**Why Forecasting Is a Waste of Time: The Three Aphorisms**

Michael Gilliland, Oscar Mayer Foods, Madison, WI
John LaBella, Oscar Mayer Foods, Madison, WI

**ABSTRACT**

The standard approach to improving forecast accuracy is to invest in more data, bigger computers, fancier forecasting models, and more people to provide input. Yet for all the time and money spent in this endeavor, improvements have been scarce -- no magic formula has been found.

We argue that the standard approach is fundamentally misguided. It is often a mistake to invest heavily in sophisticated forecasting systems because many processes cannot be forecasted well. Instead, effort should be focused on simplifying and smoothing the processes being forecasted. By "making the data forecastable" you will achieve better forecasts with much less cost and effort.

Using an example from the consumer products business, we suggest a way to lower the volatility (and unpredictability) of sales patterns. We show that the theoretical limit of forecast accuracy is determined by the variability of a process about its rule, and that forecasts can never be very accurate (no matter how sophisticated your model) until this variability is minimized.

**INTRODUCTION**

Of course it is beneficial to know the future. If a company knows its sales next week, next month, and next year, it will invest only in the equipment, materials, and staffing it needs. A gambler will make only the profitable wagers -- if he knows which horses will win. There are huge opportunities for everyone to minimize costs and maximize profits if we know what tomorrow will bring. But we don't.

Forecasting is seen as the cure-all for this uncertainty. Yet for all the time and money invested in forecasters and forecasting systems, how much uncertainty have we eliminated? How much value have we added to our products and services by these costly efforts to forecast? The answer is simple: not very much.

The problem is not in our technology. We have access to more data, bigger computers, and more sophisticated forecasting techniques than ever before. The problem is in the wasteful misapplication of this technology to processes which are essentially unforecastable!

In this paper we make a distinction between processes it makes sense to forecast -- where there is hope of improving forecast accuracy, and processes where no improvement is possible. We provide examples of "unforecastable" processes, and argue that many common business problems (such as forecasting sales) may fall in this category. Through three aphorisms, we provide guidelines on how to eliminate wasted efforts in the forecasting process, and suggest more efficient ways to achieve knowledge of the future.

**APHORISM 1: FORECASTING IS A HUGE WASTE OF MANAGEMENT TIME**

Count the number of people in your organization involved in forecasting. This would include sales representatives and their managers, financial analysts and their managers, production and inventory planners and their managers, as well as marketers, strategic planners, and maybe even full time forecasters. There are also systems people involved in the process -- developing and maintaining the statistical algorithms, and generating all the reports.

How much high cost management time is spent forecasting by these people? How much value do they add? Forecasting is seen by most participants as a necessary evil. Few have a true interest in doing it, fewer still have the training and tools to do it properly.

There is also a subtle political interest in everyone who provides a forecast. Might marketers chronically overforecast -- to better sell their ideas to top management? Do sales reps chronically underforecast -- to avoid the appearance of missing their targets? The fact is, nearly all participants in the forecasting process have some vested interest in the numbers they provide. So when you ask for a forecast, you can't even count on getting an honest answer!

Organizational leaders continue to demand forecasts, yet are rarely satisfied by their accuracy. Knowledge of the future is a legitimate objective, but the traditional approach -- investing in more sophisticated forecasting systems and calling for more human input -- is misdirected. Rather, the attention should be placed on the process being forecasted.
APHORISM 2:
THE SUREST WAY TO GET BETTER FORECASTS IS TO MAKE THE DATA FORECASTABLE

COROLLARY:
ANY KNUCKLEHEAD CAN FORECAST A STRAIGHT LINE

It's trivial but it's true: smooth, stable, repeating patterns are easy to forecast with simple algorithms. Wild, volatile, non-repeating patterns are impossible to forecast -- even with highly sophisticated and costly computer models. Yet the common response to forecast -- even with highly sophisticated and poor forecasting performance is to seek more data, a better statistician, and a fancier forecasting model: The net result of such action may be a few percentage points increase in forecast accuracy -- but this is hardly worth the effort! The question that should be addressed is not "How can I better forecast this process?" but "How can I make this process forecastable?"

Consider an example: Why can we forecast the exact time of sunrise 10 years from now, but not next week's sales? The reason is that sunrise follows a very precise pattern, governed by a few rules of physics which have strong theoretical and empirical support. Sunrise follows a "rule" which is known to us -- and it exhibits little (if any) variation about the rule.

