Worst Practices in Forecasting
The Mechanics of Forecasting
Table of Contents

Introduction ......................................................... 1
  Just Don’t Do the Stupid Stuff! ................................. 1
Worst Practices in the Mechanics of Forecasting ............... 2
  1. Model Overfitting and Pick-Best Selection ............. 3
  2. Confusing Model Fit with Forecast Accuracy ........... 8
     Factors Affecting Accuracy ................................. 9
  3. Accuracy Expectations and Performance Goals .......... 9
     The Perils of Benchmarking ............................... 10
     Accuracy Expectations ........................................ 10
     Arbitrary Accuracy Objectives ............................. 11
  4. Failure to Use a Naive Model or Assess Forecast Value Added ....... 11
     Forecast Value Added ....................................... 11
  5. Forecasting Software Selection ............................ 13
     Blaming the Forecast ......................................... 13
     Buying Software Without Proper Vetting............... 13
     Becoming an Educated Software Buyer .................. 14
     Require Demonstrated Forecasting Performance .......... 14
Addendum: Model ‘Fit’ Versus Model ‘Appropriateness’ ....... 15
References .......................................................... 18
  SAS® Forecasting White Papers ............................... 18

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Introduction

There is certainly no shortage of articles, books, consultants and even software vendors willing to tell you (or sell you) their version of forecasting best practices. This white paper, however, is going to take a different angle. Instead of talking about the so-called “best practices” in forecasting, we will instead expose the seamy underbelly of the forecasting profession. Rather than asking you to implement all the various things the really good forecasting organizations do, we want to help you avoid the things the really bad forecasting organizations do. Perhaps the surest way to achieve process improvements is by identifying and eliminating the worst practices in forecasting.

You are sure to recognize many of these worst practices. Of course, not as anything you yourself have ever done, but perhaps as something you’ve heard about, or maybe observed a colleague or a friend commit. The point of exposing these worst practices is not necessarily to embarrass anyone, or to poke fun at the organizations that commit them. Often the best way to learn is by making mistakes, and that’s why we all feel perfectly at home in the forecasting profession, as opposed to being in a profession such as brain surgery. The purpose of this white paper is to help you make new mistakes, not repeat those made by yourself, your colleagues or this author.

Just Don’t Do the Stupid Stuff!

Let’s begin with some words of wisdom from Cecil Moore of Revman International. Moore was fond of a phrase similar to “Just don’t do the stupid stuff” – and he was correct. A lot of business woes derive from a small number of really bad business mistakes. Now when it comes to forecasting, perhaps the biggest mistake is worrying about chasing the perfect forecast – which is something no one will ever achieve. We aren’t gods blessed with omniscience and foreknowledge – we are mortals. We are lucky if we can correctly forecast rain tomorrow, let alone how many hurricanes are going to strike the Gulf Coast next season, or exactly how many gallons of milk, how many toolboxes, or how many Hawaiian shirts a particular store is going to sell next week.

As Tom Wallace and Bob Stahl state in their book Sales Forecasting: A New Approach, forecasting is a process, and as such, forecasting can be improved using standard process improvement techniques. They argue that it is more beneficial to pursue process improvement than to focus narrowly on forecast accuracy. Another way to put it is this:

The objective of the forecasting process is to generate forecasts as accurate and unbiased as we can reasonably expect them to be, and to do this as efficiently as possible.

We may not have total control over the accuracy achieved, but we can control the process used and the resources we invest. By focusing on that process, and on eliminating the waste and inefficiency and worst practices in the process, you can develop forecasts about as accurate as they are ever going to be.
In some situations this may be very accurate, as when you have long-running, stable demand patterns that are amenable to statistical modeling. In other situations – in perhaps the vast majority of situations – demand is not so well-behaved, and it is completely unrealistic to expect highly accurate forecasts. When there is a high degree of volatility and randomness in a demand pattern, there may be nothing anyone can do to achieve the level of accuracy desired because the nature of the demand won’t let us. However, it is a fairly common worst practice for organizations to squander resources pursuing unachievable levels of forecast accuracy.

**Worst Practices in the Mechanics of Forecasting**

This white paper focuses on the mechanics of forecasting, where several fundamental mistakes are commonly made.

