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Digital transformation of planning in the pharmaceutical sector

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Digital transformation of planning in the pharmaceutical sector

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Purpose: *To adjust the inventory supply planning, through digital transformation that allows automation and tracking of demand behavior in real time and with low cost tool.*

Methodology: *The collected database is loaded into an Excel along with the required input variables in each of the inventory policies. The data is processed and imported into Python, the demand forecasting is made and the policies are simulated to choose the one that generates the lowest cost.*

Results: *The algorithm indicates the inventory scheduling to be implemented by the company according to the policy that allows the lowest costs and that supplies the demand of each product.*

Originality: *The design of an original tool, that allows obtaining accuracy of the inventory management, with easy interaction of the user and the algorithm, through the reception of information and output of results in Excel, processed by python, across the synergy between the two programs.*

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1 Introduction

Nowadays, the digital transformation throughout the supply chains forces to immediately improve the response to the demands of essential products (pharmaceuticals, health, beauty, baby, and personal care) required by consumers through quick commerce.

As the third largest market in Latin America, the pharmaceutical sector in Colombia grew exponentially throughout the pandemic, due to a greater demand for generic drugs formulated by public health institutions; manufacturing grew by 6% and sales by 10.1%. Several organizations of these supply chains, as it is the company under study, had to transform, adapting their operation to the needs of the digitization of processes to respond to the increase of quick commerce (SOLUNION, 2022).

For the present study, a pharmaceutical company with almost one hundred years of experience is taken as a reference, which has identified inflection points to improve its supply through digital transformation, reducing costs and increasing the reliability of prediction in the face of the change in consumption behavior. This company has a planning area, which depends on a software that makes suggestions for product supply from the distribution center to its sixty-three stores in the country. Unfortunately, this software is very rigid for the diverse types of demand these products have, which generates a lack of synchronization between demand and supply. Likewise, additional management is performed in loading and updating information, prompting delays and slow response capabilities in the supply chain.

This scenario becomes an opportunity to review inventory planning management. And in this way, the question arises of how to implement an accessible digital transformation in terms of costs and applicability in the supply chain, for this a tool that integrates these characteristics and has a progressive adjustment in inventory planning in a distribution center is proposed.

Real-time automated planning is achieved under an algorithm chained in Python, which provides an assertive response to future demand and the changing market, through a variety of inventory and supply policies, consistent with the behavior of the demand for each SKU (Stock Keeping Unit), maintaining a logistics cost and a controlled inventory for the operation.

This article begins with the introduction and exposes the background. Subsequently, the concepts associated with this investigation are described. In Section number four the methodology is described, followed by the description of the results. In section number six the improvements are identified and finally, the conclusions are presented.

2 Theoretical Background

2.1 Context of the industry

Colombia is the third largest pharmaceutical market in Latin America, accounting for 4.1% of the country's GDP (Rincón, 2021). Given this growth generated by the constant increase in demand for products, the organization under study, in the past, has had to deal with sporadic and immediate growth in its operation, assuming a high logistical cost, influenced by the restrictions of the national panorama.

In Colombia, logistics cost represents 12.6% of sales, highlighting that the highest item focuses on the cost of storage and inventory with 43.2%, followed by the cost of the transport category that occupies 30.7% of the total logistics costs due to inadequate planning of inventories along the supply chain. (DNP, 2020)

In addition to this situation, there are a plethora of situations, such as smuggling, counterfeiting, and unfair competition, which continue to affect market prices. For this reason, this retail sector finds it necessary to explore new tools to connect suppliers with their stores throughout the country, even more so with the emerging growth that was obtained with the pandemic by going from 50 to 63 stores in 3 years. Therefore, a shift in the way of planning and creating sourcing policies for the 14,000 SKUs is proposed (Investincolombia, 2022).

2.2 Literature Review in Inventory Planning

For the development of this project, it was necessary to go deep into research based on the use of Machine Learning and its application in terms of optimal decision-making in product supply.

It can be inferred that the way in which markets operate to make optimal decisions of their supply has come through the implementation of models that use mixed linear programming, which are based on algebraic modeling software (Liliana Delgado Hidalgo, 2020).

