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ABSTRACT

MULTIPLE OBJECTIVE DECISION SUPPORT FOR FARM MANAGERS

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The principal issue addressed in this study is the conceptual framework for design of effective decision aids for farm managers. The concept of decision support emphasizes the design of tools which extend human capacities, aiding documented weaknesses in decision making while supporting intuitive human abilities.

Rationalist and Behavioralist paradigms differ with respect to the role of human cognition, acceptable research context and procedures, and the operational objectives of decision research. Behavioral researchers have documented common violations of rationalist assumptions. These violations reflect the limited information processing capacity of the human cognitive system, which is characterized by selective perception, serial processing of data, limited computational capacity, limited short term memory and dependence on context variables. This study outlines certain areas of decision support which permit limited integration of the two perspectives, and the impact of characteristics of and interactions between decision situations, decision makers and decision tools.

Behavioral research has emphasized the importance of multiple objectives in management decisions. Interactive multiple criteria decision making (MCDM) procedures offer the prospect for integrating optimization procedures with evaluation of decision prospects along multiple dimensions. Interactive Multiple Goal Programming (IMGP) is

selected as a technique promising such a synthesis, and a decision aid for support of land rental decisions of cash grain operators was designed and implemented. Risk and return objectives were modeled as competing objectives in the Goal-directed Search Model (GOALDIR). Elicitation procedures were designed to obtain data for farm-specific application of the aid, including probability elicitation. Preliminary field testing of the aid indicated that:

1. Elicitation procedures to obtain farm-specific data may be unacceptable because they consume considerable amounts of the manager's time.
2. The probability elicitation procedure used is feasible, but its reliability is untested.
3. Subjects found graphic representations easier to interpret than numeric data.
4. Subjects found explicit consideration of multiple objectives reasonable, but were confused by optimization procedures.

A decision support research agenda is proposed to investigate elements of synthesis between behavioral and rationalist principles. Particular benefits are seen from integration with respect to probability elicitation, preference relationships, decision rules and graphical representations. Frameworks for evaluation must be developed to accelerate progress in decision aid design.

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Finally, the traditional acknowledgement to one's spouse seems inadequate when the spouse has also gone through the same long process. Judy, we survived.

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CHAPTER I

INTRODUCTION

1.1 Motivation of the Study

This research has evolved from a concern that the apparently boundless optimism with which many agriculturalists view new developments in decision theory and computer technology ignores fundamental gaps in knowledge of management decision processes. The set of formal principles which economists have developed and utilized with some success for prediction of aggregate variables and for prescriptions for economic policy may be an insufficient basis for advice to individual farm managers. Although there is little concrete evidence to evaluate the impacts of training in decision-theoretic principles, such impacts are not immediately obvious to an observer of farm manager behavior.

One reaction to managers' slow adoption of sophisticated decision techniques is to impugn the vision and judgement of farm operators. Managers are 'stubborn', 'fixed in their ways', or 'don't know what is in their best interest'. A contrasting perspective is adopted in this research. There is intelligence and purpose in most decisions of farm operators. The obstacles to better decisions are to be found principally in poor understanding of current decision processes and of managers' perceived constraints and objectives. If more careful attention is paid to these factors, and conceptual frameworks and operational techniques are modified accordingly, progress in decision support techniques for farm managers can be expected.

A related motivation for the research is concern for the role of computer technology in support of farm management decision making. Automation of many management functions is currently feasible with extremely fast and powerful electronic technology, and some agriculturalists contend that computerization brings unambiguous benefits for farm businesses and families. The position taken here is that computers and humans each have relative advantages for some operations and types of decisions. Efforts should be devoted to description of decision processes, determination of relative strengths and weaknesses of humans and computers in different types of decisions and assistance for managers to extend their capabilities with decision tools which may or may not include computer technology. The overriding motivation of such a perspective is to support manager decision making, not displace it.

1.2 An Evolutionary Approach to Decision Support Research and Design

The current study does not follow the traditional research pattern of problem definition, literature review, model development, empirical testing. The 'problem' examined here is the design of effective decision tools for farm managers. The research approach is that variously described in the decision support literature as 'evolutionary', 'adaptive' or 'iterative' design. The objective of this approach is not a polished, finished decision aid, but development of an aid which embodies promising concepts of decision support, and which can be expeditiously implemented, evaluated and reformulated on the basis of research experience. The principal objective of aid development is not analysis of model solutions, but analysis of concepts and techniques which integrate conceptual frameworks of decision making, which may be isolated and more rigorously tested, and which open new avenues for applied decision research.

The current orientation for decision research is not derived from a single theoretical perspective. No single discipline provides an adequate basis for management decision support research. Instead, a synthesis of elements from contrasting perspectives are sought. Two competing paradigms of decision making are defined and investigated in Chapter 2, and their relative advantages for supporting individual decision makers are discussed. The research literature of the two camps (not surprisingly) emphasizes the importance of different concepts and methodologies for describing decision processes. Issues which are particularly emphasized by the school defined as 'rationalist' are optimization, quantification and the conceptual distinction between preferences and beliefs. Particularly emphasized by the contrasting 'behavioral' school are limited cognitive information processing capacity, multiple preferences and aspirations in decisions, the practical limits of rational decision making and the importance of feedback and learning. Issues which are generally accepted as equally important in both paradigms include the assumption of fixed preferences (at least as an operational construct for research) and the quantification of beliefs as probabilities.

Both decision paradigms are primarily concerned with unaided individual decision making. An applied research perspective of decision support has developed (concurrently with improvements in computer technology) which contends that computer-based aids can improve decisions. Some researchers have focused their investigations on the computer tools themselves, with relatively little attention to individual characteristics of users. Other researchers contend that individual problem-solving style is an important determinant of success in decision aid usage. Chapter 3 examine the relatively new and unstructured literature on the interaction between characteristics of decisions, individuals and aids.

To synthesize and operationalize the decision concepts of the contrasting paradigms, a third body of literature is examined in Chapter 4. Given the relative emphasis on optimization procedures by one school and on multiple objectives by the other, multiple objective mathematical models are examined that use conditional optimization for solution search. Interactive methods which iterate towards solutions preferred by the decision maker in response to articulated preference information are shown to operationalize many concepts from both paradigms of decision making. One multiple objective technique, the Interactive Multiple Goal Programming (IMGP) method, promises considerable flexibility for such integration.

To evaluate the feasibility of this technique for implementation as a real time microcomputer decision aid, a decision problem was sought which is perceived by farm operators as important to their business, for which many operators may desire assistance, and which is characterized by multiple attributes or objectives (see Chapter 4). The cropland rental decision for cash grain farms was indicated by operators at extension meetings as important, and was chosen for aid development. The consequences of financial stress in the cash grain sector have included a more active land rental market (as some farmers have liquidated their holdings) and a desire for more careful consideration of existing and potential rental agreements. Many operators must improve their revenues to relieve debt burden or compensate for lower government support, but are hesitant to make risky rental decisions which could jeopardize their financial viability. The risk and return preferences of managers can be modeled as distinct objectives in a decision aid implementation of the IMGP technique. Although certain problems could be foreseen with this implementation (such as the effect of rotation cycles and the 'lumpiness' of rental decisions), the principal characteristics desired for a case study of decision aid design were satisfied. Chapter 5 documents development and field testing of the goal-directed search (GOALDIR) decision aid.

The final chapter completes a cycle of the evolutionary approach to decision support research. Principal conclusions from the dispersed literature of decision theory, decision support and multiple criteria modeling, from the model development and from the field testing are discussed. The decision support research agenda described in the final section constitutes the last phase of the current research cycle (and the first phase of the next).

CHAPTER II

PARADIGMS OF DECISION MAKING

2.1 Introduction

Kuhn defines a paradigm as a set of ". . . universally recognized scientific achievements that for a time provide model problems and solutions to a community of practioners." (1970: viii) A paradigm is thus a professionally acceptable network of concepts, theories and methods used to investigate a certain body of phenomena. The following chapter first examines the empirical and conceptual relationship between management and decision making, and proceeds to describe and analyze two contrasting research paradigms with respect to the phenomenon of individual decision making. Each paradigm offers different evidence concerning decision making ability and particular approaches to aiding decision makers. The paradigms generally do not take into account the insights offered by the other perspective. The chapter concludes with a short discussion of some elements which may provide a basis for integration of the two perspectives at the level of individual decision support.

2.2 Management and Decision Making

What is farm management? Initially, a clear distinction must be made between the practice of farm management (as an empirical phenomenon) and the study of farm management (as a conceptual perspective of the phenomenon). The former connotation pertains to the actual behavior of farm operators, while the latter pertains to the analysis of empirical phenomena through the lens of a research paradigm. Researchers sometimes do not clearly distinguish between the practice of farm management (what is) and their particular disciplinary and logical perspective of 'correct' management (what should be). For example, textbooks on the subject often define farm management as ". . . the subdivision of economics which considers the allocation of limited resources within the individual farm.." (Heady and Jensen 1954: 6).

A definition of farm management more closely corresponding to the practice of farm management is given by Dillon. Farm management is:

> The process by which resources and situations are manipulated by the farm manager in trying, with less than full information, to achieve his goals. (Dillon 1980: 258)

Several important elements should be noted in this definition. First, farm management is clearly defined as a process, with no specified beginning or end. The definition emphasizes that managers act with incomplete information about the current state of the system managed, about functional relationships and possibly about the satisfaction which can be expected from actions. Finally, the indication that farm managers may attempt to achieve goals other than profit maximization illustrates that a multi-dimensional perspective may be necessary to model farmers' decisions. This definition makes the generalization that a single person decides and executes managerial actions, an assumption which has become progressively less tenable as farm spouses and other family members provide more input to both routine and strategic management decisions. The goals sought by the management group may thus be a less than perfectly reconciled set of personal and interpersonal preferences.

What distinguishes 'management' from 'decision making'? Conceptually and empirically, management performs functions extending beyond the reflective and anticipatory role of making decisions. A typical conceptual framework of management functions is given by Johnson and Halter (1961):

1. Problem definition
2. Observation
3. Analysis
4. Decision
5. Execution
6. Responsibility bearing

Decision making as conceptualized includes at least the analysis and decision functions, and may be defined to include as well the problem definition and observation functions. Many researchers equate management with decision making. Johnson states, "While all of the managerial functions depend on each other, the decision function is so crucial that management is sometimes referred to as decision-making." (1977: 18) A prominent text on decision analysis (Anderson et al. 1977) does not mention management in its index. Management functions, however, include execution and control processes not generally considered within conceptual frameworks of decision making or decision research experiments.

Although clearly acknowledging the critical importance of all management functions in the farm firm, this study is limited to analysis of individual decision making. The general conceptual scheme of decision functions accepted here is the widely recognized framework of Simon (1965), who identifies the following phases of decision making:

1. Problem identification. In this stage, the decision maker may progress from a vague sense of dissatisfaction concerning the present situation with respect to preferences, to an identification of the source of dissatisfaction and causal linkages to other elements of the current situation.

2. Design. In this stage, the decision maker is involved in generation of alternative actions which may be both feasible and promise to change the current state to another thought to better satisfy preferences.

3. Choice. Alternative actions are compared either against each other or against some criteria, and an alternative may be chosen.

There are several competing paradigms of decision research, each with differing theoretical foundations, research methods and research objectives. The two schools of thought examined here are alternative treatments of the same phenomena, and may be labeled the Rationalist and the Behavioralist schools of thought. Other terms used in the literature for the rationalist school include decision-theoretic, normative, prescriptive and axiomatic. The behavioralist school is also sometimes called empiricist or descriptive. Most of these terms carry more emotive than descriptive meaning, and the labels are used here without endorsing any such connotations.

Both approaches examine the efficiency with which means are utilized to reach goals, and accept the positivist or conditionally normative view that nothing scientific can be said about questions of intrinsic goodness or badness of goals. No intrinsic preference is attached to means, and both tend to regard goals or preferences as fixed for purposes of the research, although behavioral research is at least open to examinations of the dynamics of preference (March 1978). The contrasting perspectives are both theories of 'innocent' decision making, disregarding any influence of other people's preferences in the decision maker's choice process. They attempt to extract individual decision makers from the social structures, organizations or groups within which most decisions are actually made. In general, the common research focus of these perspectives is goal-seeking behavior or means-ends analysis (Checkland 1985).

The approaches differ principally with respect to the role of human cognition, acceptable research context and procedures, and the operational objectives of decision research. Behavioralist investigators place the structure and mechanisms of cognition at the center of decision research, while rationalist investigators do not attempt to probe unseen cognitive processes. Research methods encouraged and acceptable within one framework are unlikely to receive acceptance within the other. By describing actual decision processes in considerable contextual detail, behavioral research attempts to induce general principles of how decisions are made. Rationalist research, on the other hand, applies logical principles to a broad range of decision types and contexts with the objective of predicting or prescribing decisions. The following sections describe the two perspectives in more detail and examine issues of dispute.

2.3 The Rationalist Perspective

Rationalist decision research seeks to describe, predict or prescribe the choice of an optimal alternative from a set of alternatives. Decision makers are assumed to have an internally consistent ordering of preferences whereby outcomes can be compared in terms of subjective value and a decision rule by which a preferred alternative-consequence can be selected. On the basis of known preferences and expectations, the decision maker examines alternatives and their consequences in view of perceived constraints, orders the consequences in terms of their subjective worth, and selects the best alternative. Choices which conform to a minimal set of logical assumptions are formally representable in a real-valued function of preference relations. There is no explicit treatment in the theory of a process whereby alternatives are developed or discovered and their consequences determined, how probabilities are formulated, or how preferences themselves are established or modified.

The appeal of rationalist models of decision making is principally their consistency with rules of logic, their parsimony and generality in depicting decision situations, and their prescriptive value in generating solutions in accordance with the measured values and preferences of decision makers. Research is driven by what Blaug (1980) calls a 'hypothetico-deductive method', in which theoretical implications generate hypotheses which are then tested empirically. Rationalist models are principally outcome-oriented, evaluated by their logical consistency and comparison of empirical results with the calculated 'best' solution. The process of individual decision making consists of implementation of the logical process, with no explicit regard for what might be called 'intuitive' human decision processes. The primary purposes of rationalist research, therefore, are prediction of actions by assumedly rational decision makers and prescription of actions which <u>should</u> be chosen by a decision maker with given preferences. Prediction may be limited to decisions of aggregate or of 'representative' decision makers. There is relatively little emphasis on the descriptive validity of the theory; that is, whether the theory reasonably describes any particular decision making process and how actual decisions may conflict with those suggested by the theory. Indeed, one perspective within the rationalist school contends that it is irrelevant whether decision makers consciously follow the logical processes implied by rationalist assumptions, only that the decision is made 'as if' they understood logical principles (Friedman and Savage 1948).

Modern rationalist decision theory, with origins in the Bernoulli concept of utility, constitutes an attempt to formalize human decision processes in non-deterministic environments. If the environment is considered deterministic and preferences are fixed (as in the static theory of economics), there is no 'decision' in the normal sense of the term. Instead, measurement of known alternative-outcome pairs and comparison against the individual's preference structure suffices to predict actions. The first formal set of axioms linking probability and utility was developed by von Neumann and Morgenstern (1944) as the Expected Utility Hypothesis (EUH). The EUH is based upon the assumptions that: 1) individuals have a stable and consistent set of preferences (evaluative judgements about the world); 2) individuals have a consistent set of expectations about events (predictive judgements); and 3) preferences and expectations are independent (no wishful thinking). (Hogarth 1980)

The following are logical axioms underlying the Expected Utility Hypothesis:

1. Ordering: All pairs of alternatives can be compared by either a preference relation or an indifference relation. For any risky outcomes **A** and **B**, individuals will consider **A** preferred to **B**, **B** preferred to **A**, or will be indifferent between **A** and **B**.

2. Transitivity: Preference relations are transitive across alternative-outcome pairs. If **A** is preferred to **B**, and **B** is preferred to **C**, then **A** is preferred to **C**.

3. Continuity: If transitivity applies across three alternatives, then for some unique probability (**p**), an individual will be indifferent between choices of the intermediate outcome with probability **p** on the one hand, and an exhaustive probability mixture of the most and least preferred outcomes (weighted by p and 1-p) on the other hand. If **A** is preferred to **B**, which is in turn preferred to **C**, then there exists some probability **p** such that the individual is indifferent between **p*B** and **(p*A + (1-p)*C)**.

4. Independence: Pairwise preference for risky outcomes is not affected by identical probability or outcome changes in the original outcomes. If **A** is preferred to **B**, then **(p*A + (1-p)*C)** is preferred to **(p*B + (1-p)*C)**, where **C** is some other outcome. (Schoemaker 1982)

The representation of beliefs or expectations for both repetitive and unique events in a manner consistent with mathematical probability is also presumed in EUH and in all of rationalist theory. The work of Ramsey (1931) and DeFinetti (1937) developed the concept of personal or subjective probability. These beliefs are purely subjective, based upon any experience, rules of thumb, historical data or other factors which the decision maker wishes to use to develop expectations. Such expectations expressed quantitatively as probabilities, however, are required to conform to the criterion of coherence (Savage 1954). This requires that the quantitative expression of beliefs (subjective probabilities) are mutually exclusive and exhaustive, and that assessments of disjunctive and conjunctive events conform to the addition, product and equivalence rules. Subjective probabilities are not required to agree with any external standards of likelihood or expectation, but they are expected to express the individuals's degree of belief that particular events will occur. It bears repeating that subjective probabilities must be independent of preferences for outcomes.

Although rationalist theory does not indicate how expectations are or should be formulated, it does state that dynamic revision of probability estimates upon receipt of new information should be carried out in a manner consistent with Bayes' Theorem. This theorem presents a logical framework to predict or prescribe probability revision. Generally, it states that the new probability estimate (expectation or belief) that a particular outcome will occur should equal the product of the prior probability estimate times the likelihood that the new information is correct, the result being normalized between 0 and 1. Bayes' Theorem does not indicate how information of less than complete reliability should be treated, nor how information should be utilized which is not expressed as a probability.

Although not strictly required by the EUH, utility functions are usually considered uni-dimensional, with the single argument of wealth or income. In some cases, however, a multi-argument utility function is assumed, but all arguments other than income or wealth are assumed to be held constant. In response to observed anomalies in decision making, the rationalist approach has been extended to Multiple Attribute Utility (MAU), functions with multiple, incommensurable preferences. This will be discussed below as one aspect of the response to behavioralist criticisms.

2.4 The Behavioralist Perspective

> Normative models gain their generality and power by ignoring content in favor of structure and thus treat problems out of context. However, content gives meaning to tasks and this should not be ignored in trying to predict and evaluate behavior. (Einhorn and Hogarth 1981: 61)

The focus of behavioral decision research is the decision process itself, that is, the strategies used to select, combine or alter information and reach decisions within specific types of decision contexts. Since cognition is unobservable, research efforts center on the observable selection of information from the environment, which may reveal characteristics of the decision process. Principal issues investigated include assessment of uncertainty and expectations assessment of uncertainty and expectations (Hogarth 1980), decision rules (Svenson 1983), information search (Bettman and Jacoby 1975) and multiple attributes or objectives (Fishburn 1978). In addition, much behavioral research has involved comparison of the performance of human decision makers against the implications of rationalist assumptions, and has raised important questions about observed discrepancies. Behavioral decision models stress the multiplicity and ambiguity of goals and the inconsistency of judgements resulting from inherent limitations on human ability to perceive, combine and evaluate information about the decision situation. Humans, it is argued, make frequent and systematic errors in assessment of expectations and logical operations, and apply rules which generate sub-optimal solutions.

Behavioral decision theory is much less formalized and more empirically based than its rationalist counterpart. It is constructed rather more on the inferences of past research results than on the implications of a formal theoretical framework. Development of behavioral decision theory can reasonably be said to have occurred in parallel and in reaction to developments in rationalist theory. Most behavioral research attempts to construct a more realistic descriptive model of how limited human memory and computational capability interact with complexities of the decision problem and its context.

> The decision makers in behavioral models lack some of the relevant knowledge; they may, in addition, fail to make use of some of the knowledge which they do have, or to which they at least have access. Their problems are incompletely structured, and the variables of interest are incompletely specified. (Loasby, 1976)

The behavioralist approach stems principally from the seminal work of Herbert Simon and his colleagues. Although the behavioralist argument has deepened and extended to areas not initially contemplated, the cornerstone of the framework is that humans are not capable of the cognitive operations implied by the rationalist perspective. All decision making is behavior within cognitive constraints. Simon (1976) contends that humans can be viewed as limited capacity information processing systems. The cognitive processing equipment is basically serial in organization, that is, it can handle only one operation at a time, and solution requires a large number of operations. The analogy to a computer is made explicit:

> Man and computer can both recognize symbols (patterns), store symbols, copy symbols, compare symbols for identity, and output symbols. These processes seem to be the fundamental concepts of thinking as they are of computation. (Simon 1976: 71)

The minimal components of a general information processing system are:

1. Memories containing discrete symbols
2. Receptors for sensing the environment
3. A set of primitive operators which interpret sensory input and transform memory contents
4. A set of rules which combine operators and memories to generate whole programs for information processing.

Therefore, a valid explanation of an observed behavior consists of an external (to the individual) program of data, rules and operators which reproduces the observed behavior. (Newell et al. 1958)

The principal functional characteristics of the human information processing system are:

1. Selective perception or limited attention. For example, Hogarth (1980) reports it has been estimated humans perceive only 1/70th of the contents of the visual field at a time.

2. Sequential processing of data. The mechanisms of the cognitive system operate serially, performing only one function at a time.
3. Limited computational capacity. The system has only limited capability to perform numerical functions.
4. Limited short term memory. Miller (1956) concludes that humans can retain in active memory only five to nine 'chunks' of information.
5. Dependence on context variables. Through experience, humans construct mental patterns of co-occuring variables. They use these patterns to select information in decision situations characterized by little direct information about the decision variables.

These information and computational restrictions limit both the number of alternatives that can be simultaneously considered and the amount and accuracy of information that is actually considered in the decision situation. As a response to cognitive information processing limitations and overwhelming information input from the environment, humans employ functional processes such as sequential and selective attention to stimuli and to one's own goals, 'efficient forgetting' of information, dependence on information from the context of a problem, and cognitively simple decision rules ('rules of thumb' or heuristics). Application of these procedures in many situations (even relatively simple ones) will result in decisions which are sub-optimal when compared to rationalist models. Simon points out the severe cognitive demands on the human decision maker or 'organism' implied by rationalist models:

> The organism must be able to attach definite payoffs (or at least a definite range of payoffs) to each possible outcome. This, of course, involves also the ability to specify the exact nature of the outcomes--there is no room in the scheme for 'unanticipated consequences'. The payoffs must be completely ordered--it must always be possible to specify, in a consistent way, that one outcome is better than, as good as, or worse than any other. And, if the certainty or probabilistic rules are employed, either the outcomes of particular alternatives must be known with certainty or at least it must be possible to attach definite probabilities to outcomes. (Simon 1979: 10)

Because of information processing constraints, decision makers seldom search all the possible alternatives for the optimal solution. Instead, alternatives are searched until one is found that is 'good enough' according to the decision maker's preferences. This 'satisfycing' principle is probably the best known of the concepts associated with behavioral theory.

Behavioral researchers do not attempt to depict the human decision maker as cognitively handicapped. Human decision making has many strengths which may never be matched by mechanical devices. Very complex problems can be solved even though they are not completely understood. Intuition and creativity are certainly strong points of cognition. Situations in which rational procedures are inappropriate also come to mind. If decisions are required quickly or if the decision is of limited importance, logical considerations may be too costly. Humans often do the best they can, forming interpretations based upon experience when faced with decisions in which preferences, information, constraints and possible alternatives all may be ill-defined. Further, simple rules of thumb may in many cases generate solutions which are not substantially different from optimizing solutions.

Decision researchers who investigate biases in human information processing argue that biases reveal much about the psychological processes that govern decision making. In addition, research on biases indicates which principles of rationalist decision making are counter-intuitive or 'unnatural', and suggests procedures which might improve the quality of decision making.

Recent developments in behavioral research have criticized the information processing approach as inadequately representing decision processes. Most of these developments have implications far beyond the limited problem solving orientation of Simon's framework. Certain research suggests that choice may precede search and evaluation, that is, action and feedback are sometimes substituted for classical decision making (March and Olsen 1976). Personal decision habits have also been studied in a wide range of cognitive style studies. This research emphasizes inherent tendencies by individuals to approach decisions in a certain manner rather than the information processing emphasis on cognitive capacity (Keen 1978). Neisser (1963) contends that the sequential processing concept of the information processing framework is the result of an inappropriate analogy of human to computer processing. The concepts of short term and long term memory have also been challenged (Glass et al. 1979). Another broad area of behavioral research includes cognitive schemas or scripts, which are coherent sequences of events expected by the individual on the basis of past experience (Abelson 1976). Many of these developments do not imply willful choice or goal-seeking behavior in the same sense as information processing or rational choice models, and will not be pursued here [1].

2.5 <u>Observed Errors in Decision Making</u>

A primary issue of behavioral research has been evaluation of humans' ability to estimate uncertainty in terms of probabilities. Subjective probabilities are quantitative expressions which reflect the individual's degree of belief about an event (Ramsey 1931). Expression of beliefs as probabilities provides an interpersonal language for expressing uncertainty, and through the probability calculus allows analysis of the logical relationships between uncertain events. It is not appropriate to assume that individuals carry around a complete set of probability distributions in their minds. Instead, a set of vaguely formulated beliefs are combined with information from memory and information from the environment to give a probability estimate. Obviously issues of probability elicitation methods cannot be separated from issues of belief formation and use in decision making. Of particular concern is whether probability elicitation methods provide a valid representation of beliefs and whether probabilities are stable, consistent and in accord with the rules of probability.

