Chapter Outline

3.1 The Management Cycle: Planning and Control
What are some of the common tasks that most managers perform?

Why does the Management Cycle have a cyclical nature?

If planning entails deciding “today” what to do “tomorrow,” what are the implications for the data used for planning?

3.2 Information for Planning
Why is it difficult to get information on potential outcomes in the planning process?

Why do most planning problems involve multiple criteria for measuring outcomes?

What is “satisficing,” and why is it often superior to “optimizing”?

Why are “rules of thumb” or “heuristics” useful in planning?

3.3 Monitoring
What are the factors to be considered in monitoring business performance?

What is a “pre-symptom” and why is it a useful concept in management control? Give an example of a pre-symptom in business practice.

3.4 Information for Control
What are the requirements for information to establish control?

How can data generated by the monitoring function be converted to support the control function?

3.5 The Management Pyramid and Management Functions
What are the three broad roles associated with the management pyramid?

Why is the information required by the three levels of the management different?

3.6 The Role of DSS in the Decision Process
What are the three phases in the decision-making process?

Why are information needs different for problem-finding and problem-solving?

How can DSS systems make a real contribution to problem-finding?

What is the difference between structured and unstructured decisions?

Minicase #7
How Do Managers Use Models?

Minicase #8
How a Manager-Model Interaction Improves the Decision

Minicase #9
A Competitive Bidding Decision Support System: The Use of Judgmental Data to Deal with Uncertainty
CHAPTER 3

DECISION SUPPORT SYSTEMS AND MANAGEMENT DECISIONS

Only by focusing on the decision first and then defining the information required to support it, is it possible to see which data are worth collecting.

Peter G. W. Keen and Michael Scott-Morton
Decision Support Systems: An Organizational Perspective

3.1 The Management Cycle: Planning and Control

To examine how a DSS can support management decisions, we need to have a broad understanding of the basic functions of management. What is “management?” We define it in terms of the tasks that managers perform. Quite simply, all managers:

- **Plan** what they want to accomplish;
- **Implement** the plan;
- **Monitor** performance; and,
- **Control** the implementation to ensure achievement of desired results.

The *planning* function entails deciding “today” what to do “tomorrow.” The planning horizon could be five years for long-range strategic planning, one year for annual budgeting, a few weeks for production scheduling, and even the next hour for a stock market trader.

Objectives have to be set and a plan has to be formulated to achieve these objectives. Once the plan is implemented, the *control* function takes over for assuring the accomplishment of the plan's objectives. This requires actual outcomes to be monitored, and corrective action to be taken when actuals deviate from planned objectives. The corrective action could encompass tactical changes to the plan, or even a revision in the original objectives. Deviations between actuals and plan could be negative or positive. In the former case, it signals a *problem* that has to be dealt with. In the latter, it reveals an *opportunity* that should be exploited.

The entire process, depicted in Exhibit 3.1, is cyclical in the sense that the control function loops back into the planning function, and the cycle repeats itself.
Consider, for example, the planning and control cycle in the marketing operations of a company. For the sake of simplicity, we will confine our attention to one brand, say a particular diet cola, with a planning horizon of one year.

The annual brand plan for the brand is usually developed at least six months before the start of the new year. This involves setting targets for sales at a given (planned) price and contribution margin or “profit” (gross revenues less cost of goods sold including marketing costs).

Once the new year starts and the plan is implemented, the monitoring of actual results starts immediately. This brings up the question of how often the actuals are monitored, which will be discussed with other issues pertaining to monitoring later in this chapter. The variances or deviations of actuals from plan would lead management to take corrective action such as: reducing the price to match a competitor if sales volume is below target or, if margins are better than anticipated, to invest the surplus in increased advertising to capture a greater market share or any of a variety of marketing actions to respond to problems or opportunities.
3.2 Information for Planning

Planning involves choices. A plan must be chosen from (perhaps many) alternative courses of action. Underlying the choice is the deployment of scarce resources - people, capital, manufacturing capacity, etc. For this purpose, information is needed on the consequences or potential outcomes of the various alternatives to enable the right choice. This is more easily said than done, due to three complicating factors:

1. The Large Number of Alternatives

The right choice is totally dependent on the variety of alternatives evaluated. For example, in developing the television advertising plan for a diet cola, an almost infinite number of alternatives is available for television spots. The problem is how to evaluate this large number in a cost-effective manner within the limited time available.

2. Uncertainty about the Outcomes

In virtually all real-world planning situations, outcomes are not known for sure. This is true even when the number of alternatives is very limited, such as in the decision whether to launch a new product or not. Although “launch” and “don't launch” are the only alternatives, the outcomes of either alternative are highly uncertain. How much will the new product draw away from our existing product line? What will be the competitive reaction to our new product? If we don't launch, will a competitor release a similar new product and cut into our market?

3. Multiple Criteria

There is no single yardstick or criterion for measuring many outcomes. For example, in a university, how can one evaluate the outcomes of a higher allocation of resources to the undergraduate program rather than to the graduate program? The outcome of a particular budget allocation is not a single measure or number - the total number of students. It is at least two numbers - undergraduates and graduate students - whose “value” might be considered quite differently, an obvious “apples” and “oranges” problem.

A DSS to support the planning process is hence not easy to design. A pragmatic approach is contained in the concept of a “satisficing” solution to a decision problem rather than an “optimum” solution.
“Satisficing” vs. “Optimizing”

The concept of satisficing was proposed by Herbert A. Simon, a Nobel prize winning economist and a true pioneer in management science and artificial intelligence. Simon observed that, for most real-world problems, finding the optimal solution would require massive searches and extensive analysis. Indeed, in many cases, the optimum may never be found. Satisficing is an approach that reduces the search time and provides the decision-maker with a solution which, although not the absolute best, is “good enough.”