Forecasting is a multistep process. When you do statistical forecasting, one of those steps is looking at historical demand, fitting a model to that demand and using that model to project the future. This all sounds well and good, and there are dozens of forecasting software packages you can use to help you with this important step. Unfortunately, it can be easy to specify inappropriate models, and forecasting software often facilitates improper model selection through poorly designed best-fit or pick-best functionality.

Another serious misunderstanding occurs when the fit of the model to history is confused with the accuracy of the forecasts the model will generate. Remember, it is very easy to look backwards in time, and anyone can concoct a very plausible explanation of anything that happened before. Just watch the business news every evening, and TV’s financial geniuses will tell you exactly why the stock market behaved like it did that day. But what good is that to you, as someone who wants to know where to put your money tomorrow? Ability to explain the past is no guarantee of being able to foretell the future. The fit of your model to history is often a very poor indicator of the accuracy of the forecasts it will generate.

Managing forecast accuracy expectations, and setting forecasting performance goals, is another area that can be improved by eliminating the worst practices. We must distinguish between what management desires to achieve, such as “All forecast errors less than 10 percent,” from what performance is reasonable to expect given the nature of your demand patterns, which may be errors of 25 or 50 percent. It doesn’t do any good to set unachievable goals, as this just demoralizes the forecasting staff and encourages everyone to cheat. And if the goals are at all ambiguously defined, then some creative forecaster will come up with some weird metric that will reach the goal.

A naive forecasting model provides the basis for all performance evaluations, but many organizations are unaware of the concept, or choose to ignore it.1

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1 We discussed naive models at length in the SAS webcast Forecast Value Added Analysis: Step-by-Step that can be viewed at sas.com/reg/web/corp/4385. You can also read about naive models in a good forecasting text such as Makridakis,’ et al Forecasting Methods and Applications.
A naive model is something easy to develop and essentially free to use, such as a moving average or a random walk (where you use last period’s actual value as your new forecast). The naive model is essentially the do-nothing forecast and provides a level of forecast accuracy that can be achieved without any fancy systems, processes or even any forecasters. Our goal, of course, is to be able to beat the accuracy of the naive model. Forecast Value Added analysis, which is subject of another SAS white paper, is a method for comparing the performance of your forecasting activities to the performance you would have achieved by essentially doing nothing.

We are going to end this discussion with a look at forecasting software selection. Companies can spend into the millions of dollars on software packages, new hardware, consulting, training and implementations. But these companies can be cruelly disappointed if the newly created forecasts do not meet their expectations. Part of this problem may be that the software itself uses flawed methods or even has errors in its mathematical calculations. These things do happen, and the forecasting literature provides several examples. But the organizations themselves may share a good part of the blame by purchasing software packages without proper vetting – without demonstrable evidence that the software will help solve their business problems.

Let’s look at some of the mechanics of statistical forecast modeling by examining worst practices in model overfitting and pick-best model selection.

1. Model Overfitting and Pick-Best Selection

We begin by remembering our purpose here, and that is to get better forecasts. A forecast is about the future – our best guess at what is really going to happen. In creating forecasts based on a statistical model of historical data, we are making two assumptions:

- First, we are assuming that our statistical model correctly captures the underlying behavior we are forecasting. In other words, we think there is some rule or structure or systematic pattern to the behavior, and that our model accurately reflects that systematic pattern.
- Second, we are assuming that same pattern of behavior will continue into the future, so that the model that fit the past is appropriate to forecast the future. Of course, if we expected future behavior to change, there would be little relevance to a model that only fit the past, and it wouldn’t make any sense to use it for forecasting.

Remember that as much as we may enjoy playing around in the data and building models, our job as forecasters is to forecast. If we are smart enough to develop sophisticated models that have a great fit to history, yet still don’t forecast worth a darn, should we get patted on the back? Of course not!
It is a fact that it is always possible to build a model that fits the history perfectly. If you have two historical data points, you can fit a line. If you have three historical data points, you can fit a quadratic. And so on. But just because we have a perfect fit of history, is that any reason to believe the model is going to deliver good forecasts? Consider this example:

Suppose you have been selling a product for four periods, and sales have been 5, 6, 4 and 7. What model should you use to create a forecast for the next three periods?

