

Evaluating a Decision Support Forecasting System

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In this article, the factors are addressed which should be considered in evaluating the suitability of an important element in most decision support systems—the subsystem that forecasts future system states. Techniques available to managers are briefly overviewed, and specific criteria that should be considered when selecting these techniques are examined. Factors to consider in either using an outside software package or developing an in-house DSS forecasting subsystem also are reviewed. The guidelines presented in this article can be applied to the evaluation of candidate DSS forecast capabilities and to improvements or revisions of existing ones as well.

INTRODUCTION

Since the introduction of on-line time-sharing in the late 1960s, managers have increasingly used computer systems to organize, manipulate, format, and distribute information to improve the quality and timeliness of their decision making. This enhanced ability to consider large amounts of data to support strategic and operational decisions is even more significant in the face of the changing

nature and competitiveness of the 1980s global marketplace. Far East and third world competition coupled with accelerating technological advances have fostered the development and adoption of decision support systems (DSS) at all organizational levels. DSS software is used to support top management strategic planning, middle management operational control, and first line support functions. Such systems come in a large range of scope, power, and cost, from large integrated mainframe-based systems priced in the hundreds of thousands of dollars to more specialized microcomputer systems priced under \$10,000 [1]. The environments in which these systems are applied also vary widely (e.g., in manufacturing, financial, medical, legal, and not-for-profit).

With the proliferation of DSS capabilities and users, consideration must be given to the likelihood of misuse. Two situations can easily lead to misuse: (1) the availability of sophisticated capabilities in the hands of an untrained user, and (2) the presentation of a "black-box" capability that uses methods unknown to the user. These issues, although critical to performance, are rarely mentioned as issues in DSS evaluation.

In this article the factors are addressed which should be considered in evaluating the suitability of an important element in most decision support systems—the subsystem that forecasts future system states. Current forecasting

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computer systems that help decision makers utilize data

literature offers many techniques with information on how forecasting methods should be applied and in what situations [2-17]. Whether a DSS provides advanced methods to untrained users or undefined forecasting methods are at work within the system itself, the potential exists for lack of accuracy and effectiveness due to application of a method unsuited to the nature of a particular environment and/or data set.

CHARACTERISTICS OF A DECISION SUPPORT SYSTEM

From the work of Keen and Scott Morton [18], Alter [19], and others it is generally agreed that DSS can be characterized as interactive computer systems that help decision makers utilize data and models to solve unstructured problems. The term "help" is used to suggest that the final decision is left to the user and the term "unstructured" implies that the problem is not routine and the solution could be approached in various ways.

More specifically, Sprague and Carlson [20] state that DSS:

1. tend to be aimed at underspecified problems;
2. combine the use of models and analytic techniques with traditional data access and retrieval functions;
3. are designed to be used by non-computer people in an interactive mode;
4. emphasize flexibility and accommodate the decision-making approach of the user.

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The basic elements of such a system include a data base subsystem (information storage), a model base subsystem (analytic models and data analysis capabilities), and a dialog subsystem (which allows the user to access and integrate the model and data bases). It is within the model base subsystem that analytic forecasting methods can be found.

While there are DSS specifically designed for forecasting, such as American Software Sales Forecasting or MSA Forecasting and Modeling System [21], the capability to forecast is common to the majority of DSS software packages. Of the 50 mainframe DSS reviewed by Leary [22], 44 (88%) were noted as having the ability to forecast based on historical data.

Forecasting capabilities in DSS typically include:

1. Correlation techniques, which may be used to determine underlying relationships between information sets within the data base (i.e., economic indicators, marketing information, financial data, operational results).
2. Time-series techniques, which uncover patterns in past data series and project the effects into the future.

EVALUATION OF DECISION SUPPORT SYSTEMS

Keen and Scott Morton [18] recognized that DSS evaluation methods were a critically important but largely neglected aspect of system development. Since that time many authors have suggested evaluation criteria to be applied to DSS and software systems in general. Reimann [23] observed that DSS differ considerably in terms of variety and quality of features. He evaluated 20 popular DSS generator products in terms of user friendliness, modeling capabilities, analysis and integration, forecasting and statistics, communications, reporting and graphics, command language, vendor support, cost, and hardware required.