The principal objectives of most behavioralist studies of probabilistic judgements has been to compare behavior to that implied by logical axioms and to determine how underlying cognitive processes are affected by the interactions between the decision characteristics

1 For a discussion of these developments in cognitive science, see Gardner 1985).

and cognitive limitations of the decision maker. Hundreds of experiments have been carried out with non-expert and experts in laboratory settings[1]. The performance of non-expert subjects in laboratory settings tends to show that ". . . man is not a good statistician." (Keen 1977: 45)

In simple tasks, such as estimating repetitive series like drawing white or black balls from an urn, people seem to judge probabilities fairly well (Peterson and Beach 1967). However, in research involving unique events in which relative frequency has less meaning, people tend to perform very poorly (Lichtenstein et al. 1977). In particular, people tend to be overconfident in their probability assessments, ignoring such factors as sample size (Tversky and Kahneman 1971), regression towards the mean (Kahneman and Tversky 1973) and the reliability of their data base (Peterson 1973). People also seem to have a very poor intuitive sense of variation and covariation (Kahneman and Tversky 1972). Individuals tend to overestimate the probability of conjunctive events and underestimate the probability of disjunctive events (Bar-Hillel 1973). Individuals tend to recall their predictions as better than was the case (Fischoff and Beyth 1975) and seem to retain memory for successes while forgetting failures (Langer and Roth 1975).

A substantial body of research has been dedicated to comparison between Bayesian probability estimates and estimates given by research subjects in experimental tasks. Edwards (1968) termed humans

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1 For reviews of this extensive literature, see Spetzler and Stael von Holstein 1975, Lichtenstein et al. 1982 or Wallsten 1983.

`conservative Bayesians' from the results of his studies, which showed that individuals underweight new information. On the other hand, a considerable number of experiments have found that individuals often ignore prior probabilities in favor of new information (Tversky and Kahneman 1980). The errors in Bayesian tasks have led most behavioralist researchers to conclude that ". . . in his evaluation of evidence, man is apparently not a conservative Bayesian: he is not a Bayesian at all." (Kahneman et al. 1982).

The evidence is less pessimistic in studies with experts (persons who have substantive knowledge of the topic or with training in probability theory). These studies have included subjects such as weather forecasters (Murphy and Winkler 1977), physicians (Lusten 1977), psychologists (Beenen 1970), security analysts (Bartos 1969) and military intelligence officers (Johnson 1977). Given outcome feedback, experience with probabilities, substantive knowledge about the topic and a reliable elicitation technique, experts can provide relatively accurate probability estimates (Wallsten and Budescu 1983). Performance in the absence of one or more of these elements may not be better than that of non-experts.

Behavioral researchers have investigated the cognitive sources of biases in probabilistic judgements. Because of information processing limitations, decision makers use simple rules of thumb or heuristics to estimate likelihood. The three heuristics described by Tversky and Kahneman (1982) are the best known:

1. Representativeness. This concerns a judgement whether event A belongs to set B. Using this heuristic, the degree to which the `essential' characteristics of A are

representative of set B determines the degree of belief (probability) that A belongs to B. This rule can explain some errors in probability assessments such as Bayesian errors, insensitivity to sample size, misconceptions of randomness or of regressiveness, and overconfidence. Anderson et al. (1977) gives an example of a farmer who judges a current short dry spell as representative of the beginning of a past drought, ignoring the prior or historical probability of drought in the area.

2. Availability. Using this rule for judging uncertainty, the frequency of an event is estimated by how easily similar events can be recalled. If two events occur simultaneously, an illusory sense of correlation may develop due to this rule. For example, a farmer's judgement of the incidence of mechanical failure among tractors of a particular brand could be unduly influenced by a neighbor's bad experience with that brand.

3. Anchoring and Adjustment. This heuristic concerns the tendency of individuals to make estimates based on some 'natural' anchor point. Subsequent adjustments from that point based on information from the decision environment is often insufficient from the perspective of rationalist choice. This rule may cause errors in revision of probabilities or of probabilities for disjunctive and conjunctive events. An example might be estimation of next year's yield by taking this year's figure and adjusting it by some percentage.

A second important area of behavioral research has been the choice rules used by subjects to edit the set of alternatives and choose a preferred solution. Considerable research and casual observation indicates that decision makers commonly make choices based upon processing of information about multiple dimensions of alternative actions. Choice rules can be categorized as compensatory or non-compensatory. Compensatory rules permit tradeoffs between dimensions or attributes of alternatives, while non-compensatory rules do not. Among non-compensatory rules are included:

1. Conjunctive rules. Alternatives which do not have satisfactory levels of any attribute are eliminated.
2. Disjunctive rules. Alternatives are evaluated only on their best attribute.
3. Lexicographic rules. Attributes are hierarchically ordered in importance, and alternatives are evaluated sequentially down the hierarchy, with choice being made as soon as one alternative has a better value than any other on a higher ordered attribute.
4. Elimination by aspects. Using this rule, attributes are selected randomly and alternatives that do not have the characteristic are eliminated. The process continues until only one alternative remains. (Hogarth 1980)

Compensatory rules include simple linear formulations reflecting relative weights of importance and scale values of the attributes (Hogarth 1980). Another rule is the 'ideal point' rule, in which alternatives are evaluated by their proximity to ideal values of the various attributes or dimensions (Zeleny 1982). A further choice rule uses the principle of dominance to eliminate all alternatives except those which have better values of one attribute.

Non-compensatory rules are much easier to apply in most choice situations characterized by incomplete data, incommensurable dimensions, information overload, time pressures and large numbers of alternatives (Slovic et al. 1977). However, choice may sub-optimal when evaluated in a utility context. Subjects may use many different rules in a multi-stage decision process, with non-compensatory rules at initial stages and compensatory rules for a reduced set of alternatives. Prediction of the type of decision problem and context which evoke a particular rule has been problematic.

Schoemaker (1982) reviews some of the most notable experiments demonstrating violations of rationalist principles. In one of the first behavioralist experiments, Mosteller and Nogee (1951) found that subjects would change preferences during deterministic and stochastic repeated choice tests. Tversky (1969) also illustrated systematic violations of transitivity in deterministic and stochastic choice. Lichtenstein and Slovic (1971) conducted experiments in which subjects were asked to select a preferred gamble and to name certainty equivalents between gambles. In many cases, the preferred gamble was seen to have a lower certainty equivalent than other gambles.

Kahneman and Tversky (1979) are among many behavioralist researchers who have replicated Allais' paradox of the following form:

```
(2.1)
Problem 1:
                 p= .10    $5 million
             /
   A []          p= .89    $1 million        B []  p= 1.0   $1 million
             \
                 p= .01    $0

Problem 2:
                 p= .10   $5 million                   p= .11    $1 million
             /                                     /
   C []                                  D []
             \                                     \
                 p= .90   $0                           p= .89    $0
```

A large majority of subjects choose B over A, but C over D. Since the second problem is formulated by subtracting a $1 million outcome of probability= .89 from A and B, the experiment clearly shows choice inconsistent with rationalist theory. Outcomes with certainty seem to be weighted more heavily than outcomes which are merely probable. The experiment has been replicated many times with probabilities and payoffs much less extreme than those above. Responding to the criticism that subjects would not commit such errors if they understood rational decision making principles, Slovic and Tversky (1974) explained the error to violators. A large proportion of such violators would not agree to change their choice.

Subjects demonstrated persistent violations of continuity and transitivity in experiments conducted by Coombs (1975). In these tests of the EUH, nearly half the subjects incorrectly ordered three lotteries in which one was a probability mixture of the other two (implying that its preference should be intermediate). In addition, many researchers have documented examples of choice situations in which different representations of formally identical problems affected choice. In these experiments (Kahneman and Tversky 1979), individuals demonstrated risk averse or risk preferring behavior depending whether identical options were presented as gains or losses. Regarding choices as either gains or losses seems to serve as an editing procedure for decision processes which operate in ways which violate rationalist axioms.

Reported biases of EUH principles also result from unreliable elicitation procedures. Hershey et al. (1982) present a comprehensive review of utility assessment procedures and discussion of sources of bias observed in experiments. They conclude that confounding effects of the measurement process and the problem context cast doubt on practical applications of the EUH.

Kahneman and Tversky (1979) have developed an alternative theory of individual decision making under risk, called prospect theory. This model describes two phases of decision processes, consisting of an initial editing phases and a subsequent phase of evaluation. The coding phase consists of coding (evaluating outcomes as gains or losses), combination (combining probabilities of identical outcomes), segregation (separating risky and riskless components) and cancellation (discarding components shared by alternatives). Many anomalies of preference can be satisfactorily represented with these editing procedures. The evaluative phase of prospect theory resembles utility theory, in that the components include a value function, an expectation, and a compensatory rule. The value function differs from a utility function in that it is defined on deviations from a reference point, it is concave for gains and convex for losses, and it is steeper for losses than gains. The expectation weights are based on probabilities, but typically do not sum to unity and small probabilities are overweighted. Although this theory presents a significant attempt to reconcile rationalist theory and behavioralist observations, there has been little additional research using prospect theory as a conceptual framework.

A critical and as yet unanswered question involves the 'reasonableness' of using probability and choice rules which violate rationalist principles. In most everyday situations, individuals would seem to be foolish to carry out an extensive rational decision process. Simple rules may also be necessary in decisions made under time pressures or when the situation itself is not well defined or understood. If these intuitive rules are functional in many circumstances, how could 'switching rules' be developed which indicate when the intuitive rules are likely to cause errors and when rationalist rules should be used? Another important question is whether utilization of particular decision rules is under the individual's cognitive control. If the mechanism which calls these rules is sub-attentional or automatic, then the prospective for helping individuals recognize decisions in which these rules are likely to cause errors and to correct those errors is not bright.

As noted above, a persistent finding of behavioral decision research is that individuals evaluate attributes (or characteristics) of alternatives rather than determining preference for each alternative in a holistic manner. Since values of attributes are often subjectively determined, this implies innumerable operational problems for uni-dimensional decision theory. Indeed, this single discovery has sparked the entire field of rationalist Multiple

Attribute Utility theory, with the expressed aim of determining utility preferences for incommensurable attributes. Behavioral researchers have indicated that adding more arguments to the individual utility function may resolve many of the preference inconsistencies observed in their decision experiments.

2.6 The Rationalist Reply

Rationalist researchers have strenuously defended their own perspective. One response to behavioral criticism by rationalist decision researchers has been to discount the quality of research which indicates violations of theoretical principles. After three decades of experiments, this argument no longer seems tenable. At least as careful attention to experimental methods has been demonstrated in behavioral research as in problem-oriented rationalist research. Many results have been replicated in various settings with different types of decision makers. For example, the Allais paradox has been replicated many times by researchers such as Kahneman and Tversky (1979) and Ellsberg (1961).

A related criticism concerns the experimental subjects and controls of behavioral research, which is said to involve trivial, artificial choices with naive, disinterested subjects. It is the contention of rationalist researchers that savvy decision makers presented with realistic incentives would not commit such errors. However, this position is not substantiated by evidence from carefully designed experiments. As noted above, subjects sometimes refuse to change their 'irrational' choices even after researchers explain their errors (Slovic and Tversky 1974). Grether (1980) found evidence supporting the representativeness heuristic and resulting biases in an experiment testing Bayesian estimation, even though monetary incentives were provided to subjects. Grether and Plott replicated an experiment showing preference inconsistencies, controlling for a wide variety of economic, psychological and experimental method effects. Despite their controls, they concluded ". . . the preference reversal phenomenon which is inconsistent with the traditional statement of preferences remains." (1979: 634).

Preference reversals and probability assessment errors have also been observed in laboratory environments with expert subjects. Slovic et al. (1977) cite several such research experiments. Trained psychologists were observed to disregard sample size in probability assessments (Tversky and Kahneman 1971). A naive strategy of predicting closing prices for selected stocks was better than predictions of stock market experts (Stael von Holstein 1972). Psychology graduate students made no better decisions in their areas of expertise than in areas of general knowledge (Lichtenstein and Fischoff 1976).

The validity of laboratory experiment results for predicting behavior in non-laboratory decisions is sometimes criticized. Ebbesen and Konecni (1980) contend that results are very specific to simple laboratory decision problems, <u>because</u> of the observed use of sub-optimal strategies. They base this contention on results of their own study of decisions in real situations (eg. setting of bail, driving a car), which indicates that real-world decisions involve many more factors related in complex patterns than do laboratory problems. Ebbesen and Konecni contend that:

> There is considerable evidence to suggest that the external validity of decision making research that relies on laboratory simulations of real world decision problems is low . . . Researchers should provide external validity evidence for claims that causal models derived from laboratory data apply to decisions in real-world settings. (1980: 42-43)

There is also some non-laboratory collaboration of behavioralist results. Gamblers pursued sub-optimal strategies in on-site casino experiments (Bond 1974). Kunreuther et al. (1978) interviewed homeowners in flood plains and earthquake zones to determine whether their disaster insurance decisions were in accord with utility theory. One-half the samples had no knowledge of disaster insurance. They found that approximately one-third of the remaining homeowners did not act in conformity with expected utility optimization. Apparently homeowners did not perceive the hazard in the same manner as expected by policy makers. Researchers in psychology and education were seen to regularly design experiments with inadequate statistical power, reflecting the same errors as experts in laboratory experiments (Cohen 1962). A classic case of such bias was reported in Berkson et al. (1940), which showed that instructors of laboratory technicians demanded more accuracy in blood cell counts than was possible given sampling variation.

Another response to the behavioralist critique has been to broaden the scope of rationalist theory. One argument includes the 'cognitive costs' of decisions (Shugan 1980). Observed 'biases' appear to violate rationality principles because the experiments do not consider the 'cost of thinking'. This notion recognizes cognitive constraints and yet preserves the concept of rationality. It would appear, however, that the cognitive cost perspective runs counter to the concept of bounded rationality, since it imposes an additional stage of cost/benefit analysis on decision making (marginal analysis of additional 'decision investments'). In addition, it should be noted that this makes a substantial part of rationalist theory untestable and unfalsifiable, and does not suggest any feasible way to improve decisions.

The cognitive cost position is also related to the principle of 'meta-rationality'. Toda (1980) points out that people make 'meta-decisions' in order to avoid the necessity of making a unique decision in each future occasion. A cognitive control mechanism will monitor and adapt rules which are persistently dysfunctional. In other words, people are 'global maximizers' with local inconsistencies (Elster 1979). Also related are concepts of adaptive rationality (Day and Groves 1975) and evolutionary rationality (Nelson and Winter 1973). If people are adaptively rational, plus preferences and the environment are stable over some period, then behavior will tend to approach the behavior postulated in individual 'calculated rationality' models. Evolutionary rationality, like adaptive rationality, emphasizes the intelligence of decisions in relation to the social or economic system.

> Rules of behavior achieve intelligence not by virtue of conscious calculation of their rationality by current role players but by virtue of the survival and growth of social institutions in which such rules are followed and such roles are performed (March 1978: 593).

However, such concepts as systemic and adaptive rationality or cognitive cost, unlike individual 'calculated' rationality, do not provide a basis for understanding behavior as a consequence of pre-established preferences. Such a re-definition of rationality also

". . . pays the cost of destroying the practical relevance of normative prescriptions for choice." (March 1978: 597).

A positivist perspective concerning the behavioralist critique is to dispute the relevance of experiments to test the descriptive validity of rationalist axioms. It is only necessary that individuals act 'as if' they understood the actual principles (i.e. only predictive power justifies a model) or that individual biases will average out in the aggregate (only macro-rationality matters). The predictive superiority of EUH models, however, has not been fully substantiated (Robison 1982), and the notion that only predictive power matters is 'epistemologically unappealing' (Samuelson 1963). This perspective also allows no grounds for aiding management decision making.

Some rationalist research has explored the possibility of modifying those requirements of rational decision theories which seem to be the cause of observed preference reversals. The independence axiom has received particular attention. Machina (1982) develops a version of the Expected Utility axioms without the independence axiom. As noted by Robison (1982), this reformulation explains some preference inconsistencies, but makes expected utility only a local measure of preference.

Application of the EUH axioms is not theoretically restricted to single argument utility functions, although utility defined on the single argument of wealth or income has been the norm. Efforts have been directed during the past two decades to extend the rationalist approach to decision making with multiple preferences. Adapting the theory to account for multi-argument utility is relatively straightforward, but formulation of testable hypotheses and operational elicitation techniques has proved extremely difficult. Theoretical and applied research has concentrated on conditions necessary for decomposition of a multiple argument utility function into a series of single dimension functions which can be assessed with uni-dimensional methods and then aggregated together to provide a global measure of utility. The most common approach is to assume that multiple argument utility functions are additively separable. Even if the separability conditions are not strictly satisfied, Yntema and Torgerson (1967) show that main effects are usually much more important than interaction effects. This indicates that the ordering of alternatives may not be affected by ignoring interactions. Operational techniques have been developed to test separability conditions and elicit utilities, but restriction to primarily riskless choice situations and the expense and complexity of elicitation have limited broader use of the techniques.

Multiattribute utility formulations are often developed as descriptions/explanations of behavioral inconsistencies with uni-dimensional utility models defined over income or wealth. Bell proposed a utility function formulation defined over two attributes, income or wealth and ex post decision regret. The latter attribute consists of ". . . the difference between the value of the outcome that occurred and the value of the outcome that would have occurred had the other alternative been selected." (1980: 29-30) Bell shows how this formulation can be used to explain a wide range of observed preference reversal phenomena, such as the Allais and Ellsberg paradoxes. This formulation, it should be noted, makes utility measurements much more bound to the context of any particular decision, as do formulations which regard preference as defined over gains and losses rather than over final asset position.

The strong theoretical ties to utility theory and the committment to dealing with the realistic complexity of decision structure make multiattribute decision analysis very attractive, its operational problems notwithstanding. This type of analysis ". . . tend(s) to blur the distinction between descriptive and prescriptive theory." (Pitz, 1984: 157). The scope of its empirical applications includes complex problems with multiple objectives, alternatives with multiple attributes, intangible or incommensurable factors, extended time horizons and risk in various formulations. The operational base of multiple attribute formulations usually depends upon the decomposability of assessed utility functions, which introduces a level of complexity not found in single attribute utility models.

A further response accepts the results which show that people commit systematic errors in decisions, and counters that behavioralist researchers should be in the forefront of developing educational techniques to correct observed errors and bring behavior into agreement with rationalist principles. However, if the cognitive limitations demonstrated by Simon and others are inherent in cognition, education efforts may not be effective. It also should be noted that decision makers recognize their decision procedures are not 'rational' but persist in decision strategies which practically guarantee choices violating rationalist principles. March (1978) suggests that such persistent behavior suggests a form of intelligence. Actions can often be seen as reasonable if contextual information about a decision is examined, even if logical procedures could not have generated the same decision. 'Reasonable' decision practices require refinement (not replacement) by the techniques of choice theory.

No alternative behaviorally-based theory exists which covers the broad range of phenomena treated in rationalist theory. As a 'stalking horse', the latter theory has been the focus of most behavioral research and has illuminated aspects of human decision making which have stimulated modifications in rationalist theory. Keen and Scott Morton state:

> Without the precision and formalism of rationalist theory, we would almost certainly have made less progress in developing descriptive insights; it has provided axioms to be challenged, hypotheses to be opposed by counterexamples, and a vocabulary that we need to use even to disagree with it. For example, the concept of consistent, absolute utility functions has been invaluable in all theories of decisionmaking, especially those that argue such functions are nonexistent. (1978: 65)

Schoemaker (1982) notes that rationalist decision theory has been a 'research heuristic' which summarizes current scientific knowledge, encourages development of mathematical tools in ways which tend to have secondary benefits, and leads to unexpected hypotheses and applications. However, he also cautions that use of the closely related 'rationality heuristic' and 'optimality heuristic' leaves the scientist susceptible to biases of attribution (assuming that since optimality models fit natural data well that nature therefore optimizes), the illusion of explanation (allowing tautology to replace explanation), and the bias of searching for confirming rather than disconfirming evidence.

2.7 Some Elements of a Framework for Integration

This chapter has examined the issues of debate between two contrasting perspectives of individual decision making. Although many of their concepts and underlying purposes of research are similar, the perspectives have tended to develop as opposite poles of a dialectic, with little room for communication or compromise on issues of theory or operational methods. Yet a need exists for more coordinated development, using the results of one school for development of the other. As mentioned above, the behavioral school would certainly not have advanced so far if it had not used the rationalist model as a basis of its research. On the other hand, there seems little doubt that rationalist theory is partly inconsistent with what is known about real decision processes. Multiattribute formulations form part of the rationalist response to new insights brought to light by behavioralist researchers, as do attempts to re-formulate utility theory in ways which explain preference inconsistencies.

However, most concessions to the opposing perspective have been grudgingly made. The possibility for more active collaboration is not bright, due in some part to disciplinary intransigence. Each discipline tends to frame real world phenomena through its own conceptual lens, and with increasingly specialized tools and language. Thus there seems less possibility of integration at the disciplinary-theoretical level. However, as one moves to problems with empirical content, out of the constructed laboratory problems and out of the realm of hypothetical choices by naive subjects, there seems to be much more fruitful ground for integration. Researchers working with individual decision makers must help them to formulate problems from what Ackoff (1974) calls 'messes', to focus and clarify their preferences and expectations, to generate alternatives and to select actions. Context, which has been shown to be critical in human decision making, cannot be reflected in axiomatic constructs. Therefore, in individual problem-oriented work, researchers seeking development of their discipline may find problems and solutions which do not correspond to the situation at hand. The complex and unique nature of individual problems requires concepts and techniques from many disciplinary perspectives, yet the very mechanism which drives disciplinary development may inhibit needed interdisciplinary research.

The distinction made between prescriptive and descriptive research also inhibits development of processes to aid individual decision makers. A prescriptive model indicates what action ought to be taken only if the 'small world' of the model incorporates all the complexity of the 'large world' of the decision maker. Few models can hope to capture more than a small part of the problem scope, the causal relationships or the preference/belief structure of particular individuals. We can hope that the optimal solution of the 'small world' model is a good solution to the 'large world' problem, but if the decision maker chooses not to follow such advice, the researcher should be more willing to question the model formulation that to impugn the intelligence of the decision maker. Such denigration of intelligence in real decision making is fostered by the 'prescriptive research' label.

At the level of individual problem solving, the behavioralist perspective falters due to its tendency to see every situation as unique, and its inability to categorize some decisions as better than others. The rationalist perspective falters due to its tendency to ignore context, to ignore human aspects of decision processes, and to make sharp distinctions between a single 'optimal' decision and all other 'irrational' decisions. A complete framework for integration of the opposing perspectives at this level is beyond the scope of the present research, but it seems possible to outline four areas where working agreement on principles and coordination of research could considerably increase our ability to improve decision making. They are: 1) the structure of preferences, 2) the nature of expectations, 3) the limits of logic in human thought processes, and 4) improvement of decision making through feedback and learning.

2.7.1 Preferences

The two perspectives tend to agree that the concept of a fixed preference structure is the only tractable framework for research on individual decision making (for an opposing viewpoint, see March 1978). However, it should be realized that in many situations preferences may be ill-defined and ambiguous, and that the decision maker may identify or refine preferences during the decision process. We should reflect the observed fact that decision makers desire multi-faceted outcomes from their actions, and that not all these outcomes are either easily measured or at all commensurable. Our models must reflect the observation that aspiration levels are formulated to avoid having to precisely define preferences, and that it is usually too difficult to evaluate choices in terms of final outcomes instead of gains and losses. And we must reflect that the most treasured preference of an individual is the desire for control over his/her own decisions. There is intrinsic value in the decision process beyond the extrinsic value of outcomes. Therefore, the more control which the decisionmaker has in the solution of the 'small world' problem, the more likely that the corresponding action will be taken in the 'large world'.

2.7.2 Probabilities

This issue provides the best opportunity for collaboration between behavioralist and rationalist research. The logic of mathematical probability provides both a common language and an established set of operations with which we can express and evaluate our expectations about future events. Other than the requirement of coherence, however, the rationalist perspective considers probability formulation as an unobservable primitive. That is, there is no a priori basis for judging correctness of probability judgements. Yet probability assessments can be wildly inaccurate even though they are precise expressions of belief. The most important factor which varies between individual choices in some situations may be differences in expectations rather than differences in preferences. Behavioralist research into the cognitive formulation of beliefs and the probability assessment errors to which humans are prone could aid the improvement of expectations.

Wallsten and Budescu (1983) cite several examinations of probability elicitation techniques. As noted above, training, experience and feedback appear to be key elements in the ability of certain individuals to give accurate probability estimates. It appears that progress is being made to identify characteristics of elicitation techniques which induce bias in probability encoding. Hogarth (1980) begins the difficult task of developing operational techniques to teach decision makers how to avoid bias in probability judgements. He suggests that progress depends upon an understanding of the sources of biases and effective teaching of probability principles. Probability training methods could be developed with stress on those principles which are counter-intuitive. In many situations, improvements may be possible by confronting individuals with differences between their subjective probabilities and other 'objective' probability evidence.

2.7.3 The Limits of Logic

A third area for integration is the recognition that there are bounds on the human ability to perform operations implied by rationalist decision theory, and yet humans make very good decisions in most circumstances. It should be recognized that ". . . human judgement is more limited than flawed.." (Hammond 1975: 76). There are significant limits to computational ability and short term memory retrieval and storage. But beings as limited as portrayed in many behavioralist experiments could not have built civilization and sent people to the moon. Humans have the ability to make judgements which are much too complex for computer models (imagine trying to program a robot to cross a busy street!). Our decision strategies serve us well, and we seem to recognize that in many cases too much rationality is unreasonable (Marschak 1975). Nonetheless, there are many situations in which our experiential or intuitive strategies fail us, and logical processes offer the best opportunity to improve decisions. Researchers and advisors should work with decision makers to identify what are good but 'irrational' strategies, what are clearly identified reasoning errors, how to identify situations which are likely to stimulate these errors, and what reasoning mechanism can be substituted at acceptable cost to the decision maker.

Rational choice researchers often attempt to replace the flawed judgement of the human decision maker with the 'objective' judgement of a dispassionate model. But only humans can attribute meaning and purpose to actions and consequences, and only they will have to bear responsibility for such actions. Therefore, we need to develop mechanisms to aid humans in overcoming systematic errors while complementing their strengths, such as integration of information of varying types and quality, long term memory associations, abstract reasoning, creativity and imagination. This decision support perspective points out the need for a people-tool conceptual approach to decision making.

