doi:10.22306/al.v8i4.240 Received: 27 July 2021; Revised: 27 Sep. 2021; Accepted: 26 Oct. 2021

SALES FORECAST FOR AGGREGATE PLANNING: CASE STUDY OF AN INDUSTRIAL PRODUCTS COMPANY IN MEXICO

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Keywords: demand planning, aggregate forecast, forecast accuracy, time series, SBC classification
Abstract: This case study presents the analysis through the use of sales estimation tools for planning demand for aggregate level as a finished product in a leading industrial products company in the market in Mexico. First, it aligned the demand plan and the supply plan, recommending the best execution scenario to increase operational efficiency and reduce the cost of operating the supply chain to increase the company's productivity and stay competitive. Then, after analysing the behaviour of the demand for selected products, the authors determined as the main affectation the inadequate precision of the method forecasting and the lack of an aggregate forecasting strategy that allows reducing the variation. Due to this, the most significant effort was concentrated on determining a better-forecasting model and the decision to aggregate the demand based on three relevant criteria: the demand pattern based on the Soft, Intermittent, Erratic or Irregular quadrant, the best method of the forecast for each product and the time in quarters. As a result, a reduction between 20% and 46% in the forecast variation can be obtained from the above.

1 Introduction

The correct alignment between the demand and supply plan is critical throughout the supply chain supplies in such a way that the entire value chain has visibility of customer demand and is synchronised to meet the customer service level and therefore achieve the strategic objectives of the company generate sales, profit margin and cash flow.

The correct balance of demand and supply helps the company to improve its level of service to customers, allows better visibility of supply requirements to suppliers to guarantee the availability of raw materials as well as operations to level the production plan for the best planning of resources and correct execution of the production plan, giving more certainty for the fulfilment of the business plan (Entringer & Ferreira, 2018).

The Sales and Operations plan is the mechanism that several companies have used to align the demand and supply plan to provide better customer service. It reduces delivery times, better control of inventory levels, provides visibility to both suppliers, such as company operations, stabilises production levels, takes better advantage of the productive capacity, and anticipates any imbalance between the demand and supply plan for the correct taking of actions to mitigate the impact on the company's business plan (Wallace & Stahal, 2014).

It is important to incorporate time series forecasting techniques for estimating sales to support the strategies and actions determined to satisfy demand, positioning the necessary resources, and reducing uncertainty in the processes that comprise the value chain (Contreras-Juarez, Atziry-Zuniga, Martinez-Flores, & Sanchez-Partida, 2016).

The scope of this case study is a 100% Mexican capital company, a market leader dedicated to the production and commercialisation of industrial products located in Mexico with ten manufacturing plants and three distribution centres with 800 employees.

This case study supports the company in integrating a formal sales estimation process into its Sales and Operations Plan through the support of time series to improve the accuracy of the forecast at the aggregate level by product family and at the catalogue level of the finished product.

2 Literary review

Every business plan in a company begins with the estimate and sales planning of its products, and based on this estimate, master plans are generated in the company, a financial plan to mention a few, so the quality of the estimate has an impact on the quality and execution of these plans.

The company's management must consider several factors to maintain optimal inventory levels, such as the financial liquidity of the company, sales behaviour such as seasonality, reliability, and availability of suppliers, available financial resources. Furthermore, an adequate inventory level reduces the potential risks of loss of sales due to the lack of inventory availability and an increase in the company's cash flow, such as the release of warehouse capacity (Malindzakova & Zimon, 2019).

The variability of demand is due to different factors such as the heterogeneity of customers, external factors such as macroeconomics, market conditions, socio-cultural factors, and internal company factors such as service, price conditions, and promotional activities. In addition, distribution policies contribute to generating this variability. It is proposed first to understand the context in which the company operates regarding the number of products, the main problems it is facing, and the root flow analysis of demand variability. The structure of the supply chain and customer behaviour in order to collect process and analyse the data, which is known as data research and have a better reference for the correct selection of the estimation model and based on the results obtained by the model propose an action plan, implementation, and evaluation of countermeasures (Kalchschmidt, Verganti & Zotteri, 2006).

The client's different characteristics induce variability in the quality of the provision of a service: The needs and desires of a client are different. They can request the service at different times. The knowledge and experience of the product or service vary between clients, their willingness to support in the provision of the service may differ, they have different opinions about the provision of the service, the communication about the provision of the service may be ambiguous, so it is essential to consider these characteristics to understand the performance baseline, recognise the opportunity for improvement and implement an action plan to increase the quality of service and customer loyalty to the company (Yang, 2011).

It can be classified into two types to measure the performance of the estimate, 1) Bias or bias is the primary measure that evaluates the degree to which a forecast model generates an estimate above or below the current data if the bias is zero. Although the estimation model is good, if the bias is positive, the current values tend to be on average above the estimated, in the case of being the negative bias, the current value is below the estimated value, 2) There are three measurements to quantify the error in the forecasts: the mean absolute deviation error (MAD), the mean square error (MSE) and the mean absolute percentage error (MAPE) (Klimberg, Sillup & Tavva, 2010).

The estimate's accuracy is generally measured as the variation of the estimate compared to current performance. Usually, this variation is generated due to the incorrect use of estimation tools and processes. Therefore, four categories are proposed to increase the accuracy in the estimate, 1) Review of the statistical estimation method, 2) Hardware and software to increase the computing capacity of the information, 3) Preparation of the estimate requires tools, processes, experience, and training of personnel, and 4) Analysis of the time series and estimation methods to recognise patterns, structures, that allow predicting and improving the accuracy of the estimate (Rieg, 2010).

