Chapter 9

Building Model-Driven Decision Support Systems

Models can help us understand business problems and help us make decisions.

Introduction

Many companies use models to assist managers. 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 John Deere 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 Decision Support Systems 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 Decision Support Systems (MDSS) 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

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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 how to build Model-Driven DSS. It summarizes commonly used models with a primary focus on terminology. The major objectives are to help managers and MIS specialists work with model builders and evaluate "off-the-shelf" development products.

Modeling Decision Situations

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

Models can help 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? 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 MDSS.

The tasks involved in building Model-Driven DSS are complex enough that a model 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 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, often repeatedly, to reflect changes and uncertainty in supply, production, the economy, sales, costs, or other environmental and internal business factors. This capability of a Model-Driven DSS is usually called “What if?” analysis or sensitivity analysis. The results from using the DSS are analyzed and evaluated by decision-makers; the model is not making the decision.

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 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. A solution method or method needs to be chosen. Also, analysts need to specify assumptions and make any needed forecasts. Forecasting variables or parameters is sometimes part of the construction of an MDSS. Building a MDSS 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?"

Model Assumptions

Assumptions are untested beliefs or predictions. We use them in building many models because we are projecting or anticipating results. We have to test assumptions through “what if” testing 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, uncertainty, or risk in a decision situation. When we build models the following types of situations need to be considered and an appropriate assumption needs to be made.

- **Certainty**. Do we have adequate information to assume certainty about relationships? Does X lead to Y? Models based on this assumption are easy to work with and can yield optimal solutions. Many financial models are constructed under assumed certainty.

- **Uncertainty**. Is information vague, unreliable and unpredictable? Is this a situation of high uncertainty? Analysts should attempt to avoid assuming uncertainty because it is very difficult to model that type of situation. Instead they should work with managers to acquire more information so that the problem can be modeled assuming a risk situation.

- **Risk**. Is some information missing or based on forecasts in the situation? Does our decision have some risk associated with outcomes? Most major business decisions are made with assumptions about risk. Several techniques can be used to deal with risk analysis. “What if” analysis is the primary means of considering risk. As previously noted, “what if” analysis is the capability of "asking" or manipulating a Model-Driven DSS to determine what the effect will be of changing some of the input data or independent 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. We can use “tool labels” like optimization and simulation 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. The terms explanatory, contemplative and algebraic explain some major differences in the purpose of decision models.

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. This explanatory model may also be used to forecast future sales.

A contemplative model indicates or forecasts what outcomes might result from introducing a specific set of parameters or changes to a model. This type of analysis is significantly more dynamic and requires a higher level of interaction on the part of a manager or analyst.

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 animates or 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. Contemplative and algebraic models are predictive models (cf., Starfield, Smith, and Blelock, 1990; Codd, Codd, and Salley, 1992).

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 contemplative 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 builder chooses appropriate models. Once models have been chosen, then 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. Also, a DSS analyst needs to choose to use either static or dynamic models, and to choose if the situation will be modeled assuming certainty, uncertainty, or risk.

General Problem Types

According to Professor Hossein Arsham, a small set of Management Science problem types have been identified. At his Web site (http://ubmail.ubalt.edu/~harsham/), he identifies these types as:

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 do we need? How much will the capital cost?

Inventory control and stockout: How much stock should we hold? When do we order more? How much should we order?

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 do we need?

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 queues? How many servers should we use? What service level are we providing?

Reliability and replacement policy: How well is equipment working? How reliable is it? When should we replace it?

Sequencing and scheduling: What job is most important? In what order should we complete jobs?

We can discuss these 10 common decision support problem types in terms of five general categories of models: accounting and financial models, decision analysis models, forecasting models, network and optimization models, and simulation models.

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 financial budgeting capital budgeting. A number of Decision Aids developed in JavaScript that use accounting and financial models are on-line at DSSResources.COM.

