v. 5, n. 1, 2025

Journal of
Engineering
Research

Acceptance date: 20/01/2025

DEVELOPMENT OF A FORECASTING MODEL FOR RESIN CONSUMPTION PRODUCTION PLANNING

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Abstract: We live in a highly competitive environment, where the market continues to transform towards a more global dimension and consumers are becoming more and more demanding. This forces companies to make strategic decisions that optimize their internal processes and allow them to remain competitive. In this context, planning takes on great importance in industries, as it facilitates the anticipation of what will happen in the near future. The objective of this article is to develop a forecasting model for the resin raw material with the highest consumption during the last 90 days, in order to anticipate the material needs for production in a world leader company in access solutions.
Keywords: In-process inventory, ABC Method, Production Planning, Quantitative Forecasting, Forecast error.

INTRODUCTION

One of the most significant challenges faced by manufacturing companies is the implementation of their production planning activities, due to the complexity of the manufacturing processes. Its main objective is to select the most efficient alternative to optimize times, processes and provide the necessary support to meet the production plan

This study presents a forecasting model for the use of resin materials, which represent 77.9% of consumption in the last 90 days. The model is intended to support production planning, allowing an adequate response to future consumption and to the commitments established by the company with its customers.

The research was conducted at a world leader in access solutions, located in Nogales, Sonora, Mexico. Currently, the molding production department is evaluating various options and methods for planning resin consumption in production, with the objective of processing the corresponding subassemblies and determining the level of reliability through forecasts

Inventory refers to the tangible assets that an organization keeps in a specific location in order to be used in production processes and transformed into goods or services, which will be subsequently marketed (Onofre-Barragán et al., 2015 ; Álvarez and Wilson, 2020) . These assets can be classified into raw materials, inputs, products in process, finished products or any resource used within the organization (Girón et al., 2018).

It is essential to classify inventory items to identify the most important ones, and thus, based on their relevance, develop specific strategies and procedures for each group, with the objective of supporting the fulfillment of the warehouse operational objectives (Peña and Silva, 2016) . The advantages of this classification lie in the fact that it allows the organization to prioritize inventory according to its importance, focusing on those items that require greater attention. This facilitates the implementation of improvement actions and strategic decision making that optimizes internal processes (Becerriil and Villa, 2017 ; Girón et al., 2018)

One of the most widely used methods for classifying inventory items is ABC, which divides inventory into three categories: A, B and C, according to the criterion that best suits the company's needs and conditions. This classification is based on Vilfredo Pareto's principle, known as the 80/20 rule, which indicates that 20% of the inventory items represent approximately 80% of the value or production volume of the inventory. In other words, a small percentage of the items on hand is key to achieving the overall objectives of the warehouse (Parada, 2009) . The ABC method is a detailed analysis of historical inventory information, whose main purpose is to classify items to determine their importance within the warehouse (Macias, Leon and Limon ., 2019)

ABC classification of inventory according to (Veloz and Parada, 2017):

- Group A represents 10% to 20% of inventory items and accounts for 60% to 80% of the total economic impact.
- Group B represents 20% to 30% of the inventory items and accounts for 20% to 30% of the total economic impact.
- Group C represents 50% to 70% of the inventory items and accounts for 5% to 15% of the total economic impact.

Production planning consists of developing a strategy that takes into account all the resources available in an organization. In this strategy, the quantity of products to be manufactured during a given period is determined, which allows the production department to organize and prepare the necessary resources to meet the established plans (Hernández Vázquez et al., 2021 ; Hall, Posner and Potts . 2021)

Forecasts play a crucial role in production planning, as they are used to manage the production process, considering production capacity, available facilities, and thus supporting decision making; in addition, forecasts allow companies to adapt to changes in demand, ensuring that customers' needs are met (Yamaguchi, 2024) .

Stephen (2006) mentions that forecasting is a technique used to project what is expected in the future, based on past experience. According to Madariaga Fernández et al., (2020) there are two main types of forecasts: qualitative forecasts, which are subjective and based on expert opinion, and quantitative forecasts, which are based on historical demand and are divided into different categories:

- Time series: Consists of analyzing the historical behavior of certain events over time for the purpose of forecasting future scenarios.
- Causal relationships: Seeks to identify and understand the factors that influence the element to be forecast.
- Simulation: Employs dynamic models, usually computer-aided, to generate projections based on established assumptions.