In some cases, it is recommended to consider the combination of estimation methods and evaluate the methods to quantify the bias and error of the estimate (Klindokmai, Neech, Wu Ojiako, Chipulu & Marshall, 2014).

A methodology (Syntetos, Boylan, & Croston, 2005) is considered to position the demand for the different catalogues of finished products within a category based on two parameters. First, the average demand interval (ADI) measures how steady the demand is in terms of time by calculating the average interval between two demands and the squared coefficient of variation (CV^2) that allows measuring the variation of the units.

It is described through four quadrants to locate each discrete category of demand considering the parameters of ADI and CV^2, as shown in Figure 1:

1. Erratic demand (ADI <1.32 and CV^2> = 0.49). Demand shows a high degree of variation between periods. For items located in this quadrant, the Syntetos and Boylan estimation method is recommended for forecasting demand.
2. Irregular Demand (ADI> = 1.32 and CV^2> = 0.49). The demand presents a high variation greater than or equal to 50%, and the average interval between demands is considered high; with this, we can deduce that there are some periods in which the demand is zero. Like items in the erratic quadrant, the Syntetos and Boylan method is recommended for forecasting demand.
3. Soft demand: (ADI <1.32 and CV^2 <0.49). Demand is at a constant level and the periods in which they are not for sale are scarce or nil. In this area of the quadrant, the Croston estimation method is recommended.
4. Intermittent Demand (ADI> = 1.32 and CV^2 <0.49). The demand shows low variation in units between the periods, but high variability in the time interval between two demands indicates zero demand periods. In this area of the quadrant, the estimation method Syntetos and Boylan is recommended.

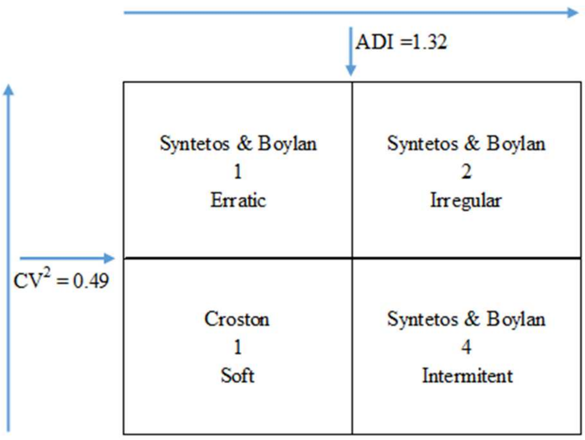

Figure 1 Illustration of intermittent demand categories (Syntetos, Boylan, & Croston, 2005)

It is essential to understand the demand pattern considering the different factors that influence its behaviour, then determine the category of intermittent demand according to the SBC classification in order to select the appropriate estimation methodology to reduce the error of the estimate (Van der Auweraer, Boute, & Syntetos 2017).

In the intermittent demand time series, demand is classified taking into account the average interval of demand and coefficient of variation according to the model of Syntetos, Boylan & Croston in their research Doszyń proposes instead of the average interval of demand recommends comparing the coefficient of variation concerning the frequency of the sale to understand better the nature of the demand behaviour (Doszyń, 2019).

Within the methodology for implementing the sales estimate, it is necessary to understand the structure of the company's supply chain, understand the characteristics of the demand, and validate the causes that generate this variability in demand. The next step is to understand the demand pattern and classify it according to the intermittent demand categories, select the correct estimation model, carry out a simulation and, based on the positive results, plan a pilot test for its subsequent implementation. This methodology was implemented in the retail sector (Balderas, Araiza, Peña & Villareal, 2019).

As part of the methodology for estimating consumable items such as spare parts where demand is intermittent or slow-moving, it is tough to forecast their consumption, so an analysis of the demand category is made in soft, erratic, intermittent, and irregular using estimation methodology according to the demand patterns for which a modification to the Croton method is proposed as an approximation method to maintain a required inventory level for a service level according to each of the demand patterns (Eaves, & Kingsman, 2004).

Once the inventory levels are established, we proceed with the levelling of the production in a period. It allows avoiding fluctuations to predict the consumption of raw materials, labour, and productive capacity to guarantee the product's availability, minimising inventories, working capital, and delivery time throughout the value chain (Narusawa & Shook, 2011).

Poor demand planning results in constant changes in production levels, so it is essential to smooth demand to optimise production resources using the double exponential smoothing methodology. Demand projections are generated as part of the evaluation of the estimate is quantified. The error in the forecasts through three measurements: MAD, MSE and MAPE, as the error does not decrease, it is decided to adjust the average demand instead of a monthly to quarterly basis, optimising the smoothing parameters α and β, it was possible to reduce the error in the estimate (Sánchez-Partida, Rodríguez-Méndez, Martínez-Flores & Caballero-Morales, 2018).

When obtaining the forecast of customer demand, it is essential to evaluate if it has the correct inventory levels through a correct inventory control policy using the EOQ to determine the optimal quantity to order with a reorder point to order when the target has reached a point in the inventory within the delivery time to meet the level of service desired by the client or if more inventory is required, evaluate the productive capacity to position inventory required to meet the client's demand (Alvarez-Socarras, Berrones, Moreno, Rodrıguez-Sarasty & Cabrera-Ríos, 2013).

ABC analysis in inventory management is a method of classifying inventories based on the book value (cost or acquisition) of the stored materials that consider using the item at its book value, classified from highest to lowest (Richards, Grinsted, 2016).

The inventory control of spare parts in an MRP system is essential to analyse the historical demand having the ABC classification in terms of inventory cost and the inventory replenishment through a point of order where the estimated demand for high-value parts A articles with a high coefficient of variation are manually validated with a criterion judgment. In this case, the articles classified as B, the criterion for selecting the estimator and its parameters are based on minimising the MAD. In articles classified as C, the demand pattern is studied to correct the estimation tool's correct selection (Syntetos, Keyes & Babai, 2009).