Sprague and Carlson's [20] factors for DSS evaluation were grouped in terms of productivity measures, process measures, perception measures, and product measures. Similar user-oriented evaluation criteria were suggested by Athappilly and Galbreath [24]: capabilities in data management, modeling, analysis, forecasting, statistics, user friendliness, communication linkages, vendor support, common language, graphics, reporting, hardware, and operating systems.

Although these authors and many others [24-28] suggest useful DSS criteria, none have considered the details of forecasting capability evaluation. They have also not suggested consideration of forecasting methods which may be imbedded in the system (beyond the control of the user). Another problem with such lists of measures is the implicit assumption that the availability of forecasting options implies proper application to data.

Dressler, Beall, and Brent [29] provide an example of a hypothetical marketing executive who sets out to forecast product line sales. He uses auto-correlation, decomposition, and regression procedures and it is suggested that his forecasting expertise was acquired during his MBA program. However, it is not clear that DSS documentation and training sessions are sufficient to bring an average user to this level of sophistication. While this marketing executive's approach to a limited number of product line forecasts may have been correct, forecasts involving different levels and time horizons may require other methods [30]. Brown [31] describes Abbott Labs' use of their DSS to regularly forecast sales of some 2000 different products.. The marketing executive's approach to this forecasting problem should be different than a single product line forecast.

Since forecasting is crucial to decision making and can have a significant impact on planning and operations, the evaluation of candidate DSS software should include significant consideration of the system's forecasting capabilities. Selecting forecasting techniques and evaluating forecast systems require that corporate needs be specified before selecting the technique. This process _ should involve representatives from distribution, marketing, forecasting, production, finance, and management information systems (MIS). Afterward, the requirements of the company can be compared to the capabilities of the system, and the cost of -fulfilling corporate forecast requirements can then be evaluated,

The remainder of this article discusses the factors that managers should consider in evaluating DSS forecasting capabilities. Techniques available to managers are briefly

overviewed, and specific criteria that should be considered when selecting these techniques are examined. Factors to consider in either using an outside DSS software package or developing an in-house DSS forecasting system also are reviewed. The guidelines presented in this article can be applied to the evaluation of candidate DSS forecast capabilities and to improvements or revisions of existing ones as well.

FORECASTING TECHNIQUES

Several types of forecasting techniques are available to designers of DSS. Table 1 summarizes the advantages, disadvantages, and most frequent application of each technique. A brief review of each technique follows.

Correlation Analysis

Correlation analysis (also known as regression analysis) is an approach to forecasting that seeks to establish a relationship between sales and exogenous variables that affect sales, such as advertising, product quality, price, customer service, and the economy. Past exogenous variables and past sales are analyzed to determine the strength of their relationship. If a strong relationship is found, the exogenous variables can then be used to forecast future sales. Corporate, competitive, and economic variables can be used in a correlation analysis forecast, thus giving it a broad environmental perspective. Correlation analysis can also provide a value estimate of each variable. Thus, variables contributing little can be dropped.

Correlation analysis is potentially one of the most accurate forecasting techniques available but requires a large amount of data. A correlation forecast model of sales, using price, gross national product, and customer service as the exogenous variables should have a minimum of 20 periods of data to be effective. For a company making 40,000 product forecasts per month (not an unusual amount) the data storage would total 3,200,000. Thus, as the number of forecasts increases, ,correlation analysis becomes less manageable. Furthermore, the large data demands make correlation analysis slow to respond to changing conditions.

Understanding the advantages and disadvantages of correlation analysis helps clarify when it is more useful as in longer-range (greater than 3 months) corporate-level

TABLE 1
Forecasting Technique Parameters

	Time Horizon	Forecast Level	Amount of Training	Amount of History	Amount of Data	Exogenous Data Available?
Correlation Analysis	Long Range	Corporate	Large	Large	Very Large	Yes
FMTS	Short Range	Product	Little	Little	Little	No
OMTS	Short to Medium	Corporate	Very Large	Very Large	Medium	No
	Range					
Subjective	All	All	Little training but much experience	Little	Little	No

forecasts for which a large amount of data on exogenous variables is readily available.

Fixed Model Time Series

In short range product forecasting, rapid changes in sales and the large number of forecasts needed often dictate the use of a simple, yet adaptable, technique. Fixed-model time series (FMTS) forecasting techniques can be effectively used in such instances.