In this situation, a very simple model would be to just take the average of the four observations, which happens to be 5.5, and use that as your forecast for the next three periods. This has the advantage of being easy to compute, but it clearly doesn’t fit the history that well, and the weighted mean absolute percentage error (MAPE) is about 18 percent. So let’s get a little more sophisticated.
Instead of just a simple average, let's build a model that looks for a trend in the historical pattern. This model actually has a slightly better fit to the historical data points with a weighted MAPE of about 15 percent. If you are selecting your model purely on the basis of historical fit, this would be your choice compared to a simple average. But can we do better?

Now things are getting interesting. Instead of a linear trend model, we are using a quadratic model, and the fit to the historical data is much better with a weighted MAPE of about 8 percent. So while the fit is better, does this make it a more appropriate model for forecasting? Maybe it does, based on the domain knowledge you have about this new product. Perhaps you know that the product has only been rolled out to a few locations so far and that demand is likely to take off once it is distributed nationwide in Period 5. Or perhaps a media blitz started in Period 4, and you expect the full impact to hit in the next few periods. Is this model good enough, or can we do even better?
As we mentioned earlier, it is always possible to find a model that fits the history perfectly. If you recall your high school algebra, with four data points, that would be a third-degree polynomial. The fascinating thing here is that your model fits the first four periods of history perfectly, but is it at all appropriate for forecasting? Do we have any reason to believe that a product that has sold no more than seven units in any of the first four periods will be selling 20 units in Period 5, 60 units in Period 6, 130 units in Period 7, and who knows how many after that?

I would say the answer is no. While this model has perfect fit to the history, unless you have some very good information indicating otherwise, it is clearly not the right model for forecasting.

The point here is this: How well a model fits your history should be a consideration when selecting forecasting models. But fit to history should not be the sole consideration when choosing your forecasting model. Blindly choosing the best-fitting model, and assuming it is the most appropriate for forecasting, can be a problem in some forecasting packages, or in the misuse of those packages.

Remember again: Our job is to create good forecasts – or at least as good as they can reasonably be. Our job is not to fit models to historical patterns. If the software you use has some form of pick-best functionality, be sure you understand how it works and what it is telling you. The key point for selection should not be the fit of the model, but the appropriateness of the model to the nature of the behavior you are trying to forecast. Good software uses more sophisticated methods to evaluate model performance, such as validating the performance over a holdout sample of the history. Just be sure to understand what your software is doing, and be sure to use it appropriately.
While this problem is easily illustrated using the new product, it also occurs with well-established products. Overfitting can occur when you build overly sophisticated models that account for imaginary patterns that don’t really exist, or that account for randomness in the historical pattern. Your model should only account for the true underlying structure or systematic behavior of the pattern. Consider this example:

Suppose demand is based on the number of heads in the tossing of 10 fair coins. In this situation, the observed pattern is simply random variation about the underlying mean of 50 percent heads. In this case you have domain knowledge – you know that over time the tossing of 10 fair coins will average about 50 percent heads.

You could fit a sophisticated model to this pattern – you could even fit the pattern perfectly – and your forecasts for the next year would have all the ups and downs of the pattern above. But this is not the right forecast – you would have overfit such a model to the randomness. The proper model in this case is a straight line at 50 percent heads. You can show mathematically that over time this will give the best forecast, even though its fit to the history is not that great.

Real-life demand patterns are not so different from this. You can think of each pattern as having a structured or systematic component and a degree of randomness. A seasonal product, for example, will follow a pattern that looks something like a sine wave, flowing up during the high season and down during the off-season. We recognize that actual demand is unlikely to follow that pattern exactly. But if the model is right, actual demand will dance about that pattern, sometimes above it, sometimes below it, due to the random element of demand.

Instead of falling for the worst practice of overfitting, the better practice is to try to find the underlying systematic behavior in the data, and model that. Here is where good software can help, by helping to filter out the random noise from the underlying signal. Coin tossing provides the perfect example because we know the underlying structure, and the rest is pure, unadulterated randomness.
2. Confusing Model Fit with Forecast Accuracy

We’ve seen that historical fit should not be the sole factor in selecting forecasting models. Suppose you’ve avoided that worst practice, and come up with the model that is the most appropriate for forecasting. We know how well that model fits the history. The next question is, how well is that model going to forecast the future?

