Chapter 10

Building Model-Driven Decision Support Systems

INTRODUCTION

Many companies use models to assist in decision making. For example, Dresdner Bank uses a model-driven DSS when making credit and lending decisions. USA Truck uses OptiStop to generate optimal routes and fueling stop recommendations. Also, at USA Truck, managers use a DSS called Strategic Profitability Analysis to allocate equipment and establish pricing for customers. Jones Lang LaSalle uses a Web-based system for planning, budgeting, reporting, and analysis. Several Deere and Co. factories are using an optimization add-in to Microsoft Excel for balancing manufacturing constraints while achieving more production output. A number of railroad companies use DSS for train dispatching. This list of model-driven DSS could go on for many pages.

Many DSS use models. For example, a sales-forecasting DSS uses a moving average or econometric model; accounting and financial DSS generate estimates of income statements, balance sheets, or other outcome measures; representational DSS use simulation models; and optimization DSS generate optimal solutions, consistent with constraints and assist in scheduling and resource allocation. Model-driven DSS may assist in forecasting product demand, aid in employee scheduling, develop pro forma financial statements, or assist in choosing plant or warehouse locations. All of these systems are model-driven DSS.

Model-driven DSS provide managers with models and analysis capabilities that can be used during the process of making a decision. The range and scope of this category of DSS is very large. New commercial products are regularly announced, new Web-based applications are being developed for established tools, and companies are developing their own proprietary systems. To exploit these opportunities, DSS analysts and managers need to understand analytical tools and modeling. Building some types of models requires considerable expertise. Many specialized books discuss and explain how to implement specific types of models like simulation or linear programming. Companies use both custom and off-the-shelf model-driven DSS applications.

This chapter is only a starting point for those who want to build or buy model-driven DSS. It provides a brief overview of issues specifically relevant to building model-driven DSS. It summarizes commonly used models with a primary focus on terminology. The major objective is to help managers and DSS analysts evaluate model-driven DSS opportunities and work with model builders.

MODELING DECISION SITUATIONS

Mathematical and analytical models are the dominant component in a model-driven Decision Support System. If a model is needed to understand a situation, then a model-driven DSS can potentially deliver the needed representation to managers. DSS Analysts can create a wide variety of alternative model-driven DSS. So actually building a model-driven DSS involves resolving a number of important design and development questions.

Models can help managers understand financial, marketing, and many other business decisions. One major issue that must be resolved is the purpose of a proposed model-driven DSS. Is the purpose to assist in credit and lending decisions, budgeting, or product demand forecasting? Will the system be used routinely in a decision process or as part of a special study? Each model-driven DSS should have a clearly stated and specific purpose. To accomplish the specific purpose of a system, more than one type of model is sometimes used in building the model-driven DSS. So, a second issue is what models should be included in a specific system.

The tasks involved in building model-driven DSS are complex enough that a modeling specialist is usually needed on a development team for a large-scale system. End users should only develop model-driven DSS for one-time and special purpose decision support needs. Therefore, managers must confront the issue of who should build a planned or contemplated model-driven DSS.

In many specific DSS, a model produces outputs displayed for users. Also, the decision variables of model-driven DSS are frequently manipulated directly by managers. As mentioned in Chapter 4, DSS builders must determine the future users of the model.

Model-driven DSS have been built using statistical software packages, forecasting software, modeling packages, and end-user tools like spreadsheets. In all of these development environments, the goal is the same: to build a model that can be manipulated and tested. The values of key variables or parameters are changed to reflect uncertainty in supply, production, the economy, sales, costs, or other environmental and internal business factors. This capability of changing a parameter in a model-driven DSS is called “What if?” analysis and expanded testing of model parameters is called sensitivity analysis. The results from using a model-driven DSS in a situation are analyzed and evaluated by decision makers.

Modeling

A typical modeling process begins with identification of a problem and analysis of the requirements of the situation. It is advisable to analyze the scope of the problem domain and the forces and dynamics of the environment. The next step is to identify the variables for the model. The identification of decision variables and their relationships is very important. One should always ask if using a model is appropriate. If a model is appropriate, then one asks what variables and relationships need to be specified, using an appropriate modeling tool. An influence diagram can be used to examine the variables and relationships. Then a solution method or methods need to be chosen. Also, an analyst need to specify assumptions and make any needed forecasts. Forecasting variables or parameters is sometimes part of the construction of a model. Building a computerized system also involves integrating models and other DSS components like data files and data analysis procedures. Model-driven DSS need to be validated, evaluated, and managed. Model validation is the process of comparing a model's output with the actual behavior of the phenomenon that has been modeled. Validation attempts to answer the question, "Have we built the right model of the situation?"

Model Assumptions

Assumptions are untested beliefs or predictions. Assumptions are important in building many models because one is projecting or anticipating results. A decision maker can test assumptions using "what if" or sensitivity analysis before accepting the results of the model. DSS analysts and managers need to make assumptions about the time and risk dimensions for a situation. Model-driven DSS can be designed assuming either a static or dynamic analysis. Making either assumption about changes in a decision situation has advantages and disadvantages.

Static analysis is based on a "single snapshot" of a situation. Everything occurs in a single interval, which can be a short or long duration. A decision about whether a company should make or buy a product can be considered static in nature. A quarterly or annual income statement is static. During a static analysis, it is assumed that there is stability in the decision situation.

Dynamic analysis is used for situations that change over time. A simple example would be a five-year profit projection, where the input data, such as costs, prices, and quantities change from year to year. Dynamic models are also time dependent. For example, in determining how many cash registers should be open in a supermarket, it is necessary to consider the time of day. This time dependence occurs because in most supermarkets there are changes in the number of people that arrive at the market at different hours of the day.

