Multi-product inventory modeling with demand forecasting

Angie Valencia Olivares and Axel Mendoza Bojórquez
Universidad de Lima, Facultad de Ingeniería
Lima, Perú
20183375@aloe.ulima.edu.pe, 20173599@aloe.ulima.edu.pe

José Antonio Taquía Gutiérrez
Universidad de Lima, Facultad de Ingeniería
Lima, Perú
jtaquia@ulima.edu.pe

Abstract

Many wholesale companies do not use an adequate control of their inventory level, and variables such as product demand tend to vary continuously due to seasonality and market trends, generating costs that reduce profitability and eventually produce customer dissatisfaction with the service offered. In this paper we propose the application of a method to reduce the level of uncertainty and risk in sales and to simulate the implementation of a policy of continuous inventory review. Using the monthly demand of the wholesale company and considering the maximization of profit, the ARIMA time series model was chosen, developed through the R programming language, and then modeled in the Arena software the results of the forecast found. The relevance of the study is to present inventory improvement tools that encourage a favorable management in terms of inventory management costs.

Keywords
Forecasting, Inventory, Simulation-Based Optimization, Arena And Time Series.

1. Introduction
Alim and Beullens (2021), Alharkanet al. (2020) and Perez et al.(2021), argue that inventory is a key element in the supply chain, as it seeks to facilitate the balance between supply and demand to maximize profitability and maintain the competitiveness of companies. In wholesale companies where sales are frequent and of large quantity, bullwhip inventory effect affects operational planning (Tao et al. 2019).

In the same line, Salas-Navarro et al.(2017) states that today many of them present problems to manage their inventories negatively impacting how the customer is attended, their competitiveness in the market and financial performance. Kourentzes et al. (2020) states that this is because the demand forecasting process is unknown to firms.

For this reason, it is important to develop a forecast for the generation of demand approximations; as mentioned by Morcillo et al. (2021), it allows a better evaluation of costs and profitability. Additionally, Benhamida et al. (2021) states that it helps to reduce the uncertainty between demand and inventory.

The time series is a set of observations correctly ordered in time presenting the crucial dependence between them, where the longer the series, the greater the probability of a mathematical model fit (Bandura et al. 2021).

In this article the Croston, Arima and Exponential Smoothing time series forecasting models will be used to obtain a forecast on a monthly basis, and then simulate in the Arena program the inventory behavior that allows to obtain variables such as the economic lot, reorder point, among others.

In reference to the above, the following question arises: Is it possible to gain benefits on supply planning management of a wholesale company through the use of forecasting and simulation tools?

At present, many wholesale companies do not use an adequate inventory level management, which results in excess expenses and the absence of control of the associated costs that initially lead to a low level of service that can then lead the business to failure.

To this end, this study analyzes the behavior of demand in order to reduce the uncertainty between it and the inventory level through historical sales data, as well as to ensure proper inventory management of the company.

In synthesis, the presented article is proposed as an informative tool for future projects related to inventory balancing and demand issues.

1.1 Objectives

- Identify a forecast model using MAPE and RMSE indicators in terms of bias and accuracy of each time series model.
- Evaluate a continuous review technique as a means of inventory control, in terms of inventory costs as a function of stochastic demand and lead time, using Arena Simulator.

2. Literature Review

The relevant literature for this study lies in demand forecasting and inventory policies. This section discusses the novelty between the present work in relation to the existing literature.

Supply chain planning assuming dynamic demand has been extensively studied. Alnahhal et al. (2021) argues its necessity for balancing service levels, maintenance costs and inventory orders. In the same vein, Norazira Abd et al. (2018) provides as a planning method, inventory management, which organizes and controls stocks through a set of policies and procedures of inventory levels.

In principle, Valencia-Cárdenas et al. (2016) states that the complexity of supply chains requires advanced methods for scheduling company inventories, and compares demand forecasting models for multiple products in order to obtain the best model and define order, inventory, cost and profit policies.

According to Gong et al. (2022) argues that there are a large number of papers that have demonstrated the effectiveness of continuous review, such is the case of the article by Petropoulos et al. (2018) where a continuous simulation was employed for the analysis of the performance of the forecasting mechanism. Where in turn, states that accurate forecasting is important for business operations, but it is wrong to employ an approach based on minimizing forecast failure, as utility should also be maximized. For Kourentzes et al.(2020) also points out that reducing forecast bias rather than accuracy provides biased forecasts, affecting inventory metrics, reorder decisions and the amount of safety stock.

