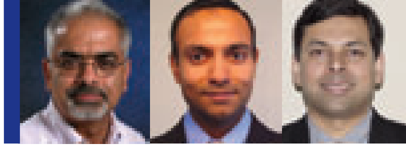
by Adeel Najmi, Harjot Sachdeva and Girish Gulvady



Najmi Sachdeva Gulvady

A Holistic Approach to Forecast Optimization

Many companies chase the elusive goal of reducing forecast error, but have little or no knowledge of how it will impact key business metrics. Why, then, do so many companies that have made significant investments in advanced planning and demand management practices continue to face these problems? Frequently, it is because they view forecasting as an independent and repetitive process designed to create a "best-guess" demand pattern, hoping to generate positive business results.

But there is a better way to approach forecast development. Forecast optimization—a diligent process that decomposes, or stratifies, information based on meaningful attributes—can help business performance. This methodology provides root-cause analysis for understanding sources of variability, while providing a closed-loop process to constantly monitor and tune the health of the forecast and the targeted business metrics. The objective of forecast optimization is not necessarily focused on creating a better forecast, but on improving the business results by whatever means possible. Undoubtedly, improving forecast quality is critical, but other associated dimensions also need to be examined to achieve desirable business results.

Forecast optimization differs from traditional demand management approaches by leveraging a deep understanding of data through rigorous segmentation along various dimensions. The tools then apply diagnostic techniques to drill down to the root cause of variability. The discipline helps generate an understanding of the impact of variables on the forecast, leading to knowledge of the parameters, or levers, necessary to control the forecast error. Many of these levers may reside in other business processes, such as manufacturing, distribution, inventory, competitive intelligence, point-of-sale (POS) information and sales methodology. Forecast optimization, then, is a holistic approach to solving a business problem while addressing the forecast-error challenge.

The key is to understand along which dimension, or for which attributes, segmentation should be performed.

Typical symptoms of high forecast variability include:

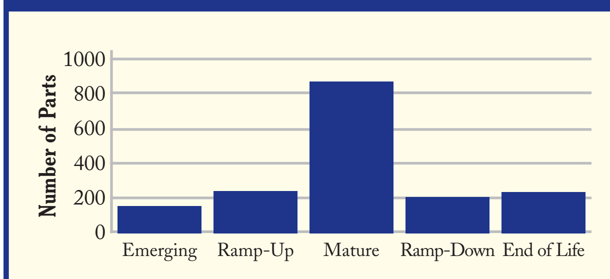
- Poor availability of parts at specific locations, despite overall high inventory levels, causing production or sales stock-outs
- High price-protection cost due to stagnant inventories
- Increased market development costs caused by lack of understanding of customer buying habits
- Poor promotions effectiveness caused by forecast padding for allocation purposes
- Product-mix issues in a capacity-constrained environment

To address these business challenges, forecast optimization delivers deeper insights into demand behavior by utilizing five key diagnostic techniques to uncover industry-specific demand traits.

Segment based on critical attributes

Buying history provides important information on customers' buying habits and parts' selling patterns, as well as on the effectiveness of the forecasting process. To perform due diligence on the forecast, the historical data must be segmented along various attributes so that individual traits—specific to a customer, part or process—can be identified and isolated. Parts can be segmented along a number of attributes including sales volume, revenue contribution, product life-cycle stage, strategic nature of parts and contractual obligations (such as those under vendor-managed inventory). Similarly, customers can be segmented by region, nature of relationship (strategic or non-strategic) or forecast reliability.

Example Life-Cycle Stages for Parts



FORECAST **CONTINUED** on Next Page . . .

A case in point: Suffering from high inventory write-offs, a leading cosmetics company conducted a forecast optimization study revealing that 80 percent of excess inventory was caused by items that had been introduced recently. Segmentation along product attributes helped pinpoint that poor execution during new product introduction was the cause of excess inventory.

Similarly, at a semiconductor manufacturer, segmentation along process attributes yielded several forecasting insights. The sales input in the short term offered a better forecast on the product mix. Product marketing had a better handle in the mid- to long-term on the product/family level. And, a combination of statistics and marketing improved the mid- to long-term forecast at a technology/regional level.

Another example: At a leading tire manufacturer, a rigorous data analysis segmented along the geography/customer dimension revealed that low customer service levels—despite low forecast error rates—were due to the fact that forecast accuracy was being measured at the wrong level: it was being measured at a customer (global) level rather than at a regional (distribution-center) level, which services individual customer sites.

The key is to understand along which dimension, or for which attributes, segmentation should be performed in order to uncover the real problem.

Identify root causes of variability

Once segmentation is performed, it exposes the intricacies of the forecast behavior and the underlying causes of variability. But a proper diagnostic technique, along the lines of a fishbone diagram, is needed to link the root causes to the top-level challenge. The cosmetics company cited previously was able to discern that the sales force was given incentives to push new products into the channel, but there was no feedback mechanism identifying the performance of the product in that market.

For the semiconductor manufacturer, analysis showed that additional segmentation was needed along the geography/customer dimension. This revealed that certain customers provided a more stable forecast than others. Further analysis exposed more customer buying patterns: different customers provided different order lead times; the customers that provided a stable forecast also usually placed orders far in advance, for example. Other customers provided highly variable forecasts despite placing orders on short notice. Other findings included that forecasters had a negative bias—under-forecasting—when a new item was launched, and then had a positive bias—over-forecasting—toward an item's end of life. (See chart below.)

Many companies that have deployed sophisticated forecasting models fail to build feedback and continuous learning into the process.

