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DEMAND-DRIVEN FORECASTING

A Structured Approach to Forecasting

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CHAPTER 1

Demystifying Forecasting: Myths versus Reality

It has been an exciting time for the field of demand forecasting. All the elements are in place to support demand forecasting from a fact-based perspective. Advanced analytics has been around for well over 100 years and data collection has improved significantly over the past decade, and finally data storage and processing capabilities have caught up. It is not uncommon for companies' data warehouses to capture and store terabits of information on a daily basis, and parallel processing and grid processing have become common practices. With improvements in data storage and processing over the past decade, demand forecasting is now poised to take center stage to drive real value within the supply chain.

What's more, predictive analytics has been gaining wide acceptance globally across all industries. Companies are now leveraging predictive analytics to uncover patterns in consumer behavior, measure the effectiveness of their marketing investment strategies, and optimize financial performance. Using advanced analytics, companies can now sense demand signals associated with consumer behavior patterns and shape future demand using predictive analytics and data mining technology. They can also measure how effective their marketing campaigns are in driving consumer demand for their products and services, and therefore they can optimize their marketing spending across their product portfolios. As a result, a new buzz phrase has emerged within the demand forecasting discipline: *sensing, shaping, and responding to demand*, or what is now being called demand-driven forecasting.

With all these improvements, there has been a renewed focus on demand forecasting as the key driver of the supply chain. As a result, demand forecasting methods and applications have been changing, emphasizing predictive analytics using what-if simulations and scenario planning to shape and proactively drive, rather than react to, demand. The widespread acceptance of these new methods and applications is being driven by pressures to synchronize demand and supply to gain more insights into why consumers buy manufacturers' products. The wide swings in replenishment of demand based on internal shipments to warehouses and the corresponding effects on supply can no longer be ignored or managed effectively without great stress on the upstream planning functions within the supply chain.

New enabling technologies combined with data storage capabilities have now made it easier to store causal factors that influence demand in corporate enterprise data warehouses; factors may include price, advertising, in-store merchandising (e.g., displays, features, features/displays, temporary price increases), sales promotions, external events, competitor activities, and others, and then use advanced analytics to proactively shape future demand utilizing what-if analysis or simulations based on the parameters of the models to test different marketing strategies. The focus on advanced analytics is driven primarily by the need of senior management to gain more insights into the business while growing unit volume and profit with fewer marketing dollars. Those companies that are shaping future demand using what-if analysis are experiencing additional efficiencies downstream in the supply chain. For example, senior managers are now able to measure the effects of a 5 percent price increase with a good degree of accuracy and ask additional questions, such as: What if we increase advertising by 10 percent and add another sales promotion in the month of June? How will that affect demand both from a unit volume and profit perspective? Answers to such questions are now available in real time for nonstatistical users employing advanced analytics with user-friendly point-and-click interfaces. The heavy-lifting algorithms are embedded behind the scenes, requiring quarterly or semiannual recalibration by statisticians who are either on staff or hired through outside service providers.

The results of these what-if simulations are used to enhance or shape future demand forecasts by validating or invalidating assumptions using domain knowledge, analytics, and downstream data from sales and marketing rather than gut-feeling judgment.

With all the new enhancements, there are still challenges ahead for demand forecasting. Many organizations struggle with how to analyze and make practical use of the mass of data being collected and stored. Others are still struggling to understand how to synchronize and share external information with internal data across their technology architectures. Nevertheless, they are all looking for enterprise-wide solutions that provide actionable insights to make better decisions that improve corporate performance through improved intelligence.

Improvements in demand forecasting accuracy have been a key ingredient in allowing companies to gain exponential performance in supply chain efficiencies. Unfortunately, demand forecasting still suffers from misconceptions that have plagued the discipline for decades and have become entrenched in many corporate cultures. The core misconception that has troubled companies for years is that simple forecasting methods, such as exponential smoothing, which measure the effects of trend, seasonality, and randomness (or what is known as unexplained randomness, or noise), can be used to create statistical baseline forecasts and enhanced (or improved) by adding gut-feeling judgmental overrides. Those overrides usually are based on inflated assumptions reflecting personal bias. The second misconception is that these judgmental overrides can be managed at aggregated levels (higher levels in the product hierarchy) without paying attention to the lower-level mix of products that make up the aggregate. The aggregation is required to manage the large scale of data that usually span multiple geographic regions, markets, channels, brands, product groups, and products (stock-keeping units [SKUs]). The sheer size of the data makes it difficult to manage the overrides at the lowest level of granularity. Companies compromise; they make judgmental overrides at higher aggregate levels and disaggregate it down using Excel spreadsheets and very simplistic, static averaging techniques. In other words, the averages are constant into the future and do not account for seasonality and trends at the lower levels. In many cases, products within the same product group are trending in different directions.

Another misconception is political bias based on the needs of the person or purpose of the department making the judgmental overrides. For example, depending on the situation, some sales departments will lower the forecast to reduce their sales quota in order to ensure that they make bonus. This is known as sandbagging. Other sales departments that have experienced lost sales due to back orders (not having the inventory available in the right place and the right time) will raise the forecast in the hopes of managing inventory levels via the sales department forecast. This method creates excess inventory as the operations planning department is also raising safety stocks to cover the increase in the sales department forecast. The problem is compounded, creating excess finished goods inventory, not to mention increased inventory carrying costs. The finance department always tries to hold to the original budget or financial plan, particularly when sales are declining. Finally, the marketing department almost always raises its forecast in anticipation of the deployment of all the marketing activities driving incremental sales. The marketing department also receives additional marketing investment dollars if it shows that its brands and products are growing. So marketing tends to be overly optimistic with marketing forecasts, particularly when they raise the forecast to reflect sales promotions and/or marketing events.

These misconceptions are difficult to overcome without a great deal of change management led by a corporate "champion." A corporate champion is usually a senior-level manager (e.g., director, vice president, or higher) who has the authority to influence change within the company.

This person usually has the ear of the chief executive officer, chief financial officer, or chief marketing officer and is also regarded within the organization as a domain knowledge expert in demand forecasting with a broad knowledge base that spans multiple disciplines. He or she usually has some practical knowledge of and experience in statistical forecasting methods and a strong understanding of how demand forecasting affects all facets of the company.

