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EOQ Inventory Model in a Metalworking MSE with Intermittent Demand: A Case Study

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Abstract. The main objective of this research article is to optimize costs and logistic KPIs applying an economic order quantity (EOQ) inventory model in a metal-mechanic MSE with intermittent demand. Firstly, the forecast model with the lowest MAD and ECM is selected. The object under study, after ABC classification, belongs to the family of products located in class A due to its valuation and participation in the inventory. The Croston method is considered the most effective forecast model. Secondly, an aggregate planning is developed to satisfy the projection. Then, the EOQ or Wilson model is implemented to reduce inventory costs. Finally, to validate the calculated data, a simulation model is built in Arena with 50 replications. As a result, the inventory costs were reduced to 22.6%.

Keywords. Intermittent demand forecasting, aggregate planning, Croston Method, ABC Classification, Pareto Chart, EOQ Model, Logistic indicators, Arena simulator.

1. Introduction

Regarding the importance of micro and small enterprises in Peru, the National Household Survey indicated 96.7% of them do not have a complete and integrated system that can record every movement [1]. They must manage their supply chain as a way of survival; however, their planning turns out to be underdeveloped despite directly influencing the company's profitability [2].

Peru's first National Logistics Survey concluded that smaller scale microenterprises face higher costs in logistic, representing 21.1% of sales value. [1]. [3] mentions that inventory management is an uncertain issue for these companies and only empirical savings are made. Indeed, this problem has been minimally developed in the scientific literature [4]. Another difficulty when retailers make inventory decisions is that exact demand functions are usually unknown and must be learned from accumulating data, so it becomes very difficult to establish an optimal inventory policy [5]. For this reason, production planning becomes a problem due to the various changes in demand [6]. In fact, intermittent demand has increased the risk of managing inventory. Therefore, a key factor is forecast with time series methods and select which one fits with the data [7].

In conclusion, the problems generated in inventories are increased because of the defective demand forecasting [8]. The ideal of any organization should be know their customer's requirements and examine that all the processes of the entity are interconnected [9].

The main objective of the current research is to optimize logistics costs and indicators applying an EOQ inventory model in a metal mechanical MSE with intermittent demand. In addition, the following specific objectives were proposed: select the appropriate forecasting method, develop an aggregate planning, establish an inventory policy, optimize the actual indicators through the EOQ model and simulate the process to validate the applied study.

2. State of Art

2.1. Literature Review

Recently, many models have been proposed for demand prediction and forecasting. [10] argues that much attention has been paid to fast moving time series modeling, but little to intermittent time series and demand forecasting. [11] shows that the Croston method is the primary work for their forecasting and has proven to be practically useful.

[12] consider that intermittency is a common problem in demand forecasting. For that reason, the connection with discrete-time renewal processes allows not only an extension based on Croston-type models, but a sequence of observations on intermittent demand methods. On the other hand, [13] propose a combined method for forecasting, considering inventory status and historical product sales.

[14] also develop a forecast for a specific type of object; the results are calculated by applying classical methods of intermittent and variable forecasting, such as Croston, Syntetos-Boylan, Neural Networks, etc. The Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAE) are compared, and the optimal model is selected.

[6] present a case study in a Mexican company, presenting a 50% non-compliance rate in customer service; a forecasting model is proposed, firstable the products are selected by family groups through the ABC classification; and then the most appropriate model is evaluated according to the MSE and MAD. As a result, delivery time complaints were reduced.

[15] motivated by incomplete information from inventory managers, analyzed if EOQ model was effective in managing inventory systems for products with stock-dependent demand and nonlinear holding cost. [16] implemented the same model to reduce costs in a transportation company. The proposal was designed integrating linear programming. As a result, costs were reduced by 85.64%.

[4] point out that the effect of inventory costs has not been fully studied. To validate the data, they apply Monte Carlo simulation in warehouses, the model assumes a revision interval R= 1 week and a constant Lead Time equal to 3 days. A total of 30 repetitions were used.

