FORECASTING: THE ISSUES (REVISED VERSION)

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This chapter argues that an organization must be concerned with a much wider set of issues, when it examines its forecasting performance, than just the problem of selecting a forecasting technique. First, an overview of the wider aspects of forecasting is presented in discussing the Forecasting Framework. This is not to say that the problem of selecting an appropriate technique or approach should be neglected. The various commonly used methods of forecasting are described here in an evaluation offered of their strengths and weaknesses. In many important applications, however, even the most accurate of methods leaves a high level of residual uncertainty. Organizations have to develop ways of limiting the impact of forecast error, and some possible approaches are described here. Most of the elements which together contribute to an effective forecasting process – the technical, the organizational and the information-gathering system in which the forecasts are based – require careful evaluation. Major benefits will accrue from improvements in the design of the organization's system of information gathering about its operating environment.

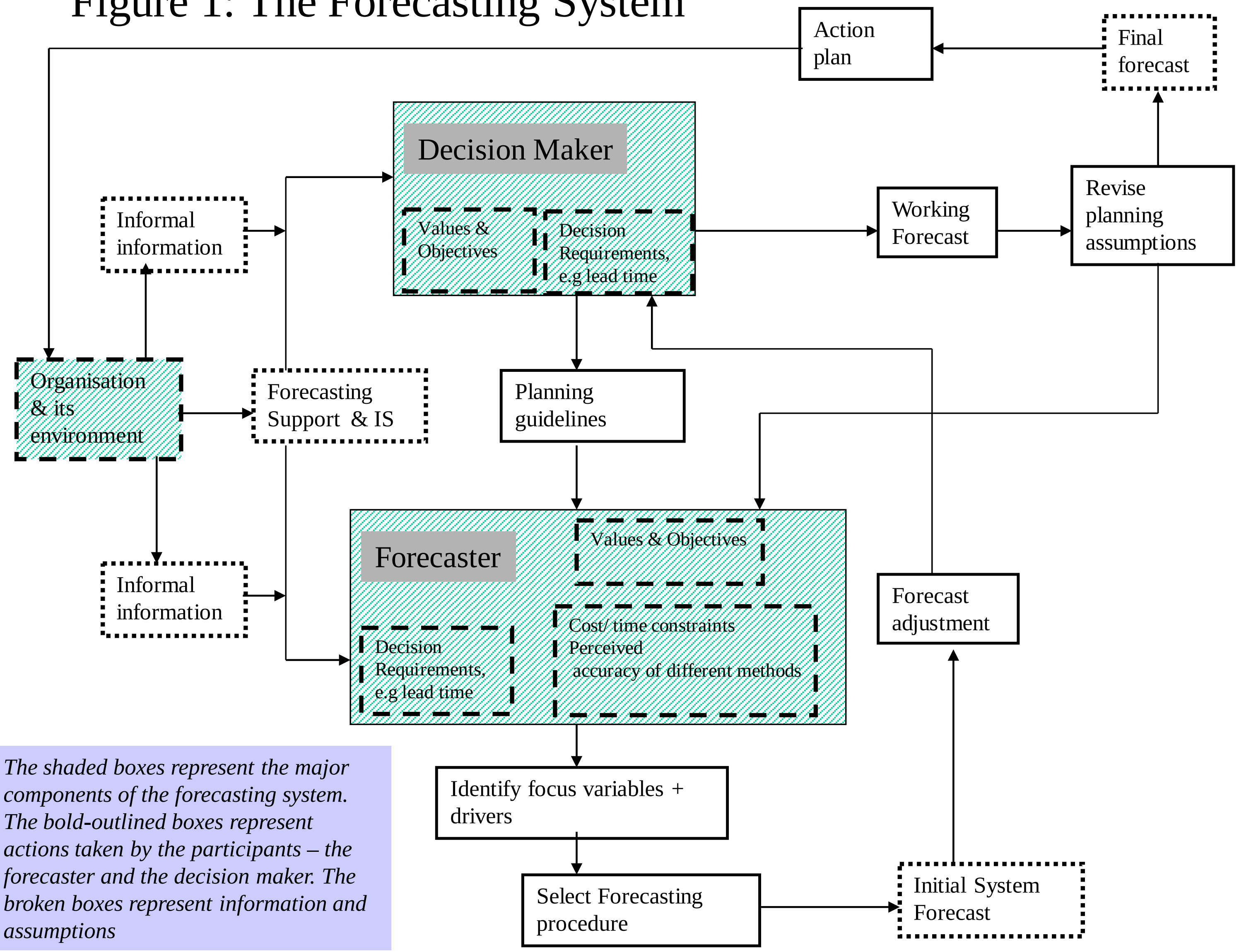
A FORECASTING FRAMEWORK

The first part of this chapter highlights the areas of forecasting that demand attention from the practical forecaster, posing and suggesting answer to questions such as: Who makes forecasts? Who needs forecasts? How are they used? What is the best forecasting method to use? Of these the aspect that has been best researched is the forecasting methods themselves. The second part of this chapter examines the most widely used methods, concentrating on their advantages and disadvantages. The aim is to show where resources can be best employed by the organization intending to improve its forecasting performance. It turns out that forecasting techniques can be improved quite easily in most organizational settings. Of more importance to overall performance, however, is the context in which forecasting takes place, the information on which it is based, and the organization's response to a forecast, and these are much more difficult to improve or reform.

Figure 1 presents a framework for understanding the process of organizational forecasting. In this model the forecaster is providing the decision maker with predictions about the consequences of a proposed set of plans. To do this, he or she uses selected information about the environment. The information might be available through a formal management information system (MIS) – but it is equally as likely to be collected on an ad hoc, informal basis. The forecaster adopts a particular forecasting procedure on the basis of cost, the time available before the forecast is needed, and the likely accuracy of the methods he or she is competent to perform. The forecaster should also takes into account the value of improving forecast accuracy.