The purpose of this book is to put to rest many of the misconceptions and bad habits that have plagued the demand forecasting discipline. Also, it provides readers with a structured alternative that combines data, analytics, and domain knowledge to improve the overall performance of the demand forecasting process of a company.

DATA COLLECTION, STORAGE, AND PROCESSING REALITY

Over the past ten years, we have seen a great improvement in data storage. For example, companies that only a few years ago were struggling with 1 terabyte of data are now managing in excess of 68 terabytes of data with hundreds of thousands of SKUs. In fact, you can purchase an external hard drive that fits in your pocket for your personal computer (PC) or laptop that can store 1 terabyte of data for less than $150. Data storage costs have gone down substantially, making it easier to justify the collection of additional data in a more granular format that reflects complex supply chain networks of companies.

Most companies review their forecasts in a product hierarchy that mirrors the way they manage their supply chain or product portfolio. In the past, product hierarchies in most companies were simple, reflecting the business at the national, brand, product group, product line, and SKU levels. These product hierarchies ranged from hundreds to a few thousand SKUs, spanning a small number of countries or sales regions and a handful of distribution points, making them fairly easy to manage (see Figure 1.1).

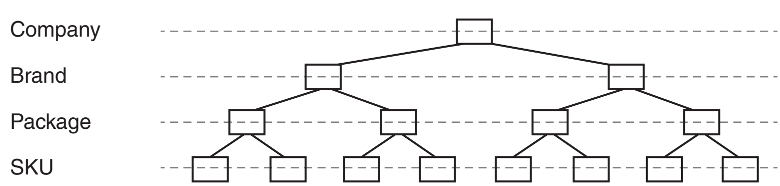

Figure 1.1 Business Hierarchy for a Beverage Company in the 1990s

During the past two decades, however, many industries have gone through major consolidations. Larger companies found it easier to swallow up smaller companies to increase their economies of scale from a sales, marketing, and operations perspective rather than growing their business organically. They realized additional benefits as they flushed out inefficiencies in their supply chains while increasing their revenue and global reach. Unfortunately, with all this expansion came complexities in the way they needed to view their businesses.

Today, with global reach across multiple countries, markets, channels, brands, and products, the degree of granularity has escalated tenfold or more (see Figure 1.2). Product portfolios of companies have increased dramatically in size, and the SKU base of companies has expanded into the thousands and in some cases hundreds of thousands. It is not unusual to see companies with more than 10,000 SKUs that span across 100 or more countries.

Further escalation occurred as marketing departments redefined their consumer base by ethnicity, channels of distribution, and purchase behavior. The resulting increased granularity has further complicated company product hierarchies. All this proliferation in business complexity has made it difficult not only to manage the data but also to process the data in a timely manner.

Given all this complexity and increase in the number of SKUs, Excel spreadsheets are no longer viable tools to manage the demand forecasting process. Excel is simply not scalable enough to handle the data and processing requirements. Excel's analytics capabilities are limited to some time series techniques and basic simple regression

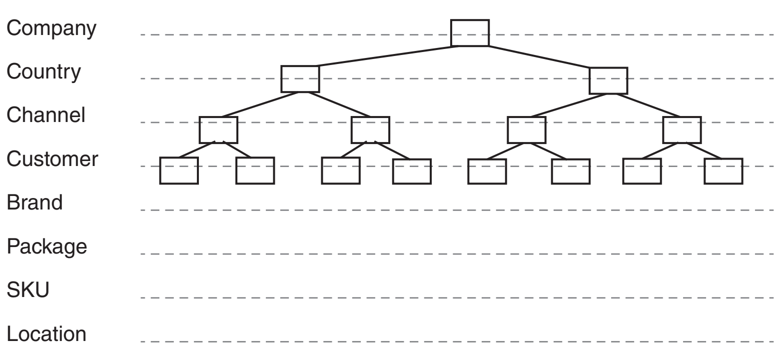

Figure 1.2 Business Hierarchy for a Beverage Company in 2013

that model trend, seasonality, and unexplainable historical patterns. Nevertheless, over 40 percent of forecasters still use Excel to do forecasting, according to several surveys conducted over the past decade by academic- and practitioner-based organizations.

In fact, a survey conducted by Purdue University and the SAS Institute found that over 85 percent of the respondents still use Excel as a workaround to existing enterprise resource planning (ERP) and supply chain management solutions due to the lack of ad hoc reporting capabilities and other related functionality.[1]

Over the past several years, the introduction of Windows NT (New Technology) servers, parallel processing, and grid computing has significantly improved the speed of processing data and running analytics on large volumes of data. Sophisticated algorithms now can be executed on a large scale using advanced statistics and business rules across company product hierarchies for hundreds of thousands of products. In fact, a large majority of products can be forecasted automatically using new enabling technologies that allow forecasters to focus on growth products that are more dynamic than mature products due to their marketplace competitiveness. Rather than spending 80 percent of their time identifying, collecting, cleansing, and synchronizing data, forecasters can now focus on those products that need more attention due to market dynamics and other related factors.

Recent development in the area of master data management and big data (both structured and unstructured) has helped standardize data structures, making it easier to manage information and untangle the years of mismanaged data storage. With all these new enhancements to data collection and processing, forecasters no longer need to worry about data quality or data availability. We can now collect, store, and process millions of data series in batch overnight and hundreds of thousands in real time in a matter of minutes and hours. Data are also streaming into enterprise data warehouses in real time via the Internet, providing forecasters with monitoring, tracking, and reporting capabilities throughout the workday.

All these improvements in data collection, storage, and processing speed have eliminated many of the barriers that prevented companies from conducting large-scale forecasts across complex supply chain networks and product hierarchies. Companies can no longer use the excuses that data availability is limited or that running statistical models across their product portfolios takes too long. Unfortunately, companies still are having problems understanding all this information. Fortunately, uncovering actionable insights in a timely manner to make better decisions is becoming easier as significant gains have been made with new technologies in data mining and text mining. Managing information and using high-performance analytics (HPA) are enabling organizations to gain competitive advantage through timely insights and precise answers to complex business questions. These insights are being utilized to support the decision-making process and will only improve over the next several years.