FMTS techniques are based on the interrelationship of four data patterns: level, trend, seasonality, and noise. Level is a horizontal sales history; trend is a continuing pattern of a sales increase or decrease; seasonality is a repeating pattern of sales increases and decreases; and noise is random fluctuation—that part of the sales history that a time-series technique cannot explain. FMTS techniques arrive at a forecast by assuming one or more of these patterns exist in a previous sales history and projecting them into the future. Exponential smoothing is the most common of the FMTS techniques.

The advantages of FMTS techniques are that they are often simple and inexpensive to use and require little data storage. Many of the techniques also adjust very quickly to changes in sales conditions. No FMTS technique, however, will be more accurate than correlation analysis if the FMTS technique assumes data patterns do not exist that are in fact in the sales history. Exponential smoothing assumes, for example, that the sales history consists of only level and noise. If trend and seasonality exist in the sales history, exponential smoothing will consistently err in its forecast.

Open Model Time Series

Open-model time series (OMTS) techniques—Box and Jenkins [32], for example—build a forecast model after analyzing sales history data to identify its existing patterns. OMTS techniques use the same four patterns (level, trend, seasonality, and noise) as FMTS techniques. However, OMTS techniques analyze the data to determine which patterns exist and then build an appropriate forecast equation. This is in contrast to FMTS techniques that have fixed equations that are based upon a priori assumptions that certain patterns do or do not exist in the data. Although much academic research has been conducted with OMTS, these techniques have been of little use in business because of their complexity and limited increase in accuracy over FMTS or subjective techniques [30].

Most OMTS forecasting techniques require extensive training and considerable analysis time. Throughout the analysis, numerous subjective decisions must be given to the model. Thus, the accuracy of the forecast is largely influenced by the abilities of the user. Many periods of sales history (often more than 48 data periods) are required to obtain usable results. Because of these factors, OMTS techniques should be used only when substantial sales history, but little exogenous data, is available (i.e., correlation analysis cannot be performed), and only when a few products are to be forecast.

Subjective Techniques

Subjective techniques are procedures that turn the opinions of experienced personnel (e.g., salespeople, corporate executives, and outside experts) into formal forecasts. An advantage of subjective techniques is that

they take into account the full wealth of key personnel experience and require little formal data. They are also valuable when little or no historical data is available, such as for new product introductions.

Subjective forecasting, however, takes a considerable amount of key personnel time. Because of this drawback, subjective techniques are typically used as a part of long-range, corporate-level forecasting or for adjustment purposes in short-range, product forecasting. The forecast committee of one auto parts manufacturer, for example, meets once a quarter to subjectively generate a 3-year forecast and once a month to subjectively adjust the product forecasts by product line (for instance, all product forecasts in a particular product line may be raised by 3%). Individual product forecasts, however, are left to a FMTS technique and the forecast managers. Individual product forecasts in the forecast committee would be a waste of valuable executive time.

Subjective forecasting with a DSS often manifests itself in the dialog DSS subsystem in the form of interactive analysis. This interactive analysis is a trial and error process that eventually leads to a forecast.

EVALUATING CORPORATE NEEDS AND LIMITATIONS

Before evaluating the various forecasting capabilities of a particular DSS, the manager must evaluate the needs of the company and each forecasting technique's ability to meet those needs. The manager must also determine if the company has any limitations that would prevent it from using a particular forecasting technique.

The Corporate Data Base

All available corporate data should be assessed before considering the practicality of a particular forecasting technique. If little sales history or exogenous data are available or if they are not in a form accessible to the DSS, then a FMTS technique will probably be chosen. As the amount of data increases, so does the potential for using OMTS or correlation analysis.

Forecasting Level

The level at which the forecast will be made is a critical consideration. Does the decision maker need industry-level forecasts, corporate forecasts, product

line forecasts, or product forecasts? Different forecasting levels often require different forecasting techniques. The lower the forecast level (i.e., toward product forecasts), the greater the number of forecasts needed and the more difficult it is to obtain acceptable accuracy. This difficulty in obtaining acceptable accuracy usually results from three factors. First, because of the large number of individual forecasts, little attention will be paid to any one forecast. This inability to provide subjective input to each forecast will adversely affect accuracy.

