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J. Scott Armstrong

University of Pennsylvania, armstrong@wharton.upenn.edu

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FORECASTING

J. Scott Armstrong
University of Pennsylvania, Philadelphia

Forecasting procedures are needed only if there is uncertainty about the future. Forecasts are unnecessary when one can control events. For example, predicting the temperature in your home does not require the use of forecasting procedures because you can control it. A forecast that the sun will rise tomorrow is of little value. Many decisions, however, involve uncertainty, and in these cases formal forecasting procedures (referred to simply as "forecasting" below) can be useful. By reducing uncertainty about changes in the environment and by better predictions of the likely effects of policy changes, managers can make better decisions. They can also obtain a more realistic assessment of the risks that they face.

Forecasting is often confused with planning. Whereas planning is concerned with what the world should look like, forecasting is concerned with what it will look like. Figure 1 summarizes the relationships. Forecasting methods are used to predict outcomes for each plan. If forecasted outcomes are not satisfactory, the plans should be revised. This process can be repeated until forecasted outcomes are satisfactory. Revised plans are then implemented and actual outcomes are monitored for use in the next planning period.

Fig. 1. Framework for forecasting and planning.

With some notable exceptions, research on forecasting in management science began in earnest around 1960. Brown (1959) introduced exponential smoothing; this implemented the principle that the most recent data should have the greatest influence on forecasts. Forecasting research was aided in 1981 by the founding of the International Institute of Forecasters, a multidisciplinary society of researchers on forecasting methodology. Also, two academic journals were founded in the 1980s, the Journal of Forecasting and the International Journal of Forecasting, and there has been an annual International Forecasting Symposium since 1981.

Progress has been rapid. Current forecasting procedures are more accurate than those available 30 years ago. Most advances in forecasting have come about through the empirical comparisons of alternative approaches to forecasting. Findings from these studies have been summarized as a set of
principles in the “Forecasting Principles Project,” which can be found at the website http://www-marketing.wharton.upenn.edu/forecast.

Forecasting methods are described briefly below. Next, guidelines are provided for the selection of methods. Typical forecasting applications in management science are then described along with suggestions on which methods are most appropriate for each situation. A discussion is provided on the assessment of uncertainty. Finally, implementation of forecasts is discussed. Along the way, major research findings are highlighted and citations are provided for key review papers.

**Forecasting Methods:** Forecasting methods can be classified as shown in Figure 2. Some methods are based primarily on judgmental sources while others use statistical sources. Going down Figure 2, there is an increasing amount of integration between judgmental and statistical procedures. A brief description of the methods is provided here. Makridakis, Wheelwright and Hyndman (1998) provide details on how to apply many of these methods.

Intentions studies ask people to predict how they would behave in various situations. Morwitz (1999) reviews the evidence on the use of intentions for forecasting. This method is widely used and it is especially important where one does not have data, such as for new product forecasts.

Clearly, roles have marked effects upon behavior. In an experiment by Cyert, March, and Starbuck (1961), subjects who were presented with the same data made substantially different forecasts depending on whether they were told that their role was as a “cost analyst” or as a “market analyst.” Role playing makes forecasts by studying the behavior of individuals as they interact in simulations of the anticipated situation (Armstrong, 1999a). Role-playing is most useful for making forecasts of the behavior of individuals who are interacting with others, and especially in situations involving conflict, such as labor-management negotiations.

Another way to make forecasts is to ask experts to predict how others will behave in given situations. The accuracy of expert forecasts can be improved through the use of structured methods, such as the Delphi procedure. Delphi is an iterative survey procedure in which experts provide independent forecasts for a problem, receive anonymous feedback on the forecasts made by other experts, and then make another forecast for the same event. For a summary of the principles related to the use of Delphi and for a comparison of its accuracy versus unstructured judgments, see Rowe and Wright (1999).

