SUPPLY CHAIN RISK MITIGATION THROUGH SALES FORECASTING IN A COSMETICS COMPANY

Daniella Frias
CEFET/RJ, Brazil
E-mail: daniellaffrias@gmail.com

Carolina Cavour Siqueira Muniz
CEFET/RJ, Brazil
E-mail: carolinacavour94@gmail.com

Pedro Senna Vieira
CEFET/RJ, Brazil
E-mail: pedro.sennavieira@gmail.com

Dominique Souza Sant'anna
CEFET/RJ, Brazil
E-mail: dominiquesouzasantanna@gmail.com

Augusto da Cunha Reis
CEFET/RJ, Brazil
E-mail: augusto.reis@cefet-rj.br

ABSTRACT

Demand forecasting has become a fundamental tool for companies' strategic planning. Represented by one of the highest growth rates in the country, the cosmetics industry faces numerous challenges in meeting the demand of consumers with a high level of service. Correctly identifying demand is critical to avoiding unnecessary extra costs for the business, such as stockout or stock over. The sales data of shampoo franchises are real values, covering the period from January 2013 to December 2018. After data organization, open-time and fixed-time time series techniques were analyzed in order to find the best forecasting technique for the type of product analyzed, i.e. the method with the smallest difference in absolute values between the actual demanded. and the estimated. The models were successfully applied, and we concluded that one of the analyzed methods could be applied in the company, because it presented smaller Mean Absolute Percentage Error.

Keywords: Risk; Mitigation; Supply; Demand; Forecast

1. INTRODUCTION

The Supply Chain analysis process makes it easy to make decision-making along the chain by coordinating information and the flow of products and services. Among the processes for supply chain management, one of the most important is demand management, which seeks to align customers' needs with the company's ability to service through a market perception. For Slack et al. (2003), without a demand estimate, it is not possible to plan for future events, but only react to them.

According to Corrêa et al. (2010), this process is extremely important for the company for identifying the factors that generates the initial information of the production process. Several risks can lead to disruptions in supply chains, and the consequences of economic crises are significant. Therefore, it is necessary that companies are prepared for unstable situations and, develop competitive advantages that involve supply chain resiliency, and the ability to adapt to changes in the external environment.

One tool to protect these companies, in view of the changes of recent years, is demand management. As mentioned, demand forecasting activity is important to ensure the service of the operating market and to avoid expenses due to overproduction and waste of raw material or delay and lack of material when desired by the customer. From this context, the present study analyzes methods for demand forecasting of a cosmetics company.

In addition, this paper also analyzes the demand forecasting techniques used, seeking to reduce forecasting error and improve demand management, mitigating the threats mapped in risk analysis. The study used the SCOR (Supply Chain Operations Reference) framework that seeks to propose improvements, through the analysis of business activities to manage the physical and temporal resources employed.

2. LITERATURE REVIEW

2.1. Supply Chain Management

Supply chain management has been recognized as managing key business processes across the network of organizations that compose the supply chain. In other words, it consists of developing and seeking the continuous improvement of activities related to the flow of transformation of products and services, from obtaining the raw material to the arrival of the final product.

1607

According to Juttner et al. (2007), Supply Chain Management focuses on the efficiency of procurement-related processes (demand fulfillment) and tends to be cost-oriented, while marketing management seeks to generate revenue (demand creation), identifying consumer value perceptions and translating into product offerings. The implementation of structured processes within the company has been stimulated over the last few years. It is now necessary to integrate processes between the areas of the supply chain, reducing costs for the supplier of the beginning of the chain, while adding value to the final consumer meeting their needs.

Christopher and Peck (2004) define resilience in supply chains as the ability to return to their status quo or move to another more desirable after suffering disruption. For Ponomarov and Holcomb (2009), resilience in the supply chain can be conceptualized as the ability to adapt the supply chain to unexpected events, responding to interruptions, recovering and continuing operations at the level Desired. One point that deserves to be highlighted in demand management is the need for a contingency plan through internal or external occasions that cause an imbalance in supply and demand.

