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The Forecaster's Toolkit

by Erik Sherman

Call him a business seer: Randy Barcus predicts the future. The chief economist of Avista, a Pacific Northwest electric and gas utility, has a remarkable track record – 2001, though, was an exception. In a typical year, the company spends $200 million buying electricity for its customers. "In [2001] we spent $500 million," says Barcus.

Surprise, Surprise

As much as the 2001 energy market caught Avista – and everyone else – unprepared, the previous year, Barcus had a surprise of a different sort, when he came within 25 percent of predictions he had made 20 years before. The results were even more impressive when real economic numbers replaced his suppositions.

"I was within 3 percent," Barcus says. "In other words, had I known the input variables well, I would have known the output." Even the experts can be surprised – happily or otherwise – when it comes to forecasting. Most companies may not seek a 20-year prognostication, but the same problems that Barcus faced await any manager trying to make decisions with an eye on a forecast. Some tools useful in one circumstance are useless in another. Results are often no better than the original data – and even then, poor understanding can render them worse than useless.

That is why understanding the vagaries of common forecasting techniques is so important to managers from the mid-level to the CEO. Virtually every industry uses forecasts, whether couched in the jargon of supply chain management or tagged as the sales department's expectations for the coming quarter. Forecasts of customer interests, factory supplies, or anything else that might influence decisions often are presented as pure numbers, without sufficient explanation or knowledge to put the figures into context. Out of self-defense, managers must know something about forecasting techniques and tools to make viable projections.

Seek First to Understand

When choosing and using forecasting tools, the first step is to understand what they are meant to do. "People often confuse forecasting and planning," says J. Scott Armstrong, Ph.D., professor of marketing at The Wharton School of the University of Pennsylvania. "Planning is what you hope to do given a set of actions." Forecasting, on the other hand, is predicting outcomes given particular assumptions and conditions.

"Most people put forecasting or knowledge of the future into a separate, mysterious category along with chicken entrails and the Delphi Oracle," says Dr. Peter Bishop, associate professor and chair of the master's program in Studies of the Future at the University of Houston-Clear Lake. Yet there is nothing mysterious about the concept. Much as a scientist might examine a cell or the sun, forecasters collect evidence, such as previous sales results or general economic data, and make inferences based on assumptions.

For his multi-decade prediction, Barcus turned to econometrics – the use of mathematical equations to model complex systems such as an economy or a business process. By accurately choosing coefficients and forming equations, the theory goes, the model comes closer to what will happen.

Some of the models are based on theories of how a system works. Others lean more toward discerned relationships among many variables – say, estimates of customer demand and the seasonal pricing of raw materials – to forecast sales profitability. Another popular application is in predicting the movement of goods in a supply chain.

According to Armstrong, there are two basic groups of forecasting tools: *statistical* (which includes system modeling, such as econometrics), and *judgmental* (commonly used when sufficient objective data is not available).

Looking to the Past

Falling into the category of statistical tools that use historical data are the various forms of time series analysis and regression that many business schools teach. Forecasters collect a series of numbers – for example, the sales history of a geographic region – and try to fit a mathematical curve that will describe the sequence of data as a function of time. The curve does not have to pass through each point;

the trick is to find a neatly described function that traces a line as close to the points as possible.

For example, a company might use historical monthly sales results as the data points. By finding the best-fitting curve, the forecaster can say that given continuing conditions, sales for the next few months will follow roughly the same trajectory. For situations where two or more curves approximate the data patterns, specialized software packages – such as Forecast Pro from Business Forecast Systems – can use brute processing power to calculate which one fits best.

Regression also uses historical data, but the difference between it and time series analysis is sharp. Whereas time series – perhaps one of the easiest and most widely implemented statistical tools – assumes that history is the only factor influencing future outcomes, regression sees other factors. In analyzing sales data, for instance, the forecaster might perceive a relationship between revenue and particular district offices, or between product line sales and distributor discount levels.

"It's increasingly called data mining," Peter Bell, Ph.D., professor at the Richard Ivey School of Business, University of Western Ontario, says of this technique. "If you're forecasting, you're trying to find relationships that will remain stable into the future."

The simplest approach is linear regression. A dependent variable, such as sales, is placed on a vertical axis and then compared to the independent data – distributor discounts – on the horizontal axis. Points are drawn that represent a given sales value corresponding to a discount value. The forecaster tries different mathematical functions to find a curve that comes close to describing the relationship. Linear regression effectively lays a ruler through the cluster of points to find the straight line.

Using the curve helps estimate the dependent value – sales, productivity, manufacturing yield, or whatever – based on expected values of the independent data. Various software packages implement standard regression techniques and compare a dependent value to a number of independent factors. Sales might be due to distributor discounts, product options, competitors' prices, or changes in household income.

Implementing .regression and time series is simpler and more straightforward than modeling systems. "The advantage is that they're really fast and cheap, so if you're doing product-dealer-level forecasts, you could program them all and get forecasts ... that won't get you into too much trouble," says Bell.

