The Lean Approach to Business Forecasting

Eliminating Waste and Inefficiency from the Forecasting Process
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Introduction

The lean approach, whether applied to forecasting, supply chain, accounting or any other business process, is all about the identification and elimination of process waste. We can’t always control the forecast accuracy we achieve, and we can’t always achieve the level of accuracy we desire. However, we can control the forecasting process we use, and we can control the resources we invest in that process.

Has anyone ever complained that their forecasts are too easy to create and more accurate than they need? Probably not. Instead, most companies spend way too much time and resources on forecasting, yet still complain about inferior results. Whether you are an employee, an executive or a shareholder of one of these companies, this situation is unacceptable. But by applying a lean approach – that is, by identifying and eliminating waste in the forecasting process – it is possible to achieve better results with much less effort.

This white paper provides simple and practical methods for applying the lean approach to forecasting at your organization. It will show you how to become more efficient in your forecasting process – spending less time and money while getting better results.

Foundations of the Lean Approach

The lean approach is motivated by the observation that many forecasting process activities are not adding value – in fact, they fail to improve the forecast and may even make it worse! Sometimes the failure is due to flawed systems (see McCullough, 2000) or flawed forecasting methods (see Gardner, 2001). Other times the failure is due to flawed organizational processes that contaminate what should be objective and fact-based forecasts with internal politics and management wishes.

The lean approach consists of gathering data, conducting Forecast Value Added (FVA) analysis, communicating the results to management, and streamlining and improving the overall forecasting process.

Key elements of the lean approach include:

- Use of a naive forecast.
- Understanding the relationship between demand volatility and forecast accuracy.
- Understanding the impact of management judgment and political biases.
- Understanding what accuracy is reasonable to expect and how to establish performance targets.

Setting reasonable expectations and appropriate performance targets is actually quite important – because if you do not know what accuracy is reasonable given the behavior you are attempting to forecast, you can reward inferior performance or waste resources pursuing unachievable targets.
Data Requirements

Your objective in the lean approach is to identify and eliminate process waste. To do this, you need to understand where you are investing resources in your forecasting process. You need to measure what each process activity is doing, and determine whether the activity is improving the forecast or is just a waste of time. Figure 1 illustrates a typical business forecasting process. The general structure can apply to manufacturing, services or other industries.

Figure 1: Typical forecasting process.

Historical demand and perhaps other causal variables are fed into statistical models that generate an initial statistical forecast. A forecast analyst can enter a manual override, and then send the forecast along to a consensus, collaborative or Sales & Operations Planning (S&OP) process.
In the consensus process, participants from sales, marketing, finance and others can provide information and opinions on demand from their own perspectives. The operations side of the business can provide information on supply constraints. At a manufacturer these constraints might be production capacity and inventory availability. The constraints may be on staffing for a call center, or on service technicians or installers for a telephone or cable company. Other examples of supply constraints include processors at an insurance or financial services company, room availability at a hotel, or seats on an airline or passenger train.

Some companies, particularly in consumer products and retail, may use a more elaborate process called CPFR (Collaborative Planning, Forecasting and Replenishment). CPFR involves not only internal resources listed in the diagram, but engages external participation from customers and suppliers.

The resulting “constrained” forecast from the consensus, collaborative or S&OP process often incorporates one final step – being sent to a general manager, CEO or executive committee for final review, update and approval.

Clearly there is a lot of high-cost management time involved in such a process, which raises the question: “Are all of these steps and participants adding value by making the forecast better?” The only way to answer that question is to gather data on the process steps and participants and measure the results.

- Actuals — at most granular level of detail.
- Forecasts from various sources:
  - Statistical model.
  - Analyst override.
  - Consensus override:
    - Individual consensus participants.
  - Executive approved.

Figure 2: Data requirements.

To begin with, you must capture your actuals – that is, your sales, shipments, insurance claims, calls received or whatever it is you are forecasting – and you should capture your actuals at the most granular level of detail. For a retailer, this could mean actual sales by item, by store, by day or by week. For a manufacturer, it could mean actual shipments by item, by distribution center, by week or by month.

Forecasts need to be captured at every step in your forecasting process, and by individual participants if such detail is available. For example, you would capture the “statistical” forecast created in your forecasting software and any overrides made by the forecast analyst. You would capture the “consensus” forecast created in your process – as well as separate forecasts by individual consensus participants if they were provided.