Conjoint analysis allows one to examine how the features of a situation (such as a new product design) affect intentions. Intentions can be related to the features by regression analysis. Each situation provides a bundle of features that have been varied according to an experimental plan. Wittink and Ber-

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**Fig. 2.** Forecasting methodology tree.
genstuen (1999) describe conjoint analysis, which has had extensive applications in forecasting sales of new products.

As with conjoint analysis, it is possible to infer experts’ rules by using regression analysis. This approach is called “judgmental bootstrapping.” It is a type of expert system that limits itself solely to inferential models based on information that experts use to make forecasts. Judgmental bootstrapping is especially useful for forecasts when one does not have data, such as in forecasting new products, or when outcomes are difficult to observe, such as predicting which executive candidate would be most effective. Once developed, judgmental bootstrapping models offer a low-cost procedure for making forecasts. They almost always provide an improvement in accuracy in comparison to judgmental forecasts, although these improvements are typically modest (Armstrong 1999b).

Extrapolation methods use only historical data on the series of interest. One can extrapolate over time (“tomorrow’s weather will be like today’s”) or it can be used for cross-sectional forecasts (“our next employee will be as successful as our average employee”). Extrapolation methods of time series have been widely used for short-term forecasts of inventory and production. The most popular and cost effective of these methods are based on exponential smoothing, which implements the principle that the more recent data are weighted more heavily. Gardner (1985) provides a review of research on exponential smoothing methods, and Filides (1988) provides a broader review of extrapolation methods.

Some important principles are to: 1) seasonally adjust data, 2) use relatively simple methods, 3) extrapolate trends when the historical trend has been consistent, 4) as uncertainty about the forecast increases, be more conservative in extrapolation of trends (e.g., forecast smaller changes from the most recent value), and 5) use long time series when developing a forecasting model.

Empirical studies have led to the conclusion that relatively simple extrapolation methods perform as well as more complex methods. For example, the Box-Jenkins procedure (Box and Jenkins 1970), one of the more complex approaches, has produced no measurable gains in forecast accuracy relative to simpler procedures (Makridakis, et al., 1984).

Quantitative extrapolation methods make no use of managers’ knowledge of the series. They assume that the causal forces that have affected a historical series will continue over the forecast horizon. The latter assumption is sometimes false. When the causal forces are contrary to the trend in the historical series, forecast errors tend to be large (Armstrong and Collopy, 1993). While such problems may occur only in a small minority of cases in sales forecasting, their effects can be disastrous. One useful principle is that trends should be extrapolated only when they coincide with management’s prior expectations.

Judgmental extrapolations are preferable to quantitative extrapolations when there have been large recent changes in the sales level and where there is relevant knowledge about the item to be forecast (Armstrong and Collopy, 1998). Quantitative extrapolations have an advantage over judgmental methods when the data are ample and changes are expected to be large (Armstrong, 1985, pp. 393-401). More important than these small gains in accuracy, however, is that the quantitative methods are usually less expensive. When a firm has many thousands of forecasts to make every month, the use of judgment is not cost effective.

Experts can identify analogous situations. Extrapolation of results from these situations can be used to predict for the situation that is of interest. This is especially useful for time series where one has few observations or even no historical data. For example, to assess the loss in sales when the patent protection for a drug is removed, one might examine the results for drugs that previously lost patent protection. Incidentally, the first year loss is substantial.

Rule-based forecasting integrates managers’ domain knowledge with statisticians’ quantitative methods. It provides a structured, yet inexpensive approach to elicit information from domain experts. It also incorporates guidelines from research on forecasting; an example would be to dampen the trend forecast as the forecast horizon increases. This information is used to apply differential weights to forecasts from different forecasting methods. Given domain knowledge, rule-based forecasting has produced substantial improvements in accuracy when compared to extrapolation methods (Collopy and Armstrong, 1992).

Expert systems use the rules of experts. Protocols are commonly used to discover how the expert makes forecast. Here an observer asks a forecaster to talk aloud as he makes forecasts. These descriptions are then translated into rules. Expert opinion, conjoint analysis, bootstrapping, and econometric models can also aid in the development of expert systems.