Also, there have been project developments based on the use of Machine Learning, more specifically in neural networks, which use algorithms that improve the accuracy of predictions mitigating their errors. The purpose of this research was to predict the inventory supply, considering demand, inventory management, and maintenance costs (He, n.d.).

Lishura Chen explored a forecasting method like the moving average but more advanced, which allows an adjustment to the annual cyclical behavior of demand, through the Python programming tool. (Chen, 2019)

On the other hand, in the article "Predictive Control of Inventory Management in Supply Chain Systems with Uncertain Demands and Time Delays" they consider a predictive control algorithm for uncertain demands and supplier delivery time delays, with the supply strategy of the balance between inventory costs and the level of customer satisfaction. (Yi-yang, 2021)

Currently developed relevant studies were also found, such as the one presented by Danielle Nyakam Nya and Hassane Abouaissa, in which a new way of controlling supply chains is sought, since currently the methods used are control strategies based on models such as stochastic, deterministic, economic and based on simulation, which play an important role, however, due to the increasing complexity of such systems, the modeling of supply chains becomes more difficult and fails to capture all the dynamic behavior of the networks in the chain. This is why a methodology is developed based on the configuration of "Modelless Control (MFC)" and its related intelligent controllers, which is developed through a mathematical description of the supply chain inventory production system in semiconductor manufacturing, which allowed the development of an internal model control design of multiple degrees of freedom and in this way control the inventory so that there is no excess of it even if it is subject to a variable demand. (Abouaissa, 2022)

On the other hand, the study "Proposing Multi-item Replenishment model for an Inventory Management System of Malaysia's SMEs studio" describes an economic modified order quantity (EOQ) for the multiple item replenishment model with the deterministic demand nature of an inventory management for companies in the Malaysian manufacturing sector. This research is developed through a function that is subject to the financial and space constraints available in organizations. If the restrictions are not satisfied under the given conditions, the Lagrange technique is applied to obtain the optimal order quantity of the multiple items. The purpose of this study is to offer a model that controls overproduction and underproduction inventories to satisfy customer demand at the right time. (Irfan ur Rahman, 2022)

Another research is concerned with the importance of available quantities in the inventory for restocking calculations and thus make the decision that the SKUs most in demand are the ones that should constantly be in the inventory. For this, they implemented a Machine Learning algorithm called clustering, which allows them to reduce the size or dimensionality of the data and achieve the classification of urgent products to be ordered more easily (Shoujing Zhang, 2020).

The authors of the article "Inventory management and cost reduction of supply chain processes using AI based time-series forecasting and ANN modeling" had tabulated and structured data, for which they applied models based on decision trees, thus managing to reduce the stock level and the monetary resources allocated for this purpose (Umamaheswaran Praveen, 2019).

Finally, Jaumot (2021) proposes that the prediction should be able to show the optimal stock level and thus offer a good customer service, reducing costs from inventory management. The stock level was obtained from the historical data of demand, without generating forecasts about it. For the execution, the author implemented Gradient Boosting algorithms guaranteeing the timeline of the time series (Jaumot, 2021).

2.3 The process

The distribution center of this organization has five basic operations: product reception, storage, picking, crossdocking, and distribution to stores.

The research focused on the planning of the supply to stores. The distribution of a product is conducted frequently, when the inventory of the references in the store is about to be sold out, due collecting, consolidation, and transport to the store are conducted.

Points of sale send a sales record for each product, the supply request, and the number of SKUs that are required. This data is stored in software that specifies the collectors the product to be supplied and the point of sale to which it must be sent. These products are accumulated in a basket. Once this basket is ready, they proceed to label the information of the products, indicating their destination and then be taken to the loading area, where they are loaded to be transported to the different stores in the country. The process is shown in Figure 1.