2.2. Supply Chain Risk Management

The risk is related to the occurrence of uncertainties. According to Heckmann et al. (2015), the risk in the supply chain lies in the possibility of loss of efficiency and effectiveness motivated by some event likely to occur. An example of a risk to the supply chain would be the mismatch between supply and demand that would result in disruption. For Juttner et al. (2007), this incompatibility can be caused by lack of information, shortage of raw materials and flow of unbalanced products.

Risk management involves planning processes, identification, quantitative and qualitative analysis, response planning and risk monitoring and control. Bradley (2014) suggests that the supply chain risk management process follows the steps (a) risk identification; (b) risk measurement; (c) prioritization of risk for mitigation; (d) evaluation of risk mitigation tactics; (e) implementation of mitigation tactics. Padoveze (2010) conceptualizes risk as follows: opportunity (the higher the risk, the greater the potential for return); hazard or threat (potentially negative events such as: financial losses, fraud, reputational damage or theft, death or injury, system failures or legal claims) and uncertainty (related to the distribution of all possible outcomes, whether positive or negative).

In this context, Felea et al. (2013) states that the goal of having good and structured risk management is to manage events related to any kind of uncertainty in the face of an increasingly

unstable markets. From this perspective, Kleindorfer (2005) suggests that effective risk mitigation can only be achieved through close collaboration between supply chain partners. Thus, risk management also translates into the resilience of the supply chain. The ability to adapt quickly to changes in the competitive environment is one of the main skills that an organization can develop to minimize the risks and impact of unmapped events.

2.3. SCOR

The SCOR model that was established in 1996 and is regularly updated to be used as a tool to align and adapt to changes. With the main objective of integrating techniques, metrics and best practices to ensure more effective communication of the various poles between suppliers, products and services offered to the end customer, the method seeks to improve the management of activities related to the improvement of the supply chain, implement systems that support members, and prepare the organization to better adapt to changes.

SCOR was developed to describe all business activities associated with customer demand service and can be used from the simplest to the most complex chains. The model is based on the six main management processes: Plan, Source, Make, Deliver, Return and Enable and can successfully be used to describe and provide a basis for chain improvement involving specific and global projects.

The model describes activities of an organization, i.e., focuses on the activity developed by the organization and not on the person or element responsible for the activity. In other words, it does not determine how the company should conduct its business. It is necessary that the company understand which business model is inserted and how to behave in its market of operation.

The SCOR structure consists of 4 main sections:

(a) Performance: For this section it is essential to define metrics to describe process performance.

(b) Processes: Description of the management processes used and the relationship between these processes.

(c) Practices: Management practices that produce significantly better process performance.

(d) People: Defining the skills needed to execute supply chain processes.

1609

2.4.   Classical Decomposition

Open model time series techniques analyze series identifying their components and creating a unique model that designs such components. A minimum of 48 periods of historical data is recommended. Classic decomposition is a method used for demand forecasts from time series in general made annually or monthly. According to Corrar and Theóphilo (2004) data from a time series may be influenced by some macroeconomic, technological factors, variations in nature and unpredictable phenomena. These and other factors determine the components of the time series that need to be decomposed.

(a) Cycle (C): represents the undulating motion or cycle of a time series. Consists in the oscillations or deviations around the trend line.

(b) Seasonality (S): Series fluctuation over a year. It refers to similar patterns that a series can offer and acts as a multiplier index. May be influenced by the weather or commemorative dates such as the sale of ice cream in summer.

(c) Residual fluctuations (U): It is the component that represents the random fluctuations of the series, which are hardly predicted.