ART-OF-FORECASTING MYTH

Contrary to what you have heard or believe, there is no art in forecasting; rather the art lies in statistics and domain knowledge. Domain knowledge is not the art of making judgmental overrides based on inflated bias assumptions to simple statistical baseline forecasts; domain knowledge refers to the act of defining and uncovering market opportunities based on knowledge (business acumen). In other words, forecasting uses the combination of domain knowledge (business experience) and analytics to validate or invalidate those assumptions. It is ironic that although we use exact science to manufacture products along structured guidelines with specifications that are within a .001 tolerance range, we use our gut-feeling judgment to forecast demand for those same products. I have an advanced degree in applied econometrics and more than 26 years of experience as a forecast practitioner with more than six companies, and I still cannot take my gut-feeling judgment and turn it into a number. I need to access the data and conduct the analytics to validate my assumptions. In other words, come up with a hypothesis, find the data, and conduct the analytics to determine whether you can reject the hypothesis. Then use the results to make adjustments to the statistical baseline forecast or, better yet, build those assumptions into the statistical baseline forecast by adding the additional data and revising the analytics.

Today, some global consumer packaged goods (CPG) companies like Nestlé, Dow, Cisco, and Procter & Gamble are switching to a demand-driven structured process with more focus on data, analytics, and domain knowledge. By doing so, they are improving their demand forecast accuracy almost immediately, which leads to positive improvements in customer service and lowered inventories. With the support of a new demand-driven enabling technology platform, these CPG companies are able to exceed their demand forecast accuracy projections by double digits. They learn quickly that demand forecast accuracy improvement drives reductions in safety stock, inventory days on hand, storage costs, and freight costs. By gaining a few points of accuracy at the national level, they are able to experience supply chain savings immediately. Their accurate demand forecasts have even benefited areas such as efficient route planning. According to these CPG manufacturers, the accuracy can be driven by a change from a 50,000-foot view of demand forecasts to a more detailed look. Also, the ability to sense demand signals associated with sales promotion lifts using more advanced analytics across their business hierarchy have enabled these companies to shape future demand by placing profitable sales promotions into the future allowing them to execute more effectively with sales/marketing. Demand forecasts are no longer adjusted using gut-feeling judgment but by using domain knowledge to shape future demand based on data and analytics.

Unfortunately, many companies are quick to dismiss any structured approach to demand forecasting, particularly when it requires data and analytics, or the "s" word: statistics. The excuse is that statistics are not always trustworthy because they can be manipulated to explain whatever you want. This excuse became clear to me when I was given a product forecast by a manager who then asked me to find the data and statistics to support it. As a young manager with an MBA in economics specializing in applied micro-econometrics, I found this somewhat amusing. Applied econometrics is supported by a very structured process (or approach) to analyzing information and data using statistical methods that have been proven in practice as well as dissected with rigor by academia over the past 100 years. Unfortunately, the manager was not joking.

Granted, some element of domain knowledge, not art, always is required to predict the demand for any product. Unfortunately, most people misinterpret the "art" to mean gut feelings rather than a true understanding of marketplace dynamics, which requires domain knowledge. Let us look at a real-life example I encountered while working at a beverage company in the late 1990s to illustrate the true meaning of domain knowledge.

END-CAP DISPLAY DILEMMA

As senior manager for global marketing research at a multinational beverage company, I was asked to support the U.S. national brand team, which was responsible for growing its sports drink business. Our goal was to provide the brand team with a way to measure the effects of marketing dollars and use the findings to shape and predict future demand as an input into the monthly sales and operations planning process. We decided to develop several advanced statistical models by brand and package size to predict the effects of marketing tactics on consumer demand using Nielsen syndicated scanner data (point-of-sale [POS] data). The purpose of this exercise was twofold: (1) to measure the effects of the marketing mix elements (price, advertising, merchandising, sales promotions, competitive activities, and any other external factors) on consumer demand, and (2) to use those measures to conduct what-if simulations to shape future demand, resulting in a more accurate demand forecast that reflected the sports drink brand team marketing strategy.

The first series of models was developed for the sports drink 64-ounce product group. We identified several internal marketing elements as significant business drivers influencing consumer demand. All the key business drivers were significant at a 95 percent confidence level, which explained roughly 92 percent of the variation in consumer demand for the 64-ounce product. However, when we added end-cap displays[2] to the model, all the other key business drivers were no longer significant and the end-cap displays alone explained over 96 percent of the variation in consumer demand. This was puzzling and, from a practical standpoint, somewhat suspicious.

We scheduled a meeting with the sports drink brand team to determine whether this made sense from a domain knowledge perspective.

The brand team explained to us that this was an anomaly in the data, most likely an error on the part of Nielsen. When Nielsen conducted its store audit that week to capture the in-store merchandising activities of all the manufacturers and retailers, the auditor saw the one 64-ounce sports drink bottle on the end-cap display and entered it into the system as a sports drink 64-ounce bottle end-cap promotion. The brand team continued to explain that it never runs end-cap display promotions for 64-ounce bottles of any beverage because the bottles are too large to fit enough on the display to justify the cost. So what happened? The end-cap display was most likely an 8-ounce sports drink 12-pack promotion with only one 12-pack left. A consumer picked up a sports drink 64-ounce bottle in the aisle and continued on to the end-cap display. The shopper saw the last 8-ounce 12-pack on promotion and decided to exchange the 64-ounce bottle for the 8-ounce 12-pack. The consumer left the 64-ounce bottle on the end-cap display, and the Nielsen auditor saw it and recorded it.

Such anomalies occur occasionally and need to be identified during the final staging and cleansing of the data. After removing the end-cap display variable from the sports drink 64-ounce bottle model, all the other key business drivers fell into place, thus making the model more reflective of the actual marketing activities being implemented to drive consumer demand. As a result, we created a set of business rules for future model development. The primary rule advised modelers to exclude end-cap displays in any 64-ounce bottle models to explain consumer demand.

From this story, we learned that (1) demand forecasting requires a collaborative effort between a statistician and a domain knowledge expert, and (2) domain knowledge is very different from pure gut-feeling judgment.