2.7.4 Feedback and Learning

People turn to outsiders for help when they don't understand the 'mess' that is bothering them. The ambiguity of choice situations can mean that their preferences are not clearly defined, that the structure and causal relationships of the problem are not understood, or that they do not feel confident with their computational or comparison ability. Sophisticated decision makers do not want ready-made solutions (or at least don't want <u>just</u> solutions), they want to learn how to better deal with the ambiguity and complexity of choice. Feedback can be distinguished by: 1) its potential to focus attention on unconfounded cause and effect relationships; 2) its frequency and or rapidity of results after actions are taken; and 3) the amount of feedback from actions. When attention is focused on available feedback, learning may occur which will benefit the quality of decisions in future situations. Learning should be a central focus for integration of rationalist and behavioralist research at the individual level. Some decision models or aids provide a simulated decision structure within which the decision maker can receive clearly defined and rapid feedback from possible actions. This opportunity is unique, because in the 'large world' we don't necessarily know there _is_ something to learn, or _what_ is to be learned, or whether we _have_ learned anything (Einhorn and Hogarth 1981). Actions which would probably not be attempted in the 'large world' can be tried with the model and feedback evaluated. An awareness of the decision model structure can lead to new insights of the real problem or re-formulation of the model. The model can be seen as externalizing and structuring the 'thought trials' mentioned by Hogarth (1981) as crucial for feedback and learning.

Ackoff states that ". . . to learn is to increase one's efficiency or effectiveness over time under constant conditions." (1974: xiii). Perhaps if we can improve our ability to design and develop decision models and aids that enable individuals to learn under the above definition, we can also improve our capacity to help decision makers adapt under changing conditions.

CHAPTER III

DECISION AIDS

3.1 Introduction

Decision aids are tools and techniques which extend the human intellect and externalize some cognitive functions. They may be as simple as a pencil and paper (to aid calculations or memory) or as complex as multi-million dollar combinations of hardware and software for managerial decision support. Decision aids may assist a single function of decision making (such as a memory aid) or automate all computational, memory and control functions of the decision process (such as might be expected in a nuclear plant).

A set of decision tools may also be termed a decision support model if its scope includes a significant portion of the decision process. Aids to support programmable or fully structured decisions relieve the individual of all decision making functions (except possibly responsibility bearing). Other aids, such as probability elicitation techniques, may play a part in a larger decision aid system or function alone as a judgement aid for an otherwise unaided decision process. The person-tool combination accomplishes the functions of making a decision, and each has some degree of influence on the outcome. The principal issue for aid designers is the appropriate division of labor between man-made tool and human decision maker (Pitz 1983).

Development of effective decision aid techniques has been an important concern for centuries. The simple technique of listing pro and con reasons for a decision was described by Benjamin Franklin in a letter to Joseph Priestley in 1772 (Bigelow 1887). The potential of decision tools has increased dramatically in recent years due to the revolution in electronics and subsequent software development. Yet the success of decision aids in improving decisions depends upon complex and little understood interactions between the characteristics of: 1) decision situations or tasks, 2) the individuals who use the tools, and 3) the tools themselves.

This chapter describes the functions and purposes of decision aids from the decision theory perspectives discussed in the previous chapter. The critical characteristics and interactions of decision task, decision makers and decision aids are examined, and the chapter concludes with a discussion of evaluation issues for decision aids.

3.2 Aids for the Decision Process

A decision aid is a set of tools and techniques designed to help humans make decisions. This may entail support for elementary information processing functions such as memory or computation, or assistance for complex routines such as problem structuring, generation of alternatives or choice of the best alternative. It can be seen that an important (but not the only) purpose of decision aids is to help the decision maker avoid information processing biases described above. Some decision aids are developed to support personal decisions, in which the individual will take primary or full responsibility for the consequences. Other aids attempt to provide objective support for decisions within an organizational context, where individuals must communicate and justify their decisions to peers, superiors or outsiders.

Although decision aids are obviously designed to support the decision maker to solve the problem at hand, they may have significant secondary effects. By externalizing the cognitive decision process, the decision maker may gain a greater understanding of personal preferences, beliefs and causal relationships (Hammond 1975). This may lead in turn to improved general problem solving ability in related or dissimilar decisions. However, few aid designers have attempted to tap this potential.

The development of a decision aid presupposes that individuals have difficulty reaching `good' decisions (according to some criteria) and can be assisted to improve their decisions. Somewhat tritely, it could be said that people use decision aids when they are sure that they don't know what or how to decide. People use decision aids when:

1. they feel unable to make a decision;
2. they want to better understand a decision they must make;
3. the problem is complex or uncertain; or
4. the stakes are high. (Jungermann 1980)

Simon (1965) conceptualizes phases of the decision making process as identification, design and choice. With respect to the identification phase, decision aids may perform certain intelligence functions of problem finding. Davis (1985) describes these functions as the ability to search internal and external data resources. Decision aids for these functions are distinguished by the type of search permitted, such as structured continuous search, structured ad hoc search and unstructured search. Aids for problem finding include the traditional report generators used to compare performance with historical data, past projections and extra-organizational data. Aids for the intelligence phase may also include problem structuring functions, such as description and clarification of objectives.

Decision aids may also support the design phase by developing and comparing alternatives. Davis (1985) proposes that support for this phase should provide iterative procedures to assist the decision maker to understand the problem and generate non-obvious alternatives. Finally, aids for the choice phase of decision include the range of computational and choice rules embodied in optimization procedures, statistical inference, dominance analysis or even ad hoc rules.

Issues of rationality with respect to unaided decision making have been examined above. The behavioralist evidence indicates that in many contexts individual decisions fall short of that predicted by rationalist principles, but many researchers argue that criticism of unaided decisions begs a more important issue. Pondy contends that ". . . what is needed is a theory of decision tools that improve the performance of person-tool combinations, not merely a descriptive theory of how humans unaided by tool extensions perform less than optimally." (1982: 311) The focus of decision support is on improving decisions with tools or extensions to human capabilities, rather than the behavioral/rationalist issue of rationality. The primary issues of decision research are the focus, techniques and application of decision aids in real problem situations and real decision makers. Rationalist and behavioralist researchers whose concern is to improve decisions thus meet on the common ground of decision aid technology, and must both deal with design, implementation and evaluation of decision aids.

Decision aid models may be similar to any other research model except that the principal purpose is to generate possible solutions to problems faced by specific decision makers and thus must incorporate to some extent the person's participation. In development and application of decision aids, both rationalist and behavioralist researchers attempt to improve problem solving behavior. A somewhat apocryphal examination of decision aids developed according to the research orientation of these perspectives may help identify significant differences in their purposes and techniques.

Rationalist decision aids presume, in general, that the decision maker can unambiguously state personal preferences and expectations if requested in the correct manner and that preferences and expectations can be represented numerically. They do not generally assume that the decision maker has all the relevant information about the problem prior to use of the aid, but do assume that new information is integrated with prior beliefs in a consistent fashion. Once preferences and probabilities (expressed numerically as utilities and probabilities) are elicited, the decision tool is often constructed so as to calculate a unique optimal solution for a uni-dimensional problem. In the uni-dimensional problem, the decision maker may function something like a data input device to the analytical model. If the individual accepts the rational decision axioms, accurately verbalizes personal preferences and beliefs, and the 'small world' model sufficiently corresponds to the real world problem, then the model solution gives the most preferred action for that individual.

If the decision maker does not accept the model solution, errors may have occurred in model specification, measurement of preferences or of beliefs; or the decision maker is making a choice in a manner inconsistent with self-interest. Computational errors which might be committed by the unaided individual are avoided by passing that responsibility to the numerical model.

Behavioral decision aids are also developed to help individuals avoid biases in important decisions. They do not necessarily assume that a problem has been identified, but usually assume that an underlying preference structure exists. The principal focus of a behavioralist aid is usually assistance for the decision maker to avoid the information processing errors identified in behavioralist decision research. The aid thus places particular emphasis on sequential display of limited amounts of data, retrieval of information from long term memory, integration of information in short term memory, explicit consideration of multiple consequences or attributes and utilization of a series of decision rules. Behavioral aids have benefitted from behavioral experiments demonstrating weaknesses of individual probability assessments, and methods of probability elicitation are chosen to minimize errors. Some behavioral decision aids go beyond assistance for information processing to reflect the effects of personality or cognitive style on decision making. The contention is not only that all cognitive capability is limited, but that individuals exhibit considerable differences in their preferred problem solving style, and that better decisions may result from the congruence of the representation techniques of the aid and the decision style of the individual.

3.3 Characteristics of Decisions

There is no accepted, well-defined taxonomy of decision types. Even within restricted subject domains, there have been few attempts to categorize decisions. Generally, researchers have attempted to delineate some of the characteristics which distinguish individual problems. Castle et al. (1972) gives five major characteristics:

1. Importance of the decision
2. Frequency of recurrence of the decision
3. Time pressure when a decision is required
4. Revocability of the decision
5. Number of available alternatives

Decision aids are more likely to be used for important decisions, in which the additional time and cost can be justified, although some types of aids may be of great benefit for frequently recurring 'smaller' decisions. However, once the rules used by the aid are learned by the decision maker, an aid is often no longer necessary. Time pressure is an important characteristic of most decisions. Jungermann notes, however, that ". . . time pressure, as perceived by the decision maker, is a function not only of the actual or perceived time available, but also of the complexity and significance of the decision to be made." (1980: 12) Decisions that must be made under perceived time pressure are not as likely to stimulate use of decision tools. Revocable decisions usually indicate less need for aids, since decision makers can try a possible solution, observe its consequences and decide whether to make a second choice. Similarly, the presence of few alternatives may also reduce the usefulness of decision aids, since the lower 'cost' of evaluating a few alternatives may induce individuals to make unaided decisions. However, the presence of few alternatives in a given decision situation may be more a result of restrictions which the decision maker has placed on the scope of the problem and the reduced effort invested in generating alternatives than a characteristic of the decision type.

Other researchers have included further important characteristics of decisions which affect the benefits of aids. Jungermann (1980) distinguishes decisions in which the status quo is a viable alternative from those in which a new action must be chosen. The decision arises because new alternatives become available, or because the status quo has not fulfilled current aspirations. Also critical is the time horizon of decision consequences. Since more uncertainty is associated with long time horizon decisions, aids may be more fruitfully employed in decisions with long range effects.

Hogarth (1980) emphasizes characteristics of decisions which combined with psychological factors may influence receptiveness to decision aids:

1. <u>Problem complexity</u> may stimulate consideration of decision aids. Large amounts of information or lack of knowledge of solution techniques may affect use of decision aids.
2. <u>Procedural uncertainty</u> implies that decision makers are not sure of the procedures necessary to solve a problem. In the presence of procedural uncertainty, individuals may be more likely to utilize aids;

3. <u>Psychological regret</u>: An individual is more likely to resort to an aid when care in judgement is necessary to avoid psychological `costs' of regret from making mistakes. In other words, a valid use of an aid is to corroborate judgement.

4. <u>Emotional stress</u>: Problems which have important consequences for which the individual must bear responsibility, or which must be made under time pressure, or which are characterized by substantial uncertainty are likely to be associated with significant emotional stress. Decision tools may contribute to lowering stress levels in such situations. Beach and Mitchell (1978) group decision characteristics as inherent in the decision or in the environment (context). Inherent characteristics are unfamiliarity, ambiguity, complexity and instability, while characteristics of the environment include irreversability, significance, accountability and time/resource constraints. If the decision maker perceives these characteristics, the situation would be more likely to initiate demand for decision aids.

In a managerial context, Simon and Hayes (1976: 121) distinguish characteristics of `structured' versus `unstructured' problems. They consider problems to be well structured or `programmable' if: 1) the conditions which define the existence and structure of the problem are well known, 2) the procedures necessary to generate or identify alternatives are feasible, and 3) unambiguous criteria exist for choosing a best solution. Completely structured decisions can be automated, and the decision maker's judgement replaced by that of a numerical algorithm. An example of such an aid might be a ration formulation programming model. Less structured problems which are nevertheless partially programmable are those in which individual preferences are regarded as important, or characterized by features such as novelty, time pressures, lack of knowledge, or non-quantifiable factors. As more ill-structured problems are encountered, the individual may find that the nature of the problem itself, the information or procedures required, or the criteria for selecting an action are not well understood. Several of the most important managerial problems have these ill-structured characteristics, such as significant expansion of the business, inter-generational transfer or a decision to disband the business.

Gorry and Scott Morton (1971) combine the structured-unstructured dimension of managerial decisions with the operational level at which decision making takes place.

1. Operational performance decisions can be made while performing the operation
2. Operational control decisions result from monitoring effectiveness of operations
3. Management control decisions relate to the acquisition and efficient use of resources
4. Strategic planning decisions involve setting policies and choosing objectives

Problems which are both well-structured and related to operational performance are most likely to be automated, with humans primarily performing an information input function. If problem characteristics are more similar to the unstructured strategic decisions such as product planning, decisions must rely more extensively on judgement. A further extension of this framework is presented by Gordon et al. (1975). Management decision types can be classified by process (structured-unstructured), by level (strategic-tactical-operational), by functional area (production, marketing, finance, etc.), or by decision output (discrete choice, scale, schedule, allocation, design or plan). Again, each factor can be seen to influence the receptiveness to a decision aid.

3.4 Characteristics of Decision Makers

Extending well beyond human information processing limitations discussed above, many psychology researchers consider how individual personality, motivational and stress-related differences interact with problem characteristics to affect decision making and the use of decision tools. According to the cognitive style perspective, the problem solving habits of the individual is consequence of psychological characteristics. Cognitive style examines the approach to decision making, not the person's ability. Keen and Bronsema (1981) contend that systematic differences between individuals significantly influence their use of information and decision aids in a manner quite distinct from the cognitive information processing limitations.

> Cognitive style refers to the process behavior that individuals exhibit in the formulation or acquisition, analysis, and interpretation of information or data of presumed value for decision making. (Sage 1981: 640)

Motivational characteristics such as ego-involvement may also affect the utilization of decision aids (Jungermann 1980). Other motivational features include whether the individual considers a formal technique appropriate for the decision (who considers a rational technique appropriate for choice of a spouse?) and why some people are paralyzed when faced with decisions. Stressful decisions affect problem solving behavior in ways which often result in dysfunctional decisions (Janis and Mann 1977). Whether decision makers under stress are more or less likely to utilize decision aids is unclear.

Huber (1983) has criticized research emphasis on cognitive and motivational types as a basis for decision tool or system design. He contends that there is insufficient evidence to support cognitive style research results as guidelines for designing decision tools, and that the effort is both unwise and unlikely to bear fruit. Progress in aiding individuals to make better decisions is, according to Huber, more likely within the context of complementing human decision strengths and in alleviating fairly well understood information processing limitations.

Pitz (1983) examines three general strengths of humans over automated procedures: 1) ability to rapidly encode, store and retrieve complex patterns of information from memory; 2) extremely rapid evaluation and classification of complex perceptual information; and 3) ability to make creative inferences in ill-structured decisions. Even within narrowly defined subject areas, there is no mechanical substitute for human ability in these functions. The automatic integration of perceptual information with other information stored in memory is extremely fast and usually quite accurate. Computerized simulations of perception and integration are as yet limited to very structured and simplified tasks (i.e. robot sensing on assembly lines). The human ability to integrate perceptual data with information from memory and to develop non-obvious insights is far beyond the capacity of current computer models, and is likely to remain so for the foreseeable future, despite progress in artificial intelligence experiments in well-defined problem areas.

Decision tools should complement these human strengths, while at the same time mechanically assist humans to transcend known limitations of short term memory, inconsistency in judgement and errors in learning. In addition, a good decision aid might help the individual to retrieve information from long term memory, or to recognize connections between previously unassociated items in ways that are conducive to creative decision making. However, since meaning, purpose and responsibility are essential ingredients in most decisions, there will almost always be advantages to having human perceptual skills and creative problem solving skills to evaluate information, just as there are advantages in reliance on mechanical aids for computational operations. The difficult task for decision support designers is thus design of optimal person-tool combinations.

Integrating what he states are the most important characteristics of decision makers with respect to the design of decision tools and systems, Bennett (1983) makes four relevant observations:

1. Decision makers use conceptualizations such as diagrams or graphs much more readily than written or numerical information. Tools should utilize such representations.
2. Decision makers need short-term (and in some cases, long-term) memory aids. Decision tools and systems should incorporate more efficient and easily used memory aids.

3. Decision makers have different styles and skills. A decision tool or system should not enforce a particular style or skill level. The additional cost of flexibility, Bennett points out, will be balanced by the benefits from utilization by more decision makers.

4. Decision makers require personal control over decision tools and systems. This does not necessarily imply personal operations, but decision maker understanding of the support process should be sufficient for the decision maker to evaluate and direct operation.

3.5 Characteristics of Decision Aids

Decision aids, like problems and decisions makers, can be examined by appraisal of their characteristics. Tools are constructed for different purposes, with different foci, and with different techniques, each of which interacts with the problem and decision maker characteristics to have considerable impact on the quality of the decision. The implicit purpose of a decision tool is often very difficult to assess. Often a decision 'aid' may be constructed to accept input of probabilities and utilities and replace the cognitive decision process of the individual with the logical process of a computer model. Other aids attempt to explicitly complement the aforementioned strengths of humans and provide support for known limitations. These might be called the 'narrow' and 'broad' perspectives, respectively.

Mechanisms to complement decision making may consist of data representations which stimulate non-obvious inferences or suggest new alternatives, memory aids which allow consideration of many information `chunks' and which can be arranged in ways which may evoke pattern or trend recognition, or output representations which facilitate comparisons of multi-dimensional consequences.

Portions of the decision process which are externalized (extracted from the unobservable cognitive process) may include systematic assessment of preferences and beliefs, extensive data computations, or application of complex decision rules. 'Narrow' decision tools which attempt to externalize most of the decision process run the risk of committing what Mittroff and Featheringham (1974) call `Type III error'. That is, if the structure, decision elements and operations imposed by the aid differ substantially from the real world problem as perceived by the decision maker, the model may generate a solution for the wrong real world problem. A subtle but not very operational distinction might be made between decision aids which facilitate better, consistent decisions and those which achieve those results while fostering creative approaches to the problem. The potential of a decision tool to stimulate new approaches to the problem, to highlight problem structure and causal relationships, and to thus create benefits which extend beyond the current decision is an important (but neglected) area of research.

In terms of decision aid purpose, one could also distinguish decision tools in terms of their consistency with rationalist decision theory. Decision analysts can provide aids with different types of decision rules, assumptions about problem structure, and data requirements. The `best' aid is useless if it requires rules, problem structure, or data that do not exist or cannot be effectively generated. A `good enough' decision aid uses unaided judgements as a benchmark in generating solutions which should be on the average better than unaided decisions (Keen 1977). Other aids might stimulate 'better' decisions, but have characteristics which are not complementary to characteristics of the problem or of the decision maker. A 'good enough' aid might then be considered as an automated rule of thumb or an efficient approximation to a more complex model.

Decision tools can also be examined according to their focus. Jungermann (1980) classifies existing aids for personal decision into three general categories: 1) aids for reaching a decision; 2) aids for sticking to a decision; and 3) aids for improving general problem solving behavior. General knowledge of decision skills could improve individuals' sense of control over their lives and their confidence in decisions, but only a few aids have been developed which specifically attempt to improve decision making ability. Instruction in rationalist decision procedures and rules is the usual focus of this type of aid. Unsystematic application and evaluation has restricted ability to draw conclusions regarding effectiveness in improving subsequent decisions. Jungermann notes that ". . . it might be more effective to teach people, as early in their lives as possible, tolerance of uncertainty and ambiguity, cognitive flexibility and avoidance of biases that influence judgment or hinder learning from experience." (1980: 22)

Another focus of decision aids is the volitional problem of following decision (a behavioral intention) with action (actual behavior). Most literature on problem solving ignores the distinction between the principally intellectual exercise of making a decision and the sometimes emotionally charged atmosphere surrounding actions to carry out the decision. Lack of confidence and anticipations of regret are important emotional factors which undermine decisions reached through logical processes, but logical principles are not particularly useful in dealing with such feelings. Research on behavior modification and cognitive therapy (Fischoff 1983) might be of some use in designing aids which foster confidence and show how anticipated regret can affect the quality of a decision.

The principal focus of existing decision aids in managerial contexts is usually the static framework of problem structuring and solving. Within this framework, decision aids may concentrate on: 1) problem structure, 2) assessment of probabilities, 3) assessment of preferences, or 4) generation of one or more solutions. Any particular aid may exhibit a mixture of these foci. The principal objective of problem structuring aids is to ". . . provide some better understanding of the interrelationships among elements of the problem . . ." (Pitz 1983: 210), in particular the decision maker's perspective of which problem characteristics, alternatives, future events, and consequences should be taken into consideration. Examination of resources (including data resources) can also be viewed as an aid to problem structuring. Few decision aids integrate problem structuring with problem solving tools.

Jungermann (1980) states that focussing only on structure might be appropriate when better understanding of structure provides a sufficient basis for decision makers to make an otherwise unaided decision, or when the individual is particularly receptive to an analyst's suggested solution. It may also be a good focus when rational procedures are not seen as appropriate by the decision maker.

Pitz states that this ". . . may be the most critical stage in the decision analysis [and is] . . . far more important than the small amount of research devoted to the topic might imply." (1983: 210) There are several reasons why more management research effort has not been carried out in this area:

1. Such an aid is more a behavioral analysis procedure than a computerized decision aid. It is unclear how the advantages of computers (rapid computation, mass data storage, etc.) can be fruitfully used in this area. Thus, such an aid would probably suggest analyst-decision maker interaction, with the computer as a facilitating memory or graphical aid.
2. The amount of analyst input is usually too great for all but the most important decisions. Also, if the 'problem' is to structure a decision situation, the range of skills required of the analyst is consequently broadened.
3. It is unclear how the benefits of a problem structuring aid could be evaluated.

The second concentration area of problem structuring and solving aids is evaluation of consequences or preference assessment. This must, of course, be kept quite separate from the predictive judgements of probability assessments. In single attribute decision making, methods are well developed for eliciting measurement of von Neumann-Morgenstern utility functions (Hershey 1982), although few attempts have been made to automate the process. The individual is not required to comprehend the measurement process. Decisions with multiple consequences of importance to the decision maker may require multi-dimensional utility assessment. The actual measurement procedures in these cases are much the same as uni-dimensional procedures (Keeney and Raiffa 1976), but also usually involve assessment of relative weights of importance for the various attributes, scaling of attributes and tests to validate separability conditions of the multi-attribute utility functions. The time required for verification of the latter conditions tends to make MAU approaches unmanageable as decision aids in all but the most important decisions.

Aids for assessment of probabilities are likely to be a major area of development in the coming decade. A wide variety of encoding techniques have been developed, and efforts have been made to devise reliable testing procedures to ensure that bias is not introduced by the encoding method itself (Wallsten and Budescu 1983). Unlike utility assessment, much stricter conditions for internal consistency can be placed on subjective probability statements. Also, behavioral decision research (as discussed above) has identified common errors in subjective probability estimation which aids should help individuals to avoid. In some situations, the external validity of probability estimates (correspondence with historical or known frequencies) can be determined and discrepancies displayed to the decision maker. Estimates may be improved by providing relevant external probability data before assessing subjective probabilities, provided that care is taken to avoid reported biases in Bayesian processes. Graphic computer representations may significantly improve the individual's ability to integrate probabilistic information and state probability estimates in accord with personal beliefs.

Evaluation of alternatives is another focus of problem solving aids, particularly decision-theoretic aids. Preconditions include that problem structure has been well defined, both preferences and probabilities have been assessed, a suitable decision rule chosen, and alternatives have been identified (either implicitly or explicitly). Then a computerized aid can be used to compare alternatives and select a set of preferred actions or a unique best solution. The power of an automated procedure is most evident in aids with this focus, as the search, memory and computational capability of computers are well suited to these actions. It should be noted, however, that the above prior problem conditions require that the individual's problem conception is veridically represented by the analytical model. Even if these conditions exist, however, a danger exists that the decision maker may reject the model solutions because cognitive control of decision making has been abdicated to the analytical model. The cognitive control element may be critical to the success of aids with this focus.

Decision tools can also be characterized by the techniques utilized. The principal characteristics (not mutually exclusive) which distinguish aids are:

1. degree of quantification;
2. context-flexibility;
3. representation of problem structure;
4. type of analytical model (optimization/simulation or deterministic/stochastic);
5. numerical/graphical input or output;

6. interactive or batch processing; or

7. operation by the decision maker or by an intermediary.

Complete quantification of monetary and non-monetary values is usually necessary for analytical decision aids. The 'fuzziness' of human language seems to serve decision makers well in normal instances, and it is clear that added precision may be traded off against significance in decision modeling. In some decision aids dealing wholly with decision structure, quantification is kept to a minimum as the focus is on providing clarity of relationships between problem elements. Fuzzy set theory, in which transition from membership to non-membership of objects in sets is gradual rather than abrupt, can represent the ambiguity of natural language. Its application to decision support has been proposed by Bellman and Zadeh (1970) as an alternative to the precise definition of values and probabilities, but no implementations have as yet been reported.

Techniques can also be characterized by the flexibility of application to a range of problem environments. Although it is normally infeasible to develop a unique decision aid for each situation, an aid may promise sufficient payoff to warrant such development. Certainly a decision tool for a major corporation would have to be made highly specific to the corporate environment and probably to the specific problem. As mentioned above, individuals have different educational characteristics and problem solving style which affect the effectiveness of aids (Keen and Scott Morton 1978). Development of a single standardized model or aid for a wide range of decision makers is certainly cost-efficient for the designer, but standard models may be inappropriate to any specific problem and thus may be considered unsatisfactory by decision makers.

If one objective of an aid is to assist the individual to better understand problem structure, the techniques used to represent analytical model structure are of considerable importance. Such a representation may be as simple as a decision tree, or as complex as CPM charts or influence diagrams (Bodily 1985). Even though problem solution rather than structuring may be the principal objective of the aid, suitable representation of structure may increase the decision maker's confidence in model solutions, or may initiate an interactive process of model reformulation. Whether such reformulation is feasible depends on the flexibility of the aid.