In the same vein Wang et al. (2021), states that in a realistic environment, where the demand process is unknown, forecasts are relied upon for their imperativeness in many areas of research and application to generate approximations of expected demand considering methods and techniques that have been studied for many years.

The study presented by Spiliotis et al. (2020) does not present strong seasonal patterns, but made a comparison between traditional statistical and Machine Learning forecasting models. From the indicators in terms of bias and accuracy they concluded that there is no level of superiority between both sets of methods, however, it is worth mentioning that in recent years Machine Learning methods have gained notoriety, being proposed as "an advantageous alternative to traditional methods", due to the use of non-linear algorithms able to learn by trial and improve their performance by observing historical data in order not to make assumptions.

Vo et al. (2021) proposed solutions to improve business supply capacity by selecting forecasting models and a policy framework to ensure optimal inventory. First, the chosen research looked at the forecasting model with the lowest error based on a collection of 60 periods; where the ARIMA model was positioned as the most optimal model for forecasting demand after comparing it with the Holt Winters regression model. From the data, the EPQ was constructed by simulation with Arena software to determine the best production lot size.

The study by Freitas et al. (2021) argues that the use of integral solutions for process analysis, such as modeling and simulation, are vital for modern systems and the demand for process intensification.

3. Methods

We analyzed a case study of a representative company in the retail industry methodological design based on primary sources that seek to ensure the reliability of the results. Therefore, 3 methods or techniques will be used with the information collected from the company's unit sales for interpretation and subsequent analysis.

In the first phase, as an exclusion method, products with history at least 37 months of demand and sales data were used. Then, in phase two, products with constant data were selected in order to eliminate products with discontinuous and intermittent demand. Pareto-based ABC technique was used to rank the product categories according to the total amount sold in soles, and then the 41 products were obtained using IBM SPSS Statistics software. Prior to using the software, the following formula was used to obtain the finite sample size.

$$n = \frac{N * z_a^2 p * q}{d^2 * (N-1) + z_a^2 * p * q} \tag{2}$$

In phase four, with the information of this last sample of historical data, a comparison of the MAPE and RMSE error metrics was made through the Exponential Smooting model in Microsoft Excel VBA software, Croston in Python language through the Pycaret library and the Arima model, through the R programming language in Rstudio software as a method of evaluation and verification to obtain the best sales forecast in a four month period range.

To conclude, we used Arena Simulator software to ensure a significant improvement accompanied by a policy of continuous review by determining the reorder point and economic lot of each product, which are expressed under the following formulas:

$$Reorder\ point = D.L + SS \tag{3}$$

Where:

SS: Safety stock
D: Demand
L: Lead time of the demand

$$Economic\ lot\ (\ Q) = \sqrt{\frac{2.D.S}{h.C}} \tag{4}$$

Where:

D: Annual demand
S: Ordering cost per batch
h: Annual percentage maintenance cost
C: Unit cost per product

As a summary of the above, Figure 1 shows a general outline of the phases of the methodology.