Simon suggested that satisficing solutions can be derived from rules of thumb or heuristics that can generally lead to acceptable answers. (1) For example, a simple heuristic for allocating an advertising budget to major markets is to do it in proportion to last year's sales in those markets. This may not be an optimal procedure, but it surely saves the time and cost of searching for the optimal solution.

In contrast, optimizing methods, such as linear programming and its extensions, zero in on “the best” solution through a formal analysis of mathematical models. The best solution, however, comes only at a price - measured in time and cost.

Rigorous optimizing models are not always the best answer. First, the assumptions of the mathematical model must fit the problem at hand - usually problems can not be bent to fit the available model. As an example of the latter, we cite the rush in the early 1960s to apply linear programming, flush from its success in manufacturing applications, to marketing problems. The linearity assumption was a reasonable approximation, for example, in the product mix model for allocating manufacturing capacity to different products so as to maximize profits subject to demand constraints. The same assumption does not, however, hold in the media selection model for allocating a fixed advertising budget to various media options for maximizing total audience exposure.

The underlying real-world behavioral process in the marketing problem is essentially non-linear and was mutilated when it was bent into a linear programming model. A more realistic (non-linear) model was developed subsequently and simple heuristics were employed in a computerized search procedure that generated media schedules superior to the ones previously generated by media planners. (2) Note the accent on simple heuristics, not a mathematical analysis, and a superior solution, not the best. The procedure was successfully commercialized as an on-line media planning system in 1968, before even the term DSS was coined.

Second, the amount of data required for a precise mathematical formulation of the problem can be significant, with attendant implications on time and cost for collecting the data. Is it really worth all that time and cost compared to a satisficing solution generated with less data combined with heuristics based on managerial experience?
Finally, managers rely on their own heuristics which they understand rather than optimum solutions based on mathematical models that are a “black box” to them. The intellectual cost of understanding a model could be considerable and a real stumbling block to implementing optimal solutions. Since managers are responsible for the decisions they make, they cannot be expected to use solutions derived from methods with which they are not thoroughly familiar.

In summary, we reproduce Simon's argument in favor of a satisficing solution over an optimum solution because of its overarching impact on DSS systems.

*In the real world we usually do not have a choice between satisfactory and optimal solutions, for we only rarely have a method of finding the optimum.*

... We cannot, within practicable computational limits, generate all the admissible alternatives and compare their relative merits. Nor can we recognize the best alternative, even if we are fortunate enough to generate it early, until we have seen all of them. We satisfice by looking for alternatives in such a way that we can generally find an acceptable one after only moderate search. (3)

### 3.3 Monitoring

The monitoring function supplies the data for exercising control to ensure that the objectives of the plan are achieved. Hence, the control function can only be as effective as the monitoring of actual performance. Several questions have to be addressed here:

*What* should be monitored? What “readings” of actual performance should be taken?

*How* should the monitoring be done? Where should the “meters” for taking the “readings” be placed?

*How often* should the “meters” be read?

*How Current?* How quickly should the readings be transmitted to management for action to be taken?

*How Accurate?* How much accuracy is necessary in the readings?

These are particularly knotty questions and they are inter-related. To illustrate, consider the problem of measuring a company's performance in the marketplace. We return to our diet cola product to explain. The distribution pipeline from the plant to the end user is shown in Exhibit 3.2.

At the outset, what is “sales?” The answer will depend on where the meter for reading sales is placed. The readily available data in all companies is the internal (hard) data on
the sales made by the company to the first stage in the distribution pipeline. This should more correctly be called “company shipments.” The company's invoicing system captures the shipments data and the traditional MIS sales reports are generated from this internal data. Is it any surprise that marketing and sales management find these reports to be of only limited value?

Exhibit 3.2

Distribution Pipeline for Diet Cola

<table>
<thead>
<tr>
<th>Shipments</th>
<th>Withdrawals</th>
<th>Purchases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant</td>
<td>Warehouse</td>
<td>Store</td>
</tr>
</tbody>
</table>

True sales are reflected in the consumer offtake of the product from the retailers' shelves. Further, the flow of the product through the distribution pipeline has also to be tracked because of the inventory build-up at each stage in the pipeline. With a soft drink product, seasonal consumption differences can introduce significant perturbations between shipments and consumer purchases.

Another related matter is the measure for sales - volume? value? both? Should the measure not extend to market share to reflect performance in relation to competition? This raises yet another question: share of which market? The total market or the particular segment in which the product competes? For a diet cola should we include the total soft drink market? or only the cola segment? or only the diet segment? or only the diet cola segment?

Fortunately, in the frequently purchased consumer packaged goods industry, an avalanche of data is available. Beginning in the 1930s with the Nielsen store audit for tracking market shares, a variety of syndicated data services now provide sales measurements at every stage in the distribution pipeline. Today, there is a veritable data explosion with some services providing detailed data on purchases collected from stores with scanners.

Contrast this situation with that of industrial product companies who make products such as steel and chemicals that are bought by other companies for use in their manufacturing operations. These companies are typically marketing-data-poor. Their major source of data on market performance vis-a-vis the competition is market intelligence gleaned by their front-line salesforce. Albeit soft, that is “the only show in town” for market share data that is timely and has the requisite level of detail. Compared to statistics published by the government or trade associations, such data from the salesforce can be very useful despite its softness.