Finally, [17] offer an inventory simulation guide with independent probabilistic demand to analyze replenishment models and service levels in 3 products. A period of 24 months and 30 replications are considered for each one. The results guarantee service levels over 93%. It is suggested to have a safety stock.

3. Methodology

The methodology is oriented to a process improvement project with a quantitative approach applied in a metal mechanical MSE. For the design, the researcher must consider his participation in the development of the events. [18] An experimental design is defined due to the manipulation of the variables.

Methodological tools are the set of techniques and instruments used to analyze the object of study. [19]. Techniques used are ABC classification, EOQ model and simulation; all of them have their respective instruments: sales register, warehouse cards, Pareto chart, structured interview, and chart flow. Now, for the subjective and intersubjective selection of indicators (through concepts and variables), they are essentially mathematical models defined in the resolution of problems. [20].

These are classified as follows: the EOQ inventory model (dependent variable) and the demand forecast (independent variable).

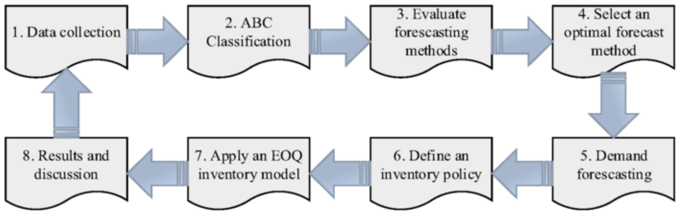

Figure 1. Methodology used in the project.

4. Implementation

PROCMET S.R.L. is a metal-mechanic company that offers to the market products or services of industrial machining and pumping equipment with high quality standards for the Transportation, Sanitation, Manufacturing/Industrial and related sectors. Products from water and sanitation line, specifically tubular pumps for deep wells, are taken as a sample.

4.1. ABC Classification

From an analytical perspective, ordering and safety stock calculations are performed at the individual item level. It is also intuitively appealing that different items should be treated differently depending on their characteristics [21].

Once the SKUs have been broken down for the 2022 period, the ABC classification is performed. This technique is intended to prioritize the products located in class A as they represent a higher level of participation and accumulative investment. The items described in Table 1 located in zone A (11,5,1,9 and 12) form a product family called "column axis" following the Pareto 80/20 principle.

Table 1. ABC Classification of SKUs

N°	SKU	%Part.	Accum. Share	Investment	Accumulate Investment	% Invest.	% Accum. Inv.	
11	Column Shaft 1045	8%	8%	S/ 28,320.00	S/ 28,320.00	21%	21%	A
5	Column Shaft 1045	8%	15%	S/ 18,677.68	S/ 46,997.68	14%	36%	A
1	Column Shaft 1045	8%	23%	S/ 16,899.8	S/ 63,897.45	13%	48%	A
9	Column Shaft 1045	8%	31%	S/ 15,120.02	S/ 79,017.47	11%	60%	A
7	Pump Shaft AISI 416	8%	38%	S/ 13,780.04	S/ 92,797.51	10%	70%	A
12	Column Shaft 1045	8%	46%	S/ 12,451.78	S/ 105,249.30	9%	80%	A
4	Pump Shaft AISI 416	8%	54%	S/ 9,264.98	S/ 114,514.28	7%	87%	B
8	Pump Shaft AISI 416	8%	62%	S/ 6,000.0	S/ 120,514.27	5%	91%	B
6	Coples	8%	69%	S/ 3,195.13	S/ 123,709.41	2%	94%	B
10	Coples	8%	77%	S/ 2,586.54	S/ 126,295.94	2%	96%	C
13	Coples	8%	85%	S/ 2,130.09	S/ 128,426.03	2%	97%	C
3	Pump Shaft AISI 416	8%	92%	S/ 1,894.51	S/ 130,320.55	1%	99%	C
2	Pump Shaft AISI 416	8%	100%	S/ 1,763.16	S/ 132,083.70	1%	100%	C

Finally, a Pareto chart allow us to observe the classification of products, especially class A family, with an approximate value of 79.7% of the investment and 46.2% of accumulated participation.

