This way, it is possible to keep the resulting model lighter and to focus on the inventory optimization part through deeper analysis.

The following are the strategic dimensions previously optimized and considered in the present analysis:

- adequate number of warehouses
- location of each warehouse
- size of each warehouse
- allocation of space for each product in each warehouse
- allocation of customer products for each warehouse.

b. Inventory Management Models

After the previously stated critical definition, the next question to answer is how much inventory the network should hold to fulfill the company's objectives at a desired service level.

Stocks may vary from company to company, depending on their need. The inventory of an electronic components trade will be different from the automobile industry. However, the industry will have a stock of maintenance machines similar to electronic trade-in components. According to Ballou (2009), numerous reasons justify the presence of stocks in supply chains. However, these can be costly when poorly managed. The reasoning in favor is linked to improving customer service by providing a level of availability of products or services, ultimately resulting in increased sales. In addition, although inventories imply maintenance costs, they also provide scale gains by providing more extended and protracted operations balanced. Inventories can absorb any changes in demand and bring savings in purchasing supplies. In contrast, the author also argues that keeping inadequate stocks is waste and does not add value directly to the product, as they absorbed capital that could have had a more profitable fate. Excess inventory also prevents potential process improvements.

i. Newsvendor

As a first example of the inventory model, the "newsvendor" problem considers how the newsperson decides how many newspapers to put in his daily sales stand. If he puts enough paper in his stand, some customers can purchase paper, generating some loss in sales. On the other hand, if he adds too many papers to the stand, the newsvendor will have paid for papers that were not sold during the day, lowering profit. In this case, the optimal stocking level, using marginal analysis, occurs when the expected benefits of carrying the next unit are less than the expected costs, as Jacobs and Chase (2008) explain. To describe this model, the expected marginal cost equation is defined as:

$$P \leq \frac{C_u}{C_o + C_u} \tag{1}$$

Where
P = probability that the unit will not be sold
Co = cost per unit of demand overestimated
Cu = cost per unit of demand underestimated

ii. Economic Order Quantity

As with location models, inventory management problems have numerous ratings. Ballou (2009) classifies them as the nature of demand, degree of aggregation of products, presence of multiple stages, and management philosophy (pushed inventory or pulled). Chopra and Meindl (2011) do not highlight classifications of control models for stocks. However, the authors introduce the economic order concept for models with constant demand. The EOQ (economic order quantity) corresponds to the lot size in which the total costs are minimal. The EOQ is given by Equation 1:

$$Q^* = \sqrt{\frac{2DS}{hC}} \tag{2}$$

Where: D is the annual demand, S is the fixed cost of the order, and C is the cost per unit.

In inventory, two decisions are important: when and how much to order. The set of these decisions is called a replenishment policy. Chopra and Meindl (2011) highlight two policies: i) continuous review and ii) periodic review.

iii. Continuous Review

As explained by Chopra and Meindl (2011), inventory is continuously tracked in this inventory replenishment policy. An order for a lot size Q is placed when the inventory declines to the reorder point (ROP). A good thing about this method is that, although the timing of orders may be irregular (depending on the variation in demand rate), the order size is constant and can be set at the optimum economic order quantity. Such continual checking on inventory levels can be time-consuming, especially when there are many stock withdrawals compared with the average stock level. Still, in an environment where all inventory records are computerized, this should only be a problem if the records are accurate.

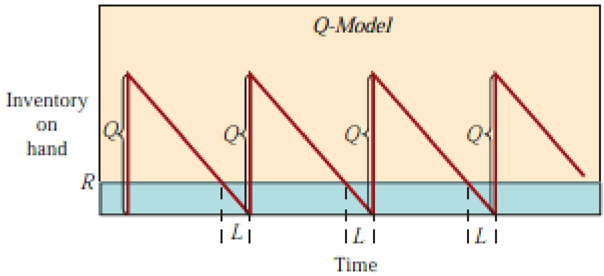

Figure 1. Basic Fixed-order Quantity Model (Jacobs & Chase, 2008)

iv. Periodic Review

The Periodic Review is an alternative, more straightforward approach that sacrifices using a fixed (and possibly optimum) order quantity. However, in this case, the inventory must be checked regularly, and an order must be placed to raise the inventory level to a specified threshold (Chopra & Meindl, 2011). Here, the periodic approach orders at a fixed and regular time interval rather than a predetermined reorder level. So, an item's stock level could be found, for example, at the end of every month, and a replenishment order was placed to bring the stock back to a predetermined level. This level is calculated to cover demand between the replenishment order being placed and the following replenishment order arriving.

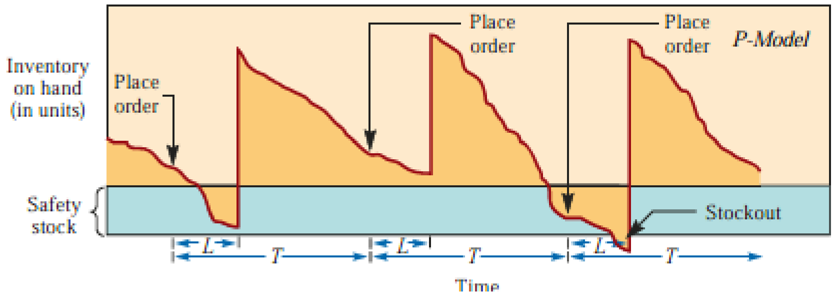

Figure 2. Fixed-Time Period Model (Jacobs & Chase, 2008)