(It is good practice to capture the forecasts of individual participants in order to identify biases and wasted efforts of separate process participants.)
If your organization uses an executive approval process, the “final approved” forecast must be captured. In practice, an executive approval step might make the forecast worse. Research on the politics of forecasting (see Deschamps, 2005) indicates that the wants, wishes and personal agendas of forecasting stakeholders can negatively affect accuracy. But unless you capture the data required to prove this is occurring, you won’t be able to bring the problem to management’s attention.

One final piece of data you need to collect is the naive forecast – the forecast you could get by essentially doing nothing. The Random Walk and the Seasonal Random Walk are the two traditional naive models, and they can be used to generate forecasts with virtually no cost and no effort. (See sidebar below for sample calculations of these two traditional naive models, or Makridakis, 1998, pp. 46-48, for a more thorough discussion.)

### Naive Forecasting Models

The Random Walk uses the most recent observation available as the forecast. For example, if you sold 10 last week, your new forecast is 10. If you sell 12 this week, your new forecast is 12. Table 1 illustrates the calculation.

The Seasonal Random Walk often can forecast much better than the Random Walk by incorporating seasonality in the data. Table 2 illustrates the calculation when we use sales from the same period a year ago as the forecast for the corresponding period this year.

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**Table 1: Random Walk.**

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**Table 2: Seasonal Random Walk.**

These are just two examples of commonly used naive forecasting models. The key point is that the naive model “uses the minimum amount of effort and manipulation to prepare a forecast” (see Jain, 2005). The accuracy of the naive forecast is what we can achieve by essentially doing nothing. The performance of more sophisticated models and processes should always be compared to the performance of the naive model. If the more sophisticated (and costly) methods do not beat the naive model, then why bother?
The naive forecast provides a baseline level of accuracy against which all other forecasting efforts must be compared. Very few companies utilize naive models, but everyone should. If you find, for example, that a naive model forecasts your business with 70 percent accuracy, but your existing systems and processes generate forecasts that are only 60 percent accurate, then something is terribly wrong! All of this sounds unfathomable – how could million dollar systems and elaborate collaborative processes produce worse forecasts than a naive model – but it happens every day. Until you've gone through this exercise and proven otherwise, don't be so sure it isn't happening in your organization.

If you don’t already use naive models, you won’t already have naive forecasts in your historical data. But as the sidebar shows, it is actually very easy to reconstruct what a naive model would have forecast in the past.

Summary of Data Requirements

At a minimum, you should be able to gather or reconstruct these data elements:

- **Naive forecast** – reconstruct if necessary.
- **Statistical forecast** – generated by your forecasting software.
- **Analyst override** – what your forecast analyst thinks the number should be, based on manual overrides to the statistical forecast.
- **Consensus forecast** – as agreed upon by your consensus, collaborative or S&OP process if you have one.
- **Final executive approved forecast** – if you go through this step.

If your process doesn’t have all these steps, then of course you won’t have the corresponding data for that step. If your process has additional steps or participants, then you should attempt to gather the data for each of them.

Potentially, you will be gathering a lot of data. You will be gathering the forecast created by each step and participant in your forecast process, in each time period, for each item and location, or whatever else it is you are forecasting. You need to have a mechanism for gathering the data automatically, and storing it somewhere readily accessible for analysis and reporting. Spreadsheets are fine for a one-time FVA analysis, and simple desktop database tools are sufficient if the amount of data you are capturing is not too large. However, most organizations will need much more scalable data integration than that, and SAS® software is ideally suited for this type of work.

Whatever software you end up using, you should gather data on all steps and participants in your forecasting process. Without the data, all you have are beliefs and opinions about what improves the forecast and what does not. As human beings, we tend to assume that everything we do has a positive impact. We believe the harder we work and the harder we work our employees, the better the results to the bottom line. We also assume that by applying more sophisticated methods, by developing a more elaborate process and by including more management participation in our forecasting efforts, we are sure to get more accuracy. But without the supporting data and analysis, is there any justification for these assumptions?
Forecast Value Added Analysis

There is perhaps no business process as full of unnecessary costs and wasted efforts as forecasting. But how would we ever know? Unfortunately, the traditional forecasting performance metrics such as Mean Absolute Percent Error (MAPE) don’t help. By itself, MAPE tells us the magnitude of our forecast error. But MAPE provides no indication of what error we should be able to achieve. And MAPE gives no indication of how efficient we are at executing the forecasting process. (See sidebar below for calculation of some common forecasting performance metrics.)

