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THE RELIABILITY MEASUREMENT IN SUPPLY CHAIN FORECAST PLANNING IN UNCERTAINTY ENVIRONMENT: ASSESSMENT OF PRODUCTION PLANNING

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Abstract- Recently the world has been experiencing a radical transformation due to the economic crisis caused by the COVID-19 epidemic. As a result, every company requires a reliable production plan to achieve maximum productivity, and to become more robust and agile in the face of economic changes and variations. In this context, the dynamism of the market makes planning and control much more complex. To face this complexity, production companies have introduced the digitization of processes in order to create a reliable decision support system. The present paper is showing a comparison study between a classic method and a developed approach in purpose to assess the production planning reliability in an uncertain environment. This enables us to check the reliability of the planning system's forecasts by identifying the gaps between the two in the planned production program. This will be present by the mean reliability as a result of the first method, and the accuracy level for the second approach which is based on a linear regression algorithm.

Keywords: Reliable Production Plan, Reliable Decision, Uncertain Environment, Planning, System's Forecasts, Accuracy, Linear Regression Algorithm.

1. INTRODUCTION

Stronger competition can improve economic performance of an industry, unveiled business opportunities and reduce the cost of goods and services. Thus, the enormous competition in terms of quality, productivity and time feedback, today's global markets are characterized by short life cycle introductions and intense customer expectations. Such factors have led industries to vigorously pursue better ways to build stronger interaction and collaboration between the various activities in the supply chain.

The management of the supply chain has become increasingly complex due to the fuzzy data, the work in uncertainty environment. The challenging manufactures today look for the right way to strong their flow, the successful key is related to the improvement of the quality level. However, the work in quality equivalent to make more investment in the resource and tools. Therefore, this strategizes reach to have a sustainable success, and stay competitive in a

Decision making in the different levels of business management has become much more impacted by the state of data and information circulating in each level. Therefore, the robustness of data has linked today with reliability and the performance of supply networks

Reliability is essential in the implementation of an operational supply chain management strategy because it improves productivity and reduces costs and limits the risks of backorders. It also ensures that stocks are delivered to customers on time.

Following the important number of research that aimed to define the world reliability and try to show the impact of that phenomena in the supply chain management, this terminology has been interpreted by [1] such the ability of a system to perform the required functions under conditions in a period determined. The [2], [3], linked the term reliability to the probability to not have failures that impacting the performance of the system in a limited horizon and under environmental conditions.

There is a huge different between supply chain reliability management which is relate for us to the capacity of a system to stay available until the end of the work, e,g the capacity of machines to produce the right quantity of product with a high quality and in the right time according to the production planning and the customers lead-time. The reliability in electric sector was seen as the capacity to perform the task in the system under certain operating and environmental conditions for a specified time [26].

And the supply reliability, which is relate to the probability to receive the goods in the right time and the exact quantity. According to [4] the Supplier reliability is linked to the probability of operating as planned during the planning horizon.

Therefore, monitoring the reliability and increasing the rate of that, is equivalent to reducing the risks of supply chain disruptions. [5] Investigated that the risk management refers to implementing strategies and plans for management Supply chain networks through continuous risk assessment and minimizing vulnerabilities to Ensuring flexibility in supply chains. Thus, request an important investment. According to [6] the perspective of responding to supply chain disruptions requires furthermore the relationships among costs.

The present paper aims to study reliability relate to the forecast, to do that, we will review the literature in the first part, followed by a presentation of the problematic of the study, where we present the first approach used and the result obtained after a test, then we are going to show the second approach with different step until determine the indicators of assessment relate to the accuracy of the forecast planning production. We are going to finish this paper with a discussion of the obtained results and a conclusion.

2. LITERATURE REVIEW

The supply chain disruption is the consequence of risks which is relate to an uncertainty environment. Furthermore, this risk can be termed as vulnerability, disaster peril or hazard. A lack of anticipation of disruption and its causes.