Dynamic models are important because they show trends and patterns over time. Also, they can be used to calculate averages per period or moving averages, and to prepare comparative analyses. A comparative analysis might examine profit this quarter versus profit in the same quarter of last year. Dynamic analysis can provide an understanding of the changes occurring within a business enterprise. The analyses may identify possible solutions to specific business challenges and may facilitate the development of business plans, strategies, and tactics. DSS analysts and managers also must examine whether it is appropriate to assume certainty about model parameters in the decision situation. Many financial models are constructed under assumed certainty. "What if" analysis is the primary means of considering risk and uncertainty. As previously noted, "what if" analysis is the capability of "asking" or manipulating a model-driven DSS to determine what the effect will be on result variables of changing some of the decision variables.

The assumptions of DSS analysts and managers limit or constrain the types of models that can be used to build a DSS for the situation. Most of the rest of this chapter discusses various types of models.

General Types of Models

Models transform user inputs and data into useful information. A model represents a real situation as an abstract framework. A model may be specified in mathematical expressions, in natural language statements or as a computer program. Managers can manipulate the input to a model to change outputs. Models update files, provide responses to user actions, and perform recurring analytical tasks. Tool labels like optimization and simulation are often used to describe categories or types of models and those terms will be used in this chapter, but let's begin with some more general concepts.

An explanatory model describes what has occurred to create current results or outcomes, and it provides an explanation or analysis of a situation. For example, the model *Sales* = f (*Advertising, Number of Salespersons*) may be based on a correlation of advertising and the number of salespersons with sales in prior quarters

An algebraic model indicates which values must be introduced into a system of simultaneous equations to create a specific outcome. A manager specifies an outcome and a starting point, and then runs the model. This type of model helps managers gain insight about what variables must be manipulated and to what extent.

Explanatory models are descriptive models that describe situations. Algebraic models are predictive models (cf., Starfield, Smith, and Blelock, 1990; Codd, Codd, and Salley, 1993).

A DSS with Multiple Model Types

As noted, a model-driven DSS may include more than one of the above types of models. For example, a specific model-driven DSS may include:

1. An explanatory regression model that identifies relationships among variables,
2. A financial model of a pro forma income statement, and
3. An algebraic optimization model like linear programming.

Some models are standard components in DSS development packages, and some must be custom-programmed. A DSS analyst chooses appropriate models.

Once models have been chosen, a decision must be made to build the models, to use "ready-made" models, or to modify existing models. The software used for creating the model component also needs to be linked to any data and the DSS user interface. The user interface provides the functionality so that a decision support analyst or a decision maker can interact with the model.

General Problem Types

Management Scientists have been analyzing and trying to solve business problems for more than 50 years. During that time a variety of problem types that can potentially be analyzed with quantitative models have been identified. For example, Professor H. Arsham identifies a small set of Management Science problem types at his Web site (http://ubmail.ubalt.edu/~ harsham/), including:

Cost-benefit analysis: Given the decision maker's assessment of costs and benefits, which choice should be recommended?

Forecasting: Using time series analysis to answer questions such as: What will demand be for a product? What are the sales patterns? How will sales affect profits?

Finance and investment: How much capital is needed? How much will the capital cost?

Inventory control and stockout: How much stock should be held? When to order more? How much should be ordered?

Location, allocation, distribution and transportation: Where is the best location for an operation? How big should facilities be? What resources are needed? Are there shortages?

Manpower planning and assignment: How many employees are needed? When?

Project planning and control: How long will a project take? What activities are most important? How should resources be used?

Queuing and congestion: How long are waiting lines? How many servers are needed? What service level is provided?

Reliability and replacement policy: How well is equipment working? How reliable is it? When should it be replaced?

Sequencing and scheduling: What job is most important? In what order should jobs be completed?

Each of these general problem types can occur in situations where a model-driven DSS could support one or more decision makers. These 10 common Management Science problem types can be analyzed using five general categories of quantitative models: accounting and financial models, decision analysis models, forecasting models, network and optimization models, and simulation models. The next five sections discuss each of these general model categories.

ACCOUNTING AND FINANCIAL MODELS

Many accounting and financial models are incorporated in specific model-driven DSS. For example, target return pricing is a popular method of choosing a selling price for a new product. This marketing analysis tool uses two models. An analyst determines a break-even point for a new product and then a target Return on Investment (ROI). After "what if" analysis, a selling price is established. Model-driven DSS can assist in analyzing the relationship between prices, advertising spending, and profits in brand and product planning. Models can assist in break-even analysis, cost-benefit analysis, and capital budgeting. A number of Decision Tools that use accounting and financial models are available on-line at DSSResources.COM.

Break-Even Analysis

A break-even calculation shows the level of operations in units produced at which revenues just cover costs (profit equals zero). The break-even volume can be computed in a number of ways. One approach divides fixed costs by the contribution margin to find the break-even quantity. The contribution margin is the selling price per unit minus the variable costs per unit. Also, the break-even quantity can be calculated by solving the expression: (Price * Quantity Sold) - (Fixed Cost + [Variable Cost per unit * Quantity Sold]) = 0.

A typical break-even model assumes a specific fixed cost and a constant average variable cost. The break-even quantity can be calculated in a spreadsheet by using a goal-seeking capability to set profit equal to zero, where profit equals revenue minus total costs. Figure 10.1 shows a model-driven DSS for break-even analysis developed in Excel.