Break-Even Analysis

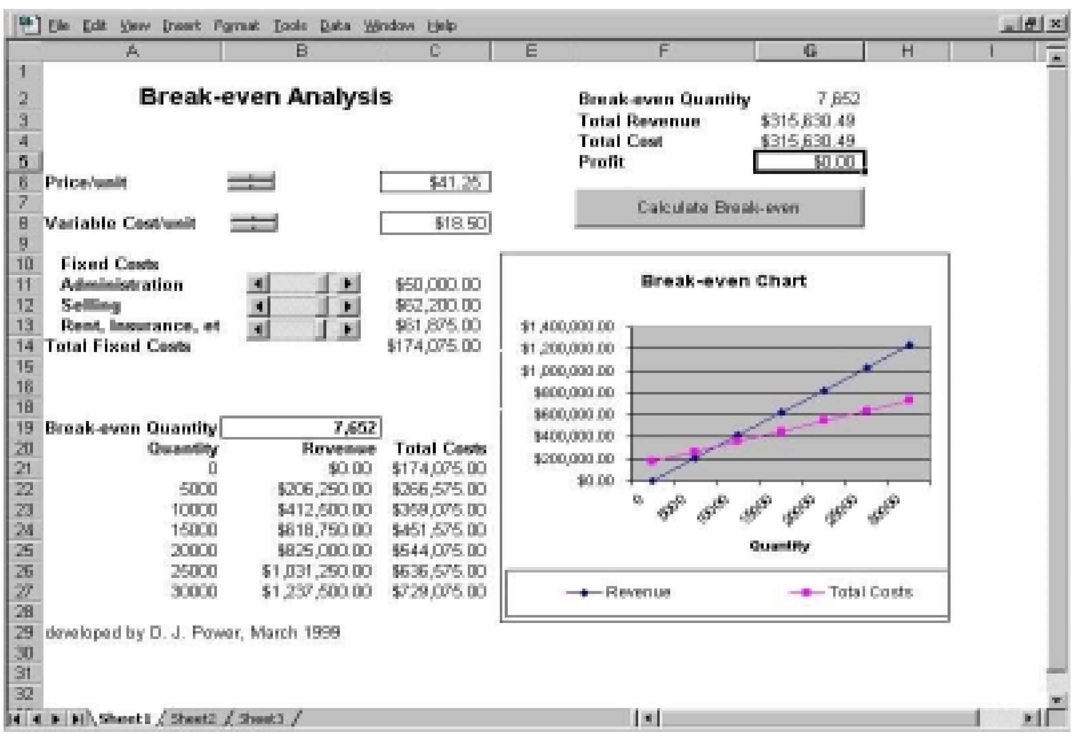


Figure 9.1 Break-even DSS developed in Excel.

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 breakeven 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 9.1 shows a Break-even DSS developed in 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 managers to become concrete 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 categories of models used in analyzing decision situations.

Decision Analysis Models

Decision situations that involve a finite and usually a small number of alternatives can be evaluated with decision analysis models. Decision analysts often help managers 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 and multiple goal decision analysis situations are usually discussed. 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 problem understanding and separate facts from priorities and preferences. This 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 directs the participants to keep the problem presentation simple and helps to extract essentials out of it.

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, DecideRight, DecisionMaker, Demos, DPL, Expert Choice, Strad, Supertree, and Which and Why.

Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process technique (cf., Saaty, 1980; Saaty, 1990) can be characterized as a multi-criteria 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 the general methodology.

The first step is to develop a hierarchical representation of a problem (see Figure 9.2). 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.

Next, in step 2 one needs to generate relational data for comparing the alternatives. This requires a decision-maker to make pairwise comparisons of elements at each level relative to the next higher level in the hierarchy. In the Analytical Hierarchy Process a relational scale of real numbers from 1 to 9 is used to assign preferences.

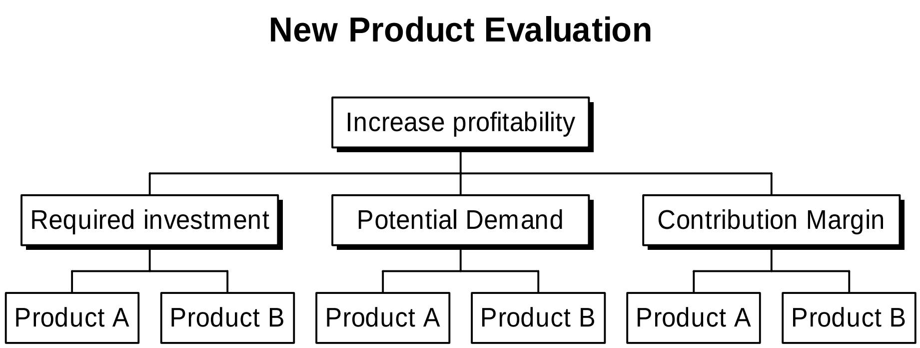


Figure 9.2 A Hierarchical Representation

Using the comparisons of Step 2 the relative priority of each attribute is determined in Step 3. In addition, a "consistency ratio" should be calculated. A user of a DSS based on the AHP model like Expert Choice (http://www.expertchoice.com) has 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 determined and displayed. AHP facilitates a comprehensive and logical analysis of problems for which considerable uncertainty exists.

A number of software packages implement AHP. The best known and most widely used is Expert Choice (visit URL http://www.expertchoice.com). HIPRE 3+ is known for its user friendliness and it is based on a fully graphic interface. It is the first fully graphical mouse-driven implementation of AHP and value tree analysis. HIPRE 3+ lets you combine different approaches such as AHP and value functions in one model. Check URL http://www.hut.fi.

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 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.