Techniques for choice of decision rule are not currently incorporated in decision aids, although concepts proposed by some decision analysts include flexible, user-controlled application of a range of decision rules to specific problems (Keen and Scott Morton 1978). Normally, rules for selection of a subset of actions (or a single alternative) from the set of feasible alternatives are pre-defined by the tool developer. Simulation models, as opposed to optimization models, do not impose decision rules and allow individuals to select alternatives according to personal decision rules.

The deterministic or probabilistic nature of the analytical model base of the aid is another distinguishing technique. Of course, the problem itself usually is affected by probabilistic factors to some extent, but the tool designer chooses to represent the problem with or without probabilistic elements. A decision maker with minimal training in probability theory might feel more confident with a deterministic model if this more closely accords with his/her perception of the problem, but it is seldom obvious whether such a solution is better or worse than that produced by a more complex (but possibly less understood) probabilistic model. Application of different decision rules in various stages of the decision process is proposed by Keen and Scott Morton (1978). Simple strategies such as conjunctive rules may first be used to reduce the set of alternatives, followed by a detailed optimization procedure applied to the reduced set. Application of heuristic rules is probably most justified in problems where structure, elements and causal relationships are less clearly defined.

Techniques for input and output representations distinguish decision aids, and the type of representation interacts with the individual's decision style to affect usefulness and learning from the aid. Spatial representations such as graphical output tap the perceptual resources of humans and greatly increase information integration. As Davis notes, "A graph is a 'chunk', yet it may provide the same input of data as a large number of data items that would each use one chunk of (cognitive) capacity." (1985 : 246) The interactive technology necessary to generate high quality, flexible and fast graphical output in a field environment is now becoming available. Techniques for model input through non-traditional media have also been developed. Digitizers, touch screens and voice synthesizers have the possibility to facilitate user input (Johnson and Loucks 1980).

Decision aids may be operated in either interactive or batch mode. With a batch process, the complete input for model computation is collected and later processed by the computer (although 'later' may only be a few minutes). Presentation of model output is then made to the decision maker at a later time. Interactive operation, on the other hand, entails input and output between the computer model and its human operators throughout at least some portion of the solution process. With microcomputer processing of decision aids, the above distinction becomes less obvious than with centralized computer processing, both in terms of time necessary for solution and user dialogue with the model. A further technique which has become possible with faster microcomputer technology is iterative solution of decision models. If operation of the model is sufficiently rapid, the output from one complete cycle of the model can be used as information input to the decision maker, who may revise his expectations, modify the problem or experiment with different goals and solve the model with these modifications. This input/output iterative process may continue as long as the decision maker wishes to explore different formulations and solutions.

Finally, decision aids differ according to the principal operator of the computer model. If the decision maker is well associated with the hardware and software operation of the aid, the aid may be used without further assistance. It is generally felt that decision makers will reap more benefits from aids which they can operate without analyst mediation. However, formulation of the analytical problem and operation of the model often must be mediated by a trained analyst.

This increases the costs of tool utilization, but may permit a broader learning experience than with solo operation.

3.6 Consequences of Decision Aids

Although computerized decision tools have been developed and disseminated for more than a decade, there is a dearth of evidence examining impacts of aid utilization on management decision behavior. One problem is the non-experimental environment of real business decisions. It is difficult to derive experimental controls which allow determination of decision tool impacts. Also, most managers are not (for obvious reasons) willing to devote enough time to carefully controlled experiments and much prefer their own intuitive evaluation of the tool.

A further problem relates to the intellectual perspectives of the previous chapter. From the behavioral perspective, the purpose of a decision aid is somewhat ambiguous. If the principal purpose of behavioral research is development of models to describe actual decisions (what Hobbs 1985 calls 'imitative validity'), there is no reasonable basis for development of decision aids. Standards for 'better' decisions or decision procedures do not necessarily exist. Many behavioral researchers (including some of those who have contributed most to our knowledge of judgemental biases) contend that consistent choice in similar contexts is a minimal basis for improving overall quality of decisions, and that a decision aid should provide both a structure and procedures to encourage such consistency. Further, if consistency is extended to include consistency with the rules of logic and probability, the rationalist perspective is reached. At the extreme of this perspective, researchers contend implicitly that aids prescribe 'best' solutions which decision makers should accept if they are 'rational'. Evaluation of such aids may be primarily a priori determination of logical coherence of the underlying analytical model.

A more pragmatic approach accepts that each perspective has some validity. Certainly decision tools should be compatible in some sense with existing decision procedures. They should establish structure and procedures which encourage consistent decisions for similar settings, and they should be internally consistent with rules of logic and probability. The principal dispute is an issue of emphasis rather than substance. Yet all involved should recognize that the principal purpose of a decision tool is to assist real decision makers and suggest 'better' decisions, however defined.

Two orientations to evaluation of decision tools can be discerned from these perspectives. An <u>outcome-oriented</u> approach focuses on the consequences of the decision made using the aid. Three general evaluation issues can be identified:

1. Are solutions logical? An a priori evaluation of the aid's consistency with logical operations based on its assumptions can be carried out.
2. Was the model solution a reasonable problem solution? Are solutions within the range of observed real world actions? Do decision makers think the solutions are reasonable? How do the model solutions compare with those of alternative models? Essentially, one asks whether the problem has been modeled in a realistic (veridical) fashion. Both the

researcher and the user will have points of view on the adequacy of the model.

3. Was the solution implemented? Were the consequences sufficient to justify use of the aid? An ex post evaluation of the decision outcome can also be carried out, although the often lengthy period between decision, action and consequences and the effects of uncontrollable or unforeseeable intervening factors usually makes experimental verification of the aid's value extremely difficult.

A second evaluation orientation is <u>process-oriented</u>. This type of evaluation attempts to assess the consequences of the decision tool with respect to changes in the decision process, regardless of the actual solution or its realized consequences. Some justification for the aid, it is argued, can be determined by evaluating whether the decision is made correctly, apart from whether the correct decision is made. However, evidence for improved decisions can only be indirect. Three aproaches can be identified:

1. Before/after changes in procedures with respect to the phases of decision processes can be evaluated. Information search, generation of alternatives, computations, and assessments of preferences or of expectations are all factors which would indicate whether the tool has affected the decision process.

2. Comparison of the procedures of the aid with those of alternative aids. Both this approach and the previous approach can include evaluation in terms of time and resources. This may include a range of factors from the

difference in time spent on the decision to cost-effectiveness evaluation.

3. The manager's conception of the decision process is also a critical factor influencing adoption and utilization of the aid. This includes several factors. The decision maker's subjective evaluation of the aid's value is the overall determining variable. Several other elements can influence that evaluation. The manager's confidence in the model solution, consideration (or understanding) of the appropriateness and complexity of the analytical formulation, and decision benefits from alternative procedures will reflect on his/her determination of the benefits. Evaluation of the aid's ease of use will indicate estimates of time, skill and resource costs necessary for the procedure.

Finally, a process-oriented evaluation should investigate changes in the decision process with respect to understanding and learning about the decision problem specifically and problem solving methods in general. Here both theory and methods fail in evaluation. Considerable evidence exists that a major benefit of decision aids is the improvement in understanding gained by examining the problem in the perspective of the decision model (Humphreys and McFadden 1980). A good decision aid can create considerable benefits to the decision maker through learning effects by highlighting problem structure, causal relationships, preferences, expectations, decision procedures, resource constraints, and even simply by displaying formerly disaggregated data in exploratory aggregate formulations. Yet little theory guides the researcher to design decision tools to facilitate such learning while solving complex decision problems (Keen and Scott Morton 1978). The 'silver lining' approach to the issue is to regard any such benefit as coincidental, but to utilize this in facilitating adoption of the technique. The 'bitter pill' approach regards the logical decision procedure as difficult but necessary for individuals to master. Given time, decision makers will 'learn' that the value of correctly made decisions outweighs the cost of learning complex skills.

Evaluation of learning effects is particularly complicated by the absence of a clear definition of learning. Even from the behavioralist perspective, there are multiple interpretations of the concept. The simplest definition is derived from the operant conditioning research tradition of psychology. Learning _is_ operant conditioning, or in other terms the conditioning of a response to a particular stimulus, rather like a Pavlovian dog. With the demise of this research approach, it was recognized that human learning involved motivational and memory factors in combination with complex patterns of stimuli. Until the last decade, human learning research was still limited primarily to memory and motor skill or simple problem solving performance in laboratory experiments (Langley and Simon 1981), and succeeded to some extent in distinguishing characteristics of 'expert' performance. The resulting research area of artificial intelligence has focused on expert performance with suprisingly little attention to the learning processes either of the experts or of ordinary humans (Simon 1981). It is widely accepted, however, that learning involves at least three somewhat distinct processes (Rumelhart 1981):

1) <u>accretion</u>, or the process of accumulating knowledge (facts, beliefs) in memory; 2) <u>restructuring</u>, the process whereby whole new knowledge structures and procedures are created; and 3) <u>tuning</u>, a process involving modification of existing structures and procedures. How these principles can be used to form a basis for experiential learning in complex problems has received little attention, primarily due to the lack of methodological framework. Langley and Simon (1981) hypothesize that although researchers are unsure how cognitive processes are affected in learning, certain principles define the conditions within which learning can take place.

1. <u>Knowledge of results</u>: Change in performance must be detectable
2. <u>Generation of alternatives</u>: The individual must be able to attempt alternative behaviors
3. <u>Causal attribution</u>: Results must be attributable to specific components of the decision environment
4. <u>Hindsight</u>: Past performance must be re-evaluated in terms of subsequent results and causal attributions
5. <u>Learning from instruction</u>: The quality and content of examples, decision rules, and causal relationships suggested by an instructor affects both what is learned and how rapidly learning takes place
6. <u>Automatization</u>: Continued practice causes improvement in speed and accuracy of performance

The rationalist perspective of learning is regretably quite barren. This is attributable principally to the static nature of rationalist decision models and the lack of interest in descriptive modeling of decision processes. A prominent decision-theoretic text in agriculture (Anderson et al. 1977) mentions learning only twice, in bibliographic references to changing subjective probability distributions by Bayesian probability revision.

'Learning' from a rationalist decision theory perspective thus indicates incorporation of new information into expectations expressed as probabilities. Rationalist decision theory has no clear perspective on formulation or reformulation of knowledge about procedures for arriving at decisions. The only recognized procedural knowledge comes from the rules of mathematical logic, and the research carried out to investigate 'learning curves' for adoption rates of innovations generally does not extend beyond the correlational analysis of static factors associated with adoption data. Procedural 'learning' is assumed to be the adoption of formal decision procedures by the decision maker as he/she realizes that such procedures generate results most likely to satisfy decision objectives.

What is learned and how is such learning facilitated by utilization of a decision aid? Generalizable answers to these questions are scarce. Certainly much depends upon interactions between characteristics of the decision problem, the decision maker and the tool, but how these characteristics interact to stimulate (or inhibit) learning is unclear. Perhaps the best approach to evaluation of learning within the constraints of current knowledge is to examine the most common claims for possible learning effects of decision aids.

1. <u>Problem structure</u>: The decision maker may re-formulate his/her perception of this and similar problems by exposure to the parsimonious analytical model of the decision aid.

The relative importance of objectives, the critical nature of certain constraints, and other causal relationships between elements of the problem may stimulate a better quality decision in the present instance or a broader knowledge base for similar or repeated future decisions. Finally, knowledge of the model structure serves as an evaluative mechanism for the decision maker to determine whether such a structure is considered appropriate for this type of decision.

2. Problem 'unfolding': Through utilization of the decision aid, the individual may learn general problem-solving techniques such as decomposing complex problems into smaller ones more amenable to analysis. The critical decomposition between what is desired (preferences or utilities) and what is believed (beliefs or probabilities) forms the basis for more consistent, reasonable decisions. Similarly, the aid may facilitate learning the implications of different decision assumptions and of conflicting decision objectives.
3. Interactive processing and/or simulation: Interactive processing is felt to greatly facilitate learning of problem structure and decomposition through relatively immediate communication between aid and user. It also facilitates simulation-based aids to stimulate learning of action-outcome relationships by allowing the user to define and test numerous strategies in a real-time environment.
4. Graphical output: Two related aspects are claimed to affect learning through graphical representation of output. First,

graphs summarize data in a spatial perspective. Learning may be facilitated by decreasing information processing requirements through `chunking' (Newell and Rosenbloom 1981), thus allowing limited attention resources to be focused on learning model structure and causal relationships. Second, graphs may be remembered better than tables, allowing more accurate comparison of model solutions. Because graphs can also be comprehended faster than tabular data, the time necessary to make decisions may decrease in repeated decisions.

Since learning necessarily refers to changes in knowledge structures, procedures and cognitive strategies over time, evidence supporting the above claims can only be obtained through long term testing and evaluation of repeated utilization of decision aids. The short term learning effects of changes in decision makers' conception of the problem, knowledge of causal relationships and confidence in their ability to make better decisions are helpful, but not conclusive, evidence of learning applicable to future decisions. Nevertheless, even the short term learning effects of aided decision making have not been examined in either laboratory or field environments (Keen and Scott Morton 1978). Methodological problems are the principal cause of this dearth of research. It is unclear what is learned, how it is learned, and what are the relative costs and benefits of different aspects of learning through decision aids. Whatever evidence that can shed light on these issues is likely to bring us closer to Pondy's ideal of a theory of decision tools.

CHAPTER IV

MULTIPLE CRITERIA DECISION TECHNIQUES

4.1 Introduction

Behavioral decision research has emphasized the importance of such factors as aspiration levels, sequential attention to multiple goals and action/feedback as functional mechanisms to compensate for information processing limitations in decision making. Rationalist research emphasizes consistency with respect to decision postulates. It has been suggested above that the design of decision aids may benefit from a synthesis of the two perspectives on decision making. This chapter will investigate a class of techniques which offers promise for development of aids.

In many decisions, individuals weigh alternatives along multiple dimensions or seek multiple objectives from a single decision or choice. Often a decision aid and underlying model may be constructed as a one dimensional problem to take advantage of powerful optimization techniques without substantially misrepresenting the decision from the perspective of the decision maker. However, explicit consideration and modeling of multiple criteria perceived by the decision maker as important to problem structure, analysis and solutions may provide potential for greater benefits from an aid than would be the case with a uni-dimensional model. This might be the case if the decision maker considers the situation to be characterized by multiple criteria and may respond negatively to less realistic formulations, or if the problem requires clarification of the decision maker's objectives and tradeoffs between objectives. Multiple criteria techniques, developed principally by operations researchers, offer the power of optimization procedures with the flexibility to handle such multiple criteria problems.

This chapter first briefly discusses research on multiple objectives of farm operators within the agricultural economics literature. Then the wide range of multi-criteria computational procedures is discussed, with particular attention to multiple objective programming techniques and interactive approaches which might be operational within a farm management context. The Interactive Multiple Goal Programming (IMGP) technique developed by Nijkamp and Spronk (1981) receives particular scrutiny for its relatively flexible data requirements, interaction with the decision maker, adaptability to group decision processes, and potential for decision maker learning with respect to the impacts of conflicting objectives.

4.2 Multiple Objectives in Agricultural Research

Although neo-classical economic theory is primarily based on the assumption of uni-dimensional preference, management researchers in agriculture have always recognized the importance of multiple objectives to farm managers. Many objectives are poorly formulated by the manager, are conflictive and/or incommensurable and are of varying importance in any particular decision. However abstract and poorly articulated, multiple objectives have been shown to be important to farm managers. In fact, the suspicion has been voiced by some farm management researchers that at least in part ". . . differences in the financial performance of farm firms (growth, profitability, leverage, liquidity) may be attributed to differences in the composition, ordering and weighting of farmers' goals, rather than to shortcomings in management ability or to attitudes towards risk." (Robison et al. 1984: 28)

Smith and Martin (1972) utilized factor analysis techniques to identify significant goals of Arizona ranchers. Although no attempt is made to determine the comparative importance of these objectives in business decisions, it is shown that social ties to the community along with monetary goals emerge as significant objectives for managers. Gasson (1971) showed that British farmers are strongly motivated by objectives intrinsic to farm work rather than by economic goals. Also, managers were seen to re-order goal priorities depending upon the type of decision under consideration.

Studies by Cary and Holmes (1982), Hatch et al. (1974), Smith and Capstick (1976), Harper and Eastman (1980), and others elicited farm managers' relative rankings of goals such as profit, consumption, risk, credit borrowing, leisure and esteem. Although relative rankings vary widely between individuals, most of these studies indicated risk and security goals as most important, followed by firm growth, living standard and income objectives. For example, Fernandez (1982) used conjoint analysis to rank order combinations of objectives, and found 56 percent of surveyed farm managers to consider risk, defined as the probability of bankruptcy, as the most important factor motivating decisions, while income and leisure objectives were considered most important by 36 percent and 8 percent of managers.

Some researchers have attempted to model management decisions on the basis of multiple objectives of representative firms. Problems arise in determining the level of abstraction necessary to adequately operationalize multiple objectives. Some objectives are hierarchical (Georgescu-Roegen 1954), with no tradeoffs between levels of the hierarchy, while others are directly competitive and can be traded off against one another. The most appropriate computational technique for such multi-criteria analysis is not well understood in agricultural research. Wheeler and Russell (1977) applied goal programming(GP) to the decision problem of planning a mixed crop and livestock farm. They propose that farmers' goals can be divided into three classes:

1. Non-quantifiable goals, such as a desire to be considered a top farmer.
2. Minimum achievement goals, such as remaining in farming. The exact achievement level is not relevant.
3. Quantifiable goals, which may be interrelated or incompatible. Goals relevant to farm planning include income goals, working capital goals, labor cost goals and labor utilization goals.

They construct an illustrative goal programming model, assuming three goals: 1) maximize gross margin, 2) minimize incidence of negative cash flow, and 3) stabilize labor utilization through the year. The effect of different possible goal priority weights on solution activities generated by the model is analyzed and discussed.

Barnett et al. (1982) utilized multi-dimensional scaling to estimate goal weights of Senegalese farmers for the assumed goals of: 1) producing sufficient food in bad years, 2) reducing cash expenditures, 3) improving income, 4) achieving more leisure time, and 5) obtaining higher yields. A goal programming model was formulated and used to estimate crop mix, net income, acreage cultivated and credit usage. Although resulting solutions were similar to observed activities in the area, the model did not outperform a similar profit maximization model. No attempt was made to evaluate the model on any basis other than its ability to imitate observed resource allocation.

Romero and Rehman (1984, 1985) describe various multiple criteria techniques, such as lexicographic and weighted goal programming, vector maximization and compromise programming. They illustrate application of some techniques to an orchard planning exercise. Of considerable interest is discussion of the similarity between risk programming techniques such as quadratic or Mean Absolute Deviation (MOTAD) programming and a certain class of multiple objective procedures. These procedures use the constraint method, in which each objective of a multi-criteria problem is sequentially optimized while all others are parametrically varied over the relevant range. Thus, all non-dominated solutions of the problem are generated. Romero and Rehman state that both Expected Value-Variance (E-V) and Expected Value-Mean Absolute Deviation (E-M) ". . . can be legitimately taken as a MOP [Multi-objective] model with two objectives." (1985: 183) They further describe the Target MOTAD programming technique developed by Tauer (1983) as a hybrid between multi-objective and goal programming, using the constraint method to generate solutions with the risk objective measured as deviations from a goal (target) value.

None of the above studies have attempted to operationalize a multi-criteria model as a decision aid for farm managers, although each suggests how such an approach might be implemented. Selection of a multi-criteria technique for aiding farm management decisions requires careful consideration of technique characteristics and requirements with respect to what is known about unaided decision making and about characteristics of successful decision aids in other contexts. Certain techniques will probably have advantages for particular types of decisions, but what is sought here is a flexible technique which can be used in many different contexts. The following sections examine the various multi-criteria techniques available with respect to their suitability as a computational model for a decision aid.

4.3 Multiple Criteria Decision Making: History and Classification

It is the contention of multiple criteria decision researchers that most economic decisions are made by decision makers on the basis of multiple, conflicting objectives, and that the objective of decision analysis should be to help decision maker(s) structure the decision problem in such a way as to clarify preferences and to allow the decision maker(s) the final judgement as to which action best satisfies preferences. They criticize 'traditional' single criterion decision research as being in fact a methodology of measurement. Elicitation and measurement, followed by computerized search procedures ". . . become the substitute for decision making . . . The decision is implicit in the measurement." (Starr and Zeleny 1977: 25) However, Rosenthal (1985) cautions researchers not to overstate their case and dismiss single objective formulations so lightly. A combination of carefully designed single objective model, multiple reformulations and intelligent post-optimality analysis may be at least as beneficial as a multiobjective formulation.

Decision theorists' concern for what has sometimes been referred to as the 'curse of multi-dimensionality' was first expressed by von Neumann and Morgenstern (1944). Writing with respect to the social exchange economy, they expressed that such an optimization problem was not a maximization problem, but a 'peculiar and disconcerting' mixture of maximization problems. That kind of problem, they state, is not treated in classical mathematics. Koopmans (1951) first defined the concept of an efficient vector, the vector of solution values for multiple objectives which is undominated by any other feasible vector of solutions. Kuhn and Tucker (1951) introduced the mathematical programming model of vector maximization and derived necessary conditions for optimal solutions.

Certain key concepts should be defined before classification and analysis of multiple criteria decision research. These terms may not be used in multiple criteria decision making (MCDM) research in quite the same manner as used in economics research.

1) An <u>attribute</u> is a descriptor of objects or processes in the real world as interpreted by each individual. The number of possible attributes of any object or process is infinite, but only a subset of all perceivable attributes are relevant to a particular decision situation. The purpose of attribute measurement is the unambiguous definition of attributes and attribute magnitudes. Example of attributes are height, heat and beauty.

2) An <u>objective</u> is functionally related to the attributes of an object. It indicates both preference and a preferred direction of change. Examples are maximization of profits or minimization of costs.

3) A <u>goal</u> is an objective with a specific desired level. Thus, reaching the moon by 1970 was a goal, target or aspiration level. The terms 'goals' and 'objectives' tend to be used interchangeably in much of the literature, although in many instances a goal could as easily be considered a constraint.

4) <u>Criteria</u> can be either attributes or objectives salient to a given decision. When problems involve mostly attributes, research is said to involve the theory of choice, while the cases dealing mostly with objectives are referred to as involving the theory of decision making. Multiple Attribute Decision Making (MADM) research usually involves selection from a limited set of explicit alternatives, while Multiple Objective Decision Making (MODM) concerns itself with the design and selection of implicit alternatives.

A significant advance in multiple criteria decision making occurred with the development of goal programming by Charnes and Cooper (1961). Major contributors to this line of multiple criteria methods are Ijiri (1965), Lee (1972) and Ignizio (1976). Following a very different tact, researchers such as Yntema and Torgerson (1961) laid the foundations of modern multiattribute decision theory with research on necessary conditions for utility function decomposition. Particularly noteworthy in the development of Multiattribute Utility Theory (MAUT) are Keeney and Raiffa (1976) and Fishburn (1965).

Linear multiobjective programming techniques, meanwhile, have developed through the works of Geoffrion (1968), Evans and Steuer (1973) and Zeleny (1982). An annual international conference on multiple criteria decision making began in 1972, encompassing all areas of multiobjective research for decision making. Later, journals such as <u>Management Science</u> and <u>Computers and Operations Research</u> devoted special issues to multiple criteria developments, and several volumes exclusively dedicated to multiple criteria problems have been published. MCDM is truly a multi-disciplinary research area, with major contributions from operations research, management science, psychology, finance, resource development, and systems science.

The three major branches of MCDM decision research are Multiple Objective Programming, Goal Programming and Multiattribute Utility approaches. Each has numerous variations which are reviewed in Hwang and Masud (1979), Goicoechea et al. (1982), Cohon (1975) and Chankong et al. (1985). Several authors have attempted to identify the critical characteristics which distinguish multiple criteria approaches. Chankong et al. (1985) develop a typology of five dimensions which can be used to differentiate MCDM approaches:

1. Stochastic versus deterministic formulation
2. Implicit or explicit constraints (with implicit constraints, alternatives are discrete, while with explicit constraints, alternatives are implicit and may be infinite)
3. Methods and assumptions with respect to preferences:
    a. Techniques which utilize the dominance principle and assume that preferences are monotonic

b. Techniques which require elicitation of preferences by priorities, weights, goals or ideals

c. Techniques which require elicitation of preferences by tradeoffs

d. Techniques which utilize some form of global preference

4. The number of decision makers which can be accomodated

5. The number and type of objectives possible in the formulation

Although each dimension is important, the authors contend that the characteristics of stochastic/deterministic formulations and explicit/implicit constraints are suitable to classify most MDCM techniques.

Another classification of the approaches, according to Hwang and Masud (1979), is formulated according to: 1) the stage of decision making at which preference information is elicited from decision makers, and 2) the type of preference information required. According to the first classification factor, research approaches fall into one of the following categories.

1) No articulation of preference information. These approaches derive the 'best' solution according to a geometric definition of closeness to a 'bliss point'. The essence of the problem thus involves finding the measure of proximity most acceptable to the decision maker.

2) 'A priori' articulation of preferences. The decision maker must make global judgements regarding tradeoffs between objectives before the formulation of the problem. The MAU approach falls in this category.

3) Posterior articulation of preferences. In this approach, a subset of non-dominated solutions are determined, from which the decision maker chooses the most satisfactory solution, ". . . making implicit trade-offs between objectives based upon some previously unindicated or nonquantifiable criteria." (Hwang and Masud 1979: 243) Only very general assumptions need be made about preferences in order to generate the efficient set. Linear and non-linear multiple objective programming methods are found in this category. Since the number of nondominated solutions might be very large, these methods are often implemented in an interactive environment, thus becoming virtually indistinguishable from the following category.

4) Progressive articulation of preferences. This line of research is principally context-specific, in that the decision maker's preferences are progressively revealed during an exploration of the feasible set. Some methods require explicit information about rates of tradeoffs between objectives, while others require little more than that the decision maker indicate the objective function values with which he/she is dissatisfied. The decision maker's participation is much more intensive than in other approaches.