The How Often question has to be examined in the context of What is monitored and How, because of the cost implications. If market share data is gathered by the salesforce, “less often” is all that one can afford because this activity cuts into selling time. On the other hand, Exhibit 3.3 shows how much information is lost when the frequency of measurement
is reduced from weekly to monthly to bimonthly. The weekly data pinpoints precisely the peaks in sales that occur when the price is reduced. This information is not so clear in the graphs of monthly data, and even less clear when the data is aggregated in the bimonthly graph. Further, if the frequency is reduced from, say, weekly to monthly, the information might be too late to be of value.

Exhibit 3.3

Aggregation Reduces the Information Content of the Data

Adapted from Glen L. Urban and Steven H. Star
Advanced Marketing Strategy, Prentice-Hall
The original data was from Information Resources, Inc.

The How Current question is linked to the How Often. Clearly, there is no point in collecting daily data if the data for today is not available tomorrow, but only next week.

How Accurate should the data on market performance be? The more accurate, the more it will cost, depending on where the meter is placed. The concept of operational accuracy that we introduced in the previous chapter dictates that data need have just enough accuracy to reach satisficing decisions.

In the final analysis, the What question dominates all the other questions in the monitoring function. A valuable concept in this regard is the notion of “pre-symptoms,” set forth by Russell L. Ackoff, a pioneer management scientist.

Pre-Symptoms to be Monitored

A pre-symptom is a predictor of a future symptom. Ackoff defines a symptom to be a “deviation of a system's behavior from what is considered to be normal.” (4) A fever in a
person is an example. In a business setting, sales that are below target would be a good example. In Ackoff’s view, the pre-symptom is the general discomfort experienced by an otherwise healthy person that portends the on-coming fever before it actually begins. In business, the pre-symptom could be a sharp increase in customer complaints about service, which could foreshadow a decline in sales.

Ackoff’s point about monitoring pre-symptoms in addition to symptoms is sound advice since it enables management to react sooner, rather than later, to problems.

The Federal Express service level measurement system referred to in Chapter 1 illustrates Ackoff’s concept of pre-symptoms. The twelve service quality indicators measure customer satisfaction in terms that are meaningful to customers, not just by internal operating statistics. A negative trend in these indicators signals a future sales problem. Hence, timely action by management to correct the cause of the service problems perceived by customers would prevent a future sales problem. Federal Express operates in a highly competitive market with much of its volume coming from a relatively few large customers. Spotting service problems early before accounts go to a competitor is a major benefit of the service measurement system. An effective DSS system should track not only the standard operating measures - sales, costs, gross margins, profits, etc. - but the factors that lead to higher or lower sales, costs and profits as well.

3.4 Information for Control

The data generated by the monitoring function has to be converted into information to support the control function. The basic requirements are quite straightforward. Variances, or deviations between actuals and plan, have to be determined and linked to their root causes. The pinpointing of the root causes is critical for the appropriate corrective action to be taken.

The above is a simple enough statement, but it encapsulates several prerequisites on the information needed for effective control.

Before discussing these requirements, we note that the control function is not driven only by variances between plan and actuals. Other differences, such as the difference between actuals for this year and last year, or between two divisions of the organization, or between “us” and “them” (the competition), can also bring problems and opportunities to the surface. Pounds observed that looking at differences or changes in situations is a manager's principal means of problem-finding. (5)

Here are some generalizations on the information required to establish control:

1. Summary reports that are generated by existing MIS systems as a means of reducing the data overload are not enough since they can hide problems.
For example, the summary report in Exhibit 3.4 indicates “no problem” at the product group level. But there is a problem and an opportunity if the data is analyzed at the individual product level. (see Exhibit 3.5) This information was lost when the data was aggregated in the summary report.
### Exhibit 3.4

#### A Summary Sales Report

<table>
<thead>
<tr>
<th>Product</th>
<th>Target ($ thousands)</th>
<th>Actual ($ thousands)</th>
<th>Variance (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group A</td>
<td>18,828</td>
<td>19,043</td>
<td>1.1</td>
</tr>
<tr>
<td>Group B</td>
<td>24,139</td>
<td>24,391</td>
<td>1.0</td>
</tr>
<tr>
<td>All Products</td>
<td>42,967</td>
<td>43,434</td>
<td>1.0</td>
</tr>
</tbody>
</table>

### Exhibit 3.5

#### How Summarization Can Hide Information

<table>
<thead>
<tr>
<th>Product</th>
<th>Target ($ thousands)</th>
<th>Actual ($ thousands)</th>
<th>Variance (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group A A1</td>
<td>3,492</td>
<td>4,105</td>
<td>17.6</td>
</tr>
<tr>
<td>Group A A2</td>
<td>6,849</td>
<td>6,213</td>
<td>-9.3</td>
</tr>
<tr>
<td>Others</td>
<td>8,487</td>
<td>8,725</td>
<td>2.8</td>
</tr>
<tr>
<td>Group A Total</td>
<td>18,828</td>
<td>19,043</td>
<td>1.1</td>
</tr>
<tr>
<td>Group B B1</td>
<td>5,139</td>
<td>5,326</td>
<td>3.6</td>
</tr>
<tr>
<td>Group B B2</td>
<td>7,826</td>
<td>7,533</td>
<td>-3.7</td>
</tr>
<tr>
<td>Others</td>
<td>11,174</td>
<td>11,532</td>
<td>3.2</td>
</tr>
<tr>
<td>Group B Total</td>
<td>24,139</td>
<td>24,391</td>
<td>1.0</td>
</tr>
<tr>
<td>All Products</td>
<td>42,967</td>
<td>43,434</td>
<td>1.0</td>
</tr>
</tbody>
</table>

2. To reduce the data overload, exception reports that spotlight data which have strayed from benchmarks or expected levels are mandatory.