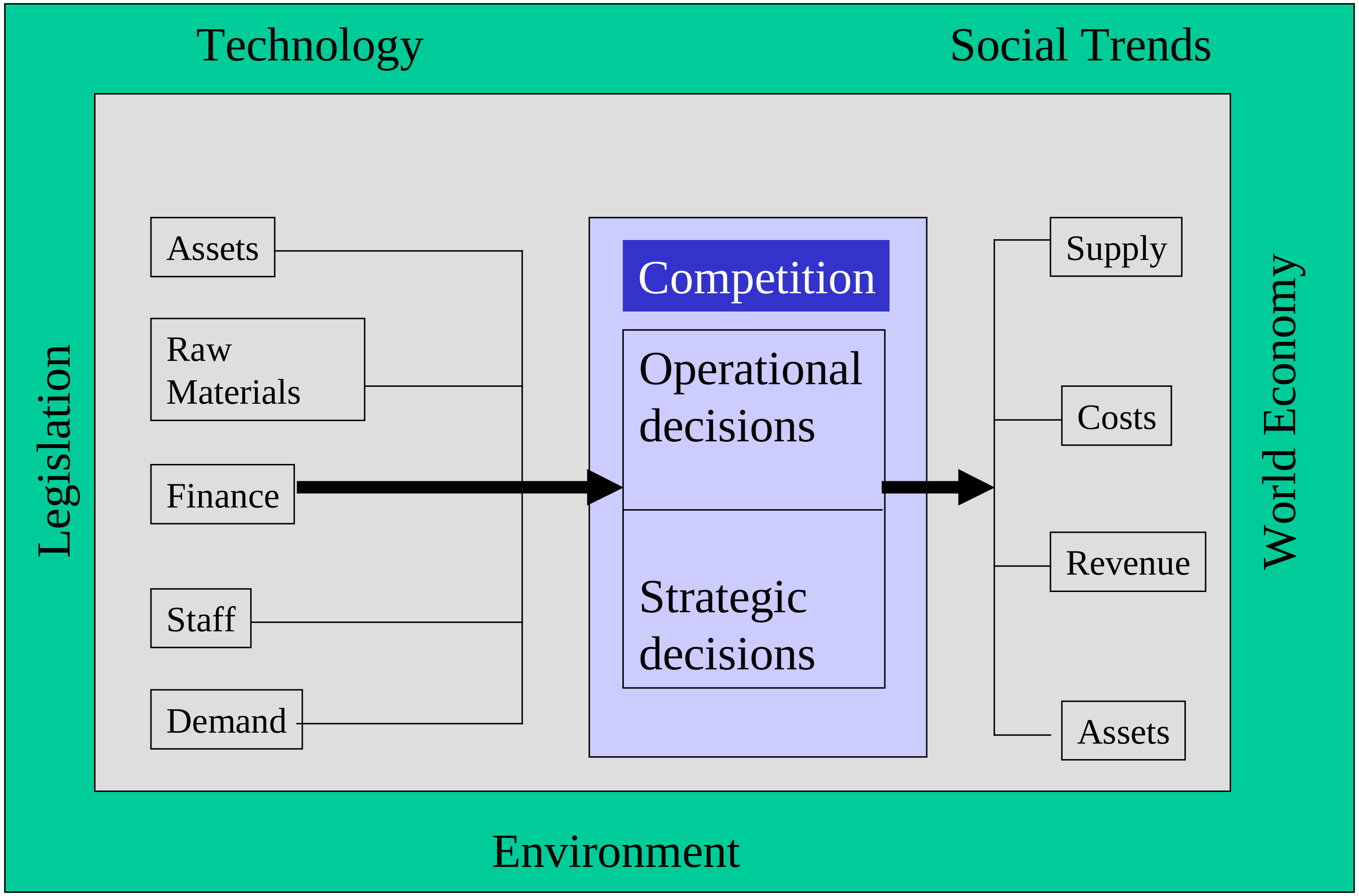
These criteria are not defined in a vacuum. The forecaster brings to bear the professional expertise that may have taken years to develop and will also have in mind his or her personal career goals (labelled the forecaster's values in Figure 1). The forecaster's organizational masters, the decision makers of Figure 1, have their values too, and these two sets of values and beliefs may not match. The forecaster is influenced by the decision-maker's values, but does not necessarily share them. In fact, as Wheelwright and Clarke (1976) showed, the forecaster's and corresponding decision-maker's views of the problem are often in substantial conflict. To the manager, the forecaster seems too technically focussed, lacking in understanding of the manager's problems, and is rarely perceived as performing cost effectively. From the forecaster's perspective, the decision maker appears to understand little, if anything, about the technical aspects of forecasting.

Figure 1: The Forecasting System



The shaded boxes represent the major components of the forecasting system. The bold-outlined boxes represent actions taken by the participants – the forecaster and the decision maker. The broken boxes represent information and assumptions

Figure 2 The Firm's Forecasting Needs



If, after producing forecasts with a chosen approach, the forecaster does not like the result, he or she will modify it; so too will the decision maker when the forecast is delivered, this time using alternative sources of information. The resulting forecast (the "working forecast" in Figure 1) may still not be accepted if it diverges from the decision-maker's initial values and objectives. In this case the planning guidelines and assumptions used for the initial set of forecasts have to be revised and the process repeated.

