Time series to improve sales planning in a supply chain. Case study.

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Abstract

The aim of this work is to provide better sales forecasting in the context of a supply chain, by using S&OP model and integrating the time series. We have supposed that difficulties encountered by partners in the forecasts come on one hand from the adaptation of existing statistical models and the other hand from the absence of collaboration and information sharing between partners. Our approach consist in a first step to present the role of forecasts in the relationship between supply chain partner's and in a second step to recast the process of forecasting relying on a collaborative approach and to develop a scientific model for a monthly sales forecasting.

Keywords
Statistical model, Collaborative approach, Forecasting process, Supply chain.

Introduction

Sales forecasts have a significant impact on the effectiveness of a supply chain, they even have an influence on firms whose final product is "made on request" (Yelland, 2006).
Therefore, we proceed, first, with the presentation of the forecasts status in a supply chain, specifically at the level of the relationship between partners, to show their interest as well as all the problems plaguing these forecasts. We have assumed that the difficulties encountered by the partners in forecasting stem from the adoption of existing statistical models and the lack of collaboration and information sharing between partners. Second, and to verify this hypothesis, we have established a forecasting processes diagnosis at the level of a beverage company. Thus, it have been proved necessary, on one hand, to retake the process of forecasts establishing and make it evolve towards greater collaboration and agility by using a collaborative method such as the "Sales and operations planning" and on other hand to establish a good visibility on the future demand by the development of a statistical model of forecast sales. A reliability and analysis of the data history was essential to detect the adequate forecasting method. The nature of the data guided the choice to the Decomposing in time series method. After establishing the forecasting model, an analysis of its effectiveness was necessary. So, we tested its results on the learning data with which it was constructed and we introduced indicators that give an idea on the accuracy of forecasts

1. Forecasts at the supply chain level

1.1. Role and difficulty of establishing forecasts in the supply chain

The Supply Chain is a set of companies connected by customer-supplier relationships. (Chopra and Meindl, 2007) defined the supply chain as all the parties involved in executing a customer order. Each agent in the chain concerned must make decisions regarding the product to be purchased, the time of purchase and quantities to be purchased using the request of its respective customers. These decisions cannot be made without forecasting. Therefore, the obligation to foresee is linked to the response time, so a large majority of companies have delivery times of a few days or even hours (pharmaceutical distributor); the storage of finished products is then imperative on pain of being in rupture. To optimize the stock level, the obligation to forecast demand is required.

Certainly forecasting is of great importance, but mishandling these forecasts can lead to catastrophic results. It is worth noting that at the supply chain stage, biased forecasts can engender a bullwhip effect. Indeed, if the demand forecasts made at the first links level are incorrect, all the forecasts based on these data will only increase the variability and further distort the anticipated demand of each chain agent. The increased variance demand perceived by the higher echelons has several negative consequences, including reduced service levels, important fluctuations in utilization rates, the need for a large stock and production capacity to ensure better safety and security (Gilbert, 2005). The impacts of the bullwhip effect are not limited to the production and warehousing functions, as (Haughton, 2009) points out; it increases the costs of transport providers, leading to operational instability.

This brings us to the difficulties of realizing these forecasts. Traditionally, forecasting is entrusted to the field man given his perpetual contact with the product and buyers. However, the latter may be confused between what he expects from the evolution of the market and what he thinks he can do with the customers. Also, there is a strong tendency to "marginal" forecasting. Thus, for example, it is sufficient for the last customer, who have been met before issuing the forecast, to place an important order, so that the forecast for the next 3 or 6 months becomes very optimistic and vice versa. Often when excessive discrepancies appear on the "forecasts", the company uses fully opposed profiles: forecasting becomes the business of statisticians. We then see the development of what we can call familiarly "the math's method": Sales become an abstract sequence of numbers, to which it is important to adjust the best model. Remoteness from any concrete reference leads to methodological self-satisfaction: the modeling concern will rapidly overflow and temporarily dominate that of forecasting. Most often, the logistics function is in charge of forecasting; and yet, logistics men are not the best placed given their isolation from the market.

Between these pitfalls, what to do? Ideally, the preparation of the forecast should be carried out jointly within a committee bringing together all the functions mentioned above.