Quantitative forecasting, also called time series forecasting, refers to the analysis of a time series composed of observations of a variable recorded at regular intervals (Medina, Rodriguez, Zorrilla, 2015) . Table 1 presents the most relevant characteristics of some quantitative forecasting methods according to Lagunes et al., (.2014)

Method	Features
Trend analysis	There is a trend in the behavior of demand, but there is no seasonality.
Moving averages	It does not present seasonality or trend, it considers the most recent data for the development of the forecast.
Simple exponential smoothing	It does not present seasonality or trend, but contemplates a smoothing parameter for the forecast.
Double exponential smoothing	It presents trend, but not seasonality, contemplating two smoothing parameters for the forecast.

Table 1. *Quantitative forecasting methods*

It is essential to highlight that the selection of a forecasting method depends on the available data, as these allow determining which one is best suited to perform the analysis. In addition, it is crucial to have enough historical information to divide the data into two sets: one to train the model and another to perform tests and partially evaluate its performance (Contreras Juárez et al., 2016).

For their part, Huang, Golman and Broomell (2024) and Doherty)(2024 define forecast error as the difference between the forecast value and the actual value obtained in a given period. Because demand contains a random component, it is inevitable that any forecast will have a margin of error. The accuracy of a forecast depends not only on how well it fits the historical data, but also on its ability to approximate the time series observed in the periods evaluated. Therefore, several performance metrics have been developed to measure both the accuracy and the level of reliability of the forecast model (Nassef, Elhebshi and Jose, ; 2018 Svetunkov, 2024) .

- Mean Percentage of Absolute Error (MAPE)

It is expressed as a percentage of the relative error for entering a single evaluation scale.

$$MAPE = \frac{\sum_{i=1}^{n} |\frac{e_t}{y_t}|}{n} * 100\%$$

Being:

$\sum_{i=1}^{n} |\frac{e_t}{y_t}|$ = The sum from i=1 to n of the absolute value of the quotient of the error between the actual value of period t

n = The number of periods over which estimates were made.

- Mean Absolute Error (MAD)

The metric evaluates how much the forecast error is dispersed, i.e. it quantifies the size of the error in terms of units. It is calculated as the absolute value of the difference between the actual demand and the forecast, divided by the number of periods:

$$MAD = \frac{1}{n} \sum_{i=1}^{n} |A_i - F_i|$$

Where:

Ai is the actual value or the observed demand for the period

Fi is the predicted value for the period

n is the total number of periods.

In a study conducted by Medina, Rodriguez and Zorrilla, (2015) a demand forecasting model was implemented in a company dedicated to the manufacture of evaporators and condensers. The objective was to mitigate problems associated with production planning, such as lack of raw materials, delays in production orders, and customer dissatisfaction due to long delivery times. To develop the model, data were collected for weeks 1 to 42 of 2014. This data was organized into a file that included part number and weekly customer demand. Additionally, a specific file was generated to analyze weekly demand behavior and trends. In the analysis, the methods of moving average, Winters model and exponential smoothing were evaluated. Finally, the exponential smoothing method was selected for its better performance in predicting demand, according to the evaluation metrics used.

METHODOLOGY

The methodology presented in this article focuses on developing a forecasting model for the most consumed resin materials in the last 90 days. This approach is structured in six fundamental stages that allow addressing the problem in a systematic and efficient way. These stages are described in detail below (see Figure 1).

Figure 1 illustrates the stages of the methodology applied in this study. The process begins with data collection and analysis, where historical information on resin consumption levels over the last 90 days is consulted. This information will be analyzed using the Pareto rule to identify the materials with the highest consumption. In the second stage, the ABC classification will be used to group the items into categories according to their relevance and level of resin consumption, highlighting those belonging to group A. Once classified, the items in group A will be plotted to analyze their behavior in the time series. In the next stage, *Minitab 19* software will be used to select the most appropriate forecasting methods according to the real consumption adjustment, evaluating their performance by means of MAPE (Mean Absolute Percentage Error) and MAD (Mean Absolute Deviation). Subsequently, forecasts will be developed for days 91, 92 and 93, applying the methods selected in the previous stage and again using Minitab 19. Finally, the generated forecasts will be compared with the actual production consumption for each part number, allowing to evaluate their accuracy and effectiveness.

