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Improvement of Demand Forecasting in a Petrochemical Company
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Improvement of Demand Forecasting in a Petrochemical Company

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Summary:

In this thesis we analyze a petrochemical company's forecasting process, compare it to a list of common practices linked to good forecasting performance, and propose modifications focused mainly on the use of quantitative methods to derive base forecasts. In the end, we propose a forecasting method that outperforms the process currently in place.



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KEY INSIGHTS

1. Improving demand forecasting accuracy leads in general to better results at the top and bottom lines.
2. Given sufficient historical records, quantitative forecasting methods often provide performance advantages over qualitative ones.
3. There are still open questions regarding the effects of forecasting accuracy improvements for firms with the ability to influence demand through price changes in commoditized markets.

Motivation

Since demand forecast is usually the first step in the resource planning process of a company, special attention should be paid to efforts aiming at improving the accuracy of said forecasts. In general, more accurate forecasts lead to better overall results both at the top and bottom lines: Accurately forecasting demand allows a company to meet it timely and efficiently, avoiding so much lost sales

and stock-outs, thus preventing customers from taking their business elsewhere and providing higher customer service levels. Increasing forecasting accuracy also allows for more accurate production plans, hence avoiding last-minute purchases and premium freight shipments. More importantly, reducing the inaccuracy of demand forecasts leads to lowering safety stock requirements, lowering inventory acquisition and holding costs and working capital requirements (Moon et al., 1998). In general, accurate demand forecasts lead to efficient resource utilization and lower operation costs.

Our sponsor company is dedicated to the production and commercialization of petrochemical derivatives such as benzene, propylene and styrene. In general, this family of products is considered part of the commodity chemicals, a price-driven, mature market with low margins, large production volumes and limited differentiation. In such conditions, efficient resource utilization and low operation costs become key drivers for company profitability. Because of this, the company is currently exploring opportunities for improvement on its demand forecasting process.

The hierarchical structure of the stock keeping units (SKUs)

The company produces five main products with up to six applications within each product. Each of these applications is split into up to three different families grouping up to 110 grades. Each individual grade can be packaged in up to seven different final presentations, referred to as materials. Overall, the company has a total of 5 products, 24 applications, 44 families, 367 grades, and 661 materials.

Practices currently in place at the sponsor company

In order to identify improvement opportunities, we mapped the current process based on the information contained in the company's processes manual and our interviews with business unit leaders and members of the production and logistics group. We found a mostly quantitative forecasting process, based on the sales expectations of business unit leaders and account managers. These initial forecasts go through a series of review rounds and feasibility checks, before being published as final demand forecasts.

A closer look at the process reveals four concerning issues: 1) There is an apparent misuse or misunderstanding of the concepts of sales and demand; 2) The fact that the initial forecasts and most of the reviews are done by the business unit leaders and/or the account managers may introduce biases due to misaligned incentives; 3) The initial forecasts are produced based mostly on experts opinions, making very limited use of the historical series, leaving potentially useful information unexplored; and 4) The way in which prices are defined each month gives commercial agents the ability to move up and down the ranges to increase sales when sales are lagging below the months objectives.

Our proposal

We propose modifications to the current process in response to the concerning factors listed above based on a list of common practices recognized as key success factors for a forecasting process (Moon et al., 1998). The proposed process includes the use of quantitative forecasting methods, makes a clear separation between the concepts of demand and sales, and allows commercial agents to include privileged information during the review rounds.

Forecasting including quantitative methods

We include seven forecasting methods to choose from when generating the base forecasts at all levels of the SKU hierarchy: naive forecasting, moving averages, exponential smoothing, Holt's method for trend corrected exponential smoothing, Winter's method for trend and seasonality corrected exponential smoothing, Croston's method for intermittent series, and a modification of Croston's method.

Before describing the method selection process, let us define its two main elements:

Forecasting window: Window of a given number of monthly observation during which the parameters of all of the forecasting methods are to be adjusted in order to minimize root mean squared error (RMSE). The forecasting method that produces the lowest RMSE is selected to be applied during the corresponding testing window.