1.2. Literature on Supply Chain Collaboration

Several research papers have highlighted collaboration at the supply chain level (Cao et Zhang, 2011; Nyaga et al, 2010; Ramanathan et al, 2011). They identified seven dimensions of collaboration: Information sharing, Efforts convergence; Decision synchronization; Incentives alignment; Resources sharing; Communication and common knowledge creation. (Nyaga et al., 2010) have shown that the sharing of information and collaborative efforts and joint investment lead to the establishment of trust between the chain elements. Many supply chain management practices have been proposed in the literature to improve this collaboration. Among these practices we find: Vendor Managed Inventory (VMI) which is defined as a concept for planning and control of inventory based on the fact that the vendor (or supplier) has access to the buyer's (or retailer's) demand data and is responsible for maintaining the appropriate inventory level and determining replenishment policies (Hana and al, 2007; Govindan, 2013; Marquès et al, 2010); Efficient Consumer Response (ECR) that is a partnership approach between industry and commerce aiming, through the real-time knowledge of sales at the point of consumption, to jointly manage supplies, promotions and new products (Reyes et al, 2004); Collaborative planning, forecasting and replenishment (CPFR) which is an initiative among all participants in the supply chain intended to improve the relationship among them through jointly managed planning processes and shared information (Seifert,2003; Hill et al, 2017) and Continuous Replenishment that is a technique based on automatic exchange of information relating to orders and inventory movements between the supplier and the distributor or retailer (Yao and Dresner, 2008). Some common benefits of supply chain collaboration are cost savings, inventory reduction, timely replenishment, and forecast accuracy (Barratt, 2004; Aviv, 2007).

Recall that, in this article we are interested in sales forecasting in a logistics chain and that we have evoked the forecasts in a Supply Chain to highlight their effects on the latter and emphasize the importance of collaboration for their establishment. This importance explains the existence of a variety of methods that help to achieve this collaboration. The method of collaboration chosen in our case is Sales and Operations Planning method, which allows us to maintain a good balance between supply and demand.

2. Collaborative and statistical approaches to forecast sales

2.1. Collaborative approach based on the Sales and Operation Planning method

Effective supply and demand management requires strong inter-functional leadership coupled with effective collaboration between leaders, managers and professionals in a company. Sales and Operations Planning (S&OP) meets these needs by bringing key people together with the right information for judicious decision-making on a monthly basis. Different definitions place the S&OP at different levels of the business plans hierarchy. For example, APICS (American Production and Inventory Control Society) defines S&OP as « a process in which all the company's business plans (customers, sales, marketing, development, manufacturing,

procurement and finance) are integrated into a general plan. The process must reconcile supply, demand, new product plans and link them to the business plan. It is an affirmation of the company's short- and medium-term objectives to cover a sufficient horizon for the support of annual planning. When properly executed, Sales and Operations Planning links the company's strategic plan with the execution and revision of performance measures for continuous improvement. It provides managers with the tools to strategically lead the company in order to achieve a competitive advantage on an ongoing basis by integrating customer-oriented marketing plans with integrated supply chain management» (Cox and Blackstone, 2002).
Sales and Operations Planning is therefore a monthly review process focused on changes and improvement from the previous month's results. Each meeting allows the management team to understand how the company has reached the current level of performance but above all to decide on future actions and anticipated/desired results and finally to reach a consensus between various functions on the actions to undertake, considering the situation of the present and future market potential opportunities, constraints and direction of the company. The five monthly order steps that constitute the S&OP are: i) Acquire; Analyze and organize data; ii) Demand Planning; iii) Resource Planning; iv) Balancing demand with resources; v) Decision making by direction.

2.2. Statistical approach to sales forecasts

Forecasting methods are differentiated into two groups of methods: qualitative and quantitative methods (Lee, Song and Mjelde, 2008).
Qualitative methods are essentially based on opinion, comparison and judgment. These methods are useful in the absence of historical data or when the data are insufficient or fail to correctly predict the future. Several methods are available: Opinion polling method (Meynaud et Duclos, 2007), Comparison method (Dortmans et Eiffe, 2004), Delphi method (Okoli and Pawlowski , 2004), and Market research.
Quantitative methods rely on the extrapolation of demand over time, using past consumption data. Quantitative methods can be divided into two groups: *causal methods* based on the identification of factors explaining variations in demand and the development of statistical models describing the links between demand and these factors such as the regression and correlation method (Foucart, 2006), simple linear regression method (Thoresen and Laake, 2007) and multiple linear regression method (Choubin et al , 2016) and Time series extrapolation methods that attempt to predict the future value of a variable based solely on the observed values of that same variable, such as moving averages method (Ramirez, Rodriguez and Echeverr, 2005), exponential smoothing method (Everette and Gardner, 2006) and Time series decomposition method (Theodosiou, 2011).
The main disadvantage of qualitative methods is that they give rise to many perceptual biases. We notice as well, that most individuals tend to produce different forecasts when they are repeatedly confronted with the same data. As for the quantitative methods, they have several advantages which explain their popularity. First, they require little information. It is enough to have historical data on the demand. Then, several quantitative methods are easy to understand and use.
The exploratory analysis of graphical representation of the historical data makes it possible to orient the choice of an appropriate forecasting model among the quantitative methods. For example, if strong correlations are observed between demands and other readily observable variables, causal methods may be preferred since they can benefit from this information. Moreover, the identification of a trend or seasonality will suggest the use of a model that can take account of these aspects, namely the method of decomposition in chronological series.
Forecasting models based on extrapolative methods, including the decomposition method, rely on historical data to draw conclusions about the future; therefore, they are always subject to estimation error given the techniques they use. Besides, the study of the forecast's accuracy has always been paramount in the fields of financial, economic and scientific modeling and has motivated the development of a vast literature corpus on the elaboration and empirical application of forecasting models (De Gooijer and Hyndman , 2006). Thus an analysis of the effectiveness of the model is needed.