Data-based multivariate models infer causality from the data. Much work has been done to apply these models to economic time series. However there is little evidence that they provide any benefits to forecasting.

Econometric models use theory to select variables, directions of relationships, and functional form. They are also used to put constraints on the
relationship estimates. Theory is drawn primarily from prior research. In addition, estimates for the model can benefit from expert opinion, especially if it is obtained in a structured way, such as by judgmental bootstrapping. Estimates of relationships can then be updated by analyzing time series, longitudinal, or cross-sectional data.

Econometric models can relate the forecasts directly to planning and decision making. They can incorporate the effects of decision variables as well as variables representing key aspects of the environment. Thus, they are appropriate when one needs to forecast what will happen under different assumptions about the environment or when considering different strategies.

Econometric methods are most useful when 1) strong causal relationships are expected, 2) these causal relationships are known or they can be estimated from various types of data, 3) large changes are expected to occur in the causal variables over the forecast horizon, and 4) the changes in the causal variables can be accurately forecasted or controlled, especially with respect to their direction. If any of these conditions does not hold, such as is typically the case for short-range forecasts of the economy, econometric methods are unlikely to be more accurate than simple extrapolations.

Important findings about econometric methods are to: 1) base the selection of causal variables upon theory and domain knowledge, rather than upon the statistical fit to historical data, 2) use relatively simple models (e.g., break the problem into a series of smaller independent problems; do not use simultaneous equations; use only models that can be specified as linear in the parameters), and 3) use a variable only if the estimated relationship is in the same direction as specified a priori.

**Selection of Methods:** Empirical literature provides guidance for choosing the method that is most appropriate for a given situation. The first issue that the analyst needs to address is whether much data are available. If not, judgmental procedures are called for.

For judgmental procedures, the next issues are whether the situation involves interaction among decision makers and whether large changes are involved. For large changes, is policy analysis involved, and if it is, what is the best source of evidence?

If one has much data, the first issue is whether the analysis is based on time series data. In either case, the next issue is whether there is knowledge about the expected empirical relationships. For example, meta-analyses have been done so that, in most situations, excellent prior knowledge exists about price elasticities. Next, one should consider domain knowledge, such as the managers' knowledge about the situation. If empirical knowledge of relationships is available, use econometric models.

For time series situations where one lacks causal knowledge, extrapolation is appropriate. If there is no prior knowledge about relationships, but domain knowledge exists (such as a manager knows that sales will increase), use rule-based forecasting.

In situations where one does not have time-series data and also has no prior knowledge about relationships, analogies are appropriate if domain knowledge is lacking. But given domain knowledge, expert systems should be used.

Figure 3 summarizes the guidelines for selecting. While these represent major considerations, the list is not comprehensive. Furthermore, the conditions may not always be clear. In such cases, one should use different approaches to the problem. The forecasts from these approaches can then be combined. Clemen (1989) reviews research on combining forecasts. For example, despite enormous efforts, Box-Jenkins procedures have not done well when compared to other methods.

Selection of the appropriate forecasting methods can also be guided by testing with data from the situation of interest. Significant progress has been made in testing procedures. For example, the original approach to selection relied upon sophisticated procedures for analyzing which models provided the best fit to historical data. A model that could not explain any of the variation in historical data would be expected to have poor predictive ability. But the fit of the data has proven to be of little value for the selection of forecasting methods (Pant and Starbuck, 1990).

Progress has also been made in the development of error measures for comparing different forecasting methods. The mean square error was once considered to be the most appropriate measure. However, it has problems with respect to the comparison of methods because it is not invariant to scale, it is highly influenced by outliers, and it does not control for degree of difficulty in forecasting. As a result, it is an unreliable measure for assessing forecast accuracy (Armstrong and Collopy, 1992). Theil's U2 solved these problems (Theil 1966, Chapter 2). It compares errors for a given model against errors for the naive, 'no change' forecast. The median relative absolute error (Armstrong and Collopy, 1992) is a simplified version of Theil's U2.