The method consists of decomposing the sales series in the components mentioned. The first step is to evaluate the duration of the seasonal period. Then moving average of the seasonal pattern of *n* duration periods is calculated, according to the equation (1):

$$MMC_{12} = \frac{\sum_{k=t-6}^{t+5} R_k}{12} \tag{1}$$

This calculation purges the seasonal effect and most of the random variations, maintaining the cyclic trend and movement as in the equation (2).

$$MM = T * C \tag{2}$$

Thus, to identify the trend of a series it is necessary to determine the curve that best adjusts to the series of moving measures. Next, cyclic movements are calculated, expressing them as a trend percentage, through the equation (3):

$$C = \frac{MM}{T} \tag{3}$$

As the original series contains the trend, cycle, seasonality and residual fluctuations components and the series of moving averages contains trend and cyclical variations, we must divide the first by the second to have a series containing fluctuations and seasonal effects (4):

$$\frac{R}{MM} = \frac{(T * C * S * U)}{T * C} = S * U \tag{4}$$

Then the seasonal factors are calculated for each historical period. As random fluctuations are being considered, it is expected that the seasonal factor of a period will be different from the calculated factor of n periods ago. To work around this question, seasonal indices are calculated, i.e., the average seasonal factors of that period. The equation (5) presents the calculation of the seasonal factor:

$$IS_{m\hat{e}s} = \frac{\sum_{k=1}^{n}(F_{s\ m\hat{e}s\ k})}{n} \tag{5}$$

If the historical series is long enough, seasonal indices can be calculated from the adjusted average, that is, purging the largest and lowest seasonal factor of each month. By calculating seasonal indices, these can be used to measure unexplained variations (random or residual). The forecast is performed by individually projecting each of these components (trend, seasonality and cycle), and then combine projections. The trend (T) is the component that shows growth or decline over time and can be calculated through the equation (6):

$$T = (\alpha * p) + \beta \tag{6}$$

In equation (6), α is the slope of the centered moving average and β the. For the initial periods in which the moving average was not calculated, the first value of the calculated cycle is repeated. For the final periods, the last calculated value is repeated.

Seasonality (S) is the fluctuation of the series over the course of a year. It refers to similar patterns that a series can offer and acts as a multiplier index. It may be influenced by the weather or commemorative dates such as the sale of ice cream in summer. If the classical decomposition is calculated for an annual seasonality time series, seasonality will be the average seasonal indices of the same months of the year. Residual fluctuation (U) is the component that represents random fluctuations in the series. Classical decomposition can generate predictions through additive or multiplier models. For the additive model, the only change would be in the final of the calculated components. The prediction formula in the Classical Decomposition method - multiplicative and additive method, respectively represented by equations (8) and (9).

$$P = T * S * C \tag{8}$$

1611

$$P = T + S + C \tag{9}$$

2.5.   Moving Average

Time Series Techniques of Fixed Models stand out mainly because they are of simple implementation and do not require very large historical series. In this way, most of these techniques quickly adjust to changes in sales behavior and are thus appropriate for short- and medium-term forecasts. It is a commonly used method and has as main advantages the operational ease and smoothing of short fluctuations, since it considers the average of a certain number of periods. Its application is indicated only for series without trend and seasonality. The use of this method in time series with such behavior can lead to unsatisfactory results because it considers that the forecast for a later period involves the addition of new data and the disregard of the previous ones. For these cases, a better choice would be the Dual Moving Average method. The longer the calculation period of the simple moving average, the longer the time limit of the monitored trend, according to equation (10):

$$P_{(T+1)} = M_t = \frac{\left(R_t + (R_{(t-1)}) + (R_{(t-2)}) + \cdots + (R_{(t-n+1)})\right)}{n} \tag{10}$$

Where:

- $P_{(T+1)}$= Forecast for the next period.

- M_t= Forecast for the next period.

- R_t= Actual value observed in the period t.

- n = Number of periods considered in the moving average.