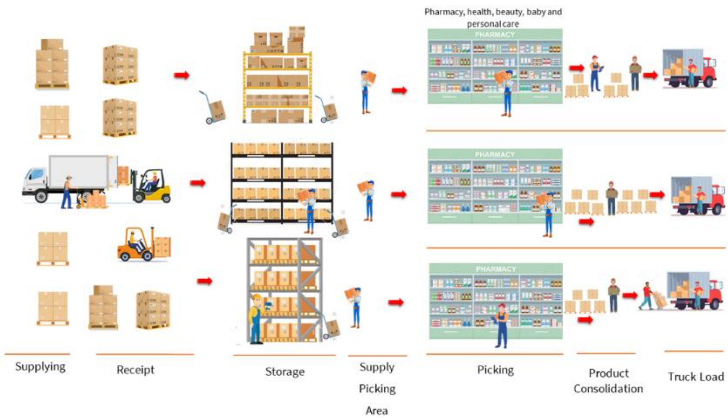

Figure 1: The process

3 Applied concepts

To achieve the construction of this model, it was necessary to understand both supply and demand. For demand, an algorithm is designed that can forecast each product's values. For supply, inventory policies are designed so that they can respond to each demand behavior, specifying shipping frequency and quantities of product to be loaded.

This shows the need to improve planning through a base of parameters designed to efficiently manage the quantity and frequency of orders, with the aim of minimizing costs and ensuring availability of products in stores nationwide.

These parameters define inventory policies, which have been created due to the dynamic environment that simulates different behaviors in demand and allow modifying the efficiency and capacity of a supply chain through the management of its resources to find an optimal solution that balances cost and service (John J. Coyle, 2019).

3.1 Inventory policies

A policy is a rule that a company implements to organize the behavior of some of its elements. The inventory policy involves determining the batch size, which includes the frequency and quantity to be ordered for inventory. Batch Size is the quantity of an item in inventory that management purchases from a supplier or manufactures through an internal process (Sunil Chopra, 2013).

Considering the literature about the existing policies in inventory management, the authors propose four inventory policies for the development of the algorithm to model different behaviors that present the demands of the SKUs that the company deals.

The proposed policies for the development of this work, which involve four variables, are set out below:

- Time(T): It is the period in which an order must be placed.
- Quantity (Q): It is the optimal quantity that must be ordered from the supplier.
- Safety Inventory (S): It is an inventory that is kept in stock used to cushion shortages produced by uncertainty of demand and delivery time.
- Roof (R): It is the possible inventory limit to keep in stock.

TQ Policy: It is a model that consists of ordering a fixed amount whenever required. The optimal quantity of supply Q is ordered each period T calculated according to the demand that in this case presents a behavior of low uncertainty being continuous and constant.

The Figure 2: TQ policy shown below is a simulation of the model with the behavior of some boxes of medicine over time, starting with an inventory of 12 days, which is 220 boxes; its consumption is represented with the red slope until it reaches the 8 days of inventory reorder point established by the company, which is 150 boxes.

To calculate the amount Q, formula 1 is used, and to calculate time T, formula 2 is used:

$$Q = \sqrt{\frac{2 * d * Cp}{Cs}} \tag{1}$$

$$T = \frac{Q}{d} \tag{2}$$

Where:

- d = Average demand over a period.
- Cp= The shipping cost that is generated each time an order is placed.
- Cs= Cost of inventory maintenance per unit.

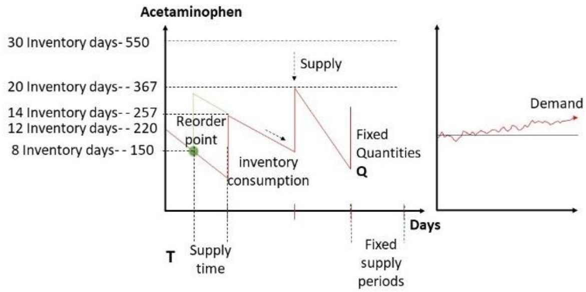

Figure 2: TQ policy

SQ policy: It consists of a model that is responsible for preventing a stock-out, calculating an inventory or safety stock that must be maintained in the face of uncertain conditions that arise when the demand has a dispersed and volatile behavior as can be seen in Figure 3: SQ policy. Under this scenario in which demand and supply times present a high component of uncertainty, the safety inventory "S" depends on the variability of demand and delivery times. In Figure 3Figure 3: SQ policy SQ policy, the first slope illustrates the consumption of the initial inventory up to the safety inventory (the first green point), which is the time at which order of quantity Q is placed. To calculate the quantity Q, Formula 1 is used. Formula 3 is required to calculate the safety stock (Sunil Chopra, 2013).

$$S = d * t + \omega * \mathrm{z} * \sqrt{\mathrm{t}} \tag{3}$$

Where,

- d= Demand. Refers to the average demand over a period.
- t= Provisioning. It is the time it takes the supplier to deliver.
- Z=Safety Factor. Adjustment factor that represents the probability of avoiding shortage, according to the normal distribution of demand.
- ω=Sigma. Standard deviation of demand.

