Faculty of Commerce, Alexandria University

Demand Forecasting Tools

Quantitative and Qualitative case study

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Abstract

Demand forecasting has become the milestone for corporate strategic planning. Therefore, a reliable accurate forecasting tool is in the focal concern of most corporations. The study looked at evidence from comparative empirical studies based on a real life data to identify methods (qualitative and quantitative) that can be useful for forecasting demand in various situations and to warn against methods that should not be used. Precisely, the case of study proved that qualitative methods are more accurate in case of forecasting over longer time horizon, while quantitative methods are more accurate in case of forecasting over shorter time horizon. In general, it is highly recommended to use structured methods, and avoid intuition. In situations where there are sufficient data, the uses of quantitative methods including computerized base programs are recommended, as the study proved so. Otherwise, the use of methods that structure judgment could be informative.

CHAPTER 1

Introduction

1.1 The Importance of Demand Forecasting

Forecasting product demand is crucial to any supplier, manufacturer, or retailer. Forecasts of future demand will determine the quantities that should be purchased, produced, and shipped. Demand forecasts are necessary since the basic operations process, moving from the suppliers' raw materials to finished goods in the customers' hands, takes time. Most firms cannot simply wait for demand to emerge and then react to it. Instead, they must anticipate and plan for future demand so that they can react immediately to customer orders as they occur. In other words, most manufacturers "make to stock" rather than "make to order" – they plan ahead and then deploy inventories of finished goods into field locations. Thus, once a customer order materializes, it can be fulfilled immediately since most customers are not willing to wait the time it would take to actually process their order throughout the supply chain and make the product based on their order. An order cycle could take weeks or months to go back through part suppliers and sub-assemblers, through manufacture of the product, and through to the eventual shipment of the order to the customer.

Firms that offer rapid delivery to their customers will tend to force all competitors in the market to keep finished goods inventories in order to provide fast order cycle times. As a result, virtually every organization involved needs to manufacture or at least order parts based on a forecast of future demand. The ability to accurately forecast demand also affords the firm opportunities to control costs through leveling its production quantities, rationalizing its transportation, and generally planning for efficient logistics operations.

In general practice, accurate demand forecasts lead to efficient operations and high levels of customer service, while inaccurate forecasts will inevitably lead to inefficient, high cost operations and/or poor levels of customer service. In many supply chains, the most important action that could improve the efficiency and effectiveness of the logistics process is to improve the quality of the demand forecasts.

1.2 Case of the study

1.2.1 The Firm

The firm appointed is named "Solvochem" (www.solvochem.com) that is actively operating tank farms in different countries in the Middle East and Africa. Each tank farm consists of tens of tanks of different holding capacities (in metric tons) that are basically used for storing various liquid chemical commodities. The firm distributes the chemical commodities to customers in bulk (no packing) to waive the cost of packing. The logistic process is continuous and rarely reaches a halt. Respectively the tight hands on the supply chain and the logistics process are crucial due to the defined holding capacity for each tank. It is imperative to forecast the market demand over a

defined time horizon as accurately as possible to set up the sales targets and roll on the supply chain, furthermore to revolve the complete cycle repeatedly.
It is a great loss to the firm in case there is less or no stock to match the market demand and incase there is more stock than the market demand. Consequently, the firm is keen to grasp the techniques for demand forecasting and assess to how extent it is efficient.

1.2.2 Statement of Problem

Throughout the years from 2000 to 2007, the firm used the Qualitative forecasting approach and its techniques to forecast future demand on a quarterly base (3 months) and build up stock to match the forecasted market demand. The firm has been alerted with several factors that are affecting the supply chain and the logistics process. The market size for each commodity has grown up by 100 ~ 500%. The COGS (cost of goods sold) has increased by 200 ~ 300%. Commercial programs that forecast demand has been remarkably developed with criteria that match the concerned industry influencing factors and parameters (growth, seasonality, trends, holidays, regulations,…,etc). The source of data has become highly reliable and more available.

These factors are driving the firm to re-evaluate the technique for demand forecasting applied and the method / tool used.

1.3 Purpose of the study

To conduct an empirical study to find out if, the firm uses the most adequate forecasting technique? Is it matching the actual demand?, How accurate is the forecasting tool used?, What-if the firm switch to another technique / forecasting tool?, What if the firm decide to switch the forecasting time horizon?.

1.4 Research Objectives

This research project has four objectives. These objectives are as follows:

1. To conduct a qualitative and quantitative empirical evaluation for the forecasted demand over a quarterly time horizon, and assess how accurate is the forecasting tool used for each sample (commodity) data.