2.6.   Dual Moving Average

The Dual Moving Average method is one of the methods for predicting trended series. The calculation can be basically summarized in five steps:

(a) Calculation of simple moving average (equation (11)):

1612

(b) Calculation of moving average based on previously calculated moving average series

$$M_t = \frac{\left(R_t + (R_{(t-1)}) + (R_{(t-2)}) + \cdots + (R_{(t-n+1)})\right)}{n} \tag{11}$$

(equation (12)):

$$M_{t'} = \frac{\left(M_t + (M_{(t-1)}) + (M_{(t-2)}) + \cdots + (M_{(t-n+1)})\right)}{n} \tag{12}$$

(c) Add to the simple moving average and the difference between the two series of moving averages (α_t) according to the equation (13):

$$\alpha_t = M_t + (M_t - M'_t) \tag{13}$$

(d) To consider the trend, the additional adjustment factor (β_t), similar to an angular coefficient (equation (14)):

$$\beta_t = \frac{2}{n-1} * (M_t - M'_t) \tag{14}$$

(e) Finally, the forecast for future periods is calculated (equation (15)):

$$P_{(t+p)} = \alpha_t + \beta_t * p \tag{15}$$

Where:

- R_t= Actual value observed in period t.

- n= Number of periods considered in the moving average.

- p= Number of future periods to be forecast.

2.7.   Naive Method

The forecast for the period t is the amount sold in the period $t-1$ (equation (16)):

$$P_t = R_{(t-1)} \tag{16}$$

Where:

- P_t= Forecast for the period t.

1613

- $R_{(t-1)}$= Real value observed in the *t-1* period.

2.8. Exponential Moving Average

The weight of demand decreases in time in a geometric progression. In the case of the exponential moving average, a new forecast with bigger weight is generated at the most recent value, based on the previous forecast and from the calculation of an error, this error is corrected by an alpha coefficient (equation (17)):

$$M_t = M_{(t-1)} + \alpha\left(D_{(t-1)} - M_{(t-1)}\right) \tag{17}$$

Where:

- M_t= Forecast for the period t.

- $M_{(t-1)}$: Actual value observed in the *t-1* period.

- α= Weighting coefficient.

- $D_{(t-1)}$: Demand in the t-1 period.

2.9. Simple Exponential Smoothing

Simple exponential smoothing's main advantage is the fact that it is non-parametric (not associated with a given probability distribution). In exponential moving average all elements of the historical series have weighted importance differently: the elements closest to time *n* have greater weight, while the farthest ones have lower weight. On the other hand, as a negative point, simple exponential smoothing does not consider possible trends of growth, growth or seasonality. The forecast is given by the equation (18):

$$P_{(t+1)} = \alpha R_t + \left(\alpha_{(1-\alpha)} * \left(R_{t-1)}\right)\right) + \left(\alpha_{(1-\alpha)^2} * \left(R_{(t-2)}\right)\right) + \cdots \tag{18}$$

Being equivalent to the equation (19):

$$P_{(t+1)} = \alpha R_t + (1 - \alpha)P_t \tag{19}$$

- $P_{(T+1)}$ = Forecast for the next period.

1614

- α = smoothing coefficient ($0 \leq \alpha \leq 1$)

- R_t = Actual value observed in the period t and.

- P_t = Forecast for period t.

2.10. Double Exponential Smoothing (DES) - Brown Method

These models stand out mainly because they are of simple implementation and use and do not require very large historical series. Therefore, most of these techniques quickly adjust to changes in sales behavior and are thus, appropriate for short- and medium-term forecasts. When using DES, it is necessary to pay attention to the initial values A_0 and A'_0 (first and second smoothing). The use of the first observation for these values implies underestimating the existing trend in a series and therefore they should be calculated according to equations (20) and (21):

$$A_0 = \alpha_0 - \frac{1 - \alpha}{\alpha} * \beta_0 \tag{20}$$

$$A'_0 = \alpha_0 - \frac{2(1 - \alpha)}{\alpha} * \beta_0 \tag{21}$$

Where:

- α_0 = Linear regression coefficient of series values.

- β_0: = Angular coefficient of regression of series values.

2.11. Double Exponential smoothing - Holt Method

Holt's model is widely used for forecast when the series presents randomness and a linear trend of growth but does not present seasonality. In addition, it can be used when the components of the series can be scorned. As it has a gradual and long-term trend, the ideal is to assume that the behavior between demand and time is linear. A is the linear coefficient, which will be the initial estimate of the mean, and β is the angular coefficient, specific to adjust the trend estimate. The prediction in the application of the Holt method is in the selection of these two coefficients.