Sales patterns, on the other hand, rarely follow an identifiable rule. There are so many factors impacting the sales process, and their interrelations are so complicated, that it is often impossible to discern a real pattern. Millions of dollars are spent each year seeking the magic formula to predict future sales, and crude patterns can be found (e.g., you sell more hotdogs and fewer snow tires in the summer). However, forecast accuracy is extremely limited due to the great variation in process behavior about its purported rule.

QUESTION: If there were a magic formula for predicting the future, wouldn't someone have found it by now?

The point of Aphorism 2 is that some processes are basically unforecastable -- or at least not forecastable to the accuracy we desire. To achieve accurate forecasts we must not only know the rule that the process follows, but the process must follow the rule with little variation! This is a key point: The theoretical limit of forecast accuracy is determined by the process variation about its known rule.

Here is a simple illustration of how process variation about its rule will determine forecast accuracy.

Consider four processes:

<table>
<thead>
<tr>
<th>PROCESS</th>
<th>OBSERVED MEAN</th>
<th>OBSERVED STD.DEV.</th>
<th>FORECAST M.A.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>50.1%</td>
<td>50.0%</td>
<td>1.0%</td>
</tr>
<tr>
<td>P10</td>
<td>50.0%</td>
<td>12.1%</td>
<td>0.9%</td>
</tr>
<tr>
<td>P100</td>
<td>50.1%</td>
<td>5.0%</td>
<td>0.1%</td>
</tr>
<tr>
<td>P1000</td>
<td>50.0%</td>
<td>1.5%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

By hypothesis we are tossing a fair coin, hence the only rational forecast for each process is 50% heads. It is easy to show analytically, or by simulation, that processes P1 - P1000 follow the same "rule" (that there will be 50% heads), and that they have decreasing variability about the rule. Figures 1A-1D show results of a simulation wherein each process was run through 1000 trials. This graphically illustrates the decreasing variability about the rule.

It is also possible to compute forecast accuracy from this simulation. Since the only rational forecast is 50% (for all trials of all processes), we obtain these accuracy results:

<table>
<thead>
<tr>
<th>PROCESS</th>
<th>OBSERVED MEAN</th>
<th>OBSERVED STD.DEV.</th>
<th>FORECAST BIAS</th>
<th>FORECAST M.A.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>48.1%</td>
<td>50.0%</td>
<td>-1.9%</td>
<td>50.0%</td>
</tr>
<tr>
<td>P10</td>
<td>50.0%</td>
<td>12.1%</td>
<td>0.9%</td>
<td>6.5%</td>
</tr>
<tr>
<td>P100</td>
<td>50.1%</td>
<td>5.0%</td>
<td>0.1%</td>
<td>1.9%</td>
</tr>
<tr>
<td>P1000</td>
<td>50.0%</td>
<td>1.5%</td>
<td>-0.0%</td>
<td>1.2%</td>
</tr>
</tbody>
</table>

As expected, all four processes have an observed mean of around 50%, and observed volatility (measured by standard deviation) drops dramatically from process P1 to P1000. This results in essentially unbiased forecasts for all four processes, but the forecast accuracy (measured by mean absolute deviation) improves from P1 to P1000. The conclusion is obvious and even trivial -- but it deserves to be stated: The less variability of a process about its known rule, the more accurately we can forecast it!

There is another important point from this example. No amount of forecasting sophistication will ever allow you to forecast process P1 better than P10, or P10 better than P100, or P100 better than P1000. By the nature of these processes (as random patterns with a certain distribution about a mean of 50%), the only rational forecast is always 50% heads. It makes no sense to try finding a better forecast because the best forecast has already been determined by the known nature of the process. Likewise, forecast accuracy has already been determined by the known volatility of the process.

There is a close tie here to Statistical Process Control. In SPC, the behavior of a process over time is expressed on a control chart. If a process is "in control" and exhibits no patterns (indicative of special causes), then the only rational forecast for the next observation is the mean of the control chart. (See the Deming (1986) reference for further details.)
EMPHASIS: We have shown that the "theoretical limit" of forecasting accuracy is determined by the variation in the process about its known rule. In practice, we will usually forecast much worse than the theoretical limit because we usually don't know the process rule. Also, we have no guarantee that the process will continue to obey the same rule.

Making the data forecastable may not be as difficult as it appears to be. You can probably find, within your own organization, practices that make a process more difficult to forecast. A vivid example is provided by sales incentive programs.