These models assume that demand and known are constant. However, this is not true in many cases, so it is essential to establish a safety stock as a buffer against stockout events. Safety stock can be estimated using different criteria, from carrying an additional percentage of the average demand to more sophisticated methods. A common approach is to use probability to define the safety stock. Therefore, the reorder point should be calculated as follows:

$$s = \mu_{DL} + k_{Los} x 2\sigma_{DL} \tag{3}$$

For the present analysis, the chosen policy will be the periodic review, considering restricted human resources availability to continuously track inventory levels at every node of the multi-tier network. It could be subject to future analysis to measure the impact of enabling software for the company.

c. Joint Location and Inventory Management Models

Since changing a facility's location is more complex than adjusting its repositions point, location decisions (strategic level) significantly impact the supply chain more than inventory management decisions (tactical level). However, location decisions can affect inventory management and vice versa. Thus, the integration of location and stocks in a single model can lead to better results than the independent approach (Diabat & Deskoores, 2016)

In addition, according to Martel and Klibi (2016), one can find several variants of location-allocation problems, such as service constraints, transshipment sites, supply sources, site-selection restrictions, bounds on platforms throughputs, and single sourcing.

d. Urban Distribution Networks

To describe the solutions to problems generated by the urban distribution of goods, Taniguchi et al. (2001) proposed a concept called Urban Logistics, which incorporates the optimization of logistics activities carried out by public or private entities in urban areas, considering factors such as traffic, congestion and energy consumption in the economic market structure. This concept is based on understanding problems that include distribution, social and environmental costs. Thus, to obtain a goods distribution system within the principles of Urban Logistics, it is necessary to involve four agents: shippers, transporters, the population, and the government (Taniguchi et al., 2001).

Moving from urban logistics to distribution networks, the first concept relates to compliance with the measures set by policymakers. The second concept talks about the decision-making process of designing the urban network. In this sense, Snoeck and Winkenbach (2020) have said that strategic network design decisions must be informed by integrated location-routing problems (LRPs) that optimize facility location and vehicle routing jointly and simultaneously. In addition to it,

> “a common approach in these systems is to establish one or more city distribution centers (CDCs) where in-and outbound shipments are consolidated for efficient distribution to the urban area. Typically, CDCs are located near the periphery of the urban zone, close to main roads. Urban delivery demand can be served directly on delivery routes starting at the CDCs or indirectly with transshipment via satellite facilities (SFs). SFs constituted a second echelon of facilities, significantly smaller than CDCs and located closer to high-demand centers. In real-life applications,

the facility and the vehicle capacities are typically limited. The corresponding class of models can be described as two-echelon capacitated location-routing problems(2E-CLRPs)."

Other approaches to the urban distribution network design include but are not limited to: large-scale urban distribution network design, stochastic urban distribution network design, and flexibility in freight distribution.

3. Methods and procedures

The methodology used to deploy the proposed solution will be the construction of an optimal inventory iterative calculator based on Python programming. First, demand will be allocated to the nearest nodes of the previously optimized distribution network, using a mathematical approach through Euclidean distance assuming demand zones as specific points in the map. After that, a model will be proposed and built for optimal inventory calculation using Python procedures in a way that can be reused and iterated for different cases. Finally, the base model will be extrapolated to the multi-echelon proposed scenario to obtain an optimal solution for the stock allocation through the network.

a. Demand Allocation for the optimized network

For the present study case, demand zones are organized in 8 different regions of the United States, with a certain amount of cities identified by specific coordinates, as shown in the table below.

Table 1. Demand regions case study

Demand Regions	Num. of Cities
East South Central	18
Middle Atlantic	11
Mountain	52
New England	6
Pacific	28
South Atlantic	31
West North Central	73
West South Central	31
Total general	**250**

On the other hand, the previously defined optimal network is formed by two manufacturers in the cities of Daegu and Taichung, each supplying a different product family. Also, two distribution centers are necessary to receive the stock and deliver it to twelve selected warehouses that are set to execute the last-mile delivery to demand zones. A model of the described Supply Chain is shown in the figure below.

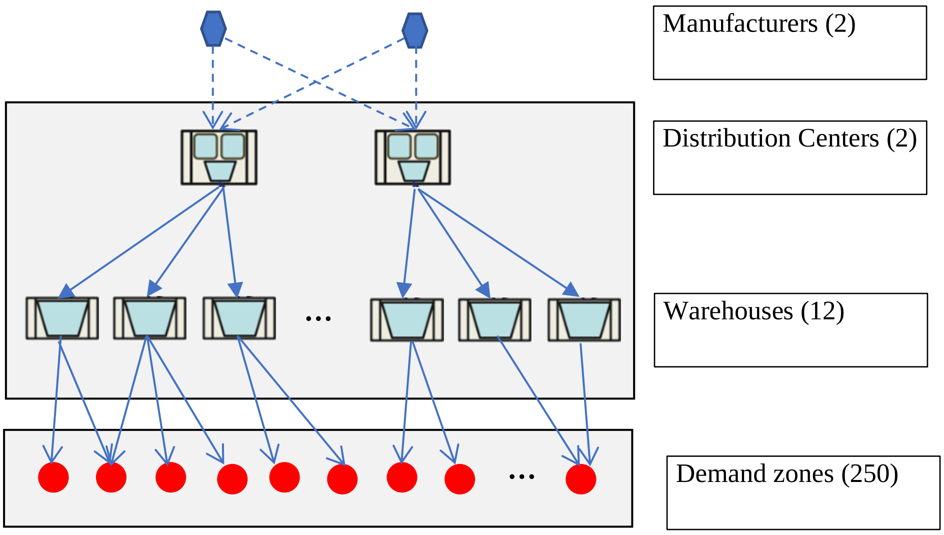

Figure 3. Multi-echelon Distribution Supply Chain Network (Source: Authors)

Once defined the network, demand needs to be allocated to each available warehouse. Hence, the given coordinates for every city will be used to measure the closest city to supply using the data in table 1.