3 Current issue

The company is currently using a linear method estimation which implies considering current sales to date to project the sales estimate for the following month based on the average of the historical demand of the last three months, that is, a moving average of three months in addition to considering public tenders as requirements of the private sector for special projects. The Commercial area proposes the sales estimate by product family and at the finished product catalogue level by business unit. Only the sales estimate is calculated for items classified A, which represents the 80-20 of the income from the sale in monetary value, products B are produced in a manufacturing environment "make to order," and the case of articles C that are special projects are produced as "design to order."

These sales estimated are used for the business's financial projection and are evaluated against the business plan to determine the month's sales and operation plan with their respective budgets for each of the company's functional areas. In addition, inventory goals and inventory maximums and minimums are determined for each of the finished products classified A for inventory control purposes.

The current environment that the company faces is very challenging when considering the market contraction, the more protectionist market policies that impose tariffs on critical raw materials for the production of its products, and the constant increases in the prices of materials premiums. Without neglecting a more significant presence of competition in the market, it has made the company rethink its strategic position to generate a competitive difference to stay and grow in the market with more innovative products, seeking efficiencies in operating and production costs and shorter response times to meet customer requirements.

As part of the efficiency in the operating, production, and distribution costs of its products, a formal method of estimating sales is required to reduce the error of the sales estimate to give more certainty to the business plan. It is also, reducing the uncertainty providing visibility of the demand both to the manufacturing plants and of the supply requirement to the raw material suppliers to ensure the availability of the material and logistics providers for the distribution of their products to determine the correct resource requirement of transportation to comply with the delivery plan committed by the commercial area.

The accuracy of the aggregate sales forecast on average is 71% as a performance baseline, highlighting a significant opportunity for the generation and execution of the Plan and Sales and Operations, as shown in Figure 2.

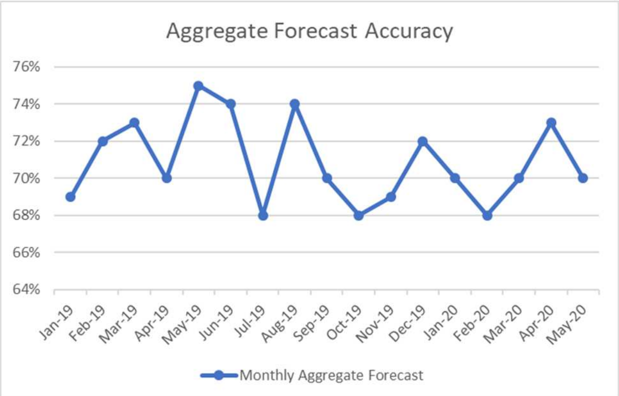

Figure 2 Accuracy of the aggregate forecast of the sale of the periods from January 2019 to April 2020

4 Methodology

The case study includes the analysis of the historical sales of the last two years of one of the manufacturing plants that generated the highest income for the company, for which historical sales were collected in terms of sales units by product family and at the level of a finished product for products classified as type A that represent 80-20 of the revenue received from the manufacturing plant.

Historical sales are stratified by product family with their respective finished products, and we proceed to understand the behaviour of sales to graph the time series to recognise patterns and structures.

The demand for the different catalogues of finished products is categorised based on the coefficients: Average demand interval (ADI) and the squared coefficient of variation (CV^2).

The demand for each of the finished product catalogues is classified into four categories considering these two coefficients: Soft, Intermittent, Irregular, and Erratic.

The finished product catalogues whose demand is Irregular and Erratic is not proposed as a method of estimating the sale, but an aggregate forecasting strategy that allows reducing the risk and the possibility that these catalogues are managed in a "make to order" environment.

For the catalogues classified in both Soft and Intermittent categories, the appropriate estimation method will thus be selected to generate the sale estimate that shows a reduction in the forecast error.

For the evaluation of the estimation method, bias is considered as the primary measure that evaluates the degree to which the forecast model generates an estimate above or below the current data, as well as the error of the estimate, will be quantified using three measurements: MAD error of the mean absolute deviation, MSE squared error and MAPE error of the mean absolute percentage.

Based on the estimate produced by the selected model with the most negligible bias and error of the estimate, the estimate of the recommended sale at the aggregate level by product family is the basis for the generation of the sales plan. In addition, the proposed sale estimate at the finished product level is updated in the manufacturing plant's production master plan to determine future production and production capacity requirements.

The net requirement proposed by the master production plan is the basis for the material requirement plan to generate the estimate of future purchase requirements for raw material suppliers, thus providing visibility to ensure the supply of raw materials. In addition, the results will be evaluated in the impact on the operational efficiency and reduction of the supply chain's operating cost to increase the company's productivity and become more competitive in the market.

5 Result and discussion

Considering the historical sales of the last two years, 2018 and 2019 of the finished product catalogues classified A of the manufacturing plant, and they are then plotted based on the Syntetos, Boylan, & Croston (SBC) matrix to identify the demand category, based on the average interval

Acta logistica - International Scientific Journal about Logistics
Volume: 8 2021 Issue: 4 Pages: 381-392 ISSN 1339-5629

coefficients of the demand (ADI) and the squared coefficient of variation (CV^2).