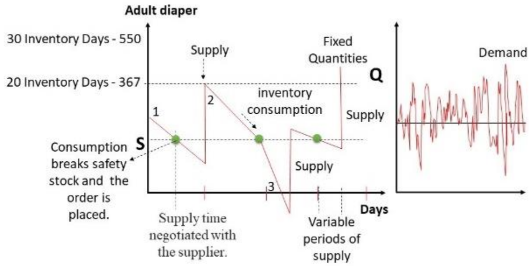

Figure 3: SQ policy

SR Policy: Consists of a model that establishes a maximum fixed inventory called roof (R) and calculates the quantity to be ordered when the current inventory is less than the safety inventory (S). This model is used when the demand has a dispersed behavior, but with a growth trend, being adjustable to any atypical behavior of the demand. The quantity to order is determined by the difference between the roof and the current inventory. Figure 4: SR policy illustrates the decrease in inventory up to the safety inventory in the first green point, in which an order equivalent to the difference between the "R" roof and the safety inventory must be placed. To calculate the safety inventory (S), Formula 3 is used and Formula 4 is required to calculate the roof (R).

$$\mathrm{R} = (D + \omega) * \mathrm{t} + \mathrm{z} * \omega * \sqrt{\mathrm{t}} \tag{4}$$

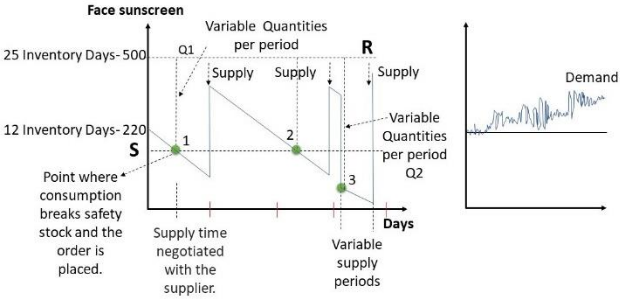

Figure 4: SR policy

TR Policy: Consists of a model that is responsible for requesting product inventory on a periodic basis, calculating the difference between the maximum inventory called roof (R) and the available inventory. It is applied when the demand has a seasonal behavior as seen in Figure 5: TR policy.

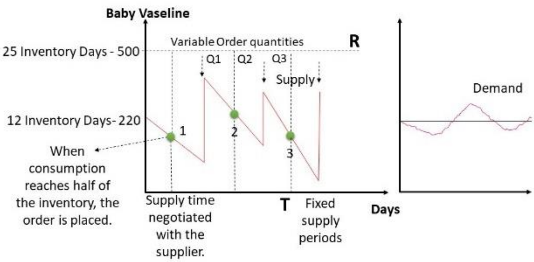

Figure 5: TR policy

Formula 2 is required to calculate the supply time (T), which considers the shipping cost (Cp), the cost of maintenance (Cs), and the average demand (d). Formula 5 is required to calculate the roof (R).

$$R = D * (t + T) + z * \sigma * \sqrt{t + T} \tag{5}$$

The four policies described above were integrated into the programming of the Python algorithm developed in this project, to automate the action for all the requested SKUs and thus optimize the order and storage rate. To do this, artificial intelligence was integrated to obtain the demand forecast that inventory policies require to adapt to the behavior of the expected demand and thus decide on the type of policy to choose.

3.2 Machine Learning

Quick and efficient data analysis is key for operational planning, as it provides support for processing and managing large volumes of information and obtaining data closer to actual market behavior. Based on this trend, it is necessary to apply or implement mathematical analysis tools to obtain accurate data which can help identify failures and opportunities for improvement in all organizational operations.

A branch of artificial intelligence called Machine Learning, allows the use of algorithms that can analyze large volumes of data to generate forecasts that help decision-making, that is, finding hidden patterns from the data, thus creating knowledge that provides increasingly real and accurate information over time, minimizing bias and errors in the quality of the information. This contributes to the minimization of costs, since the information about the operation is available in real time, achieving adequate management (Karagiannakos, 2020).