One can use a generalized Decision Analysis program to model the following situation, based on Lee, Moore, and Taylor, 1985. Our company has two possible choices: Either we introduce our product (A1), or we don't (A2). If we introduce our product, we incur $100,000 in R&D costs. If we introduce the product our competitor may introduce a competing product. So Alternative 1 can have two outcomes: Our competitor introduces a competing product (O1), or does not (O2). Based on our knowledge of the marketplace, our competitor, and some marketing intelligence, we assess the probability of O1 to be 70%, and that of 02 to be 30%. O1 and O2 are outcome or chance nodes. The final outcomes of the Promotional Campaign can depend, among other things, on our actions, our competitor's actions, the size of our promotional campaign, and the size of our competitor's campaign. Thus, we can analyze the final outcomes in terms of three possible promotional campaigns: We launch a big campaign (N1), we launch a medium campaign (N2), or we launch a small campaign (N3). We need to estimate the profitability and probabilities associated with N1, N2 and N3. The "best" strategy depends on the criterion used. In a marketing analysis, the criterion is typically maximizing Expected Monetary Value (EMV). Figure 9.3 shows part of the decision tree for this decision situation.

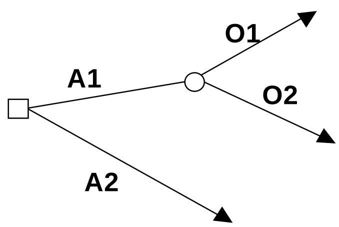


Figure 9.3 Decision Tree

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 in which there is certainty regarding the attribute levels of the alternatives. Another operations research 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.

Influence Diagrams

Another Decision Analysis tool is called an influence diagram. It provides a graphical presentation of a decision situation. It also serves as a framework for expressing the exact nature of relationships. The term influence refers to the dependency of a variable on the level of another variable. An influence diagram maps all the variables in a management problem. Influence diagrams use a variety of geometric shapes to represent elements.

The following conventions for creating influence diagrams were suggested by Bodily (1985) and others.

- A rectangle is a decision variable
- A circle is a uncontrollable or intermediate variable
- An oval is a result or outcome variable; either an intermediate or final result

The three types of variables are connected with arrows that indicate the direction of the influence. The shape of the arrow also indicates the type of relationship. Preference between outcome variables is shown as a double-line arrow. Arrows can be one-way or two-way (bi-directional). Influence diagrams (see Figure 9.4) can be constructed at any degree of detail and sophistication. This type of diagram enables a model builder to remember all of the relationships in the model and the direction of the influence.

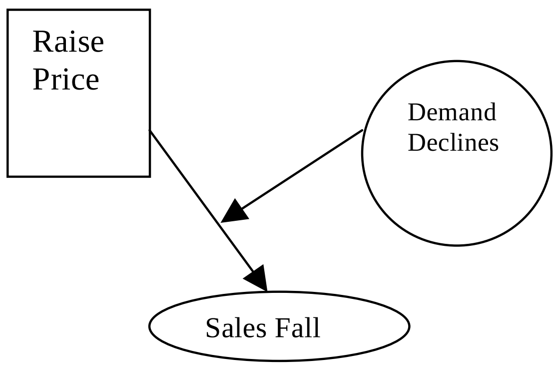


Figure 9.4 A Simple Influence Diagram

Several software products are available that help users create and implement influence diagrams. Some products include: **DAVID** that helps a user to build, modify, and analyze models in an interactive graphical environment; and **DPL** (from ADA Decision Analysis, Menlo Park, CA) that provides a synthesis of influence diagrams and decision trees.

Forecasting Models

The quality of a decision often depends on the quality of a forecast. Forecasting models are an integral part of many DSS. One can build a forecast model or one may use preprogrammed software packages.

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" we want to evaluate the results. For example, in an investment decision we may be interested in prices and income a year from today, while in a capital investment decision we may be interested in projected prices and income during the next five years. Generally speaking, we distinguish between two types of forecasts: (a) short run, where the forecast is used mainly in deterministic models, and (b) long run, where the forecast is used in both deterministic and probabilistic models.

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. We can select forecasting methods 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 our knowledge about 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. 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 naive methods. Also, simple methods are preferable to complex methods; they are easier to understand, less expensive, and seldom less accurate.

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. However it provides limited accuracy.

Judgment Methods. Judgment methods are based on subjective estimates and expert opinion, rather than on hard data. They 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. The results are not necessarily accurate, but the experts may be the best source of forecast information.

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.

Time-series Extrapolation. 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. Managers use time-series analysis in decision-making because they believe that knowledge of past behavior of the time series might help understand the behavior of the series in the future. In managerial planning we often assume that history will repeat itself and that past tendencies will continue. Time-series analysis efforts conclude with the development of a time-series forecasting model that can then be used to predict future events. Both moving average and exponential smoothing use a time series of data.