In this method, three equations are used:

1615

- Level: Equation that results from the addition of the term related to trend estimation to the formulation of Simple Exponential smoothing (equation (22)).

$$N_t = \alpha * R_t + (1 - \alpha) * (N_{t-1} + T_{t-1}) \tag{22}$$

- Trend: Equation used to adjust the trend estimate by pondering the previous and the most recent from the β coefficient (equation (23)) coefficient of regression of series values.

$$T_t = \beta * (N_t - (N_t - 1)) + (1 - \beta) * T_{t-1} \tag{23}$$

Prediction: Equation that results in forecast for *p* periods (equation (24)):

$$P_t + p = N_t + pT_t \tag{24}$$

Where:

- N_t= Component level;

- T_t= Trend component.

- α = Smoothing coefficient ($0 \leq \alpha \leq 1$).

- β = smoothing coefficient for trend estimation ($0 \leq \beta \leq 1$).

- R_t= Real value observed in period t.

- p = Number of future periods to be foreseen and.

- $P_{(t+p)}$= Forecast for the period *t + p*.

2.12. Triple Exponential Smoothing (TES) - Winter Method

Triple Exponential smoothing is usually used when the time series has level, trend and seasonality components. At first, the correct thing is to take the seasonality of the series and calculate the level and trend to obtain demand-based factors after extracting seasonality.

1616

In the TES method there are three equations – level N component, seasonal component S_t and T trend component – and in addition we have three smoothing coefficients for seasonality estimation – α, β, and all vary between 0 and 1. Below, below, below seasonal adjustment equation for each period (equation (25)):

$$S_t = \gamma \left(\frac{R_t}{N_t} \right) + (1 - \gamma) * S_t - c \tag{25}$$

In the equation, the term (R_t/N_t) represents the seasonal adjustment for each period t. The term $S_t - c$ refers to the seasonal adjustment calculated c periods ago. Therefore, $c = 12$ is considered. The coefficient is used to weigh the two plots. Equation for calculating trend component T, is given by equation (26):

$$T_t = B * \left(N_t - (N_{t-1}) \right) + (1 - \beta) * T_{t-1} \tag{26}$$

The level is calculated, considering the seasonal adjustment, through the equation (27):

$$N_t = \alpha * \left(\frac{R_t}{S_t - c} \right) + (1 - \alpha) * ((N_{t-1}) + (T_{t-1})) \tag{27}$$

The forecast is found through the equation (28):

$$P_{(t+p)} = (N_t + pT_t) * (S_{t-c+p}) \tag{28}$$

- S_t = Seasonal component.

- N_t = Component level;

- T_t = Trend component.

- α = smoothing coefficient ($0 \leq \alpha \leq 1$).

- β = smoothing coefficient for trend estimation ($0 \leq \beta \leq 1$).

- R_t = Actual value observed in period t.

- p = Number of future periods to be foreseen and.

1617

- $P_{(t+p)}$ = Forecast for the period $t + p$ and.

- Ɣ = smoothing coefficient for estimating seasonality ($0 \leq Ɣ \leq 1$).

As in the Holt Method, the selection of smoothing coefficients is essential to obtain a satisfactory degree of accuracy. The prediction through the exponential model presents better trend and seasonality results when compared to the classic decomposition model that uses simple moving averages.

3. METHODOLOGY

The data used in the present study were provided by employees in the Supply Chain department of a French multinational company based in Brazil. The company shared data about the demand and sales information and explained which forecast methods are used.   After collecting sales data from the products covered at this paper, analyses are performed from the application of time series techniques for demand forecasting, both from the fixed model and the open model. All analysis will follow the premise of adopting the model with the lowest MAPE – Mean Absolute Percentage Error – which means the average percentage of the error estimated in the forecast.