REALITY OF JUDGMENTAL OVERRIDES

Many companies still value judgment over analytics, and as such, judgment is used almost exclusively to manipulate the statistical baseline demand forecast to meet their needs. There are still situations where the demand forecasting process is used to generate and justify sales targets based on stretch goals. The end result is a forecast that reflects someone's wishes rather than reality. In my years of experience, I have never been able to turn my gut feelings into a number to enhance the accuracy of a forecast. However, if you provide me with a hypothesis based on your domain knowledge, I can identify the appropriate data and use analytics to validate or invalidate your hypothesis. If the hypothesis is validated, we would add the data as an explanatory variable to a more sophisticated model to improve the accuracy of the statistical baseline forecast.

As a result, there would be no need to make a judgmental override because we already would have incorporated your domain knowledge into the statistical baseline forecast.

Unfortunately, those individuals making manual overrides to the statistical baseline forecast actually feel that they are enhancing the accuracy of the forecast by touching it with their judgment. At least this is one of the major reasons forecasters made adjustments to 75 percent of statistical baseline forecasts at four U.K. companies, according to a recent study by Fildes and Goodwin.[3] In fact, at these companies, the researchers found that when forecasters and/or planners raise the forecast, they are almost always wrong, thus making the forecast less accurate. Often they are overly optimistic when raising the forecast. Conversely, when forecasters or planners make judgmental overrides that lower the forecast, they tend to enhance its accuracy because they are more conservative. But senior management tends to frown on disclosing that a business is declining rather than growing. Overall, Fildes and Goodwin found that very small changes to the forecast, up or down, had virtually no impact on forecast accuracy and were simply a waste of time.

The real issue is that most companies have been sold a bad bill of goods by academics, practitioners, and software vendors. It is popular to advocate that you can take a simple time series statistical model, such as exponential smoothing, and enhance the forecasts by making manual overrides based on pure judgment. Simple methods such as this can work with well-behaved and easy-to-forecast demand but can produce highly inaccurate forecasts in more challenging forecasting situations. I have rarely seen the accuracy of a statistical baseline forecast improve by making a manual override using gut-feeling judgment rather than *informed judgment using domain knowledge*. Nevertheless, almost every process designed and supported by software vendors advocates this method, as it is easy to systematize these simple time series statistical methods. It is also easy to collect, store, and manage the historical data required to enable such methods.

The accepted demand forecasting process of making manual overrides using pure judgment needs to be modified to incorporate more analytics by creating a hypothesis using domain knowledge (informed judgment), not gut-feeling judgment. Demand forecasting is a collaborative process that requires a statistician and a domain knowledge expert. More sophisticated methods should be introduced, such as autoregressive integrated moving average, autoregressive integrated moving average with exogenous input, and dynamic regression models. These models can capture the relationships and influences of factors other than trend and seasonality, such as price, advertising, sales promotions, marketing events, and economic information. Domain knowledge could then be used to identify the factors that affect those particular brands, product groups, and products, providing a hypothesis as to why and how they can be influencing demand. Finally, the hypothesis should be tested to determine which factors are influencing demand and incorporate them into the statistical baseline forecasts. In other words, the judgmental assumptions that are used to justify making manual overrides using data and analytics rather than someone's opinion, or gut feelings, should be validated through the data and analytics.

This brings to mind two real-life situations. The first occurred in the early 1990s at a large international household products company and the second more recently during a process assessment review with an SAS (my current employer) customer. The first story illustrates the perfect structured process using domain knowledge to identify a hypothesis, and the second story illustrates the worst-case scenario.

OVEN CLEANER CONNECTION

As the director of demand forecasting and marketing technology at a large international household products company, I was responsible for providing marketing support to a U.S. national oven cleaner brand. The brand was declining in sales for several periods with historical unit sales decreasing at an exponential rate. Under normal circumstances, the product manager would have waited for the new statistical baseline forecast to be updated and then make manual overrides without validating his assumptions. He would have taken the forecast down slowly, phasing out the brand over time, or would have adjusted the forecast slowly upward to support assumptions that existing sales and marketing campaigns would turn around the brand. The latter course would more likely have been followed if gut-feeling judgment was used. The actual sales would have most likely come in somewhere in the middle. By the way, the statistical baseline forecast only modeled the seasonality, trend, and any unexplained randomness associated with its past historical unit sales. It could not build in the dynamic effects of sales promotions, marketing events, pricing, advertising, and other related sales/marketing activities. See Figure 1.3 for actual oven cleaner shipment history.

Fortunately, we had just implemented a new structured demand forecasting process supported by a new enabling technology solution. The new demand forecasting solution utilized advanced analytics capabilities, which were supported by an enterprise-wide data warehouse. The product manager came to the demand forecasting analyst responsible for supporting the brand with a hypothesis that addressed the reason that unit sales were declining for the oven cleaner brand. The brand manager explained to the demand forecasting analyst that there was a possible negative correlation (relationship) with the oven cleaner brand and self-cleaning ovens. In other words, as more people

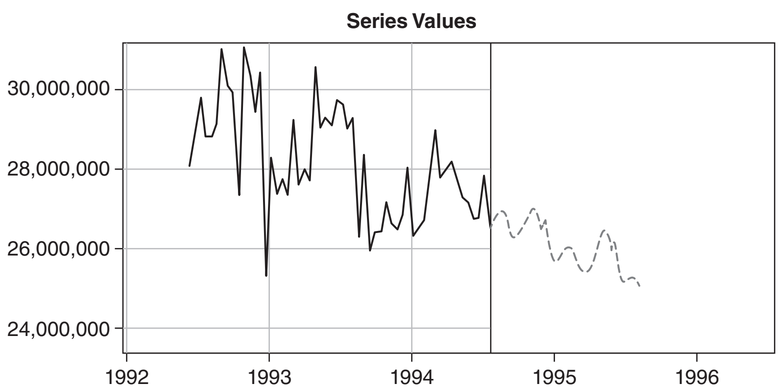

Figure 1.3 Oven Cleaner Shipment History and Forecast Using Simple Time Series Method

purchased self-cleaning ovens, the less they used the oven cleaner. The task for the analyst was to validate or invalidate the negative relationship (hypothesis) between the oven cleaner brand and the increased purchases of self-cleaning ovens. The real dilemma facing the analyst did not involve analytics but, rather, where to find self-cleaning oven data to conduct the analysis. As it turns out, there is an oven association, and membership was $95 per year. After becoming a member, our company was able to download all the self-cleaning oven sales data we needed.

