# Black art of forecasting


*SupplyChain Review's* ***Tom Rafferty*** *uncovers the black art behind forecasting and its link to Hollywood disaster movies*

"Everything I've ever cared about, everything I've worked for, has all been preparation for a future that no longer exists."

These fateful words were uttered by Laura, in the climate change disaster movie The Day After Tomorrow. It's a shame that Laura didn't know something about forecasting — she'll just never get the weather gig on Channel 9!

It may be possible to infer the following things from Laura's statement:

1. Laura appeared to have a plan
2. Laura hoped that the plan was going to have a positive effect on her future
3. Laura believed that it was actually worth planning for the future.

So what have we discovered? From this simple quote and application of logic we can see that Laura would have use for some good way of predicting the future. But she has some issues.

There are some simple principles and rules for forecasting that you should know and not ignore. Laura didn't know these rules, or worse still, she was an infernal optimist and thought it couldn't happen to her!

There are three things you need to know about forecasts:

1. They're always wrong
2. The further ahead you forecast, the more wrong you'll be
3. If you aggregate the data you'll get a better forecast

It's important to understand these three very basic principles — that's why I wrote them in very simple English. So, now that you understand, you're probably asking yourself, what's the point?

Most of the problems I see in forecasting for the supply chain have their basis in these three principles. If you are going to use statistical forecasting (using numbers to forecast the future) we need to add a fourth principle … but I'm getting ahead of myself … let's go back to Laura and The Day After Tomorrow.

Laura looks like she is about 18 years of age. When I was 18 I had plans too. I believe it went something like:

1. Weekend
2. Sport
3. Beer
4. Girls!

Unlike rugby league teams, I generally had trouble getting past the beer, but three out of four ain't bad! Trouble is, that is only a 75 percent service level, and 75 percent is rarely good enough — and face it, if you're 18 and get things right 75 percent of the time you should join the Australian Labor Party. They might need you 40 years from now.

If you subscribe to the generally accepted definitions of logistics management and supply chain management, you must agree that the reason we do whatever it is we do, is to "meet customers' requirements". If you don't, stop reading now.

If you have a system of service or product delivery that is incredibly agile, flexible and responsive you don't need to forecast so you can stop reading now.

If you've reached this paragraph, you're either very bored or hoping to learn something really useful. I hope it's the latter, so let's go.

There are essentially two broad categories that all forecasting methods fit in too. There are Qualitative Methods — this is where we use our judgement to guess the future.

Some of these methods are more robust then others; for example, the Delphi Method is probably regarded as on of the better (if not the best) qualitative methods of forecasting. We can also include in this group such scientific wonders as horoscopes, numerology and stockbrokers' newsletters.

If you detect a touch of cynicism in that last sentence it's probably due the state of my share portfolio and my belief that most of the people are decent, most of the time. Let me put it another way, if you have a red-hot stock tip, please don't call me — except of course if you're doing a bit of insider trading and we can't get caught.

The other category of forecasting methods is referred to as Qualitative or Statistical methods. If you wish to use a qualitative forecasting method, you need two things:

1) historical data
2) the data must be in the form of numbers.

There are two types of qualitative methods, time-series and explanatory analyses.

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Explanatory (or regression) analyses use one or more variables to predict the value of the thing you are interested in.

For instance, you may notice that there is a relationship between sales of a product and the price you charge for the product. So if you set your price at say $x, you might sell Y number of widgets. If you set it at x-2, you might sell Y+50 widgets, and so on.

In this case, you just might be able to use price to predict sales volume. Explanatory analysis can be messy — first, you have to be sure that there is actually a relationship between your two variables and this is not as easy as it sounds.

Time-series methods use historical data to predict the future. These are probably the most useful methods of forecasting supply chain activities and are certainly the most popular.