Table 1 Results of the ADI, CV2 coefficients and classification Syntetos, Boylan, & Croston

PRODUCT	J-1	J-5	H-6	D-7	S/F-11	D-12	H-13	G-14
2018 & 2019 Total Demand	11484	4645	3145	791	2618	949	2086	908
Periods without demand	0	0	1	1	0	1	0	0
Constant/Intermittent	C	C	I	I	C	I	C	C
Periods with demand	24	24	23	23	24	23	24	24
ADI	1.000	1.000	1.043	1.043	1.000	1.043	1.000	1.000
CV^2	0.171	0.406	0.350	0.170	0.234	0.085	0.228	0.143
CLASSIFICATION	Soft	Soft	Soft	Soft	Soft	Soft	Soft	Soft

PRODUCT	A-15	H-18	S/F-20	A-23	F-24	S/F-25	D-26	F-28
2018 & 2019 Total Demand	3390	906	1056	2472	422	1566	332	428
Periods without demand	0	0	0	1	0	10	1	0
Constant/Intermittent	C	C	C	I	C	I	I	C
Periods with demand	24	24	24	23	24	14	23	24
ADI	1.000	1.000	1.000	1.043	1.000	1.071	1.043	1.000
CV^2	0.456	0.226	0.310	0.404	0.282	0.336	0.325	0.370
CLASSIFICATION	Soft	Soft	Soft	Soft	Soft	Soft	Soft	Soft

PRODUCT	D-37	D-29	D-35	B-38	B-21	F-22	K-27
2018 & 2019 Total Demand	2074	75	110	672	2068	320	228
Periods without demand	1	16	16	8	0	1	0
Constant/Intermittent	I	I	I	I	C	I	C
Periods with demand	23	8	8	16	24	23	24
ADI	1.043	3.000	3.000	1.500	1.000	1.043	1.000
CV^2	0.248	0.484	0.161	0.484	0.636	0.989	0.674
CLASSIFICATION	Soft	Intermittent	Intermittent	Intermittent	Erratic	Erratic	Erratic

PRODUCT	J-3	C-9	H-10	B-16	G-34	C-19	J-4	B-30
2018 & 2019 Total Demand	4953	159	2266	1927	121	76	2906	633
Periods without demand	0	5	1	0	3	7	12	11
Constant/Intermittent	C	I	I	C	I	I	I	I
Periods with demand	24	19	23	24	21	17	12	13
ADI	1.000	1.263	1.043	1.000	1.143	1.411	2.000	1.840
CV^2	0.698	1.474	0.903	0.695	0.882	0.726	0.837	3.579
CLASSIFICATION	Erratic	Erratic	Erratic	Erratic	Erratic	Irregular	Irregular	Irregular

From the results presented in Table 1, the proportion corresponding to each quadrant can be determined, being 54.84% of the finished product catalogues located in the soft quadrant, 9.68% with Irregular demand, 25.81% with Erratic demand, and 9.68% with Intermittent demand (see Figure 3).

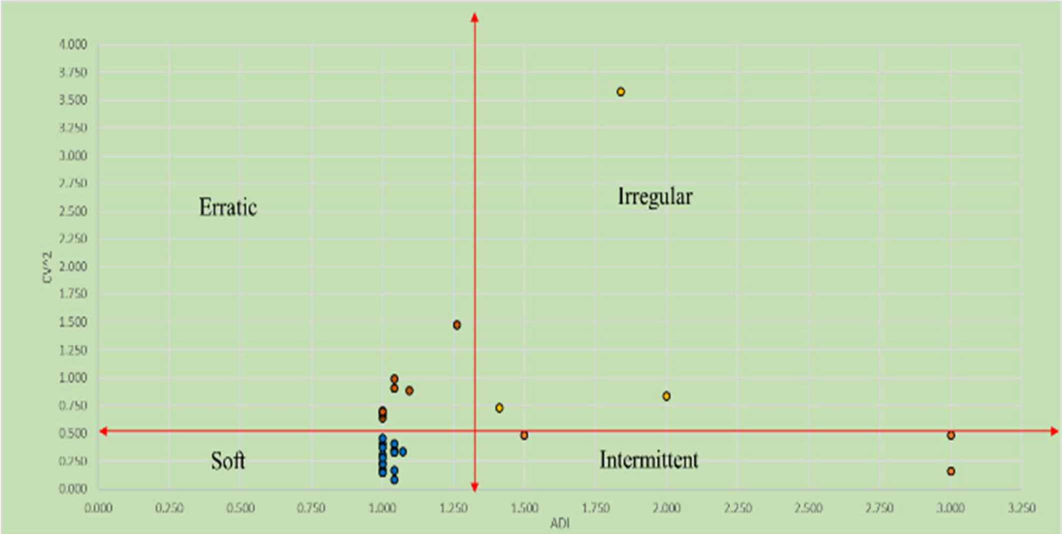

Figure 3 Classification of the Manufacturing Plant demand (Syntetos, Boylan, & Croston, 2005)

As described in the percentage and reflected in the graph, several products are located in the Erratic area and the same number of products in the Irregular and Intermittent areas. Once each item is located in its respective quadrant, we calculate a better forecasting method for each item. In Tables 2 and 3, the summary of the results of the demand estimate through the method used by the organisation and the proposal of a new method that allows reducing the forecast error is shown. The value of each value of the necessary softeners of the proposed method for each product.