The scope of this paper involves the processes of demand forecasting of a multinational company in the cosmetics field, taking into account the fluctuations in market demand, high competition due to low barriers of entry and strategy of production of large quantities of inventory so that the product is always distributed and available. Although the company operates in several countries, the study centralizes its analysis in the forecast model used in the subsidiary installed in Brazil, with national management and production and focuses on the political, economic and social scenario of the country considering the risks of production and supply chain throughout the process.

4. CASE STUDY

The organization studied is a multinational present in 130 countries and in 2018 was considered the third most valuable French brand. However, despite the expertise gained after years of experience in the beauty sector, the company needs to have a detailed planning of the strategies and forms of action in the different markets it operates, each with its specificity and consumption profile. The economic crisis culminated in the closure of the Rio de Janeiro plant. This fact indicates that despite high investment and planning, there are points that can be

1618

improved. One of the reasons raised, in addition to the high cost to maintain the factory, was the idle capacity of employees, a factor that should be more analyzed mainly when there are situations of rupture of some items sold by the company.

The current sales forecast of the analyzed company is made through "future master", a tool that consolidates information on production capacity and availability of supplies aligned with the demand and supply of factories. The method used in the software is Double Exponential smoothing and MAPE is the error indicator used. Nowadays, the MAPE obtained by the company is about 32%. The equation (29) is used for calculating MAPE. The calculation of the percentage errors set out below reflects the difference in absolute values between the actual value demanded in a period *t* and the estimated value for this same period.

$$EMP_t = \frac{R_t - P_t}{R_t} \tag{29}$$

$$MAPEp = \frac{\sum_1^n EPM}{p} \tag{30}$$

5. ANALYSIS OF RESULTS AND DISCUSSION

Two datasets were collected for analysis and testing of prediction methods, both from January 2013 to December 2018. The first dataset contains the sales of a one-brand item: Shampoo 200ml of the ABC xyz brand franchise. In a second moment, sales data of all Shampoos in the 200ml format of the xyz brand were collected, that is, involving all franchises and resulting in about 35 products.

For the calculation of both data series, techniques of open model time series - Classic Decomposition with some variations in calculation - and fixed model - Simple Moving Average (SMA) of two to ten periods were used to calculate the least error, Double Moving Average (DMA) of nine and ten periods (periods with the lowest mms error), Naive Method, Simple Exponential Smoothing (SES), Double Exponential smoothing (DES) applying the Brown and Holt methods and Triple Exponential Smoothing (TES) by applying the Winter method. Figure 1 and Figure 2 represent the comparison between the forecasting methods for a specific shampoo item 200 ml for the ABC franchise and for franchises of all 200 ml shampoos, respectively:

1619

Table 1: Methods comparison summary for ABC 200 ml shampoo

MOVING AVERAGE		DOUBLE MOVING AVERAGE		SIMPLE EXPONENTIAL SMOOTHING	
MMS	MAPE	MMD	MAPE		MAPE
MM2	27.80%	MMD9	24.94%	SES	24.17%
MM3	25.47%	MMD10	23.17%		
MM4	24.77%			DOUBLE EXPONENTIAL SMOOTHING - BROWN	
MM5	25.55%	NAIVE			MAPE
MM6	25.33%	MMD	MAPE	DES BROWN	21.24%
MM7	24.99%	MMD9	30.60%		
MM8	25.30%			DOUBLE EXPONENTIAL SMOOTHING - HOLT	
MM9	24.43%				MAPE
MM10	24.34%			DES HOLT	20.13%
				TRIPLE EXPONENTIAL SMOOTHING - WINTER	
					MAPE
CLASSICAL DECOMPOSITION	MAPE			TES WINTER	19.46%
T x C x S	16.14%				