Second, product level sales are often subject to considerable short range fluctuations. For many forecasting techniques, it is difficult to accurately track these fluctuations. This creates a need for more reactive forecasting techniques on the product level that can make many forecasts in a short period of time, primarily FMTS techniques.

Third, product level forecasts do not have the benefit of statistical convolution that is experienced in higher level forecasts. In any given forecast period, forecasts will be low for some products and high for others. When higher level forecasts are made, these high and low forecasts are aggregated and, thus, the errors tend to cancel each other.

Time Horizon

The time horizon of the desired forecasts should also be considered. As mentioned in the previous section, short-range forecasts are needed but are often subject to wide sales fluctuations. Long-range forecasts, on the other hand, tend to be more stable in terms of fluctuations, but are affected by numerous environmental factors that must be considered and projected for the future. For these reasons, the quick adaptability of FMTS techniques makes them well suited for short-range forecasts. The ability to consider exogenous factors makes correlation analysis and subjective techniques more appropriate for long-range forecasts [30].

Forecast Quantity

The number of forecasts necessary to support a decision helps dictate the technique to be used. Forecast quantity is a function of the time horizon, the forecast level, the number of products, and the number of locations and/or channels the company maintains. A company that makes a yearly forecast for one product (a telephone

a need for more reactive forecasting techniques

company forecasting new phone line installations, for example) has a fairly simple forecast scenario and can use more sophisticated OMTS or correlation analysis techniques to achieve superior accuracy. The auto aftermarket manufacturer previously mentioned makes monthly forecasts for each of its 15,000 products in each of its four marketing channels, constituting 60,000 forecasts per month. By necessity, corporate management must compromise potential accuracy by using simpler FMTS techniques to handle the large number of forecasts the situation requires.

The Need for Subjective Input

The degree to which subjective input is required and/or desired and how readily different techniques accept subjective input should always be considered when selecting a DSS and the techniques included in the forecasting subsystem. Various techniques require subjective input to forecast accurately. For FMTS techniques, the value of a smoothing constant must be selected to weight past data. Correlation analysis requires subjective input to select the exogenous variables. OMTS, especially per Box and Jenkins [32], requires a great deal of subjective input to arrive at a forecast model. The need and desirability of subjective input from the company's perspective should be first considered, and then the ease with which the DSS allows such input should be evaluated.

Personnel Sophistication

The sophistication of the personnel to be involved in DSS operation and use should also be considered in the forecasting technique decision. If the personnel are not well trained in statistics and forecasting, a simple technique should be chosen initially, with the goal of eventually moving to more advanced methods.

The training of DSS personnel is imperative. Personnel must have a basic knowledge of the techniques available and fully understand the forecasting techniques desired so that an appropriate DSS can be chosen and unrealistic

expectations and incorrect applications of the forecast can be avoided.

The Forecasting Budget

The size of the company's forecast budget is critical to the DSS selection decision. Operating costs vary widely among DSS and forecasting techniques. Thus, when a large number of forecasts are required but the budget is limited, the user should consider one of the less-expensive techniques, probably in the FMTS group. Furthermore, a DSS will have to be selected that can process a large number of forecasts and automatically incorporate the forecasts into the overall DSS operation. When budgets are more liberal, an investment in DSS and personnel expertise can be made to develop more informed and, hopefully, more accurate forecasts.

Considering Individual Product Forecasts

The customer base and sales volume for each product should be considered in selecting among optional forecasting techniques. FMTS, OMTS, and correlation analysis are most often used when a large volume of broad customer-base products from a variety of demand points provide the statistical base necessary. Most new (i.e., low-volume) products must be forecast by subjective techniques, as should high-volume products with a narrow customer base. The extreme of this latter case is the high volume product that sells only to one customer. In such a situation, the forecast may be nothing more sophisticated than the forecaster calling the customer to ask the estimated demand for that product over the forecast horizon. This straightforward "market research" then becomes the subjective forecast. The example can be expanded to a reasonable number of customers and still hold. Finally, low volume, low profitability products are not worth the expense of sophisticated techniques and may only warrant simple subjective forecasts.

The cost of improved accuracy may far exceed the benefits.

DETERMINING FORECAST COST-EFFECTIVENESS

Before evaluating the forecasting capabilities of DSS software the manager must decide whether potential benefits justify the cost of improved accuracy.