3. A *drill-down* capability is essential for accessing detailed data to trace a problem to the root cause. The following example illustrates the point:

> Duracell CEO C. Robert Kidder manipulated a mouse attached to his workstation to search for data comparing the performance of the
Duracell hourly and salaried work forces in the U.S. and overseas. Within seconds the computer produced a crisp, clear table in colors showing higher sales per employee in the US. He asked the computer to “drill down” for more data to explain the difference. At the end of the data-browsing session the real problem was found: too many salespeople in Germany wasting time calling on small stores. (6)

The above example highlights the features necessary in the DSS - screen-oriented, color, extremely easy-to-navigate so that users can quickly home in on real problems.

4. Graphics capability is a must, since comparisons can be made in seconds as opposed to several minutes to absorb the same information from a tabular report. For example, the cumulative expenditures graph in Exhibit 3.6 clearly shows not only that actual expenditures are consistently above budget, but that the gap between budget and actual is widening. This is, probably a more illuminating graph than the monthly expenditure graph of the same data in Exhibit 3.7, which suggests that, even with graphics, there is a question of the “right” graph.

Exhibit 3.6

Graph of Cumulative Expenditures vs. Budget
5. It is not sufficient to know just “what happened.” There should be a minimal analysis capability to evaluate the consequences of performance to date. A simple example is provided in Exhibits 3.8 and 3.9. A “standard sales report” is shown in Exhibit 3.8, presenting information on year-to-date sales vs. targets. Observe that the performance of product P2 is not up to expectations, whereas that of P3 is above target. While that information is useful, it is more important to see what impact this has with regard to achieving the annual targets. Exhibit 3.9 presents a more complete picture. For the P2 product, the monthly average sales for the balance of the year has to be more than tripled from its current level to achieve the annual target. On the other hand, product P3’s current speed (or monthly average) is much higher than what is needed to achieve its annual target. The last column of numbers in Exhibit 3.9 synthesizes all the information to assess the consequences of performance to date.

6. Finally, the data explosion of the 1990s is making it difficult for users to sift through exception reports to determine the priorities for action. Further, the drill-down capability does not, by itself, signal to the user that there are problems at lower levels which are not transparent in the higher-level reports. Some of the newer software tools have embedded rule-based expert systems to spot exceptions at a lower level. These exceptions are highlighted with visual clues in the higher-level summary reports, such as a “down arrow” or colored numbers that stand out from the surrounding numbers.
### Exhibit 3.8

<table>
<thead>
<tr>
<th>Product</th>
<th>Actual</th>
<th>Target</th>
<th>% of Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>100</td>
<td>120</td>
<td>83%</td>
</tr>
<tr>
<td>P2</td>
<td>100</td>
<td>180</td>
<td>56%</td>
</tr>
<tr>
<td>P3</td>
<td>100</td>
<td>90</td>
<td>111%</td>
</tr>
<tr>
<td>Totals</td>
<td>300</td>
<td>390</td>
<td>77%</td>
</tr>
</tbody>
</table>

* The fiscal year begins in April for this firm.

### Exhibit 3.9

<table>
<thead>
<tr>
<th>Product</th>
<th>Actual</th>
<th>Target</th>
<th>% of Target</th>
<th>Annual Target</th>
<th>Bal. to Achieve</th>
<th>Current Speed *</th>
<th>Speed * Req’d</th>
<th>Chg. in Speed *</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>100</td>
<td>120</td>
<td>83%</td>
<td>150</td>
<td>50</td>
<td>11.11</td>
<td>16.67</td>
<td>50%</td>
</tr>
<tr>
<td>P2</td>
<td>100</td>
<td>180</td>
<td>56%</td>
<td>240</td>
<td>140</td>
<td>11.11</td>
<td>46.67</td>
<td>320%</td>
</tr>
<tr>
<td>P3</td>
<td>100</td>
<td>90</td>
<td>111%</td>
<td>120</td>
<td>20</td>
<td>11.11</td>
<td>6.67</td>
<td>(39%)</td>
</tr>
<tr>
<td>Totals</td>
<td>300</td>
<td>390</td>
<td>77%</td>
<td>510</td>
<td>210</td>
<td>33.33</td>
<td>70</td>
<td>210%</td>
</tr>
</tbody>
</table>

* “Speed” = Average Monthly Sales. For Product P1, for example, 100 units have been sold in the first nine months of the fiscal year, so Current Speed = 100/9 = 11.11 units per month. In the three months remaining in the fiscal year, 50 units have to be sold to reach the target, or the Speed Required = 50/3 = 16.67 units per month, a 50 percent increase over the current speed.

### 3.5 The Management Pyramid and Management Functions

Having outlined the nature of the information required to support the planning and control functions, we turn now to the question of who performs those functions in an organization. Recall from Chapter 2 that the user (or user group) should be the owner and driver of a DSS system for the simple reason that the whole purpose of the system is to support that particular user (or group). The starting point for designing a DSS is, hence, the user and the specific task of that user which the DSS aims to support. In this context, the level of the user in the organization has an important bearing, since it defines the scope of the tasks that the user is responsible for. In fact, the particular type of DSS that has been labeled Executive Information Systems was developed in response to the needs of top management for information to support them in their sphere of responsibility.

A useful framework for viewing the management functions in relation to the three broad tiers of an organization was provided by Robert N. Anthony in a classic treatise on planning and control systems. According to Anthony, top management should be
Decision Support Systems and Management Decisions

concerned with strategic planning, middle management with management control, and lower management with operational control, which he defined as follows: (7)

**Strategic Planning:** the process of deciding on objectives, on the resources used to attain these objectives, and on the policies that are to govern the acquisition, use, and disposition of these resources.

**Management Control:** the process by which managers assure that resources are obtained and used effectively and efficiently in the accomplishment of the organization's objectives.