For the development of Machine Learning algorithms, Python is the programming language with the most growth today, and the one that has allowed competitiveness in companies (Tokio School, 2020), due to its simplicity, ease of machine learning and open source. This makes the Python app ideal for time series forecasting.

The algorithm designed for the research in question uses the following libraries to perform demand forecasting and inventory policy implementation:

- Pandas: Python library specialized in the management and analysis of data structures (Alberca, 2022)
- NumPy: Python library specialized in numerical computing and data analysis, especially for high volume data (Alberca, 2022)
- Statistics: Provides functions for the calculation of statistical values in the field of real numbers (Interactive, s.f.)

- Math: Used for complex mathematical operations that use floating point values, including logarithms and trigonometric operations (Anon., 2022)
- Keras: It is an open-source library of artificial neural networks, it is designed to build each neural network in blocks, which are the ones that allow training deep learning models (Anon., s.f.)

For the execution of the model, the Jupyter Notebook application was used, which allows the deployment of notebooks that support forty programming languages including Python.

4 Methodology

4.1 Stages

The methodology used in this study comprises several stages for treating the data set using Excel and Python, as follows:

Data acquisition: Among the products used to conduct the proposed research, those medicines that do not require a medical prescription, personal care, beauty, and baby care products stand out. The obtained data were the result of the information provided by the planning staff of the company under study, for this it was necessary to hold several meetings with this area in 2021. The products taken are classified into three types of references (A, B, and C), and their mode of operation is cross-docking, that is, none of the references has storage. This indicates that the minimum time it takes for a product to leave the distribution center is 3 days and the maximum is 7 days; for this reason, all products were considered high turnover.

Data upload: the historical demand data obtained from the company is loaded into a base Excel spreadsheet. The demand for each SKU is in a column, organized with its corresponding date as shown in Table 1. Additionally, the input variables that are required to identify the cost of the inventory policy of each product are entered, which are: t (supply time), Cp (shipping cost), Cs (maintenance cost), Cf (missing item cost), Ns (Service level) and Ii (initial inventory) as shown in Table 2.

Table 1: To modify input demand

FECHA	**D1**	**D2**	**D3**	**D4**	**D5**
1/01/2017	9	6	3	12	42
2/01/2017	34	7	3	5	10
3/01/2017	89	33	4	40	55
4/01/2017	108	24	27	40	46
5/01/2017	110	41	45	57	64
6/01/2017	93	16	59	29	43
7/01/2017	7	5	59	3	5
8/01/2017	60	18	41	42	101
9/01/2017	42	12	6	15	54
10/01/2017	102	37	29	42	47

Table 2: To modify input variables

Provisioning	Shipping Cost	Cost maintenance	Shortage Cost	Service Level	Initial Inventory
2	150	10	60	0.95	100
4	230	12	60	0.95	200
3	315	14	60	0.95	150
4	400	12	50	0.98	200
5	150	10	55	0.98	170
2	220	12	40	0.98	100
3	320	15	45	0.98	200
4	130	13	80	0.98	350
3	140	14	65	0.98	100
3	260	10	55	0.98	200

Data pre-processing: For the model to be implemented to function properly and yield adequate results, the data needs to have the required quality. Therefore, the outliers and missing values should be treated in Excel, while data is normalized in Python.

Demand projection: for this stage, the data projection model is built with the use of Machine Learning. The model's projection results are used to calculate inventory policies.

Inventory Policy Algorithm: The algorithm that simulates inventory behavior is constructed based on the parameters established in each policy, as described in chapter 3.1. so that the policy that generates a lower cost for each SKU is chosen. The results obtained will be displayed in Excel as shown in table 3

4.2 Model formulation

The model simulates the behavior of inventory policies from the demand forecast, based on the historical data provided by the pharmaceutical distribution center. As a result, the policy that generates a lower cost is determined, according to the desired level of service. The process is shown in Figure 6: Understanding the algorithm.