Specifying Forecast Accuracy

Specifying the required level of accuracy is perhaps the most crucial, yet most overlooked, prerequisite to actual technique evaluation. It is common to simplify this process by setting a goal of the highest accuracy obtainable. However, this approach ignores the fact that the cost of improved accuracy may far exceed the benefits. Accuracy requirements should be determined by the benefits that will be gained from a more informed decision. In the case of a manufacturing application, these benefits may be reflected in improved customer service and more effective use of assets—manifested in lower levels of inventory in the short run and in the elimination of over- or under-capacity facilities in the long run.

Different levels of accuracy should also be specified for different forecasts. Some forecasts are more important to decisions and some decisions are more important than others and therefore require greater accuracy. The yearly corporate forecast, for instance, may have far reaching financial and strategic implications and thus warrant considerable attention to accuracy. In comparison, the forecast of one product for the next month may have a minor impact on corporate operations and not require great accuracy.

Even on the product level, different products represent varying degrees of importance to the company which, in turn, determines the forecast accuracy required. An ABC classification scheme is often used to place each product into categories of products based upon their contribution to corporate overhead and profitability. "A" class products, the most profitable, are given much higher required accuracy levels than the more marginal "B" and "C" class products.

Forecast Cost

Using a particular technique involves not only the cost represented by the user's time but also the computer costs of the DSS operation generating the forecasts. Actual user time tends to increase with technique sophistication. The level of user training and, therefore, the money invested, also increases with the more sophisticated forecasting techniques.

Forecast Output

A final criterion for determining the cost-effectiveness of the forecasting technique within a DSS is the forecast output (that is, the form of the information presentation to the user and the overall DSS). Such output must meet two criteria: it must be understandable by users, and it must provide information on a level and time horizon compatible with the DSS and the user's needs. Receiving an accurate forecast of nationwide sales for the next year does the user little good if information on southeastern regional sales for the next 5 years was needed.

SELECTING FORECASTING CAPABILITIES IN A DSS SOFTWARE SYSTEM

After a set of forecasting techniques is identified as desirable, a DSS software system with these capabilities must be selected. This forecasting subsystem must tap the necessary data resources, generate forecasts, measure accuracy, produce reports, and interact with the DSS. Such software can be purchased as existing packages or developed in house. Lists of available DSS designed for specific types of organizations usually can be found in the trade literature that covers that industry or discipline (e.g., Leary [22], Maher [33], and Negovetic [34]).

Any forecast subsystem, whether purchased or developed in house, should be implemented at a basic level and gradually upgraded to a more complex system. Initial

use of the system should begin with the simplest technique applied to a few forecasts.

DSS Software Packages

The forecasting subsystem of a DSS software package should be selected for its ability to satisfy forecast needs. Users, therefore, should be certain that they fully understand the package's forecasting capabilities. Several considerations for evaluating the forecasting subsystem within DSS software packages are:

- **Compatibility**—The types of reports that the package provides and the user's ability to design new reports depend on the package's compatibility with the corporate MIS system, that is, the computer hardware and program languages. A package that produces reports that are either unintelligible or contain the wrong information is worthless.
Limitations—The package must be able to handle the number and types of forecasts required.
Flexibility—For different forecasts, varying types of data might be available and necessary. The package flexibility with respect to data input variations, subjective adjustments, report capability, and forecast technique as well as data volume variations, must be considered.
- **Versatility**—Many packages use only one forecast technique, while others offer a variety. If a forecast manager has analyzed company products and determined that different product groups will require different forecasting techniques (not an unusual situation), then a package with multiple technique capabilities is required.
- **Analysis capabilities**—Individual product analysis is often necessary to help the forecaster select the appropriate technique. If such analyses are desired, management should adopt a package offering such capabilities, or management should be willing to obtain a separate analysis package.

In-House Designed DSS Forecasting Subsystems

Corporate DSS capabilities are often limited by adoption of an outside software package. This "fitting

the job to the tool" approach has led many companies to reject packaged software and, instead, design an in-house DSS to fit the corporate requirements. To accomplish this, companies must either develop sophisticated DSS/MIS/Forecasting knowledge or bring in outside expertise.

A company should consider the capabilities it wants in such a package. Should the DSS system be interactive with the corporate MIS system? Interactive capability might be warranted only when a large number of analyses tap the MIS. However, if relatively few such interactions are needed, an MIS interactive system might not be worth the cost.