2. To conduct a qualitative and quantitative empirical evaluation for the forecasted demand over a monthly time horizon, and assess how accurate is the forecasting tool used for each sample (commodity) data.

3. To evaluate the results in order to identify which forecasting tool / Technique is more accurate over the selected time horizon.

4. To provide applicable recommendations to the firm.

CHAPTER II

Theoretical Background

All firms forecast demand, but it would be difficult to find any two firms that forecast demand in exactly the same way. Many different forecasting techniques have been developed. Many such procedures have been applied to the practical problem of forecasting demand, with varying degrees of success. Most commercial software packages that support demand forecasting include dozens of different forecasting algorithms that the analyst can use to generate alternative demand forecasts. While scores of different forecasting techniques exist, almost any forecasting procedure can be broadly classified into one of the following four basic categories based on the fundamental approach towards the forecasting problem that is employed by the technique.

2.1 General Approaches to Forecasting of demand

1. Judgmental Approaches. The essence of the judgmental approach is to address the forecasting issue by assuming that someone else knows and can tell the right answer. That is, in a judgment-based technique the knowledge and opinions of people who are in a position to know what demand will be gathered.

2. Experimental Approaches. Another approach to demand forecasting, which is appealing when an item is "new" and when there is no other information upon which to base a forecast, is to conduct a demand experiment on a small group of customers and to extrapolate the results to a larger population. For example, firms will often test a new consumer product in a geographically isolated "test market" to establish its probable market share. This experience is then extrapolated to the national market to plan the new product launch. Experimental approaches are very useful and necessary for new products, but it is not for existing products that have an accumulated historical demand record. It seems intuitive that demand forecasts should somehow be based on the demand experience.

3. Relational/Causal Approaches. The assumption behind a causal or relational forecast is that, simply put, there is a reason why people buy the product. If the reason (or set of reasons) could be understood, that understanding could be used to develop a demand forecast.

4. "Time Series" Approaches. A time series procedure is fundamentally different than the first three approaches. In a pure time series technique, no judgment or expertise or opinion is sought. The technique does not look for "causes" or relationships or factors which somehow "drive" demand. Further, it does not test items or experiment with customers. The essence of the approach is to recognize (or assume) that demand occurs over time in patterns that repeat themselves, at least approximately. If these general patterns or tendencies could be described, without regard to their "causes", this description could be used to form the basis of a forecast.

In one sense, all forecasting procedures involve the analysis of historical experience into patterns and the projection of those patterns into the future in the belief that the future will somehow resemble the past. The differences in the four approaches are in the way this "search for pattern" is conducted. Judgmental approaches rely on the subjective (qualitative), ad-hoc analyses of external individuals. Experimental tools extrapolate results from small numbers of customers to large populations. Causal methods search for reasons for demand. Time series techniques simply analyze (quantitative) the demand data themselves to identify temporal patterns that emerge and persist.

2.2 Forecasting methods

This section provides brief descriptions of the forecasting methods and their applications. Detailed descriptions are provided in forecasting textbooks such as Makridakis, Wheelwright, and Hyndman (1998). Forecasting methods and the relationships between them are shown in Figure 1, starting with the primary distinction between methods that rely on judgment and those that require quantitative data.

Methods based on Judgment approach

Unaided judgment

It is common practice to ask experts what will happen. This is a good procedure to use when experts are unbiased, large changes are unlikely, relationships are well understood by experts, experts possess privileged information and experts receive accurate and well-summarized feedback about their forecasts. Unfortunately, unaided judgment is often used when the above conditions do not hold. Green and Armstrong (2005a), for example, found that experts were no better than chance when they use their unaided judgment to forecast decisions made by people in conflict situations.

Delphi

The Delphi technique was developed at RAND Corporation in the 1950s to help capture the knowledge of diverse experts while avoiding the disadvantages of traditional group meetings. The latter include bullying and time-wasting. To forecast with Delphi the administrator should recruit between five and twenty suitable experts and poll them for their forecasts and reasons. The administrator then provides the experts with anonymous summary statistics on the forecasts, and experts' reasons for their forecasts. The process is repeated until there is little change in forecasts between rounds – two or three rounds are usually sufficient. The Delphi forecast is the median or mode of the experts' final forecasts. Software to guide the user through the procedure is available at forecastingprinciples.com. Rowe and Wright (2001) provide evidence on the accuracy of Delphi forecasts. The forecasts from Delphi groups are substantially more accurate than forecasts from unaided judgment and traditional groups, and are somewhat more accurate than combined forecasts from unaided judgment.