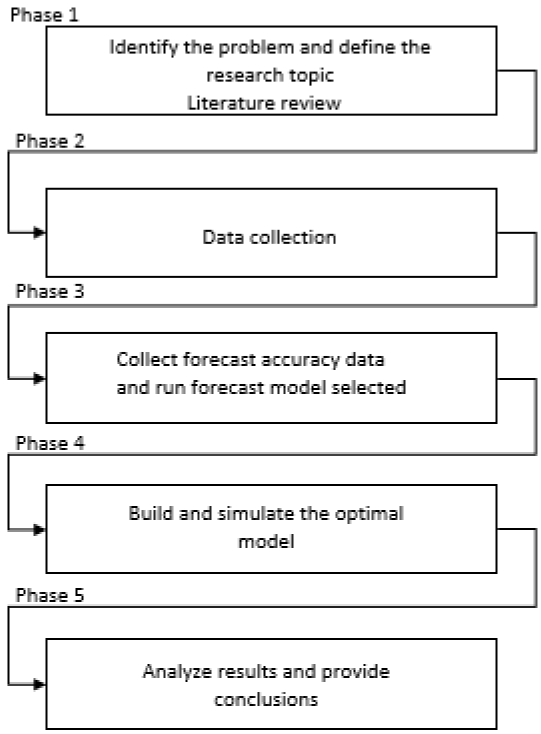

Figure 1. Diagram of the methodology phases

4. Data Collection

For this research we worked with a Peruvian company dedicated to wholesale that wants to implement an improvement model in its inventory system since it maintains 2,900 skus that require a supply program. We obtained for the improvement model, a sample of 41 products selected after the exclusion methods already mentioned in the previous chapter.

5. Results and Discussion

5.1 Numerical Results

Initially, the temporal models were applied to the 41 selected products, one of which is ARIMA, through a code in R programming language, as well as the Croston model through the PyCaret library and the Exponential Smoothing method, through VBA language.

Then, between the results of the MAPE and RMSE precision indicators of each of them, a comparison was applied to determine the most optimal model.

As can be seen in Table 1, according to the performance of each model, ARIMA presents higher accuracy compared to the Croston and Exponential Smoothing models.

Table 1. Metrics of the Arima, Croston and Exponential Smoothing models

	Arima		Croston		Exponential Smoothing	
Product	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
Ajinomen gallina 80g	15.80%	3864.47	16.08%	4045.931	39.36%	8593.291
Colgate triple acción 150ml	15.28%	581.744	18.24%	648.97	25.75%	719.316

Deleite aceite 1 lt	32.85%	2823.082	33.39%	2965.636	33.54%	3094.161
Dento triple acción 150ml+Cepillo	56.10%	1011.451	59.50%	1176.315	96.95%	1583.091
Emsal sal cocina marina 1 kg	20.02%	1891.911	20.28%	1972.143	29.38%	2788.746
Heno/Pravia amarillo 150g	25.74%	2141.059	27.28%	2309.519	45.28%	3590.288
Ideal amanecer 395g	23.18%	8314.37	23.61%	9431.657	36.43%	9791.784
Neko verde extra protec. 125g	38.83%	1141.768	41.42%	1246.223	40.44%	1251.409
Sedal Sacheton Ceram. 45ml	35.57%	3357.185	40.83%	4114.016	81.18%	8166.044
Yogurt Gloria Fresa 1 lt	25.26%	780.543	27.78%	880.358	38.35%	1139.056
Pantene SH. Restau. 18ml+AC. 9ml	31.95%	3430.125	35.85%	3985.089	33.16%	4509.028
Doña Gusta Gallina 7g	21.75%	12080.473	22.06%	12232.384	59.41%	29739.075

For the inventory optimization proposal simulated in ARENA software, through a continuous review policy, parameters, variables and necessary factors were established. Among which the reorder point, also called replenishment point, stands out, because it identifies the need to replenish a SKU for the continuous satisfaction of the demand and is calculated in the formula (3). Another important concept is the economic lot, which refers to the number of units to be replenished, in order to minimize the cost associated with the purchase and maintenance of the inventory. This last concept is found in Arena through formula (4).

Table 2. Variables required for the continuous review policy

Product	Reorder point (units)	Cost of ordering (S/).	Cost of storing (S/).	Days to replenishment
Ajinomen gallina 80g	9151	1.013	0.387	6
Colgate triple acción 150ml	1160	1.322	0.528	6
Deleite aceite 1 lt	4051	1.288	0.7	7
Dento triple acción 150ml+Cepillo	2029	1.291	0.661	9
Emsal sal cocina marina 1 kg	5180	1.033	0.556	9
Heno/Pravia amarillo 150g	6685	1.339	0.477	5
Ideal amanecer 395g	14499	1.373	0.675	10
Neko verde extra protec. 125g	2942	1.078	0.655	6
Sedal Sacheton Ceram. 45ml	5659	1.444	0.354	10
Yogurt Gloria Fresa 1 lt	1499	1.295	0.403	11
Pantene SH. Restau. 18ml+AC. 9ml	8342	1.226	0.743	10
Doña Gusta Gallina 7g	25781	1.142	0.404	9

5.2 Graphical Results

Figure 2 shows an optimization in the profit value. Average profit of the 41 products amounts to 11906.33 soles, with respect to the initial value of 8096.3 soles, equivalent to 47.06 % in percentage terms.