With the continued development of powerful interactive computer systems, the latter approach has received much attention in MCDM research. The interests of operations researchers in obtaining solutions acceptable to decision makers and of behavioral researchers in avoiding some of the perceived inadequacies of the rationalist approach have stimulated development of a wide range of research efforts.

4.4 Mathematical Formulation of Multiple Objective Techniques

The general mathematical representation of the multiple objective decision for any of the Hwang and Masud classifications is:

(4.1)

$$\text{Max } F = F[f_1(\underline{x}) \ldots . f_k(\underline{x})]$$

subject to

$$\underline{x} \in X$$

A set of feasible solutions $\underline{x}$ is contained in n-dimensional space, and a set of scalar-valued objective functions f are defined on X. The model has n decision variables, m constraints and k objectives. Any or all of the functions may be nonlinear. Rosenthal (1985) notes that there is no precise mathematical definition of this maximization because there is no natural ordering of the vector function F.

> With no such ordering, given two feasible alternatives y and z, there may be no definite answer as to whether F(y) is greater than, less than, or equal to F(z) . . . A reasonable statement of the problem is: find a feasible solution x so that the most preferred vector of objective function values, F($\underline{x}$) is attained. (Rosenthal 1985: 135)

The use of the subjective term 'preferred' indicates that additional rules or information must be imposed on the problem in order to achieve a unique solution. This is accomplished in various ways by multiobjective techniques, either by eliciting preferences from affected decision makers or by utilizing mathematical rules as substitutes for preference mechanisms. The following section discusses some of the more important methods within each of the Hwang and Masud (1979) classifications.

The first classification, whose sole methodology is the 'method of global criterion' or 'compromise programming (Zeleny 1982), requires no further information from the decision maker other than the quantification of constraints and objectives. A vector of 'ideal' values of the decision variables is calculated by solving the k succesive single objective problems:

(4.2)

$$\text{Max} \quad f_j(\underline{x}) \qquad\qquad j= 1....k$$

subject to

$$\underline{x} \in X$$

The unique solution is found according to some global criterion which minimizes deviations from an ideal solution consisting of the vector of solutions from the above optimizations.

(4.3)

$$\text{Min } d^* = [(f_j(\underline{x}) - f_j(\underline{x}^*)) / f_j(\underline{x}^*)]^p$$

subject to

$$\underline{x} \in X$$

The difference measure is considered to be a proxy for human preferences. That is, decision making is assumed to function as if the geometric concept of 'closeness' were applicable to cognitive processes. Choice of the parameter p is arbitrary, but can greatly affect the computed model solution. Choice of p=1 reflects a disregard of for deviations of an individual objective from the ideal - only the sum matters. If p=2, the function is the typical sum of squares distance. As p becomes very large, only the objective with maximum deviation matters. As p is decreased from 1 to 0, the smallest deviation is given relatively more weight in the total sum. The advantage of the global criterion approach is that no specific preference information is required. There is, however, no empirical or theoretical evidence whether preferences are realistically modeled with distance measurements.

The second class of multiple objective decision approaches (a priori articulation of preferences) includes both Multi-attribute Utility (MAU) and Goal Programming (GP) approaches. MAU is the only axiom-based multiple criteria technique. The MAU decision problem is formulated as:

(4.4)

$$\text{Max } U = U(f_j(\underline{x})) \qquad j = 1 \ldots k$$

subject to

$$\underline{x} \in X$$

U is the von Neumann-Morgenstern utility function with multiple arguments f_j. The utility function must be defined over all objectives and measured before solving the decision problem. Such estimation becomes very difficult even for the most elementary problems. Therefore, in empirical problems the concepts of preferential and utility independence are applied to determine whether the utility function can be considered either additively or multiplicatively decomposable into single dimension functions (Keeney and Raiffa 1976). The major advantage of the approach is that if U has been accurately measured, it will insure (by definition) the most satisfactory solution to the decision maker. The major difficulty is that the decision maker is required to articulate rather precise judgements about preferences in a situation devoid of information about the problem at hand. Optimal actions based upon such utility assessment are also likely to be time and state dependent. Empirical applications of MAU to public policy are documented in Drake et al. (1972), while Green and Wind (1973) explore marketing applications of MAU.

Goal programming (GP), originally proposed by Charnes and Cooper (1961) and further developed by Ijiri, Lee and Ignizio is one of the earliest operational techniques reflecting multiple objectives. Goal programming approaches attempt to determine one or more solutions which come 'as close as possible' to satisfying aspirations or targets. It is sometimes considered as an operational basis for modeling satisfycing behavior, but Spronk (1980) shows how GP can incorporate optimizing behavior. Goal programming is based on well-established mathematical programming methods (usually with linear formulations) and documented behavioral characteristics of decision processes (use of aspiration or target achievement levels and hierarchical ordering of objectives). A common formulation of a multiple goal problem is:

(4.5)

$$\text{Min } (P+_j \, d+_j, \; P-_j \, d-_j) \qquad j = 1....K$$

subject to

$$f_j(\underline{x}) - d+_j + d-_j = f_j^{*}$$

$$\underline{x} \in X$$

The objective function reflects preferences for positive and negative deviations $d+_j$ and $d-_j$ from the aspired levels f_j^* of the objective functions f_j, and $\underline{x}$ is a vector of activity variables in the feasible region. The deviations are weighted by the respective P+ and P−. The feasible region delimited by the activity variables $\underline{x}$ is assumed convex, as is its projection in objective function space.

Two major approaches to multiple goal programming differ in their interpretation of the weights P. The preemptive weights version is consistent with a lexicographical interpretation of utility preference for multiple objectives (Lee 1972). That is, objectives are considered to be ordered in hierarchies, with satisfaction of higher ranking objectives required before considering solutions to lower objectives. Such non-compensatory preferences for objectives are inconsistent with classical utility analysis.

In the second approach, the weights P are considered compensatory, which therefore focuses the problem on estimation of preference weights between conflicting objectives. This weighted linear multiple goal programming formulation is also commonly utilized. Note that this formulation is general enough to accomodate a wide variety of formulations, with the typical maximization of each objective function as a special case. Using as an example a model with a single objective function:

(4.6)

$$\min \left(w+_j \, d+_j \; + \; w-_j \, d-_j \right) \qquad j = 1....k$$

subject to

$$\underline{x} \in X$$

It can be seen that since $d+ + d- = 0$, the choice of w determines the type of optimization. If $w+_j = 1$ and $w-_j = 0$, minimal overachievement of the objective is sought. The converse is true for $w+_j = 0$ and $w+_j = 1$. If both are set equal to one, exact attainment of the aspiration level is sought. Setting $w+_j = 1$ and $w-_j = -1$ could be used to minimize the objective function, while reversing the values will maximize the function. As an approximation of a continuous concave preference function, a piecewise linear objective function can be formulated to indicate different marginal contributions of the activity variables at varying levels of objective function achievement.

The disadvantages of goal programming are similar to those of most programming models. Uncertainty associated with parameter estimates and other commonly encountered violations of model assumptions compound empirical difficulties. Added to these difficulties are the required a priori specification of two other types of parameters: the relative weights between objectives and the relevant aspiration levels of the decision maker with respect to each objective. However, the latter drawbacks can be alleviated through interactive procedures. Zeleny (1982) shows that in addition to incompatibility with traditional utility concepts, if aspirations levels are set too pessimistically, goal programming may fail to identify unbounded solutions and may indicate solutions which are in fact dominated. Goal programming has been used in a very broad range of private and public applications, including manpower planning (Charnes et al. 1968), production planning (Goodman 1974) and academic resource allocation (Lee et al. 1980). In agricultural research, applications have included intergenerational transfer (Dobbins 1978) and farm planning (Wheeler and Russell 1978, Flinn et al. 1980 and Barnett et al. 1982).

In the 'a posteriori' class of decision models, the non-dominated subset of all feasible solutions is identified and presented to the decision maker for choice of the most preferred solution. This class of techniques basically requires that the decision maker's preference function is monotonic in the objective functions. The Multiple Objective Linear Programming (MOLP) or Vector Maximum approach is the best known of this class. It is formulated as:

(4.7)

$$\max \quad f_j(\underline{x})$$

subject to

$$f_k(\underline{x}) \geq b_k \qquad\qquad i \neq j$$

$$\underline{x} \in X$$

In this formulation, each f is a linear function of the activity variables $\underline{x}$. The complete set of efficient extreme points of the convex set formed by the linear constraints is generated. Any interior non-dominated solution can be expressed as the linear combination of adjacent extreme points. This process removes any subjectivity from the mathematical formulation, since the operation of generating the efficient set is well defined. There are numerous techniques for determining first an initial non-dominated extreme point and subsequently the entire set of non-dominated extreme points. Applications of MOLP to problems such as transportation, portfolio planning and production planning are documented in Zeleny (1982). An application to capital budgeting in agriculture was described by Candler and Boehlje (1971). The principal disadvantage of the approach is the lack of assistance for the decision maker if a large number of undominated solutions are generated. Therefore, 'a posteriori' techniques are usually combined with interactive approaches which elicit local preferences for intermediate undominated solutions.

Interactive and iterative methods for progressive articulation of preference information have received increasing attention in applied decision analysis. As stated by Cohon:

> The philosophy of iterative approaches to multiobjective problems is an appealing one: involve the decision maker directly in the solution process in a manner that will allow that person's best-compromise solution to be discovered. (1978: 211)

The search for the preferred solution (or a small set of equally preferred solutions) involves an exchange of information at each iteration between decision maker and decision analyst. In response to local information about non-dominated solutions generated by the analyst, the decision maker is asked to express local preferences between objectives. This information is then used by the analyst to generate more preferred solutions. The decision maker can thus learn about relative tradeoffs between objectives implied by decision constraints. Since the decision maker controls the direction and termination of the decision process, the solution obtained should have a better chance of being implemented.

Local preference information may be more accurate than global information required by 'a priori' methods. Some techniques require explicit information from the decision maker concerning rates of tradeoff between objectives, while others require little more than that the decision maker indicate which objective should be improved. All these techniques, however, are critically dependent upon the accuracy of local preference information. Some do not guarantee that a single preferred solution can be obtained in a reasonable number of iterations, and considerable input may be required from the decision maker. Several interactive methods of this class have been implemented for private or public planning. No interactive multiobjective method has been applied in agricultural research. Four methods are examined briefly for their suitability to farm management planning: the methods of Geoffrion et al. (GDF), Zionts and Wallenius, Steuer and Nijkamp and Spronk (IMGP).

4.4.1 The Method of Geoffrion

The method proposed by Geoffrion, Dyer and Feinberg (1972) is the earliest interactive method, and is formulated as follows:

(4.8)

$$\max U = U[f_1(\underline{x}) \ldots f_k(\underline{x})]$$

subject to

$$\underline{x} \in X$$

The objective functions f and the constraints are assumed to be explicitly known by the decision maker. The preference function $U(\underline{f})$ is assumed only implicitly known (but everywhere differentiable and with positive first derivative). The procedure assumes: 1) the constraint set is convex and continuous, 2) $U(\underline{f})$ is differentiable and concave with respect to $\underline{x}$, 3) each f_j is concave with respect to $\underline{x}$, 4) $dU / df_j > 0$ in the neighborhood of any local solution $\underline{x}^i$, where f_j is some reference objective.

The model is solved using the Frank-Wolfe nonlinear programming algorithm, which belongs to the class of programming techniques known as gradient methods. These techniques solve for global optima using a series of linear approximations to a preference function. The solution procedure consists of two repeated steps. In the first step, the optimal direction of improvement in the utility function is determined by eliciting information about relative tradeoffs between objectives. The decision maker must be able to accurately express the marginal rate of substitution between objectives (using some objective as a reference). The second step involves calculation of the optimal amount of change in the direction of greatest improvement. This information is usually elicited from the decision maker in response to graphical display of effects of various possible step sizes on the objective functions.

Hwang and Masud state that ". . . the lack of a systematic assessment procedure for tradeoffs is a drawback of this method . . ." (1979: 121) Certainly the information demands of the decision maker are not trivial. Nevertheless, it has been used in some empirical planning efforts (Geoffrion et al. 1972). Further developments of this technique have attempted to alleviate the rather stringent information requirements.

4.4.2 The Method of Zionts and Wallenius

The method of Zionts and Wallenius (1976) is formulated in a manner somewhat similar to that of GDF. All objective functions and the constraint set must be linear in the decision variables. Again, the preference function is assumed only implicitly known by the decision maker. The preference function may be assumed linear in the various objective functions, or more generally be assumed a concave function of the objectives. In the latter case, the information requirements of the decision maker are somewhat more stringent, but the authors indicate the additional requirements are not excessive.

The method involves a cycle of four steps. First, an arbitrary set of weights (λ_j) is chosen to create a linear proxy for the utility function:

(4.9)

$$\max \quad \Sigma_{j=1}^{k} \; \lambda_j \; f_j(\underline{x}) \qquad j= 1....k$$

subject to

$$\underline{x} \in X$$

This function is optimized to produce a non-dominated solution. Then a set of 'efficient' variables is identified from the non-basic variables, having the characteristic that if introduced into the basis, such variables cannot increase one objective function without decreasing at least one other function. A set of w_{ij}, which are decreases in the objective function f_j stemming from introduction of the non-basic variable x_i into the solution are estimated around the solution point found in the optimization. A number of tradeoffs implied by the w_{ij} are presented to the decision maker, who expresses whether the tradeoffs are desirable or undesirable or whether he/she is indifferent to the proposed tradeoffs. Essentially, the decision maker is allowed to explore whether a move to one of the adjacent non-dominated solutions would be desirable. Questions are posed as, "Would you accept a decrease of 6 units in objective 1 for an increase of 2 units in objective 2 and 1 unit in objective 3?" A new set of weights λ_j is found which is consistent with all responses. An optimum is reached when the decision maker rejects all proposed tradeoffs. The optimum is reached in a finite number of iterations, since each tradeoff increases the implicit utility function. Information demands on the decision maker are considerably less with this method compared to the GDF method.

This approach does require that all the constraint and objective functions can be linearly approximated. If the implicit utility function is assumed concave, the procedure is slightly modified and the number of iterations required is significantly increased. There is also a possibility for suboptimization if a proposed solution is surrounded by other equally efficient solutions with approximately the same utility level. Zionts and Deshpande (1978) describe how the method was used in a U.S. Department of Energy planning model.

4.4.3 The Method of Steuer

The method of Steuer (1976) is an extension of the 'a posteriori' articulation of preferences techniques. As discussed above, these techniques generate the subset of feasible solutions which are undominated. However, the number of non-dominated solutions may impose severe information processing requirements on the decision maker. This general class of interactive methods thus seeks techniques to reduce the number of possible solutions to manageable size. The general model is to find all λ, $\underline{x}$ so as to:

(4.10)

$$\max \ \Sigma_{j=1}^{k} \ \lambda_j \ f_j(\underline{x})$$

Subject to

$$\underline{x} \in X$$

$$\Sigma_{j=1}^{k} \ \lambda_j \ = 1$$

The set of undominated feasible solutions can be unmanageably large for realistic problems. This is because the linear weighting parameters λ_j can take on any values from zero to one in the absence of information about decision maker preferences for the various objectives. Steuer's interactive method therefore relies on an reduction of weighting parameter ranges based upon iterative elicitation of the most preferred solution from a selection of proposed efficient solutions. The tighter are the interval ranges for the λ_j parameters, the smaller will be the non-dominated, preferred set of extreme points.

At each iteration, the current interval ranges of λ_j are used to generate efficient solutions consistent with the weights. To reduce demands on the decision maker, only a subset of such efficient solutions are presented to the decision maker (based upon the distance function concept of 'closeness' of solutions). The decision maker only has to indicate the most preferred solution in this set, after which the weighting parameter intervals are tightened in a manner consistent with the preferred solution and another iteration initiated. Provision is made for 'backtracking' if the decision maker is no longer satisfied with the solutions restricted by a previous decision. The process continues until a small portion of the non-dominated set is identified which contains the globally preferred solution. The principal advantages of the procedure are:

1. The relaxation of information requirements from the decision maker, both in terms of the weights associated with objective functions and the number of candidate solutions presented by the decision maker. At each iteration, the decision maker must only select the most preferred solution from a small set of proposed solutions.

2. The procedure converges in a finite number of iterations.

The method requires the assumption of an additively decomposable utility function, and the computational procedures implied by the gradient cone analysis utilized in this efficiency approach are not trivial. Steuer and Schuler (1978) describe an application of this method to forestry management.

4.4.4 The Method of Nijkamp and Spronk

Nijkamp and Spronk (1981) present an interactive goal programming method which does not require a priori information about goals, or explicit a priori information about the decision maker's preference function. It is not necessary to specify weighting factors for objectives, since the decision maker implicitly states which objective function is considered to be the most important at each proposed solution. Nor must the decision maker specify by how much the objective should be improved. Information known a priori, however, can be incorporated within the procedure if certain objective function values are considered important by the decision maker. Of course, explicit definition of the relationships between activities, constraints and objectives is required. The decision maker is required only to express local preferences for prospective solutions presented as vectors of objective function values. The method also uses well known linear programming techniques, which greatly simplifies its application and interpretation. The general formulation of the Nijkamp and Spronk method (called the Interactive Multiple Goal Programming method - IMGP) is the same as the normal goal programming model:

(4.11)

$$\min U = U(P+_j \, d+_j \, , P-_j \, d-_j) \qquad j = 1....k$$

subject to

$$f_j(\underline{x}) - d+_j + d-_j = f_j^*$$

$$\underline{x} \in X$$

The functions f_j and g_i are assumed linear in the decision variables. The preference function U is assumed to be only implicitly known to the decision maker and is assumed monotone nondecreasing in both the objective functions and the decision variables. The decision maker does not have to explicitly indicate the weighting factors (P+ and P-), since the order of selection during the interactive process indicates the importance of particular objectives to the decision maker. The aspiration levels f^* are minimally acceptable levels of the objective functions and the decision maker is not required to stipulate initial values. However, if certain values are of particular interest to the decision maker, they may be incorporated in the IMGP procedure.

This interactive version of linear multiple goal programming attempts to avoid the problem of specifying a priori target values by starting with a set of minimum goal levels which are satisfied by a large number of alternatives. The set of minimally acceptable goal values is called the 'pessimistic' solution. These values may be defined by the decision maker, or may be computed through the mathematical formulation of the problem. The MOLP problem corresponding to the general IMGP problem is (assuming all objectives are to be maximized):

(4.12)

$$\begin{aligned}
&\max \quad f_1(\underline{x}) \\
&\quad\vdots \qquad \vdots \\
&\max \quad f_k(\underline{x}) \\
&\text{subject to} \\
&\qquad f_j(\underline{x}) - d+_j + d-_j = f_j^* \\
&\qquad \underline{x} \in X
\end{aligned}$$

Each of the k single objective maximization problems is solved sequentially , and the implied values of all other objectives are calculated. The vector of all optimum values is called the 'optimistic' solution. In general, the optimistic solution will be infeasible. It will serve as an ideal point which should satisfy preferences, but is not feasible considering conflicting objectives and limited resources. As mentioned above, the set of minimally acceptable objective values is the 'pessimistic' solution. If the decision maker does not indicate preferred values, the vector of pessimistic values is formulated as the minimum of each objective function in any of the k successive single objective problems used to calculate the optimistic values. The final solution preferred by the decision maker and consistent with the feasible set should be found between the ideal and pessimistic solutions.

Trial solutions are proposed to the decision maker (starting with the pessimistic solution), who is asked to indicate which objective function should be improved. The indicated function is increased, either to the next higher aspiration level indicated by the decision maker or (arbitrarily) one-half the distance to the maximum level consistent with the pessimistic levels of all other objectives. The trial value of the indicated objective is augmented to the constraint set as a 'hard' constraint and new ideal values of the other objectives are calculated. The decision maker is then presented output showing the necessary decrease in potential improvement of some of the (k-1) objectives implied by increasing the indicated objective. If the decision maker considers the consequent effect on the other ideal values too extreme, the amount of improvement in the objective is scaled back until an increase is found that is acceptable in terms of its impact on other objectives. Then the decision maker is asked if the trial solution is acceptable, or whether another objective should be increased. The process continues until a single preferred compromise solution is reached or a non-dominated (preferably small) set of solutions is obtained to which the decision maker is indifferent (improvements in any objective are matched by unacceptable deterioration in other objectives).

Sensitivity analysis can be carried out to provide the decision maker with more information once a small non-dominated set of solutions is identified. As in traditional linear programming, sensitivity analysis can help explore the effects of relaxing right hand side constraints (in this case either resource constraints or current minimally acceptable objective levels). This information may help the decision maker investigate further tradeoffs.

IMGP combines many advantages of goal programming and interactive decision procedures within a traditional linear programming framework. It can incorporate multiple objectives, both satisfycing and optimizing behavior, and compensatory or hierarchical treatment of objectives. Only local preferences with respect to well-specified solutions are required, not global preferences. Information on priorities among objectives or aspiration levels within objectives is not required, but can be incorporated if available.

The decision process is structured, in that the decision maker is directed towards final consideration of solutions that are non-dominated, but maintains considerable flexibility through control of the solution procedure by the decision maker. Increased participation in the decision process should lead to better understanding of the problem and of the tradeoffs between objectives. Considerable emphasis is thus placed on the learning potential of the problem. Spronk states that ". . . the interactive approach can be regarded as an operational application of learning theory." (1980: 104) Learning may be stimulated by use of the procedure for a 'quasi-simulation' of changes in priorities of objectives, sensitivity analysis of constraint relaxation, and possible reformulation of the entire model describing the decision problem.

The procedure benefits from use of well-known linear programming techniques. Spronk (1980) states that existing linear programming packages can be adapted by addition of external processing routines to compute the necessary steps efficiently. Convergence of the procedure to a unique solution is assured if the structure of decision maker preferences is such that a unique solution exists (the 'satisficer' is a caveat).

IMGP shares some disadvantages with traditional linear programming. The assumptions of LP which restrict its application in some situations are well known (see Hillier and Lieberman 1980). Another disadvantage may be the large number of objectives which created the need for a multiple objective analysis in the first place. The information processing required of the decision maker in a problem with many objectives could be excessive. A further drawback is the progression of IMGP from dominated solutions to non-dominated solutions. An objection could be made that such a procedure should permit the decision maker to explore the much smaller set of non-dominated solutions. Although the procedure permits correction of errors in expressed local preferences, the IMGP procedure assumes that a consistent preference function exists.

4.5 Selection of a Multiobjective Technique

The selection of a multiple objective decision support technique, it appears, is itself a multiple objective problem. Such a technique should satisfy at least the following requirements:

1. The procedure should structure and define the decision problem in order that the decision maker may define

alternative actions and investigate and clarify how preferences relate to actions and to possible outcomes.

2. The procedure should aid computation to investigate a larger number of alternatives than otherwise possible, and should define a subset of feasible efficient solutions from which the decision maker can select a set of preferred solutions, or (in some cases) can identify a single preferred alternative.
3. The procedure should permit solution of the decision model in a manner analogous to an unaided sequential decision process.
4. The procedure should be adaptable to group decision making processes.

With respect to the behavioralist/rationalist debate on decision making, multiobjective techniques offer varying potential for an operational synthesis of the two perspectives. The following are important elements to consider in choosing a formulation for a multiobjective decision:

1. <u>Multiple criteria problem solution</u>. By definition, any of the techniques discussed above reflect this as an important factor in problem solving. However, techniques vary in the number of objectives which can be modeled in formulations designed to operate in real time. Further, the accuracy and relevance of information reflecting tradeoffs between objectives may distinguish the techniques. This behavioral decision orientation of any multiple criteria technique

contrasts with the rationalist orientation of a revealed or measured uni-dimensional preference structure.

2. Target or aspiration values. Behavioral research has suggested that individuals anchor their decisions on context-specific values of desired objectives. Use of target values in a technique may permit satisfycing behavior. This contrasts with the rationalist emphasis on 'smooth' preferences.

3. Interactive operation in real time. Complexity in modeling a decision problem must be traded off against the need for fast turnaround with managers whose time and attention span is limited. The bottom line in terms of decision support is to keep waiting time for model computations to a minimum. The rationalist perspective does not require this as a criteria for judging the 'goodness' of a decision model.

4. Data input. Most techniques will require the same type and quantity of data for a particular problem, but each multi-criteria procedure will vary in its requirements for elicitation and incorporation of preference information. Given a decision support focus, techniques which permit interactive declaration of preferences between objectives are of special interest.

5. Output information. Most multi-criteria procedures are based on optimization algorithms, and thus are to some extent consistent with a rationalist approach. As Willis and Perlack (1980) indicate, the maximum information which

can be generated by a multi-criteria technique is the complete set of nondominated solutions and all pairwise local tradeoffs among objectives. Since the number of non-dominated solutions is often very large, this characteristic runs counter to the objective of rapid turnaround and may violate information processing restrictions of the decision maker. Therefore, most techniques will present a subset of non-dominated solutions to the decision maker, either chosen by some rule or by a priori interactively elicited preference information. The relative tradeoff weights may be considered and manipulated directly by the decision maker, or indirectly through indications of preference for one objective or another.

CHAPTER V

A MULTIPLE OBJECTIVE DECISION AID

5.1 Introduction

The current research began with an examination of the principal issues of dispute between two schools of thought with respect to individual decision making. The major argument of the behavioralist school is that certain innate cognitive functions can be dysfunctional and may cause individuals to take actions that are not in their best interest. The perspective of decision support seeks to construct tools which complement human strengths in perception, pattern recognition and creative inference, while supplementing recognized weaknesses in computational ability, probabilistic inference, and decision rules. The framework of decision support research is thus improving decision behavior within known information processing constraints.