**Operational Control:** the process of assuring that specific tasks are carried out effectively and efficiently.

Anthony goes on to clarify that while strategic planning is concerned with the “big picture,” management control is concerned with the continual administration of the organization, and takes place within the objectives defined in the strategic planning process. Thus, management control is concerned with both the planning and execution of unspecified activities, whereas operational control deals with the execution of specified tasks. In a nutshell, the function of top management is, to a large extent, planning; that of middle management involves less planning and more control; and, as we go down to the bottom of the pyramid, the control function becomes more and more important.

What are the implications on the information support for each tier of the management pyramid? The following observations can be made about the attributes of the information required:

1. The **scope** of the information is narrow and well-defined at the lowest tier and becomes wider and fuzzier as one moves up the pyramid.

2. The **sources** of the data required at the top management level is largely external - involving competition, customers, trends in the economic environment, social trends, etc. On the other hand, most of the data required for operational control at the lower levels of the organization is internal, with one notable exception - the sales function. The very nature of that function requires external data on customers and competitors to be available all the way down to the front-line salespeople.

3. The **time horizon** of the information required is mostly historical at the lower level as against mostly about the future at the top level.
4. The *level of detail* in the information required at the different levels is not as straightforward as the previous attributes. The operational control function requires detailed data on specific tasks. Since the scope of the responsibility at the lower level is narrow, this detail can be absorbed by the users and acted upon. Moving up the pyramid, the scope of responsibility and, hence, the information required gets wider. Conventional wisdom suggests that, as you go up the pyramid, the information presented to management should be more and more summarized and compact.

Should only summarized data be provided to the top levels of management? Traditional MIS systems say “yes,” in order to avoid the data overload problem. However, as pointed out in the previous section, summary reports may not reflect real problems and opportunities. Further, unless detailed data is accessible, the upper levels of management cannot trace problems to their root causes. A philosophic issue also has to be addressed here.

Should top management have these capabilities in their information support systems? Or, should they delegate these tasks to their staff or the middle layer of management? There is, of course, no absolute or correct answer to this question since it all depends on the management style of senior managers. We’ll talk more about this a bit later in this chapter.

One factor that has propelled the ability of top management to use detailed data, despite the wide scope of their responsibility, is the tools available to eliminate the problem of drowning in the detail. The capabilities for exception reporting, graphical analysis, and intelligent drill-down that we discussed earlier are all means of extracting the real “news” in the data. The benefits of accessing detailed data for senior management are best reflected in the following comment by a senior executive:

> . . . the DSS gives us the information we need - not what someone wants to give us after it has been massaged and sanitized. And we get it when we want it, which is usually immediately. (10)

3.6 The Role of DSS in the Decision Process

A DSS is, by definition, a means of supporting decision-making. In this section, we discuss what this process entails and the way in which a DSS supports that process; how the extent to which the decision task is structured or unstructured affects the information support for that task; and the impact of the individual manager's style on DSS systems.
The Decision Process

Herbert Simon suggested that the manner in which human beings solve problems, regardless of their position within an organization, can be broken down into three phases:

(11)

Phase I: Intelligence
Phase II: Design
Phase III: Choice

In calling the first phase “intelligence,” Simon borrowed the military meaning, and noted that the first phase in the decision-making process is “searching the environment for conditions calling for decision.” In other words, the problem (or opportunity) has to be first identified. Next, the possible courses of action have to be developed - the “design” phase. Finally, the “choice” phase involves the selection of a course of action from the available alternatives. Simon cautions that each of these phases could itself be a decision-making process. For example, the design phase may require new intelligence. Or, a problem could be comprised of subproblems which have their own intelligence, design, and choice phases. Yet, Simon concludes that:

The three large phases are . . . closely related to the stages in problem solving first described by John Dewey: “What is the problem? What are the alternatives? Which is best?”

(12)

Drawing on Simon's model, the decision process can be viewed as consisting of two major stages: problem finding and problem solving. A few pages back we quoted William Pounds who noted that managers often look at differences of many different sorts in order to find problems. Problem solving requires, first, design of what actions might be taken, then, making a choice and, finally, a review of the results. This could, in turn, lead to finding a new problem (or opportunity).

Role of a DSS

DSS systems, if properly designed, can make a significant contribution at the problem-finding stage to determine the real problem underlying an observed symptom. The example of the CEO of Duracell “drilling down” through layers of data illustrates how a DSS can trace an observed symptom to the root causes so that appropriate corrective action can be taken. By the same token, DSS systems can be quite helpful in the review or post-facto evaluation of the results of past actions to get a better insight into “what happened” and further, “why did it happen?”

In contrast, the design of alternative courses of action to address the problem at hand is essentially a creative task. A DSS can support this task through an analysis of relevant
historical date, if available, to show what worked and what did not work. The decision-maker can benefit from these lessons of history when thinking up alternative solutions to the current problem. An exciting development is the emergence of expert systems that deliver knowledge to support this process. For example, the concept of an electronic marketing advisor to support a product management team planning its promotional program for the coming year is an offshoot of this technological development. (13)

We turn now to the “choice” stage. DSS systems can provide support in one of the following ways:

1. Identifying the best action through an optimizing model like linear programming. The caveat here concerns the applicability of the assumptions of the model to the problem in question.

2. Determining a satisficing solution using heuristics.

3. Performing a “what if” analysis of a finite set of alternatives using a simulation model.

A summary of the above discussion is presented in Exhibit 3.10.