The following Figure 2 shows the distribution of the values of the profit indicator according to each scenario.

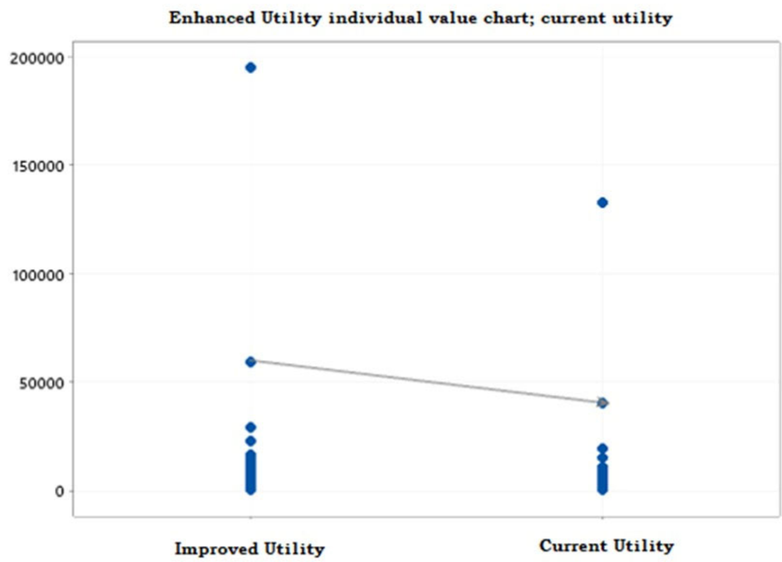

Figure 2. Graph of individual utility values

In addition, some graphs are shown that represent the company's sales data in the R language.

The following Figure 3 shows the summary of the 36 months of a product selected from the sample, where it is interpreted in which month it could be more feasible to acquire that product.

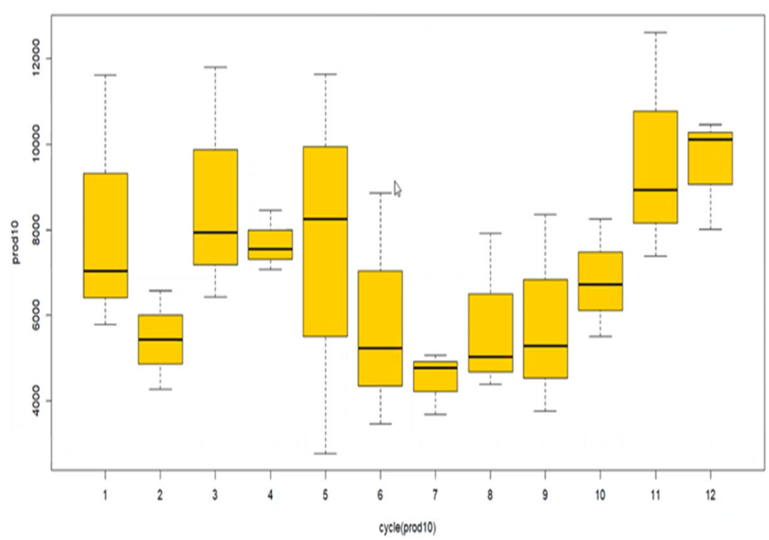

Figure 3. Boxplot of sales of the product deleite aceite 1lt.

Next, the data for a product chosen after sampling is shown below, demonstrating how seasonal patterns are emphasized and, also, evidence of changes in them over time to identify the existence of variation in peaks and troughs over the years.