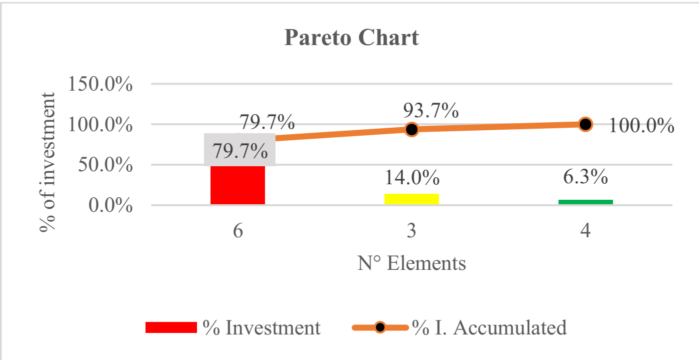

Figure 2. Pareto Chart.

4.2. Evaluation of Forecasting Models

Intermittent demand is characterized by infrequent demand arrivals, where many periods have zero demand. When demand behavior is neither smooth nor continuous, commonly used forecasting methods are not effective. We proceed to select the forecast model with the lowest mean absolute deviation (MAD) and average absolute error (ECM). The forecasts to be evaluated are simple exponential smoothing (SES), SES with optimal alpha and Croston.

4.2.1. Simple Exponential Smoothing (SES) Forecasting

SES forecasting is essential for demand records where the impact of historical irregular periods with recent periods of demand is to be discarded. It is considered to use a smoothing constant α = 0,01. A MAD= 25 and ECM= 693.86.

4.2.2. Forecasting by SES with optimal alpha

The Solver tool offered by Excel was necessary to elaborate this forecast. In addition, it adjusts the values of the decision variable cells; values >= 0 and <=1 is defined as restrictions. In the Table 3 an α = 0.01 is observed; however, when using this tool, the result is a α = 0.098. The results obtained with the new α were a MAD=17.60 and ECM=573.37.

Table 2. Forecasting by SES with optimal alpha

				Optimal alpha	**0.098**
Month	**Demand (units)**	**Forecast**	**Error**	**ABS error**	**Error squared**
January (2021)	0	15.31	-15.31	15.31	234.45
February	0	13.81	-13.81	13.81	190.61
March	0	12.45	-12.45	12.45	154.97
April	0	11.22	-11.22	11.22	125.99
May	0	10.12	-10.12	10.12	102.43
June	0	9.13	-9.13	9.13	83.28
July	0	8.23	-8.23	8.23	67.70
August	48	7.42	40.58	40.58	1646.80
September	0	11.41	-11.41	11.41	130.18
October	0	10.29	-10.29	10.29	105.84
November	0	9.28	-9.28	9.28	86.04
December	0	8.36	-8.36	8.36	69.95
January	73	**7.54**	**65.46**	**65.46**	**4284.82**
February	0	**13.98**	**-13.98**	**13.98**	**195.39**
March	0	**12.60**	**-12.60**	**12.60**	**158.85**
April	0	**11.36**	**-11.36**	**11.36**	**129.15**
May	17	**10.25**	**6.75**	**6.75**	**45.61**
June	0	**10.91**	**-10.91**	**10.91**	**119.05**
July	0	**9.84**	**-9.84**	**9.84**	**96.79**
August	46	**8.87**	**37.13**	**37.13**	**1378.59**
September	0	**12.52**	**-12.52**	**12.52**	**156.79**
October	0	**11.29**	**-11.29**	**11.29**	**127.47**
November	0	**10.18**	**-10.18**	**10.18**	**103.64**
December	0	**9.18**	**-9.18**	**9.18**	**84.26**
		Totals	**7.48**	**211.21**	**6880.39**
				MAD	**17.60**
				ECM	**573.37**

4.2.3. Forecasting with Croston's method

Croston's method highlights a major drawback of simple exponential smoothing in a forecast for intermittent demand, by assigning the highest weight to the most recent observation, the highest forecasts would be obtained just after a demand observation and the lowest just before. Croston proposed to run SES separately at times between demands and positive demand sizes. With a α = 0.01, a MAD= 13.27 and ECM=475.38 is obtained.