3. Implementation of both approaches in a beverage company

3.1. Improved sales forecasting process using the S & OP collaborative method

Before revealing the dysfunction in the forecasting process and proposing optimization solutions, obtaining a detailed picture of the correlated or interactive activities that transform the input elements into output elements is necessary. Several methods exist to carry out the mission of identification and description, among others, the method Mapping Process is the most pragmatic and palpable.
Recall that the aim is not the modeling of all business processes but a tactical mapping in order to analyze and detect dysfunctions at the level of the forecasts sales planning. The method is based on four steps:

• *Step 1:* Process characterization. This is done by answering the following questions: What is the generating event? (Events that are at the origin of the process); For what purpose? (Final event of the process), and what is the field of study? (Input / output, related processes, requirements).
• *Step 2:* Phase identification (Title of each identified phase (macroscopic cut)) and Actors (Designation of the actor (function), team or department), which gives rise to a clear view of the responsibility of each actor in the sales forecast planning process.
• *Step 3:* Development of the phase sequence diagram using the flowchart which allows to visualize the progress of a process or a segment of processes and to explain it, while conducting a reflection on the whole of these steps. (See Annex)
By analyzing the steps in the flowchart, the criticisms that we have been able to address to the forecasting process are as follows:
• The final forecasts obtained are transmitted to the planning departments at the beginning of each year n. They are monthly and valid for 12 months and are rarely updated, whereas normally the forecasts must be updated monthly.
• The lack of synergy between the various departments, some of which do not play the role assigned to them.
• Forecasting does not follow a rational approach, since it starts from an objective targeted by the group and not from sales.
• Forecasts developed by the sales administrator must trace the real need of finished product and give a fairly clear idea of the strong sales seasonality. The increase in sales in year n-1 by a percentage, whatever it is, does not allow it, since sales cannot be always and constantly on the rise.
Our analysis revealed that implementing a reform in the current sales forecasting process, through a mechanism of collaboration and information exchange to manage organizational conflict and cover data gaps and information that leads to biased predictions, is the most effective way to overcome the unreliability of forecasts (Oliva and Watson, 2009).
In this way, we have reviewed the current process, using Sales and Operation Planning, which, through monthly and executive meetings, provides a balance between sales objectives and marketing plan, financial and internal capacities of the company in order to draw up a unique and feasible plan. The purpose of the S&OP process is ultimately to help reach a consensus in order to allocate critical resources to achieve the objectives.

3.2. Scientific Forecast Model

Before starting the study, it is necessary to process, modify the raw data. For example: evaluation of missing data, replacement of accidental data, sub-series division, standardization in order to arrive at fixed length intervals and finally data transformation.
In order to establish a model choice, we used the exploratory analysis of the graphical representation of historical data (see figure 1).
This graph shows that the high season which runs from May to September and coincides with the period of the high heat, records double sometimes the triple of the quantities sold during the low season which highlights the existence of seasonality. The presence of seasonality implies the use of a model that can take account of this aspect, namely the method of decomposition in chronological series.

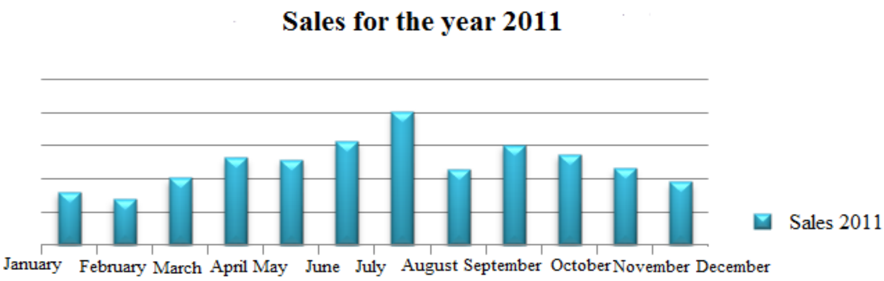


Figure 1. Sales trends for the year 2011

The steps for calculating forecasts using the time series decomposition method are:
- <u>*Step 1: Determination of the seasonal factor.*</u>

The seasonal factors are representative of deviations from the periodicity average, here in relation to the annual average. We therefore calculated for each period (set on the month in our case) the moving centered annual average.
• *Calculation of the Centered Moving Average*:
It is necessary to calculate at time t an average of the variable values studied over a period, x_i: sales of the month i. It is mobile because it is calculated for each time t of the history. For a period of 12 months, the moving average MMC input calculated on the basis of the following formula:

$$\boldsymbol{MMC = \frac{(\sum_{n-11}^{n+11} x_i + 0{,}5 * (x_{(n+12)} + x_{(n-12)}))}{12}}$$

• *Calculation of the ration (multiplicative model) or the difference (additive model) of the variable observed at the center moving average:*

We calculated the relationships between series values and the corresponding centered averages for the multiplicative model and their difference in the case of the additive model. The calculation of the average ratios for the multiplicative model is the sum of the ratios of a given period (for example, every January month) divided by the number of occurrences.