Table 2 The proposed method for calculating the demand forecast for products classified in the Soft and Intermittent quadrant

PRODUCT	CURRENT FORECASTING METHOD	CV^2	ADI	MAD
J-1	Moving Average	0.171	1.000	162.143
J-5	Moving Average	0.406	1.000	121.556
H-6	Moving Average	0.350	1.043	88.175
D-7	Moving Average	0.218	1.043	13.206
S/F-11	Moving Average	0.234	1.000	45.889
D-12	Moving Average	0.085	1.043	9.651
H-13	Moving Average	0.228	1.000	29.937
G-14	Moving Average	0.143	1.000	12.381
A-15	Moving Average	0.456	1.000	78.810
H-18	Moving Average	0.226	1.000	15.476
S/F-20	Moving Average	0.310	1.000	18.630
A-23	Moving Average	0.404	1.043	79.048
F-24	Moving Average	0.282	1.000	6.730
S/F-25	Moving Average	0.336	1.071	50.980
PRODUCT	CURRENT FORECASTING METHOD	CV^2	ADI	MAD
D-26	Moving Average	0.354	1.043	6.860
F-28	Moving Average	0.370	1.000	9.380
D-37	Moving Average	0.270	1.043	41.390
D-29	Moving Average	4.357	3.000	1.587
D-35	Moving Average	1.452	3.000	2.540
B-38	Moving Average	1.089	1.500	30.300

PRODUCT	SBC CLASSIFICATION	BEST FORECASTING METHOD	ALFA PARAMETER	BETA PARAMETER	MAD
J-1	Soft	Brown	0.0001		159.841
J-5	Soft	Brown	0.0001		102.767

H-6	Soft	Brown	0.0001		63.194
D-7	Soft	Holt	0.0977	0.1867	12.166
S/F-11	Soft	Holt	0.0001	0.0001	42.671
D-12	Soft	Brown	0.5545		10.793
H-13	Soft	Brown	29.1300		31.074
G-14	Soft	Brown	0.0004		10.414
A-15	Soft	Holt	0.5310	0.1090	59.301
H-18	Soft	Brown	0.0020		13.821
S/F-20	Soft	Moving Average			18.630
A-23	Soft	Brown	0.0004		61.696
F-24	Soft	Brown	0.3989		6.470
S/F-25	Soft	Holt	0.5740	0.0040	47.580
D-26	Soft	Brown	0.3091		6.080
F-28	Soft	Holt	0.3240	0.0200	8.770
D-37	Soft	Brown	0.0004		38.590
D-29	Intermittent	Holt	0.3420	0.0470	1.220
D-35	Intermittent	Holt	0.3990	0.0510	2.190
B-38	Intermittent	Brown	0.9999		18.700

Table 3 A proposed method for calculating the demand forecast for products classified in the Erratic and Irregular quadrant

PRODUCT	CURRENT FORECASTING METHOD	CV^2	ADI	MAD	SBC CLASSIFICATION
J-3	Moving Average	0.698	1.000	144.905	Erratic
C-9	Moving Average	1.474	1.263	6.238	Erratic
H-10	Moving Average	0.903	1.043	70.079	Erratic
B-16	Moving Average	0.695	1.000	52.492	Erratic
B-21	Moving Average	0.636	1.000	62.206	Erratic
F-22	Moving Average	0.989	1.043	9.476	Erratic
K-27	Moving Average	0.674	1.000	6.220	Erratic
G-34	Moving Average	1.152	1.095	3.680	Erratic
J-4	Moving Average	0.837	2.000	70.095	Irregular
C-19	Moving Average	0.726	1.411	3.476	Irregular
B-30	Moving Average	12.199	1.840	46.380	Irregular

PRODUCT	BEST FORECASTING METHOD	ALFA PARAMETER	BETA PARAMETER	MAD
J-3	Holt	0.3409	0.0001	134.321
C-9	Holt	0.0233	0.9999	4.743
H-10	Holt	0.0206	0.8819	63.331
B-16	Holt	0.5150	0.0210	45.712
B-21	Holt	0.0650	0.2490	47.281
F-22	Brown	0.0004		8.428
K-27	Brown	0.0004		5.330
G-34	Holt	0.3390	0.0001	3.570
J-4	Holt	0.4568	0.2287	69.297
C-19	Holt	0.0471	0.0001	2.660
B-30	Brown	0.0004		35.900

In 90.3% of the cases, a better method was found to reduce the demand forecast error; 41.94% of the products are better forecast through the Brown method, which allows us only to have an alpha smoother (α). In this case, the same percentage of 48.3% of the products improves their prognosis by Holt's method, using the alpha and beta (α, β) softeners. Once the best forecasting method for each product was identified, they were classified by quadrant of the SBC method, it is the best forecasting method to use the strategy of an aggregate forecast that allows reducing

the relative variability further increase the forecast precision, and that allows reducing the requirements of the safety stock in inventories.

Table 4 describes the demand for each period of 2018 and 2019 of the items located in the Irregular quadrant and Holt's method and the total aggregate demand for each period of the items classified according to their quadrant and their best method.

Table 4 Irregular classification and Holt's forecasting method

	PRODUCT	J-3	C-9	H-10	B-16	B-21	G-34	AGGREGATE
2018	January	153	2	43	79	35	13	325
	February	21	1	9	78	11	5	125
	March	169	2	17	56	88	1	333
	April	487	1	0	30	42	1	561
	May	77	4	38	146	73	0	338
	June	154	0	144	75	42	1	416
	July	109	5	96	41	26	4	281
	August	69	0	130	78	102	4	383
	September	426	6	11	52	82	2	579
	October	219	10	121	103	95	1	549
	November	254	3	16	102	134	2	511
	December	639	23	79	31	53	4	829
2019	January	373	2	134	144	72	4	729
	February	409	0	9	73	18	0	509
	March	201	5	161	29	301	2	699
	April	16	0	62	15	1	4	98
	May	487	0	2	13	52	6	560
	June	89	3	1	7	41	4	145
	July	56	7	107	18	109	14	311
	August	111	14	144	160	135	6	570
	September	138	8	84	106	203	22	561
	October	189	9	225	118	178	12	731
	November	47	44	373	317	53	9	843
	December	60	10	260	56	122	0	508