Table 3. Forecasting by Croston method

					Alpha α	**0.01**
Demand forecasting under Croston's method						
Month	**Demand (units)**	**nt**	**zt**	**Counter n**	**Forecast demand**	**Error squared**
		6.33	48.50			
January (2022)	73	6.32	48.75	5	**7.66**	4269.59
February	0	6.32	48.75	1	**7.71**	59.49
March	0	6.32	48.75	2	**7.71**	59.49
April	0	6.32	48.75	3	**7.71**	59.49
May	17	6.29	48.43	4	**7.71**	86.25
June	0	6.29	48.43	1	**7.69**	59.15
July	0	6.29	48.43	2	**7.69**	59.15
August	46	6.26	48.40	3	**7.69**	1467.59
September	0	6.26	48.40	1	**7.73**	59.71
October	0	6.26	48.40	2	**7.73**	59.71
November	0	6.26	48.40	3	**7.73**	59.71
December	0	6.26	48.40	4	**7.73**	59.71
January (2023)					**7.73**	59.71
Total	136					6179.91
			Croston Method		MAD	**13.27**
					ECM	**475.38**

Finally, Croston is chosen as the optimal method because of its lower MAD= 13.27 and ECM=475.38. If the value is low, the error decreases and the forecast is better.

4.3. Calculation by Croston's method

The following variables are defined for Croston's method.

- xt= Observed demand in period t.
- yt= Binary variable equal to 1 if demand greater than zero occurs in period t; otherwise, equal to zero.
- zt= $xt * yt$= Size of demand occurred in period t.
- nt= Number of periods elapsed since the last demand greater than zero, until period t.
- $\hat{n\tau}$ = estimated value of n at the end of period t.
- $\hat{z\tau}$ = estimated value of z at the end of period t.
- α= smoothing constant. It is suggested to use a smoothing constant $\alpha = 0.01$.

If: $xt>0;\ \hat{n\tau} = \alpha nt + [1-\alpha]\ \hat{n\tau}{-1};\ \hat{z\tau} = \alpha xt + [1-\alpha]\ \hat{z\tau}{-1}$ (1)

If: $xt=0;\ \hat{n\tau} = \hat{n\tau}{-1};\ \hat{z\tau} = \hat{z\tau}{-1};\ 0 \le \alpha \le 1$ (2)

As Table 3 describes, the value nt must be updated in each period independent of whether a distinct demand occurs, if no demand or null value occurs the counter increments by 1 but if a positive demand occurs the value resets to 1, it cannot reset to 0 for the minimum number of periods. $\hat{zo}$; $\hat{no} \neq 0$; in case it happens, it is proposed to do it with the last historical data of the requests. The historical trend is graphically represented and then the coefficient of variation of demand (CVD = Standard deviation of demand/Average demand) is measured, resulting in a 2.09; as the CVD is greater than 1, the existence of an intermittent demand in the company is reaffirmed.

5. Results

This chapter details the main findings based on the problems presented in the company. It justifies the decisions taken, the way they were implemented and validates the results.

5.1. Croston-Adjusted Demand Forescast

PROCMET doesn't present a detailed analysis of the demand forecast. As the company's manager pointed out in a structured interview, the logistics area of the company seeks to "stock up" based on experience or when they perceive a stockout. A correct forecast reduces the uncertainty in future. Applying this forecasting method, it can adjust the average demand to 8 units/month, decreasing the standard deviation from 23.73 units/month to 0.02 units/month; generating a safer and more effective impact on forecasting model.