Perhaps the most obvious omission from this model of the interrelationship between the forecaster and the decision maker is that it fails to include the organizational framework in which the two protagonists (or participants) work. Hidden assumptions in different parts of the organization will influence what variables are considered crucial and what modifications will take place. Also, forecasts of the same variables may well be produced in different parts of the organization and are therefore subject to differing pressures, depending on the organizational source. Marketing staff, for example, take an optimistic view of the likely outcome of sales and marketing interventions they have planned in the forecast period, and therefore of overall sales. The finance department, by contrast, tasked with preparing predictions of future sales that may be shared with the stock market, are often inclined to be conservative in their predictions. In this case, the personal and organizational penalties for over-forecasting are substantially greater than those for under-forecasting, and this tends to make them cautious. Presented with the same data, these two different groups may produce contrasting sales forecasts, each with different errors.

The next sections examine the forecasting system we have just described with a view to establishing priorities for improvement.

Links between the Forecasting and Decision-Making Systems

The links between the forecasting and decision-making function are weak in many organizations, because decision makers and forecasters differ in their priorities. What are the most productive organizational designs that link the two? Fildes and Hasting (1994) and Wheelwright and Clarke (1976) suggested some solutions. The key to evaluating the organization's forecasting performance is to examine how forecasts are used, not just how they are produced.

The Quality of the Management Information System (MIS) and Forecasting Support System (FSS)

Most forecasting procedures build on the premise that information useful to the organization is readily available. However, many firms do not keep adequate records, nor have they thought through a consistent approach to collect information. For example, volume and price figures for homogeneous product groups are often not available. Whilst it is true that advanced techniques require suitable information to be collected over a number of years, forecasting should not be delayed until a suitable database is developed. Instead the database should be designed with a number of alternative forecasting procedures in mind.

It might be objected that the MIS should not be the concern of an article surveying forecasting problems. However, the slow adoption of quantitative forecasting techniques can perhaps be explained only by reference to an often ill-developed MIS. The routine collection of data (on such variables as sales and marketing) is a necessary aid to decision making. Well developed ERP systems such as SAP contain forecasting components that rely on sales data. Alternatively stand –alone forecasting systems deliver forecasts to other components of the organization's IS. However, these are often not well designed, either from a statistical viewpoint or from a user's perspective (Fildes et al., 2006). Nor do they contain the breadth of data often relevant to producing a satisfactory forecast (Fildes and Hastings 1994). Instead, informal sources of information are used since there's nothing more reliable available.

Selecting Key Variables to Forecast

There are two ways of looking at the selection of key variables – how it is done and how it should be done. The first mistake is to neglect to forecast a key variable. The effect is that items that should be treated as variable and subject to forecasting are assumed to be constant. Consider, for example, an item such as "time taken by a debtor to pay," which is an input into a monthly cash flow forecast. Historically this may well have been treated as fixed. For debtors, however, the time taken to pay creditors depends on their cash flow position; in a recession the time is likely to lengthen. Thus, just when it is most important to be realistic about cash flow, the assumption that "the time taken by a debtor to pay is fixed" is least likely to be valid.

A related issue is when two interdependent items, for example, sales volume and margin on sales, are treated separately. While margin on sales *may* be decided by the administrative fiat of the finance director as an input into the annual corporate plan, to neglect the effect of this assumption on sales volume would very likely undermine the revenue forecasts in the plan.

These two simple examples point to the importance of identifying items that should be treated as variable. The interrelationships of the planning assumptions and the variables that are forecast also need to be systematically considered, as the second example shows. This is a particularly dangerous problem when a new planning system is introduced.

Casual empirical evidence suggests that many managers are confused by the differences among forecasts, plans, and targets. Forecasts should represent the most likely (or expected) value. Plans are a response by the organisation to the forecasts in order to move towards its objectives. The forecast outcomes of a plan are themselves contingent on the input forecasts (such as sales and cost forecasts) and the procedures the organization proposes to implement. Targets often represent optimistic estimates of what might be achieved (and should therefore be based on the corresponding forecast). In the example above, the margin on sales is a target – the danger occurs when this is built in to the organization's budgeting.

One approach to establishing the firm's forecasting needs is shown in Figure 2. An organization operating in a competitive environment, buying and transforming resources such as labour, finance, and raw materials into a supply of products and services needs particular forecasts to support strategic and operating decisions. In the short term, most variables can be regarded as fixed. As the time scale of decision making lengthens, it becomes increasingly necessary to consider slowly changing variables in the social, legislative, and technological spheres that can reasonably be ignored in operational decision making.

By considering a checklist of variables and their likely impact on the decisions being currently contemplated, it becomes possible to identify those that most require attention. The sensitivity of the decisions to forecast error also places an upper limit to expenditures on forecasting. For example, if an error of 10% in a product sales forecast leads to increased costs (or loss of revenue) of €100,000, it is worth spending up to €100,000 to eliminate that 10% forecast error.

Cost and Benefits of Improving Forecasting

The value of eliminating forecasting error is only one consideration in evaluating forecasting procedures. A second aspect requires the forecaster to take a view on likely improvement in accuracy as a function of expenditure on forecasting. Put more formally, improved accuracy is a function of expenditure on forecasting (possibly increasing), while the benefit from forecasting is a function of improved accuracy. This argument leads us to the truism that there is an upper limit on *profitable* expenditures on forecasting. It also highlights what we would like to know: what is the relationship between expenditure and accuracy, and between accuracy and benefits. Fortunately, the cost of forecasting is relatively simple to calculate for any chosen approach. (Later in this chapter what is known about the accuracy of various methods employed in forecasting is examined in some detail.) The remaining element in the equation is the estimation of likely benefits derived from improvements in accuracy. This estimation is made by calculating the consequences of various levels of forecast error and comparing the results with what would have been obtained if perfectly accurate information had been available. For example, Gardner (1990) simulated the effects of improving the forecasting system used to support spare parts supply in the US Navy. An improved forecasting model delivered major improvements in service (for the same inventory cost) or alternatively, a reduced inventory could deliver the same service.