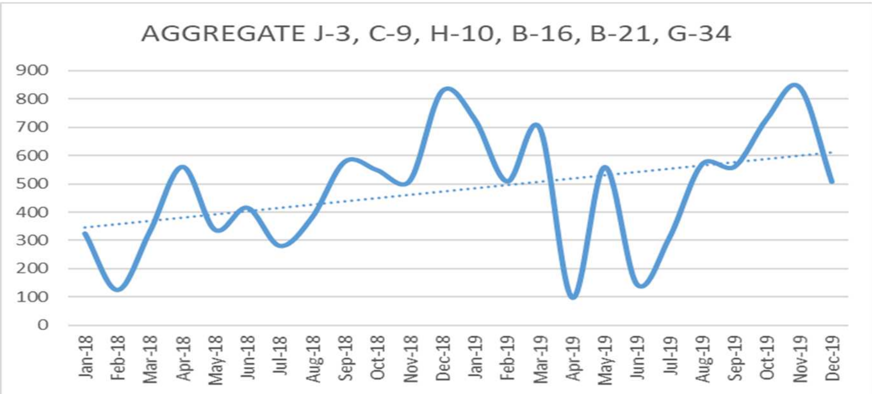

Figure 4 Graph of the aggregate demand of Irregular products and Holt's forecasting method

Subsequently, the estimation of the demand forecast for the aggregated data was carried out to contrast if there is an improvement in the variation and the forecast precision. Table 5 shows the primary statistic of the aggregated data, and Table 6 details the results of the forecast estimation calculation.

The graph of the values of the aggregate demand is made, allowing us to visualise its behaviour and pattern. It can be seen that it still presents a vital variation and a positive linear trend, as shown in Figure 4.

Table 5 The average value, standard deviation, CV and CV^2

Mean	478.917
Deviation	208.818
CV	0.436
CV^2	0.190

Table 6 Results of the aggregate forecast for the Erratic classification and Holt's method, values of the softeners, and their MAD

Product	SBC Classification	Best Forecasting Method	Alfa Parameter	MAD Disaggregated	MAD Aggregated
J-3	Erratic	Holt	0.074	298.958	158.376
C-9	Erratic	Holt			
H-10	Erratic	Holt			
B-16	Erratic	Holt			
B-21	Erratic	Holt			
G-34	Erratic	Holt			

From the result obtained using the aggregate demand forecast, a MAD error of the forecast can be determined with a value of 158,376; this can be described as an improvement of 47% concerning the MAD error of 298.958 treating disaggregated demands.

It was also considered to evaluate a strategy of adding the SBC classification, the best forecasting method, and quarters. Figure 5 shows only the results of the basic statistics of the proposal to consider adding the demands in quarterly periods.

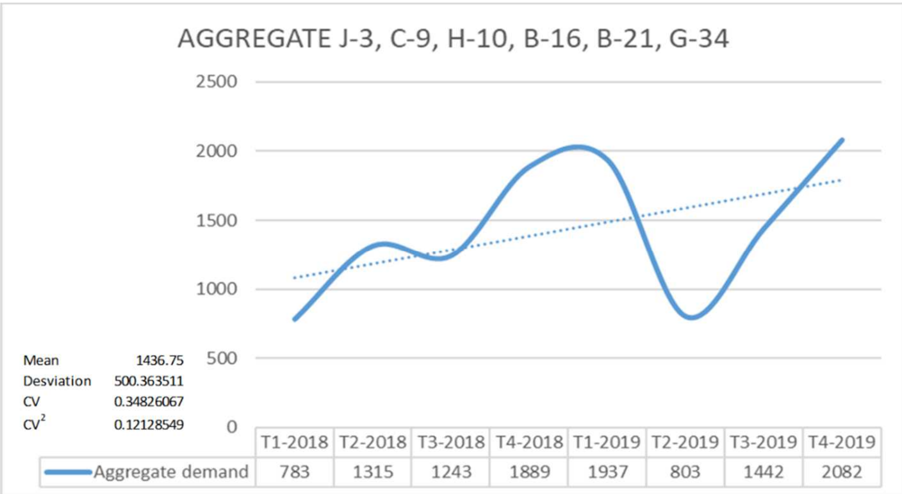

Figure 5 Aggregate demand considering the SBC classification, best forecasting method, and the periods in quarters

It can be seen in the graph how the variation reduces considerably, allowing the variation to be reduced by 20.18% concerning the strategy of adding only the SBC classification and the best forecasting method, from 0.436 to 0.348 in the variation coefficient.

Figure 6, based on data from Table 7 and Figure 7, based on data from Table 8, show the results of the aggregate demand for products in the Soft classification with the Brown method and the periods in quarters, as well as for the products with Soft and Intermittent classification, with the Holt method and the periods quarterly.