However, in this way have emerged several phenomena due to the inferior reliability in the chain of supply, we imply the risk of the management of the chain of supply that has clearly appeared in this pandemic that has known the whole world that is virus corona. Several research we emphasize on that, we find the work of [8]. The supply chains may have been disrupted by a lack of workers in the coronavirus crisis and a lack of product orders coming in from other nations in the post-Coronavirus crisis period. The demand shock, associated with a supply crisis, occurred on a global scale [9].

Therefore, risk management in supply chain business involves a couple of major projects, sensing and response policies to disruptions [10]. Hazard sensing is a measure of control over risk, it has been defined to be implementing a set of steps based on thorough threat analyzes to avoid hazards [11, 12].

The study presented by [13] demonstrated a favorable response of rapid confidence and cooperation among catastrophe recovery actors upon the resilience of the supply chain. In addition, they assessed the previous contributions of advanced supply chain operational trust and Blockchain in the enhancement of rapid confidence.

Nevertheless, previous Research on risk management in the supply chain has outlined a variety of tactics that vary from within organization tactics (i.e., investment in critical inventories, agility, and the culture of risk management) to supplier management (i.e., supplier sustainability, flexible sourcing, alternative supplier) to demand generation (i.e., deferral, dynamic pricing, multiple modes of transportation). (i.e., supplier sustainability, flexible sourcing, alternative supplier) to demand management (i.e., deferral, active costs) [14, 15, 16, 17, 18].

Risk management in the supply chain focuses on reducing the susceptibility of the supply chain through reactive and proactive tactics [19]. The highest degree of risks capability allows a locally owned company to guarantee continuity in their business transactions, the production and delivery of high-quality goods to their clients within time, and the delivery of high-quality goods to their clients in case of disruptions [20].

In supply chain, the blockchain approach has brought in a distributed numerical register for managing transportation [21]. Likewise, it may be deployed in blockchain along with real-world advantages including efficient, fast, and seamless operations. If we are faced with a complicated chain, with N suppliers, n factories and *n* nodes, the probability of error is very high, hence the need to put a system that allows to supervise the whole that a digital infrastructure like the blockchain. Which allows to maintain a high level of reliability and to keep all the transactions of the chain [22].

The COVID-19 pandemic has uncovered a new context beyond a momentary and event-driven understanding of failure. Characterized by prolonged and intense uncertainty about current and future conditions, resulting in an expansion of SC viability [23]. When [24] presented a new approach to assessing the reliability of forecasts in a production planning system using the numerical solution to explain and justify the causes of variances and described how to establish them.

3. SOLUTIONS FOR VARIATION DATA: THE NEED FOR A COMMON LANGUAGE

Several factors could it be the race of the problem, in order to minimize the source of this issue we should analyze our supply chain and the several actors in it. In purpose to find a common language between them.

"Diversity of players ... Diversity of flows ... The Supply Chain brings together several thousand companies, from suppliers to points of sale, including manufacturers, logistics providers, wholesalers and retailers". For Thierry Jouenne, "there is a need to find a common language for all these companies to analyze situations and seek to improve through performance indicators".

As part of the or carried out at FAFST (French Association for Standardization), four levers are used to define these indicators: Jouenne, for whom, "for logistics, reliability consists of the ability to respond to customer demand according to a fixed level of service" The indicators likely to measure this logistics reliability are the customer service rate, the supplier service rate, the transport service rate, the rate of complaints or disputes, the rate of reliability of forecasts, the rate staff absenteeism, etc. Logistical reliability. "An organization is said to be reliable when the probability of fulfilling its mission over a given period corresponds to that specified in the contract or the specifications', explains Thierry Jouenne (Figure 1).

The rationale for converting a failure to a value less than unity is that once a failure has been investigated and remedial actions have been implemented on that defect type, the chance of its reappearance is reduced. The questions then become, "How much should the defect be reduced?" and "How should the number be determined? An explanation might be to employ professional judgment; for example, a group of experts would accept that failure probability has been decreased by fifty percent or ninety percent, therefore, a value of 0.5 or 0.2 should be assigned to the failure. The apparent limitations of such a procedure are that it is arbitrary and that it is difficult to reach an agreed solution. For these reasons, the statistical database was chosen, which is reproducible and less random [7].