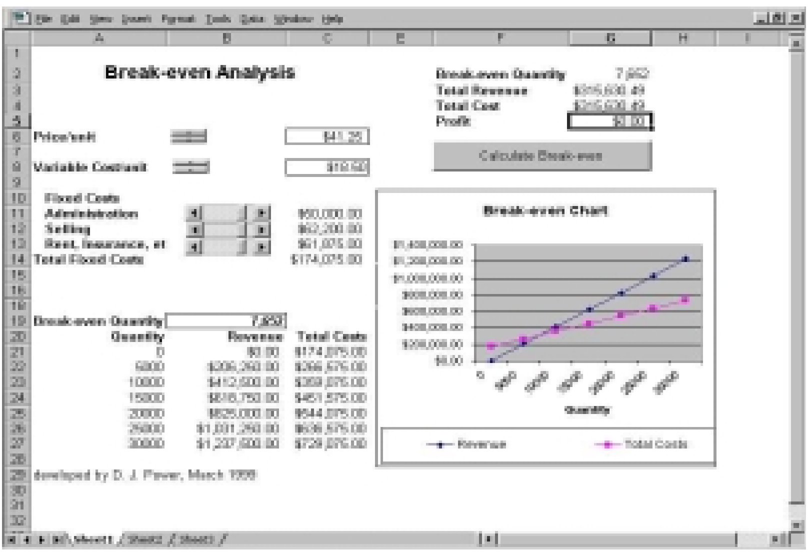

Figure 10.1 Break-Even DSS Developed in Microsoft Excel.

A break-even model provides a quick glance at price, volume, and profit relationships. Actually determining fixed and variable costs can be difficult, but in most cases, managers can make reasonable assumptions. Also, break-even analysis ignores demand for a product, so it is often desirable for a manager to use various forecasting models in conjunction with a break-even analysis.

Budget Financial Models

Budgeting DSS are an especially popular enterprise-wide application. Lockheed Martin wanted to improve the quality of their budget information while they cut the number of staff hours needed to develop it. They implemented Comshare (http://www.comshare.com) BudgetPLUS. Sunoco Retail, a division of Suncor Energy, was burdened with an inflexible, labor-intensive in-house budgeting system. Comshare BudgetPLUS "has resolved Sunoco's budgeting needs and given the Company a centralized financial data repository, while empowering users who now have control over their own budgets." Budget models can also be built and tracked for divisions, products, or projects.

Companies are making major changes in their budget planning and forecasting processes. The process is becoming a company-wide effort, with many managers contributing inputs using Web-based support tools. Both large and medium-size companies are trying to combine the traditional bottom-up approach to budget preparation, in which department heads submit budget requests that are rolled up into a corporate budget, with a top-down approach in which budgets are prepared in line with strategic objectives outlined by top management. Companies are also revising budgets throughout the year. Using Web technologies, changes can be made quickly to the budget model estimates, and the cost of deployment is much less than with mainframe-based, enterprise-wide systems.

Products from a number of vendors support participative budget processes. Comshare, Adaytum Software, and Hyperion Solutions have products that assist in strategic planning, budgeting, management reporting, analysis, and financial consolidation, and are innovating with new Budgeting DSS. BudgetHub.org is an on-line resource for enterprise budgeting information.

Pro Forma Financial Statements

Financial analyses and projections can be very important in strategic planning. A projected or pro forma income statement summarizes the projected financial results for a specific future time period. Gross sales are forecasted, and costs are estimated based on historical data and projections. Profit or loss is calculated based on accounting relationships.

In many ways, developing financial projections using a model-driven DSS forces a manager to become concrete about revenues and costs and to deal with "business reality." Managers must quantify financial outflows and inflows to arrive at projected financial statements for a proposed plan. One can develop projections that are either revenue or profit driven. Also, the various pro forma statements can be linked together to speed up "what if" analyses in which assumptions and numbers are changed. Pro forma financial statements are useful for developing detailed financial plans, evaluating the progress of the strategic plan, pinpointing problem areas, and taking corrective action. The pro forma financial statements are also valuable when used as aids in the implementation of a strategic plan.

What are key questions to keep in mind when developing pro forma financial statements? What assumptions were made when the pro forma financial statements were prepared? How sensitive are these financial statements to changes in assumptions? Was a "what if" analysis conducted? Can we justify the numbers of the pro forma financial statements? For outside stakeholders, pro forma financial statements will be a critical part of their evaluation of a strategic plan, new venture plan, corporate acquisition, or new product introduction. For this reason, the statements must present a convincing case, be consistent with other elements of the strategic business plan, and present a realistic picture of the financial consequences of strategic actions.

Ratio Analysis

Financial ratio analysis is a process where an analyst or manager evaluates a firm's financial statements. Even though accounting differences can distort financial results, ratio analysis can be useful in a number of ways, and a model-driven DSS can assist in ratio analysis.

First, ratio analysis can aid in interpreting and evaluating company and competitor income statements and balance sheets by reducing the amount of data contained in them. After computing key ratios, a DSS can support a comprehensive analysis of a firm's financial position. For example, a DSS can show a time series of sales growth or a table of key ratios.

Second, financial ratio analysis can make financial data more meaningful. Any ratio shows a relationship between the numbers in its numerator and denominator. By selecting sets of numbers that are logically related, only a few ratios may be necessary to comprehensively analyze a set of financial statements. Lenders and some investment analysts use ratio analysis.

Third, ratios help to determine relative magnitudes of financial quantities. For example, the amount of a firm's debt has little meaning unless it is compared with the owner's investment in the business. Therefore, the debt/equity ratio shows a relationship that lets managers compare relative magnitudes rather than absolute amounts.

Because of these advantages, financial ratio analysis can help managers or business analysts make effective decisions about a firm's credit worthiness, potential earnings, and financial strengths and weaknesses.

There are many other specific accounting and financial models that can be incorporated in model-driven DSS. For example, cost-benefit models, portfolio models, and capital budgeting models have been used in DSS. The next section explores a more general category of models used in analyzing some decision situations.

DECISION ANALYSIS MODELS

Decision situations that involve a finite and usually small number of alternatives can be evaluated with decision analysis models. Decision analysts often help managers in novel decision situations identify alternatives and attributes. Decision alternatives are listed with their potential forecasted contributions to a goal or goals, and the probability of realizing such a contribution in a table or a graph. Then, one evaluates the results on some attributes to select the best alternative.