• *Adjusted S value:*

For the multiplicative model, the sum of the ratios must be equal to the number of periods constituting the periodicity (12 if the periodicity is annual). We have thus multiplied the ratio by the number of periods and divided it by the sum of the ratios to arrive at normalization where the total conforms. As for the additive model, the sum of the ratios must be zero. So we normalized by calculating the average of the differences and subtracting it from the raw differences.

The seasonal coefficients are the standardized ratios (or differences).

STEP 2: Determine the value of the trend and the equation underlying it.

Before determining the trend, we were asked to calculate the seasonally adjusted series, that is, sales excluding seasonal variations. Thus, we divided real sales by the corresponding seasonal ratio in the case of the multiplicative model and subtracted the differences for the additive model.

• Trend:

First, we have specified the type of trend T that best applies to the data (linear, quadratic, etc.), and then we determine the additive and multiplicative trend by regression on the corresponding seasonally adjusted series. We chose the method of least squares such as:

$$a = \frac{\sum x_i y_i - n\overline{X}\overline{Y}}{\sqrt{\sum x_i^2 - n\overline{X}^2}} = \frac{\mathrm{cov}(x, y)}{\mathrm{var}(x)}$$ And $$\overline{y} = a\overline{x} + b \qquad b = \overline{y} - a\overline{x}$$ with $$T = a*t + b$$

Where $\mathbf{y_i}$ seasonally adjusted sales (multiplicative or additive) of the month i, **b** is called the constant (ordered at the origin), **a**: the trend coefficient (slope of the regression line whose coefficient is R2), while **t** is simply the period chosen.

STEP 3: Forecasting (P) for the selected period

Before proceeding to predictions, it was first necessary to validate the model and choose between additive and multiplicative method. We thus classically began by applying the model to the past. In a first step, we calculated the trend and then we seasonally adjusted the series obtained. In the case of the multiplicative model, we multiplied the values of the trend by the corresponding seasonal coefficient. For the additive model, we added the seasonal difference.

Forecast models, based on extrapolative methods such as the decomposition method, are based on historical data in order to draw conclusions about the future, so they involve estimation errors because of the techniques used. The best way to validate a forecasting method is by applying it to the past.

Let $\mathbf{y_t}$ be the value taken by a variable (in our case sales) on the date t (t = 1,..., T), ŷ the forecast that has been made of it and $\mathbf{e_t}$ the forecast error. The error: $\mathbf{e_t} = \hat{y} - y_t$ is simply the difference between reality and the value calculated by the model, the absolute error $\mathbf{e_t} = |\hat{y} - y_t|$ gives an idea of the quality of the forecast regardless of the error type, and Mean Absolute Error (MAE) MAE $= 1/T \sum |\mathbf{e_t}|$ allows not to widen the gap in contrast to other indicators such as MSE (Hyndman and Koehler, 2006) and (Armstrong, 2001). Also, one of the interests of this indicator is that for T, if the error is normally distributed, we can estimate the standard deviation of the error σ_e:

$$\sigma_e = \sqrt{\frac{\pi}{2\mathrm{MAE}}} \approx 1{,}25\ \mathrm{MAE}\,.$$

Other indicators are used: Predictive accuracy = ((Σ ŷ per article - Σ $\boldsymbol{e_t}$ per article) / Σ ŷ per article) which gives an idea of the forecasts accuracy, working on a moving year, and comparing sales versus forecasts. As well as the drift signal on a moving history of 1 year: Drift signal = Σ $\boldsymbol{e_t}$ / mean| $\boldsymbol{e_t}$ | which reveals where the forecast is biased. Its value must be between -4 and +4.

4. Results and analysis:

4.1. New forecasting process

The reformulated process includes a series of steps in which each department updates and communicates its plan to other departments (see figure 2). A review and coordination meeting between departments is held monthly to approve these plans.