Testing window: Window of a given number of monthly observations during which the performance of the selected forecasting method is to be recorded and compared to that of the current qualitative one. The length of the evaluation window also defines the frequency at which the election of the forecasting methods will be conducted, so, if we had an m months long testing window, we would need to do the forecasting method selection once every m months.

The forecasting method is based on selecting the best fitting model for each of the series to be forecasted, by choosing the one with the lowest RMSE during a training window, and using it during the corresponding testing window, repeating the process of selecting a forecasting method at the end of each testing window.

Due to the discovery of time series that seem to change their behavior over time, we include a filtering mechanism that requires the quantitatively derived forecasts to outperform their qualitative counterparts during a given number of testing windows before choosing the former over the latter.

Reconciling the forecasts

In order to produce forecasts that add up consistently through the hierarchy, we test eight methods in addition to the current qualitative one

and the generation of forecasts at all levels of the hierarchy independently. These methods can be split into two groups: 1) Forecasting the series at a given level of the hierarchy and aggregating them in order to obtain forecasts for all the higher levels; and 2) Forecasting the series down to a given level of aggregation and combining them through the optimal combination forecasting method (Hyndman et al., 2011). This method is based on the generation of a set of weights that combines the forecasts at all the levels of the hierarchy, so that they add up consistently, and are RMSE optimal. An interesting characteristic of this method is that the so called optimal set of weights is dependent on the structure of the hierarchy only.

Conclusions, recommendations and opportunities for further research

Improving forecasting accuracy leads, in general, to better results in both the top and bottom lines by allowing the company to better prepare to meet demand on a timely and cost effective manner, making better use of the available resources and lowering operation costs (Moon et al., 1998). All these becomes even more important for a company such as our sponsor, competing in a commoditized market in which price is mostly the order winning characteristic.

In order to identify improvement opportunities, we mapped and analyzed the forecasting process currently in place at the sponsor company, and found a mostly qualitative process that made very little use of the available historical data. Furthermore, there is an apparent misunderstanding of the concepts of sales and demand, the base forecasts are influenced by sales objectives, and the entire process allows commercial agents room to maneuver and affect the distribution of demand by moving up and down within price ranges. Based on this analysis and on a list of common practices identified as conducive to better forecasting, we propose a modified process, based on the utilization of quantitatively derived forecasts as a second source of base demand forecasts. Our proposal makes a clear distinction between demand and sales forecasts, while still allowing commercial agents to introduce privileged information.

We obtain the best performance improvement when using 12-months-long training windows, 3-months-long testing windows, and requiring the quantitative methods to outperform the qualitative ones. The best performing of the methods to produce

reconciled forecasts is the generation of base forecasts at the grade level and their aggregation into the higher levels of the hierarchy by simple addition. This method yields a 9.39% of RMSE reduction at the most aggregated level, and average reductions of 7.08%, 5.27%, 4.87% and 0.58% at the product, application, family and grade levels respectively.

Determining the impact of the reductions on RMSE on bottom line results requires further analysis. On one hand, known methods for determining profit optimal inventory policies require estimates of demand and its distribution, but the data we analyzed corresponds to sales and not demand information. On the other, we did not find forecasting methods that include the effects of price elasticity in demand, a very important characteristic for commoditized markets such as the one the sponsor company competes in. Building demand functions dependant on sales and market prices is key to determining optimal pricing and inventory policies.

One particularly interesting finding on the quantitative approaches was that, contrary to what was shown by Hyndman et al.(2011), optimal combination forecasting did not improve on the results obtained by the bottom-up approach in this particular case. We believe this may be due to two facts: 1) The fact that we applied the forecasting methods to sales and not demand series, when sales may be affected by inventory positions and production capacity constrains; and 2) The distortions introduced by the price changes allowed during the month. Taking a closer look at the tests Hyndman et al. (2011) conducted, we noticed that they did not include intermittent time series. This could also explain the discrepancy in the results, but further research is needed to conclude on the performance of the optimal combination forecasting approach when SKUs with intermittent demand are included.

Cited sources

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