Table 2. Required Variables

q_i	Coordinates for the point q (city)
p_i	Coordinates for the point p (warehouse)

For the mentioned task, the Euclidean distance formula below will be used for every pair of points (city and warehouse) to evaluate the smallest possible distance and assign each demand point to a certain warehouse. We will assign only one demand zone to each warehouse for this case study to optimize inventory.

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{4}$$

Once every distance is calculated, the warehouse p assigned to every city q will be defined by comparing all the results $d(p,q)$ for each city q.

$$X(p,q) = \min_{i=1\ to\ n} d(p_i, q) \tag{5}$$

A procedure in Python will be used as part of the solution proposed to complete these calculations.

b. Inventory optimization model

After allocation is completed, the next step is to build an inventory model that can be used on the different echelons of the network. For that matter, a periodic review model will be built, as mentioned in the previous chapter.

For the model to work properly, the data sets and variables related to inventory costs, demand behavior, and the company's internal parameters must be defined, as shown in the following tables.

Data sets related to products, demand zones, distribution centers (DC), and warehouses must be defined. The detail of their definition can be found in table 2.

Table 3. Required data sets

L^i	Set of products considered ($i \in L^i$)
L^j	Set of distribution centers considered ($j \in L^j$)
L^v	Set of warehouses considered ($v \in L^v$)
L^D	Set of demand zones considered ($l \in L^D$)

Demand data used in the study will be considered normally distributed, with the following notation.

Table 4. Demand data

Di_l	The yearly demand for the product i on zone l
di_l	Monthly demand for the product i on zone l
σi_l	The monthly standard deviation of demand for the product i on zone l

On the other hand, relevant costs to consider in the inventory model can be found in the following table.

Table 5. Relevant cost data

c_i	Purchase (manufacturing) cost for the product *i* ($/unit)
h_i	Annual inventory holding cost for the product *i* ($/unit)
c_{ti}	Fixed ordering cost for the product *i* ($/order)
c_{si}	Shortage costs for the product *i* ($/unit)

Finally, important company policy and logistics variables must be identified to complete the model representation.

Table 6. Relevant parameters

L_{ij}	Replenishment Lead time for the product *i* to DC j (days)
M_{jv}	Replenishment Lead time from DC *j* to warehouse *v* (days)
Q_{ij}	The order quantity for product *i* on DC *j* (units/order)
Q_{iv}	The order quantity for product *i* on warehouse *v* (units/order)
T_{ij}	Order cycle for the product *i* on DC *j* (days /order)
T_{iv}	Order cycle for the product *i* on warehouse *v* (days /order)
k_i	Service i on DC *j* (days /order)

For the periodic review proposed policy, Chopra and Meindl (2011) state that the main parameters to calculate to define the inventory policy are R (review period) and S (order up-to-level). It can also be considered a hybrid system that considers a reorder point (s) to confirm whether an order should be placed at the given period. For the present study, the focus will be on the pure periodic review policy (R, S), considering the limited resources of the company previously mentioned,

The company policy gives the value of R as an input. The objective up-to-level will be calculated as aggregating the demand during the lead time plus the review period—the desired safety stock to fulfill the industry's required service level. At the same time, the safety stock is calculated considering the objective service level *k* and the standard deviation over the lead time plus the review period. It is important to remember that all the periods must be the same to calculate each parameter correctly.

$$S = \mu_{DL+R} + k\sigma_{DL+R} \tag{6}$$

In addition to the main parameters mentioned above, it is important to consider the cycle stock's value as part of the total cost calculation. Considering the logic behind the policy, the average order quantity Q is calculated as the demand required during the review period, as shown in the following formula.

$$Q = D_i * R \tag{7}$$

From there, the cycle stock would be calculated as half the value of Q, the estimated average inventory available on every network point.

$$Cycle\ Stock = Q/2 \tag{8}$$

Finally, with all the parameters calculated, the total inventory cost needs to be defined to measure the efficiency of the proposed solution. For that goal, the cost parameters previously mentioned need to be used alongside each inventory amount calculation.

The cost of cycle stock would be:

$$Cost\ of\ Cycle\ Stock = c_i h * (Q/2) \tag{9}$$

Moreover, the cost of safety stock is calculated as follows:

$$Cost\ of\ Safety\ Stock = c_i h * (k\sigma_{DL+R}) \tag{10}$$

c. Multi-Echelon Inventory optimization model

Multi-echelon inventory optimization accounts for optimizing inventory allocation within a supply chain. This optimization aims to achieve a service level while minimizing the supply chain costs.

The model presented below is generally designed for a single node or warehouse of a certain network. However, the present study intends to extrapolate the obtained results to a multi-echelon network as defined above.

The proposed strategy is to build a bottom-up structure to calculate the inventory policy to fulfill the objective. Therefore, the starting point will be to apply the optimization model to the nodes closest to the customer: the 12 warehouses attending the defined demand zones. That first analysis leads to the second tier, where the added demand variability reduces the impact of the standard deviation because of the statistic aggregation property. Finally, the top tier of the network has to be optimized following the same criteria and obtaining a more stable demand with a more efficient structure.