The previous paragraphs describe the economic costs and benefits of improved forecasting. These are not the only considerations – the forecaster and the decision maker each have their preferences for one particular approach or another. Often these preferences seem to over-rule the economic arguments and lead to the neglect of more rational analysis. While lip service is paid to accuracy, there is often an organisational preference for over (or sometimes under) forecasting because of the organizational consequences of the two types of error (Sanders and Manrodt, 1994), Such neglect can be costly. It is important that organizations with their forecasting unit estimate the economic consequences of inaccurate forecasting and, when there is potential, try to move toward a more cost-effective forecasting system.

Selecting a Forecasting Procedure

Early writers on forecasting speculated on which methods are most accurate. If one turns to these works, one finds that the evaluations offered boil down to the principle, “increased sophistication is good,” leaving aside any questions of cost. Even on their own terms this begs the question: If we want to forecast a particular variable, how do the various methods perform? Since these early publications, the prescriptions offered have been subject to empirical criticism which, in particular circumstances, showed them to be misleading. Armstrong (2006) has recently summarized the empirical evidence on forecast accuracy, and his book (Armstrong, 2001) has laid down various principles that offer help in selecting among the various methods. Nevertheless, support for any particular principle is often weak, and the forecaster will rarely be able to select a method (within the cost constraints) confident of its accuracy compared with that of competing approaches.

Nor will the analyst usually search through all alternative methods, comparing and evaluating although such a systematic search would help. This approach is ruled out for all except the most important projects because of time and/or cost. . Instead, choices are made on the basis of a range of considerations, as follows:

> *Expertise of the Forecaster*. If only one method is known, that is the one that will be used. If a long time has been spent learning a complicated method, that effort is likely to influence the choice of method unduly. Previous experience and related research by the forecaster will also be important influences. (See Fildes and Lusk (1984), for further discussion of this.)
>
> *How the Forecast Is to Be Used*. If the decision maker requires an evaluation of the impact of, say, advertising as a part of the market forecast, the approach selected will have to answer that question.
>
> *Complexity and Comprehensiveness.* If a model is too complex for the decision maker to understand, it is unlikely to be used. On the other hand, if a model fails to include those elements the decision maker regards as important, the model again will be rejected.
>
> *Comparative Testing.* If a more thorough selection process is undertaken a few of the more plausible methods will be developed in parallel and tested for their forecasting performance. They should be benchmarked against some established method or current organizational practice.

Important decisions, sensitive to forecast inaccuracy, require a careful search through a range of alternatives. An all too common mistake is to limit consideration to a narrow range of forecasting methods. Armstrong (2001) has argued persuasively that there are invariably advantages to trying more than one approach, and the more disparate the approaches the better. Moreover, he provides substantial evidence that combining forecasts usually leads to improved accuracy. Organizations therefore need a forecasting procedure that, for important problems, permits easy comparison of a range of alternatives. This means that the FSS should include a wide range of methods and procedures for comparing their forecasting accuracy and that records of past forecasting performance should be kept. The ongoing costs of such record keeping are small and, once the system is complete, time can be spent on forecasting rather than data collection. Developments of user-friendly software have to a certain extent facilitated the comparison of forecasting methods. The likely effect of implementing these improvements is more accurate forecasts, based on the effective use of a wide variety of methods and information sources.

Adjusting the Forecasts

Often both forecaster and decision maker alter the resulting forecasts. The adjustments take place for a number of reasons: to make the results more “plausible,” to better meet the expectations of the decision maker and to comply with some pre-specified target. More importantly, perhaps, adjustments can take information into account that has not been included in the model-based forecast, for example information about a sales promotion. However, there is only weak evidence that these adjustments improve the final forecast significantly (Fildes et al., 2007;2009).

Three alternatives exist for integrating prior beliefs and current knowledge into a forecasting procedure: (1) as formal input into the model, (2) as adjustments of the type just discussed, and (3) by formally combining an independent judgemental forecast with a model based forecast.

Macroeconomic forecasters regularly constrain their forecasts to accord with the latest information they have on the economy. Such constraints seem to improve forecast accuracy (Fildes and Stekler, 2002). Demand planners supporting supply chain operations rarely have a full sales forecasting model that incorporates all the drivers that affect sales. They therefore modify the system forecast quite substantially, with some organizations adjusting 70%+ of the system forecasts. As Fildes et al (2009) show, however, some improvement in forecast accuracy can be gained, although the record is far from perfect and the effectiveness of the adjustment process can certainly be enhanced.

In contrast to this approach to the incorporation of subjective information, decision support systems in marketing may require the user to specify a number of parameters, such as "advertising effectiveness." The model can then be adjusted until the forecaster is happy both with the chosen parameter and the resulting forecast.

Unfortunately, we just do not know which of these various procedures for judgemental adjustment is likely to produce the better forecast. Both forecasters and decision makers typically believe such adjustments are necessary. It is therefore important to monitor performance both with and without the adjustments. Forecasting Support Systems should be designed to implement such monitoring though few commercial systems have the capacity.

Revising Plans

The final stage of the planning round arises if the conditional forecasts derived from a particular business plan are at odds with the objectives set by the decision maker. The decision maker or planner will then search for alternative courses of action. With revised actions in prospect (for example, if increased brand sales are required, new marketing activities can be introduced) the forecasts are revised leading to outcomes more in line with the decision maker's original objectives. Discussion of this topic is left to the planners, however.

A PROBLEM IN ORGANIZATIONAL DESIGN?