Common Forecasting Performance Metrics

There are dozens of forecasting performance metrics available. Perhaps the most widely used metrics are Mean Absolute Percent Error (MAPE) and its variations such as Weighted MAPE (WMAPE), which tell you the magnitude of forecast error. An alternative to these, Forecast Accuracy (FA), has the advantage of always being scaled between 0 and 100 percent, making it easier to interpret and a better choice for management reporting. Table 3 illustrates the calculation of these metrics over four time periods:

| Period | Forecast | Actual | |F - A| |APE| Max(F,A) |
|--------|----------|--------|---------|-------|------|--------|
| 1      | 100      | 75     | 25      | 33%   | 100  |
| 2      | 125      | 200    | 75      | 38%   | 200  |
| 3      | 50       | 100    | 50      | 50%   | 100  |
| 4      | 75       | 25     | 50      | 200%  | 75   |
| TOTAL  | 350      | 400    | 200     | 321%  | 475  |

\[
\text{APE} = \frac{\text{Absolute % Error}}{100} = 100 \times \frac{|F - A|}{A}
\]

\[
\text{MAPE} = \frac{\sum \text{APE}}{\# \text{Observations}} = \frac{321\%}{4} = 80\%
\]

\[
\text{WMAPE} = 100 \times \left( \frac{\sum |F - A|}{\sum A} \right) = 100 \times \left( \frac{200}{400} \right) = 50\%
\]

\[
\text{FA} = 100 \times \left\{ 1 - \frac{\sum |F - A|}{\sum \text{Max}(F,A)} \right\} = 100 \times \left\{ 1 - \frac{200}{475} \right\} = 58\%
\]

Table 3: Calculation of MAPE, WMAPE and FA.
Rather than assuming that all the extra effort and sophistication is paying off by delivering better forecasts, we can use the Forecast Value Added metric to illustrate a different approach.

Consider a simple example. Suppose you have some decent statistical forecasting software at your company, and you have configured it to automatically generate your forecasts each week. In addition, let’s suppose that you don’t entirely trust the software under all circumstances so you permit your forecast analysts to review and modify the numbers if they feel it is appropriate. Such a simple forecasting process would look like this:

Demand History ➜ Statistical Model ➜ Statistical Forecast ➜ Analyst Override

Figure 3: Simple forecasting process.

You assume, of course, that your analysts are making the forecast better with their overrides, but how would you know?

It is common sense that we should be permitted to apply judgment to our forecasts. In some situations, such as forecasting for an entirely new type of product for which there is no relevant data to model in statistical software, it may be essential to rely on human judgment. But there are many situations where decent statistical software can do just fine at forecasting, and research has shown that applying human judgment in some cases can make the forecast worse. Some research even suggests that forecasting software should make it purposely difficult to override the statistical forecast. (See Goodwin, 2006, for discussion and references.)

By definition:

**Forecast Value Added** is the change in a forecasting performance metric (such as Forecast Accuracy, Bias or MAPE) that can be attributed to a particular step or participant in the forecasting process.

It is important to note that the Forecast Value Added can be positive or negative. In fact, the whole point of FVA analysis is to identify and eliminate forecasting process activities that are failing to add value. When you conduct this analysis you may find that many or even most of the things you are doing actually are making the forecast worse.

FVA analysis is based on simple science, and it is unfortunate we seem to forget about science once we start our business careers. In science, you evaluate the performance of something, such as a new drug treatment, compared to the alternative of doing nothing and just taking a placebo. In forecasting, doing nothing can mean simply not overriding the statistical forecast, or not requiring marketing to provide input into the forecasting process or not letting executive management have final approval over the forecasts. And if we absolutely want to do nothing at all, the naive model works as our placebo, generating forecasts automatically without us having to do anything more.
The reason to focus so much attention on process efficiency and the elimination of waste is that we ultimately have a lot more control over the forecasting process we choose to use than the forecast accuracy results we achieve. Smooth, stable, repeating patterns can be forecast accurately with simple techniques. Wild, volatile, erratic patterns may never be forecast to the degree of accuracy we desire, no matter how much money, effort and statistical sophistication we apply to the problem. This is the harsh reality. We can’t just set an arbitrary accuracy goal, such as “MAPE must be less than 10 percent” and then think that throwing a lot of money at the problem is going to guarantee that we can forecast that accurately. Simply put:

If the nature of the demand is so gracious as to allow us to forecast it at 10 percent MAPE, then with good software and processes we should be able to achieve that goal. But if the nature of the demand does not permit it to be forecast with a 10 percent MAPE, then we never will ... no matter how much time and money and effort and sophistication we apply.