Regression and Econometric Models. Association or causal forecasting methods use data analysis tools like linear and multiple regression 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 the situation. Second, they use sophisticated statistical techniques for evaluating variables. Causal approaches are most appropriate for intermediate term (3-5 year) forecasting. An econometric model using simultaneous equations for a supply-demand system is x demand= f (x price, yield, etc...) and x supply = f (x price, production inputs prices, etc...) Econometric Resources on the Internet (www.oswego.edu/~kane/econometrics/) by John Kane contains links to a variety of resources. You can work with Fairmodel, a macroeconometric model of the USA economy, to forecast the economy and do policy analysis (fairmodel.econ.yale.edu).

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 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. We can use the models 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, we 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 you can use to efficiently plan, manage, and communicate project information. Project managers can enter actual costs for tasks and assignments. Check http://www.microsoft.com/office/project. 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% 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, multinational cash flow management, and integrated production-inventory-distribution. Often a network model can be depicted as a set of nodes and arcs. Nodes may be sources of product and or demanders of product. Units of product can move from one node to another across arcs. For more information check Richard Barr's Survey of Network Models at www.seas.smu.edu/~barr/ip/ch0/ch0.html.

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 organizations. Many books have been written for courses in Management Science, Quantitative Analysis and Operations Research. Managers and 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. An on-line Web-based tutorial on Using MS Excel Solver for Spreadsheet Optimization is at the Frontline Systems Web site (http://frontsys.com/).

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.

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 you specify. This process is called constrained optimization; the equations or inequalities are called constraints. Every linear programming problem is composed of six elements:

Decision Variables. These variables are unknown values that are searched for by applying the model. Usually decision variables are designated by $\mathbf{X_1}$, $\mathbf{X_2}$, …, $\mathbf{X_N}$.

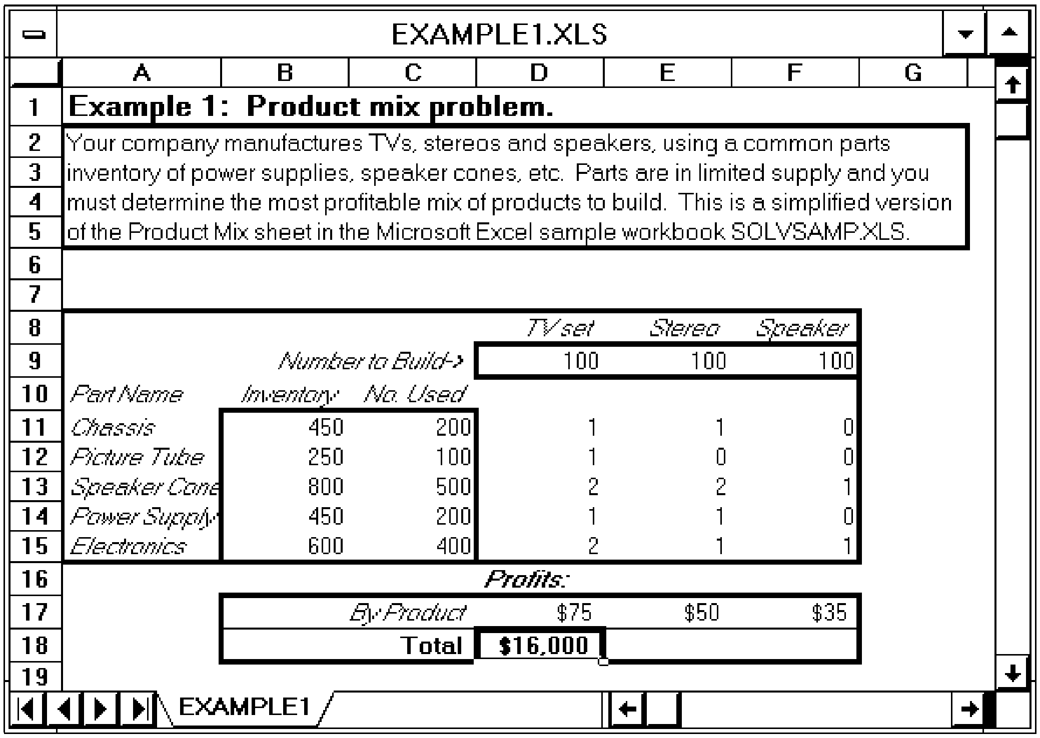
Objective Function. This is a mathematical expression that shows the linear relationship between the decision variables and the single goal that is the focus of the model. The objective function is a measure of goal attainment. Examples of such goals are total profit, total cost, and market share.

Coefficients of the Objective Function. The coefficients of the variables in the objective function are called the profit or cost coefficients. They express the rate at which the value of the objective function increases or decreases by including in the solution one unit of each of the decision variables.