What are the important issues in forecasting? The previous section has shown that the technical aspects of forecasting are just a small part of the challenge of generating cost-effective forecast information and then acting effectively on it. Distortions and inefficiencies creep in from a variety of sources. Leaving aside the technical issues for the moment, the major weakness of the system just described is the system itself: an information system set up by accountants and therefore unconcerned with markets and not future oriented, a forecaster entranced with the sophisticated statistical hardware of the profession, or, equally commonly, one who knows little about formal forecasting methods, and a decision maker whose primary concern is saying what his or her bosses want to hear (a caricature certainly and only one of many possible). However, it underscores the major theme of this paper: because we do not know how best to improve the information flow from the environment to the decision maker, we have to experiment; to evaluate and measure the effectiveness of forecasts. Information systems can be improved, and (in the companies we have examined) there is clearly scope for such improvement. Technical staff can be deployed so that they understand the manager's problems but are not subject to the same political pressures. Decision makers can distinguish between an objective forecast and the political actions they wish to take for their own or their organization's success.

No single solution to the behavioural problems in forecasting can be applied across all organizations. With experimentation and monitoring of the results of the experiments, it is not unreasonable to hope for major improvements in the effective generation and use of forecasting information. Analysis of such experiments by researchers should result in a better understanding of how forecasting and information systems best fit with an organization's needs and how the recommended improvements should be implemented. We could then more reasonably move on to worry about the technical issues.

APPROACHES TO FORECASTING

The Methods

Of all the aspects of forecasting, the most studied is the technical details of the various forecasting methods. The methods can be broken down into three classes:

> *Judgmental.* Individual opinions are processed, possibly in a relatively complex, systematic fashion
>
> *Extrapolative.* Forecasts are made for a particular variable using only that variable's history. The patterns identified in the past are assumed to hold into the future.
>
> *Causal (or structural).* An attempt is made to identify relationships between variables that have held in the past, for example, volume of brand sales and that product's relative price. The relationships are then assumed to hold into the future.

Most forecasters use more than one of these approaches. But before going into how these approaches fit in with the general questions already raised, this section describes some of the more common methods under the foregoing headings and evaluates them.

Figures 3, 4 and 5 give brief definitions of the most important methods in each class. Standard forecasting text books, for example Makridakis, Wheelwright and Hyndman (1998) or Levenbach and Cleary (2006) describe how they are used in more detail. Armstrong (2001) and his co-authors offer a full evaluation. For the moment these definitions will suffice.

Judgmental Forecasting

Judgmental approaches all rely on individual judgments, potentially combined to produce a final forecast. Figure 3 describes the standard judgmental methods of forecasting. A recent survey is given by Lawrence et al (2006).

Extrapolative Forecasting

Extrapolative methods can be used whenever there is a time series history on which to base the forecast, and in the remainder of this section Y_t is used to denote the variable to be forecasted, measured at time t. Y can be a quantitative variable like sales or a classification such as whether a football team wins its fixtures or whether a consumer is in credit. Figure 4 gives a brief description of the most well known models. McCarthy (2006) and earlier, Mentzer and Kahn (1995), have examined the use of extrapolative methods where, of the various formal approaches to forecasting, the simpler methods such as exponential smoothing have been adopted rather than more complex alternatives.

Causal (Structural) Methods

The aim of these models is to link the variable being forecast to the causes that historically have influenced it and to use their established relationship to forecast. Figure 5 lists the well known approaches and offers a brief definition.

Figure 3. Judgmental Methods – Definitions

Method	**Definition**
J1 Individual (subjective)	Individual makes a judgment about future without reference to any other set of forecasts.
J2 Intentions survey (Morwitz, 2001)	Potential customers can be surveyed as to their prospective purchases and willingness to pay for various features on offer
J3 Committee	Committee aspects of forecasting are all too familiar although virtual meetings are a new variant.
J4 Sales force composite	This aggregates the opinions of the sales force or “experts” on future prospects for particular segments of the market.
J5 Delphi (see Rowe and Wright, 2001)	Delphi has three attributes that distinguish it from the committee method: anonymity, feedback, and group response. Typically, participants are unknown to each other. The forecasting exercise is conducted in a series of rounds with each participant offered a summary of the opinions expressed earlier.

Figure 4. Extrapolative Methods - Definitions

Method	**Definition**
E1 Trend curves (Meade and Islam, 2001)	Past observations are described as a function of time and the identified pattern is then used to forecast ahead. Typical functions are the straight line, the exponential and the S-shaped curve. Available computer software provides a number of alternative curves. The method is often used for long-term forecasting. Meade (Meade and Islam, 2006) gave a recent evaluation.
E2 Decomposition	The time series is thought of as having four components, trend (long-term behaviour), cyclical (longer-term swings around the trend), seasonal (within year) fluctuations, and a random component left over. Once the systematic components are identified they can be reintegrated to generate forecasts.
E3 Exponential smoothing	The forecast is based on a weighted sum of past observations. The weights depend on so-called smoothing parameters, which have to be chosen either by the user or through statistical techniques. The method can be easily adapted to take into account trend and seasonal factors. Gardner (2006) offers a recent

	survey.
E4 Box-Jenkins (or ARIMA)	Like exponential smoothing, forecasts are based on a weighted sum of previous observations. However, the choice of weights is much more complex. ARIMA models offer the analyst a range of different models, and the most appropriate is selected for the particular application.
E5 Neural Nets	While other extrapolative models are essentially linear, Neural nets, building on an analogy with the brain and how it processes information, provide a wide range of non-linear models. Because of the range of models included within this class the issue of model choice is critical. Adya and Collopy (1998) and Zhang et al. (1998) offer evaluations.