The unfortunate fact is that fit to history can be a very poor indicator of how well the model will actually forecast. If someone comes to you bragging about how well they’ve been able to fit their history, your response should be, “So what? You haven’t proven anything yet!”

Historical fit is virtually always better than the accuracy of the forecasts generated. In many situations the historical fit is much better than the accuracy of the forecasts. Any one of you who has done statistical forecasting knows this. You might have a MAPE of 5 percent in your historical fit, but a MAPE of 50 percent in your forecasts – that would not be at all unusual. As a practical and career-extending suggestion in communicating with your management, don’t tell them the MAPE of your historical fit – they don’t need to know it! Knowing the MAPE of your historical fit will only lead to unrealistic expectations about the accuracy of your future forecasts.

The reason why historical fit is not the same as forecast accuracy is that the best a model can ever do is capture the systematic behavior, and then project that behavior into the future. Even in the best behaving patterns, there is always an element of randomness, and the degree of randomness limits the amount of forecast accuracy you will ever achieve.

Furthermore, you are assuming that your model is correctly capturing the systematic behavior and this behavior is not changing over time. If you are using the wrong model, then of course this is not likely to yield good forecasts. And if the behavior is fundamentally changing over time, the historical patterns may have very little relevance.

The Makridakis text has a couple of good quotes reaffirming this message:

• “Having a model that better fits historical data is not a guarantee of more accurate post-sample predictions.”
• “Established time series patterns can and do change in the future.”

The marketing literature for forecasting software often touts its ability to adjust over time to take into account changes in demand patterns. When properly implemented, this can be a good thing. For example, you may have heard about the “Oprah Effect” – that whenever a product received favorable mention on The Oprah Winfrey Show, it received a huge bump in sales. This sort of thing is known as an “event,” and SAS® Forecast Server makes it possible to incorporate historical (and future) events to help you build more appropriate forecasting models. The impact of an event can be a “pulse” or a one-time blip, it can be a sudden level shift – where the pattern is now permanently shifted up or down, or can be a slower ramp up or down. These are some of the event types that SAS Forecast Server can accommodate.
Factors Affecting Accuracy

As a better practice, it is important to understand what factors affect forecast accuracy.

We can expect accurate forecasts when we have figured out the appropriate model, when there is little random deviation from the model and when the underlying behavior expressed by the model is not changing over time.

Forecast accuracy is often worse, and sometimes far worse, than we desire because we are using an inappropriate model, there is too much randomness in the behavior and the behavior is changing over time.

This is not to say that there is no hope of doing good forecasting. But forecasting can be a huge waste of management time. An organization must understand what forecasting can achieve and what it cannot. An organization must focus its efforts on generating usable forecasts, forecasts as accurate as the nature of the demand patterns allow us to be, and to focus on achieving this level of accuracy as efficiently as possible. Waste and worst practices occur when an organization pursues the unachievable – the perfect forecast, or accuracy that simply cannot be achieved due to the nature of the demand. The following statement is worth remembering:

*If the nature of the demand is so gracious as to allow us to forecast it with 10 percent MAPE, then with good people, systems and processes, we should be able to achieve that level of accuracy. 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.*

3. Accuracy Expectations and Performance Goals

Let’s now look at the worst practices relating to misguided accuracy expectations and inappropriate forecasting performance goals, beginning with a simple question: Just how forecastable is your demand?

Once you’ve spent a little time in the forecasting profession, you realize that some demand patterns are inherently easier to forecast than others. If you have smooth, stable, long-running patterns, you just might be able to forecast these very accurately with simple methods. However, if you have lots of new products and promotions, short product life cycles and highly volatile demand, you may never be able to forecast these with the degree of accuracy desired, no matter how much effort you put into it.

Management certainly has expectations for forecast accuracy and these are often expressed in performance goals, such as “MAPE must be less than 20 percent.” But is there any basis for these kinds of objectives, and what accuracy is reasonable to expect?
The Perils of Benchmarking

Sometimes management bases accuracy expectations and performance targets on industry benchmarks. Benchmarks need to be viewed with extreme caution, however, because there are a number of potential problems.