Constraints. The maximization or minimization is performed subject to a set of constraints. Therefore, linear programming can be defined as a constrained optimization problem. These constraints are expressed in the form of linear inequalities or, sometimes, equalities. They reflect the fact that resources are limited or they specify some requirements.

Input-Output (Technology) Coefficients. The coefficients of the constraints' variables are called the input-output coefficients. They indicate the rate at which a given resource is depleted or utilized.

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



EXAMPLE1.XLS

	A	B	C	D	E	F	G
1	**Example 1: Product mix problem.**						
2	Your company manufactures TVs, stereos and speakers, using a common parts						
3	inventory of power supplies, speaker cones, etc. Parts are in limited supply and you						
4	must determine the most profitable mix of products to build. This is a simplified version						
5	of the Product Mix sheet in the Microsoft Excel sample workbook SOLVSAMP.XLS.						
6							
7							
8				*TV set*	*Stereo*	*Speaker*	
9			*Number to Build->*	100	100	100	
10	*Part Name*	*Inventory*	*No. Used*				
11	*Chassis*	450	200	1	1	0	
12	*Picture Tube*	250	100	1	0	0	
13	*Speaker Cone*	800	500	2	2	1	
14	*Power Supply*	450	200	1	1	0	
15	*Electronics*	600	400	2	1	1	
16				***Profits:***			
17			*By Product*	$75	$50	$35	
18			**Total**	**$16,000**			
19							

EXAMPLE1

Figure 9.5 An Example Optimization Model developed in Microsoft Excel

In Figure 9.5 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 9.5 in Excel. A support person may need to help in conceptualizing the problem or in testing the end user application. For more information on Optimization and Linear Programming check Harvey Greenberg's excellent Mathematical Programming glossary at URL http://www.cudenver.edu/~hgreenbe/glossary/intro.html and Michael Trick's Operations Research Page at URL http://mat.gsia.cmu.edu/index.html.

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, which 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, minimizing costs, maximizing quality or minimizing the risk of failure (cf., http://frontsys.com/tutorial.htm).

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. Discrete event simulations and costing models 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 models represent or abstract reality, while simulation models usually try to imitate reality. In practical terms, this means that there are fewer simplifications of reality 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 DSS have been built using simulation models. The increased use of this approach can be attributed to a number of factors. First, simulation theory is relatively easy to understand. A simulation model is a collection of many elementary relationships and interdependencies. 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 simulations easier to build.

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.

Simulation Methodology

Simulation involves setting up a model of a real system and conducting repetitive experiments on it. The methodology consists of a number of steps. The following is a brief discussion of the process:

Problem Definition. A problem is examined and defined. The analyst should specify why simulation is necessary. The system's boundaries and other such aspects of the problem should be stated.

Constructing the Simulation Model. This step involves gathering the necessary data. In many cases, a flowchart is used to describe the process. Then the model is programmed. Figure 9.6 shows a visual simulation model.

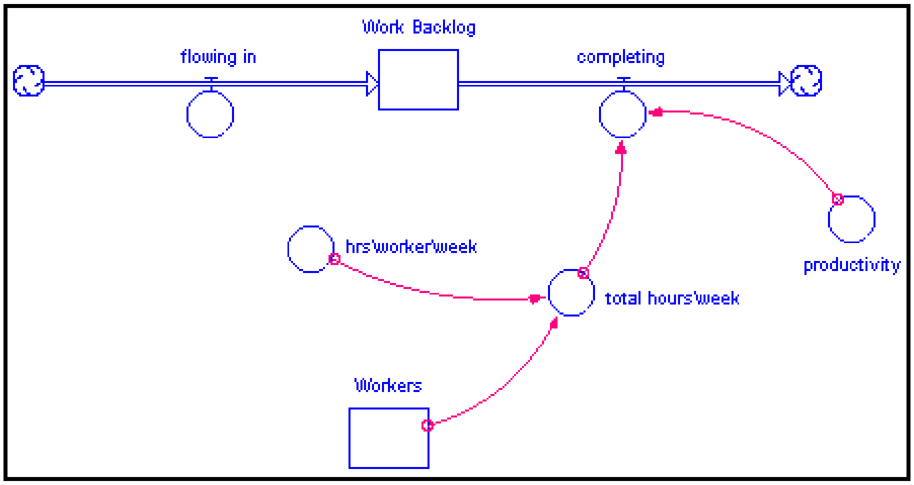


Figure 9.6 Example of a Visual Simulation Model

Testing and Validating the Model. The simulation model must accurately imitate the system under study. This involves the process of validation.

Design of the Experiments. Once the model has been validated, the experiment is designed. In this step the analyst determines how long to run the simulation. This step deals with two important and contradictory objectives, maximizing the accuracy of the model and minimizing the cost of developing the model.