FIGURE 5. Causal (structural) Methods - Definitions

Method	**Definition**
C1 Single equation regression	The dependent variable Y_t is thought of as determined by a number of "causes," or "exogenous factors," as well as past values of the dependent variable itself. The relationships between Y and its causes are identified by examining past data. To forecast, either assumptions need to be made concerning the values of the exogenous factors in the future or these values have to be forecasted. Fildes (1985) and more recently, Allen and Fildes (2001) have offered evaluations. Indicator or factor models build on the same econometric techniques but use an often large number of indicator variables without paying any attention to an explicit economic model.
C2 Simultaneous system	These have a structure similar to the single equation regression models but have more than one dependent variable. The dependent (or endogenous) variables are forecasted by making assumptions about the future values of the exogenous (externally defined) variables. Allen and Morzuch (2006) do not regard this approach except through the VAR models as likely to produce effective forecasting models.
C3 VAR Models	VAR Models have developed rapidly in the last 20 years and have been shown by Allen and Fildes (2001) to have excellent performance characteristics. The models typically take a small number of variables, writing the variable of interest as a linear sum of lagged values of the dependent variable and current and lagged values of the other variables. These secondary variables are written in similar format, to produce recursive forecasts.
C3 Simulation	Like simultaneous system models, simulation models are

	concerned with a large number of variables and their interrelationships with exogenous factors. Simulation modellers stress model structure (rather than the linear structures of the regression and simultaneous system models). Typically they include a lot more detail of the system being modelled, for example, information flows. Identifying the model is usually much more ad hoc than with the rigorous statistical models C1 and C2. System dynamics models, while usually focused on policy, usually have a forecasting aspect to them and have been used for example, in telecommunications forecasting (see Fildes, 2002, pp.512-513).
C5 Cross-impact analysis	A list of events likely to have an impact on the system being analysed is generated. The probabilities of each of these events happening are then estimated. The conditional probability of event A happening given that event B has happened, for all possible events A and B, is also estimated. From these assumptions it is possible to define scenarios made up of a mixture of these various events and to calculate the associated probability of each scenario. Those sets of events with low probability are eliminated.

Other Approaches

The foregoing list of forecasting method is not all-embracing. It neglects in particular a range of adaptive extrapolative methods (Fildes, 1979)(Williams, 1987), leading indicator methods (Lahiri and Moore, 1991), and the wide range of ideas that go under the heading of social and technological forecasting. Any method can be employed either badly or well, and a careful analysis of how the organization uses its chosen procedures should usually lead to improvement. However, the major technical issue is how to choose among the competing approaches.

EVALUATION OF THE FORECASTING METHODS

No one method can be relied on to produce the “best” forecasts in all circumstances. Each of the methods has its strengths and weaknesses, and these are summarised in Figure 6.

Each of the methods discussed in Figures 3-5 has been evaluated on a set of criteria, and the results are summarised in Figures 6 & 7. Armstrong’s (1985) Exhibit 14-1 takes a similar approach. The conclusion that stands out from Figure 7 is that the problem of selecting a forecasting procedure is far from straightforward. No one method is better than the others on all the dimensions considered.

SELECTING A FORECASTING PROCEDURE REVISITED

An earlier section briefly considered some of the issues involved in selecting a forecasting procedure. Here the information that would help a forecaster select the appropriate procedure for the problem in hand is reviewed.

Ideally the forecaster would be able to describe the problem to be forecasted on a series of dimensions, for example, certain simple statistical characteristics of the variable, the forecast lead time, the level of aggregation in the data (are the data firm, market, or macroeconomic data?), the type of economic or social system in which the forecasted variable is generated, and so on. With a stable relationship established among these problem characteristics and the performance of the various methods, the choice of method only depends on the returns from forecast accuracy. In essence, this relationship would suggest the appropriate forecasting method to use.

If this sounds too fanciful, certain authors have attempted to do exactly this (Makridakis (Makridakis and Hibon, 1979), although with only limited success. Armstrong (1985) has also evaluated a wide range of forecasting cases and has attempted to generalise about when to use which method. This early work has recently been updated (Armstrong, 2006). Makridakis and Hibon (2000), and Fildes et al. (1998), through large-scale forecasting competitions, which compare the performance of alternative methods, have attempted to develop guidelines for selecting among extrapolative methods. The question Makridakis and colleagues have addressed is a very practical one regularly faced by companies, as they seek better methods to support their operations. Criteria for carrying out such comparisons have been laid down by Fildes and Ord (2002).

As part of the attempt to understand the circumstances where forecasting fails or succeeds, Asher (1978) has attempted an evaluation of forecasting success (and failure) for a number of problem areas, for example, energy, population, and transport. In a similar vein, Schnaars considered why so many technological forecasts go wrong whilst Sherden (1998) has cast a very baleful eye over the whole of business of forecasting, arguing that there are few examples where forecasting has value. In reviewing the book, I argued that he had wilfully mis-represented the results of the research carried out in forecasting that, other researchers, for example, Armstrong (2001, 2006) have reported on. However it is an entertaining ‘airport read’ and certainly delivers a powerful message of caution about financial forecasters. These various studies have all increased our knowledge of predictability and have changed our views on the likely success of alternative methods. Unfortunately, the residual uncertainty is very high, and as we move from short to medium term forecasting, the situation in which increased accuracy probably has the highest payoff, our ability to recommend specific methods decreases to almost zero. For us, the major issue in selecting a forecasting procedure remains how to link simple measures of the information that characterise the forecasting problem to likely forecast accuracy. Without substantial further progress, decision makers and their organizations will have to give more attention to the final topic here, the avoidance of forecasting.