Decision makers are also observed to evaluate alternatives and take strategic actions with the intention of seeking multiple and sometimes conflicting objectives or goals. Mathematical programming decision models have sometimes reflected hierarchical relationships among multiple objectives as 'hard' constraints, but there have been few attempts to implement a decision aid which explicitly models a multiple objective decision problem. The previous chapter examined the range of relatively new multiple criteria techniques to determine if any offered some possibility for synthesis of rationalist decision principles and behavioralist decision insights within an operational decision aid. This chapter describes the decision model and aid constructed during the current research for supporting an important planning decision of cash grain operations.

5.2 Advantages of IMGP

Some of the advantages of IMGP as a multiobjective solution procedure have been mentioned in the previous chapter. Unlike lexicographic or weighted goal programming, it is not required that the decision maker specify a priori aspiration levels and weights reflecting the relative preference for different objectives. The decision maker is not asked to provide sufficient information to generate a measure of global preference, but instead must express only local preferences for the specific combination of objective function levels generated at each iteration.

Spronk (1980) indicates additional advantages of the IMGP approach. A considerable range of preference relationships can be modeled by the procedure. Figure 5.1 demonstrates some functional relationships between one objective and a preference function. Cases (a) and (b) are relatively straightforward cases of monotone increasing and decreasing preference. The general formulation of a goal programming model for these cases is:

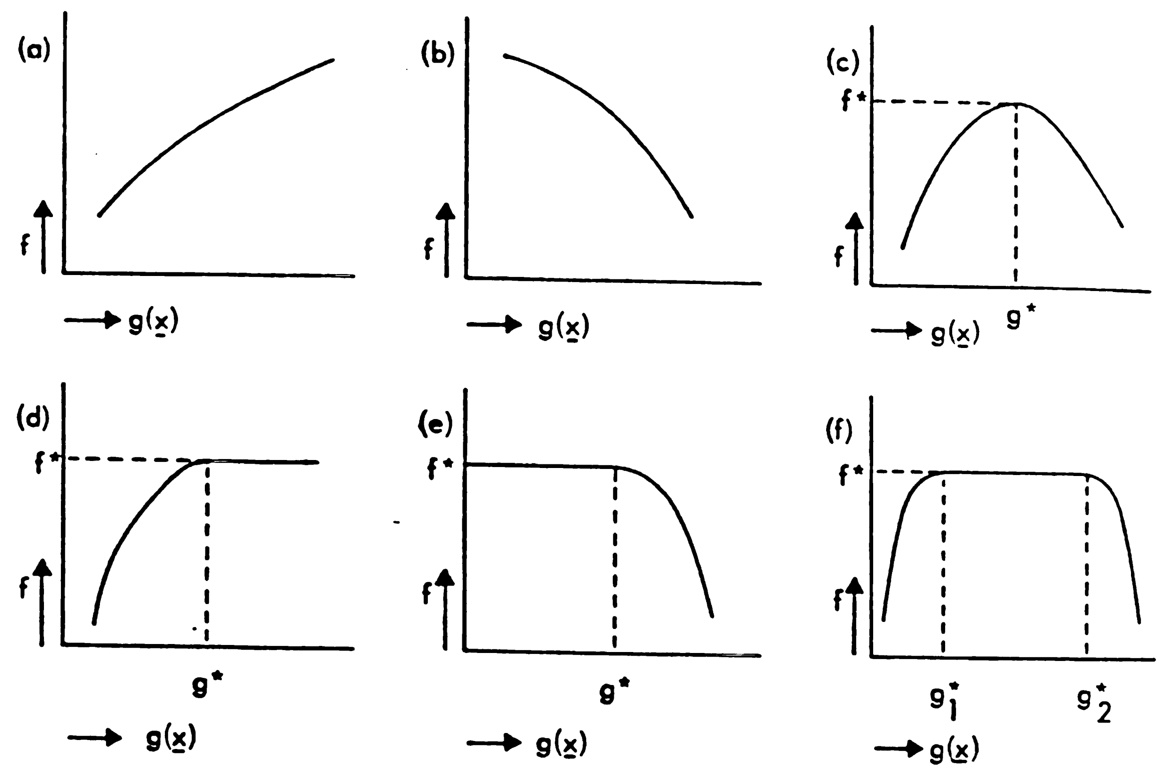
(5.1)

$$\min \; P^{+}_{1} d^{+}_{1} + P^{-}_{1} d^{-}_{1}$$

subject to

$$\underline{x} \in X$$

$$g(\underline{x}) - d^{+}_{1} + d^{-}_{1} = g^{*}$$



Source: Spronk 1980

FIGURE 5.1 FUNCTIONAL RELATIONSHIP BETWEEN A PREFERENCE FUNCTION (f) AND ONE OBJECTIVE FUNCTION (g)

P+, P- are weights assigned to positive and negative deviations (d- or d+) respectively. The set of activity variables $\underline{x}$ is contained in the feasible region X. The final equation reflects positive and negative deviations from the aspiration level g^*. For case (a), g^* can be set at some unattainable level and P+ set to zero, thus minimizing deviations below the aspiration level or in other words maximizing the objective function $g(\underline{x})$. Case (b) can be handled in an analogous manner. Spronk (1980) calls this 'one-sided goal programming'. Of course, with only one objective function, case (a) can be modeled directly as:

(5.2)

$$\max \quad g(\underline{x})$$

subject to

$$\underline{x} \in X$$

Case (b) could be similarly formulated directly as a minimization model. If the preference relationship of case (c) occurred, then the objective function $g(\underline{x})$ could be split into two other functions ($g_1(\underline{x})$ and $g_2(\underline{x})$), respectively monotone increasing and decreasing in preference. Assuming g^* is known:

(5.3)

$$\min \quad (d+_1 \,, d-_2)$$

subject to

$$\underline{x} \in X$$

$$g_1(\underline{x}) + d-_1 \leq g^*$$

$$g_2(\underline{x}) + d+_2 \geq g^*$$

The functional relationships in cases (c) and (d) can be similarly solved by minimizing d- or d+ respectively. These satisfycing formulations do not produce unique solutions because of preference indifference in the 'flat' areas of the function. Case (f) is somewhat different, in that there are two aspiration levels (g_1^* and g_2^*). This might occur if the decision maker prefers values in the interval between g_1^* and g_2^* to values outside that range. An example might be a preferred range of inventory holdings. Note that the function is monotone increasing below g_1^*, monotone decreasing above g_2^* and flat (indicating no additional preference) between g_1^* and g_2^*. This can be expressed as a two-sided formulation, minimizing negative deviations below g_1^* and positive deviations above g_2^*. Spronk also describes how an objective function g can be formulated as a piece-wise linear function of an activity variable x in order to approximate a smooth concave functional relationship between activity variables and objectives.

IMGP as an interactive technique also lends itself to decision support. The relatively small number of responses required of the decision maker in an IMGP session are concrete evaluations of the desirability of objective function magnitudes and indications of a desire for improvement in one or more objectives. This contrasts with the cognitively more complex rates of tradeoff required by the GDF procedure or the greater number of evaluations required by the Zionts-Wallenius procedure. Although IMGP can reflect aspiration levels, which behavioral scientists contend are widely used by decision makers, the decision maker is not forced to give a priori established targets. Instead, vectors of objective function values can be formulated mathematically which represent the worst goal values which are necessary to accept (which Zeleny (1982) calls the 'anti-ideal') and the best goal values possible (the 'ideal'). Priority weights for goal deviations need not be explicitly expressed by the decision maker. Instead, priority is implied by the decision maker choosing objectives to be improved. The flexibility of IMGP with respect to functional relationships, aspiration levels and priority weights thus considerably extends the applicability of goal programming techniques and appears to make it the best currently available candidate for decision support applications. If constraint functions are linear and objective functions can be reasonably approximated as linear or piecewise linear in the activity variables, then use of efficient linear programming algorithms in the decision aid may enable fast enough turnaround to provide real time decision support.

IMGP can be shown to be a more general formulation of both MOTAD and Target MOTAD (Romero and Rehman 1985). Given the two objective (goal) function of return and risk:

(5.4)

$$\mu = \Sigma_{j=1}^{n} \underline{c}_j \; x_j$$

$$R = \Sigma_{r=1}^{s} d+_r \; / \; s$$

$$\text{where } d+_r = \max\,(0,\ T - \Sigma_{r=1}^{s} c_{rj} \; x_j)$$

The first objective is the sum of expected net returns ($\underline{c}_j$) per unit of activity x_j times the activity level. The second objective is risk, which is identified in this discrete formulation as a non-decreasing function of deviations from a target level T. If T equals expected returns, then the model corresponds to a MOTAD formulation. If instead the target level is some fixed value, the model is a Target MOTAD formulation. Risk is the average deviation, or the net return for each state of nature (c_{rj}) weighted by the activity level (x_j) and divided by the probability of occurrence (1/s). In goal programming terminology, we want risk to be 'as close as possible' to the minimal level of zero. We also want maximal overachievement of the return objective. This implies a one-sided goal programming formulation with two goal functions, as shown below:

(5.5)

$$\min\ (d^-_1,\ d^+_2)$$

subject to

$$\underline{x} \in X$$

$$\Sigma_{j=1}^{n} c_{rj}\, x_j + d^+_{2r} \geq T \qquad r = 1 \ldots s$$

$$\Sigma_{r=1}^{s} d^+_2 / s \leq \infty$$

$$\mu + d^-_1 = \mu^*$$

The deviation variable of returns (d^-_1) represents the amount by which expected returns fall below the unattainable aspiration level μ^*. Similarly, the deviation variable d^+_2 measures the amount by which returns in state r fall below the target return level. The objective of this model is to minimize some functional formulation of (d^-_1, d^+_2). With preemptive weights, one objective function would be optimized (receive absolute priority), then the other. This would make no sense in the current example, since the one-sided formulation of both objectives forces the solution to be either the maximum expected return (if the return objective has priority) or zero (if the risk objective has priority). With weighted goal programming, a linear function of (d^-_1, d^+_2) is formulated with a priori weights reflecting the acceptable rate of tradeoff between objectives. It appears unreasonable to expect decision makers to express a fixed tradeoff rate between risk and return without knowledge of possible magnitudes of the two objectives. IMGP does not require an explicit formulation of weighted objectives. Thus the interactive goal programming formulation seems to have particular potential to represent this type of risk-return decision. While MOTAD and Target MOTAD are designed to trace the entire set of solutions which are efficient in risk-return space, IMGP can be effectively used for decision support to reduce the number of feasible and efficient solutions to a small set (possibly a singleton) of feasible, efficient and preferred solutions. Target MOTAD also requires a target value. Although this introduces an additional parameter (T) which must be estimated or elicited during model formulation, it can be seen as an implementation of the behavioral concept of target or aspiration levels in decision making. By expressing some income level as particularly important, the decision maker expresses an abrupt change in marginal preferences for income.

5.3 <u>IMGP Consistency with Decision-theoretic Principles</u>

This section will examine logical properties of the general IMGP model, in particular the conditions under which (given a fixed preference structure) the procedure converges to a unique optimal solution according to decision maker preferences. Given the formal equivalence between a particular formulation of IMGP and the more traditional single objective MOTAD and Target MOTAD risk-return models, the consistency of general risk-return models with stochastic dominance and expected utility principles is also discussed.

IMGP is not intended to model the complete preference structure of an individual. Instead, IMGP is intended to determine the most preferred element (or subset of preferred elements) within a preference structure characterized as a total quasi-ordering. The procedure assumes that such a preference relation exists. Spronk (1980) contends that IMGP can be used to model various functional relationships between objectives and weakly convex preference relations (which include lexicographic ordering or traditional utility relationships. In particular, Spronk shows that when the feasible region in activity variable space is described by linear constraints (i.e. is convex) and the objective functions are linear (thus implying that the feasible region in objective function space is also convex), IMGP converges to an ϵ-neighborhood of the most preferred vector g^* (which may not be unique) if the decision maker is able to indicate at least one solution to be satisfactory, that responses are correct according to personal preferences and that preferences do not change during the solution process. Piece-wise relationships can be used to approximate concave functions to any degree of accuracy.

The two-criteria IMGP model in this particular implementation is formally identical to that of a Target MOTAD model as described by Tauer (1983). The latter model can be considered a multiple criteria model with return and risk as objectives. That is, a preference function U defined on m evaluative (variously called objective or goal) functions $g_1(\underline{x})$ .. $g_m(\underline{x})$, where x is a vector of activity variables, each of which is a concave function of x (as is the preference function) is a more general model than a real-valued function increasing in mean and decreasing in risk. Expected return is defined as the sum of expected net return per unit of activity multiplied by the activity level. Risk is defined as the probability-weighted sum of return deviations below some target return level. This risk-return model is discussed by Fishburn (1977) as a special case of mean-risk dominance models in which the mean of a probability distribution function F is denoted as $\mu(F)$ and risk is defined by a two-parameter function:

(5.6)

$$R(F) = \quad (t - x)^{\alpha} \quad dF(x) \qquad \alpha > 0$$

Deviations are counted from the target level t, while α indicates the decision maker's attitude towards below-target deviations. If $t = E(x)$ and $\alpha = 2$, the result is a mean-variance model, while if $t = E(x)$ and $\alpha = 1$, then a mean absolute deviation (MAD or MOTAD) model ensues. If t is fixed across distributions, then the result is a target semivariance model for $\alpha = 2$ and target MOTAD for $\alpha = 1$.

Risk is thus a non-decreasing function of returns, and is equal to zero at or above the target level. According to this type of risk-return model, individuals are risk-neutral for returns above the target level, and have risk preferences for returns below target determined by the parameter α. Risk averse behavior is implied by

$\alpha > 1$, risk neutral behavior by $\alpha = 1$, and risk preferring behavior by $\alpha < 1$. The class of α-t risk models has been generalized from the specific mean-variance and mean-MAD models because of both theoretical and empirical criticisms of those formulations. Mean-variance models require that the utility function be of quadratic form or that return distributions be normally distributed and utility functions be of exponential form (Goldberger 1964). Mean-variance efficient sets may not be consistent with second degree stochastic dominant (SSD) sets (Levy and Hancock 1970), and have been shown to perform poorly in rankings of alternative distributions (Pope and Ziemer 1984). The same criticisms (and more) apply to the MOTAD model. More generally, a behavioral assumption of any risk formulation based on a parameter which varies between distributions is that the individual considers variability of returns to be risk and consequently to be avoided, regardless of whether such variability is below or above the expected value and regardless of the resulting wealth position or obligations of the individual.

Empirical concerns were expressed by Mao (1970) and others that managers in investment decisions often associate risk with failure to achieve some target return. Fishburn summarizes these observations, ". . . most individuals in investment contexts do indeed exhibit a target return - which can be above, at, or below the point of no gain and no loss - at which there is a pronounced change in the shape of their utility functions." (1977: 122) He concludes, "The idea of a mean-risk dominance model in which risk is measured by probability-weighted dispersions below a target seems rather appealing since it recognizes the desire to come out well in the long run while avoiding potentially disastrous setbacks or embarassing failures to perform up to standard in the short run." (Fishburn 1977: 118)

Porter (1974) developed the concept of target semivariance and showed solutions derived by this criterion to form a subset of the SSD set. Fishburn (1977), as noted, extends Porter's results to the more general α-t class of models. He proves that α-t efficient sets are implied by (subsets of) first degree stochastic dominant sets (FSD) for all $\alpha \geq 0$, second degree stochastic dominant sets for all $\alpha \geq 1$, and third degree dominant sets (TSD) for all $\alpha \geq 2$, except when means and risk are identical. Tauer (1983) proves the specific case that target MOTAD is implied by the SSD set.

With respect to preference functions, Fishburn (1977) states that a decision maker's preferences satisfy a mean-risk utility model if and only if there exists a real-valued function U in mean and risk such that for all distributions F and G:

(5.7)

$$F \dashrightarrow G \quad \text{iff}$$

$$U(\mu(F), R(F)) > U(\mu(G), R(G))$$

R() is a risk function as defined above, U is monotonically increasing in μ and decreasing in R, and "-->" indicates "is preferred to." Such utility models are not necessarily consistent with von Neumann-Morgenstern (vNM) utility axioms, in particular since single-peakedness requires more stringent assumptions. In order for the two models to be congruent, Fishburn (1977) shows that vNM utility must be reformulated as:

(5.8)

$$u(x) = x \qquad \text{for } x \geq t$$

$$u(x) = x - k(t-x)^{\alpha} \qquad \text{for } x < t$$

where k is a positive constant defined as:

$$k = \frac{u(t) - u(t-1)}{u(t+1) - u(t)} - 1$$

Fishburn examines a variety of vNM utility functions published in the literature and found certain evidence of support for congruence between the α-t and vNM models. Several utility functions demonstrated a significant change in shape at some fixed income level at, above, or below the point of no loss or gain. However, risk neutrality (linearity) above the target level was shown to hold in only a minority of cases. Figure 5.2 shows representative utility functions for individuals with three attitudes towards deviations of income below a target value.

Fishburn (1977) emphasizes that although mean-risk models are only approximations to more complex preference relations, they have a considerable degree of compatibility with stochastic dominance and expected utility criteria, and offer computational advantages over some other techniques for modeling individual choices. However, selection of a particular α-t model depends upon alternative computational facilities for the particular decision situation, and relevance of the solutions depends upon choice (or measurement) of the relevant α level and identification of the situation and time-specific target level.

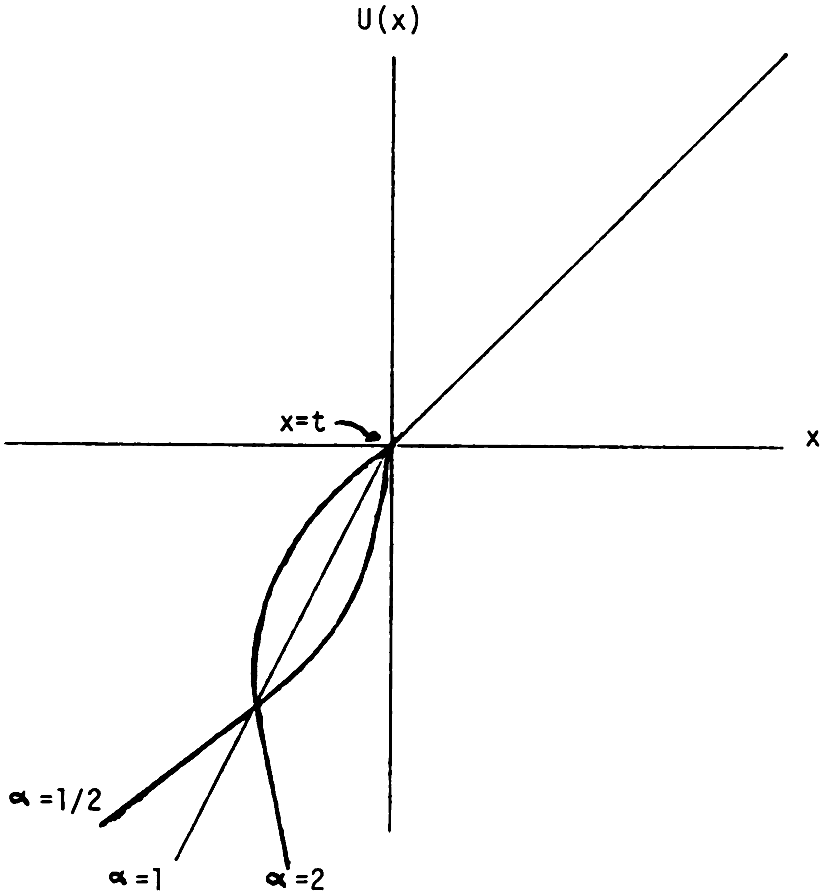


FIGURE 5.2 UTILITY FUNCTION WITH α-t RISK

5.4 An Example IMGP Formulation

To illustrate a simple risk-return IMGP formulation, the farm planning problem illustrated by Kennedy and Francisco (1974) is utilized. The problem consists of allocating resources to cropping and livestock activities in order to generate efficient combinations of risk and return values. The activities possible include wheat, barley and sorghum crops and pasture, which can be sold or used as feed for lambs or merinos (adult sheep). Resources include 370 acres of crop land, 830 acres of pasture land, 3000 annual hours of labor and $12000 (Australian) of operating capital. Material balance equations are also formulated for supply and demand of feed for winter and for the rest of the year. Only pasture supplies winter feed, but grains can supply feed in other seasons. Estimated gross margins are calculated from historical enterprise gross margin data for each enterprise estimated over each of the past five years.

Assuming a target income value (possibly a breakeven point or fixed costs plus living expenses) of $10000, Table 5.1 presents the efficient risk-return combinations.

TABLE 5.1 RISK AND RETURN SOLUTIONS, KENNEDY/FRANCISCO PROBLEM

	Expected Returns	Risk*
Plan 1	$10300	57
2	10749	161
3	10843	190
4	11136	320
5	11780	1433

* Risk is defined as the mean deviation of income below the target level of $10000.

Figure 5.3 presents the solutions in risk-return space, with the extreme points connected and labeled as A thru E. The solution process consists of six steps:

1. Sequentially optimize the single objective problems:

(5.9)

$$\max \quad \mu = \Sigma_{j=1}^{n} \underline{c}_j \, x_j$$

subject to

$$\underline{x} \in X$$

$$\Sigma_{j=1}^{n} c_{rj} \, x_j + d+_r \geq T \qquad r = 1 \ldots s$$

$$\Sigma_{r=1}^{s} d+_r \; / \; s \leq \infty$$

$$\min \quad R = \Sigma_{r=1}^{s} d+_r \; / \; s$$

subject to

$$\underline{x} \in X$$

$$\Sigma_{j=1}^{n} c_{rj} \, x_j + d+_r \geq T \qquad r = 1 \ldots s$$

$$\Sigma_{j=1}^{n} \underline{c}_j \, x_j \geq \theta$$

Calculate the implied values of the other objective in each formulation. Call the optimal values μ^b and R^b (for 'best'), and the corresponding values of the other variables μ^w and R^w (for 'worst'). Formulate the potential matrix P_θ as follows:

$$P_\theta = \begin{vmatrix} \mu_\theta^{\,b} & R_\theta^{\,b} \\ \mu_\theta^{\,w} & R_\theta^{\,w} \end{vmatrix}$$

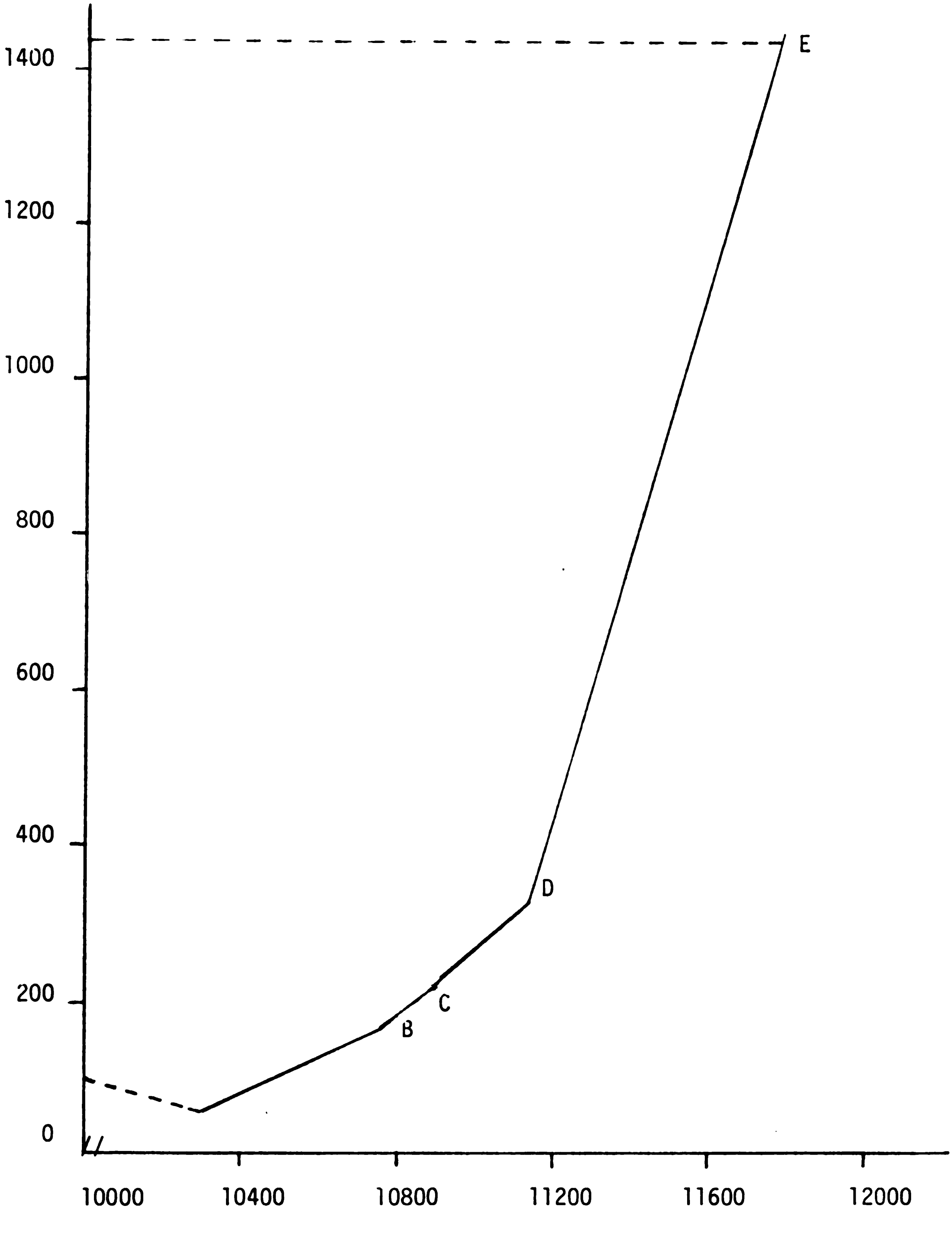


FIGURE 5.3 RISK-RETURN EFFICIENT SOLUTIONS, KENNEDY AND FRANCISCO PROBLEM

2. Present the values to the decision maker as (μ_0^b, R_0^b) and $\mu_0^w, R_0^w)$. The latter is the worst solution that need be accepted, while the former represents an unattainable ideal solution of best return and lowest risk. Ask the decision maker: Given the worst and best values implied by the problem constraints, which objective should be improved?
3. Using the response, improve the worst value of the objective indicated by the decision maker by one-half the amount between the current worst and the current best value.
4. Append the adjusted value as a constraint to the optimization model of the other objective, and re-solve.
5. The best value of the objective not indicated to be improved has now been altered (worsened) because of the more restrictive constraint imposed by the improved objective. Formulate the second matrix as:

   $$P_1 = \begin{vmatrix} \mu_1^b & R_1^b \\ \mu_1^w & R_1^w \end{vmatrix}$$

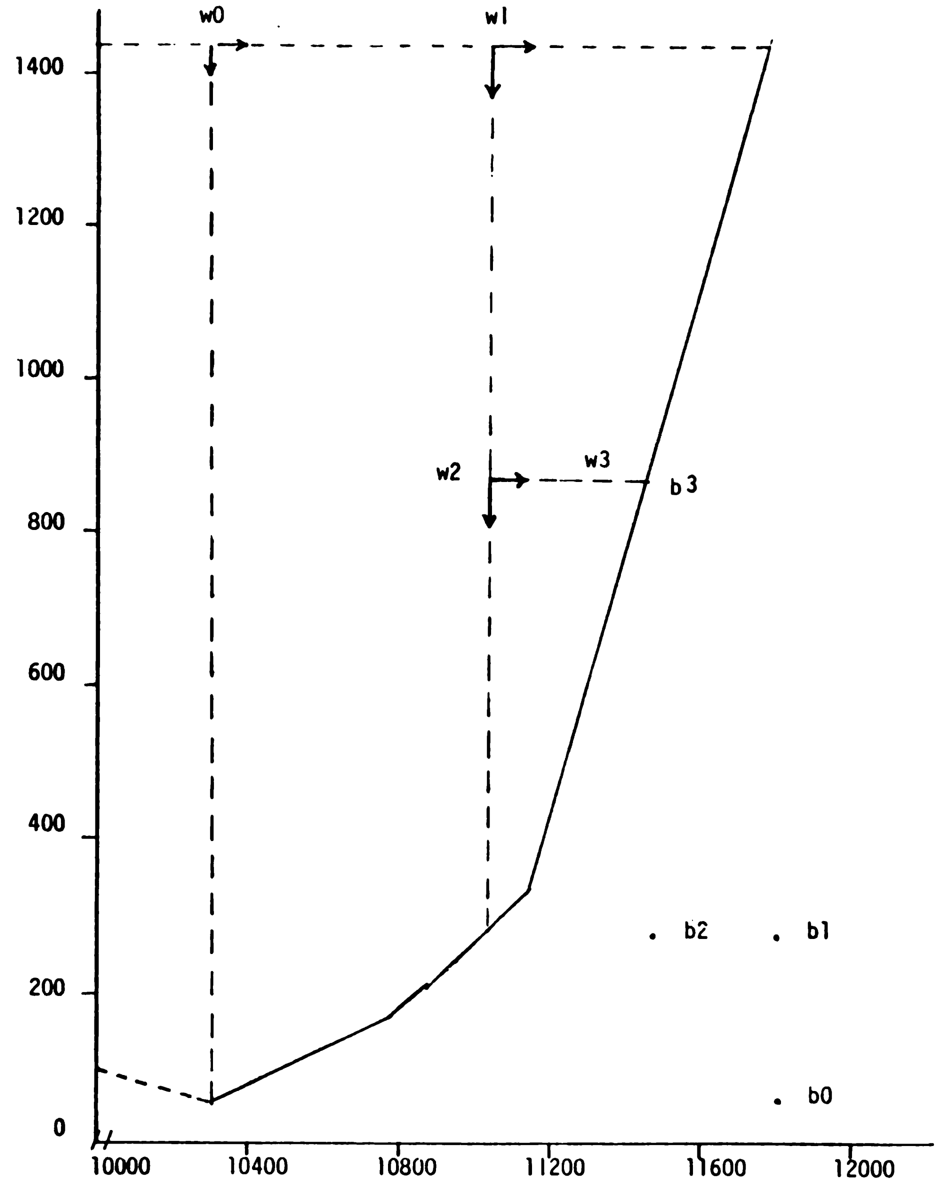
   Two diagonal elements will have been changed, one by halving the amount between the previous worst and best values, the other because of tradeoffs imposed by the improved objective. Present the decision maker with the current and previous solutions and the same question as step 2.

   a. If the decreased potential of the unimproved objective is too great, the decision maker may indicate the solution is unacceptable. If so, reduce the current worst value of the improved objective to one-half the amount between the current worst and the previous worst value. Return to step 4.

b. If the solution is acceptable, return to step 4.

6. If the decision maker cannot indicate which objective should be improved, display the activity values of the current solutions. This may initiate further iterations. Otherwise, the individual is indifferent between solutions. As the difference between best and worst values narrows, at some point the problem may be collapsed to the current best value of one objective.

Figure 5.4 shows a hypothetical session with the Kennedy-Francisco problem. The decision maker has improved minimally acceptable expected returns in steps 1 and 3 and risk in step 2, and has accepted as a final solution the plan with expected returns of $11445 and mean deviation below target of $855. In other words, the decision maker has discovered a solution which is only three percent less than the profit-maximizing (best return objective) solution, but which is characterized by forty percent less risk. Sensitivity analysis of an accepted solution can be presented to the decision maker to investigate the effect of changes in net return coefficients and right hand side constraints. For example, sensitivity analysis of the crop land constraint of the above solution shows that basis changes occur if crop land increases by more than 100 acres or decreases by 70 acres. If the potential crop land base is not certain, sensitivity analysis may indicate the need for an additional session with other projected values.



Potential matrix

		Return	Risk
	Best :	μ^b	R^b :
	Worst :	μ^w	R^w :
Step 0:	P_0 = :	11780	57 :
	:	10300	1433 :
Step 1:	P_1 = :	11780	277 :
	:	11040	1433 :
Step 2:	P_2 = :	11445	277 :
	:	11040	855 :
Step 3:	P_3 = :	11445	855 :
	:	11445	855 :

FIGURE 5.4 BEST (b) AND WORST (w) OBJECTIVE FUNCTION VALUES FOR THREE STEPS OF IMGP SOLUTION PROCESS, KENNEDY AND FRANCISCO PROBLEM

Given the described potential of IMGP as a multiobjective decision support technique and the formal equivalence of a two objective risk-return IMGP formulation to a linear MOTAD or Target MOTAD model, an initial test of the empirical usefulness of IMGP can be carried out by constructing a risk/target return decision support aid. If severe problems are discovered in testing a relatively simple implementation, it is unlikely that the technique would prove useful in a broader context of more objectives, different functional forms or larger problems. The following sections document the goal-directed search aid (GOALDIR) developed in this research for supporting land rental/crop mix decisions for cash grain operators.

5.5 Land Rental Decisions

Within constraints of current labor, machinery and financial resources and longer term committments for crop rotations and leasing, cash grain operators must evaluate each year the set of land rental opportunities and select cropping activities for both owned and rented land. In the current economic environment, a careful decision may mean the difference between failure or continuation of the business. Contraction or failure of farm businesses has fostered a more active than usual land rental market in many locations of Michigan. A wide variety of rental arrangements are utilized, including cash and share rent with various obligations for landlord and tenant, dates of payment and adjustments for realized yields and prices. Often the rental decision is a decision with multi-year consequences, the operator knowing that if land available this year is not rented, it may well not be available again for the foreseeable future. If a neighbor rents the land, the implicit right to continue renting the tract as long as desired may have been granted by the landlord. Therefore, decisions made this year may affect resource utilization and growth possibilities for years to come.

Crop rotations also instill a multi-year character to the rental decision. If rotation requirements were to completely determine what crops must be planted on a specific tract, the only flexibility in determining overall crop mix would be the decision to rent or not rent the land. At the other extreme, if any potential crop can be planted on each land tract, then the decision involves both whether to rent a tract and how much of each crop should be planted. With several land tracts and only a few potential crops, the possible permutations quickly multiply. Real decisions usually are not characterized by either extreme. Rotation requirements are extremely important for some tracts (particularly for owned land), while crops on other tracts may depend almost entirely on economic prospects. Rental and crop mix decisions are also strongly affected in the current economic environment by government feed grain programs. Given massive stocks, continued high production and expected low prices for most cash grains over the next several years, there is considerable incentive to participate in government price support programs, which limits acreage for program crops.

A common decision procedure then involves consideration of machinery and labor resources, crop rotations, government price support programs, potential yields and prices (in the short or longer run) in the selection of a preferred crop and rental mix with owned cropland. The set of activities actually selected is considered to be the best compromise between the business objectives, which may be (and usually are) competing to some degree. The abstract objective with highest priority is usually 'to secure the highest possible current period profits'. It is an abstract objective in many cases because operators have only the vaguest notion of their variable and fixed costs and poorly formed expectation of crop prices, and thus can make only 'seat of the pants' conjectures of crop mix and rental impacts on profits. Operators also usually attempt to avoid risk, perhaps conceived as 'to avoid disaster level losses'. Although avoidance of risk can be incorporated as an attitude towards profit distributions as in the expected utility framework, it is often more realistic and useful for decision analysis purposes to consider risk as a second (and competing) objective in the decision process. Indeed, operators seem to distinguish these as separate goals (Harper and Eastman 1980). A more precise definition of these objectives will be given below as the decision model is described.

Other objectives, possibly of lesser importance in this decision context, might be 'to provide adequate opportunity for business growth', or 'to maintain high soil fertility'. Given the natural fixed supply of land within reasonable distance from the home, access to land resources has great influence on the growth potential of the business. Rejection of rental opportunities this year may force the operator to rent land in more distant locations in later years in order to accomplish growth objectives. In addition, if land becomes available for sale, it may well be the current rentor who is given first chance to purchase the land. Soil fertility objectives are accomplished through multi-year programs of crop rotations and fertilization plans. Conceptually, these objectives can be incorporated into a multi-period model. The current decision model, however, assumes that the current period objectives of returns and risk are predominant and does not attempt to model other objectives.

Selecting activities which are hoped to result in the most preferred level of the objectives is particularly prone to error because of the lack of 1) accurate cost, yield and price data, and 2) a solution procedure or algorithm to search for the best solution. Without farm-specific data, the best intentions and solution algorithms may be of little benefit. Thus, an argument can be made that establishment of farm level record keeping systems is a precondition for any substantial improvement in decision making. On the other hand, careful introspection or elicitation procedures might provide sufficiently accurate data on which to base a solution procedure promising a better result in terms of the objectives. Even though data may be available for cost and price expectations, operators may not use procedures which are likely to indicate 'good' solutions. 'Back-of-the-envelope' calculations are prone to error, and a simple static partial budgeting procedure in itself can cause dramatic mistakes in a dynamic whole-farm context for several reasons. First, revenue-cost partial budgeting of land tracts ignores the importance of other objectives for the operator, principally risk avoidance but also other objectives such as long term growth. Setting data parameters at expected levels does not consider variability in those parameters or the covariation between yields of potential crops for a particular location or between locations, nor is price covariation between crops considered. Even when variability of crops and yields is considered, evaluation of individual tracts can indicate rental and crop mix choices which are not preferred with respect to objectives because the solution procedure fails to to consider the whole business context. For example, rental of one high net revenue-high variability land tract may imply unacceptable risk for the enterprise taken as a whole.

A number of potential stategies may be calculated by farm operators, limited by the time and effort necessary to estimate returns. Even if a proposed whole set of alternative crop acreages and rental opportunities are considered simultaneously, risk avoidance and other objectives are usually not considered formally. This 'hunt and peck' solution process offers no assurance that other strategies not contemplated might offer better results at no additional cost. Nevertheless, it is probable that the perspective, experience and knowledge of the operator compensates for lack of adequate solution procedures.

Although research as discussed in section 4.2 has shown that multiple objectives are clearly important in farm decisions, the manner in which individual operators formulate their objectives is unclear. Growth and security objectives, for example, can be formulated in several a priori valid ways. One formulation of a growth objective might be an increase in the resource base of the business, while another might be an increase in revenues through more intensive use of existing resources. The formulation of a risk or security objective is particularly critical for the operation. Extension agents and directors interviewed for this research generally considered that farm operators view the likelihood of net cash flow from cropping activities falling below some critical value (usually related to family living and other cash obligations) as an intuitive measure of risk.

5.6 Modeling the Decision Problem

5.6.1 Assumptions

Modeling of such a planning decision involves consideration of the preference structure of the individual or individuals making the decisions, the resource base and other constraints on actions, the activities possible with the resource base, the relevant technical and economic parameters and the particular mathematical formulation used to solve the problem in a decision aiding context. Boundaries must be placed on the real problem so that a mathematical model may be constructed. In the end, it is hoped that the solutions generated by the mathematical model will assist the decision maker to deal with the real problem. It is assumed that the only objectives sought by the operator are 1) to obtain the highest possible expected net return and 2) to obtain the lowest possible risk mixture of cropping activities on owned and rented land. Risk is defined as probability-weighted deviations below some situation-determined minimally adequate level of net returns, as in Target MOTAD (Tauer 1983).

Farm operators are assumed to accurately describe their beliefs and expectations for yields for possible crop on owned and rentable land tracts and for prices at harvest for each crop in terms of probability distributions. An assessment procedure was implemented to elicit those distributions as part of this research. The rental decision is made after determining the landlord's asking price (either in cash or share) for a particular property and after determining whether the property would be included (if eligible) in the government feed grain program. Variable costs for each crop considered possible to plant on the property are assumed known with certainty before rental. Consistent with the assumption of known probability for yields, this assumption implies that fertilizer and related costs are estimated in a manner consistent with yield potential of the land. Machinery resources are fixed for the relevant decision horizon. Own and hired labor are assumed sufficient so as always to be less restrictive than the machinery capacity.

5.6.2 The Mathematical Model

The model utilizes the efficiency principle, in that no solution indicated by the model is dominated in terms of the objectives. Given the optimization framework, and given that a decision aid must operate in real time, all functional relationships are assumed adequately represented by a linear programming (LP) formulation. Principal among the relevant limitations of LP in the current problem is the divisibility assumption. An LP model does not distinguish between renting 0.1 or 100 acres, even though rental agreements must be made for an entire tract. This issue will be discussed below with respect to preliminary testing of the model. Also relevant is the necessary condition of proportionality, which assumes that a fixed amount of output is produced by a particular amount of input, no matter what the level of the activity.

The mathematical formulation consists of optimization of a two-objective IMGP model, with the objectives: 1) maximize expected net cash revenue from cropping activities, and 2) minimize expected deviations below a subjectively determined net cash revenue target, subject to constraints on: 1) total tillable acres available on each potential tract, 2) chance-constrained field hours available for each planting and harvest period, 4) possible maximum acres for each crop, and 5) wheat acres already planted the previous fall. In addition, acreage of certain crops is restricted for tracts entered in government feed grain programs. Since optimization of more than one objective function is an ambiguous mathematical formulation, the decision aid is formulated to sequentially solve single objective models which differ only in the objective row and iteratively redefined constraints on minimal/maximal levels of the other objective. The relevant variables and model equations are listed in Appendix 1.

Certain variables and parameters are elicited from the particular farm operator, while others are imposed on the problem as reasonable estimates for data which is otherwise difficult or impossible to elicit. Elicited data includes price and yield distributions, land acreages, rents and government program status, variable costs of production, planting and harvesting machinery capacity and the target net revenue level. The decision aid components used to elicit this data will be described below. External data which is imposed for any farm operation includes the correlation matrices of price and yield, yield penalties for untimely field operations, corn moisture and related drying costs, and estimated field hours for planting and harvest operations. Sources for the external data are included in Tables 5.2 through 5.6.

TABLE 5.2 ESTIMATED YIELD CORRELATIONS, MAJOR CROPS*

	Corn	Soy	Navy	Wheat
Corn	1.0	.4	.3	.1
Soy	.4	1.0	.6	.2
Navy	.3	.6	1.0	.1
Wheat	.1	.2	.1	1.0

SOURCEs: USDA, Wheat Situation, Various Issues.
USDA, Feed Outlook and Situation Report, Various Issues.

* Yield correlations are estimated from detrended national average yields, except navy beans for which Michigan yields were used.

TABLE 5.3 ESTIMATED PRICE CORRELATIONS, MAJOR CROPS*

	Corn	Soy	Navy	Wheat
Corn	1.0	.7	.3	.8
Soy	.7	1.0	.4	.4
Navy	.3	.4	1.0	.3
Wheat	.8	.4	.3	1.0

SOURCEs: USDA, Wheat Situation, Various Issues.
USDA, Feed Outlook and Situation Report, Various Issues.

* Price correlations are estimated from national average annual prices, deflated to 1967=100, except navy beans for which Michigan prices were used.

TABLE 5.4 YIELD PENALTY MATRIX FOR UNTIMELY FIELD OPERATIONS

PENALTY FOR UNTIMELY FIELD OPERATIONS--CORN*

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	1.00	0.99	0.95
5/11-5/20	0	0.95	0.94	0.90
5/21-5/30	0	0.82	0.85	0.81
6/1-6/30	0	0	0	0

PENALTY FOR UNTIMELY FIELD OPERATIONS--SOY BEANS

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	0.98	0.94	0.86
5/11-5/20	0	0.98	0.93	0.86
5/21-5/30	0	0.96	0.91	0.83
6/1-6/30	0	0.76	0.71	0.69

PENALTY FOR UNTIMELY FIELD OPERATIONS--NAVY BEANS

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	0	0	0
5/11-5/20	0	0	0	0
5/21-5/30	0	0	0	0
6/1-6/30	0.99	0.95	0	0

SOURCE: Estimated from Black, J. (1974) and Rotz and Black (1985)

* Yields are penalized by the indicated factor for field operations carried out in the indicated planting/harvesting period.

TABLE 5.5 PERCENTAGE POINTS REQUIRED TO DRY CORN FOR DIFFERENT PLANTING/HARVEST PERIODS*

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	15	9	6
5/11-5/20	0	19	13	10
5/21-5/30	0	21	15	12
6/1-6/30	0	0	0	0

SOURCE: Estimated from "Corn-Soybeans Planning Guide", TELPLAN User's Guide No. 18. Department of Agricultural Economics, Michigan State University, 1976.

* For corn planted and harvested in the indicated periods, the table displays the number of percentage points that corn must be dried. Cost of drying is calculated at $.025 per bushel.

TABLE 5.6 ESTIMATED FIELD HOURS AVAILABLE FOR PLANTING AND HARVESTING OPERATIONS, EAST LANSING *

Planting Period	Clay WD**	Clay PD	Clay loam WD	Clay loam PD	Sandy loam WD	Sandy loam PD	Sandy WD	Sandy PD
			Planting Operations					
4/21-5/10	108	48	124	63	140	125	162	139
5/11-5/20	73	52	74	64	73	76	84	74
5/21-5/30	88	89	85	81	89	95	90	81
6/1 -6/30	247	220	249	225	260	238	237	251
			Harvesting Operations					
9/1 -9/15	83	74	86	78	96	89	105	99
9/16-9/30	77	68	81	72	91	84	102	95
10/1-10/31	160	140	167	149	189	173	211	197
11/1-11/30	124	101	133	110	159	140	188	171

SOURCE: Estimated from Rosenberg, et al. (1982).

* Estimated field hours at 80% probability level for East Lansing area for various major soil types. Planting operatons field time appropriate for all major crops. Harvest operations field time appropriate for soy, wheat and navy.

** PD = Poorly Drained, WD = Well Drained

Before discussing the data elicitation, it is convenient to describe in more detail the software components of the decision aid. Commercial microcomputer applications software was utilized to the extent possible in order to hold down development costs and time. Other components were developed in the Pascal programming language on a microcomputer. The components are: 1) data elicitation spreadsheet templates, 2) a matrix generator program which creates the LP tableau according to the deterministic and probabilistic data input, and 3) a linear program solver, and 4) a solution display program for iterative reformulation of objective function levels. The farm operator interacts with the decision aid through the analyst for the data elicitation and solution display software, and not at all with the matrix generator and LP solver. The model decision process can be depicted as in Figure 5.5.

5.6.3 Data Elicitation

It was considered that response of operators to data and probability elicitation would be better if they could see questions and responses displayed on a computer monitor. Spreadsheet templates (See appendix 2 for templates) were prepared for elicitation of:

1. land information
2. crop budget data
3. yield probability distributions
4. harvest price probability distributions

For each owned or rented tract, information is requested concerning total and tillable acres, soil type (each tract is classified according to its prevailing soil type), government program

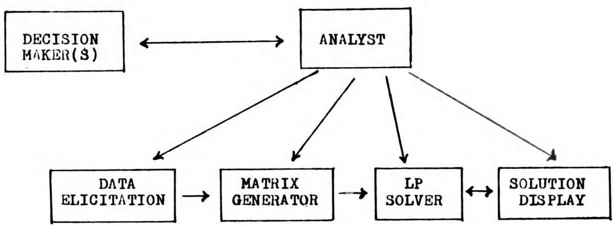


FIGURE 5.5 INFORMATION FLOW IN GOALDIR DECISION AID

eligibility, base acres and yields. This information is stored to be entered as input to the matrix generator program.

Variable cost budgets for medium yields of relevant crops as estimated by farm management specialists are stored as defaults in another template. Since different tracts have varying yield potential and corresponding crop variable costs, a budget may be associated with a single land tract. Each default budget is divided into dollar amounts for variable cost categories such as fertilizers, weed and pest chemicals, fuel and lubricants, seed, repairs and maintenance and other expenses. The operator may change any of the dollar amounts or accept the defaults as suitable for a particular land tract or soil type. Elicited budgets are then stored for later input to the matrix generator.

Probability elicitation techniques differ widely in their procedures and complexity of application, their assumptions about the subject's expertise and understanding of probability concepts, and their reliance on feedback mechanisms to facilitate comparison between stated beliefs and estimated probabilities. An elicitation technique should produce probabilities which: 1) are consistent with the rules of probability, and 2) are consistent with the belief structure of the individual. Questions of technique accuracy (for known distributions), reliability (consistency of an individual's estimates) and acceptability (the individual's attitude towards the elicitation technique) should be addressed in choosing an elicitation technique (Ludke et al. 1980). Unfortunately, there is little evidence indicating clear superiority of one technique over another, and there is no theoretically superior method to compare and evaluate techniques. Indeed, techniques which work well in one situation may fail in another (Wallsten and Budescu 1983). Until more extensive comparisons of techniques can be carried out, selection of elicitation technique for decision aiding purposes should probably be based on factors such as the following:

1. Confidence that results both adequately reflect the individual's beliefs and are consistent with formal probability rules
2. Time necessary for elicitation
3. Visual and verbal feedback for the subject and encouragement for adjustment.

Under these criteria, the "conviction weights" method developed by Nelson (1978) is a good choice. It is an indirect elicitation procedure, in that the subject does not state numeric probabilities. Indirect methods serve to 'reveal' probabilities in a way particularly suitable for farm operators, who are not assumed to have explicit training or understanding of probability concepts. In this method, the subject assigns weights to discrete outcome intervals according to strength of conviction as to their likelihood. The subject is asked to indicate the most likely (modal) interval, to which a weight of 100 is assigned. For all other relevant intervals, weights from 1 to 100 are assigned according to the perceived likelihood of outcomes in that interval as compared to the most likely interval. Thus, an interval which is perceived as one-half as likely as the most likely interval would receive a weight of fifty.

Endpoints of the distribution are elicited, with zero probability beyond these points. However, the subject may legitimately place considerable probability in the last intervals. The probability of each interval is calculated by dividing its weight by the sum of all weights. This assures that probabilities sum to unity by design, which of course may not reflect true (although incoherent) beliefs (Wallsten and Budescu 1983). Feedback given to the subject may serve to correct some inconsistencies with the subject's beliefs. Another advantage of the process is its avoidance of cumulative error, which in some techniques may cause serious problems. The conviction weights technique allows subjects to anchor their convictions on the most likely interval, which is closely related to unaided assessment procedures as described by cognitive scientists (Hogarth 1980).

Equal interval widths are used for both yield and price distributions, since subjects may be confused by unequal intervals. The width of yield intervals can be established during the elicitation process, although many crop yield distributions lend themselves to division into 10-15 intervals. For example, an interval of ten bushels per acre of corn gives fifteen intervals between twenty and one hundred seventy bushels. No research appears to have been carried out which investigates the effect of interval width on elicited distributions. An extremely wide interval (and consequently a smaller number of intervals) would tend to overestimate dispersion in tails with abruptly declining probability and could also bias estimates of central tendency. On the other hand, extremely narrow intervals may exceed the discrimination capacity of the subject and encourage frivolous estimates or ad hoc smoothing techniques. The automatic recalculation of intervals with these templates and display of all intervals on the computer monitor greatly facilitates the elicitation process.

Farm operators are less likely to have a thorough understanding of the causal factors underlying price distributions than of yield distributions, and hence may not have well-formed expectations about prices. To aid in focussing their expectations, default conviction weights are displayed and used an an anchor for price elicitation. It is recognized that a farm operator may be willing to accept an expert's estimates or to base his assessment on that of an expert for planning decisions, just as he/she might accept an economic forecast of interest rates for such purposes. These default weights were elicited from a Michigan State University price analyst. No claim of additional validity or accuracy is made for these weights, only that they represent the opinions of an marketing expert. Although useful as a reference, unthinking acceptance of the defaults would result in rental activities which do not reflect the operator's beliefs. For this reason it is emphasized to the operator that there is no reason why attention must be paid to the default weights, and that he/she is free to accept or modify the weights as desired. However, there is no reason to assume that the operator must disagree with the expert, particularly when present market conditions indicate that there is likely to be very little price movement in major grains. Whether operators will indicate distributions substantially different from the default is an empirical issue.