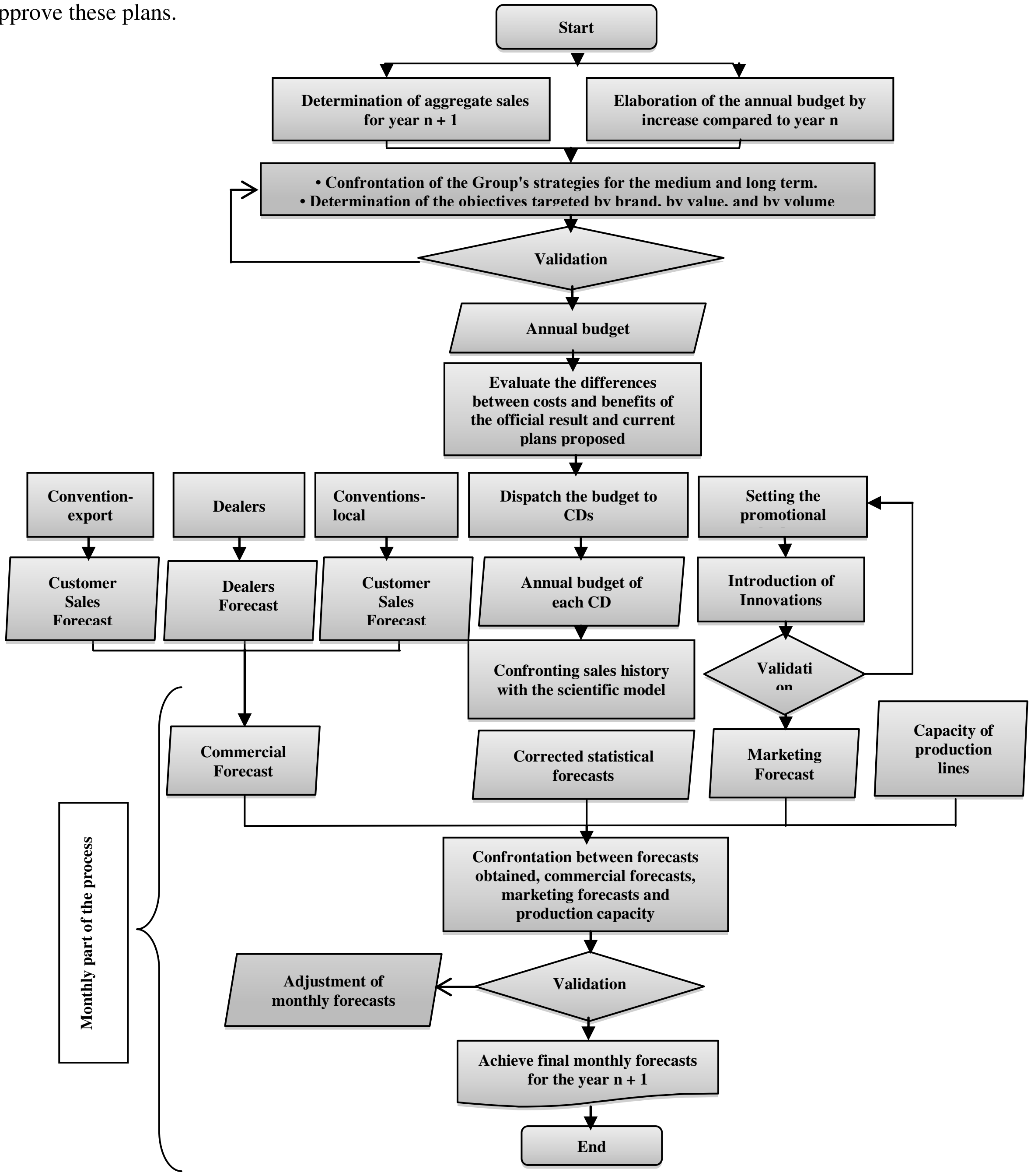


Figure 2. Forecasting process improved by the Sales and Operation Planning method

4.2. Static prediction model:

After making sales history more reliable, we have grouped all of the forecast calculation steps using the time sales series decomposition method in an Excel spreadsheet (see figure 3).

cov(t,y)	-168049,032	-158410,9891
var(t)		50
mean(t)		12,5
mean(y)	308013,1975	306515,3333
b	350025,4555	3461,0806
a	-3360,98064	-3168,219783

Sum	391388,349	426072,0424
MSE		
MAE	16307,84787	17753,00177
Standard deviation	142,7753825	148,9672857