FIGURE 6. Advantages and Disadvantages of the Forecasting Methods

Method	Advantages	Disadvantages
Judgemental		
J1 Individual experts (subjective)	Can be inexpensive; flexible, can forecast anything; anybody can do it	Accuracy suspect (Armstrong, 2001), although perhaps quality of judgments can be improved by various forms of feedback; skills are embodied in the person rather than the organization; subject to all problems of human judgment. Hogarth and Makridakis (1981) provides a still current survey.
J2 Intentions	Effective for shorter term forecasting of new products and services and has the advantage of reflecting potential consumers' beliefs as to their future courses of action.	Expensive – and while the respondents appear to give helpful answers (once de-biased) circumstances in the market place change, thereby affecting longer term forecasts.
J3 Committee/survey	Brings different perspectives to bear on problem, plus has advantages listed for J1	One loudmouth can dominate, and this person might not be best forecaster; no one wants to disagree with boss; more expensive than individual method; problems in selecting participants and organizing meeting. A survey may say more about people's *current* attitudes and expectations than about future activities.
J4 Sales Force Composite	Aggregates different opinions based on detailed knowledge of the product or region. The aggregation aims to remove individual biases.	Motivation to produce accurate forecasts limited. Each individual is subject to the problems of J1. Takes a long time and can be expensive.
J5 Delphi	As J1 and J2, but attempts through anonymity to eliminate effects of authority and group domination	Can take a relatively long time; Complex; pressure towards consensus as rounds progress; no necessary convergence to agreed forecast; reluctance to take part in more than one round; not necessarily an improvement on more straightforward committee, but research evidence on both how to carry out an effective Delphi and the accuracy improvements is available in Rowe and Wright (2001).

Extrapolative		
E1 Trend	Easy to learn, to use, and to understand. Can be programmed in Excel.	Almost too easy to use and therefore encourages thoughtlessness; particularly in long term: why should a curve depending only on time provide suitable description of distant future? Nevertheless, in various application areas such as telecoms has been proved useful. See Meade and Islam (2006) for a recent review.
E2 Decomposition	Intuitively plausible	Limited statistical rationale; not ideally suited to forecasting, and suffers from the same problems as trend curves; a useful method of identifying trend, seasonal, and cyclical factors
E3Exponential smoothing	Easy to computerise for large number of products; very cheap to operate; easy to set up monitoring schemes; easily understood; good performance in forecasting competitions. Widely used. Can be extended to give the modeller considerable flexibility.	Misses turning points. Many different variants so a 'selection method' is needed. Often ineffectively programmed, therefore careful attention needs to be given to its implementation, particularly the choice of smoothing parameters. Prediction intervals are likely to be mis-calculated (Gardner, 2006).
E4 Box-Jenkins (or ARIMA)	The choice of weights is wide, allowing user to identify much more subtle patterns in data than with previous methods; offers philosophy of modelling based on principle of parsimony: the simpler the model the better, so long as it passes range of suitable diagnostic checks	Complex and difficult to understand, but automatic versions are now available in many software packages; for many users it promises more than it delivers. It seems that for many applications, the flexibility is a dis-advantage as the identified patterns don't persist into period to be forecast.[Not a term you have used before, too technical compared to the rest of the discussion]
E5 Neural Nets	Very flexible through its non-linear formulation and a theoretical proof that Neural Nets can approximate a wide range of relationships.	Complex with no standard software implementations. This leaves the user to choose a wide variety of parameters including the input vector and the non-linear transformation function as well as elements defining the optimisation routines. A survey and evaluation of early evidence is given by Zhang et al. (1998) and Adya and Collopy (1998).

FIGURE 6. (*Continued*)

Method	**Advantages**	**Disadvantages**
Causal (structural)		
C1& C3 Single equation regression and VARs	Sufficiently reliable models typically out perform alternatives (Allen and Fildes, 2001); are ideal in that they answer question, “How does company influence sales?”; can be used for control to establish policies (such as pricing) as well as in forecasting	Models difficult to develop, requiring expert staff and large amounts of data that organizations often fail to collect; problem in forecasting exogenous factors (see Ashley, 1983;1988). However the VAR models, defined by a system of equations with lags in them, do not usually include exogenous variables and have proved effective.
C2 Simultaneous system	Many systems do not naturally fall into the format of single equation model, for example, sales and advertising may be jointly determined; simultaneous system models capture these interrelationships	Large data requirements; hard to understand, statistically complex; difficult to define model; expensive; no evidence simultaneous approach better than VAR models in forecasting.
C4 Simulation	If properly implemented can offer decision maker substantial help; can be designed to be simple to use and understand; can also solve “right” problem	Expensive; often large data requirements, although has the flexibility to incorporate judgemental estimates; no clear rationale behind construction; requires careful validation
C5 Cross-impact Analysis	Can deal with unlikely events that have major impact; can deal with both quantitative and qualitative events. See Scapolo and Miles (2006) for a recent evaluation.	Probabilities usually have to be estimated through various judgmental methods, which may affect which scenarios are given full consideration; choice of which events to include is potentially crucial; no evidence is available that cross-impact has predictive value!

FIGURE 7. Evaluation of Various Forecasting Procedures (The scores are only suggestive)

	Criteria for Evaluating Forecasting Procedures						
			Staff Expertise[b]				
METHOD	Data requirements[b]	Statistical basis[b]	To set up	To use	Comprehensibility of forecasts[c]	Assessability[c]	Reported effectiveness[b]
Judgmental							
Individual	0	0	0	0	0	4	1
Intentions	4	2	3	2	4	3	3
Committee/survey	1	1	4	1	0	4	2
Delphi	2	2	4	2	1	4	3
Extrapolative							
Trend curves	2	1	1	1	1	3 (few data points)	2
Decomposition	2	1	1	2	2	1	2
Exponential smoothing	1	2	1	1	2	1	4
Box-Jenkins	2	2	1	2	3	2	2
Neural Nets	3	2	2	3	4	3 (method implementation not routine)	2
Causal							
Single equation/VAR	3	3	3	2	2	2	4
Simultaneous system	4	3	4	4	3	2	2
Simulation	2-4	4	4	2	2	1	3
Cross impact	1	4	4	4	2	4	1

[a] “Assessability” denotes the ease with which the procedure under discussion can be evaluated. It measures whether the procedure is completely specific or not.