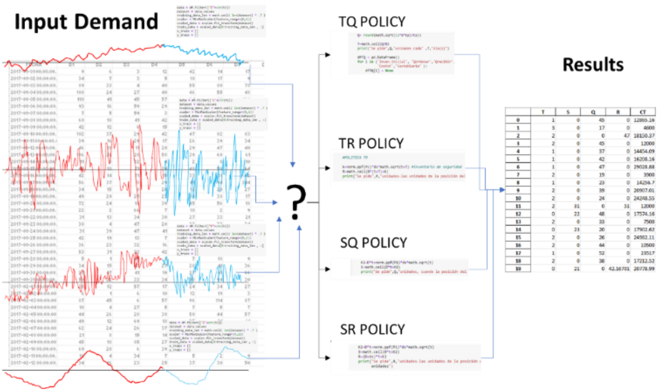

Figure 6: Understanding the algorithm

The projection of historical demand is made based on the artificial intelligence method called neural networks. Artificial neural networks are grouped by layers or neurons that form a neural network. The neurons take a value or weight in each training iteration until they fit with the test dataset. This allows, when the history is entered, to predict the number of values, according to the weights they retain, and the projection is approximate (Anon., 2019).

To make use of neural networks, the training data set corresponding to 70% of the demand history is first obtained and normalized because it is a requirement to use the time series in the neural network. For the above, we have a database provided by the pharmacist for five months.

The model is trained with groups of twenty data points that is updated chronologically and predicts the following position. Figure 7: Algorithm training representation illustrates the training process with six data points and clusters of three. The training begins by predicting the value of the demand on day 4 based on the grouping of the first 3 data points of the time series, then the value of the demand on day 5 is predicted, based on the grouping of days 2 to 4 and so on until an adjustment and creation of the neural network model is generated.

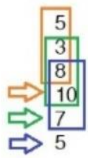

Figure 7: Algorithm training representation

The algorithm uses a neuron that iterates one hundred times, and it adjusts considering the weights of the connections of the neurons of the Adam method, as it has an exceptionally good behavior in forecasting with the time series. (Velasco, 2020)

Once the model has been trained, the demand for the following 60 days is predicted, the inverse of the data normalization is conducted and a Data Frame with sixty positions is created to store the prediction that will support the inventory policies.

The data obtained from the demand prediction are simulated to show the behavior of the inventory in each of the policies according to the input variables mentioned above. Each policy has the order of the structure shown below:

1. The inventory policy is calculated, that is, the quantity to be ordered and how often to order.

2. The projected data are saved in the data frame.
3. The quantity to be ordered and received is assigned in accordance with the inventory policy, as follows:

TQ POLICY: For the quantity to be ordered, if day i is a multiple of the order frequency T i.e., if (i/T -integer (i/T) =0 then on that day Q units are ordered, otherwise it is assigned an amount of 0. For the quantity, it is configured so that the data stay in the data frame on the order day plus the supply time.

TR POLICY: For the quantity to be ordered and the quantity to be received in this policy, it works the same as with the TQ policy, but unlike it, the quantity to be ordered is R (roof) minus the position that the inventory has on day i.

SQ POLICY: For the quantity to be ordered, the entire data frame is traversed, so that if the inventory position is less than the safety stock, Q units are ordered, which would be received in (i + t) days.

SR POLICY: For the quantity to be ordered and the quantity to be received in this policy, it works the same as with the SR policy, with the difference that in this policy, the quantity to be ordered is R (roof) minus the position that the inventory has on day i.

1. The daily costs of shipping, maintenance, and missing item are calculated, and they are totaled at the end. In this way, if at position i of the Quantity to be ordered there is a positive value, the shipping cost will be equal to Cp, otherwise it is 0. If the inventory at the end of the day has a positive value the maintenance cost is Cs by the number of units, otherwise it is 0. If the inventory at the end of the day has a negative value, then a Cf cost is assigned, otherwise it is 0.
2. The costs of all the days projected for each policy are totaled.
3. The policy that generated the lowest total cost is chosen

5 Results

The results are presented in a table from the Excel spreadsheet associated with the algorithm, which indicates the type of policy to be used according to each SKU. SKUs are identified with an integer value of one digit and their results are presented in the same order in which they were entered. Figure 6: Understanding the algorithm shows the process for obtaining the results. In summary, the historical demand data is first inserted in Excel, then the algorithm is executed and finally the results are obtained in Excel. The variables found in the result table are T (supply time), Q (quantity to be ordered), R(Roof) and S (Safety stock). To identify the policy to which each product belongs, it is necessary to verify which cells of the table contain a numerical value and to which column it belongs. For each SKU, two numerical values must appear in the table. For example, in the table 3 for the pilot shows that product 1 has a TQ policy, which means that each frequency(T) of 3 days 200 units of product (Q) must be ordered from the supplier.