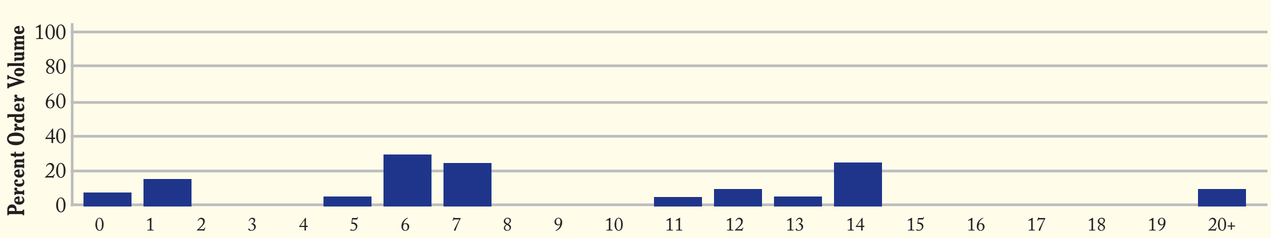
For the tire manufacturer, the diagnostic process showed that there was little correlation between customer service levels and forecast accuracy at the customer (global) level, while there was a strong correlation between customer service level and regional (distribution-center-level) forecast accuracy.

Understand sensitivity of variables on forecast error

After establishing the root causes of forecast error, the next step is to determine which variable impacts the forecast in what way and by how much by conducting a sensitivity analysis. For the cosmetics company, salespeople were stuffing stores with excess inventory to avoid stockouts on highly promoted items. The result was high write-off costs, because markdowns would have hurt brand image.

For the semiconductor company, the forecast was sensitive to the mode by which it was generated—for example, by sales input, marketing input or statistics. Thus, the recommendation was to generate the forecast based on certain rules. For example, in the close horizon, use sales inputs based on the latest customer buying pattern at a weekly granularity; in the midterm, use a blend of sales and marketing at a monthly granularity; and for the long term, use a combination of marketing and tailored statistics

Example Order Lead Time (Days)



at a monthly granularity level. Customer order lead-time information was deemed significant and was used in postponement and staging inventory at different locations to improve service levels despite forecasting challenges.

At the tire manufacturer, segmentation along sales volume (high, medium or low) proved to be significant. For each of the sales-volume segments, the forecast was further stratified, based on risk, into the categories of Firm (forecast for which parts can be manufactured ahead of time), Flex (parts manufactured no earlier than three months in advance, based on market conditions) and Risk (parts manufactured only one month in advance, based on latest market intelligence). This particular approach was selected because of the unique tire-manufacturing process, which is run in campaigns to minimize costs.

Tire Manufacturer Example Template

Sales-Volume Segment	Risk-Based Forecast Stratification		
	Flex	Firm	Risk
Very High			
High			
Medium-High			
Medium			
Medium-Low			
Low			
Snow Tires			

Monitor forecast and business performance continuously

Fixing the forecasting process is not a one-time exercise. It is a continuous learning process with a closed feedback loop. This loop helps determine whether the root causes are still valid or new ones need to be explored, or whether the current techniques of forecasting work in this dynamic business environment. The cosmetics company determined that instead of pushing 12 to 16 weeks of inventory into the channel for the launch of strategic products, it should only deploy five to six weeks of inventory, keep the rest in a pool upstream and then, on a daily basis, monitor the POS data for performance of the inventory at a store or regional level. This strategy created a closed-loop process between forecasting and inventory management.

At a different semiconductor manufacturer, the closed-loop monitoring process highlighted the need for a significant shift in inventory deployment. Root-cause diagnostics showed that customers were requiring shorter order lead times. Therefore, they had to be serviced from a closer distribution center. Previously, the inventory was deployed from the upstream, die-bank (intermediate/sub-assembly) level.

Likewise, the tire manufacturer's forecast partition into Firm, Flex and Risk was based on monitoring the market conditions, as well as on keeping a pulse on product segmentation, based on volume. The company learned that the monitoring process should automatically detect when a product's demand volume changes, and move it to a different sales-volume segment with different forecast-partitioning parameters.

Manage and tune forecast parameters

Many companies that have deployed sophisticated forecasting models fail to build feedback and continuous learning into the process. As time progresses, business conditions change. The forecast optimization paradigm calls for monitoring changes and tuning the parameters to control the forecast quality and impact business results. This requires institutionalizing the knowledge gained from the forecast optimization process, with a clear ability to manage this as a repeatable process. Again, these parameters may not be directly linked to the forecast, but will impact the desired business metric.

As a result of this process, the cosmetics manufacturer projected a 20 to 40 percent reduction in post-launch inventory and a 25 to 50 percent improvement in availability metrics. One semiconductor company anticipated a 10 to 25 percent reduction in forecast error within the order lead time, with reductions in inventory safety-stock levels. The tire manufacturer projects a 5 to 10 percent increase in forecast accuracy across various product types and an improvement in customer service rates.

Summary

Forecast optimization methodology establishes a detailed, systematic and closed-loop process to manage forecasting and its linkage to other supply chain processes. It is not an independent effort to simply improve the forecast, but a process that looks at all variables holistically—whether related to customers, competition, inventory, manufacturing or sales—with the end objective of improving business performance.

Dr. Adeel Najmi is a senior technical director in Research and Development and an i2 Fellow. **Harjot Sachdeva** is a solutions director in i2's High Tech industry group.
Girish Gulvady is founder and principal consultant of Stratemorphics, Inc.