Game theory

Game theory has been touted in textbooks and research papers as a way to obtain better forecasts in situations involving negotiations or other conflicts. Green (2002, 2005) tested the ability of game theorists, who were urged to use game theory in predicting the outcome of eight real (but disguised) situations. In that study, game theorists were no more accurate than university students.

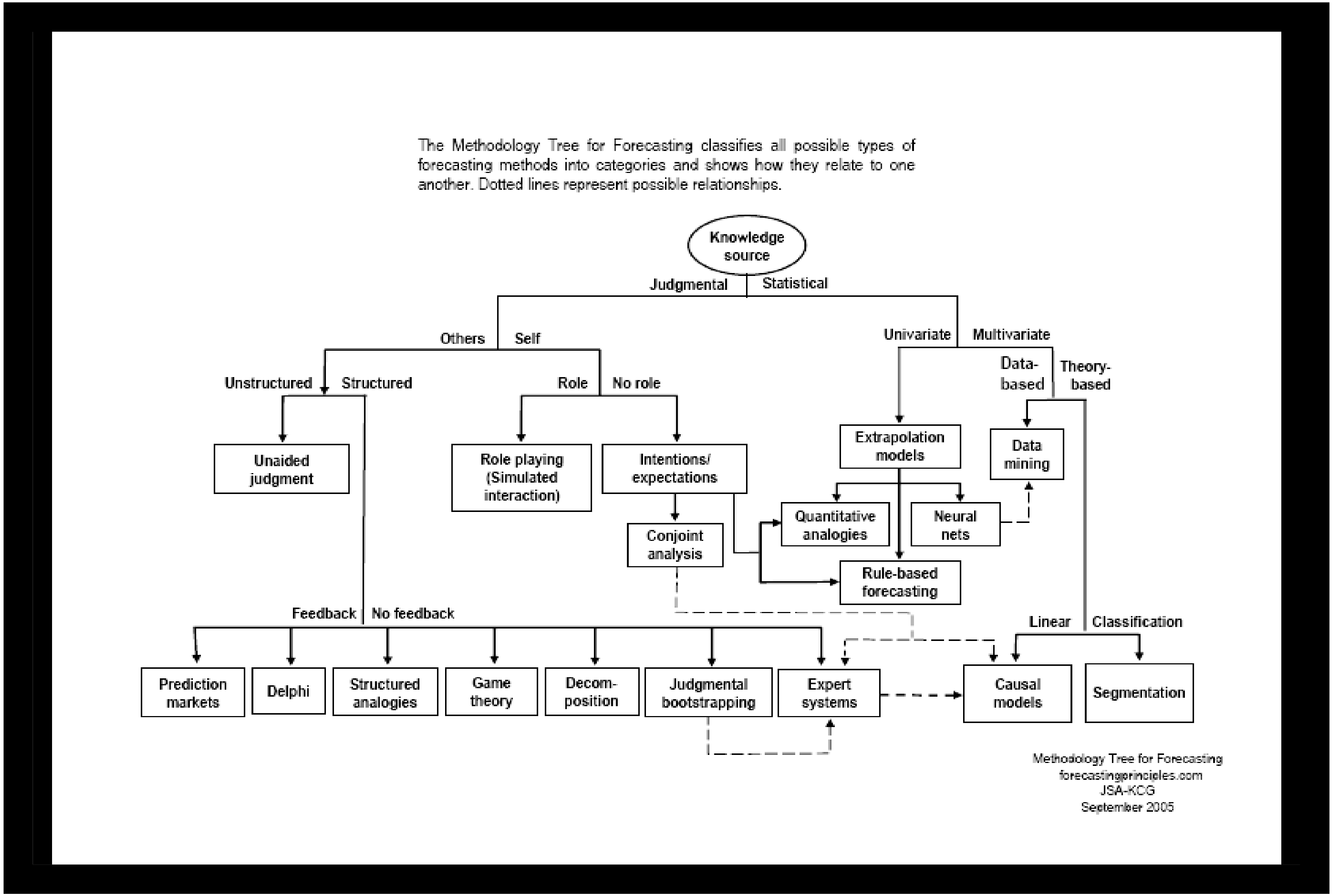

Fig .1 Methodology tree for forecasting

Structured analogies

The outcomes of similar situations from the past (analogies) may help a marketer to forecast the outcome of a new (target) situation. For example, the introduction of new products in one market can provide analogies for the outcomes of the subsequent release of similar products in other countries. People often use analogies to make forecasts, but they do not do so in a structured manner. For example, they might search for an analogy that suits their prior beliefs or they might stop searching when they identify one analogy. The structured-analogies method uses a formal process to overcome biased and inefficient use of information from analogous situations. There has been little research on forecasting using analogies, but results are promising. Green and Armstrong (2005b) found that structured analogies were more accurate than unaided judgment in forecasting decisions in eight conflicts.