Table 7 Trimestral aggregate demand

Product	SBC Classification	Best Forecasting Method	Alfa Parameter	MAD Disaggregated	MAD Aggregated
J-1	Soft	Brown	0.806	504.741	393.93
J-5	Soft	Brown			
H-6	Soft	Brown			
D-12	Soft	Brown			
G-14	Soft	Brown			
H-13	Soft	Brown			
H-18	Soft	Brown			
A-23	Soft	Brown			
F-24	Soft	Brown			
D-26	Soft	Brown			
D-37	Soft	Brown			

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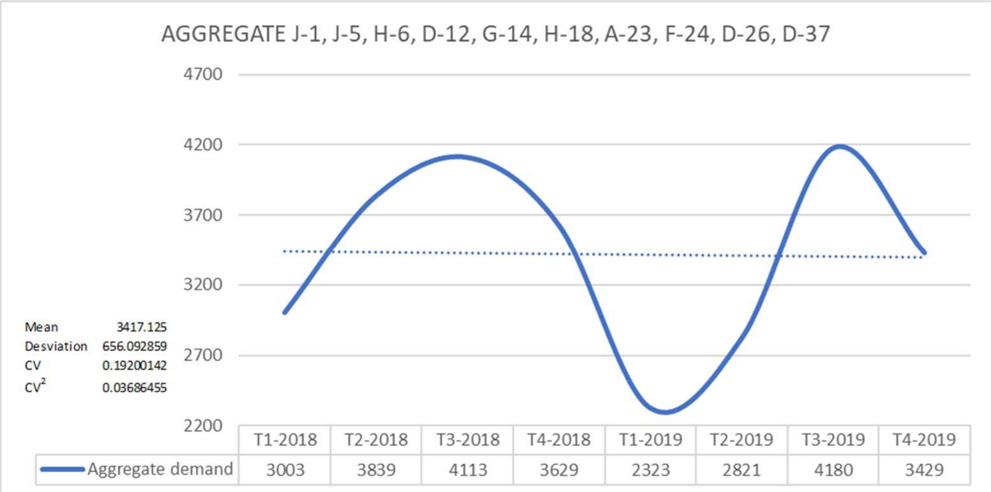

Figure 6 Aggregate demand considering the Soft SBC classification, Brown forecasting method, and the periods in quarters

Table 8 Trimestral aggregate demand

Product	SBC classification	Best Forecasting Method	Alfa Parameter	Mad Disaggregated	Mad Aggregated
D-7	Soft	Holt			
S/F-11	Soft	Holt			
A-15	Soft	Holt			
S/F-25	Soft	Holt	0.515	173.898	104.416
F-28	Soft	Holt			
D-29	Intermittent	Holt			
D-35	Intermittent	Holt			

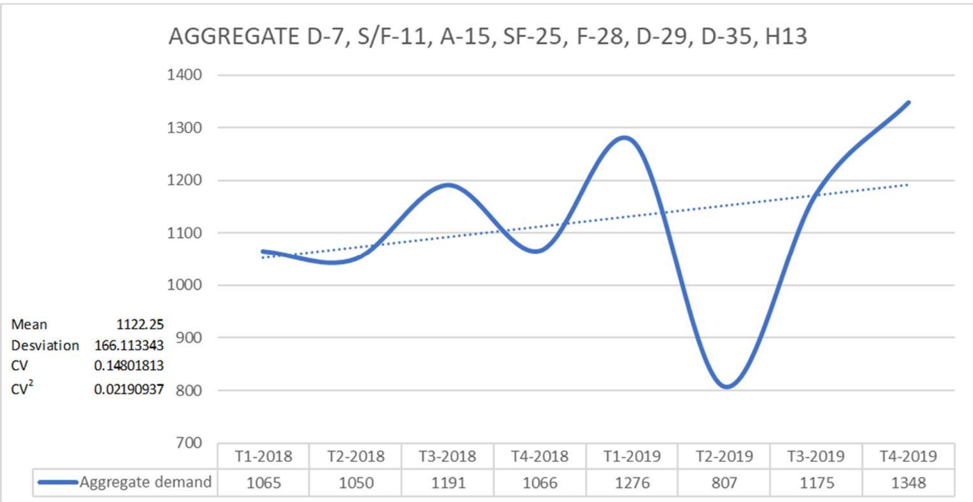

Figure 7 Aggregate demand considering the Soft and Intermittent SBC classification, Holt forecasting method, and the periods in quarters

The results of the proposal to classify the products according to their demand pattern, find a better forecasting method that allows pursuing the demand pattern, add the demand by the classification proposed by Syntetos, Boylan, and Croston. Moreover, their best method, forecasting and for quarterly periods, allow reducing the relative variability, an essential increase in the forecast precision that will reduce the requirements of the safety stocks for the raw materials, which in our case are the same for the majority of the products.

6 Conclusions

The importance of maintaining optimal inventory levels that allow the company to satisfy the needs of its customers at the lowest cost requires an understanding of the key factors that describe the behaviour of demand patterns. In these circumstances, the effectiveness of forecasting and inventory management schemes becomes essential.

The case study described in this document seeks to improve the demand forecast level for a sample of representative items from the production plant of industrial products, limited under this study. The organisation was dealing with having an excessive level of variability in the consumption of raw materials given the lack of a forecasting method, with greater assertiveness; this caused high inventory management, which allowed the continuity of production at a high cost to avoid stoppages due to lack of supplies.

An in-depth analysis of the contribution to this excess variance was conducted and found that forecasting performance could be improved to improve inventory levels. The analysis results made it possible to implement a classification based on the methodology of Syntetos, Boylan, and Croston, to group the analysed products under affinity and a change in the method for calculating the forecast to reduce the error. Once the classification and forecasting method was defined for each product, an aggregate forecasting strategy was implemented for the products found in each classification with each forecasting method, obtaining a variation reduction between 20% and 46% in each estimated case.

Based on the results found in this study, the organisation will gradually implement the changes in its management system, the modifications required to establish the methods and parameters suggested in this document, as well as include the rest of the articles produced by the plant at the same treatment—moreover, experimentation to analyse your results. The description of the methodology used in this case study has been satisfactory and shows evidence of improving the precision of the forecasts.