An in-house DSS design will be simplified if one technique is selected for all forecasting activities. If several techniques are to be used, however, or if a simple technique will be used initially and a more complex one later, all of the necessary techniques and selection rules must be included in the system. The use of subjective forecasts and/or subjective adjustments to the system forecasts must also be addressed.

Figure 1 illustrates the features and capabilities to be designed into the forecasting subsystem of an in-house DSS for typical product sales forecasting. The flow chart illustrates the basic functions necessary for the forecasting subsystem to produce results: accessing the corporate MIS system; making forecasts and measuring forecasting accuracy; dispatching the forecasts to the overall DSS, management decision makers, and production and inventory control systems; and measuring effectiveness. Measuring effectiveness involves more than merely measuring forecast accuracy: the impact of the forecast on inventory levels, customer service, the cost of operations, and the effects each of these has on the decision should also be analyzed. This effectiveness analysis helps users make more informed decisions about required accuracy in the future.

An optional aspect of any forecasting subsystem is the forecast test system component. This typically constitutes a menu of possible forecasting techniques, access to the DSS data base, and availability of a simulation model of the corporate operations system. This system allows the forecast analyst to try different forecasting techniques and measure their impact upon forecast accuracy and the operations system. Thus, a heuristic procedure of trying several forecasting techniques and selecting the most appropriate one for the product under analysis before releasing the forecast to the rest of the subsystem can be followed.

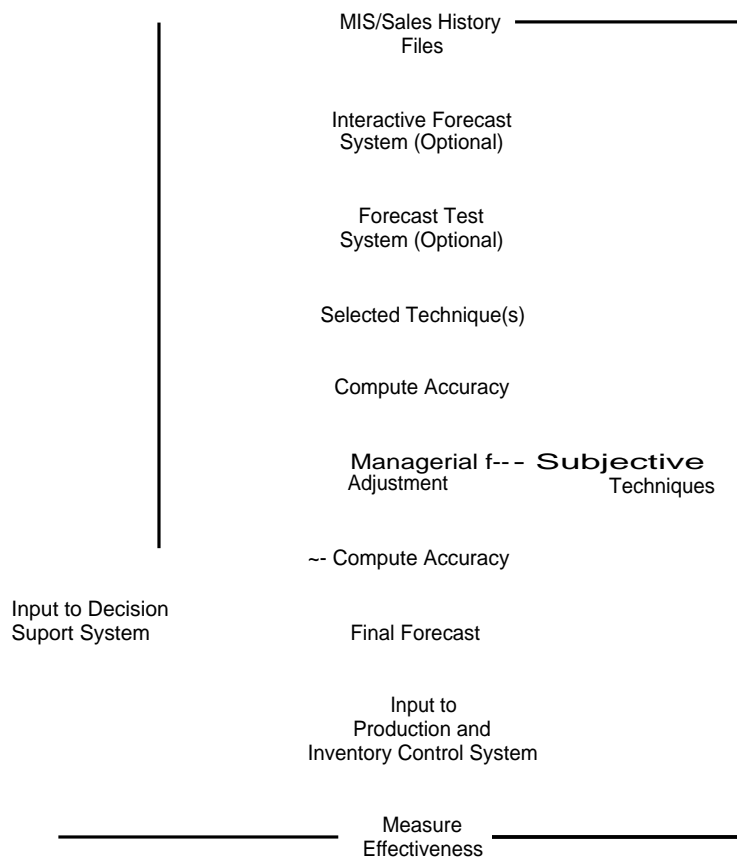


FIGURE 1. In-House DSS Forecasting Subsystem Flow Chart

MEASURING FORECAST ACCURACY

The following section details a recommended approach to measuring forecast accuracy. This approach incorporates a measure of accuracy, exception reporting, and feedback from the DSS to the forecasting subsystem.

Mean Absolute Percent Error

A common measure of accuracy useful to managers is the mean absolute percent error (MAPE). The MAPE equation follows:

$$\text{MAPE} = (11(F - D)/D/n) \times 100$$

where: F = forecast

D = demand

n = number of forecast periods

MAPE indicates, on the average, how far off the forecast has been (measured as a percent of demand). Thus, a manager who wanted forecast error to be less than 10%

would specify that MAPE must always be less than 10%. Regardless of the measure used, error should be measured every time a forecast is made and adjusted. In this manner, forecast accuracy and the effect of forecast adjustments can be maintained.