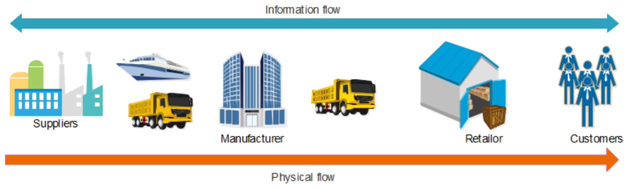

Figure 1. Supply chain flows direction

3.1. Assessment of Forecast Reliability - 1

Ensuring a satisfactory level of forecast reliability is an essential objective for any Supply Chain Manager who must anticipate the mobilization of tools and resources.

The purpose of measuring reliability is to check the quality of the forecasting process, which mainly depends on the choice of forecast parameters and data.

There are several methods of assessing the reliability of a forecast. The choice of the appropriate method must be made based on its practicality of use both in terms of calculations and its operation.

The demand planning process is based on sales forecasts. This is an exercise that is a priori systematic, including for products managed in MTO (Make to Order). On the other hand, in certain cases, we can dispense with making forecasts, in particular for products with a low turnover volume and low exit from stock (number of picks), because their level of reliability will be mediocre with regard to the investment.

3.2. Assessment of Forecast Reliability - 2

As a prelude to the calculation of the indicators for controlling the reliability of a forecast, the prior choice of the following elements is essential and will condition the choice of the forecast method:

* The level of aggregation of the items to which the forecast applies: a forecast is better at a higher level of consolidation, but it takes homogeneous groups in terms of consumption behavior;

* The unit of consumption knowing that the monetary units' specific to budgets cannot be appropriate;

* The unit of time of the forecast period: too coarse a unit can smooth some important variations to take into account;

3.2.1. Demand Backward

The first consequence that we can take from the phenomenon of forecast error is the non-response to customer demand that we have modeled by:

$$DB = \sum (FD_n - FP_n) / \sum FD_n \quad (1)$$

Equation (1) is referring to the number of non-respond demand that is the difference between Firm Demand (*FD*) and Forecast plan (*FP*) this indicator (Figure 2) that we call Bias is an indicator more often used because it is more tactical. Eliminating the Bias is a priority because it is the type of forecasting errors with the most negative impact. Indeed:

A systematic overestimation of forecasts to ensure, a better level of service, to carry out the annual plan despite drastic environmental changes or to deal with a tendency of production under produce, has very negative consequences on the level of stocks, even on increasing capacity as a response to supply difficulties.

An underestimation of forecasts, for example to reduce stocks or play with available industrial capacity, can lead to delivery delays and unreached service levels.

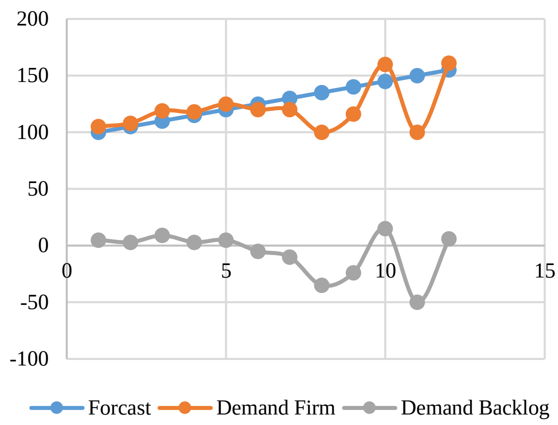

Figure 2. Demand backlog

Calculate on time series comprising N observations, the *MAD* (Mean Absolute Deviation):

$$MAD = \left(\sum \left| FD_n - FP \right| \right) / N \quad (2)$$

The Equation (2) aims to show the average error for the period this indicator more often used, in the operational level. While the bias is at a more advanced level which is the tactic

Therefore, we took a case study on which we followed the variation of the demand that is generate error in forecast plan causing non-response on orders.