Judgmental Decomposition

The basic idea behind judgmental decomposition is to divide the forecasting problem into parts that are easier to forecast than the whole. One then forecasts the parts individually, using methods appropriate to each part. Finally, the parts are combined to obtain a forecast. One approach is to break the problem down into multiplicative components. For example, to forecast sales for a brand, one can forecast industry sales volume, market share, and selling price per unit. Then reassemble the problem by multiplying the components together. Empirical results indicate that, in general, forecasts from decomposition are more accurate than those from a global approach (MacGregor 2001). In particular, decomposition is more accurate where there is much uncertainty about the aggregate forecast and where large numbers (over one million) are involved.

Judgmental bootstrapping

Judgmental bootstrapping converts subjective judgments into structured procedures. Experts are asked what information they use to make predictions about a class of situations. They are then asked to make predictions for diverse cases, which can be real or hypothetical. For example, they might forecast next year's sales for alternative designs for a new product. The resulting data are then converted to a model by estimating a regression equation relating the judgmental forecasts to the information used by the forecasters. The general proposition seems preposterous. It is that the model of the man will be more accurate than the man. The reason is that the model applies the man's rules more consistently.

Simulated interaction

Simulated interaction is a form of role playing for predicting decisions by people who are interacting with others. It is especially useful when the situation involves conflict. Green (2005) found that forecasts from simulated interactions were substantially more accurate than can be obtained from unaided judgment. Simulated interaction can also help to maintain secrecy.

Intentions and expectations surveys

With intentions surveys, people are asked how they intend to behave in specified situations. In a similar manner, an expectations survey asks people how they expect to behave. Expectations differ from intentions because people realize that unintended things happen.

Methods based on time series approach

Extrapolation

Extrapolation methods use historical data on that which one wishes to forecast. Exponential smoothing is the most popular and cost effective of the statistical extrapolation methods. It implements the principle that recent data should be weighted more heavily and 'smoothes' out cyclical fluctuations to forecast the trend. Statistical extrapolations are cost effective when forecasts are needed for each of hundreds of inventory items. They are also useful where forecasters are biased or ignorant of the situation (Armstrong 2001b). Allow for seasonality when using quarterly, monthly, or daily data. Most firms do this (Dalrymple 1987). Seasonality adjustments led to substantial gains in accuracy in the large-scale study of time series by Makridakis et al. (1984). They should be dampened because seasonal adjustment programs tend to over-adjust for seasonality (Miller and Williams 2004); this follows the principle of being conservative in the face of uncertainty. Software for calculating damped seasonal adjustment factors is available at forecastingprinciples.com.

Quantitative analogies

Experts can identify situations that are analogous to a given situation. These can be used to extrapolate the outcome of a target situation. For example, to assess the loss in sales when the patent protection for a drug is removed, one might examine the historical pattern of sales for analogous drugs.

Rule-based forecasting

Rule-based forecasting (RBF) is a type of expert system that allows one to integrate managers' knowledge about the domain with time-series data in a structured and inexpensive way. In many cases a useful guideline is that trends should be extrapolated only when they agree with managers' prior expectations. When the causal forces are contrary to the trend in the historical series, forecast errors tend to be large (Armstrong and Collopy 1993). Although such problems occur only in a small percentage of cases, their effects are serious. RBF is most useful when substantive domain knowledge is available, patterns are discernable in the series, trends are strong, and forecasts are needed for long horizons. Under such conditions, errors for rule-based forecasts are substantially less than those for combined forecasts (Armstrong, Adya, and Collopy 2001). In cases where the conditions were not met, forecast accuracy is not harmed.

Neural nets

Neural networks are computer intensive methods that use decision processes analogous to those of the human brain. Like the brain, they have the capability of learning as patterns change and updating their parameter estimates. However, much data is needed in order to estimate neural network models and to reduce the risk of over-fitting the data (Adya and Collopy 1998). There is some evidence that neural network models can produce forecasts that are more accurate than those from other methods (Adya and Collopy 1998).