Sum	Sum	Sum	Sum	Moyenne	Sum
12,08394828	45795,58333	12,08394828	12	3816,298611	0

Month	Period	Sales	MM centered	Ratio	Differences	Average ratio	Normalized Ratio	Average differences	Differences Normalized	Seasonally adjusted sales (multi)	seasonally adjusted sales (additi)	Trend (multi)	Trend (addit)	Forecast (multi)	Forecast (additi)	Absolute error (multi)	Absolute error (addi)
1	1	221771				0,647994448	0,643492772	-108036	-111852	344636	333623	346664	342950	223076	231098	1305	9327
2	2	178057				0,532670277	0,52896769	-138660	-142476	336611	320533	343303	339782	181597	197305	3540	19248
3	3	262088				0,741007573	0,741007573	-75307	-79123	356166	341211	339943	336613	250150	257490	11938	4598
4	4	338921				1,04030831	1,033081194	11785	7969	328068	330952	336582	333445	347716	341414	8795	2493
5	5	362283				1,071748197	1,064302665	20898	17082	340395	345201	333221	330277	354648	347359	7635	14924
6	6	390246				1,251761435	1,243065335	72166	68350	313938	321896	329860	327109	410037	395459	19791	5213
7	7	523002	327364	1,5976181	195638,4167	1,597618143	1,586519345	195638	191822	329654	331180	326499	323941	517996	515763	5006	7239
8	8	568335	325576	1,1313333	42759	1,13133391	1,123473915	42759	38943	327854	329392	323138	320772	363037	359317	5298	8620
9	9	392141	322800	1,21481291	69341,5	1,21481291	1,206373495	69342	65525	325058	326616	319777	317604	385770	383129	6371	9012
10	10	330146	319409	1,03366166	69341,5	1,033616691	1,026373495	10737	6921	321643	323225	316416	314436	324780	321357	5366	8789
11	11	351295	315872	1,11214235	10737,45833	1,112142353	1,10441662	35423	31606	318082	319689	313055	311268	345743	342874	5552	8421
12	12	221524	312475	0,70893455	35422,66667	0,708934555	0,704009522	-90951	-94767	314661	316291	309694	308099	345743	213333	3497	8191
1	13	198879	306915	0,6479944	-90950,5417					309062	310731	306333	304931	218027	193079	1756	5800
2	14	158047	296707	0,53267027	-1080035,667					298783	300523	302972	301763	197123	159287	2216	1240
3	15	215462	290769	0,7410075	-138660					292803	294585	299611	298595	160263	219472	5009	4010
4	16	304164	292379	1,04030831	-75306,9538					294424	296195	296250	295427	220471	303396	1886	768
5	17	312171	291273	1,0717481	11785,29167					293310	295089	292889	292258	306050	309340	449	2831
6	18	358811	286645	1,251761	72166,125					288650	290461	289528	289528	311722	357440	1091	1371
7	19	421000								265361	229178	286167	285922	359902	477744	33009	56744
8	20	225353								200586	186410	282806	282754	454009	321696	92372	96343
9	21	392610								325446	327085	279445	279585	317725	345111	55495	47499
10	22	368311								358825	361390	276084	276417	283382	283338	84929	84973
11	23	286586								259491	254980	272723	273249	301200	304855	14614	18269
12	24	175165								248811	269932	269362	270081	189633	175314	14468	149
1	25											266001	266913	171170	155061		
2	26											262640	263744	138929	121268		
3	27											259279	260576	190793	181453		
4	28											255918	257408	264384	265377		
5	29											252557	254240	268797	271322		
6	30											249196	251071	309767	319421		
7	31											245835	247903	390022	439725		
8	32											242474	244735	272413	283678		
9	33											239113	241567	288460	307092		
10	34											235752	238399	241984	245320		
11	35											232391	235230	256657	266837		
12	36											229030	232062	161239	137295		

Figure 3. Forecast calculation steps

To determine the seasonal coefficients, we first calculated for each period, the annual centered average. This average was used to calculate the ratio (case of the multiplicative model) and the difference (case of the additive model) to the observed variable. Once calculated, we proceeded by normalization in order to obtain adjusted seasonal coefficients which will later undergo a regression (by the least square method) to have the additive and multiplicative tendency. Finally, the forecasts are obtained by multiplying the trend by the seasonal coefficient, in the case of the multiplicative model, and by adding the seasonal difference, in the case of the additive model.
The model provides sales for year n + 1 from a sales history of years n and n-1. The choice between the multiplicative or additive model is done automatically by the model based on the standard deviation between forecast sales and actual sales.
We made the forecasts assuming that the trend will follow the same evolution, and that the seasonal variations will be the same. We thus obtain an estimation of the sales evolution that the figure 4 illustrates.

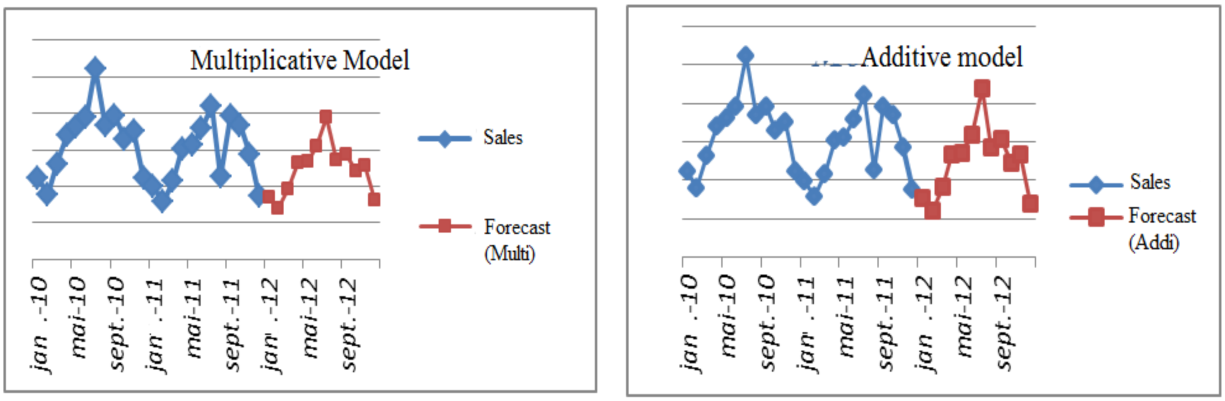


Figure 4. Evolution forecast-sales for an item X by the additive and multiplicative model

A decomposition is correct (good choice of trend, good choice of model, correct estimation of each component) when the adjusted series is "close" to the mother series.
To judge the effectiveness of the model, we have tested the results on learning data (the past data) with which it was constructed. The final graphs (see figure below) show that past sales coincide with forecasts over past periods, hence the validity of the model on past data.