In order of that it has become opportune to measure the reliability of the forecast this is in purpose to know in what level it is in adequacy with the customer variation demand. Then our previous analyzes are completed by calculating the adherence of the demand plan which is an intermediate solution between the Bias and the *MAD*, according to the following equation:

$$RDP(\%) = \left(FP_n - \left| FP_n - FD_n \right| \right) / FP_n \quad (3)$$

The Equation (3) attempts to measure the respect of demand plan (*RDP*) (Figure 3) in another way to show the reliability in the Forecast Plan.

In the end of the study, the last measure that we can summarize following our analysis is reliability with respect to compliance with customer demand who is the driving force behind all this study (Figure 4).

In summary this analyze allow us to determine the reliability indicator such the important one to ensure the quality of our forecasts and to align with the uncertainty that characterizes customer demand. So, the results that we have found in this study, allows us to know the average of the reliability of our forecast as illustrate as:

Mean Reliability	89.57%

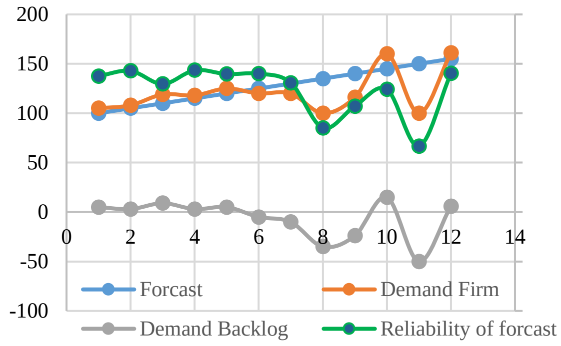

Figure 3. Reliability of forecast

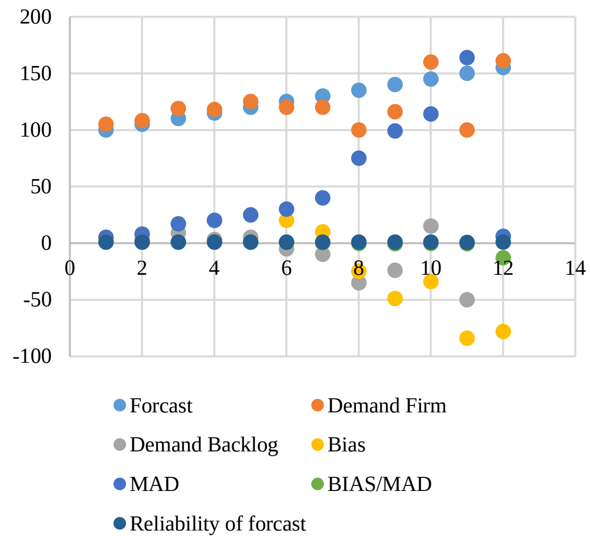

Figure 4. Reliability towards the customer

Therefore, in the automotive sector, where we have seen it applied and where the search for total quality is the rule, the approach should be zero tolerance for any deviation. For this, the measurement of accuracy and probability is the proper option to ensure a high level of reliability of forecasts.

In Table 1 we can see the sample that we took for our study carried out.

Table 1. Sample to measure the reliability of the forecast plan

Forecast	Demand Firm	Demand Backlog	Bias	MAD	BIAS/MAD	Reliability of forecast
100	105	5	5	5	1	95.00%
105	108	3	8	8	1	97.14%
110	119	9	17	17	1	91.82%
115	118	3	20	20	1	97.39%
120	125	5	25	25	1	95.83%
125	120	-5	20	30	0.666666667	96.00%
130	120	-10	10	40	0.25	92.31%
135	100	-35	-25	75	-0.333333333	74.07%
140	116	-24	-49	99	-0.494949495	82.86%
145	160	15	-34	114	-0.298245614	89.66%
150	100	-50	-84	164	-0.512195122	66.67%
155	161	6	-78	6	-13	96.13%

4. MACHINE LEARNING IN SUPPLY CHAIN FORECASTING

In life is impossible to predict the future with 100% certainty, but that doesn't mean we can't forecast effectively. In the business the forecast is the start for any plan, which is critical part of supply chain. It affects everything and a competent supply chain professional must have at least some understandings of the field. Critics will detract because of the error inherent in forecasting; it's a truism that the forecast is always wrong, but today with the high level of competition, the forecast of demand process and supply become the key to sustainability in a fiercely competitive market.