Benchmarks are usually based on self-reported survey data and have not been audited. We don’t know that the respondents are using consistent measurements, yet different versions of an error calculation (such as MAPE, weighted MAPE and symmetric MAPE) can give significantly different values. And worst of all, benchmarks fail to take into account the underlying forecastability of the demand pattern being forecast. A company may have “best-in-class” forecast accuracy because it has the easiest demand to forecast, not because their people, systems or processes are the least bit admirable.

Consider a worst-case example. Company X has the lowest MAPE in a benchmark survey, gets studied and written up by consultants and academics, and other companies change their forecasting processes to use X’s so-called “best practices.”

Upon further review, a technique called Forecast Value Added (FVA) analysis is applied. We will touch on FVA analysis below, but the basic idea is to compare an organization’s forecasting performance to what it would have achieved by doing nothing, and just using a naive forecast.

What if FVA analysis reveals that Company X had very easy-to-forecast demand, and it would have had even better forecasts had it just used a moving average? In other words, X’s so-called “best practices” just made the forecast worse!

Accuracy Expectations

Perhaps the only reasonable expectation for forecasting performance is to beat a naive forecast and to continuously improve the process. Improvement is demonstrated not only by reducing the error and bias in the forecast, but by increasing the FVA and by becoming more efficient at executing the forecasting process. If you can achieve a MAPE of 25 percent by using automated statistical forecasting software or can achieve 25 percent MAPE using an elaborate collaborative and consensus process occupying several hours every month of all your sales reps, planners and executive staff – which is the better way to go? The cost of using automated software is probably much less than occupying all that high-cost management time. And as FVA analysis can demonstrate, elaborate forecasting processes with lots of management touch points and approvals will often just make the forecast worse!
Arbitrary Accuracy Objectives

Before we move on, consider one last worst practice – that of setting arbitrary forecast accuracy objectives.

If management states, without any basis for the number, that forecast accuracy must be kept at least 80 percent, what are the dangers?

One danger, which really isn’t too bad if you’re a forecaster, is that if the target is set too low, you might be able to reach it with no effort at all. If it turns out you can beat the objective using a naive forecast, that is great news for you because you don’t have to do any work! Just call in sick or go to the beach every day and you’ll still meet your performance objective.

On the other hand, if the objective is unreachable, then why bother to even try? Rather than spending your time trying to develop forecasts that will never beat an unachievable target, you are better off polishing your résumé in anticipation of being fired or finding a way to beat the target by cheating.

The better practice here is to ignore what others are doing and focus on the nature of your own demand patterns. Measure your performance with respect to the forecastability of your demand and set objectives based on what is reasonable to expect given the nature of your demand.

The most fundamental performance goal is always to beat a naive forecast (or at least do no worse than one). If you and your systems and processes are unable to do better than a naive model – why bother?

4. Failure to Use a Naive Model or Assess Forecast Value Added

We’ve mentioned the notion of a naive forecast throughout this paper, and touched on the method of FVA analysis. There are articles and white papers on this topic listed in the references. You can also review the various SAS forecasting webcasts for additional explanation and examples.

Forecast Value Added

FVA is very useful – in fact much more useful than MAPE alone – in evaluating forecasting process performance. Alone, traditional forecasting performance metrics such as MAPE tell you the magnitude of your forecast error. But MAPE alone will not tell you how efficient you are at achieving that level of accuracy or what level of accuracy you should be able to achieve.

The value added by your forecasting efforts can be positive or negative. But it is only with FVA analysis that you can identify and eliminate the waste and worst practices from your process, making it more efficient and delivering better forecasts.
Here is an example of FVA analysis applied to a very simple forecasting process. In this process, historical demand is loaded into forecasting software that generates a statistical forecast, which is then reviewed by a forecast analyst. The analyst can make an adjustment to override the statistical forecast if necessary.

The table below shows what an FVA report looks like. After selecting some period of time to evaluate, such as the last year, the MAPE of the statistical model and of the analyst override are found to be 20 percent and 25 percent. We also reconstruct what a naive model, such as a random walk or a moving average, would have done over that time frame and find that a naive forecast would have achieved a MAPE of 30 percent.