Single goal situations are approached by the use of a decision table or decision trees. Multiple goal situations can be analyzed by several techniques including multi-attribute utility analysis and the analytical hierarchy process.

The focus of decision analysis techniques is to help decision makers clarify their understanding of a problem, and separate facts from priorities and preferences. This result is achieved by structuring problems into a hierarchy of objectives and by studying the performance of decision alternatives on specific criteria. The interactive structuring and prioritization process encourages a user to keep a problem presentation simple and helps one extract the essentials decision elements.

A decision analysis is oriented towards finding the best alternative. The aim is to avoid eliciting any priorities that do not help to reach this goal. The modeling philosophy is to include only those goals that are relevant in each decision-making situation and that help to distinguish the alternatives from each other.

In general, computerized decision analysis tools help decision makers decompose and structure problems. The aim of these tools is to help a user apply models like decision trees, multi-attribute utility models, bayesian models, and Analytical Hierarchy Process (AHP). Examples of decision analysis software packages include AliahThink, BestChoice3, Criterium Decision Plus, DPL, Expert Choice, Strad, Supertree, TeamEC, and Which and Why. These tools may be used as part of a special decision study or more routinely as a DSS in reoccurring decision situations.

This section examines three decision analysis models: the analytical hierarchy process, decision trees and multi-attribute utility models.

Analytical Hierarchy Process (AHP)

The AHP technique (cf., Saaty, 1980; Saaty, 1990) can be characterized as a multicriteria decision technique that can combine qualitative and quantitative factors in the overall evaluation of alternatives. This section provides a brief introduction to AHP with an emphasis on a general decision process method.

The first step is to develop a hierarchical representation of a problem (see Figure 10.2). At the top of the hierarchy is the overall objective, and the decision alternatives are at the bottom. Between the top and bottom levels are the relevant attributes of the decision problem, such as selection criteria. The number of levels in the hierarchy depends on the complexity of the problem and the decision maker's model of the problem hierarchy. This step creates the model for a model-driven DSS.

Next, in Step 2, the DSS user generates relational data for comparing the alternatives. In step 3, the software determines the relative priority of each attribute using the comparisons of Step 2. A user of a model-driven DSS developed using software like Expert Choice (http://www.expertchoice.com) would have the option of redoing the comparison matrix. In Step 4, the priorities or weights of the lowest level alternatives relative to the top-most objective are then determined and displayed.

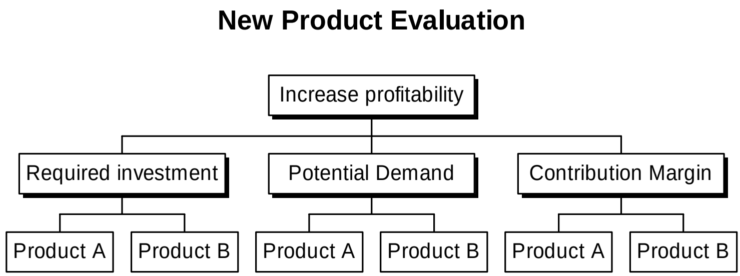

Figure 10.2 A Hierarchical Representation

A number of software packages implement AHP. The best known and most widely used is Expert Choice (visit URL http://www.expertchoice.com). Known for its user friendliness, it is the first fully graphical, mouse-driven implementation of AHP. A group support version Team Expert Choice, or TeamEC, is a software solution that is equipped with keypads for multiple voters. TeamEC can be used to create a communications-driven or group DSS.

Decision Trees and Multi-attribute Utility Models

A decision tree uses two types of nodes: choice nodes, represented by a square, and chance nodes, represented by a circle. An analyst constructs a decision tree. For the chance nodes, the probabilities along each outgoing branch must sum to one. One then calculates the expected payoffs for each branch in the tree. A decision tree has two major advantages. First, a decision tree shows graphically the relationships among the problem elements. Second, it can deal with more complex situations in a compact form.

Managers or decision analysts can use a generalized Decision Analysis Support System to develop a model of a complex, contingent situation. The off-the-shelf tool supports decision making for a special study or a non-routine problem analysis. For example, a company has two possible choices: Either introduce a product (A1), or not (A2). If the product is introduced, the firm incurs $ 100,000 in additional R&D costs. If the product is introduced, a competitor may introduce a competing product. So Alternative 1 can have two outcomes: Competitor introduces a competing product (O1), or not (O2). Based on knowledge of the marketplace, the competitor, and some marketing intelligence, the probability of O1 is 70 percent, and that of O2 is 30 percent. O1 and O2 are outcome or chance nodes. The final outcomes of the Promotional Campaigns (N1, N2, and N3) can depend on, among other things, the firm's actions, a competitor's actions, the size of the promotional campaign, and the size of a competitor's campaign. Thus, with a computerized model a decision maker can analyze the final outcomes in terms of possible promotional campaigns (based on Lee, Moore, and Taylor, 1985). The "best" strategy depends on the criterion the decision maker uses. In a marketing analysis, the criterion is typically maximizing Expected Monetary Value (EMV).

Multi-attribute utility analysis (MAUA) is a popular decision analysis tool. When this tool is used, the attributes are sometimes called decision factors or criteria. The attributes are then given importance weights. The decision maker provides information about each alternative on each attribute. This step involves measuring the decision maker's utility or perception of usefulness of an alternative in terms of the desired attributes. There is an extensive specialized literature on multi-attribute utility analysis (cf., Watson and Buede, 1987; Golub, 1997).

MAUA has traditionally been used in selection problems like choosing a site location in which there is certainty regarding the attribute levels of the alternatives. Another Management Science technique, subjective probability assessment, can be used to develop a distribution of attribute levels when there is uncertainty in these values. These probability distributions can be used in conjunction with MAUA to provide a consistent framework for making selection decisions.