There are many methods available, ranging from something as simple as an average, right through to Box-Jenkins modelling (aka ARIMA modelling – ARIMA means Autoregressive Integrated Moving). Box-Jenkins modelling is horribly complex — if you read Messer's Box and Jenkins' riveting book, Time Series Analysis, and you don't drop into a deep coma after the table of contents, you'll be doing very well indeed.

A time-series is a pattern and the pattern generally contains four elements. The four elements are Trend, Seasonality, Cycle and Error. You have to be able to identify if these elements are present in your data so you can fit the correct time-series model.

In order to identify these patterns you will, unless you have a brain the size of a planet, need to graph the data. So let's have a quick primer on what you might expect to see.

Trend: if the overall level of data is increasing or decreasing, you generally have yourself some trend.

Seasonality is probably the most misunderstood term of the four. But really, it's quite simple. For the pattern to be seasonal it must repeat regularly and be identifiably regular. The classic seasonal "blip" in many businesses is Christmas — it has been happening for a very long time now (actually since 1582 when we adopted the Gregorian calendar).

So Christmas has been happening pretty much at the same time every year for over 400 years. This makes it regular and identifiably regular. And it kills me when I hear suppliers saying, "we got caught out by Christmas".

What is it with these people? Are they still on the Roman calendar, are they dumb or are they not trying?

A classic seasonal pattern shows the seasonal peaks and seasonal troughs.

The pattern for cycle is very hard to spot. In fact, most of the time we talk about "trend-cycles" because it is very hard to successfully decompose cycle from your data.

When you hear talking-heads rattling on about the "business cycle" this is what they're on about. Business cycles can be quite long, five to seven years, and many of us will struggle to come up with five to seven years of good reliable data. So, unless you are into long-range forecasting, don't lose any sleep.

The trick with cycle, is to pick the turning point. If you can do that with any precision keep it to yourself — you'll make a fortune on the stock market.

If we decompose the trend-cycle and seasonality from a data set, what remains is called Error. Error is also referred to as "the irregular component", "the random component" and in regression analysis, the "residual".

You have to laugh at the number of ways we can say, "the bit we screwed up", without actually saying it.

When you see the Error graphed, there should be no pattern — it must be random. This is another rule-of-thumb; if the errors are random they will be normally distributed (they will fall reasonably neatly into a "bell-curve").

If there is a pattern to the errors, they will not normally distributed. In this case, you may have made a mistake in model selection — so don't use that model to forecast with, you're likely to get it more wrong than you really want to be. So, the fourth principle I alluded to earlier is — the errors should be normally distributed!

## SEASONAL TRAPS

Seasonality comes in many shapes and sizes are just a few:

- Monthly seasonality may be apparent in your bank account, assuming of course that you are paid monthly. So you'll see a spike in your balance on pay day followed, if you're anything like me, by an equally alarming trough. Monthly seasonality can also be seen in the picking activities in many warehouses — it's directly associated with orders that are placed to take advantage of credit terms (note: if we changed the credit terms would we "smoothen" demand).
- Weekly seasonality is apparent in the parcel delivery business. Friday is generally the busiest days for pick-ups (it's the "we've got to get it out by the end of the week syndrome").
- Daily seasonality is experienced by restaurants. Some open for lunch, take a siesta and then open for dinner. ATM's in the central business district are generally most busy at lunch time and the cocktail hour — no prizes for guessing why. n

Finally, there is a very important assumption made when using historical data to forecast the future, it's called the "assumption of continuity". This is really important; what we are saying is, that whatever happened in the past, is likely to happen in the future.

Now, what if the marketing department schedules a new advertising campaign at a time of the year that was previously very quiet? How would a change to the billing cycle effect demand? Come to think of it, if you are trying to forecast demand what data would you use? Here comes the only formula of the article:

Demand = Sales + Lost Sales

So, if you use sales data to forecast future demand and you have not trapped information on the volume of lost sales, you've just got to be wrong. The question is, are you Laura, planning for a career, sorry, future that no longer exists? n