<table>
<thead>
<tr>
<th>Method</th>
<th>MAPE</th>
<th>FVA vs. Naive</th>
<th>FVA vs. Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Model</td>
<td>30%</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Stat Model</td>
<td>20%</td>
<td>10%</td>
<td>.</td>
</tr>
<tr>
<td>Override</td>
<td>25%</td>
<td>5%</td>
<td>-5%</td>
</tr>
</tbody>
</table>

Comparing the statistical forecast to the naive forecast, we see that our forecasting software added value. In fact, our MAPE is 10 percentage points lower by using a more sophisticated statistical model rather than just using a simple naive model. This is the good news. The not-so-good news is that while our analyst also beat the naive model, by five percentage points, the analyst’s adjustments to the statistical forecast actually made it worse by five percentage points!

This sort of thing happens all the time in the real world of forecasting. The problem – the worst practice – is that most organizations fail to evaluate their forecasting performance properly. They fail to use a naive model as the baseline against which all other forecasting efforts are compared, and they fail to use FVA analysis to expose the waste and inefficiencies of their forecasting process.

In short, FVA analysis is used to identify and eliminate process waste. FVA analysis is used to compare the performance of every step and every participant in your forecasting process. Activities that are failing to add value and are not making the forecast more accurate and less biased need to be identified and mercilessly eliminated from the process.

Forecast Value Added (FVA) is defined as the change in a forecasting performance metric (such as MAPE, accuracy or bias) that can be attributed to a particular step or participant in the forecasting process.
The magic of the FVA approach is that by eliminating those practices that are actually making the forecast worse, you end up with better forecasts with less cost and effort! What could be better than that? For more information on this topic, see the SAS white paper *The Lean Approach to Business Forecasting* or the APICS magazine article “Your Forecast on a Diet.”

**5. Forecasting Software Selection**

No discussion of worst practices is complete without a few remarks on forecasting software selection.

**Blaming the Forecast**

Management is inclined to blame all business woes on bad forecasting, but is this really fair? Have they ever analyzed their sales and marketing and financial practices to determine what impact these have on demand patterns? If yours is like most organizations, your practices (such as pricing policies and promotional activity) are designed to add volatility to demand – which is just the opposite of what you should do for better forecasting. People celebrate when they have a record sales week, not when they are able to smooth demand. Yet record weeks are harder to forecast than smooth demand, and much more costly to serve.

While you are at it, take a look at the predictability of other organizational processes, such as production or procurement. Does your supply chain provide the quantities it promises in the times they are promised? You should actually measure the MAPE of your supply plans as compared to what the actual supply turns out to be. You may discover, as some companies have, that there is as much uncertainty in supply as there is in demand! This is even more of a problem today, with more outsourced production and longer manufacturing lead times.

Also consider who has final say in your forecasting process. Does the final forecast express an unbiased best guess of what the future will be? Or does it express what management wishes the future to be? If your forecast is ultimately determined by what management wants to see, as opposed to what the marketplace is really saying, then software and statistics aren’t going to solve your problem until you fix the process.

**Buying Software Without Proper Vetting**

When you buy forecasting software, you should have some idea of what accuracy it will be able to achieve forecasting your demand. You should determine whether it can deliver accuracy that is meeting your business needs, and, of course, it should be able to beat a naive forecast!

It is also critical to determine whether the software can handle the volume of forecasts it will be required to produce. Can it do the batch runs in minutes, or hours or at least overnight? And what is the experience going to be like for interactive users? When loaded with your volumes of data, is the response time acceptable? Or will users abandon it because it just takes too long to work in?
References can be a great source of information about the software you are considering, but beware of some pitfalls. Make sure you understand customers’ motivations for being a reference. Are they truly in love with the software or did the vendor give them some financial incentive to take a reference call? If you are speaking to someone on the software selection or implementation team at the reference site, are they giving you an honest answer or just trying to justify the decision they made in selecting the software? Consider this: If you had convinced your organization to spend $1 million on a new forecasting package that turned out to be a disaster, would you be going around telling the world about your poor judgment? Probably not. People have a natural tendency to continue justifying their decisions even when the decision proves clearly wrong and leads your organization into a quagmire.