Figure1 *methodology*

Dia	039A0347	039-0541-000	039A0291	Dia	039A0347	039-0541-000	039A0291
1	7202.64	4048.65	2943.48	46	10693.346	3904.152	
2	6696.977	3995.1	156.94	47	12896.504	2823.144	606.48
3	4248.692	3719.4	173.28	48	14396.269	4677.27	2517.12
4	5247.922	5238.48	2627.32	49	6402.562	3603.15	2127.24
5	3239.964	4599.2	2763.36	50	8491.924	3587.703	1588.02
6	3467.824	3959.38	1621.46	51	8350.552	2554.232	1160.172
7	5314.124	3693.77		52	12906.777	3973.14	413.658
8	5011.736	4680	866.4	53	7982.783	4913.46	2959.44
9	3052.088	3791.52	2313.44	54	13367.721	4466.67	1322.02
10	1624.986	4618.8	2905.48	55	10359.161	4107.39	2523.2
11	4038.496	3999.6	5956.14	56	9003.76	4916.298	2760.7
12	3118.478	4662	6394.314	57	4822.844	5131.404	2286.08
13	1786.88	3754.8	7261.86	58	4438.36	5143.818	810.16
14	3839.665	3999.6	4683.335	59	6453.078	7362.114	221.16
15	4005.728	3647.34	3149	60	8447.732	4259.28	2334.72
16	6787.058	2494.8	2419.257	61	5143.872	5868.336	2975.4
17	5921.707	2211.3	1125.6	62	7229.828	4658.4	1901.52
18	11853.74	2002.41		63	8167.48	4380.39	3067.36
19	8401.366	4376.064		64	13948.872	4330.71	30.4
20	7762.637	5689.055		65	17622.009	4597.08	
21	5229.423	5668.62	2329.4	66	22788.18	3857.49	
22	6908.128	2351.616	1885.56	67	7757.597	2865.675	
23	4301.337	2845.2	2031.86	68	7232.714	3389.52	1307.58
24	5893.632	2312.16	398.62	69	9536.063	3484.49	2713.2
25	9303.032	3956.256	388.64	70	14848.039	4689.35	1878.72
26	2707.51	4999.68	7103.998	71	12208.602	3501.036	2820.36
27	3007.49	4439.208	9744.336	72	10104.491	5928.48	2681.28
28	2771.756	742	6580.192	73	5470.312	5098.624	2514.08
29	7781.472	2406.6	5643.728	74	7392.429	6493.748	
30	8765.921	4239	4690.613	75	8051.08	5287.232	
31	7987.844	5616	1700.88	76	7790.958	4661.5	
32	4401.498	5894.37	2993.64	77	12780.002	3939.632	
33	6509.21	6684.53	2953.36	78	19174.461	3244.046	
34	9632.54	4526.76	179.36	79	5316.697	3596.979	
35	8633.944	4103.1		80	13818.73	3430.26	
36	9064.714	3712.95		81	10313.967	4298.172	
37	7897.733	3871.8	1500.24	82	2309.476	4226.49	
38	9474.046	3966.132	4104	83	5780.362	5018.31	2523.96
39	6159.43	1475.532	1507.46	84	7326.57	3232.248	2298.24
40	10886.5	3842.16		85	11640.442	5912.46	3185.54
41	7935.306	4797.45		86	10329.243	2749.826	2297.34
42	9335.148	4708.35	1179.52	87	8534.371	3663.42	606.216
43	5142.264	4282.548	2318.76	88	8924.572	3269.996	

44	6232.45	4927.446	2928.28	89	10902.538	3728.514	225.72
45	9789.085	3488.62	1427.28	90	12032.732	4578.63	3224.28