Conducting the Experiment. Conducting the experiment involves issues such as how to generate random numbers, the number of trials or time period for the experiment, and the appropriate presentation of the results.

Evaluating the Results. The last step is the evaluation of the results. In addition to statistical tools, managers/analysts may conduct "What If" and sensitivity analyses.

Types of Simulation

There are several types of simulation. The major types are probabilistic simulation, 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 so that we can 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)."

Several software products are available for the implementation of simulations. Simul8 (from Visual Thinking Inc.) is a PC-based simulation package that costs about $500. It has animation and it interfaces with Visual Basic. Extend (from Imagine That! Inc.) is a more expensive and more complex modeling package. @RISK from Palisades uses Monte Carlo simulation. For more information on Simulation visit the INFORMS College on Simulation Web page at http://www.informs-cs.org/.

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 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 modeling tool. A spreadsheet is based on the structure of an accounting spreadsheet that is basically a column-and-row pad. The intersections of the columns and rows are called cells. The user places numeric data or text in these cells. Then, the user writes formulas using functions to manipulate the data. Spreadsheets have many advantages over a paper accounting worksheet. Most notable is the modeling capability; users can write their own models and also conduct "What-If" analysis, scenario analyses and goal seeking. A scenario is a statement of assumptions about the operating environment of a particular system at a given time. In DSS, a scenario refers to conducting analyses with alternative assumptions about a financial model.

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. In addition to the ability of writing models with a spreadsheet, the software usually includes large numbers of built-in statistical, mathematical, and financial functions.

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 detail on past and current developments see "A Brief History of Spreadsheets" by Daniel Power at URL http://dssresources.com/history/sshistory.html.

A major capability of spreadsheet programs is that numbers can be changed and the implications of these changes can immediately be observed and analyzed. A spreadsheet can be used to build static of dynamic models. A static model does not include time as a variable. For example, spreadsheets are used to build balance sheets. A dynamic model, on the other hand, represents behavior over time. For example, the balance sheet for a given year can be shown together with those of the five previous years.

Spreadsheets are used in almost every kind of organization in all functional areas. Some of these applications are not strictly DSS; they are more in the nature of the traditional MIS. The point is that with a spreadsheet, users do not have to wait a long time for the IS department to build an application. Managers can build applications on their own or with help from an Information Center very quickly and inexpensively.

End-user developed Model-Driven DSS will frequently 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?

Spreadsheets were developed for microcomputers, but they are also available for larger computers. A representative list of spreadsheet software is on the DSS Spreadsheet page at URL http://dssresources.com/spreadsheets/spreadsheet.html. Check Excel from Microsoft (Redmond, WA) and Lotus 1-2-3 from Lotus Development Co. (Cambridge, MA). Spreadsheets are very popular modeling tools. The programming productivity of building DSS can be enhanced with the use of templates, macros, and other tools.

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.

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

There are many planning and modeling languages on the market. Typical applications of 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.

Conclusions and Commentary

Learning to build models and Model-Driven DSS is a complex task that requires extensive preparatory work. MIS professionals who want to build 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 DSS, they should cultivate a very broad understanding of Decision Support Systems and focus less on 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 in a short time, tested, and improved in several iterations. This development approach helps us 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.

On-line Analytical Processing (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 Decision Support Systems 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 Group DSS should not distract managers from the need to update existing model-based systems and 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 model-driven analyses for companies. As the emphasis upon flexibility and competition increases, more and more individuals within companies will need to build and use Model-Driven DSS. Managers and DSS analysts need to be actively involved in identifying the need for and purpose of Model-Driven Decision Support Systems.

Audit Questions

1. Are any Model-Driven DSS used in your company? If so, what types of models are used and for what purposes?
2. Who uses the Model-Driven DSS? Managers? Analysts? No one!
3. Who develops and maintains Model-Driven DSS? MIS unit? Users?

Questions for Review

1. What is linear programming?
2. What are the general components of a quantitative model? What are decision variables? Uncontrollable variables? Result variables?
3. What are the major types of models used in Model-Driven DSS?
4. What is multi-criteria decision-making? What is risk analysis? What is a decision tree?
5. What are the advantages of developing and using models is a DSS?
6. What is goal seeking? How can it be used? What is solver software?
7. What are the advantages of using simulation?
8. What is a scenario? What is a financial scenario?
9. Explain “What If” and sensitivity analysis.

Questions for Discussion

1. Why is sensitivity analysis used with Model-Driven DSS?
2. What is the role of forecasting in decision support?
3. Suppose you have several factories and want to find the best locations to manufacture different products to meet demand in nearby cities. You want to maximize profits and minimize shipping costs. What kind of model would you use? How would you deal with the uncertainties in demand?

Exercises

1. Try developing a Spreadsheet-based Model-Driven DSS. For example, try the product mix example problem at URL http://www.frontsys.com/prodmix.htm. Also, you could try to implement the Break-Even DSS in Figure 9.1.