FORECASTING MODELS

Forecasting models are an integral part of many model-driven DSS. One can build a forecasting model or one may use a forecasting software package. Forecasts may be made for a special decision study or a model-driven DSS for making forecasts may be used routinely in a business decision process. A forecasting model component may also be included in a broader purpose model-driven DSS. The quality of many decisions depends on the quality of a forecast.

The major use of forecasting is to predict the value of variables at some time in the future. The future time period of interest depends on when results will be evaluated. For example, in an inventory decision one may be interested in prices a year in the future, while in a capital investment decision one may be interested in prices and income five years in the future. Generally speaking, a decision analyst distinguishes between short-run and long-run forecasts.

Many types of forecasting models exist, but forecasting remains an extremely difficult task (cf., Makridakis and Wheelwright, 1982). What is going to happen in the future depends on many factors that are uncontrollable. Furthermore, data availability, accuracy, cost, and the time required to make a forecast play an important role in choosing a forecasting method. Forecasting methods can also be chosen based on convenience, popularity, expert advice, and guidelines from prior research. In general, the last two approaches should be used in building Forecasting DSS.

The best Web resource on forecasting models and methods is the Forecasting Principles site (hops.wharton.upenn.edu/forecast) maintained by J. Scott Armstrong. It provides a comprehensive review of forecasting. The site also provides: evidence showing the relevance of forecasting principles to a given problem, expert judgment about the applicability of forecasting principles, sources of data and forecasts, details about how to use forecasting methods, and guidance to locating the most recent research findings.

Forecasting methods can be grouped in several ways. One classification scheme distinguishes between formal forecasting techniques and informal approaches such as intuition, expert opinions, spur-of-the-moment guesses, and seat-of-the-pants predictions.

The following paragraphs review the more formal and analytical methods that have been used in building forecasting DSS, model-driven DSS for making forecasts. The methods reviewed include naïve extrapolation, judgment methods, moving averages, exponential smoothing, time series extrapolation, and regression and econometric models. Each method is discussed briefly, and major issues associated with using the methods are summarized. According to Scott Armstrong, given enough data, quantitative methods are more accurate than judgmental methods. He notes that when large changes are expected, causal methods are more accurate than naïve methods. Also, simple methods are preferable to complex methods since simple methods are easier to understand, less expensive, and rarely less accurate.

Judgment Methods. Judgment forecasting methods are based on subjective estimates and expert opinion, rather than on historical data. These methods are often used for long-range forecasts, especially where external factors may play a significant role. They also are used where historical data are very limited or nonexistent. A Group DSS could be used with a judgment method like the Delphi technique to obtain judgments. A communications-driven DSS can also collect estimates of sales staff. The results are not necessarily accurate, but the experts may be the best source of forecast information.

Naïve Extrapolation. This technique involves collecting data and developing a chart or graph of the data. The user extrapolates or estimates the data for future time periods. This technique is easy to update, and minimal quantitative knowledge is needed. It is easy and inexpensive to implement using a spreadsheet. It provides however, limited accuracy.

Moving Average. This type of forecast uses an average of historical values that "moves," or includes the new period in each succeeding forecast. It is for short-run forecasts and the results are easy to manipulate and test. Overall, a Forecasting DSS built using a moving average model will be easy to understand and inexpensive.

Exponential Smoothing. The historical data is mathematically altered to better reflect the forecaster's assumptions about the future of the variable being forecast. This model is similar to the moving average model, but it is harder to explain. A short-term forecast based on exponential smoothing is often acceptable.

Other Time-Series Extrapolations. Naïve extrapolation, moving average, and exponential smoothing are simple means to use a time series of data for forecasting. A time series is a set of values for a business or economic variable measured at successive intervals of time. For example, quarterly sales of a firm make up a time series. More complex methods are also used that are beyond the scope of this book. Managers use time-series analysis in decision making because they believe that knowledge of past behavior of the time series will help understand the behavior of the series in the future. In managerial planning, managers often assume that history will repeat itself and that past tendencies will continue.

Regression and Econometric Models. Data analysis tools like linear and multiple regression can be used in special studies to find data associations and, if possible, cause and effect relationships. Causal methods are more powerful than time-series methods, but they are also more complex. Their complexity comes from two sources: First, they include more variables, some of which are external to a decision situation. Second, they use sophisticated statistical techniques for evaluating variables. Causal approaches are most appropriate for intermediate term (3 to 5-year) forecasting.

In general, subjective forecasting methods are used in those cases where quantitative methods are inappropriate or cannot be used. Time pressure, lack of data, or lack of money may prevent the use of quantitative models. Complexity of historical data may also inhibit its use. Model-driven DSS primarily incorporate quantitative forecasting methods and often use multiple forecasting models.

NETWORK AND OPTIMIZATION MODELS

Project planning and control, location, allocation, distribution, and transportation problems can often be formulated using network and optimization models. These models can be used to determine: Where is the best location for an operation? How big should facilities be? What resources are needed? Are there shortages? Networks can define many relationships, and network problems are most often solved using optimization models.

For example, one can define and analyze a network of project activities using project management software. Project management is a popular category of off-the-shelf decision support software. The best selling package is Microsoft Project. It is a powerful application that can be used to efficiently plan, manage, and communicate project information. Project managers can enter actual costs for tasks and assignments. More information can be found at microsoft.com. While many computer users are familiar with project management software, not everyone realizes it is based on network flow models. These models are specially structured linear programming problems.

DSS analysts can define other networks. For example, one can develop a network of possible airline routes and schedules and compare costs. A set of routes or paths can be analyzed using a number of heuristic or quantitative tools. It has been estimated that 70 percent of all linear programming applications are network flow problems or have a substantial network structure. In addition to project management and aircraft routing, applications include: production planning and aggregate scheduling, personnel planning and scheduling, land use allocation, classroom scheduling, plant location, and multinational cash flow management.