Data mining

Data mining uses sophisticated statistical analyses to identify relationships. It is a popular approach. Data mining ignores theory and prior knowledge in a search for patterns.

Causal models

Causal models are based on prior knowledge and theory. Time-series regression and cross-sectional regression are commonly used for estimating model parameters or coefficients. These models allow one to examine the effects of marketing activity, such as a change in price, as well as key aspects of the market, thus providing information for contingency planning. Causal models are most useful when (1) strong causal relationships are expected, (2) the direction of the relationship is known, (3) causal relationships are known or they can be estimated, (4) large changes are expected to occur in the causal variables over the forecast horizon, and (5) changes in the causal variables can be accurately forecast or controlled, especially with respect to their direction. Reviews of commercial software that can be used to develop causal models are provided at the forecastingprinciples.com site.

Segmentation

Segmentation involves breaking a problem down into independent parts, using data for each part to make a forecast, and then combining the parts. To forecast using segmentation, one must first identify important causal variables that can be used to define the segments, and their priorities. For each variable, cut-points are determined such that the stronger the relationship with dependent variable, the greater the non-linearity in the relationship, and the more data that are available the more cut-points should be used. Forecasts are made for the population of each segment and the behavior of the population within the segment using the best method or methods given the information available. Population and behavior forecasts are combined for each segment and the segment forecasts summed. Where there is interaction between variables, the effect of variables on demand are non-linear, and the effects of some variables can dominate others, segmentation has advantages over regression analysis (Armstrong 1985). Segmentation is most useful when there are benefits from compensating errors. This is likely to occur where the segments are independent and are of roughly equal importance, and when information on each segment is good. Segmentation based on a priori selection of variables offers the possibility of improved accuracy at a low risk. Dangerfield and Morris (1992), for example, found that bottom-up forecasting, a simple application of segmentation, was more accurate than top-down forecasts for 74% of the 192 monthly time series tested. In some situations changes in segments are dependent on changes in other segments. Efforts at dependent segmentation have gone under the names of micro simulation, world dynamics, and system dynamics. While the simulation approach seems reasonable, the models are complex and hence there are many opportunities for judgmental errors and biases. Armstrong (1985) found no evidence that these simulation approaches provide valid forecasts and we have found no reason to change this assessment.

SELECTING METHODS

Choosing the best forecasting method for any particular situation is not a simple task, and sometimes more than one method may be appropriate. The flowchart shown in Figure 2 has been developed for selecting forecasting methods.

The first issue the analyst needs to address is whether the data are sufficient to permit quantitative analysis. If not, judgmental procedures are called for. Some cases call for both approaches.

For judgmental procedures, the first issue is whether the situation involves small or large changes. For small changes, where no policy analysis is needed and where one gets good feedback, unaided judgment can work well. But if the feedback is poor, it helps to use many experts as with Delphi or prediction markets. Where the analyst wishes to predict the effects of different policies, he must determine whether predictions from experts or from participants such as potential customers would be most appropriate. If it is inappropriate to ask potential customers for predictions, judgmental bootstrapping or decomposition will help to use experts' knowledge effectively. Where the conditions are met for conjoint analysis, it may be possible to obtain useful forecasts from surveys of potential customers. For cases where large changes are expected but policy analysis is not required, one should consider expectations or intentions surveys.

Where large changes are expected and only a few decision makers are involved, competitors or suppliers for example, simulated interaction is the best method. If experts are able think of several analogous situations, structured analogies are also likely to provide useful forecasts.

If one has a lot of time-series data, the analyst should determine whether there is knowledge about what empirical relationships might exist, and their magnitudes. For example, in most situations there is excellent prior knowledge about price elasticity (Tellis 1988). If empirical knowledge of relationships is available, use causal models. In addition, one should consider using domain knowledge, such as a manager's knowledge about the situation. Extrapolation or neural networks may be useful in situations where large changes are unlikely.

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 if a manager knows that sales will increase due to advertising of a price reduction), use rule-based forecasting.

In situations where one lacks time-series data and knowledge about relationships, quantitative analogies are appropriate. In the presence of domain knowledge or where policy analysis is needed, expert systems can be used.

The conditions may not always be clear. In such cases, one should use two or more relevant methods, and then combine the forecasts.