Our goal is not forecasting perfection, but to generate forecasts that are as accurate and unbiased as we can reasonably expect them to be — given the nature of the demand — and to do this as efficiently as possible. We may never be able to control the accuracy achieved, or achieve the level of accuracy desired. However, we can control the forecasting process we use and the resources we invest.

Conducting FVA Analysis

After you’ve gathered the data, you can conduct the Forecast Value Added analysis. FVA analysis compares the results of each process activity to the results that would have been achieved without doing the activity.

The naive forecast (as the do-nothing forecast) provides the ultimate baseline for comparison. But we must also evaluate the performance of sequential steps in the process.

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</table>

*Figure 4: Sample FVA report.*

Figure 4 is an example of an FVA report based on a simple process we showed earlier. The only steps in the process are a system-generated statistical forecast and an analyst override. We see that the statistical model added value, reducing MAPE by 12.55 compared to the naive model. However, the manual override actually made the forecast worse.
There are many ways to present the FVA analysis. In this example, just three alternatives need to be compared: the naive model, the statistical forecast and the analyst’s override to the statistical forecast. Even though we don’t show the naive model in the process diagram, it should always be used in the FVA analysis because it shows what performance you could achieve without any forecasting efforts at all.

In the more general case, there could be several additional rows and columns in this report, representing the forecasts provided by additional sequential stages in the forecasting process. For example, you could include rows for the consensus forecast and executive approved forecast, if those are steps in your organization’s process.

Users of SAS Forecast Server software can create a SAS Stored Process for FVA analysis, or develop additional tools of their own. SAS software makes it easy to create your own custom reports and analyses.

FVA analysis is used to identify the wasted efforts in your forecasting process, so these efforts can be mercilessly eliminated. Eliminating the waste allows you to achieve better forecasts with less effort. And it allows you to redirect that effort into more productive areas.

**Communicating FVA Results to Management**

The results of an FVA analysis can be embarrassing to some people. As a forecast analyst, how would you like to be told that you forecast worse than a Random Walk? As a forecasting department manager or director, how would you like to be told that your department has failed to add value and needs to be eliminated? As a general manager or CEO, how would you like to be told that the millions of dollars you have spent on forecasting systems and staffing has been a colossal failure – that your forecasts are no better now than they were before?

The results of FVA analysis should be presented in an objective, dispassionate and tactful way to the people who may be embarrassed by the results. You don’t want to make enemies, and you don’t want to ambush your colleagues publicly and be fired for it. Your objective, after all, is to improve the forecasting process, not just cause a commotion.

If you follow the lean approach and focus your efforts on eliminating waste and improving process efficiency, you can be confident that improved accuracy will follow. This is largely because FVA analysis has eliminated the process steps that were making the forecast worse.
Setting Accuracy Expectations

Most people outside of forecasting have completely unrealistic expectations for what type of forecast accuracy can be achieved. Unfortunately, these unrealistic expectations tend to be perpetuated by many people in the profession who should know better. The harsh reality is that unless you are blessed with omnipotence and foreknowledge, projecting the future is a very difficult thing!

The best a forecaster ever can do is discover the underlying structure or rule guiding the behavior that is being forecast, finding a model that accurately represents the underlying behavior — and then hoping that the underlying behavior doesn’t change.

Unfortunately, there is an element of randomness that surrounds virtually all behavior, and the degree of randomness will limit the accuracy you can achieve. Consider four processes you are asked to forecast:

- **P1** – the tossing of 1 fair coin.
- **P10** – the tossing of 10 fair coins.
- **P100** – the tossing of 100 fair coins.
- **P1000** – the tossing of 1000 fair coins.

Each day the coins will be tossed, and you have to forecast the percentage of heads in each process. This isn’t meant to be rocket science or brain surgery, and it isn’t a trick question. The only rational forecast for each process is 50 percent heads. Figure 5 shows the results of 100 trials of each process.