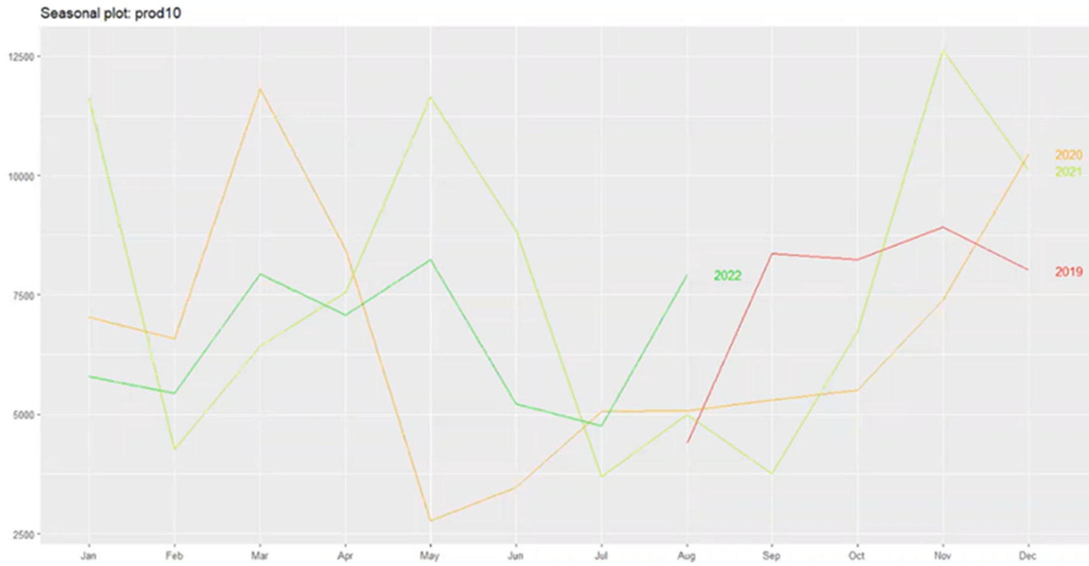

Figure 4. Seasonal plot of the product deleite aceite 1lt.

Additionally, a boxplot, histogram and density graph of the sales data of the aforementioned product can be seen, from which the boxplot and whiskers diagram can be appreciated, to identify the monthly data mentioned, as well as a summary of five descriptive measures.

On the other hand, the histogram, which shows the data values, as well as evaluates the shape and dispersion of the data distribution, and finally, the density graph, which plots the distribution of data for the 36-month time interval.

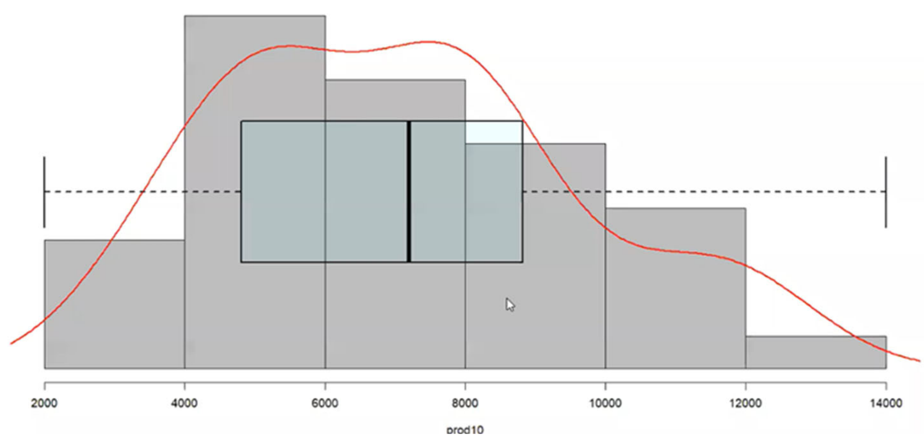

Figure 5. Boxplot, histogram and density of the product deleite aceite 1lt.

5.3 Proposed Improvements

The first proposal considers the application of ARIMA model. This is achieved using R programming language in order to reduce the uncertainty of future demand.

The second improvement proposes to apply a continuous revision policy together with the logistic parameters to significantly reduce the difference between demand and inventory.

Also, the optimization in Arena allowed to determine the economic lot per product in order to perform replenishment while minimizing inventory holding and ordering costs.

In summary, the simulation model was useful in determining the parameters of the ideal inventory system.

Table 3. Economic lot results obtained from the ARENA software improvement model.