Analysis of the data revealed that the brand manager was absolutely correct. That one causal factor—the negative correlation between the oven cleaner brand and increasing purchases of self-cleaning ovens—improved the accuracy of the forecast by 10 percent. Additional research was conducted that indicated that most people did not like using their self-cleaning oven feature for several reasons: (1) it took over four hours to run, (2) heated up the kitchen, and (3) smelled terrible. As a result, the company repositioned the oven cleaner brand in its national advertising messaging to say "Use our oven cleaner in between oven self-cleaning to spot clean your oven." Using the oven cleaner would allow people to use their self-cleaning feature less frequently. Today, the oven cleaner is still a very strong U.S. national brand. The same message continues to be delivered in U.S. television advertisements. In fact, only a few short years later the brand was beginning to turn around (see Figure 1.4).

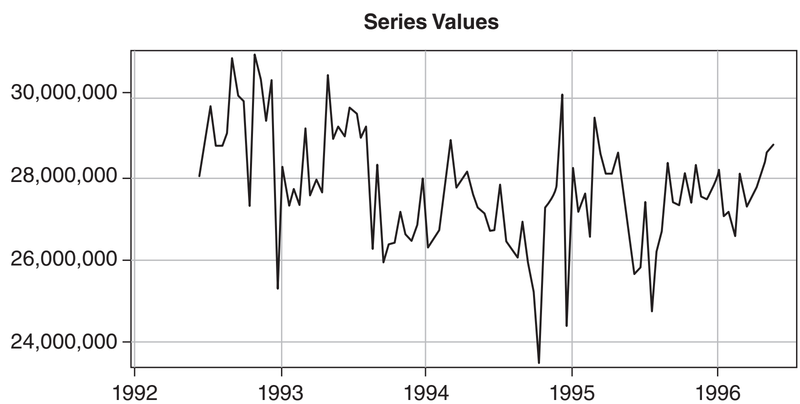

Figure 1.4 Oven Cleaner Shipment History Several Years Later

The oven cleaner story is a great illustration of sensing demand signals and using analytics to shape future demand, not to mention shaping brand positioning and messaging. Unfortunately, the next story does not illustrate the best practices in demand forecasting but rather the worst.

MORE IS NOT NECESSARILY BETTER

Several years ago during a customer visit with a large national restaurant chain, the SAS team uncovered an abnormally large number of people in the demand forecasting process. We were called in to help the company assess its demand forecasting process and recommend a solution to enable the process. The first question we asked was how many people participated in the current demand forecasting process. The restaurant marketing manager explained that 100 people participated in the process. When we asked if all 100 people created the forecast, the manager explained that only 8 people actually created the statistical baseline demand forecasts. We then asked what the other 92 people did. The marketing manager replied that they made manual overrides to the statistical baseline forecasts. In this customer's scenario, there were 92 chances of adding personal bias to the statistical baseline forecasts, making them less accurate.

We explained that the restaurant chain needed to conduct a forecast value added (FVA) analysis to determine if value was added to the statistical baseline forecasts when manual overrides were made by all the individuals in the demand forecasting process. In other words, we advised measuring the accuracy of the demand forecast before and after each touch point in the process to determine if the forecast accuracy improved after each manual adjustment. If not, then that touch point should be eliminated. Although the process of elimination may be long and tedious, it is truly the best way to test the value each person brings to the process when he or she adjusts the statistical baseline forecast with personal judgment. Getting people to buy into this new FVA performance metric usually requires some level of change management supported by a champion, as most people prefer not to be measured or held accountable for their judgmental overrides. The purpose of FVA is not to punish people for adjusting the statistical baseline forecast but rather to improve the accuracy of the overall demand forecasting process by reducing unnecessary touch points. It has been proven in practice that the statistical baseline forecast is usually very close to actual demand; thus, a statistical baseline forecast, especially if augmented by more sophisticated methods including causal factors like sales promotions, external events, and other dynamic business drivers, usually will be more accurate by itself than with judgmental overrides. However, forecasters need to understand that when using more advanced statistical methods, such as regression, it is important to have company and external data that match the requirements of the independent and dependent variables. This is discussed in more detail in Chapters 6 and 7.

From these two stories, we learned that (1) the more people touching the forecast, the more chance you have to introduce biases and reduce accuracy; and (2) the more fact-based (information/data supported) and mathematically derived the forecast, the more likely the forecast accuracy will improve.

Judgment almost always introduces personal bias based on the purpose or needs of the person making the override. Unfortunately, many people within the demand forecasting process do not feel they are adding value unless they touch the forecast. However, most people do not want to be measured, as they are concerned it will be used to evaluate their performance rather than to understand why their adjustments are not adding value. This is a corporate cultural issue that requires change management driven by an internal champion, someone who can demonstrate how structure and analytics can validate or invalidate the assumptions used in making judgmental overrides, thus reducing the number of adjustments and putting more structure around the way sales and marketing shape future demand using analytics.

REALITY OF UNCONSTRAINED FORECASTS, CONSTRAINED FORECASTS, AND PLANS

Well-intentioned academics and consultants tout the concept of one-number forecasting. Enthusiastic supply chain executives have drunk the Kool-Aid, as they say. But the reality is that it does not reduce latency and it is too simplistic. The sole concept of a one-number demand forecast is that "If everyone is focused on one number, the probability of achieving the number is great." As a result, the concept adds unintentional and, in many cases, intentional bias, or forecast error, to the demand forecast. The reason is it is too simplistic, but the reality is that all the participants have different purposes, or intentions. I ask supply chain managers, "What is the purpose of your forecasting process?" They say, "To create a demand forecast." I respond, "What is the true purpose of the demand forecasting and planning process? Is it to set sales targets, create a financial plan, or create a true unconstrained demand forecast?" They pause and say "All the above." I respond: "All the above are plans, not an unconstrained demand forecast. There is only one unconstrained demand forecast or as close as possible to unconstrained with some inherent constraints, whether self-inflicted or customer specific." The people who push this concept really do not understand demand forecasting and planning.