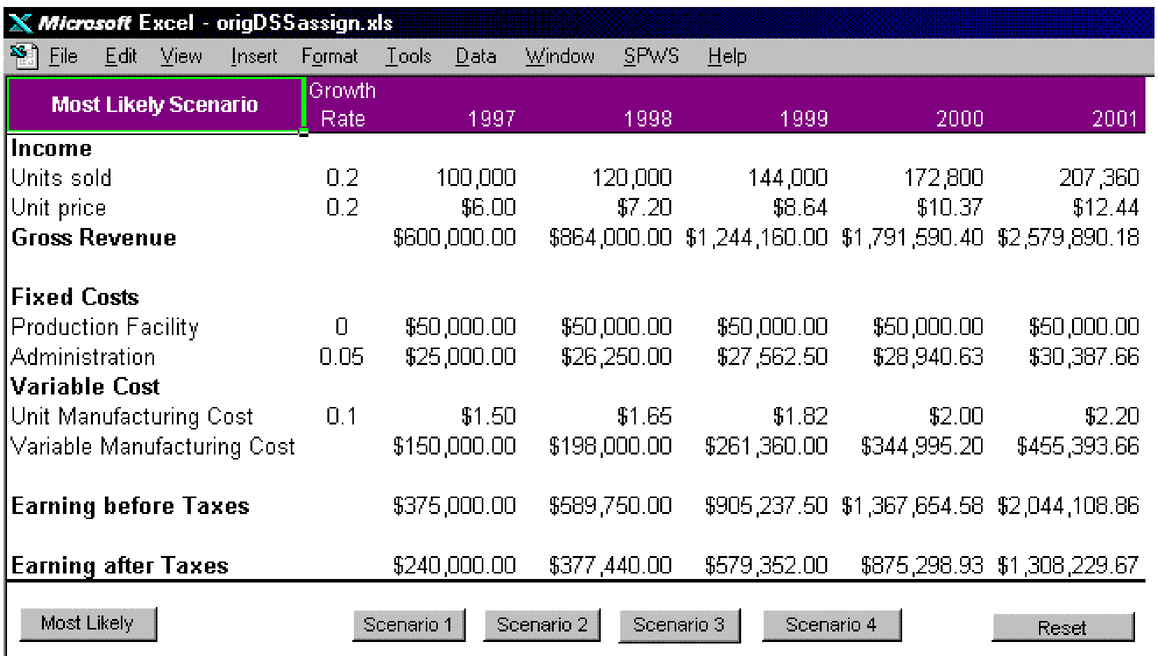
2. Visit Harvey Greenberg's Mathematical Programming glossary at URL http://www.cudenver.edu/~hgreenbe/glossary/intro.html and Michael Trick's Operations Research Page at URL http://mat.gsia.cmu.edu/index.html.

3. Complete the ithink case study and tutorial at http://www.hps-inc.com/bus_solu/fable/fable1.htm. XYZ Manufacturing is having problems. They've been working overtime for weeks, but can never seem to catch up. To add insult to injury, their bottom line has been suffering—with expenses running substantially above normal. Use ithink to develop a map of what might be causing the overtime problem.

4. Visit the Colorado River Decision Support System project web page at http://cdss.state.co.us/overview/bigoverview/crdsscov.html. The DSS is a simulation model of the Colorado River Basin that evaluates river and reservoir operations throughout the Colorado River System.

Excel Project

You are working with an entrepreneur who has developed a new product and is seeking venture capital to go into immediate production. She wants you to develop a spreadsheet application. She has orders for 100,000 units in the first year at a selling price of $6.00 per unit. According to her most likely scenario, both numbers are expected to increase 20% annually. She is able to rent a production facility for $50,000 a year for five years. The variable manufacturing cost is $1.50 per unit and is projected to increase at 10 percent a year. Administration costs another $25,000 a year and will likely increase at 5 percent annually. Develop a five-year financial forecast similar to that in Figure 9.7 showing profits before and after taxes. You should assume a tax rate of 36 percent.



Most Likely Scenario	Growth Rate	1997	1998	1999	2000	2001
Income						
Units sold	0.2	100,000	120,000	144,000	172,800	207,360
Unit price	0.2	$6.00	$7.20	$8.64	$10.37	$12.44
Gross Revenue		$600,000.00	$864,000.00	$1,244,160.00	$1,791,590.40	$2,579,890.18
Fixed Costs						
Production Facility	0	$50,000.00	$50,000.00	$50,000.00	$50,000.00	$50,000.00
Administration	0.05	$25,000.00	$26,250.00	$27,562.50	$28,940.63	$30,387.66
Variable Cost						
Unit Manufacturing Cost	0.1	$1.50	$1.65	$1.82	$2.00	$2.20
Variable Manufacturing Cost		$150,000.00	$198,000.00	$261,360.00	$344,995.20	$455,393.66
Earning before Taxes		$375,000.00	$589,750.00	$905,237.50	$1,367,654.58	$2,044,108.86
Earning after Taxes		$240,000.00	$377,440.00	$579,352.00	$875,298.93	$1,308,229.67

Figure 9.7 A Pro Forma Spreadsheet DSS.