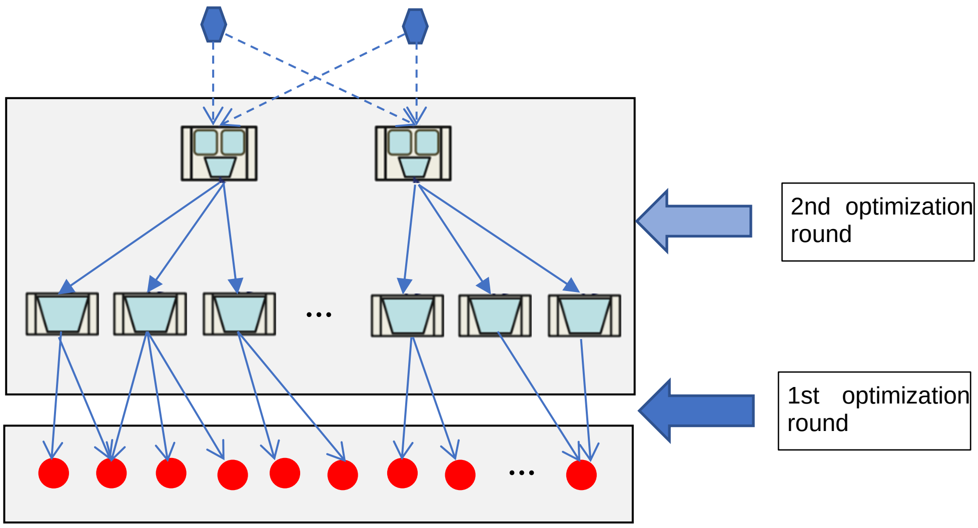

Figure 4. Optimization iteration (Source: Authors)

d. Guaranteed-Service Model (GSM)

The GSM assumes that the safety stock is used exclusively to sustain demand variations up to a certain level. Once the demand exceeds this predetermined level, other means shall be employed to meet this demand (e.g., order delay, overtime, fast shipments). Based on these foundations, the model can optimally allocate safety stocks across a multi-echelon supply chain.

Vandeput (2020) states that each site on a distribution supply chain should cover all its incoming risk period (i.e., until the first upstream node holding safety stocks) or none. Even for very wide distribution supply chains (tens or hundreds of sales points), only a few cases are worth checking to find the optimal case.

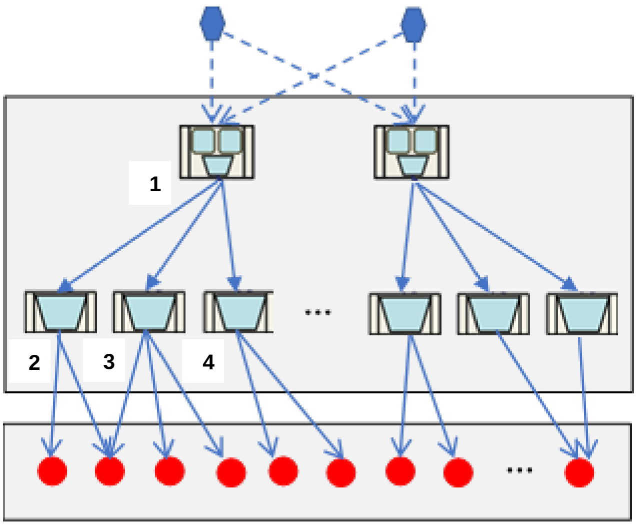

Figure 5. Distribution multi-echelon supply chain, highlighting the nodes numbered from 1 to 4 (Source: Authors)

Distribution supply chains sometimes have their nodes aggregating the demand of the nodes immediately downstream of their position. For this, it is necessary to assume that the demands from the cities are independent (not correlated) and normally distributed. We can consider that assumption covered since the aggregation of the independent demand of several clients forms them,

Therefore for the supply chain shown in figure 3, the demand pooling would be characterized as follows:

$$d_1 = d_2 + d_3 + d_4 \sim N(\mu_{d2} + \mu_{d3} + \mu_{d4}, \sigma_{d2}^2 + \sigma_{d3}^2 + \sigma_{d4}^2), \text{ where}$$

d = demand for each node
μ_d = mean of the demand for each node
σ_d^2 = variances of the demand for each node

4. Case study or numerical setting

Following the previously discussed parameters and definitions, this section will analyze the case study in more depth and detail to apply and evaluate the results of the proposal.

As stated before, the data comes from a case study of a tech company selling two types of products in the US market: a low-value product family (LowVal) and a high-value one (HighVal), with the details shown in the table below.

Table 7. Products families description

	LowVal	**HighVal**
Selling Price	$750 / pallet	$3,800 / pallet
Assortment range	5 SKU	20 SKU
Demand Variability	Low	High

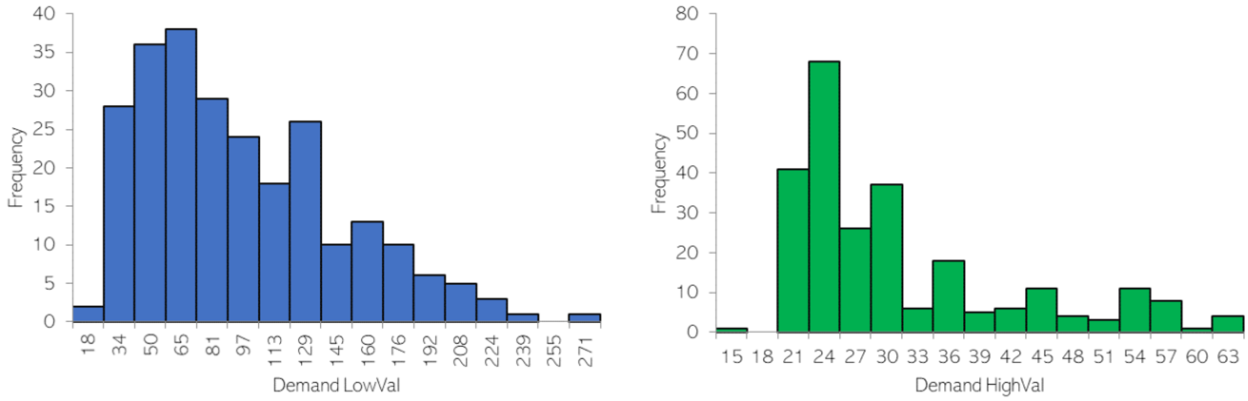

Figure 6. Demand histograms for both product families (Source: Authors)