Table 2: Methods comparison summary of the 200 ml shampoo family

MOVING AVERAGE		DOUBLE MOVING AVERAGE		SIMPLE EXPONENTIAL SMOOTHING	
MMS	MAPE	MMD	MAPE		MAPE
MM2	25.32%	MMD9	23.83%	SES	21.94%
MM3	21.01%	MMD10	90.35%		
MM4	22.37%			DOUBLE EXPONENTIAL SMOOTHING - BROWN	
MM5	23.26%	NAIVE			MAPE
MM6	23.15%	MMD	MAPE	DES BROWN	21.24%
MM7	23.51%	MMD9	28.37%		
MM8	24.27%			DOUBLE EXPONENTIAL SMOOTHING - HOLT	
MM9	24.09%				MAPE
MM10	24.67%			DES HOLT	20.13%
				TRIPLE EXPONENTIAL SMOOTHING - WINTER	
					MAPE
CLASSICAL DECOMPOSITION	MAPE			TES WINTER	19.46%
T x C x S	13.79%				

After the application and analysis of the methods and their variations it is perceived that there are several variables that can determine the service of a company and influence its positioning in the market. The level of service, for example, is a decision that directly influences the customer's perception because it is the measurement of processes according to the expectation and quality.

Making decisions to increase the level of service means better service to customers, receiving the products in the requested period, making on-time deliveries, producing quality products and having a good after-sales service. Reviewing methods to improve the level of service should be a constant study for high-sized companies to mitigate risks and position themselves better versus their market competitors.

Reducing the percentage of forecast error means better alignment with market demands, leveraging resources and labor more efficiently and making the company more prepared to react to external factors. A low level of service enables it to increase but remain at a level that

1620

ensures the minimum level of service required by consumers. It is necessary to seek the balance between these two indicators.

In the highly competitive beauty market and with the consumer's buying profile with low loyalty, delaying the delivery of a family of shampoos for example in a shopkeeper means that the customer will buy from the competition to keep the shelves stocked. This fact presents several negative factors for the company such as loss of space of its products on the shelves, decreased market share in the customer, the public accustomed to buying in that retail environment migrates to substitute products from others brands, in addition there can be damage to the company's commercial reputation with the shopkeeper.

Studies and investment to better empower teams can bring not only long-term financial gains, but also operational for the company in question and to the Supply Chain area. With a routine analysis of the forecast methods every two years, comparing the company's strategy with market reality, it is possible to serve internal and external customers with a higher level of service and reduce the average percentage error of calculation. It is extremely important to keep a constant study of identification and mitigation of risk variables always reviewed and updated. Identifying the balance between the level of service and inventory management is one of the biggest challenges that organizations face in demand management. After all, the interpretation of the inventory level says a lot about the demand forecasting process: Inventory surplus raises the financial costs and the lack of inventory translates into loss of sales. In both, there is the opportunity cost behind the misguided demand planning.

6. CONCLUSION

The main objective of this paper was to identify the current demand forecasting method in the company analyzed and to evaluate the importance of generating improvements to the existing process. Thus, other methods were analyzed that could return smaller statistical errors. From the entire theoretical framework studied, we observed quantitative methods of demand management and apply them on top of the demand history of different product franchises of the mentioned company. Quantitative models offer projected values in statistical calculations, thus providing a better dimension of the expected margin of error and, therefore, a greater accuracy in the information.

In the case of qualitative models, the margin of error, as well as the forecast itself, is based on subjective criteria, thus being able to influence from the subjectivity of those who are analyzing the data. Therefore, the use of qualitative-only models may not be the best choice,

1621

and the influence of quantitative easing scans is fundamental to bring unbiased results. Analyzing the case study in the company's data in the cosmetics field, it was clear the need to review methods used every two years mainly when it comes to a very competitive market such as beauty and in a country like Brazil , with its cultural, political and environmental complexities.

Looking for ways to find the lowest percentage error of calculation for the forecast, linked with a higher level of service for consumers and a study to minimize the costs of the company is an objective that all teams should keep in mind and, with the present study , it was clear the importance of having a team completely aligned with the management of the supply chain and use of resources, since even a company with 110 years of experience in the market and presence in 130 countries, presents opportunities for improvement in the effectiveness of its processes.

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1623