Create 4 additional scenarios for this situation - Scenario 1 is rapid increase in sales (30% per year) and slow increase in variable costs (5% per year); Scenario 2 is rapid increase in sales (30% per year) and rapid increase in variable costs (15% per year); Scenario 3 is slow increase in sales (10% per year) and slow increase in variable costs (5% per year); Scenario 4 is slow increase in sales (10% per year) and rapid increase in variable costs (15% per year).

Your worksheet should be completely flexible and capable of accommodating a change in any of the initial conditions or projected rates of increase, without having to edit or recopy any of the formulas. One way to meet this design goal is to create a table of the assumptions about initial conditions and rates of increase, and then reference the table cells as absolute references when building formulas.

Model-Driven DSS Examples – Airline Industry

Airlines are using decision support tools to project travel trends and to cut costs. 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.

American Airlines. One type of airline DSS is a Yield Management System. This Model-Driven DSS solves a problem that is described as a non-linear, stochastic, mixed integer mathematical program that requires data, such as passenger demand, cancellations, and other estimates of passenger behavior that are subject to frequent changes. This DSS 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 sub-problems 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 (a flight that required manual attention) and increased pricing flexibility with a discount allocation process. Between 1988 and 1990 productivity for each analyst using DINAMO increased by over 30%. Overall Yield Management has provided quantifiable benefits of over $1.4 billion for 1988-1990 (see Smith, Leimkuhler, and Darrow, Yield Management at American Airlines**, Interfaces**, 1992, pp. 8-31). American Airlines also uses a Flight Scheduling DSS.

United Airlines. United 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 DSS application saved more than 27,000 minutes of potential delays, which translates to $540,000 savings in delay costs, and the number of flight delays charged to aircraft controllers in the systems operations control dropped by 50%.

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.

Discussion Questions:

1. What types of models are used in the various Airline Industry DSS?

2. Why do you think so many DSS have been developed for Airline Companies?

Airline Industry DSS Vendors and Web sites

- Airline Automation Inc., http://www.airauto.com. Primary DSS product area is Airline Distribution Cost Reduction.
- Caleb Technologies Corp., http://www.calebtech.com. Primary products are OpsSolver, ManpowerSolver and Crew Scheduling.
- Carmen System, http://www.carmen.se
- Sabre Technology Solutions, http://www.sabre.com. Primary products for Cost Management, Flight Operations, Planning and Scheduling, Pricing and Yield, and Revenue Maximization.
- SH&E, http://www.sh-e.com, offers software tools in key commercial areas like Network and Schedule Analysis and Yield Management.
- Talus Solutions, http://www.talussolutions.com/. Talus focuses on pricing and revenue optimization.
- Trydon Airline Services, http://www.trydon.com. OPTIMACH Cruise System is a resource management and cost-indexing tool designed for airlines. Trydon has software packages designed to facilitate the management of airline operations.

Thanks to Saksatit Sverundra for his help in investigating Airline Industry DSS.

Model-Driven DSS Software

Products: Analytica 2.0
Developer: Lumina Decision Systems
URL: http://www.lumina.com/

It is a quantitative modeling software package that uses a graphical interface to develop a model. Capabilities include scenario analysis, influence diagrams, dimensional modeling, and risk analysis. Try it free for 30 days with the Analytica trial.

Product: DPL (Decision Programming Language)
Developer: Applied Decision Analysis, Inc. a subsidiary of PricewaterhouseCoopers
URL: http://www.adainc.com/sw/index.html

A package implementing both decision trees and influence diagrams. Three versions are available: standard, advanced, and developer. A demonstration version that does not save models is available.

Product: Expert Choice
Developer: Expert Choice, Inc.
URL: http://expertchoice.com/

It is based on the Analytic Hierarchy Process (AHP), a multi-criteria hierarchical decision-making approach. Expert Choice assists decision-makers by organizing complex problem-related information into a hierarchical model consisting of a goal, possible scenarios, criteria, and alternatives. The importance of criteria, preferences for alternatives, and likelihood of scenarios are evaluated by using the method of pairwise comparisons. Expert Choice then derives the priorities. Try the EC2000 trial version.

Products: ithink and Stella
Developer: High Performance Systems, Inc.
URL: http://www.hps-inc.com

ithink software facilitates creating visual simulation models. Check the online case study and tutorial. You can download a disabled demo.

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