Table 2. *Results of the Pareto rule analysis*

Part No.	Consumption	Indiv.	% Accum	Ranking	%
039A0347	721,864.18	44.5%	44.5%	A	77.9%
039-0541-000	372,443.63	22.9%	67.4%	A	
039A0291	170,831.76	10.5%	77.9%	A	
039-0522	109,117.37	6.7%	84.6%	B	16.5%
039A0324	88,484.74	5.4%	90.1%	B	
039-0537-000	54,230.48	3.3%	93.4%	B	
039A0513	15,482.89	1.0%	94.4%	B	
039A0358	14,544.12	0.9%	95.3%	C	5.6%
039-0544-000	14,204.89	0.9%	96.1%	C	
039-0538-000	13,815.13	0.9%	97.0%	C	
039A0444	13,043.18	0.8%	97.8%	C	
039A0320	11,344.19	0.7%	98.5%	C	
039A0318	10,318.56	0.6%	99.1%	C	
039A0471	7,321.48	0.5%	99.6%	C	
039A0446	2,219.68	0.1%	99.7%	C	
039A0443	1,140.00	0.1%	99.8%	C	
039A0293	976.24	0.1%	99.9%	C	
039A0504	666.32	0.0%	99.9%	C	
039A0330	463.73	0.0%	99.9%	C	
039A0294	373.73	0.0%	99.9%	C	
039A0289	360.97	0.0%	100.0%	C	
039A0357	295.72	0.0%	100.0%	C	
039A0299	195.00	0.0%	100.0%	C	
Total	**1623738**	**100%**			**100%**

Table 3. *ABC analysis.*

Percentage	Ranking	No. Items	% Items	Consumption	% Accum. Consumption
0 - 80%	A	3	13.04%	77.92%	77.92%
80% - 95%	B	4	17.39%	16.46%	94.38%
95% - 100%	C	16	69.57%	5.62%	100%
Total		**23**	**100%**	**100%**	

Table 4. *Overall results of ABC classification*

RESULTS AND DISCUSSION

The following is a description of how each of the stages of the methodology proposed for the case study was developed.

DATA COLLECTION AND ANALYSIS

A 90-day period was taken for data collection, Table 2 shows the consumption production levels in pounds of the part numbers on that day:

According to Table 3, the three main part numbers account for 77.9% of the total resin consumption in the last 90 days, with the first item accounting for 44.5% of this consumption, making it the item with the highest utilization. Therefore, implementing strategic forecasting actions for these key items will allow the production department to anticipate resin consumption needs and organize the necessary resources to meet them effectively.

ABC CLASSIFICATION

The ABC classification made it possible to identify the inventory items in process for each group, as well as the most consumed part numbers (see Table 3, Table 4 and Figure 2).

The 13.04% of the various resin part numbers correspond to 77.92% of the total production resin consumption (type A, green color); 17.39% of the materials comprise 16.46% of the total production resin consumption (type B, yellow color) and finally, 69.57% of the part numbers impact only 5.62% of the total production resin consumption (type C, red color).

For this study, the forecast model will be developed specifically for items classified as type "A", since they are the ones that have registered the highest level of resin consumption in the last 90 days of production. The part numbers selected are: 039A0347, 039-0541-000 and 039A0291.

CONSUMPTION ANALYSIS

The historical data collected in the first stage (Table 2) were used to train the model, where consumption of the three resin part numbers representing 77.9% of the total production consumption is presented graphically. Figure 3 shows the time series of the resins, considering the 90 days of historical data.

It is observed that the behavior of the different resins is very similar, the pattern shown is slightly stable, the data oscillates in the same environment where the series is located. On the other hand, resin 039A0291 does not show continuity in the time series since there are days when there was no consumption, which could generate an unreliable forecast.

SELECTION OF THE FORECASTING METHOD

With the support of Minitab 19 software, data were entered to identify and select the forecasting method in order to perform the quantitative analysis that best fits the actual consumption. For this purpose, the MAD and MAPE performance metrics data were collected, the results of which are shown in Table 6:

As shown in Table 6, the best performing forecasting method according to the lowest error that can occur is the **moving average** for the three part numbers. However, for part number 039-0541-000 it can be observed that the level of forecast error for the trend analysis method, simple exponential smoothing and double exponential smoothing also presents a good level of error, which would make it easy to be used. For the purposes of the work to be done, the moving average method will be selected for the three resin part numbers mentioned above.