Combining forecasts

Combined forecasts improve accuracy and reduce the likelihood of large errors. In a meta-analysis, Armstrong found an average error reduction of about 12% across 30 comparisons. They are especially useful when the component methods differ substantially from one another. For example, Blattberg and Hoch (1990) obtained improved sales forecast by averaging managers' judgmental forecasts and forecasts from a quantitative model. Considerable research suggests that, lacking well-structured domain knowledge, unweighted averages are typically as accurate as other weighting schemes (Armstrong, 2001d). Judgmental and statistical methods should be integrated. Armstrong and Collopy (1998) summarize research in this area. Integration is effective when judgments are collected in a systematic manner and then used as inputs to the quantitative models, rather than simply used as adjustments to the outputs. Unfortunately, the latter procedure is commonly used.

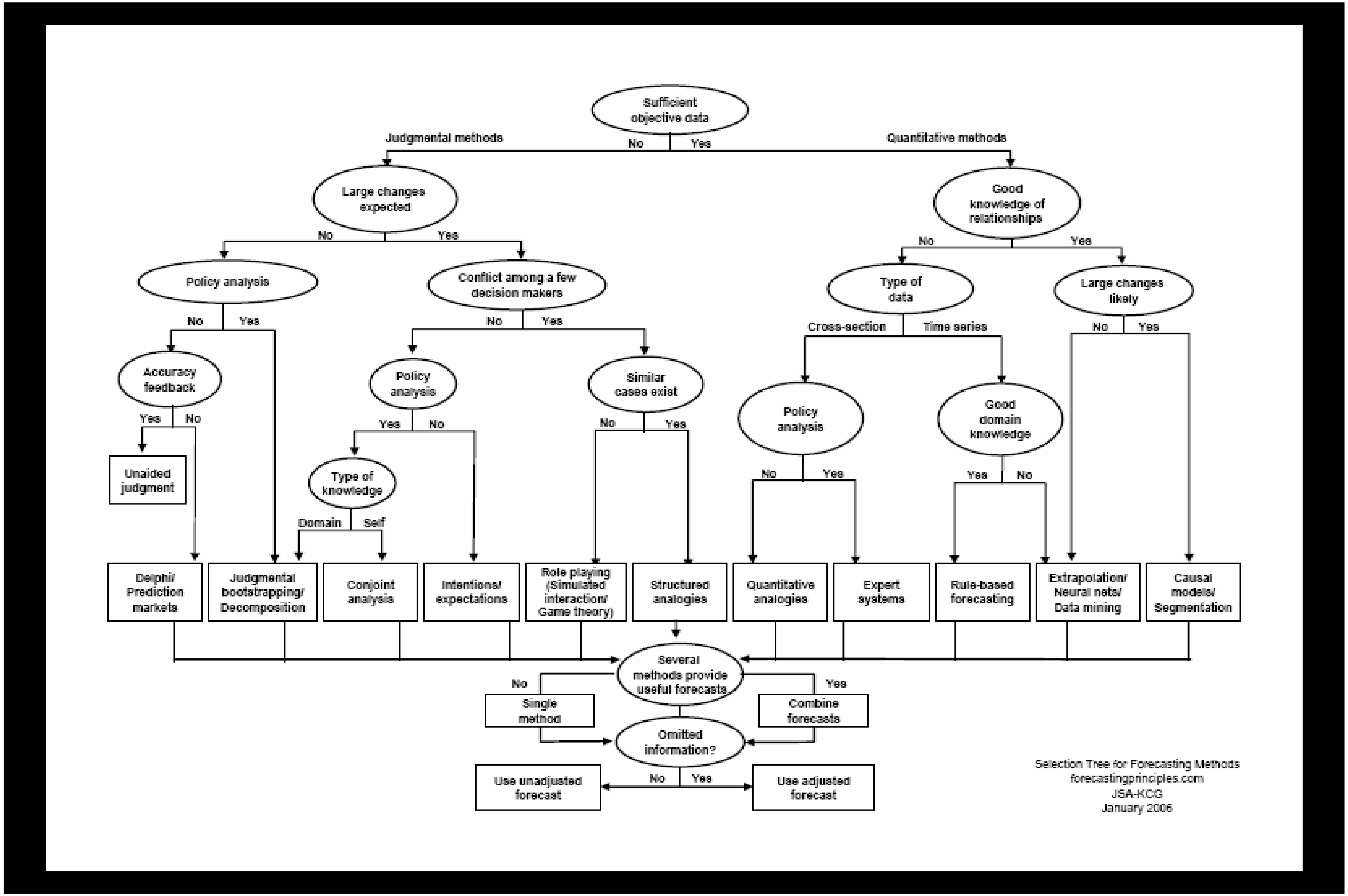

Fig .2 Selection tree for forecasting methods