To manage a large volume of data with a multitude factor, we need a strong tool or a developed technology like machine learning, therefore [25] employed machine learning to monitor a multitude of data from the wind industry.

Indeed, a considerable work has been done to find an optimal solution to the predictive planning problem. The [7] outlined a method to recover out-of-bag error predictions which greatly enhances their data efficiency.

Therefore, in this part we are focus in building a model of forecast plan, based on a machine learning algorithm that provide us an accuracy in the result and allow us to measure the reliability of our model of forecast plan.

Thus, we are going to focus in Time series forecasting process, and the practice of this process is the only way to get good forecasts and improve the reliability of the model.

We investigate the three-part view of a time series, this decomposes a time series into season, cycle, trend and noise which for us is related to the uncertainty in the supply chain data.

In which y_t is the input, St is the Season Component, T_t is the Cycle-Trend Element, and R_t is the Residual Element, all within the time period t. In contrast, a multiply decomposition would be written in the Equation (4) as follows:

$$\sum Y_t = S_t \times R_t \times T_t \times \varepsilon \tag{4}$$

The incremental breakdown is more appropriate when the size of the variation in the season, or the fluctuation about the cycle-trend, doesn't fluctuate as the size of the time series rises. When the fluctuation of the pattern of seasonality, or the variability of the cycle trend, tends to be proportionate to the time series level, then a multiplying breakdown is more suitable. Multiplying breakdowns can be performed in economical time series, we visualize the data as a plot presented in the Figure 5.

A substitute for a multiplying breakdown would be to transform the input data until the series variation seems to be constant through rhythm, and then employ an incremental breakdown of the data. When a logarithmic conversion has been employed, this is analogous to a multiplying sequence because:

$$\begin{gathered}\sum Y_t = S_t \times R_t \times T_t \Rightarrow \\ \log(Y_t) = \log(S_t) \times \log(R_t) \times \log(T_t)\end{gathered} \tag{5}$$

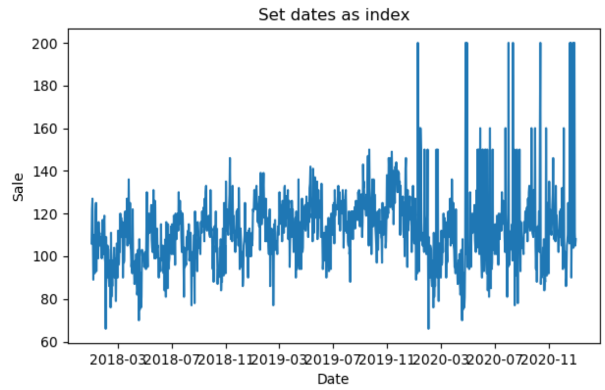

Figure 5. Typical time series set

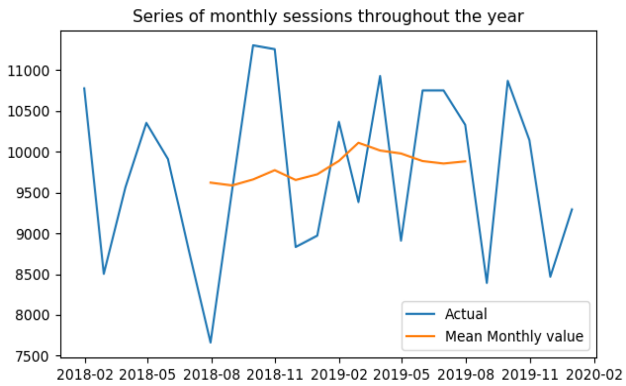

Figure 6. Series of monthly sessions throughout the year

Based on the centralized means, we may proceed to standardize by the seasonal value. In the case of a multiply plotted model, this is accomplished by dividing the current value by the centered running average that we just computed for every time frame, which we will term the seasonal ratio (SR) Equation (6). Figure 6 shows the Monthly average sales during the year.

$$SR = Y_t / MVA \tag{6}$$

After obtaining the SR, we can now move on to calculate the uncorrected season index (USI). While we are examining monthly data, this represents an average of all the months in this dataset, so that each month can be independently corrected for the seasonality observed in the month. The same is evidently applicable to all other months in the dataset, which must be adapted separately. The usual way to proceed is to calculate the average of each individual month in the time series to get the mean to be corrected. We just breakdown this method in an obvious way if it is not completely straightforward.