As we said before, the company just finished the network optimization process. The next critical step related to the supply chain network strategy is to set up the best possible inventory policy that the warehouse and human capacity restrictions can support. Furthermore, for that matter, the main objective of the analysis is to reduce inventory cost and, with that, potentiate revenue generation.

The network structure is already defined in figure 3, and the demand allocation will be developed in the next point of the document. However, before that, it is important to consider each product's routing to reach the customer through each echelon.

The multi-modal transportation method sends products from manufacturers to DCs, with an FTL from the provider to the nearest port and ocean freight to cover the international movement. Once in US land, additional FTL transportation is needed to reach the DC. After the product is in stock in the DC, one more FTL must be executed to reach each warehouse to fulfill demand.

A representation of the network flow is shown in the figure below.

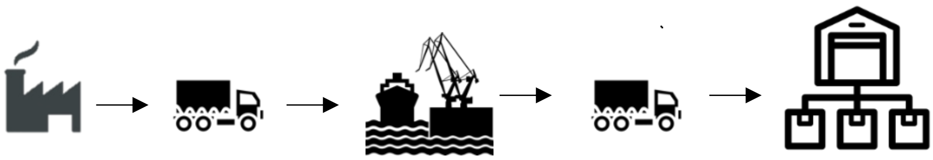

Figure 7. Full transportation route (Source: Authors)

To determine each route from the manufacturer to the DCs, a comparison was made between the offered lead times to decide the fastest way to reach each position. The obtained results are shown in the table below. It is important to mention that the fastest routes are also the cheaper ones.

Table 8. DC route definition

Origin (manuf)	Destination (DC)	Via	Lead time
Daegu	Atlanta	**Houston**	**28**
		Los Angeles	32
	Oceanside	Houston	30
		Los Angeles	**28**
Taichung	Atlanta	**Houston**	**35**
		Los Angeles	36
	Oceanside	Houston	37
		Los Angeles	**32**

A similar exercise was done for the warehouse routing to calculate the required lead time to replenish the inventory of each product family in every warehouse, obtaining the following result.

Table 9. Routing & Lead time warehouse definition

Origin City	Destination City	Lane_type	Distance (km)	Time (days)
Oceanside	Amarillo, Texas	interfacility	897.6	3
Oceanside	Casper, Wyoming	interfacility	892.5	3
Oceanside	Cedar City, Utah	interfacility	389.0	1
Atlanta	Des Moines, Iowa	interfacility	739.2	2
Atlanta	Louisville	interfacility	319.9	1
Atlanta	Macon, Georgia	interfacility	76.4	1
Atlanta	Milwaukee	interfacility	668.4	2
Atlanta	Montgomery, Alabama	interfacility	146.1	1
Oceanside	Portland	interfacility	892.0	3
Oceanside	Reno, Nevada	interfacility	453.3	2
Atlanta	San Antonio	interfacility	882.7	3
Atlanta	Scranton, Pennsylvania	interfacility	712.3	2

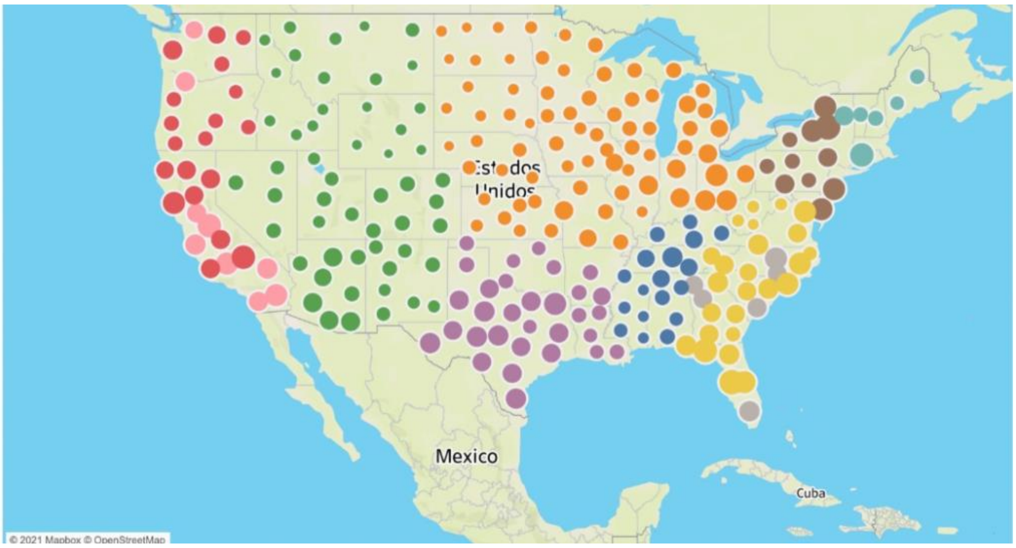

Figure 8. Demand areas distributed by clusters as outlined in Table 1 (Source: Authors)

With all the information previously mentioned, the structure shown in figure 10 helps us recognize and evaluate the availability of all the data sets and parameters needed to calculate the inventory policy for each echelon.