Linear programming is the most widely known technique in a family of tools called mathematical programming. There are many possible uses of mathematical programming, especially of linear programming, in creating DSS. Many books have been written for courses in Management Science, Quantitative Analysis, and Operations Research. Managers and many DSS specialists are usually not experts in using optimization or simulation tools. Small-scale optimization DSS can be built using a spreadsheet program like Microsoft Excel.

Linear programming attempts to either maximize or minimize the values of an objective function. A solver program can be used for both equation-solving or goal-seeking and constrained optimization, using linear programming, nonlinear programming, and integer programming methods. An on-line Web-based tutorial on Using MS Excel Solver for Spreadsheet Optimization is at the Frontline Systems Web site (http://frontsys.com/).

Users of a model-driven DSS, based on a linear programming model, can find input values that satisfy a set of simultaneous equations and inequalities. When a user does this, there is usually more than one satisfactory set of input values. So, a solver can find the "best" set of input values that maximizes or minimizes some other calculated formula that a user specifies. This process is called constrained optimization; the equations or inequalities are called constraints. Every linear programming problem is composed of six elements (cf., Lee et al., 1985; Turban, 1995):

Decision Variables. These variables are values that a decision maker can change.

Objective Function. This is a mathematical expression that shows the linear relationship between the decision variables and the goal that is the focus of the model. The objective function is a measure of goal attainment. Examples of such goals are total profit, total cost, and market share.

Coefficients of the Objective Function. The coefficients of the variables in the objective function express the change in the value of the objective function by including in the solution one unit of each decision variable.

Constraints. Maximization or minimization is performed subject to a set of constraints. Constraints are most often expressed in the form of linear equation. Each constraint reflects the fact that resources are limited or that some requirement must be met.

Constraint Coefficients. Coefficients of a constraint's variables are called the input-output coefficients. They indicate the rate at which a given resource is depleted or used.

Capacities. The capacities or availability of the various resources are usually expressed as some upper or lower limit. When a problem is formulated, the capacities also express minimum requirements.

In Figure 10.3 the decision variables are the quantities of TVs, stereos, and speakers to build. The objective function is to maximize total profits. The constraints are from the parts inventory. Managers should be able to build a simple model-driven DSS like Figure 10.3 in Excel. A support person may need to help in conceptualizing the problem or in testing the end-user application. Most often optimization models are included in a DSS to assist in resource allocation. Managers are often required to allocate productive resources like raw materials, people, money, or time that can be used in a variety of different ways. The problem is to determine the best way to use the resources. Managers need to determine what "best" means, but usually it implies maximizing profits or minimizing costs. Optimization may be incorporated in a DSS used routinely in a firm or a management scientist may build an optimization model for a special decision support study.

	A	B	C	D	E	F	G	H
1								
2		**Product Mix DSS**						
3								
4								
5					**TV Set**	**Stereo**	**Speaker**	
6			**Number to Build -->**		100	100	100	
7		**Part Name**	**Inventory**	**No. Used**				
8		Chassis	450	200	1	1	0	
9		Picture Tube	250	100	1	0	0	
10		Speaker Cone	800	500	2	2	1	
11		Power Supply	450	200	1	1	0	
12		Electronics	600	400	2	1	1	
13								
14			Profits by Product:		$75	$50	$35	
15			Adjust per Unit Profits					
16								
17								
18				Total Profits:	$ 16,000		Solve	
19								
20								
21	developed by D. J. Power, 2001							
22								
23	This is a simplified version of a Microsoft Excel sample workbook.							

Figure 10.3 An Example Optimization Spreadsheet DSS

SIMULATION MODELS

Often, companies are faced with planning the production of a new product or building a new factory. Although these may seem like straightforward analyses, managers need to make many interrelated decisions. For example, production of a new product involves decisions regarding equipment, scheduling and control, and manufacturing philosophy. Many factors influence these decisions, including the need to meet production volume goals and costs associated with achieving these goals. Simulations can help evaluate complex, interrelated decision issues.

Simulation has many meanings, depending on the professional discipline where the term is being used. To simulate, according to many dictionaries, means to assume the appearance or characteristics of reality. It also means a model that generates test conditions approximating actual or operational conditions. In a DSS context, simulation generally refers to a technique for conducting experiments with a computer-based model. One method of simulating a system involves identifying the various states of a system and then modifying those states by executing specific events. A wide variety of problems can be evaluated using simulation, including inventory control and stock-out, manpower planning and assignment, queuing and congestion, reliability and replacement policy, and sequencing and scheduling.

Major Characteristics of Simulation

Simulation is a specialized type of modeling tool. Most quantitative models are an abstraction or simplification of reality, while simulation models usually try to imitate reality. In practical terms, this means that there are fewer simplifications in simulation models than in other quantitative models. Simulation models are generally complex.

Second, simulation is a technique for performing "what-if" analysis over multiple time periods or events. Therefore, simulation involves the testing of specific values of the decision or uncontrollable variables in the model and observing the impact on the output variables.

Simulation is a descriptive tool that can be used for prediction. A simulation describes and sometimes predicts the characteristics of a given system under different circumstances. Once these characteristics are known, alternative actions can be selected. The simulation process often consists of the repetition of a test or experiment many times to obtain an estimate of the overall effect of certain actions on the system.

Finally, simulation is usually needed when the problem under investigation is too complex to be evaluated using optimization models. Complexity means that the problem cannot be formulated for optimization because assumptions do not hold or because the optimization formulation is too large and complex.