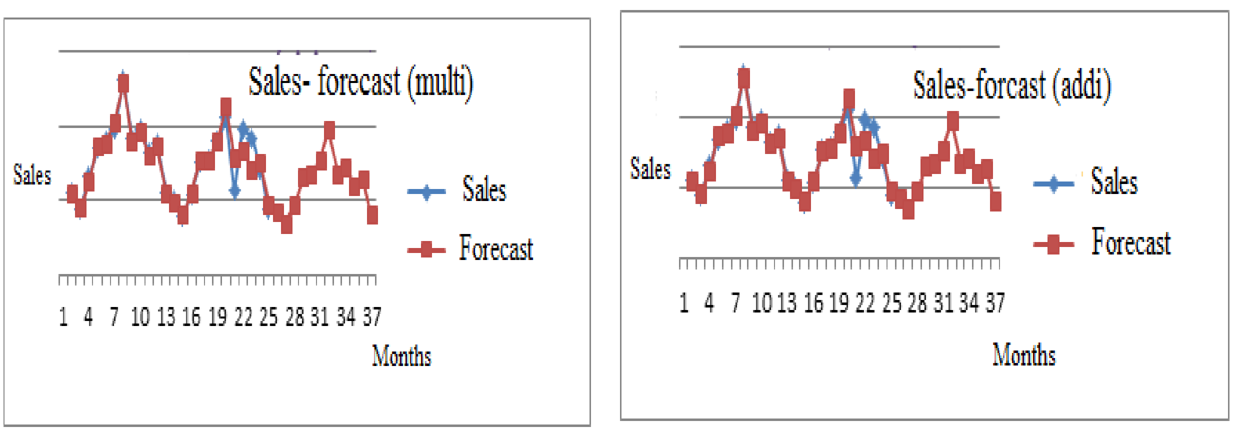


Figure 5. Application of the multiplicative and additive model to the past values

We evaluated the quality of forecasts using two complementary values, namely Predictive Accuracy (see table 1) and Derived Signal (see table 2).

Table 1: Calculation of forecast accuracy

Historical period	Σ 12-month forecasts	Σ e_t 12 months	Precision of model	Business Accuracy
12 month	57763	3243	94%	82%
12 month	61693	4852	92%	87%

We found that the model contributes to improving business prediction.

Table 2: Calculation of the drift signal

Σ e_t	Mean ($\|e_t\|$)	Drift signal
3243	945	3,431746032
4052	1140	3,554385965

We noticed that the values found are indeed between -4 and +4, hence the validity of the model.