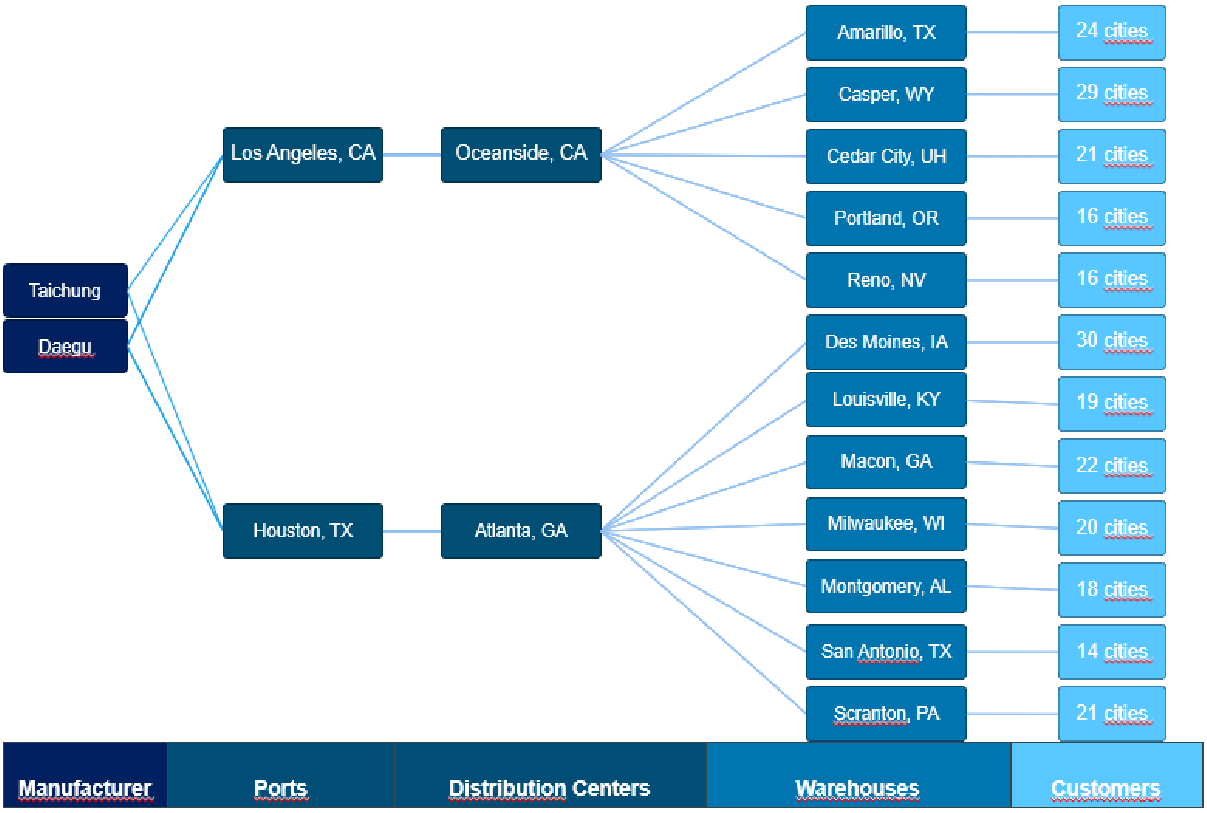

Figure 9. Optimized supply chain with all its echelons – Manufacturer, DCs, Warehouses, and Customers (Source: Authors)

5. Results and Discussion

A code was developed in Python to perform the demand allocation calculations for each node and echelon by the outline demand pooling criteria in section 3.d. In addition, a sensitivity analysis was performed for each warehouse and distribution center to examine how the service level can play a major role in defining how the safety stock will be deployed across a supply chain network.

It is important to consider the relevant parameters and costs to analyze the results. Since the focus of this research has been the periodic review policy, the main parameter of sensitivity would be the safety stock, considering that the cycle stock would not vary with a fixed review period.

We can observe in figures Figure 10. Safety Stock results for each warehouse and distribution center for LowVal productand Figure 11 that the safety stock is highly sensitive to the service level we intend to provide. In the 95% service level vicinity, we see a steep increase in the safety stock needed for both product families. In addition, as we could expect due to its demand variability, the HighVal product presents larger safety stock requirements, even though its mean expected demand is low compared to the LowVal.

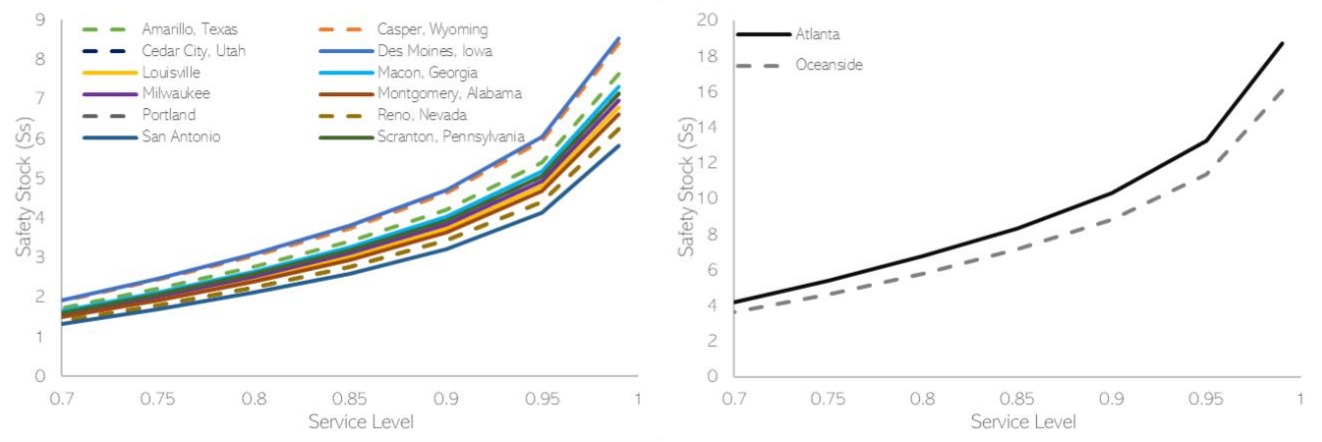

Figure 10. Safety Stock results for each warehouse and distribution center for LowVal products (Source: Authors)