<table>
<thead>
<tr>
<th>Exhibit 3.10</th>
<th>Stage</th>
<th>DSS Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Role of a</strong></td>
<td><strong>Problem-Finding</strong></td>
<td>Ability to trace root causes to</td>
</tr>
<tr>
<td>DSS in the</td>
<td>to find the real problem</td>
<td>enable the proper corrective action.</td>
</tr>
<tr>
<td>Decision</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Process</td>
<td><strong>Problem-Solving</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>Design</strong></td>
<td>Analysis of historical data.</td>
</tr>
<tr>
<td></td>
<td>finding suitable courses</td>
<td>Expert Systems that deliver knowledge.</td>
</tr>
<tr>
<td></td>
<td>of action</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>Choice</strong></td>
<td>Optimization models.</td>
</tr>
<tr>
<td></td>
<td>selecting among them</td>
<td>Heuristic models.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Simulation models.</td>
</tr>
<tr>
<td></td>
<td><strong>Review</strong></td>
<td>Ability to determine “what happened”</td>
</tr>
<tr>
<td></td>
<td>evaluating the results</td>
<td>and “why it happened.”</td>
</tr>
</tbody>
</table>
Structured vs. Unstructured Decisions

We turn back to Herbert Simon to further consider the nature of management decisions. He examined how humans solve problems, regardless of their position in the organization, and distinguished between programmed and nonprogrammed decisions:

Decisions are programmed to the extent that they are repetitive and routine, or to the extent that a definite procedure has been worked out for handling them so that they don't have to be treated de novo each time they occur. Decisions are nonprogrammed to the extent that they are novel, unstructured, and consequential. There is no cut-and-dried method for handling the problem because it hasn't arisen before, or because its precise nature and structure are elusive or complex, or because it is so important that it deserves a custom-tailored treatment. (14)

The terms structured and unstructured were suggested by Anthony Gorry and Michael Scott Morton in place of programmed and nonprogrammed because they relate more directly to the basic nature of the decision task. (15)

A structured decision is one where a decision rule can be specified and even automated, such as applying the Economic Order Quantity or Economic Lot Size formula to inventory reordering decisions. Conversely, unstructured decisions are largely made on the basis of judgment and intuition. An example would be the choice of a person to head an organization. In between the two extremes is the category of semi-structured decisions which Keen and Scott Morton define as follows:

... decisions where managerial judgment alone will not be adequate, perhaps because of the size of the problem or the computational complexity and precision needed to solve it. On the other hand, the model or data alone are also inadequate because the solution involves some judgment and subjective analysis. Under these conditions, the manager plus the system can provide a more effective solution than either alone. (16)

An example of a semi-structured decision is production scheduling. The two minicases at the end of this chapter are intended to provide a feel for how the “manager plus the system” can produce a more effective solution than “either alone.” We should also point out that decisions lie in a structured-to-unstructured continuum; and, as the power and sophistication of information technology advances, decisions previously designated as unstructured are becoming semi-structured, and semi-structured decisions are becoming more structured, well-defined, and even automated.
In concluding this discussion, we reproduce an observation by Anthony Gorry and Michael Scott Morton who, to our knowledge, were the first to use the Decision Support Systems label for information systems to support non-structured decisions. In their view:

/systems that support structured decisions encompass/ almost all of what has been called Management Information Systems in the literature - an area that has had almost nothing to do with real managers, but has been largely routine data processing. (17)

DSS systems are different, and one of the things that is different about them is that they (must) deal with real managers. We turn now to considering an important aspect of the user - his or her approach to the management task, or “management style.”

Management Style

A DSS must be compatible with the user's “style” of management for it to be used. Of course, if the DSS system is not used, it is useless.

What is management style? Consider the following observation of McKenney and Keen, who distinguish between systematic thinkers and intuitive thinkers:

Systematic thinkers tend to approach a problem by structuring it in terms of some method which, if followed through, leads to a likely solution.

Intuitive thinkers usually avoid committing themselves in this way; their strategy is more one of hypothesis-testing and trial-and-error. They are much more willing to jump from one method to another, to discard information and to be sensitive to cues that they may not be able to identify verbally. (18)

If some users are more systematic thinkers than others, this will obviously have an effect on their decision-making and, hence, the information that he or she favors or rejects. Mason and Mitroff put it well:

*What is information for one type will definitely not be information for another. Thus, as designers of MIS, our job is not to get (or force) all types to conform to one, but to give each type the kind of information he or she is psychologically attuned to and will use most effectively.* (19)

This is sound, albeit not easy-to-follow, advice for DSS system designers. All too often, we do not give due consideration to the users' style(s) and run the significant risk of having the system rejected because it is not “useful,” or “appropriate.” Watch for code words like these from users - they may signal a misfit with their decision-making style and be a pre-symptom of a “useless” DSS.
We reiterate the points made in Chapter 1 about management misinformation systems that were summarized in Exhibit 1.3. Information, by itself, is not particularly interesting. Information must be used, and to be truly useful, must become the basis for action. This also entails a system-manager balance to be maintained when positioning a DSS system. Information quality can be upgraded much more easily and rapidly than management process. When only the level of information is raised significantly, it will not automatically lead to better management process. A possible danger is that it could throw the “management system” out of balance and result in poorer decisions because of the confusion and resentment generated by the manager's inability to deal with the more sophisticated information. More likely, the manager will reject the DSS. Organizations must recognize, therefore, that the management system needs as much attention as the DSS to avoid the pitfalls of an imbalance between the two.

Minicase #7

How Do Managers Use Models?

Here is an impression, albeit anecdotal, of how managers actually use models.

The operations research department of a major oil company recently did a survey on the use of mathematical programming in production scheduling at their refineries. Refinery scheduling was a pioneer application of mathematical programming and has been an active research area for 10-15 years. At one refinery the dialog between the interviewer and the local OR analyst went somewhat as follows:

Interviewer: “Do you make regular mathematical programming runs for scheduling the refinery?”

Analyst: “Oh yes.”