Figure 5: 100 trials of each process.
By assumption (the tossing of fair coins), each process behaves according to the same underlying rule or structure. Over long periods of time, each process will average about 50 percent heads. The only rational forecast each day for each process is 50 percent heads. However, as you can see by these charts showing the results of the daily coin tossing over 100 days, the randomness or noise in each process is vastly different.

When there is a lot of randomness in the behavior, you should never expect to forecast it very accurately. The amount of randomness limits how accurate you can ever be. What is important to note is that there is nothing you ever could do to forecast P1 more accurately than P10. Likewise, you could never forecast P10 more accurately than P100, nor P100 more accurately than P1000. The nature of each process – its underlying structure plus its random variability – determines the level of accuracy we can achieve.

Real-life demand patterns are not so different from this. They too consist of an underlying structure, plus varying degrees of randomness. But what makes real-life demand patterns even more difficult to forecast is that the underlying structure or rule guiding their behavior may not be so apparent, and you need good software and a competent analyst to uncover it. But even then, if you can discover and model the underlying behavior, there is no guarantee that the behavior won’t change over time.

The coin tossing example illustrates that there are limits to the forecast accuracy we can achieve. We can’t just assume that by working harder and applying more data, bigger computers and more sophisticated software, we can always achieve the level of accuracy we desire. So it is important to understand the limits of forecast accuracy and what level of accuracy is reasonable to expect for a given demand pattern.

Whatever it is you are trying to forecast, there are three questions to address:

- What level of accuracy is reasonable to expect?
- Is there an upper limit on accuracy?
- How should I set forecasting performance goals?

**Accuracy Expectations for Ongoing Products and Services**

Let’s start with the easiest case – demand for ongoing products or services – things that have been around for awhile and have some history. For these, it is reasonable to expect forecasts to be at least as accurate as a naive forecast. This sounds pathetic, but you have to start somewhere.
You might think it would be pretty difficult to forecast worse than a naive model, but plenty of organizations find ways to do so. Probably the most common way is through elaborate consensus or collaborative processes, where lots of participants can have a say in the final number. There is the old expression that too many cooks in the kitchen spoil the broth, and that is exactly what can happen in this situation. Each contributor to the forecasting process has their own biases and personal agendas, and they can play politics with their forecast. For example, if it is quota-setting time and you ask salespeople what they are going to sell next year, their natural bias is to forecast low, to keep their quota low and make it easier to win a bonus. However, during the rest of the year, the same salespeople might bias their forecast too high, to make sure there is plenty of inventory and capacity available (so when customers want to buy, there is plenty available to sell).

The forecast should express the voice of the marketplace and reflect an unbiased best guess of what is really going to happen in the future. More management involvement is not necessarily better when it comes to forecasting. Either inadvertently while acting in good faith, or purposely to meet their own personal agendas, excessive management participation can contaminate the forecasting process. A traditional forecasting performance metric such as MAPE, by itself, will not tell you this. But FVA analysis will expose participant biases and process inefficiencies.

**Upper Limits of Forecast Accuracy**

A much more difficult question is determining the upper limit for forecast accuracy. The naive forecast creates a reasonable lower limit for accuracy expectations, but what is the best we can do? And can we achieve arbitrary levels of accuracy just by trying harder?

Obviously the answer is no – as demonstrated in the coin tossing examples. There are limits to the accuracy you can ever achieve, and these limits are based on the randomness in the behavior. The best we can hope for is to correctly determine the structure or rule guiding the behavior, express that in our forecasting model and hope the underlying behavior does not change.

A good model captures the underlying rule or structure, but should not reflect the randomness. A common problem in poorly designed forecasting software, when put in the hands of unskilled users, is the “over-fitting” of the model to the historical data. An extreme example of this would be creating a model that perfectly fits your historical data. It is always possible, using a polynomial of sufficiently high order, to fit your history perfectly. But your job is to create good forecasts, and such a perfectly fitting model will probably not be the best at forecasting because it is interpreting historical randomness as structure and projecting that randomness into the future.

As you might suspect, determining the underlying rule and the degree of randomness is not a trivial problem. There is some research occurring on this subject, but as yet no definitive solution. The Spring 2009 issue of *Foresight: The International Journal of Applied Forecasting* has several good articles in a special feature on assessing forecastability. See also Bunn and Taylor (2001) or Kahn (2009) for more on this topic.
As we have seen, the upper limit of accuracy depends on three things. First, our ability to detect the underlying structure or rule that guides the behavior we are trying to forecast. Second, the amount of randomness that is in the behavior. And finally, accuracy depends on whether the underlying behavior remains the same or changes over time. As the behavior changes, our previously constructed models become less and less relevant.