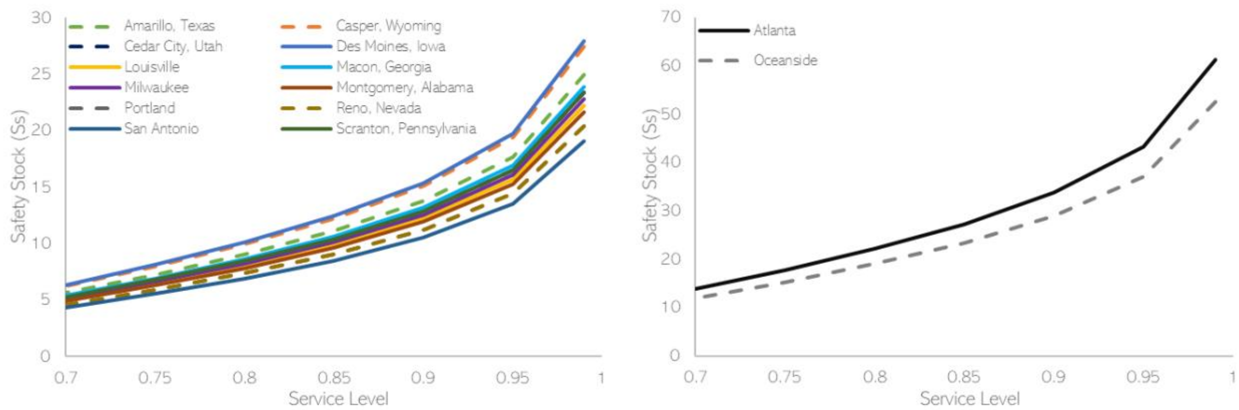

Figure 11. Safety Stock results for each warehouse and distribution center for HighVal products (Source: Authors)

As shown in figure Figure 9, Oceanside has fewer warehouses to serve; therefore, its requirements for safety stock, regardless of the product, are lower than the requirements observed in Atlanta, which has to deal with greater demands.

- Des Moines, IA, and Macon, GA, have the larger safety stock requirements, even though they do not have the larger demand requirements. On the other hand, these cities have larger demand variances; therefore, with bigger uncertainty, the safety stock requirements follow the same trend.

- Portland, OR, Reno, NV, and San Antonio, TX, have the lower safety stock requirements for both products. As discussed above, they present less uncertainty regarding their demands.

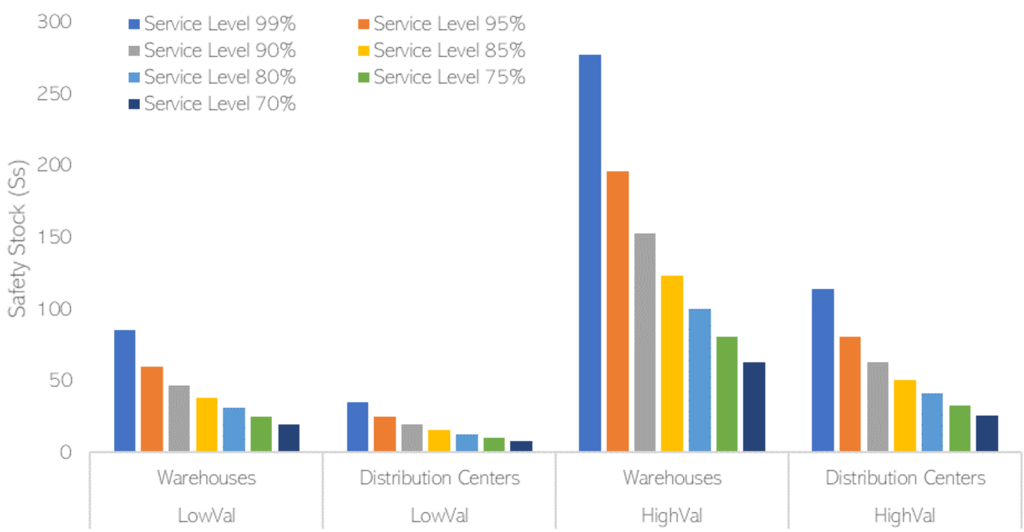

Figure 12. Side by Side Safety Stock for warehouses and distribution centers (Source: Authors)

Considering the product distribution, the occupancy of the safety stock on each node is mainly dominated by the HighVal product, even when the demand for the LowVal is 74% of the company's total demand. This result shows the impact of the variability on the definition of the safety stocks and inventory policy, as shown in figure 14.