Another thing to ask references is whether the forecast is truly adding any value to their forecasting process. Are they better off than they were before? Most likely they are not even measuring this, but it is worth asking. Also investigate the history, financial stability and future prospects of the software vendor. Is it an ethical organization with a customer-centric focus that has the financial means to continue development and support of the product? Or is the company likely to fail, disappear in an acquisition or stop answering your phone calls once it closes the sale?

Software usability, like performance, will largely determine its acceptance by the forecasting users. Is the package something the users requested, or is it being forced on them as part of a larger ERP package implementation?

**Becoming an Educated Software Buyer**

Do what you can to become an educated buyer by joining a professional organization, reading the forecasting journals and attending forecasting conferences. Network with fellow professionals and ask questions in online discussion groups such as those supported by the International Institute of Forecasters, the Institute of Business Forecasting or on SAS’ Forecasting User Forum available through the sas.com website. You can even attend the users group meetings of software candidates to try to get the real scoop from current users.

Overall, just be extremely skeptical of everything you hear, consider the source and be wary of conflicts of interest.

**Require Demonstrated Forecasting Performance**

The last suggestion is to ignore the marketing hype and the unproven promises. Don’t just look at how well the software can fit the history – look at how well the software can forecast your demand. It is often necessary to do a proof-of-value exercise, using a holdout sample of your own data, to compare how well the software can do compared to your existing process. A proof-of-value is not free to conduct, so expect to pay the vendor to provide this service. But it is a good way to really understand what improvement you are likely to achieve with the new forecasting package.
Good forecasting software can be a big investment, costing hundreds of thousands or even millions of dollars. But the payback in automation, efficiency and forecasting performance can make a difference to both the top and bottom lines.

When seeing the demonstrations and hearing the promises, remember that fitting a model to history is easy, but generating a good forecast is not. When selecting software it is worth making the effort, and taking the time, to make the right choice for your organization.

**Addendum: Model ‘Fit’ Versus Model ‘ Appropriateness’**

While fit to history should be a consideration when selecting a forecasting model, it should not be the sole consideration for model selection. Our examples showed that you can always construct a model that perfectly fits the historical data, but that model may be completely inappropriate for generating good forecasts. The key here is the distinction between “fit” of the model to history and “appropriateness” of the model for generating forecasts.

The initial step in constructing a forecasting model is to “diagnose” the historical data and determine what type of model is most appropriate. One of the great features of SAS Forecast Server is its sophisticated diagnostics capabilities, which can automatically determine what classes of models will be most appropriate for forecasting based on the historical pattern.

Suppose, for example, that the historical data shows no trend or seasonality and looks something like this:

![Graph showing random data pattern](image)

This pattern was created by generating random numbers between 0 and 100 for 52 weeks. An appropriate type of forecasting model for this pattern is simply a flat horizontal line. Since there is no indication of trend or seasonality, we can’t do any better than that. Here is an example of an appropriate type of model for this pattern, forecasting out for the next 13 weeks:
While this is the appropriate “type” of model, it is not the best possible fit to the data. So once you have figured out the appropriate model type, you need to optimize the model parameters to get the best fit. Here, then, is the forecasting model we would use:

While this is the appropriate “type” of model, it is not the best possible fit to the data. So once you have figured out the appropriate model type, you need to optimize the model parameters to get the best fit. Here, then, is the forecasting model we would use:

It is the appropriate type of model for forecasting when the historical pattern has no trend or seasonality and the model parameters are optimized to provide the best fit of the history.

What if you blindly select models based only on fit, without considering whether the model is appropriate for forecasting? Here is an example:
No one in their right mind would want to use a model like this for forecasting this pattern. By Week 65 your demand is pretty much forecasted to be infinity!

Poorly constructed software has no ability to determine model appropriateness, and makes its selection based purely on model fit. The right approach, the approach used by good software such as SAS Forecast Server, is to first determine the type of model that is appropriate and then optimize the model parameters to find the best fit.

Bad software will just select the model that has the best fit to the history, and as we have seen in our examples, the best fitting model may be completely inappropriate for forecasting the future.
References


SAS® Forecasting White Papers

- The Lean Approach to Business Forecasting
- Fundamental Issues in Business Forecasting
- Turbocharging Spreadsheets
- Looking Inside SAS® Forecast Studio
- Large-Scale Automatic Forecasting Using Inputs and Calendar Events
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