**Setting Performance Objectives**

The central message of this white paper is that we need to focus attention on forecasting process efficiency, not just on forecast accuracy. The accuracy you achieve is determined more than anything by the nature of the behavior you are trying to forecast. There are some characteristics, such as stable patterns, that are good for forecasting. And there are many things, such as new products and volatile demand, that make it tough to forecast accurately.

The accuracy we achieve is largely a function of the volatility of the behavior we are attempting to forecast. Figure 6 shows a scatter plot of the relationship between Forecast Accuracy and Sales Volatility at a consumer packaged goods manufacturer. Each of the 5,000 dots represents an item at a distribution center. As volatility (measured by coefficient of variation) increases, the forecast tends to be less accurate.

*Figure 6: Forecast accuracy vs. volatility scatter plot.*
Forecasts are probably never quite as accurate as everyone wants them to be, but management must recognize that what it wants it may not be able to get, and that setting unachievable targets is simply demoralizing and encourages everyone to cheat.

Perhaps the only reasonable expectation for forecasting accuracy is to beat a naive model, and to continuously improve your process. Improvement is attained by getting better accuracy and less bias, and also by streamlining the process and being more efficient.

Setting blanket performance goals is wrong – goals must be appropriate to the nature of the demand that is being forecast. A blanket goal such as “MAPE must be less than 20 percent” may express what the organization desires, but such a goal can be very damaging if it is set arbitrarily with no relation to what the forecasting process is capable of delivering.

**Setting Unreasonable Accuracy Expectations**

Suppose you are working for an organization in a strange line of business involving the daily tossing of a fair coin. Your job as forecast analyst is to predict heads or tails for each daily toss, and over a lengthy career you have achieved forecast accuracy of 50 percent.

A new CEO is hired who doesn’t really understand your peculiar business of tossing fair coins. Unfortunately, this CEO doesn’t really understand much about randomness or variation either, but he is a big fan of setting new goals as a way to motivate increased employee performance.

Your goal is now set to 60 percent forecast accuracy or you will be fired. So what do you do next? Given the nature of the behavior you are asked to forecast – the tossing of a fair coin – your long-term forecast accuracy will be 50 percent, and it is impossible to consistently achieve 60 percent accuracy. Under these circumstances, your only choices are to resign, stay around and get fired, or figure out a way to cheat!

It is important to understand what level of forecast accuracy is “reasonable to expect” given the nature of the behavior you are attempting to forecast. When forecasting performance objectives are set arbitrarily, without consideration for what is reasonable, two types of problems occur. If the accuracy objectives are set too low, such as below what a naive forecast would achieve, then inferior performance is rewarded (a forecast analyst could sleep at his desk all year and use a naive model to exceed his performance objectives). If the forecast accuracy objectives are set too high, your organization wastes resources pursuing unrealistic or even impossible objectives.

What can happen if management insists on setting arbitrary performance goals? We saw in the sidebar that management set a forecast accuracy goal that not only was unreasonable, it was impossible. In these circumstances, the only way to meet your objective is to cheat.
If you are a forecasting department manager or director, why would you ever want to set impossible objectives that would only demoralize your staff members and encourage them to cheat? But you can easily do just that, unless you know what accuracy is reasonable to expect given the demand your employees are trying to forecast. Do not confuse the accuracy management desires with the accuracy the forecasting process is capable of delivering.

Practical First Steps
See the SAS white paper Forecast Value Added Analysis: Step-by-Step for more details on data collection, FVA analysis and reporting. This white paper also documents an FVA stored process for use in SAS Forecast Server.

Conclusion
The lean approach is about identifying and eliminating process waste. There is perhaps no business process as full of wasted efforts as forecasting, but traditional performance metrics (such as MAPE) by themselves give no indication of waste and inefficiency.

This white paper has described how the Forecast Value Added metric can identify process steps and participants that are failing to make the forecast any better. By eliminating those steps and participants that are adding no value (or may even be making the forecast worse), you get better forecasts with less cost and less effort. Those wasted efforts can then be redirected into more productive activities.
References


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