Advantages and Disadvantages of Simulation

Recently, more model-driven DSS have been built using simulation models. The increased use of this approach can be attributed to a number of factors (cf., Render and Stair, 1988; Turban, 1995). First, simulation theory is relatively easy for managers to understand. A simulation model is a collection of many elementary relationships. Second, simulation allows the manager to ask "what-if" type questions. Third, DSS analysts work directly with managers because an accurate simulation model requires an intimate knowledge of the problem. The model is built from the manager's perspective, using his or her conceptual model of the system.

Fourth, a simulation model is built for one particular problem and, typically, will not solve any other problem. Thus, no generalized understanding of a problem is required of the manager; every component in the model corresponds one-to-one with a part of the real-life model. Fifth, simulation can handle an extremely wide variation in problem types, such as inventory and staffing, as well as long-range planning decisions. Sixth, managers can use simulation to experiment with different variables to determine which are important, and with different alternatives to determine which is best. Seventh, new software packages and tools like Java and C++ make it much easier to build simulations.

Finally, simulation allows for the inclusion of the real-life complexities of problems; simplifications are not necessary. Due to the nature of simulation, a great amount of time compression can be attained, giving the manager some information about the long-term effects of various policies. Also, with a simulation, it is easy to include a wide variety of performance measures.

There are three primary disadvantages of simulation. First, an optimal or "best" solution cannot be guaranteed. Second, constructing a simulation model is frequently a slow and costly process. Third, solutions and inferences from a specific simulation study are usually not transferable to other problems.

Types of Simulation

There are several types of simulation. The major types are probabilistic, time-dependent, and visual simulation. In a probabilistic simulation one or more of the independent variables is conceptualized as a probability distribution of values. Time-dependent or discrete simulation refers to a situation where it is important to know exactly when an event occurs. For example, in waiting line or queuing problems, it is important to know the precise time of arrival to determine if a customer will have to wait or not.

Visual simulation is the graphic display of computerized results. Software for visual simulation is one of the more successful new developments in computer-human interaction and problem solving. Animation and visual simulation helps explain results to managers. Eliot (1997) notes, "If you are analyzing a call center, you might show graphic icons of phones on the computer display and indicate the phones being answered as calls come into the call center. You could use colors, such as green for call completed and red for call abandoned, and otherwise make the simulation visually attractive to help other personnel understand just what the simulation is trying to do." (p. 14)

MODELING LANGUAGES AND SPREADSHEETS

Models can be developed in a variety of programming languages like Java and C++ and with a wide variety of software packages including spreadsheets and modeling packages. Spreadsheets are commonly used for desktop model-driven DSS. Modeling packages attempt to help users create and manipulate models. A model management system tries to provide support for various phases of the decision modeling life cycle.

Modeling and Data Summarization

DSS development packages for On-Line Analytical Processing (OLAP) and modeling have a variety of quantitative models in areas like statistics, financial analysis, accounting, and management science. These small models can be executed using a single command, such as AVERAGE or NPV. AVERAGE calculates the average of a number and may be used in a larger model; and NPV calculates the net present value of a collection of future cash flows for a given interest rate. It also may be a part of a make-versus-buy model.

Functions are often building blocks for other quantitative models. For example, a regression model can be a part of a forecasting model that supports a financial planning model. Several statistical functions are built into DSS generators. All major spreadsheet packages have extensive statistical tools. For example, Excel has analysis of variance, correlation, covariance, descriptive statistics, exponential smoothing, f-test, histograms, and moving average.

In addition, many DSS generators can interface with quantitative stand-alone packages. Such packages are usually much more powerful than the built-in routines. “Canned” or preprogrammed models can reduce the programming time of the DSS builder.

Electronic Spreadsheets

Spreadsheets are a very popular end-user decision support modeling tool. A spreadsheet is based on the structure of an accounting spreadsheet that is basically a column-and-row pad. In spreadsheets, reports can be consolidated, and data can be organized or sorted in alphabetical or numerical order. Other capabilities include setting up windows for viewing several parts of a spreadsheet simultaneously and executing mathematical manipulations. These capabilities enable the spreadsheet to become an important tool for analysis, planning, and modeling.

The current trend is to integrate spreadsheets with development and utility software, such as database management and graphics. Integrated packages like Microsoft Office with Excel are more popular in businesses than purchasing stand-alone spreadsheets. For more details on spreadsheets, see “A Brief History of Spreadsheets” at DSSResources.COM.

A major capability of spreadsheet programs is that numbers can be changed and the implications of these changes can immediately be observed and analyzed. Spreadsheets are used in almost every kind of organization in all functional areas. Managers can build small decision support applications on their own or with help from a DSS Analyst very quickly and inexpensively.

End-user developed model-driven DSS will have errors. All of the problems with this type of development that were discussed in Chapter 4 need to be addressed. One way to reduce errors and improve the usefulness of a model-driven DSS developed in a spreadsheet is to have an MIS staff member evaluate the application based on the following criteria:

- Accuracy. Are the results and calculations correct?
- Flexibility. Is it easy to change assumptions, parameters, and values? Is the application well documented?
- Understandability. Is it easy to understand the purpose of the model-driven DSS and how it is implemented in the spreadsheet?

- Auditability. Is it easy to audit the application? Is the organization of the workbook easy to understand? Can dependencies be traced in the application?
- Aesthetics. Are the spreadsheet screens attractive and well designed? Are any printouts easy to read?
- Documentation. Are formulas and related cells clearly defined and identified?

Development Packages

Many DSS applications deal with financial analysis, and some tools help develop such applications. While spreadsheet software can be used, specialized tools are often more efficient or effective. Since the 1960s, planning models have advanced from an obscure concept for large corporations to an appropriate tool for planning in almost any size company.

Some modeling packages require developers to enter equations. Spreadsheets, on the other hand, create their models with a computation or calculation orientation. The definition of a planning model varies somewhat with the scope of its application. For instance, financial planning models may have a very short planning horizon and a collection of accounting formulas for producing pro forma statements.

