

# Decision Support and Problem Formulation Activity

David Paradice

Florida State University, USA

## INTRODUCTION

While decision choices are certainly important and warrant appropriate attention, early stages of the decision-making process may be even more critical in terms of needing adequate support. The alternatives from which a decision maker may be able to choose are integrally tied to the assumptions made about the problem situation. Consequently, decision support systems (DSSs) may be more effective in helping decision makers to make good choices when support for problem formulation is provided. Research validates the notion that support for problem formulation and structuring leads to better decisions. This article explores this concept and looks at opportunities in emerging software trends to continue development of problem formulation support in DSS-type settings.

## BACKGROUND

From its inception, the domain of DSS has focused on providing technological support for decision-making processes in ill-structured environments. Simon's (1977) model of decision-making processes has been a cornerstone of DSS design since the inception of the decision support movement. Simon outlined four processes that he believed account for most of what executives do:

The first phase of the decision-making process—searching the environment for conditions calling for decision—I shall call *intelligence* activity (borrowing the military meaning of intelligence). The second phase—inventing, developing, and analyzing possible courses of action—I shall call *design* activity. The third phase—selecting a particular course of action from those available—I shall call *choice* activity. The fourth phase, assessing past choices, I shall call *review* activity. (Simon 1977, p. 40)

Human nature being what it is, the success or failure of choices made in particular decision-making situa-

tions often gets the most attention. The early days of the DSS movement implicitly focused most heavily on the choice phase of Simon's model. At the beginning of the DSS movement, DSSs were still constructed from programming languages such as FORTRAN (formula translator) or PL/1 (programming language 1), although DSS environments containing interactive modeling languages were soon developed. In these environments, construction of the model that would form the basis of the decision process often fell on technical experts with little or no direct stake in the decision outcome. These experts simply translated a model specification into the appropriate programming code and returned a "system" to the ultimate decision makers. The actions of the decision makers involved executing the model, typically with varying combinations of input values, so that various scenarios could be examined to determine which set of input values led to the most desirable outcome. In other words, the function of the user was to choose one of several alternatives. In some cases, claims were made that the users had designed a solution and consequently that the DSS had supported the design stage of Simon's model. Closer examination, however, shows that the design stage of Simon's model was executed in the specification of the model to be programmed.

The power of the model was well documented in the work by Pounds (1969). Pounds learned that problem finding is essentially the recognition of a difference between reality and what a decision maker expected, where expectations were typically based upon some preexisting model. The model may be the decision maker's own mental model, based on historical events or personal experience, or it may be a model constructed by someone else. Regardless of their origin, the models used by decision makers were critical in their efforts to recognize and address problems. Pounds found that even though business models were quite naïve compared to decision-making models in scientific domains, model-building techniques were making significant contributions to management effectiveness.

Models are comforting because they provide a means of removing uncertainty. Humphreys and Berkeley (1985) note seven types of uncertainty in the process of conceptualizing decision problems. Decision theory can adequately account for only four of the uncertainty types. These uncertainties are primarily related to the likelihood of outcomes and events. Procedural uncertainty, such as specifying the relevant issues, what information to seek, and how to structure it, is not addressed by decision theory. When a decision model is constructed, much of the procedure for attacking the problem is then specified. One collects the appropriate data, executes the model, and assesses the results. These activities are much less cognitively straining than the construction of the model.

Of importance here is that these models, once specified and constructed, rarely have been examined at later times to determine whether they remain accurate models of reality. Decision makers (typically managers) specify a model to be constructed based on their experiences and perceptions, and programming professionals translate this specification into a functioning DSS. Once a model is producing acceptable results, rarely has anyone asked later, “Is this model still correct?” The assumptions underlying the model specification have been assumed to be accurate still. This is a critical aspect of DSS, for the alternatives from which a decision maker may be able to choose are integrally tied to the assumptions made about the problem situation.

Because decision makers “satisfice” (Simon, 1976), they will naturally be driven to consider ranges of feasible alternatives rather than choosing maximizing or optimizing behavior. Simon identified premises (i.e., assumptions) as the most fundamental unit of analysis in decision making. According to Simon, the premises that one recognizes are the most relevant to a decision situation. These control the alternatives considered. Consequently, premises dictate behavior. Schein (1985) has concluded that understanding a culture and a group’s values and overt behavior requires understanding the underlying assumptions. These are typically unconscious but actually determine how group members perceive, think, and feel.

Churchman’s (1971) examination of inquiring systems most clearly illustrates the fundamental dependence that models have on assumptions. Churchman developed the notion of inquiring systems—systems that create knowledge—by examining the design of

such systems based on the philosophies of five Western philosophers. Beginning with Leibnitz and working through the philosophies of Locke, Kant, Hegel, and Singer, Churchman showed that the basic assumptions regarding how knowledge is created drive all other aspects of the system.

In the Leibnitzian system, formal logic is the guarantor of knowledge. Consequently, inputs to the system must be well formed and amenable to formal rules of logical conclusions. Lockean systems depend on consensus; therefore, agreement on labels and properties of objects becomes critical. Kantian systems allow for multiple realities, with the best fit of data to model determining how conclusions are drawn. Hegelian systems depend on the dialectic. It is in these systems that overt examination of the assumptions of different realities occurs. Singerian systems rely on continual measurement and a “sweeping in” of new model variables to refine models.

Churchman’s students have certainly recognized the importance of assumptions. Mason (1969) and Mitroff, Emshoff, and Kilmann (1979) were early leaders in recognizing the need to identify assumptions in models. Mason recommended dialectic processes as a way to surface assumptions for review and reconsideration. He suggested this process could lead to the identification of new and relevant assumptions that strategic planners should consider. Mitroff and his colleagues demonstrated that Churchman’s and Mason’s ideas formed a good basis for formulating ill-structured problems.

Another of Churchman’s students, Russell Ackoff (1981), has argued that examination of the models that are developed in decision-making situations leads to important and valuable knowledge. He argued that it is precisely due to making explicit that which is not normally made explicit (i.e., the assumptions of the model) that improvement of the decision-making system is possible. The assumptions should be made open for examination and criticism by decision makers and other researchers.

Later, Mitroff and Linstone (1993, p.15) built on Churchman’s work to define a “new way of thinking.” They argue for explicit consideration of multiple realities when dealing with complex problems. Their basic premise is that no one perspective of a complex situation will ever embody all of the assumptions of all of the stakeholders involved.

The importance of assumptions is not espoused solely by Churchman and his students. Huber (2004,

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