A demand forecast is hierarchical around products, time, geographies, channels, and attributes. It is a complex set of role-based, time-phased data. As a result, a one-number thought process is naive. An effective demand forecast has *many* numbers that are tied together in an effective data model for role-based planning and what-if analysis. Even the eventual demand plan is sometimes not reflective of the original demand forecast due to capacity restraints, which results in demand shifting to accommodate supply constraints. In fact, most companies that describe demand shaping are actually describing demand shifting, not demand shaping. The difference between demand shaping and demand shifting is discussed in detail in Chapter 2.

A one-number plan is too constraining for the organization. A forecast is a series of time-phased plans carefully architected in a data model of products, calendars, channels, and regions. The numbers within the plans have different purposes to different individuals within the organization. So, instead of a one-number forecast, the focus needs to be a *common set of plans* for marketing, sales, finance, and operations planning with different plan views based on the *agreement on market assumptions and one unconstrained demand response.* This requires the use of advanced forecasting technology solutions and the design of the system to visualize role-based views that can be found only in the more advanced demand forecasting and planning systems.

The term *forecast* often is used far too loosely in most companies. It seems that everyone has a forecast. For example, there is a sales department forecast, a marketing department forecast, a financial department forecast and plan (budget), an operations forecast, and a demand forecast. In reality, there is only one unconstrained demand forecast that predicts the unlimited demand for a company's product. From that unconstrained demand forecast we create a constrained plan, not a forecast, by matching supply to demand. In many cases demand outstrips supply, requiring companies either to lower their unconstrained demand forecast or to incur additional costs to increase supply. Normally, in order to increase supply, companies would add manufacturing shifts or hire a third-party co-packaging company to fill the gap. It is amazing how many companies still refer to their constrained operations plan as the operations (or shipment) forecast. This becomes confusing as most companies have multiple forecasts, when in reality they should have one unconstrained demand forecast and an operations (supply) plan, which really is a constrained demand forecast. Generally there are numerous departmental forecasts within a company. These forecasts usually start with a statistical baseline forecast, to which domain knowledge is added through manual overrides by departmental planners or analysts to create a departmental perspective of unconstrained demand. Those departmental forecasts are used as inputs to create a consensus demand forecast. The overarching goal is to create a consensus demand forecast that captures all the domain knowledge and views of the key departments within the company. In concept, if designed properly, this process can improve the accuracy of the demand forecast. However, like many concepts, the reality is a result of the how it is implemented. In most cases, the implementation is flawed. The challenge is that most companies do not hold the groups within the organization accountable for their bias and error. Each group within the company has a natural bias (purpose) and corresponding error based on incentives. The old adage "Be careful what you ask for because you may get it" is true. Unless the process has structure regarding error reporting, the process of consensus forecasting and planning will distort the demand forecast, adding error despite well-intended efforts to improve the forecasting and planning process.

In many cases, companies have redesigned their consensus (collaborative) demand forecasting processes multiple times. Normally it is to improve the user interface to make data collection easier by sales. This is what I refer to as automate-what-I-do, but-don't-change-what-I-do syndrome. In each redesign, not once does anyone question the value and appropriate uses of the sales input or apply structure around the input that was driving a 40–60 percent forecast over-/under-bias. We struggle with why more companies do not apply the principles of lean to the consensus forecasting and planning process through FVA analysis.

This point is best described by Mike Gilliland in his book *The Business Forecasting Deal: Exposing Myths, Eliminating Bad Practices, Providing Practical Solutions* (John Wiley & Sons, 2010.). In its simplest form, FVA measures the impact of each touch point in the consensus demand forecasting process before and after the statistical baseline forecast is adjusted by one of the participating organizations (e.g., sales, marketing, finance, and operations planning). If that particular touch point is not adding value, it should be eliminated or the bias should be weighted up or down. Doing this requires that all the forecasts be captured each cycle and compared to determine any bias.

What if you don't have the authorization to eliminate a bias input in the consensus forecasting process? We now have the capability to create automatically a weighted consensus demand forecast based on each department's forecast accuracy over time. For example, if the statistical baseline forecast is consistently more accurate over time, then it would get the most weight—say, 50 percent. If the sales department forecast was the next most accurate forecast over time, it would get a weight of 30 percent; the marketing forecast may get 10 percent; the finance forecast, 5 percent; and the operations forecast, 10 percent. The weights would be multiplied to their corresponding forecasts and then summed, thus creating a weighted consensus demand forecast.

The next story illustrates how a simple weighted demand forecast can be created to improve the overall accuracy of an unconstrained consensus demand forecast.

NORTHEAST REGIONAL SALES COMPOSITE FORECAST

While working at an international household products company, I, along with my department, was responsible for collecting and summing the U.S. regional sales department demand forecasts. The purpose was to create a "sales composite" forecast as an input to our consensus demand forecasting process. At the time we did not call it the consensus demand forecast; we simply called it the sales forecast. It was an unconstrained consensus demand forecast that resulted from a typical forecasting process where we started with a statistical baseline forecast and then captured the domain knowledge of each department (sales, marketing, finance, and operations) through manual overrides. Each month we would conduct a consensus forecasting meeting where each department would defend its position with the vice president of sales, who was responsible for determining the final consensus sales forecast.

Over time we realized that the U.S. northeastern regional sales team sent the most accurate demand forecasts. So we traveled to the northeastern regional sales office in Baltimore to meet with the sales analyst to determine what the sales team was doing to produce such an accurate demand forecast. The sales analyst outlined a simple approach that became the basis for future consensus forecasting methodologies that eventually were implemented throughout the sales regions. The analyst explained that when he received forecasts from each divisional manager, he noticed over time there was a distinct trend associated with them. For example, one divisional manager was on average 5 percent higher than actual demand every month, another was consistently 2 percent lower, and another was always very close to the actual demand. During the collection process, the analyst would take each divisional sales manager's demand forecast and adjust it accordingly based on the manager's accuracy over time. After adjusting each divisional manager's demand forecast, the analyst summed them to create the weighted northeastern regional demand forecast. This simple methodology worked extremely well to eliminate the personal bias of each divisional sales manager, resulting in a more accurate demand forecast.