On the other hand, corporate planning models often include complex quantitative and logical interrelationships among a corporation's financial, marketing, and production activities. Most financial models are dynamic, multiyear models. Accounting formulas are true by definition, such as profit = revenue - expenses. Empirical relationships have been derived from past data, e.g. sales support expenses = $ 48.50 * no. of salespeople. Managers hope empirical relationships remain valid long enough to use them for prediction or planning.

In addition to generic DSS-based planning models, there are several industry-specific ones for hospitals, banks, and universities. For example, many universities use EDUCAUSE's Financial Planning Model (EFPM). Comshare is a major vendor of planning and budgeting software.

There are few planning and modeling languages currently on the market. One of the best known such products was IFPS, interactive financial planning system, marketed by EXECUCOM. Gerald R. Wagner and his students originally developed IFPS in the late 1970s. Until a few years ago, an extended product, Visual IFPS/PLUS, was distributed by Comshare, which purchased EXECUCOM. A few of the current planning and modeling language products include Comshare Planning, Visual DSS from TrueBlue Systems, and CUFFS-88 from Cuffs Planning and Models, Ltd.

Typical decision support applications built using planning models include: financial forecasting; manpower planning; pro forma financial statements; profit planning; capital budgeting; sales forecasting; marketing decision making; investment analysis; merger and acquisition analysis; tax planning; lease versus purchase decisions; and new venture evaluation.

MODEL-DRIVEN DSS AIRLINE INDUSTRY EXAMPLES

Airlines are using decision support tools to project travel trends and to cut costs. Model-driven DSS benefit customers by reducing or controlling expenses, evaluating ticket prices, shortening lines in the terminal, and reducing delays. Also, airlines are using DSS to reduce their seat inventories and schedule flights.

Jessica Davis (1999) reported in *InfoWorld* that using the "Broadbase data mart, United's staff of 60 analyst/schedulers, typically MBA/economists, can load ' what if' scenarios—testing whether a new flight to Chicago would be more profitable using a larger or a smaller aircraft." She noted schedulers take into consideration passenger demand, constraints of airports, the maintenance needs of the aircraft, the cost of flying individual aircraft, crew resources, and other factors.

Another example of a model-driven DSS in the airline industry is a yield management system. This type of DSS uses a nonlinear, stochastic model that requires data, such as passenger demand, cancellations, and other estimates of passenger behavior. It had been estimated it would require approximately 250 million decision variables to solve the system-wide yield management problem. American Airlines developed a model that reduced the large problem to three much smaller subproblems that could be solved efficiently.

American Airlines' yield management system is called DINAMO (Dynamic Inventory and Maintenance Optimizer). It was fully implemented in 1988. Since then the system has improved productivity by automating the identification of critical flights and increasing pricing flexibility with a discount allocation process. Between 1988 and 1990 productivity for each analyst using DINAMO increased by over 30 percent. Overall, yield management provided quantifiable benefits of over $ 1.4 billion for 1988-1990 (Smith, Leimkuhler, and Darrow, 1992).

United Airlines deployed the System Operations Advisor (SOA), a real-time decision support system, at its operations control center (OCC) to increase the effectiveness of its operational decisions. United Airlines developed the SOA and implemented it in August 1992. From October 1993 to March 1994, this model-driven DSS application saved more than 27,000 minutes of potential delays, which translated into $ 540,000 savings in delay costs (Rakshit, Krishnamurthy, and Yu, 1996).

United Airlines also uses a crew scheduling DSS, a gate assignment and planning system and a customer service manager DSS. The crew scheduling system at United Airlines is estimated to save about $ 12 million annually in credit time for crewmembers and about $ 4 million annually in hotel costs.

Airline industry DSS vendors include: Airline Automation, Inc., Caleb Technologies, Carmen System, Sabre Technology Solutions, SH&E, Talus Solutions, and Trydon Airline Services.

CONCLUSIONS AND COMMENTARY

Learning to build models and model-driven DSS is a complex task that requires extensive preparatory work. In most situations, MIS professionals who want to build quantitative models need a strong background in management science and operations research. If managers and MIS professionals want to design and build successful model-driven DSS, they may need to expand their skills. If management scientists want to contribute more in building these model-driven DSS, they should develop a very broad understanding of DSS and focus less on using only specific quantitative tools and technologies.

Models are very important components in many DSS, but “bad” models result in “bad” decisions. Many models can be implemented quickly using prototyping. Using prototyping, a new DSS can be constructed, tested, and improved in just a few iterations. This development approach helps test the effectiveness of the overall design. The downside of prototyping is that a new DSS may be hard to deploy to a wide group of users. Managers and DSS analysts need to make sure the scaled-down DSS will work when it is deployed more widely in a company.

OLAP is one example of a hybrid system that uses simple analytical techniques to analyze large data sets. Many other model-driven DSS can be built that use a variety of organizational and external data sets. Managers should be consumers and developers of model-driven DSS. Widely used model-driven DSS need to be built systematically by a team of model specialists, MIS and network specialists and managers. Small-scale systems can be purchased or built using tools like Microsoft Excel. New model-driven DSS must capture the complexity of a decision and be easily implemented and integrated into existing systems.

Model-driven DSS remain important support tools for managers. The interest in data-driven DSS and GDSS should not distract managers from the need to update existing model-based systems and to develop new capabilities that can be implemented using Web technologies. The development environment for building model-driven DSS is powerful and increasingly “Web-friendly”.

Historically, a small number of experts in management science and operations research have performed sophisticated special decision studies for companies. As the emphasis upon rapid response to competition increases, more and more individuals within companies will need to build and certainly use model-driven DSS. Managers and DSS analysts need to be actively involved in identifying the need for and the purpose of innovative model-driven DSS and Analytical Information Systems.