**Assessing Uncertainty:** In addition to improving accuracy, forecasting is also concerned with assessing uncertainty. Early approaches to this issue generally relied upon the fit to historical data as a
way to infer forecast uncertainty. On occasion, this would provide a reasonable approximation for prediction intervals, especially for cross-sectional data. However, for time series, the historical fit typically leads to prediction intervals that are too narrow. Some empirical studies have shown that over half of actual outcomes are well outside of the 95% confidence intervals (Makridakis, et al., 1987). This overconfidence could mislead decision makers.

Chatfield (1995) describes procedures for the estimation of prediction intervals. When possible, the best approach is to simulate the actual forecasting procedure as closely as possible and make forecasts for holdout data. Then use the distribution of the resulting \textit{ex ante} forecasts to assess uncertainty. So to assess the uncertainty associated with a five-year-ahead forecast, one would like to assess the accuracy of many five-year-ahead forecasts.

**Applications of Forecasting in Management:** Forecasting methods can be applied to many areas of management. Figure 4 provides a description of some areas and outlines how these relate to one another.

The forecasting method will vary depending upon the situation. For example, econometric methods are often appropriate for long-range forecasting of the environment and industry. Extrapolation methods are useful for short-range forecasting of costs, sales, and market share. Forecasts of competitors’ actions could be made judgmentally. Role-playing can be used to forecast decisions by parties in conflict.

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**Fig. 3:** Accuracy of methods by situation.

**Fig. 4:** Some needs for forecasts in firms.
IMPLEMENTATION OF FORECASTS: Progress in forecasting has been achieved through application of structured and quantitative techniques. Despite this, managers continue to rely heavily on subjective forecasts for important decisions. Even when quantitative forecasts are made, managers use their judgment to revise them. Judgment sometimes aids the forecast, but often it harms it. As a general rule, experts are especially skilled at determining the current state of affairs, but are less competent in predicting change. Thus, judgment improves the forecast when it is used to reduce uncertainty about the current level, but it often harms the forecast of change.

The challenge is to develop procedures that will most effectively blend quantitative and judgmental methods. Armstrong and Collopy (1998) discuss five different approaches to such integration: using extrapolations to revise judgmental forecasts, combining extrapolation and judgmental forecasts, using judgment to revise extrapolation forecasts, rule-based forecasting (where extrapolations are combined based on weights derived from domain knowledge, and econometric forecasts (where judgments are an input to the model). Perhaps the primary principle for integration is that judgment should be used as an input to the quantitative forecasting, not as a way to adjust the quantitative forecasts.

Implementation of forecasts depends not only on the intrinsic merit of the forecast, but also upon its acceptability to the organization. This, in turn, may depend upon the capability of users and upon current procedures. It is useful, then, to assess how well different procedures perform in realistic settings. Unfortunately, little such research has been done. However, Betschneider, et al. (1989) studied forecasting practices by state governments and concluded, for example, that the use of complex procedures harmed forecast accuracy.

Accurate forecasts are often ignored, particularly when they involve bad news. Scenarios which are stories about alternative futures, can aid implementation in such cases by making a forecast that will catch the attention of the decision maker. Various techniques can be used to increase the plausibility of a scenario (Gregory, 1999). These include using concrete examples, showing a logical sequence of causal events, having the decision maker describe how he or she would act in the scenario, and using past tense when writing the scenario.

CONCLUSIONS: Research on forecasting since 1960 has relied heavily upon empirical testing of alternative approaches. More recently, the research has begun to address the conditions under which various methods are most appropriate. These research strategies have provided useful findings. Often the findings conflict with expectations of statisticians and managers, and this has slowed adoption of new methods. As a result, many organizations have not yet adopted developments of the past few decades. On the positive side, we have many principles that have been shown to improve accuracy and to enable a better assessment of uncertainty. Some principles seem intuitively obvious, such as "include a manager's knowledge in making forecast." Others are not so intuitive, as "do not use judgment to revise the forecasts from a model."

See Delphi method; Exponential smoothing; Inventory control; Stochastic processes.

References