It is observed in the Figure 3 a better fit in the forecast trend line, following a linear function with a *R*2 = 0.3538, representing a linear fit, considering it a very forecastable model.

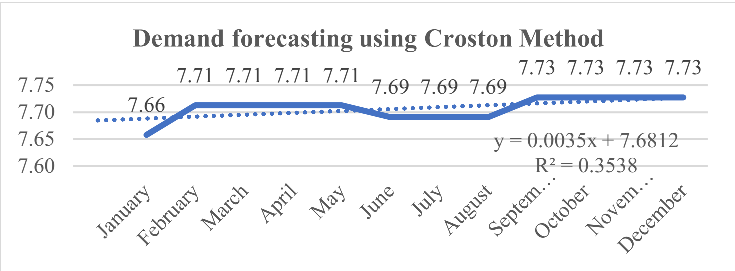

Figure 3. Demand forecasting using Croston Method.

5.2. Develop Aggregate Planning

After getting a stable demand characteristic, a plan can be developed to reach the projection. Aggregate planning is a planning method with a short-term horizon, usually on an annual basis, and is a process to determine optimal levels of production, capacity, subcontracting, inventory, and stock-outs. [22].

Table 4. Production indicators in PROCMET S.R.L

Average production per operator	**0.51**	unit/day
Initial current operators	**2**	operators
Production time per unit	**227**	min/unit
Workday	**8**	hours/day
Work shifts	**1**	shift/day
Production decrease factor	**0.80**	
Human efficiency factor	**0.50**	
Machine efficiency factor	**0.60**	
Daily cost per day	**S/ 80.00**	PEN/wage
Cost of hiring an operator	**S/ 1,500.00**	PEN/operator
Cost of laying off an operator	**S/ 2,000.00**	PEN/operator
Cost per storage	**S/ 194.45**	PEN/unit
Cost due to lack of stock	**S/ 581.20**	PEN/unit
Overtime cost	**S/ 12.50**	PEN/overtime

It is important to determine the strategy to follow during the aggregate production planning; in this case, a mixed strategy will be used, which will seek a balance between the chasing and leveling strategies. As a result, we have an aggregate demand of 153 units, which strengthens the forecast for the following period.

Table 5. Aggregate production planning

Aggregate Production Planning with mixed strategy										
Month	**Work. days**	**Demand**	**Unit / operator**	**Operators required**	**Current operat.**	**Hired operat.**	**Operat. laid off**	**Operat. used**	**Units produced**	**Invent.**
Jan.	25	8	13	1	2	0	1	1	**13**	26
Febr.	24	8	12	1	1	0	0	1	**12**	30
Mar.	27	8	14	1	1	0	0	1	**14**	36
Apr.	23	8	12	1	1	0	0	1	**12**	39
May	26	8	13	1	1	0	0	1	**13**	44
June	26	8	13	1	1	0	0	1	**13**	50
July	24	8	12	1	1	0	0	1	**12**	54
Aug.	27	8	14	1	1	0	0	1	**14**	60
Sept.	26	8	13	1	1	0	0	1	**13**	65
Oct.	25	8	13	1	1	0	0	1	**13**	69
Nov.	25	8	13	1	1	0	0	1	**13**	74
Dec.	24	8	12	1	1	0	0	1	**12**	78
Total	**302**	**96**	**153**	**12**	**13**	**0**	**1**	**12**	**153**	**624**

5.3. Establish an Inventory Review Policy

An inventory policy should establish the frequency of inventory revision, as well as know the quantity and the optimal time to request an order. According to [23] a continuous review system may be better suited to the characteristics of a type A product.

This method indicates that when the inventory is below the Reorder Point (ROP) a purchase order is issued specifying an optimum replenishment quantity for the next period. For the present case study, a continuous review policy is proposed based on the previous analysis.

5.4. Logistic Lead Time Calculation

PROCMET identified 5 elements that make up the supply chain in the logistics area for the Class A. Table 6 shows the lead time for an order lot of 240 units.