To begin with, we pick each month and then abstract out all the relevant monthly data.

4.1. Seasonality

To perform the decomposition of a multiplicative model, we first isolate the seasonal component. At this point, we will look at an annual cycle that has seasonal patterns in each month, as shown in Figure 7. Specifically, we make the assumption that each first month will be like a second month, and each month will be like a third month, and so on throughout the years. We seasonally adjusted the data to obtain the trend components (Y_{t-s}), as shown in Table 2.

$$Y_{t-s} = Y_{ts} = C_t \times T_t \times \varepsilon \tag{7}$$

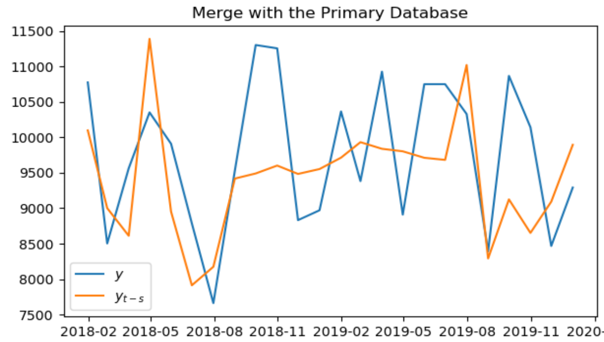

Figure 7. Combine with the actual data

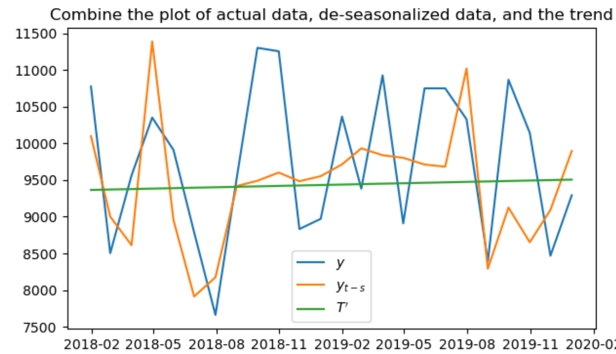

Figure 8. Combine the plot of actual data, de-seasonalized data and the trend

Table 2. The de-seasonalized data in first year

Date	y	MVA	SR	USI	ASI	Y_{t-s}
2018-01-31	3356	NaN	NaN	1.122230	1.126787	2978.381038
2018-02-28	2650	NaN	NaN	0.872108	0.875649	3026.326665
2018-03-31	3405	NaN	NaN	1.067665	1.072000	3176.307202
2018-04-30	2797	NaN	NaN	0.945307	0.949145	2946.861908
2018-05-31	3398	NaN	NaN	1.080003	1.084388	3133.565713
2018-06-30	3005	NaN	NaN	0.919224	0.922956	3255.843108
2018-07-31	3436	3213.583333	1.069211	1.059444	1.063746	3230.094893
2018-08-31	3170	3252.583333	0.974610	0.974610	0.978567	3239.431177
2018-09-30	3458	3281.500000	1.053786	1.053786	1.058065	3268.230916
2018-10-31	3138	3306.750000	0.948968	0.948968	0.952821	3293.378815
2018-11-30	3503	3349.250000	1.045906	1.045906	1.050152	3335.706962
2018-12-31	3247	3384.166667	0.959468	0.959468	0.963364	3370.482439

4.2. Trend

The trend is extracted using the linear regression techniques. The trend may also be non-linear, in which case we may be required to perform a transformation to adjust the linear model. In terms of technology, we will calculate the trend-cycle component (T_tC_t) as an alternative to simply measuring the trend component directly. This can reflect a Structural Change. In all instances, the $T_tC_t=T'$, we illustrate in the Figure 8 the combination between the different data forms.