[b] In the scoring system, 0 is equivalent to “low” or “easy” and 4 to “high” or “hard”.

[c] In the scoring system, 0 is equivalent to “easily understood” basis of the forecasts or “easily assessed” as to its accuracy.

AVOIDING FORECASTING

If accurate forecasting with reliable estimates of error bounds is often impossible, what alternatives exist? Of all the issues in forecasting, this remains perhaps the least researched, particularly as it applies to long-term forecasting processes. Most forecasting research has concentrated on the short term.

In rough-and-ready terms, forecasting for the short term may be described as (1) choose a plausible forecasting procedure, (2) modify it to take into account special factors, (3) estimate the likely magnitude of the error (see Chatfield (2001) and (4) carry enough stock or do whatever else is necessary to reduce the impact of forecasting uncertainty. We are used to responding to uncertainty in our decision making. Any unexpected inaccuracy in our estimate of the error is blamed on forces beyond the forecasting departments knowledge, and for a brief period the department is inundated by irate telephone calls from those affected by the large errors. But the forecasting process settles down after this period of chaos. Stability is restored.

Contrast this with the long-term forecaster's problem. Forecaster error can lead to under- (or over-) employed factories. The history of corporate growth is littered with examples of companies which for a while were very successful and then failed to recognize competitive products emerging (Makridakis, 1990). Such poor performance can even lead to bankruptcy or opportunities missed forever. Unlike the inventory control example, the mistake will not quickly go away.

A number of answers have been developed that can help the long-term decision maker avoid the consequences of very poor forecasts.

Insurance

In contrast to the stock control example, covering the residual uncertainty in long-term forecasts and riding out the consequences may sometimes be regarded as too dangerous. Instead the risk is reduced by sharing the consequences of any disaster with an insurance company. The effect, of course, is a reduced return as insurance policies always cost money.

A subtler variation of this idea has been described by Quinn (1989) as "logical incrementalism." Simply described, it is the recommendation that where uncertainty is high, only those decisions are contemplated that are viable over a wide range of possible futures. For example, in planning a power station, the decision on which fuel to use may be postponed, plans being based on either coal or oil as the power source. While costly, such duplications overcome the very high uncertainty in fuel price forecasts. As the forecasting (and planning) lead time reduces, uncertainty is also reduced and more definite choices can be made. Decisions here are seen as sequential rather than one-off. The cost, more limited than the straightforward "insure" option, derives from the alternative courses of action being kept open for a longer period than if the decision had been made once and for all. Such an approach also demands sophisticated planning.

Portfolio Procedures

It has long been known that if two alternative investments can be found with similar returns but with outcomes negatively or zero correlated, a portfolio investment in both decreases the risk level, leaving the return unchanged. The same idea can be used in examining whether diversification (of products or businesses) can lead to decreased risk. In effect, the forecaster needs to forecast not just the returns from different projects but their interrelationships as well. Although in some contexts improvements necessarily derive from considering a portfolio rather than its individual components, the problem remains one of identifying alternative investments that are negatively correlated with one's own. The difficulties associated with the portfolio approach do not negate the usefulness of seeking out countercyclical investments. It is a solution that should prove profitable.

Organizational Flexibility

The time horizon of a forecast is made up of a number of distinct components: the time to gain information (the information lead time), the time to plan and execute a course of action (the planning lead time), and the time during which the action reaps its consequences (the action lead time). The first two of these are under the control of the organization. By increasing the speed at which internal information is made available and by increasing the organization's responsiveness to a problem, the need to forecast is minimized. For research-based organizations such as pharmaceuticals, however, this is only of limited help, in that the action lead time is considerably longer than the other two.

Leverage (Gearing)

Forecasting attempts to reduce risk at only a limited cost. But there are a number of alternative structural solutions that the organization can sometimes adopt. For firms funded by both debt and equity, an increased proportion of funds deriving from equity (reducing leverage) has the effect of lowering the degree to which fluctuations in pre-interest profits are amplified in terms of post-interest profit. Low leverage also reduces exposure to interest rate fluctuations.

Leverage is a concept primarily associated with finance, but it also applies to functions such as purchasing, production, and sales. For example, raw materials (and foreign currency) can be purchased through futures markets that the amount to be paid for a future need is known now. In marketing, long-term contracts can be made with large purchasers. Although all of these devices cost money (even though the cost is sometimes hidden as an opportunity cost), they do meet the aim of lessening the need to forecast.

FORECASTING – WE CANNOT DO AWAY WITH IT

The ideas just discussed do not eliminate the need for forecasting long term. Portfolio procedures shift the emphasis from forecasting for one business unit to forecasting for joint performance of all the units. Insurance shifts the problem to the insurer, but at some cost. Organizational flexibility and leverage have only limited applicability. No means are thus available to allow an organization to avoid forecasting altogether. Instead, two questions have to be faced squarely:

> How can the organization best produce effective forecasts?
> How can the organization estimate the likely forecast error reliably?

As argued here, the answers are both technical and organizational. The latter has received little attention, and in the longer term it seems to hold the most promise for helping avoid the worst consequences of what often seems to be an increasingly challenging future.

RESOURCES

There are two professional forecasting journals, the *Journal of Forecasting* and the *International Journal of Forecasting*. In addition, the professional society, the *International Institute of Forecasters* runs conferences and publishes a professional, highly accessible, journal summarising practical forecasting issues. The journal is called *Foresight*.

The best general web site for information is www.forecastingprinciples.com. The are many specialist sites including the Lancaster University Centre for Forecasting site: *www.lums.lancs.ac.uk/pages/Research/Centres/forecasting* and this links to Sven Crone's site on neural nets and Alastair Robertson's on Telecoms.

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