Table 6. Lead time logistic in PROCMET S.R.L

Lead time logistic PROCMET S.R. L	30	days	Purchasing management.
	36	days	Order management by supplier.
	40	days	Transport time from Chinese supplier.
	0.028	days	Transport to the warehouse and unloading of the order.
	0.021	days	Reception and quality inspection.

5.5. Implementation of EOQ Inventory Model

The results and parameters considered for lead time optimization in inventory management are presented. The formulas used belong to a continuous review system.

Table 7. Calculations carried out by implementing an EOQ inventory model

Annual demand (D)	153.00	units/year
Average monthly demand	13.00	units/month
Standard deviation of demand (σD)	0.64	units/month
Days per month	30	days
Days per year	360	days
Lead time (Lead time)	3.53	months
Reorder point (ROP: D*L + SS)	48.00	units
Safety stock (SS)	3.00	units
Service Level (CSL)	95.0%	
Z (95%)	1.65	
E(Z)	0.026	
Standard deviation of supply time (SL)	0.09	months
Demand deviation during lead time (σL)	1.72	

5.6. Analysis of Logistic Indicators

One of the determining factors for the success of any process, is the design and implementation of an adequate model of indicators to measure the management of these processes [24]. For MSEs, inventories are often the most important asset, as well as the largest expense. The implementation of an EOQ inventory model allows to optimize the relevant annual costs by validating its efficiency in inventory management [25].

Table 8. Relevant costs in inventory

Average price paid per purchased unit (C)	S/ 194.45 PEN
Fraction of unit cost (h)	20%
Fixed order cost (S)	S/ 6,292.11 PEN
Cost for lack of stock (k)	S/ 581.20 PEN

Finally, the cost curve and the inventory behavior under the EOQ model are plotted, reaffirming the concept that an optimal order batch reduces the relevant total costs.

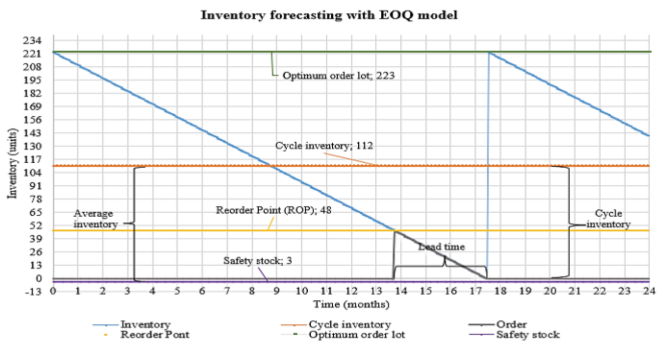

Figure 4. Graph of projected inventory behavior.

5.7. Data Validation through Arena Software

The simulation software allows you to compare historical data with the actual results of your system. Arena uses the discrete event method; a minimum of 50 replications is considered. In general, we must make sure that it is large enough [26]. A replication time of 240 hours is considered, equivalent to 8 hours of work for 30 days.

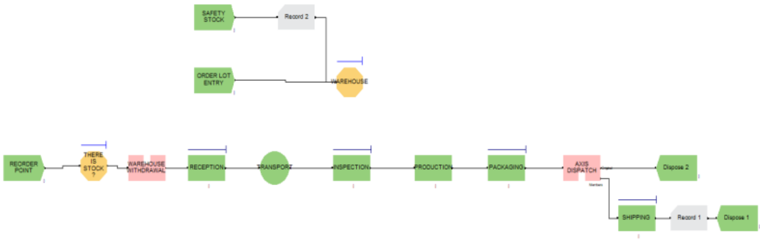

Figure 5. Model developed in Arena Simulator.

6. Discussion

It is important to break down each indicator pointing out its relevance in the supply chain and demonstrate its improvement through engineering tools and concepts.

Table 9. Variation of logistic indicators in PROCMET S.R.L.