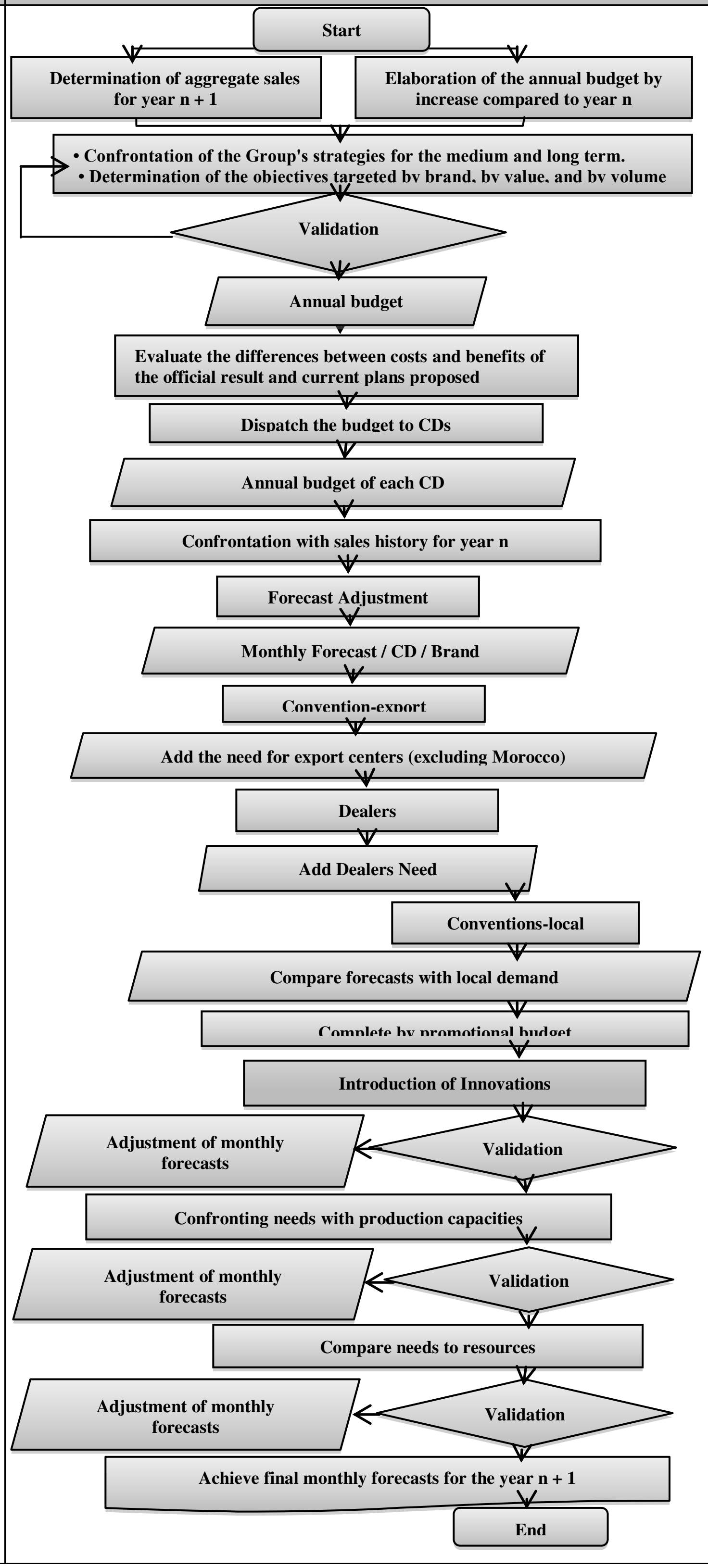
4.3. Analysis

In light of these results, it appears that the application of the S&OP process has a significant impact on the profitability of the company by: improving sales and promotions planning; improving visibility and identification of potential problems (capacity issues); fostering teamwork and communication with members of all departments (sales, marketing, operations and finance), and reducing inventory levels and delivery times, thereby improving customer service and productivity. Therefore, the application of the scientific model based on the time series sales decomposition method improved the business forecasts, which were mainly derived from medium and long-term business strategies. They were rather sales orientations than forecasts and did not express the real need.
No method is perfect. It is clear that the method of decomposing sales in time series is also of limited utility in situations where demand varies depending on factors that are under the control of the firm. For example, these methods would be useless to forecast sales of a product if the price varies from week to week. Also the method assumes that the random variations in different periods are independent of each other. There are obviously situations where this assumption is not realistic. For example, strong demand may indicate a temporary craze will not be repeated during the next period. There are many techniques that take into account the correlation between stochastic variations (including those of Box and Jenkins) but this is beyond the scope of this text.
In spite of these limitations, the method has proved its effectiveness by being applied to the learning data, so that the parent series and the adjusted one coincide indicating the correctness of the decomposition performed (good choice of model, right choice of trend, estimation correct each component) without forgetting the evaluation indicators considered: the accuracy of forecasting and drift Signal, who claim the same result.

Conclusion

Given the push-flow management environment that characterizes multiple firms, and the set of factors that affect demand (the portion of total demand that reaches a company is the result of interactions of different market forces), the reliability of the sales forecast is self-evident. So, in the first instance, we were forced to retake the sales forecasting process in order to detect and correct any anomalies, based on the Sales and Operation Planning approach, which aims to strengthen and facilitate collaboration and the sharing of information in a logistics chain. The benefits of such approach are manifold and can include cost reduction, inventory reduction, enhancement of customer satisfaction and a better adjustment of medium-term business strategy. In the second instance, we developed a statistical model of monthly forecasts based on the time series decomposition methodology, which contributed to an improvement in business forecasts stemming mainly from the company's strategies, as an example of our study, in the medium and long term.

Annex:

What function?	What?	How?
Shareholders Shareholders Finance Sales administrator Sales administrator Sales administrator Commercial Commercial Commercial Marketing Production Supply chain		-Each part presents its medium-term strategy for year n + 1. -Annual meeting between shareholders and the company - Annual budget is made every 12 months, as results of the annual meeting of these two parties -Evaluate the impacts of the strategies taken. - Specify the annual need for finished product for each center. -Confrontation made in relation to the history of the year n, an increase on the numbers. -Sales administrator adjusts values based on history -Sales department introduces the sales forecasts of the customers-export. - Commercial department must add sales forecasts of dealers, whose number is three (Tangier, Agadir, Oujda) - Local demand (GMS, wholesaler, distributors, etc.) must be taken into consideration. -Marketing department adds the annual promotion budget. - In the case of innovative products, prices are based on market research. -If the forecasts already elaborated, do not respond to marketing and commercial strategies, a meeting will take place to review it. - According to the capacities of the production lines of the group. -Supply Chain department studies the feasibility of its forecasts according to the resources available to the group, and after validation, the final forecast / CD / month / article is obtained

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