Further research should involve the interaction with finished good inventory forecasting based on the forecasting model proposed in this study in order to notably reduce the uncertainty presented in the use of forecasts as inventories are the support that the forecast model has in the face of significant changes by the demand. Under these circumstances, the effectiveness of the forecasting and inventory management schemes becomes important in an industrial environment, which may lead to significant inventory and production cost reductions and improve customer service levels.

Acknowledgement
The corresponding author wants to acknowledge the Popular Autonomous University of the State of Puebla (UPAEP University).

References

[1] ENTRINGER, T., FERREIRA, A.: Proposal for a Reference Model for Sales & Operations Planning and Aggregate Planning, *International Journal of Advanced Engineering Research and Science*, Vol. 5, No. 8, pp. 277-284, 2018.

[2] WALLACE, T., STAHL, R.: *Sales & Operations Planning,* The Executive's Guide. 9th ed. United States of America: TF Wallace and Co.AIR, J.: *Effective time management, how to save time and spend it wisely*, London, Pan Books, 2014. doi:10555/al/article

[3] CONTRERAS JUÁREZ, A., ATZIRY ZUÑIGA, C., MARTÍNEZ FLORES, J. L., SÁNCHEZ PARTIDA, D.: Análisis de series de tiempo en el pronóstico de la demanda de almacenamiento de productos perecederos, *Estudios Gerenciales*, Vol. 32, No. 141, pp. 387-396, 2016. doi:10.1016/j.estger.2016.11.002 (Original in Spanish)

[4] MALINDZAKOVA, M., ZIMON, D.: Design Supply Cycle for Inventory Management, *TEM Journal*, Vol. 8, No. 3, pp 894-899, 2019. doi:10.18421/TEM 83

[5] KALCHSCHMIDT, M., VERGANTI, R., ZOTTERI, G.: Forecasting demand from heterogeneous customers, *International Journal of Operations and Production Management*, Vol. 26, No. 6, pp 619-638, 2006. doi:10.1108/01443570610666975

[6] YANG, C.: Implementation and effectiveness of strategic actions used to reduce customer variability, *The Service Industries Journal*, Vol. 31, No. 4, pp. 527-544, 2011.

[7] KLIMBERG, R.K., SILLUP, G.P., BOYLE, K.J., TAVYA, V.: Forecasting performance measures – what are their practical meaning?, *Advances in Business and Management Forecasting*, Vol. 7, pp. 137-147, 2010. doi:10.1108/s1477-4070(2010)0000007012

[8] RIEG, R.: Do forecasts improve over time?, *International Journal of Accounting & Information Management*, Vol. 18, No. 3, pp. 220-236, 2010. doi:10.1108/18347641011068974

[9] KLINDOKMAI, S., NEECH, P., WU, Y., OJIAKO, U., CHIPULU, M., MARSHALL, A.: Evaluation of forecasting models for air cargo, *The International Journal of Logistics Management*, Vol. 25, No. 3, pp. 635-655, 2014. doi:10.1108/ijlm-05-2013-0049

[10] SYNTETOS, A.A., BOYLAN, J.E., CROSTON, J.D.: On the categorisation of demand patterns, *Journal of the Operational Research Society*, Vol. 56, No. 5, pp. 495-503, 2005. doi:10.1057/palgrave.jors.2601841

[11] VAN DER AUWERAER., S., BOUTE, R.N., SYNTETOS, A.: Forecasting Spare Part Demand with Installed Base Information, *SSRN*, Vol. 2017, pp. 1-35, 2017. doi:10.2139/ssrn.3104452

[12] DOSZYN, M.: Intermittent demand forecasting in the enterprise: Empirical verification, *Journal of Forecasting*, Vol. 38, No. 5, pp. 459-469, 2019. doi:10.1002/for.2575

[13] BALDERAS, M., ARAIZA, A., PEÑA, M., VILLAREAL, B.: *Improving Forecast Accuracy to Reduce Variability of Customer Service Level*, Proceedings of the International Conference on Industrial Engineering and Operations Management, Pilsen, Czech Republic, 2019.

[14] EAVES, A.H.C, KINGSMAN, B.G.: Forecasting for the ordering and stock-holding of spare parts, *Journal of the Operational Research Society*, Vol. 55, No. 4, pp. 431-437, 2004. doi:10.1057/palgrave.jors.2601697

[15] NARUSAWA, T., SHOOK, J.: *Kaizen Express: Fundamentals for your Lean Journey*, Cambridge MA. USA: Lean Enterprise Institute, 2011.

[16] SÁNCHEZ-PARTIDA, D., RODRÍGUEZ-MÉNDEZ, R., MARTÍNEZ-FLORES, JL, CABALLERO-MORALES, S.-O.: Implementation of Continuous Flow in the Cabinet Process at the Schneider Electric Plant in Tlaxcala, Mexico, *Interfaces*, Vol. 48, No. 6, pp. 566-577, 2018. doi:10.1287/inte.2018.0966

[17] ÁLVAREZ SOCARRÁS, A.M., BERRONES, A., MORENO, G.J., RODRÍGUEZ SARASTY, J.A., CABRERA RÍOS, M.: Practice summary: Enhancing Forecasting and Capacity Planning Capabilities in a Telecommunications Company, *Interfaces*, Vol. 43, No. 4, pp. 385-387, 2013. doi:10.1287/inte.2013.0684

[18] RICHARDS, G., GRINSTED, S.: *The logistics and supply chain toolkit*, 2nd ed., pp. 123, 143, 161, Great Britain: Kogan Page Limited, 2016.

[19] SYNTETOS, A.A., KEYES, M., BABAI, M.Z.: Demand categorisation in a European spare parts logistics network, *International Journal of Operations & Production Management*, Vol. 29, No. 3, pp. 292-316, 2009. doi:10.1108/01443570910939005

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