PROCMET logistic indicators	Actual	Improved	Variation
Q (Requested lot)	240	240	0%
Optimum order lot (Q*) √(2DS/H)	210	223	6.2%
Cycle inventory (Q*/2)	105	112	6.2%
Average inventory (Q*/2) +SS	179	115	-35.8%
Maximum inventory (Q*+SS)	284	226	-20.4%
Annual Inventory Turnover D/(Q*/2+SS)	**0.76**	**1.33**	**75.1%**
Inventory coverage (1/Inventory turnover)	**473.82**	**270.59**	**-42.9%**
Stock out per supply cycle E(z)*σL	**91.9%**	**4.5%**	**-95.1%**
Number of orders per year (D/Q*)	**0.65**	**0.69**	**5.9%**
Average flow time (Q*/2D)	**18.53**	**17.49**	**-5.6%**
Availability level (CSL)	**89.9%**	**76.6%**	**-14.8%**
Optimal annual ordering cost (D/Q*) *S	S/ 4,074.89 PEN	S/ 4,317.01 PEN	5.9%
Annual holding cost of the Iprom =Iprom*h*C	S/ 6,961.18 PEN	S/ 4,472.26 PEN	-35.8%
Annual cost of shortage or loss: (D/Q) *k*σL*E(z)	S/ 345.99 PEN	S/ 17.85 PEN	-94.8%
Total anual logistic costs	**S/ 11,382.06 PEN**	**S/ 8,807.12 PEN**	**-22.6%**

- *Annual inventory turnover*: A low inventory turnover means that there is excess inventory, increasing storage costs. In the Table 9, this indicator increases by 75.1%, which is positive for the company since there is greater sales capacity and the replenishment of its inventory is accurately measured.
- *Inventory of stock coverage*: This indicator represents the number of days that the demand can be covered with the stored material. With the proposed model, decreases its coverage to 270.59 calendar days; this is justified due to higher inventory turnover.
- *Stock out:* Companies make enormous efforts to meet their customers' expectations. In summary, stock out refers to not fulfilling an order, affecting the level of sales. Following an adjustment in lot size, the stock out results in 4.5%. Compared to the current situation, the proposed model reduces the stock out % by 95.1%.
- *N° of orders:* This indicator increases to 0.69 orders per one-year period. This is due to greater precision in the lot size ordered and an increase in sales capacity.

- *Average flow time*: It represents the minimum total time that a batch takes to pass through the system. With EOQ model it is reduced by 5.6%.
- *Relevant annual inventory cost*: Relevant inventory costs are reduced by 22.6%, which is very favorable to the company, demonstrating that applying an EOQ model to its inventories generates greater profitability.

7. Conclusions

Metal-mechanical medium small enterprises (MSE) have knowledge of how to manage a supply chain; however, the levels of implementation are low. In inventories, policies are only promoted empirically. It is observed that the company under study has an intermittent demand; a situation that in turn is experienced by several MSE. For this reason, simple application methods are offered, without generating higher costs. First, it is considered necessary an ABC classification; this tool provides a better overview of the SKUs that the company handles during a given period. In this case, priority is given to those classified in category A due to their level of participation and accumulated investment. The evaluation of forecasting methods for intermittent demand are filtered by the MAD and ECM, fundamental factors to select the optimal method. This step is important to further develop an aggregated planning that will provide a more realistic analysis for the next period. Therefore, an adjustment is necessary due to factors such as shrinkage, efficiency, among others, considered in the research article. Once the aggregate demand is known, an EOQ model is implemented to optimize the requested lot size. Finally, to validate the profitability of the EOQ model and the improvements of the indicators, it is pertinent to develop a simulation. Arena allows to verify more accurately the results and to program the implemented steps. Finally, it is suggested to MYPES, regardless of the sector or business category they belong to, to give more analysis to their supply chain, especially inventories through techniques offered by industrial engineering; improvements can be seen in the short term and their implementation will bring greater profitability to the company.

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