Interviewer: “Do you implement the results?”

Analyst: “Oh no!."

Interviewer: “Well, that seems odd. If you don't implement the results, perhaps you should stop making the runs?”

Analyst: “No. No. We wouldn't want to do that!”

Interviewer: “Why not?”

Analyst: “Well, what happens is something like this: I make several computer runs and take them to the plant manager. He is responsible for this whole multi-million dollar plumber's paradise.”
“The plant manager looks at the runs, thinks about them for a while and then sends me back to make a few more with conditions changed in various ways. I do this and bring them in. He looks at them and probably sends me back to make more runs. And so forth.”

Interviewer: “How long does this keep up?”

Analyst: “I would say it continues until, finally, the plant manager screws up enough courage to make a decision.”

What is the plant manager doing here? Before speculating on this, let me recount some experiences with people using MEDIAC, a media planning model developed by L. M. Lodish and myself. (20) The first step in using the model is preparing the input data. This requires a fair amount of reflection about the problem at hand, a certain effort spent digging out numbers, and usually subjective estimates of several quantities. Thereafter, the model is run and a schedule is generated.

The user looks at the schedule and immediately starts to consider whether it makes sense to him or not. Is it about what he expected? Sometimes it is and, if so, usually that is that. Oftentimes, however, the schedule does not quite agree with his intuition. It may even differ substantially. Then he wants to know why. A process starts of finding out what it was about the inputs that made the outputs come out as they did. This usually can be discovered without too much difficulty by a combination of inspection, consideration of how the model works, and various sensitivity analyses.

Having done this, the user decides whether he is willing to go along with the results as they came out. If not, he can, for example, change the problem formulation in various ways or possibly change his subjective estimates. Sometimes he finds outright errors in the input data. Most of the time, however, if he has been careful in his data preparation, he will agree with the reasons for the answers coming out as they did and he has, in fact, learned something new about his problem. The whole process might be described as an updating of his intuition. The model has served the function of interrelating a number of factors and, in this case, not all the implications of the interrelations were evident to him when he started. Notice, incidentally, that he has by no means turned over his decision making to the computer. He remains the boss and demands explanations from his electronic helper.

I believe the same type of process is going on with the plant manager in the earlier example. He is involved in an analysis-education-decision process built around man-model-machine interaction in which the man does not lose responsibility or control and instead of understanding less, understands more.

Minicase #8

How a Manager-Model Interaction Improves the Decision

A lesson learned by one of the authors may help clarify the differences between structured and unstructured decisions - and the cost of not recognizing them. In the late 1950s, business schools provided advanced seminars on the use of the new technique of linear programming for obtaining optimal answers to business problems. This state-of-the-art methodology seemed like magic; the student who was armed with optimal solutions would, of course, rise to the top of the organization, inevitably and rapidly. During one such seminar, the author in question was required to write a term paper illustrating the application of linear programming to a real situation. He and a friend rushed to the treasurer of a major American corporation, with whom he had some connections.

The treasurer felt he had no problems for which linear programming could be at all useful, but admitted that his staff members might. Further discussion with these personnel revealed that one of the treasurer's main jobs was to manage cash balances. His department was linked by Teletype to the company's primary bank, which was in turn linked to 250 bank branch locations in which the company maintained checking accounts. The treasurer examined the balances in these accounts each Friday and decided how to invest this idle cash over the weekend. This was an operational control decision that generated $8 million in interest income. It involved a talented senior executive who saw it as an unstructured task.

The students examined this situation and concluded that linear programming was the obvious solution. This was clearly a structured task. They built a model and tested it using six months of historical data on actual cash balances. The LP solutions would have generated $1,750,000 of additional interest. The students presented their conclusions and generously asked for only 30 percent of the savings. The treasurer asked several questions and said he could not use the model. After the students delicately pointed out that he was old-fashioned, reactionary, narrow minded, and perhaps a little stupid, he asked what the model would do if interest rates in London suddenly rose. The LP formulation would, of course, result in all the company's spare cash being “optimally” shipped to London for the weekend. Since the rising rates might reflect expectations of a devaluation and a consequent attempt by the London money market to prevent funds from suddenly being withdrawn, this would be a foolish and obvious mistake. The LP model would lose in a weekend more than the company made in interest over several years.

The students accepted the point and rushed off to “fix” the model. The treasurer raised a second set of questions, and a third, and then a fourth. The model grew larger and more cumbersome, no real progress was made, and the students stopped their work. The final outcome was a compromise; the treasurer got the original system and the students got no money. He had realized that the model made better decisions than he could for most weeks but that it also occasionally made very bad ones. He found it helpful to run the
model and review its recommendations. If he found no obvious problem or felt there was no special factor to take into account, he would implement the LP's decision. Otherwise, he used his unaided judgment.

The treasurer recognized one of the main points underlying the DSS approach. The system alone or the manager alone was far less effective than the two combined. This semistructured problem could be best solved by delegating to the system routine computations and resolution of interactions too complex for the manager to perform, while leaving the judgments that the algorithm could neither make, nor recognize were needed, to the human. The students learned that there is a middle ground between the analyst's perception that problems are structured and the manager's general assumption that his or her own job is special and cannot be handled by a computer routine.

Minicase #9

A Competitive Bidding Decision Support System
The Use of Judgmental Data to Deal with Uncertainty

Problem Setting

In a competitive bidding situation, it is necessary to consider several factors that are subject to uncertainty:

- What bid the competitor will make
- The likelihood of us getting the contract if our price is above the competitor’s price
- The likelihood of us getting the contract if our price is below the competitor’s price
- The amount of the price differential

Consider a simple situation where we have three alternatives to choose from: bid $100,000, $200,000, or $300,000. Our competitor will also submit one of the same three bids. If we receive the contract, our cost will be $95,000. Further, we believe our stronger reputation gives us an edge over the competitor.