ELABORATION OF THE FORECAST

At this stage, forecasts were generated for days 91, 92 and 93 from the data collected, using *Minitab 19* software to represent the time series and the selected method for each of the part numbers, which is shown in Figure 4:

Table 7 shows the predicted consumption result in pounds of the part numbers:

No. Part	Method	Predicted consumption (Lb)		
		Day 1	Day 2	Day 3
039A0347	Prom. Mobile	10690.6	10690.6	10690.6
039-0541-000	Prom. Mobile	3826.41	3826.41	3826.41
039A0291	Prom. Mobile	1070.48	1070.48	1070.48

Table 7. *Forecast*

Once the forecasted consumption of the 3 part numbers is known, using the moving average method, this will be taken as the basis for the acquisition of the resin for the next few days, in order to have sufficient inventory for production. Subsequently, the production plan

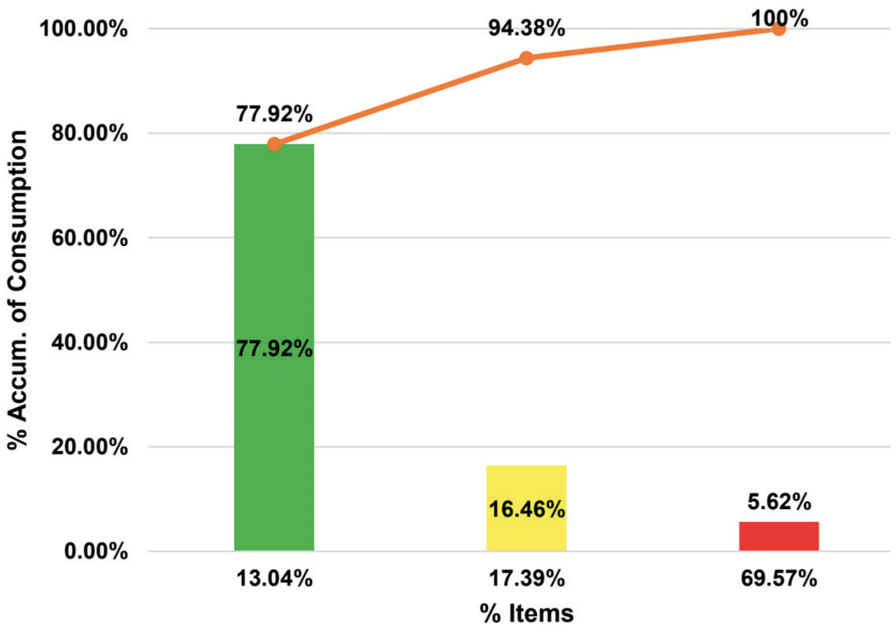

Figure 2. *Pareto Diagram: ABC Classification*

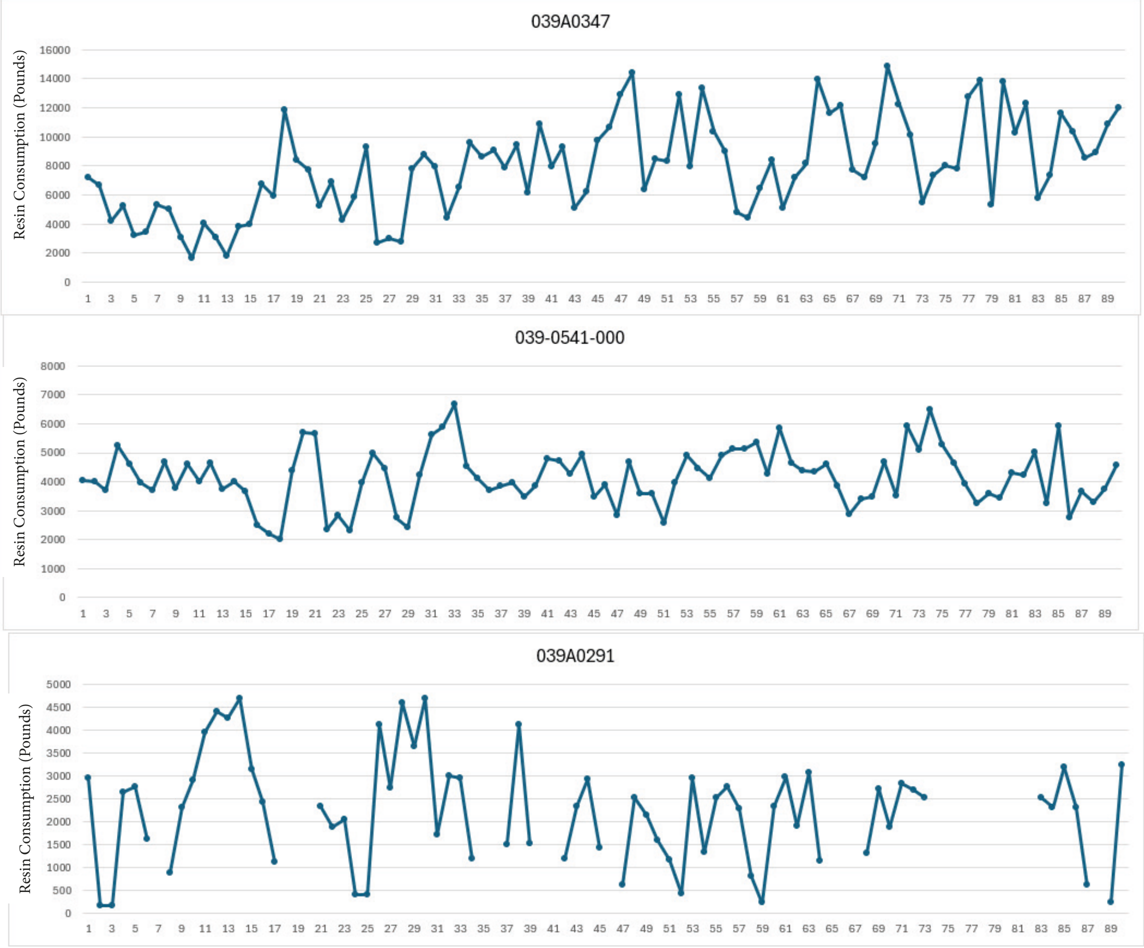

Figure 3. Time series of the resins.

Part No.	Trend Analysis		Prom. Mobile		Smooth. Exp. Simple		Smooth. Exp. Double	
	MAD	**MAPE**	**MAD**	**MAPE**	**MAD**	**MAPE**	**MAD**	**MAPE**
039A0347	2191	32.0%	1721	26.0%	2225	34.0%	2426	36.0%
039-0541-000	760	20.0%	607	16.0%	824	22.0%	864	22.0%
039A0291	955	126.0%	786	64.0%	984	125.0%	1124	88.0%