5. PLANNING FOR A FORECASTING EXERCISE

Now, we have all the components that we require to perform our prediction. We are going to take the results of our test dataset and run the linear model over the time horizon for which we are predicting, and then multiple all the elements to obtain our forecast as describe in the Equation (8) and illustrate in Figure 9.

$$Y' = T'S'\varepsilon' \tag{8}$$

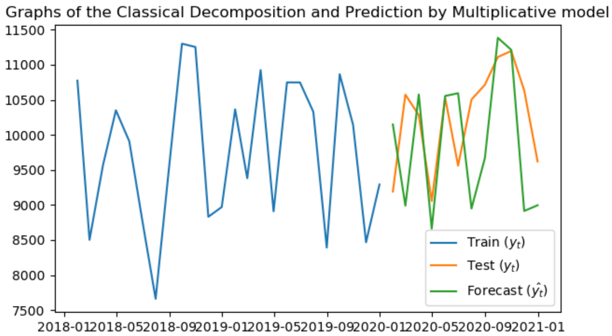

Figure 9. Graphs of multiplicative Actual data, train data and forecast

Firstly, we have to aggregate our survey data to monthly bands to ensure that we have a fair and reliable comparison. However, the table 3 below illustrate the result of the forecast for the next year.

In Table 3, we illustrate the result of the three models, thus show the good results for the forecast.

Therefore, the approaches described above are extensively employed in the prediction field, especially in the supply chain. Nevertheless, we hope that by proceeding in this way, we can highlight some of the weaknesses of this approach, despite its pervasiveness. Some of the problems with this method stem from the assumptions made. The most important is that it assumes that seasonal trends are reproducible in each period, results shown in Table 4 confirm the performance of the model.

5.1. Discussion and Conclusion

The reliability of forecasts is an essential element for the optimization of industrial and logistics systems, for the objective of profitability of the capacities invested and the minimization of stocks throughout the chain.

The first method is a classic approach that help to measure the reliability relate to simple planning, for the complex chain this method is not applied.

For the second approach, in this case study, we regarded various machine learning methods for time series prediction. Sales forecasting is more like a regression problem rather than a time-series issue. The time-series approaches applied to sales forecasting provide us with strong results. The precision on the proof set is a strong driver for selecting an optimum iteration rate for machine learning applications. The impact of generalizing machine learning is to capture the features in the data set.

Table 3. The list of the forecast and the error of the next year

date	series	y	month	trend	forecast	error
2020-01-31	1	9192	1	9511.376251	10148.889097	-956.889097
2020-02-29	1	10574	2	9517.508329	8991.135990	1582.864010
2020-03-31	1	10282	3	9523.640408	10575.996294	-293.996294
2020-04-30	1	9056	4	9529.772487	8662.279747	393.720253
2020-05-31	1	10530	5	9535.904565	10555.000215	-25.000215
2020-06-30	1	9561	6	9542.036644	10594.300548	-1033.300548
2020-07-31	1	10504	7	9548.168723	8949.326249	1554.673751
2020-08-31	1	10715	8	9554.300801	9669.974015	1045.025985
2020-09-30	1	11111	9	9560.432880	11384.938749	-273.938749
2020-10-31	1	11197	10	9566.564958	11213.098722	-16.098722
2020-11-30	1	10635	11	9572.697037	8915.090355	1719.909645
2020-12-31	1	9621	12	9578.829116	8995.958872	625.041128

Table 4. The forecast metrics

	y	forecast	error				
1	122978.0	118656.0	793.0	8.0	4322.0	986.0	4.0

Whatever the lead time of the Supply Chain, forecasts are necessary to identify trends useful for capacity sizing, but also to reveal abnormal demand behavior from time series analysis.

The work on reliability measurement helps to consolidate the management of supply chain risks. Thus, we can consider that our study is a solution to control the potential risks related to the data exchanged upstream and downstream of the company, as well as contributing to reduce the uncertainty in the supply chain.

This would be the subject of our next paper which aims to do a manufacturing process modeling and simulate the whole set of feasible situations in order to arrive to results we are going to analyze and debate in the following stage.

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