Where is the uncertainty in this problem? How should we handle it? What will help to throw some light on the uncertainty in this problem?

The Decision Problem
The decision problem is quite clear: which bid should we submit: 100? 200? or 300? (We will drop the dollar signs and the trailing zeros to make the discussion easier to follow.)

**Consequences of Each Alternative**

If I bid 100, I could win or lose. If I win, I make 100-95=105. If I lose, I make 0. Similarly I would make 105 if I bid 200 and win, or 205 if I bid 300 and win. In each case, of course I make nothing if I lose. The uncertainty is the heart of the problem. Obviously the uncertainty has relates to our likelihood of getting the contract, which depends on what the competitor will do.

**Getting off the Ground**

Let’s begin with some hypothetical figures, just to get started. If I bid 100 and the competitor bids 100, what are my chances of winning? What little (very judgmental) data that we have indicates that my chances are greater than 50/50. (“Further, we believe our stronger reputation gives us an edge over the competitor.”) How much of an edge? Let’s say our “stronger reputation” translates into a chance that is 20 percent greater than 50/50, or a 60 percent chance of winning, or 0.6 probability. What if I bid 100 and the competitor bids 200? Let’s say I have a 0.8 probability of winning. If I bid 100 and the competitor bids 300? Say 1.0 probability that I’d win.

Putting down similar probabilities for the other combinations of my bid and the competitor’s bid, we might have something like the following:

<table>
<thead>
<tr>
<th>Our Bid</th>
<th>Competitor’s Bid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>0.6</td>
</tr>
<tr>
<td>200</td>
<td>0.4</td>
</tr>
<tr>
<td>300</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**More Uncertainty to be Dealt With**

The above table quantifies the uncertainty in our winning the contract, but under different assumptions of what the competitor will bid. For example:

- If we bid 100, our chance of winning is: 0.6 if the competitor bids 100
- 0.8 if the competitor bids 200
- 1.0 if the competitor bids 300.

What is my “average” chance of winning?

If we know *nothing* about what the competitor will bid, we would assume *equal* chances of the competitor bidding 100, 200 and 300 respectively; and, take a *simple average*. 
to arrive at our chance of winning the contract.

But if we know from our market intelligence that there is a very small probability that the competitor will bid 300; and, that he is a little more likely to bid 100 than 200; then, we would replace the equal chances of the competitor bidding 100, 200 and 300 with something like the following:

Probability of competitor bidding 100: 50% or 0.5  
 200: 40% or 0.4  
 300: 10% or 0.1

Now, our “average” chance of winning the contract is not a simple average, but a weighted average, with the weights being the above probabilities. Our chance of winning the contract now computes to:

\[0.6 \times 0.5 + 0.8 \times 0.4 + 1.0 \times 0.1 = 0.72\]

If we do a similar calculation for the other two possible bids, 200 and 300, we come up with the following:

<table>
<thead>
<tr>
<th>Our Bid</th>
<th>Chance of Winning</th>
<th>Chance of Losing</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>0.72</td>
<td>0.28</td>
</tr>
<tr>
<td>200</td>
<td>0.52</td>
<td>0.48</td>
</tr>
<tr>
<td>300</td>
<td>0.245</td>
<td>0.755</td>
</tr>
</tbody>
</table>

**What Should We Bid?**

One approach would be to choose the alternative with the highest probability of winning the contract. With the above soft data, it would be 100. Would it be different if the probabilities of the competitor bidding 100,200, and 300 are 0.1,0.2 and 0.7 respectively?

This approach ignores the payoff associated with each bid. After all, we make only 5 with a bid of 100, but much more, 105, with a bid of 200. The latter bid has a respectable chance of winning - more than 50%. How can we factor in the payoffs with the chances of winning the contract?

Another approach that could be considered looks at the “average” payoff that would be realized for each bid. The situation here is as follows:
If We Win | If We Lose
---|---
Our Bid | Payoff | Chance | Payoff | Chance
100 | 5 | 0.72 | 0 | 0.28
200 | 105 | 0.52 | 0 | 0.48
300 | 205 | 0.245 | 0 | 0.755

The “average” payoff for each bid should not be calculated as a straight average of the two payoffs corresponding to “If We Win” or “If We Lose,” but as a weighted average again, with the weights being their respective probabilities. This results in the following table:

<table>
<thead>
<tr>
<th>Our Bid</th>
<th>Weighted Average Payoff</th>
<th>Chance of Winning Contract</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>3.6</td>
<td>0.72</td>
</tr>
<tr>
<td>200</td>
<td>54.6</td>
<td>0.52</td>
</tr>
<tr>
<td>300</td>
<td>50.225</td>
<td>0.245</td>
</tr>
</tbody>
</table>

Now, what should we bid? The approach of picking the alternative which maximizes the weighted average payoff would lead to a bid of 200.

**Discussion Questions**

1) What bid would you select? Explain your rationale.

2) How would you interpret the weighted average payoff figures calculated in the case?

3) What is the limitation of the approach that maximizes weighted average payoff?

4) Carry out a sensitivity analysis of the soft data inputs to see their impact on the bid that you selected in response to Question 1.

5) Outline the type of market intelligence you would collect to improve the quality of your soft data inputs.
REFERENCES


(8) Quoted to one of the authors in the course of a consulting assignment.


(12) The writer quoted by Herbert Simon is John Dewey, the preeminent American philosopher. Dewey was often referred to as “the dean of American philosophers,” and was perhaps the greatest single force in re-shaping our conceptions of education. His best-known work is *Human Nature and Conduct*.