Table 6. *Performance metrics*

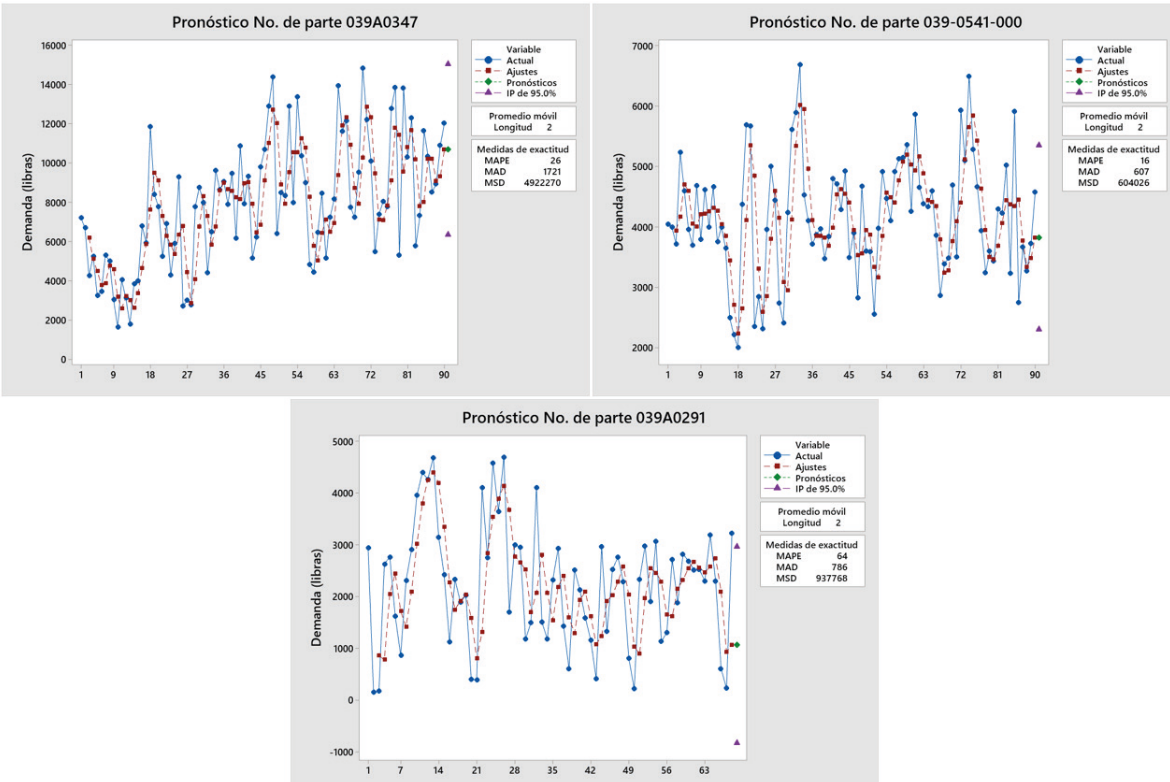

Figure 4. *Minitab Forecast Preparation*

No. Part	Day	Actual consumption (Lb)	Predicted consumption (Lb)	Difference (Lb)	%
039A0347	1	8932	10690.6	1758.6	119.7%
	2	9776	10690.6	914.6	109.4%
	3	11414	10690.6	-723.4	93.7%
039-0541-000	1	4337	3826.41	-510.59	88.2%
	2	3456	3826.41	370.41	110.7%
	3	3225	3826.41	601.41	118.6%
039A0291	1	1303	1070.48	-232.52	82.2%
	2	778	1070.48	292.48	137.6%
	3	933	1070.48	137.48	114.7%

Table 8. *Evaluation of the forecast (Actual vs. predicted consumption).*

was made considering the customer orders already established for the next three days.

EVALUATION OF THE PROGNOSIS

In this last stage, a comparison was made between forecasted consumption and actual consumption, in order to evaluate the level of reliability of the forecast. This information was recorded as follows (Table 8):

As can be seen in Table 8, both positive and negative differences of raw material emerged; on the one hand, resin 039A0347 on day 1 and 2 the forecasted consumption covered the actual consumption unlike day 3 which had a negative difference -723.4 pounds, means that the forecast did not meet the production consumption. On the other hand, resin 039-0541-000 the forecast does not cover the actual consumption on day 1 a difference of -510.59 pounds above the forecast unlike days 2 and 3. Finally, part number 039A0291 the actual consumption was not covered on day 1 by the forecast, generating a difference of -232.52 pounds, the rest of the days complies satisfactorily with a surplus of raw material.

Since the forecasts are estimates of future consumption, it is difficult to match the calculation exactly with the actual consumption of resin materials. However, for the purposes and effects of this analysis, the results are positive because most of the forecast days have covered the actual consumption, and the differences are not significant, with the exception of day 2 of part number 039A0291. This discrepancy was due to a change of priority by production due to opportunities presented in the manufacturing process, which shows that the forecasts do not take into account exceptional situations or atypical events. It is crucial, therefore, that forecasts are made as accurately as possible to minimize the margin of error and ensure efficient production planning

CONCLUSIONS

Working based on forecasting and applying the principles of ABC inventory classification allows companies to create strategies to plan their production. For items classified as "A", forecasting models can be developed in order to produce to stock, as they have the highest consumption, ensuring sufficient inventory to meet the production plan.

Forecasts are fundamental for production planning, as they allow anticipating what is expected in the future, providing key information that allows the production department to organize the necessary resources to meet production deadlines and meet production plans. This generates greater control and order in the activities, reducing the possibility of incidents during the process.

The challenge of developing an appropriate forecasting method lies in graphically analyzing historical consumption behavior. Since there are many different methods and techniques, it is crucial to perform a preliminary diagnosis to identify patterns that will help select the most appropriate forecasting approach. In addition, it is important to evaluate the accuracy of the forecast, calculating the corresponding metrics to measure performance and margin of error.

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