Table 3: Results

Time (T)	Safety Inventory(S)	Quantity(Q)	Roof (R)	Total Cost
1	0	45	0	12865.16
3	0	17	0	4600
2	21	0	47	18150.37
2	0	45	0	12000
1	0	37	0	14454.09
1	0	42	0	16208.16
1	0	47	0	29028.88
2	0	19	0	3900
1	0	23	0	14256.7
2	0	39	0	20907.01

Additionally, the table shows an average daily cost that would be incurred to implement the policy according to each product, this cost is unleashed because it is the minimum compared to the cost that would be generated if the other policies were implemented.

The proposed solution is a low-cost tool that allows innovation in the planning of complex operations of small and medium-sized distribution centers. 4.0 technology is used to make the company more competitive by having real-time information and being able to generate an action plan that allows it to predict the future and respond to the behavior of its market. Considering that in Colombia only 78% of companies implement some type of technology such as Excel, QR readers, software, among others, this research has been conducted in the pharmaceutical sector to show that implementing these types of tools is not expensive and allows competitiveness in the sector.

6 Improvements

The fourth industrial revolution has brought about good practices hand in hand with technology, evidenced in applications, software, and robots from another generation. However, the adaptation of PYMES (small and medium enterprises) and even large companies are still in the process of starting this transformation and improvement. One of the objectives of this article pretends to give another meaning to this modernization. The substitution of some software's in the organizations are already possible. Professionals with new skills and knowledge in both logistics and programming are showing it. This stage of the industry is based on solving problems with low budgets, being innovative and creative with accessible resources with minimum cost.

Although the tool designed in this document helps to improve supply planning, as an opportunity for improvement, it is proposed to integrate the use of machine learning not only for the projection of demand but also for the determination of the inventory policy. The objective is that the algorithm acquires the ability to identify patterns in the behavior of the established policies, based on historical predictions and achieve a graphical display of them.

As well, this improvement will help to process a greater amount of data demand for each SKU analyzed. By having the history of the demand of at least one year, it is possible to identify the seasonality in the behavior and with it a better adjustment to the forecast.

On the other hand, it is necessary to look for an alternative that allows obtaining the optimal values of the parameters used in the neural network for the prediction, because the estimates lack well-defined criteria.

Finally, it is proposed that the user interacts only with Excel, or with a dynamic python interface that allows him to enter data easily and intuitively; without the need to open the Jupyter Notebook application, as it is considered more complex.

7 Conclusions

The digitization of planning has become an icon of the supply chain, key for its direction to be consistent with market behavior, managing to maneuver and persuade different demand behaviors.

Optimizing and trying to eliminate the activity from the planning is our proposal. Numerous planning activities that have been managed in the chain, as well as cost overruns generated by lack of forecasting or rapid changes, are some problems faced by several organizations, as they do not have a rapid response model to the uncertainty of the markets.

The model to propose is based on self-planning, which, through four inventory policies (TQ, SQ, SR and RT) responds to a changing demand, where the model learns to project the demand, and, which, according to its behavior, the algorithm locates an optimal sourcing policy for the type of demand it is presenting.

This digital transformation brings many benefits in the sector of this organization, allowing PYMES:

- To optimize the management of inventories, picking, and cross-docking to each store.

- To have information in advance, with greater certainty, to react and cope with the increases or decreases that the market presents; this makes the distribution center react whether to place or not frequent orders, in its supply.
- To reduce both the administrative costs of planning, as well as the errors and impacts that these generate in the chain.
- To substitute storage costs for responsiveness, interpreted with more credible data and synchronized with the market.
- To modernize and learn modern technology, through the use, maturation, and customization of an algorithm that can assertively expedite shipping products to different country stores.

It should be noted that it is not possible to quantify the performance of the model proposed in this article, compared to the implemented models seen in the literature review, since they do not share databases or some quantified result, which allows distinguishing the improvement of the proposed model.

Finally, the proposed improvements allow for greater foresight and identification of the inventory policy to be used, as well as greater practicality in manipulating the model and improving processing times.

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