From this story, we learned that weighted combined demand forecasts based on accuracy over time tend to eliminate personal bias, thus improving overall accuracy. This is surprising, given that researchers have recommended combining forecasts for over half a century. In fact, surveys of forecasting methods by several well-known trade organizations claim to use combined forecasts. Research conducted over the past half century concludes that simple averaging of two or more forecasting methods, including judgmental methods, can lead to improvements in forecast accuracy. Furthermore, combined weighted forecasts tend to eliminate practitioner bias. Unfortunately, most organizations use combined forecasts in an informal manner and thus miss most of the benefit, according to Scott Armstrong (professor at the Wharton School, University of Pennsylvania).[4] A more detailed methodology, weighted combined forecasting, also known as sales composite forecasts, is discussed in Chapter 8.

HOLD-AND-ROLL MYTH

One of the most common approaches to demand forecasting is what is referred to as hold-and-roll or snowplowing, which has been entrenched in corporate cultures across all industry verticals worldwide for well over three decades. In this environment, the demand forecasting process is strongly influenced by C-level managers to serve two purposes: (1) tie the demand forecast to the financial plan and (2) set sales targets for the field sales organization. Usually the vice president of finance or marketing influences the participants in the monthly consensus forecasting meetings to adjust the demand forecast to reflect the financial plan even in the face of declining demand. In many cases, they actually raise the demand forecast for the next period (month/week) by rolling missed demand forward from the previous period so they can hold to the original annual financial plan.

It is hard to understand why C-level managers think they will be able to make up missed demand in the following month. It takes a minimum of three to six months as well as additional discretionary marketing spending to put programs in place to drive incremental demand. A common response to the question “What makes you think you can make up last month’s missed demand next month?” is that “The sales organization will be focused.” “But weren’t they focused last month?” “Yes, but they will be ‘more’ focused next month.”

In my experience, the hold-and-roll philosophy never works long term. It may work for a quarter or even two quarters before the company eventually takes a large write-off or loss in demand as it can no longer roll the missed demand forward. Normally, the company will take a huge one-time loss on the profit and loss statement, a lot of people do not receive a bonus that year, and the stock price declines due to missed projections to Wall Street. Sales, not marketing or finance, is usually blamed for the missed demand. Finally, people are laid off due to the lack of demand, and many times these companies file for Chapter 11 bankruptcy. I worked for two companies that used this approach to demand forecasting. One was acquired by a larger company, and the other filed for bankruptcy.

Many people lost their jobs, and some legacy brands were discontinued.

The hold-and-roll approach is a corporate cultural issue that is hard to change within most companies. It requires a great deal of change management led by a champion, usually a C-level manager. This approach puts little emphasis on analytics and stresses the use of judgment, not domain knowledge, to justify all the assumptions that support rolling the missed demand to the next period and holding to the annual financial plan. The change management remedy to correct this corporate cultural issue is a more structured process that emphasizes the use of analytics combined with domain knowledge. Using what-if analysis, the company can shape future demand in a more proactive environment that facilitates corporate strategies. Then and only then can change occur to break the vicious cycle of hold and roll. The main defense of hold and roll is that if everyone is working toward the same demand forecast, it will happen. This is wishful thinking, particularly when the company is experiencing declining demand.

The next story gives an example of how to overcome this hold-and-roll philosophy.

THE PLAN THAT WAS NOT GOOD ENOUGH

During my tenure at that same international household products company, we were required to submit an annual plan to our corporate headquarters. Each year we would spend weeks analyzing our product portfolio brand by brand to determine annual unit volumes, corresponding revenue sales, and market share to develop an annual financial budget (plan).We would fly to the global corporate headquarters to present and defend our annual plan. After hours of presentations and a multitude of questions from the chief executive officer, chief financial officer, chief marketing officer, and other corporate staff members, we would be told that the plan was not good enough. The plan number was always too low. The global corporate senior management team would prescribe an overall plan number that was usually 10 to 20 percent higher than our original plan. We would push back by explaining that we could not achieve the higher plan number because demand in our division (North America) was weak and stimulating demand would require additional discretionary marketing and sales programming (investment). They would ask us if we had any supporting information to justify our plan number and how we would invest any discretionary sales and marketing dollars to drive more unit volume and profit. We would provide them with a lot of qualitative information about the market, what additional sales promotions would add incremental unit volume, and, finally, how we were experiencing increased pressure from our competitors, causing demand for our products to decline. In the end, not only did they raise the annual volume and revenue plan, but they also reduced the supporting budget. In other words, we had to deliver more unit volume and revenue with less budget support. Michael Gilliland refers to this as "evangelical" forecasting, where upper-level management provides numbers, and the forecaster's job is to work out the details to match the target/forecast given by upper management.[5]

In the end, we were told that our rationale was not good enough to convince them to accept our annual plan number. We returned to the North American divisional headquarters and backed into the higher annual plan number brand by brand. We then asked ourselves how we would ever be able to stimulate enough incremental demand to meet our new financial plan, particularly given the reduction in budget spending. That year we missed our annual unit and revenue target, and no one received a bonus, resulting in low morale for the year.

The next year we developed more sophisticated models around each brand to determine how the marketplace would respond to various amounts of marketing spending for sales promotions and other activities. We ran what-if analyses to validate our assumptions and strategies to fill any suspected budget gaps the global corporate headquarters would present from a target perspective. When we defended our plan to the global corporate senior management team, we were prepared with data, analytics, and contingency plans. When we were asked to accept a higher volume and revenue target, we showed them all the data and analysis. We continued to explain how we ran what-if simulations to determine what needed to be done to close the gap between our plan and the new corporate target. We asked for a $2 million incremental discretionary marketing spending fund to close the gap based on our analysis. The global corporate senior management team was so impressed that it lowered our annual volume and revenue target and gave us an additional $1 million in discretionary marketing spending to drive more demand. That year we not only met our target but exceeded it. As a result, everyone received a bonus.

From this story we learned that companies continue to use the demand forecasting process as a target-setting exercise that is not always reflective of true demand. As demand forecasters, it is our responsibility to validate unconstrained demand using sophisticated methods that can be used to provide practical recommendations to close gaps and minimize exposure to corporate game playing.