Product	Economic lot (units)
Ajinomen gallina 80g	324
Colgate triple acción 150ml	164
Deleite aceite 1 lt	161
Dento triple acción 150ml+Cepillo	96
Emsal sal cocina marina 1kg	186
Heno/Pravia amarillo 150g	197
Ideal amanecer 395g	383
Neko verde extra protec. 125g	103
Sedal Sacheton Ceram. 45ml	269
Yogurt Gloria Fresa 1 lt	119
Pantene SH. Restau. 18ml+AC. 9ml	198
Doña Gusta Gallina 7g	536

5.4 Validation

Initially, for the validation of the proposed improvement, the company provided the current results of the profit in monetary terms, which was used as a criterion for comparison with the scenario that considered the parameters of the continuous review policy and the demand forecast as an improvement as evidenced in chapter 5.1.

The following is the indicator to find the projected utility of including the proposed improvements.

Monthly profit per product:

$$Profit = Inv\ Vendido * Mg - Cost\ Log\ Tot \tag{5}$$

Where

InvVendido: Inventory sold
Mg: Profit margin
Cost.Log. Tot: Total logistics cost

The following Table 4 is a statistical comparison of the two utility results for each scenario.

Table 4. Monthly profit by product (Peruvian currency)

Product	Current utility	Improved utility
Ajinomen gallina 80g	4857	7142
Colgate triple acción 150ml	4842	7121
Deleite aceite 1 lt	40277	59232
Dento triple acción 150ml+Cepillo	877	1290
Emsal sal cocina marina 1 kg	3041	4472
Heno/Pravia amarillo 150g	3665	5390

Ideal amanecer 395g	15526	22832
Neko verde extra protec. 125g	2668	3924
Sedal Sacheton Ceram. 45ml	818	1204
Yogurt Gloria Fresa 1 lt	2110	3103
Pantene SH. Restau. 18ml+AC. 9ml	769	1131
Doña Gusta Gallina 7g	3063	4505

The table above shows the profits of 12 products, where an increase in the scenario of profit improvement of 156 211 soles (peruvian money currency) is evidenced, representing an increase of 47.06% on average with respect to the current scenario.

Finally, to corroborate the statements presented, a statistical analysis was performed comparing the results of both scenarios in Minitab. We present paired t-test with 95% confidence interval, where the null hypothesis (Ho) states that there is no difference between the profits of both scenarios (Table 5).

Table 5. Estimation of the paired difference

Average value	Standard Deviation	95% CI for the difference
3810	9957	(667;6953)

Null hypothesis (Ho) was rejected, i.e. there is a difference between the utilities and can be optimized in the improvement scenario (Table 6).

Table 6. Paired t-test results

Paired t-test	
Null hypothesis	H_0:_difference $\mu = 0$
Alternative hypothesis	H_1: difference $\mu \neq 0$
Valor T	2.45
Valor p	0.019

6. Conclusion

From the results in the previous section, it is concluded that it is feasible to optimize the inventory management process by implementing a forecast based on the ARIMA technique, since products tend to be mostly stationary.

Short-term forecasting approach accompanied by an inventory policy significantly reduces the level of imbalance between demand and inventory thanks to the tools of the review model such as the reorder point, the economic lot quantity, and the replenishment period. However, this must be complemented with the implementation of the simulation software, in this case the ARENA program.

In summary, this research used simulation modeling and optimization to determine the inventory policy parameters for different products.

Finally, as for the practical implications of this study, the proposed improvement tools were used to encourage efficient inventory practices for companies focused on wholesale.

Acknowledgements
This paper has received the support from the Universidad de Lima - Scientific Research Institute (www.ulima.edu.pe/en/scientific-research).

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Biographies

José Antonio Taquía is a Researcher professor at Industrial Engineering faculty from University of Lima He has worked in areas such as data analysis and scientific research methodology. Expert in Machine Learning, Business analytics, and application programming using R, Java and Python of operations and services. Actually he leads an Industry 4.0 and predictive analytics research group using quantitative methods. (https://bit.ly/IDICJTaquiaEng).

Angie Valencia is graduated with outstanding mention of the industrial engineering career of the University of Lima. She is also a purchasing assistant of a company dedicated to Providing industrial supply solutions to the main companies and projects of the country. With interest in supply chain research, retail distribution and time series modeling.

Axel Mendoza is graduated with outstanding mention of the industrial engineering career of the University of Lima. In addition, he is a logistics assistant for a company in the state, dedicated to the supply of pharmacological supplies to the main health centers with care for the insured. With interest in research of supply chains and operations.