Hammering with the Screwdriver

The simple choice of the tool used can bias the results. Not all techniques are equally applicable to all problems. "In certain applications, regression models work pretty well," says Frank Bass, system professor of management at the University of Texas at Dallas and a nearly legendary figure in forecasting techniques. "For example, if you are forecasting the sales growth of consumer durable products, you [might] take into account housing starts, income changes, and various economic effects. Presumably you would have historical data and would have regression estimates of the parameters."

Yet regression techniques often are misapplied. "They don't work well for new products," Bass notes. "The underlying influences are quite different for new products than they are for established products." Even when the new products are similar to others on the market, a regression technique may be unable to recognize factors such as the imitation effect, in which people start using a new type of product because they see others doing the same.

In the imitation effect, the growth rate of product adoption increases as the number of people already using the product increases. Then there is the diffusion effect of learning about new products and services. Imitation and diffusion "tend to dominate these other effects," Bass says.

Beyond Numbers

Judgmental forecasting, in which a business without any relevant data can ask people whether they think a product and advertising plan might sell, is another category of forecasting tools. The best-known methods are surveys and opinion polls.

A rarely used tool, judgmental bootstrapping, offers great promise. Instead of surveying large numbers of people, the technique relies on a smaller collection of expert opinions. "You need between 5 and 20 experts, it turns out," Armstrong says. "The expert is reporting his or her judgment about the behavior of perhaps thousands of people. It's a very simple and powerful technique that is much less expensive than conjoint analysis."

Conjoint analysis is a technique that allows forecasters to learn about the demand for new products before their introduction. It offers a way to establish relationships among a number of factors and a given outcome. Say a consumer electronics firm is marketing a television. By using conjoint analysis, it can learn how screen size, resolution, price, and other features influence purchasers.

"A lot of forecasting textbooks don't even mention judgmental methods," notes Armstrong, "and the most important forecasts are done with judgmental methods. Where should we build our plants? Who should we hire to run our company?" These everyday decisions use implicit forecasting: hiring a CEO involves certain expectations of the board of directors that the candidate will accomplish certain corporate goals, even if hazily identified.

Judgmental methods are important because they help express the otherwise unquantifiable. Economic, production, or sales data can never capture the interests, intentions, and opinions of people. When companies use judgmental methods, they often go overboard, fooling themselves into thinking that they are collecting important statistical information. For example, many organizations rely on focus groups, although this approach was created only to help develop questions for a formal survey process; focus groups by themselves do not provide a statistically reliable result.

Getting the Data Right

One thing all forecasters have in common is the need for relevant and accurate data. Because the forecaster bases outcomes on that information, faulty data can lead to unwarranted expectations. Unfortunately, the data may be sorely lacking in integrity, according to Mitchell Parker, director of sales at Questerra, a geographic information systems solutions provider. In forecasting future business from current leads and prospects, he has found that what is presented as potential business often isn't.

Throughout his career, Parker has often had to question his staff to find out just how close a sale was. "Someone would say the order will be in this month," Parker says. "I'd ask, What's the purchasing process? Who needs to sign off? How long does it take to get the PO signed?" If a PO took several weeks to process and a purchase had not received final approval, there was virtually no chance of seeing a sale the same month. Because the data were bad, even a short-term forecast into the next quarter was unlikely to be accurate.

Understanding the Outcome

It is unrealistic to expect pinpoint accuracy in forecasts, yet their very format may encourage such interpretation, with damaging results. "A lot of techniques, like moving average, only give you a point," Bell says. Because of their inherently statistical nature, forecasting results are actually ranges of values. A $24 million sales forecast, for example, might actually be a range from $20 million to $28 million. But by focusing on a single number, a company creates problematic psychological reactions.

"If you tell a sales manager that the forecast is $24 million, he's going to give you $24 million," says Bell. With a range of $20 million to $28 million, there is a chance of making more. There is also a chance of making less, but pretending that a reasonable forecast does not include that possibility is willful foolishness. "The firm needs to have in place provisions to manage the risk within the forecast error," he says. "If you think your forecast is going to be between $20 million and $28 million, you'd better be prepared to deal with any number in that range."

Part of managing a business is being ready to react in the face of unexpected results, which is why experienced forecasters often create multiple sets of forecasts using different assumptions. Managers can then build scenarios-full sets of alternative strategies-for each variation.

An advanced tool for integrating alternatives is a Monte Carlo simulation. "Basically, you sum up the probabilities of the basic outcomes and that is your expected outcome," says David Bradford, executive vice president of Advisen, a New York company providing information and analytic tools for the insurance industry.

Armstrong suggests using a variety of forecasting methods. "Make sure that you're getting independent forecasts that are free of bias," he says. "The simplest rule is to weight the forecast from each method equally. Don't put more weight on one of the forecasting methods than any other. Just average them."

Forecasting tools can provide important guides. But because mathematics is a double-edged sword, requiring intellectual integrity on the part of those using it, management must use those tools responsibly. "The danger in having too much stuff mathematical is that you can fiddle with the input assumptions and come up with whatever forecast you want," Barcus says.