Exception Reports

Exception reporting can also be used to gauge the forecast subsystem. The user's analyses of acceptable accuracy levels for each forecast should be input into the DSS system. When accuracy falls outside the specified acceptable level, an exception report is presented to the user giving the forecast, specified accuracy, and actual accuracy. The user then is responsible for taking action to improve accuracy.

An example of exception reporting use is that of a manufacturer in the aerospace industry. Out of its 50,000 monthly product forecasts, 300 did not meet accuracy requirements. When these exceptions occurred, an exception report was prepared for each product, including

TABLE 2
Exception Report-Inappropriate Technique

Required MAPE < 0.15
MAPE = 0.37

Period	Actual	-1	Percent Error	1	Forecast
8	1574.00		*		1079.74
9	1677.00		*		1129.17
10	1953.00				1183.95
11	2143.00		*		1260.85
12	2171.00		*		1349.07
13	2256.00				1431.26
14	2284.00				1513.74
15	2720.00		*		1590.76
16	2965.00				1703.69
17	3322.00				1829.82
18	3292.00		*		1979.04
19	3385.00		*		2110.33
20	3380.00				2237.80
21	3991.00		*		2352.02
22	4271.00		*		2515.92
23	4499.00		*		2691.43
24	4506.00		*		2872.18
25	4631.00		*		3035.56
26	4723.00		*		3195.11
27	4812.00		*		3347.90
28	5596.00		*		3494.31
29	5706.00		*		3704.48
30	5964.00		*		3904.63
31					4110.57

TABLE 3
Exception Report-Appropriate Technique

Required MAPE < 0.15
MAPE = 0.12

Period	Actual	-1	Percent Error	1	Forecast
8	1574.00			*	2369.72
9	1677.00			*	2440.18
10	1953.00				2285.77
11	2143.00		*		2238.17
12	2171.00		*		2312.21
13	2256.00		*		2317.45
14	2284.00		*		2422.61
15	2720.00				2526.93
16	2965.00				2803.36
17	3322.00		*		2932.03
18	3292.00		*		3027.61
19	3385.00		*		3061.43
20	3380.00		*		3194.56
21	3991.00		*		3400.00
22	4271.00		*		3761.46
23	4499.00		*		4027.59
24	4506.00		*		4148.67
25	4631.00		*		4194.47
26	4723.00		*		4339.64
27	4812.00		*		4701.45
28	5596.00		*		5114.06
29	5706.00		*		5350.48
30	5964.00		*		5422.48
31					5458.58

sales and forecast history, required accuracy, the actual MAPE value, and a graph of the monthly percent error over the previous 23 months. The graph of one product, with a MAPE of 37%, revealed that the forecast was consistently low (Table 2). Further investigation found that sales had a positive trend and the low bias resulted from using a FMTS forecasting technique that assumed no trend existed in the data. The DSS user switched to a FMTS technique that included trend and MAPE for the product fell to 12% (Table 3).

Forecast System Interaction

Forecast accuracy can be measured automatically through the interaction of the forecast subsystem with the overall DSS. If the forecast subsystem that supplies information to the DSS includes exception reporting, all forecasts that meet acceptable accuracy levels can be automatically fed to the DSS for appropriate use. Forecasts of insufficient accuracy are routed to the forecast group, where the inaccuracies are then adjusted before release to the DSS.

CONCLUSIONS

Decision support systems are becoming increasingly important to managers at all levels in the corporation. Even with considerable recent publication of DSS evaluation criteria, specific evaluation of the forecasting subsystem has not been explored. Rather than suggesting that an evaluator check that the candidate system provides certain forecasting options, it has been shown that the capabilities should be matched to the needs of the situation. Descriptions of commonly available forecasting technique options have been provided along with considerations for their use. With this additional information, an improved evaluation of forecasting elements within a candidate DSS can be made.

Regardless of how it was developed and what techniques are used, an effective forecasting subsystem must meet accuracy requirements; it must make the necessary type, level, and volume of forecasts; and it must provide the correct information to key decision makers in an understandable form. Only when these requirements are fulfilled is forecasting useful to management.

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