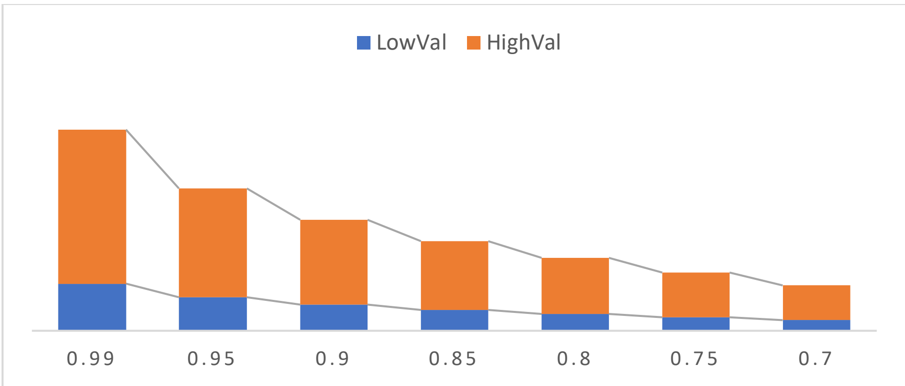

Figure 13. Safety stock composition by product family (Source: Authors)

On the other hand, regarding relevant costs, for this analysis, the value of the inventory holding cost is the same in DCs and warehouses, giving us a view between nodes similar to the safety stock quantity analysis. The main difference is the increased gap between HighVal and LowVal products because of the high unit cost of the HighVal and the higher variability.

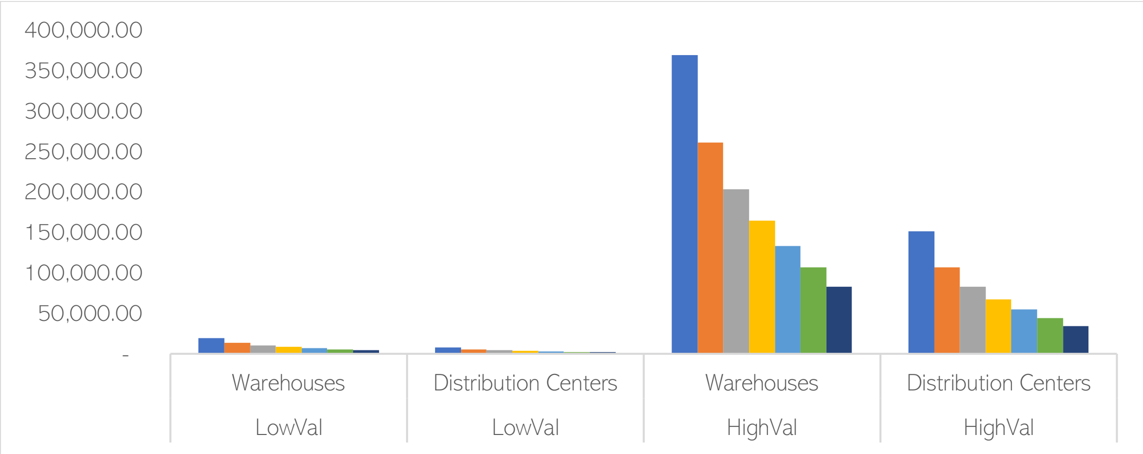

Figure 14. Side by Side Safety Stock value in US$ (Source: Authors)

It is important to keep in mind that in most cases, storage sites closer to urban areas where the demand is located tend to be more expensive and might be a decision variable on the location of the inventory, pushing companies to move upstream or downstream the safety stock to achieve better costs.

6. Conclusions and future research

Analyzing the safety stock from the service level perspective is useful for negotiating deals with counterparts in the supply chain. Small increases in the service level can contribute to a larger necessity of stock and, therefore, increase the costs of a supply chain actor. This analysis also allows the modeler to identify imbalances in each supply chain node and echelon.

Demand variability also plays an important role in safety stock calculations. The high variability in Des Moines, IA, and Macon, GA warehouses places them in the top positions to hold larger safety stocks. On the other hand, Portland, OR, Reno, NV, and San Antonio, TX, have lower safety stock requirements as they have lower variance numbers.

Varying the service level at the same amount for the entire supply chain will produce similar effects for the echelons considered in the simulation, as was observed in this study. It would be good to consider expanding this research by taking different service level agreements within the different echelons and, if possible, within the different nodes, which brings the model closer to reality.

It was found that the order up-to-level responds little to changes in the service level, as it has stronger ties with the safety stock, and the amount of safety stock needed is low compared to the value of the order up-to-level.

It is also important to consider that the amount of demand is not the main driver in defining the size of the safety stock but the variability and lead time of the product. That is shown in the comparison between the LowVal and HighVal products in which the more stable one (LowVal) has the lowest safety stock despite its bigger sales volume, which means companies should consider the trade-off between reducing lead times by approaching a product to the customers and the benefits of a reduced variability by applying demand pooling.

On the other hand, the relevance of costs should be considered when applying the methodology to a different data set. As mentioned above, it is common to find higher inventory holding costs as we move closer to urban areas. Therefore, a new trade-off about where to place the inventory must be considered.

For further studies, an analysis of the type of inventory along with its packaging could be considered. Adding holding cost, space, cargo size, and vehicle constraints to the equation, in addition to safety stock numbers, would add other layers to the simulation model and, therefore, difficulties and more processing time. Constraints like these are closer to reality, allowing the modeler to quantify the accuracy of the results produced by the model.

Another possibility to consider is modeling a supply chain with more echelons than what was considered. This model would allow us to analyze the safety stock equation by each echelon and see if the standard deviation of predicted safety stock levels increases as it moves upstream. Based on these results, a conclusion could be made regarding which actor (suppliers, distributors, retailers) absorbs more risks within the supply chain network.

Finally, the next step should be to do a full network optimization considering network design and inventory allocation to get a full view of how the optimal network should be built. The greatest challenge in this option would be the computing power necessary to process big networks making it difficult to run different scenarios quickly.

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