There is a common practice in the consumer products business called "trade loading," wherein a manufacturer's sales policies encourage the retailer to "forward buy." Simply put, the manufacturer offers a significant discount to the retailer to buy extra large quantities of the product -- much more product than the retailer needs to meet current consumer demand. Obviously, this practice adds huge costs to the system -- manufacturers must stockpile materials and run overtime to meet the sales peaks, distribution facilities are stressed to hold oversized inventories and then ship them out, and the retailer must warehouse the excess product until it sells. (Between $75 and $100 billion in grocery inventory is stuck in the pipeline from manufacturer to retailer -- over 25% of annual sales. See the Buzzell (1990) and Doyle (1992) articles.)

The retailer makes money on trade deals because the price discount is enough to cover the excess costs. It is ultimately the consumer who pays for the inefficiency, both through higher prices, and through "stale" product which spends several weeks in storage before reaching the store shelf. (It takes the typical grocery product 84 days to travel from factory to store shelf. Again, see Buzzell and Doyle.)

Trade deals impact forecast accuracy by creating spikes in sales patterns -- artificial spikes that are not present in the true consumption of the product. Figure 2 illustrates shipments to retailers vs. sales to consumers for one product line. Both average about 2.4 million lbs/week, and consumption does display some seasonal variation (higher in summer, lower in the fall). But retail shipments follow an up and down pattern featuring quarter-end spikes (and quarter-beginning valleys) indicative of short sighted and costly sales incentive programs. (Incentives may include not only trade deals, but sales contests which reward the sales person for forcing volume into a specified week or period.)

Volatility, as measured by the coefficient of variation of the pattern, is over 3 times higher for retail shipments than it is for consumer sales. This is a serious point because spiked and erratic patterns are fundamentally more difficult to forecast than smooth and repeating patterns. Not only does the spiked pattern increase costs by requiring excess production, inventory, and distribution capacity -- it adds the further cost of uncertainty.

One obvious way to get better forecasts -- by making the data forecastable -- is to remove the incentives that artificially distort demand. Smooth patterns can be forecasted accurately by simple algorithms with little or no human intervention. Complex patterns will forever be difficult to forecast, even with the aid of high priced computers, software, and management involvement. Rather than spend lots of time and money to improve the forecast of a process you will never forecast well, it makes more sense to focus on smoothing the process.

APHORISM 3: WHY FORECAST THE FUTURE WHEN YOU CAN KNOW THE FUTURE

We have seen that forecasting takes up lots of time, and in most cases doesn't yield very good results. Because of the inherent unpredictability of many processes (such as sales), it may be foolish to make heroic efforts to forecast them. Beyond making the process more forecastable, what is the next step toward achieving our goal of knowing the future?

The only way to know the future -- tomorrow's needs of your customers -- is to become one with your customer. Too often the customer is seen as an adversary, needed but despised. We cannot expect to know what our customer needs until the customer shares everything with us. That means becoming partners, based on a relationship of trust and long term commitment. Together, the supplier and the customer can drive out inefficiencies in the system. This makes both more profitable while providing better value to the consumer.

A consequence of the customer/supplier alliance is the linking of information systems. Some retailers, such as Wal-Mart and K-Mart, are requiring their suppliers to use Electronic Data Interchange for managing orders. The benefit to the supplier may be knowing the customer's inventory, knowing the sales patterns, and knowing the promotional activity that the customer is planning. It allows the supplier to plan a customer's orders for them. When you have reached this state with your customer you will no longer have to guess the future because you will know the future!
CONCLUSION

We have highlighted the fact that some processes, by their very nature, are easier to forecast than others. Many complex processes will never be forecasted accurately, no matter how much effort and technology we throw at them. The nature of the process is key. We must learn to distinguish the forecastable process from the unforecastable, and not waste our time on those whose forecasts cannot be improved.

For those processes that cannot be forecasted well, the most effective solution may be to challenge the process itself -- to eliminate the factors which cause volatility and unpredictability. By "making the data forecastable" we will achieve more accurate forecasts with much less effort.

Finally, we want to emphasize the importance of partnership in the customer/supplier relationship. By linking systems and building a customer's orders for them, your view into the future will be better than any forecasting system can provide.

REFERENCES


ACKNOWLEDGEMENTS

Thanks to Mike Dutt for contribution of Figure 2.

AUTHORS

Michael Gilliland
Forecast Communication Manager

John LaBella
Corporate Production Planning Manager

Oscar Mayer Foods Corporation
910 Mayer Avenue
Madison, WI 53704
(608) 241-3311

FIGURE 1A

% OF HEADS IN 1 TOSS OF A FAIR COIN

PI: % OF HEADS IN 1 TOSS OF A FAIR COIN
FIGURE 1B

FIGURE 1C
P1000: % OF HEADS IN 1000 TOSSES OF A FAIR COIN

FIGURE 1D

SHIPLEMENTS VS. CONSUMER SALES

FIGURE 2