PACKAGE TO ORDER VERSUS MAKE TO ORDER

The demand forecasting process in most companies is focused on make to stock. They describe how they need to plan ahead and then deploy inventories of finished goods into distribution centers to support demand at the source to more efficiently restock customers. This way, once a customer order materializes, it can be fulfilled immediately, as most customers are not willing to wait as long as it would take to actually make the product and ship it. Given the long lead times to acquire raw materials from multiple sources globally, it makes sense for companies to maintain finished goods inventories in designated markets at distribution centers in order to provide faster order cycle times. As a result, virtually all companies need to rely on a forecast of future demand. The ability to accurately forecast demand provides a means for companies to improve supply chain efficiencies through a reduction in costs, not to mention improve their customer service. Even those companies that claim to make to order, when in fact they are really packaging to order, need to rely on more accurate demand forecasts to order raw materials and common subassemblies. This is especially true in the electronics industry and among PC manufacturers in particular that take customer orders over the Internet.

"DO YOU WANT FRIES WITH THAT?"

Let us take for example a fast-food restaurant. On your way home after a long day at work, you are looking for a quick pick-me-up meal at the local fast-food restaurant. You are looking forward to getting your food quickly the way you want it. When you enter the restaurant, you see a large bin filled with French fries. Alongside the bin are large, medium, and small packages that the server fills with a scoop when someone orders a side of fries with a meal. The fast-food restaurant is actually packaging to order, not making to order. However, most manufacturers describe this process as make to order. In any case, someone had to forecast demand for French fries so that they would be available when the customer walks into the restaurant.

The same is true when you order a laptop from a PC manufacturer. All of the standard components are in stock and available to fill each order as it is entered via the manufacturer's Web site or called in by phone. Someone is forecasting the number of hard drives, different size monitors, memory, central processing units, and other items that make up each different configuration offered and stocking them in the assembly plants so that each order can be filled and shipped within a short time frame. Realizing the critical nature of this situation, many electronic manufacturers are purchasing enterprise-wide software licenses from forecasting software providers to forecast all those various components. If the PC manufacturer over-forecasts the various components and subassemblies, the company might be forced to discount the various components and subassemblies in order to reduce inventories, which in turn lowers the manufacturer's profit margin. If the PC manufacturer under-forecasts the appropriate components and subassemblies, it might be forced to expedite delivery of the components at a higher cost or back-order the product with the chance of losing the order completely. Both scenarios would have a negative impact on revenue and profit, not to mention the possibility of losing a customer. Alternatively, the PC manufacturer could choose to truly make to order, which means the consumer would not receive the PC for weeks or months.

Let us return to our fast-food restaurant example. Suppose a consumer entered the fast-food restaurant and ordered French fries, but this time the fries were truly made to order. The server would take the order and then call the purchasing office. The purchasing planner would then place an order with the local fry distributor, which then would ship the fries to the local fast-food restaurant. In this scenario, the consumer most likely would receive an order of French fries in about three to five working days rather than a few seconds, or as long as it takes the server to walk over and scoop up the fries. Only a handful of industries, such as aerospace, actually make to order. In the aerospace industry, when the U.S. government places an order for Apache helicopters, the U.S. government receives those helicopters several years later. The helicopters are not stocked in inventory.

In make-to-order situations, the customer or consumer is willing to wait long periods for the product to be manufactured and delivered. However, the majority of companies like fast-food restaurants and computer manufacturers that actually package to order require some level of a demand forecast to stock the right components and subassemblies (work in process) that make up the product and the right staffing actually to perform the assembly. In these situations, the consumers of the products are not willing to wait very long, and they demand high customer service. Essentially all products and services require some level of demand forecasting. Overall, accurate demand forecasts lead to more efficient operations and higher levels of customer service; inaccurate forecasts inevitably lead to supply chain inefficiencies due to higher-than-normal operations costs and/or poor levels of customer service. In many supply chains, the most important action a company can take to improve the efficiency and effectiveness of the process is to improve the quality of demand forecasts.

SUMMARY

As a C-level manager, I have always served in a change management role as the champion of demand forecasting. Demystifying demand forecasting by educating senior management on its myths and realities has always been part of my job responsibilities. However, I was successful in creating change only when I relied on data and analytics to validate assumptions and provide a mechanism to develop strategies using simulation tools and applications. Members of the demand management team have always had to demonstrate that analytics outperforms judgment, and it has always been difficult to change long-held opinions. In corporate settings, there will always be skeptics who enjoy the game playing associated with target setting versus true demand forecasting. A traditional demand forecasting process provides a mechanism for those nonbelievers to touch the demand forecast without being held accountable. Structure and analytics are means for eliminating personal bias.

As agents of change, it is our responsibility to create an environment that eliminates personal bias and gaming in the demand forecasting process. Using proven analytics combined with domain knowledge, not pure gut-feeling judgment, is the only means to break the current cycle of making manual adjustments to simple statistical baseline forecasts. We can no longer afford to continue this process, given the pressures to deliver more with less. It is our responsibility to provide senior management with a more robust set of tools and applications that can help them sense, shape, and predict demand in a more proactive way, eliminating the guesswork associated with developing viable strategies that maximize volume growth and revenue.

NOTES

1. Charles W. Chase, Ritu Jain, and Kenneth B. Kahn, "Demand Planning Maturity Model: Strategies for Demand-Driven Forecasting and Planning," joint paper by Purdue University and SAS, 2009.
2. End-cap displays can be found at the end of each aisle in a retailer's store. They display products that are tied to a specific sales promotion. Not only are the products placed at the end of the aisle in the end-cap display, but they also can be found in the corresponding aisle on the shelf positioned with competitors' products. End-cap displays allow a manufacturer to feature its product exclusively. In many cases,

retailers use this in-store merchandising vehicle as a loss leader to drive more traffic in the store. The consumer can choose to take the product from its normal shelf position in the aisle or simply take one from the end-cap display. Both are priced the same.

3. Robert Fildes and Paul Goodwin, "Good and Bad Judgment in Forecasting: Lessons from Four Companies," *Foresight: The International Journal of Applied Forecasting* (Fall 2007): 5–10.
4. J. Scott Armstrong, *Long-Range Forecasting: From Crystal Ball to Computer*, 2nd ed. (New York: John Wiley & Sons, 1985).
5. Michael Gilliland, "Fundamental Issues in Business Forecasting," *Journal of Business Forecasting* (Summer 2003): 1–13.