Figure 5.6 shows displays of probability distributions, histograms and cumulative distributions corresponding to hypothetical conviction weights. The histogram provides the subject with a visual comparison between stated conviction weights and underlying beliefs. In particular, the skewness of the elicited distribution and computed histogram is an initial check on expectations above and below the modal range. Explanation of the implied probabilities for modal and near-modal intervals and cumulative probabilities in the tails are described in terms of 'years out of ten' for yields and 'chances out of ten' for prices. The explanation of yield distributions in terms similar to historical frequencies is based on the contention that yield variations (given timely field operations) are primarily based on random weather variations, and that expectations are usually related to historical yield frequencies. Of course, new technology, new varieties or weather variations never personally experienced can prove yield expectations to have been very inaccurate estimates if historical records alone determine expectations. The operator is encouraged to formulate yield expectations in terms of constant technology and 'normal' weather patterns.

The terms used by the interviewer and the sequence of questions and explanations all may contribute significantly to elicitation accuracy, replicability and acceptability. A complete protocol of the elicitation procedure is reproduced in Appendix 2.

5.6.4 Matrix Generator

The matrix generator program (NORMGEN) is a Pascal program developed during this research to calculate random revenue vectors and other rows of an LP tableau. The data obtained in the elicitation phase of the decision aid process serves as input to the matrix

[SCREEN 1]

	Yield Range	Weights
Name:	0- 9	
John Q. Farmer	10- 19	
	20- 29	
Crop:	30- 39	
Corn	40- 49	
	50- 59	
Yield Unit:	60- 69	
Bu.	70- 79	
	80- 89	
Farm No.:	90- 99	10
1	100- 109	30
	110- 119	50
Soil Type:	120- 129	60
Brookston Loam	130- 139	100
	140- 149	50
Interval:	150- 159	40
9	160- 169	10
	170- 179	5
	180- 189	

[SCREEN 2]

Yield Range	Probability That Yield: In Range	Equal or Less Than Range	
0- 9			
10- 19			
20- 29			
30- 39			
40- 49			
50- 59			
60- 69			
70- 79			
80- 89			
90- 99	.03 ***	.03	
100- 109	.08 ********	.11	
110- 119	.14 **************	.25	Std. Dev.:
120- 129	.17 *****************	.42	18.12
130- 139	.28 ****************************	.70	Coef. Var.
140- 149	.14 **************	.85	.14
150- 159	.11 ***********	.96	Exp.Yield:
160- 169	.03 ***	.99	131
170- 179	.01 *	1.00	
180- 189			

FIGURE 5.6 MONITOR DISPLAYS OF HYPOTHETICAL CONVICTION WEIGHTS AND IMPLIED PROBABILITIES

generator program. Data imposed from external sources is also utilized at this point. Random vectors of net cash revenue for all possible crops on each land tract are generated based upon moments of elicited price and yield distributions, variable costs, rents and government payments. Since this is a significant part of the model matrix, an explanation is warranted.

The matrix generator performs two functions: 1) simulation of sample vectors of returns for cropping activities consistent with the elicited data, and 2) generation of a data matrix in the format necessary for the LP solver. A sample vector of returns is defined by the following matrix equation:

(5.10)

$$NCF = (P' Y) - V - R + G - D$$

NCF = Net cash flow per acre for all crops for sample state of nature s.

P = Random vector of crop prices at harvest

Y = Random vector of yields per acre

V = Deterministic vector of cash variables costs per acre

R = Deterministic vector of rental costs per acre

G = Random vector of government payments per acre

D = Random vector of drying costs per acre

Stochastic price and yield distributions determine random government payments and drying costs. Total net revenue per acre is calculated as the product of random yield times random price plus government payments (dependent on random prices) minus variable costs, rent and drying costs (dependent on random yield and planting/harvest period). Therefore, a sample vector of returns, which can be regarded as a sample 'year' or state of nature, can be calculated by Monte Carlo sampling from a multivariate distribution of yields and prices. If the distribution of net revenues is judged to be reasonably approximated by the multivariate normal distribution, then the moments implied by the elicited marginals and estimates of correlation coefficients completely describe that distribution. Anderson et al. (1977) state that appeal to the central limit theorem for justification of the normality assumption becomes more reasonable as the number of random variables increases or the more independent are the random variables. While farm operators can be expected to have fairly well-formed marginal distributions for yields and prices of individual crops, they seldom have similar joint expectations for correlated yields or prices, and have even less conception of statistically independent underlying variables associated with weather variability, such as sunlight or rainfall (King 1979). Joint elicitation of random variables is a very time-consuming procedure of untested reliability for both research and decision support purposes. Such procedures have thus seldom been carried further than textbook explanation (Anderson et al. 1977). Research has also indicated poor results for attempts to directly elicit correlations between random variables, and there seems to be little evidence that farm operators are better equipped to estimate correlations than other subjects (Tversky and Kahneman 1973). Historical aggregate data can be used to estimate correlation coefficients for both yield and price variables and thus used in conjunction with directly elicited marginal distributions. Given generally short farm-specific yield data series and confounding time trends, it may be expedient to estimate correlation coefficients outside the decision session from aggregate county, state or (in the case of some price correlations) even national level data. Although marginal yield variances from aggregate yield data tend to underestimate individual farm variances, correlations are much less affected than marginal variances, and generally are not expected to significantly affect Monte Carlo sampling.

A procedure to generate variates from a multivariate normal distribution is described in Naylor (1966) and implemented in a FORTRAN program by King (1979). The estimated correlation (and corresponding covariance) matrix can be used to determine a unique lower triangular matrix. When this matrix is multiplied by a vector of independent standard normal variates and the resulting vector is summed to a vector of marginal means, the result will be multivariate normally distributed with covariance matrix closely approximating the original covariance matrix and means approximating the original estimated values. The only restriction placed on the correlation/covariance matrix is that it be positive definite and symmetric. In matrix notation:

(5.11)

$$X = CZ + E$$

E is an Nx1 vector of elicited means of the marginal distributions, Z is an Nx1 vector of independent standard normal variates, C is a lower triangular matrix of dimension NxN calculated from the estimated covariance matrix (constructed from the elicited variances and the imposed correlations), and X is the resulting Nx1 vector of values for one state of nature drawn from the correlated multivariate normal distribution with expected values and covariance matrix approximately equal to the original estimates. Appendix 3 lists the Pascal procedure used to generate dependent multivariate normal variates. The procedure depends importantly on the premise that correlations are preserved through the transformations made by the described process. King (1979) provides evidence to support that assumption, reporting original and generated correlations which differ by no more than 0.05 in his tests. Examination of the procedure implemented in this research also showed only minor discrepancies between input and output correlations. In the current decision model, a variate is generated according to the above process for each relevant crop yield on each tract and for each crop price. For example, if there are ten land tracts and three crops are considered for each tract, thirty three variates would be generated.

Another major exogenous factor affecting yield has not yet been considered - uncertain field days available for planting and harvesting periods. Farm operators are constrained from profitably farming more acres by their capacity to complete field operations in a timely fashion. Researchers such as Rotz and Black (1985) indicate considerable decline in yield potential for crops planted or harvested outside certain optimal field work periods. King (1979) suggests that for modeling purposes, random variates for estimated field time available can be generated, upon which yield potential would depend. This would considerably increase the number of variates to be generated and the complexity of model formulation. For applied decision purposes, farm operators may be willing to accept a more simplistic but plausible rule that yields of crops planted before or after recommended periods are adjusted by a fixed penalty matrix based on the mean yield reduction expected per day during the relevant planting/harvesting period as determined in agronomic experiments. Table 5.7 shows the penalty matrix used for the current model.

As noted, the more or less continuous decline in yield potential outside the optimum periods is approximated by discrete penalties when field operations cannot be completed in timely fashion. It is not clear how to best establish reasonable expectations for field time likely to be available in various periods of spring and fall at the individual farm level. Extension experts state that farm operators often use the rule of thumb that they would like to be able to handle field operations in a timely manner in four of every five years. Machinery complement purchases seem to be based on this heuristic. Many optimization models have therefore used a chance-constrained programming approach to estimate available field time limits such that the probability that actual field time is less than that estimated is less than 0.2 (corresponding to the heuristic), or in other terms:

(5.12)

$$\text{Field time limit} = Pr(h \leq H) \leq 0.2$$

The probability operator is denoted as Pr, H is actual field time, and h is estimated field time. The estimates for field hours available used in the current research are calculated from Rosenberg et al. (1982), which presents a simulation model of 'go-no go' field days based on temperature, precipitation and pan evaporation. Predictions of the model were found to vary from historical records by

TABLE 5.7 YIELD PENALTY MATRIX FOR UNTIMELY FIELD OPERATIONS

PENALTY FOR UNTIMELY FIELD OPERATIONS--CORN*

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	1.00	0.99	0.95
5/11-5/20	0	0.95	0.94	0.90
5/21-5/30	0	0.82	0.85	0.81
6/1-6/30	0	0	0	0

PENALTY FOR UNTIMELY FIELD OPERATIONS--SOY BEANS

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	0.98	0.94	0.86
5/11-5/20	0	0.98	0.93	0.86
5/21-5/30	0	0.96	0.91	0.83
6/1-6/30	0	0.76	0.71	0.69

PENALTY FOR UNTIMELY FIELD OPERATIONS--NAVY BEANS

Planting Period	Harvest Period 9/1-9/15	9/16-9/30	10/1-10/31	11/1-11/30
4/21-5/10	0	0	0	0
5/11-5/20	0	0	0	0
5/21-5/30	0	0	0	0
6/1-6/30	0.99	0.95	0	0

SOURCE: Estimated from Black, J. (1974) and Rotz and Black (1985)

* Yields are penalized by the indicated factor for field operations carried out in the indicated planting/harvesting period.

approximately fifteen percent on average over soil types. Table 5.6 presented the estimated field hours for four soil types in the East Lansing area.

Field hours are computed from the predicted field days in Rosenberg et al. (1982) by assuming six day work weeks and twelve hour work days for the planting/harvesting equipment. Sufficient labor is assumed available to operate machinery during these periods. It should be noted that the East Lansing estimates represent extrapolations from Bad Axe data, since Rosenberg presents only summary estimates for that locations. The model itself is unfortunately not available to estimate more location-specific estimates for a wider range of Michigan sites.

Subsequent development of the model described in this research should include more extensive investigation of field time constraints, which is a major factor affecting selection of optimal cropping and rental activities. In this model, as described above, additional acres are planted/harvested according to the capacity of existing machinery complements until the field time limit is reached for a particular period. Field operations in subsequent periods may be subject to additional yield penalties, thus forming incentives for timely operations.

Machinery resource data is elicited from decision makers, and machinery technical coefficients are then estimated from White (1978). The acres covered per hour by a given planting/harvesting machinery complement is estimated by:

(5.13)

$$\text{Acres/hour} = W\ M\ E$$

in which W = operating width of equipment

M = operating speed of equipment

E = efficiency factor for the given type of equipment, reflecting necessary stops for lubrication, turning at the end or rows, etc.

A vector of net cash revenues is then calculated by multiplying the vector of random yields for each tract (adjusted by the yield penalty matrix) to obtain production valued at harvest prices. Government payments are then calculated by multiplying base acreage times base yields times the difference between target and cash prices (if the latter is above the government program loan rate). Diversion payments for set aside acres are added and costs of planting a cover crop on set aside acres are included. No consideration is given for interest income implied by timing of payments. This amount is then distributed across planted acreage[1].

To summarize, the data input by the analyst to the matrix generator includes the following:

1. Yield expected values and coefficients of variation for each crop on each tract, and yield correlations between tracts
2. Price expected values and coefficients of variation for each crop, and correlations between all prices
3. Variable costs for each crop on each tract

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1 There is no requirement in the model that government program crops be planted on all eligible acres. Nevertheless, the difference in revenue per acre for all tracts with government base acreage using likely relative prices indicates that generally all eligible acres would be planted.

4. Total and tillable acreage of each tract and rental payments if applicable
5. Government program information for each separately listed Agriculture Soil Conservation Service farm number, including base acreage and base yield
6. Chance-constrained estimated field hour time limits for planting and harvesting periods
7. Technical coefficients for planting/harvesting operations
8. Operator-specified cash revenue target below which deviations under any state of nature will be penalized.

The second function of the matrix generator program is to create a data file suitable for generation of the LP tableau. This process creates and stores a file of row and column labels, coefficients, constraint equality directions and resource quantities. The coefficients and resource quantities are calculated either as described above from farm-specific data entered by the analyst or from default values coded in the program. This function is specific to the format required by the LP solver utilized in this research, although a new procedure could be easily written to generate other formats. A final function of the matrix generator program is to store a small file containing basic information for each land tract for later use by the solution display program.

5.6.5 LP Solver

The function of the LP solver within the decision aid is to read and solve the linear system of equations created by the matrix generator program and subsequent modifications of certain values indicated by the farm operator through the solution display software.

Creation of unique LP solver procedures for a particular decision aid is not a cost-effective investment of programming resources, and a commercial LP solver is also likely to provide more extensive capabilities and faster solution time. The disadvantages of a generic LP solver include the requirement to purchase the software for each installation and interfacing problems for input from the matrix generator or output to the solution display software.

The microcomputer LP solver used in this research is a commercial software product called LP88 [1]. This stand-alone set of programs will solve problems as large as 500 constraints and 2500 variables. It operates under the MS-DOS operating system and supports the Intel 8087 numeric microprocessor. All calculations are carried out in double precision (16 digits), and additional error control is provided by optional matrix inversion of basis columns. Control of the program may be directly (interactively) through selection from menu displays or indirectly (batch) from a file of commands. Data input and editing can also be carried out from a previously written file or directly from the keyboard with a spreadsheet-like data editor.

Output reports of various types can be generated, and sensitivity analysis can be carried out on constraint or objective function coefficients modifications. Solution values can also be stored in a format readable by other programs, the basis of coefficients in the optimal solution can be stored and reused. This option is extremely useful for solving similar large linear systems, since a previous solution usually provides a better starting point than a basis

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1 Eastern Software Products, P.O. Box 15328, Alexandria, Virginia 22209

consisting of singletons and artificial variables. As described below, the solution process of the decision aid consists of sequential solution of moderately large but very similar linear systems of equations. The time necessary to solve large systems from a slack/singleton can be substantial, but subsequent solution time utilizing a stored coefficient basis is reduced significantly.

5.6.6 Goal-directed Solution Display Program

The principal functions of the goal-directed search program (GOALDIR) are to display the effects of the current and previous LP solutions on the revenue and risk objectives of the decision problem, accept input from the operator with regard to modification of acceptable objective levels, and create files to alter the relevant LP matrix and update a summary of previous steps. GOALDIR is a stand-alone program developed in Pascal for the current research. It takes as input three files: 1) the land information file created by the matrix generator; 2) the current solution file created by the LP solver; and 3) (after the first step) a file created during the previous step which contains the LP solution from the previous step plus a summary of all previous steps. The current solution consists of the optimal values of activity variables resulting from optimization of one objective subject to feasibility constraints and a minimal/maximal constraint on the other objective.

The program first displays information to the farm operator concerning the most and least preferable (best and worst) levels of the two objectives within the constraints of the feasible set. These values are displayed for both objectives in tabular and graphic form, as shown in Figure 5.7. The graphs and tables show changes in the best and worst levels of both objectives based upon the changes indicated by the decision maker in the previous step. In addition, a partial cumulative probability table is displayed which indicates: 1) the probability that net cash inflow from cropping activities will fall below the pre-determined target level and 2) the cash inflow resulting from the five worst states of nature. Since each state of nature is equally probable (drawn from a random distribution with equal likelihood), arranging net revenues from all simulated states of nature in ascending order gives a discrete approximation to a cumulative distribution of net cash revenue from cropping activities. The table provides the decision maker with additional information concerning the probabilities of very low revenue from the current solution.

To evaluate the consequences of decisions from the previous step, the decision maker may review in identical format the results from the previous step. To review all previous trial solutions, the decision maker can also review a summary table of objective levels. Finally, the decision maker may review the cropping activities on each land tract implied by the current solution. Sample screens are reproduced in Figures 5.7, 5.8 and 5.9.

Basing decisions on the above information, the decision maker may choose to alter the 'worst acceptable' value of one objective. The program requests the decision maker to indicate the objective, then suggests a new value equal to one half the difference between the current worst and current best values. The decision maker may accept

```
                    C U R R E N T   S O L U T I O N
                      Objective  :  NET REVENUE
WORST                                                                  BEST
===========================================================================

GLOBAL :   10000 :                                      : 150000 : GLOBAL
CURRENT:   10000 :                                      : 150000 :CURRENT

                 Possible Net Revenues and Probabilities
===========================================================================
Net Revenue     20000     19500     19300     18000
Probability      0.09      0.06      0.03      0.00
===========================================================================


                      Objective  :  RISK
WORST                                                                  BEST
===========================================================================

GLOBAL :    5000 :                                      :      0 : GLOBAL
CURRENT:    5000 :                                      :      0 :CURRENT

 0=save/quit, 1= last step, 2= current activities, 3= summary, 4=alter values
```

FIGURE 5.7 BEST/WORST SOLUTION VALUES OF RISK AND RETURN, GOAL-DIRECTED SEARCH PROGRAM

CURRENT ACTIVITIES

Tract Description	Total Acres	Land Num.	Crop	Acres Planted
John Wesley Hardin	650	1	CORN	350
			SOYBEANS	100
			WHEAT	200
Abraham Lincoln	150	2	WHEAT	10
Tomas Borge	280	3	SOYBEANS	130
			WHEAT	150

FIGURE 5.8 ACTIVITES IMPLIED BY CURRENT SOLUTION, GOAL-DIRECTED SEARCH PROGRAM

S U M M A R Y   O F   P R E V I O U S   S T E P S

	NET REVENUE		RISK	
	Best	Worst	Best	Worst
Step 0	150000	10000	0	2000

FIGURE 5.9 SUMMARY OF RISK/RETURN VALUES FOR PREVIOUS STEPS, GOAL-DIRECTED SEARCH PROGRAM

this default or enter another more preferred value. The program then creates and stores two files: 1) a record of the previous solution and updated summary of previous solutions and 2) a file containing commands to the LP solver to modify the current tableau according to the preferences expressed by the decision maker and to re-solve the problem. As described above, the resulting new solution is then read by the GOALDIR program and displayed to the decision maker. This process of modifying with GOALDIR and re-solving with the LP solver continues until the decision maker is satisfied with the solution.

5.7 Preliminary Empirical Evaluation

Preliminary testing of the decision aid was carried out with three extension agents and two farm operators to evaluate operational features of the GOALDIR system. Individuals were visited at their home or place of business, interviewed about the rental and crop mix decisions, and asked to represent the farm operator/decision maker in a session with the GOALDIR aid.

Extension agents were interviewed for several reasons. First, their experience in observing and assisting farm operators to make these decisions can provide valuable information concerning the nature of the decision, the ability of farm operators to master the concepts and procedures, and the likelihood that managers would incorporate such an aid into their decisions. Agents would also be the intermediaries in most manager use of GOALDIR, since operation of the aid requires computer operations skills not common among farm operators. Extension agents were also included because of the unfortunate timing of field testing for GOALDIR. During spring planting, few farm operators can afford the time necessary for the aid, especially since the rental decision has already been made for the current year.

The interviews with extension agents and farm operators are presented as structured documentaries, with particular discussion of: 1) the operator's opinion of the rental decision; 2) the characteristics of the individual interviewed; 3) the data elicitation procedure, including land, budget, yield expectation and price expectation elicitation; 4) model operation, including reactions of the individuals to the multiple objective framework and the optimization/dominance procedures utilized in the decision aid. Other factors of interest are the relative effectiveness of graphical versus tabular data in elicitation and solution display, and the analyst-mediated interface of the aid with the user.

5.7.1 Interview of First Agent

The first agent interviewed is from Barry County, in which a significant proportion of farm operators rent cropland. In the opinion of the agent, rental decisions are made infrequently (not each year) when a relatively small number of properties become available for rent. A landlord generally does not put properties on the rental market is the current rentor wishes to continue the arrangement. Stable access to resources (land) is often more important than current year profits for the rentor.

The agent has skills and understands principles to an extent uncommon to most county extension personnel. He has a good command of budgeting principles, and understands major concepts of statistics and

probabilities. For example, he understands the distinction between modal and mean values, the symmetry/asymmetry characteristic of probability distributions, and the concept of variance. His thoughtfulness and inquisitiveness were demonstrated clearly by unsolicited suggestions for improvement of aid procedures.

The reaction to interactive data elicitation procedures was very favorable, particularly with respect to yield and price assessments. The use of variable cost budget defaults from aggregate data was considered a good mechanism to prompt operators for cost data and to induce them to place attention on cost factors in cropping decisions. He considered this procedure to be useful for purposes other than the rental decision considered here.

Approximately twenty minutes were required to explain the probability elicitation procedure to the agent. Subsequently, elicitation of each probability distribution required approximately ten minutes. Hypothetical price and yield distributions were elicited for several crops. Although the agent had little difficulty with probability elicitation procedures, his familiarity with probability concepts stimulated a tendency to directly state probabilities for yield/price intervals rather than the indirect conviction weights requested by the aid. There were no obvious signs of bias in probability assessment.

With a sophisticated subject such as this agent, direct elicitation of probabilities is probably a more efficient elicitation procedure. Graphical output of yield probability density functions (PDF) was specifically mentioned as helpful for checking the symmetry of elicited distributions against intuitive expectations. The displayed PDF table was examined and easily interpreted with little explanation from the analyst, but the cumulative distribution function (CDF) tabular data was largely ignored.

This interview used an earlier version of the price distribution elicitation procedure which displays a default CDF price distribution and requests direct CDF subjective probabilities for price. Intervals of the default price distribution varied, with equal probabilities in each interval. CDF probabilities were regarded as both difficult to express and to interpret. This procedure was not acceptable to the agent, who suggested that the procedure used for yield elicitation also be used for price elicitation. In subsequent interviews, price elicitation was conducted using the conviction weights method. Explanations and data elicitation required approximately two hours.

A previously constructed hypothetical farm situation was then explained to the agent and solved with GOALDIR (the agent playing the part of decision maker). The decision framework of tradeoffs between multiple, conflicting objectives was intuitively reasonable to the agent. Expected return as probability-weighted returns from random draws as a current returns objective, and probability-weighted deviations below a target value as a risk objective were seen as acceptable operational forms of important objectives sought in farm rental decisions. However, the intuitive definition of risk considered most reasonable by the agent is the probability of returns falling below variable costs (akin to focus-loss).

Considerable attention was paid to the graphical output as contrasted to numeric output. The agent asked questions about model structure and function, and understood some of the principles underlying linear programming and the IMGP procedure. Whatever was not understood about the optimization procedures was accepted on faith as reasonable.

This agent can be viewed as the most promising potential intermediary for GOALDIR use in extension assistance for land rental decisions. He has substantive experience and knowledge, and a propensity for inquiry which mark him as an innovator. His inquisitiveness was demonstrated by the suggestions made during the interview, some of which stimulated reformulation of the decision aid. For example, he suggested yield probability elicitation should be carried out before variable cost budgets were elicited, so that yield goals and fertilization levels could be established and made consistent. An unrelated fertilization decision application was suggested for the yield elicitation procedures. It was recommended that price and yield elicitation should be carried out with the same conviction weights method. For the solution display procedure, risk should be indexed from 1 to 100 instead of values of mean deviation below target, since the latter are not intuitively recognizable to farmers. Finally, he recommended a probability graph instead of a table for the solution display procedure.

5.7.2 Interview of Second Agent

The second agent interviewed is from Ionia County. There is considerable renting of parcels for cash grain farming in this county, with some operations renting from as many as twenty landlords. Considerable flux has been observed in rental arrangements in recent years, including some instances of rent adjustment at harvest conditional on actual yield and price. Modification of rental arrangements with current landlords is much more common than switching of farms rented from year to year.

This agent had more difficulty with probability concepts. For example, he was unable to distinguish between modal and mean yields without explanation. In addition, he was much less familiar with computer hardware and software operations than the first agent. However, the agent does have sound budgeting skills.

A favorable reaction was expressed concerning interactive elicitation as a useful method to induce farm operators to identify relative variable costs. The simple procedure of displaying default variable cost budgets and eliciting farm-specific budgets was considered to be very useful for planning assistance to farm operators in combination with agent consulting. Yield and price probability distributions were elicited for several crops with minimal difficulty. The method was explained and illustrated in approximately fifteen minutes, and each distribution was elicited in twenty minutes or less. Little preference was expressed between display of PDF versus CDF probability information. The histogram was used as a visual check on correspondence between elicited probabilities and intuitive judgement with respect to symmetry. The agent expressed the opinion that yield probability distribution procedures would be useful in several other contexts, such as fertilization decisions.

Solution of the hypothetical farm rental problem proceeded much the same as with the previous agent. The concept of multiple competing objectives was not difficult to grasp, but the agent's relative lack of understanding of probability concepts made the operational definition of risk and return difficult to comprehend. Confusion was obvious when the agent was presented the best/worst solutions of GOALDIR. Solution of the problem by goal-directed search seemed backwards to the agent. Preference was expressed for a similar aid procedure which would allow direct selection of trial rental plans. This agent also focussed his attention on graphical display of goal tradeoffs, with less attention on numeric tables.

Explanation and application of data elicitation procedures required approximately two hours. Another hour was required for illustration of the solution display procedure.

5.7.3 Interview of Third Agent

In Gratiot county, there has been considerable flux in the rental market as some farm businesses undergo severe financial stress. There is considerable land rental in this county, and even in mid-May some land had not yet been rented. The financial crisis has made land available which would not normally have been on the rental market. Some operators with financial difficulties have taken apparently risky decisions by bidding high cash rents for large acreages, in hopes of significantly improving their financial status.

It is unlikely that this agent understands probability concepts well enough to instruct farm operators in formal risk analysis procedures. Some difficulty was encountered in understanding concepts such as expected value, modal value, variance and skewness while explaining the probability elicitation procedures, but after a short practice the agent apparently used the concepts in comparing the elicited probability values with his beliefs. This agent also was less familiar with the capacities and limitations of computers.

The agent made relatively few comments about land and budget elicitation. Although pleased with the detail and flexibility of the budget elicitation spreadsheets, he expressed the opinion that few farm operators would be able to provide records upon which to base the variable cost information requested. In his opinion, this indicated two problems for successful implementation of the aid: 1) the procedure would take considerable time to elicit budget information, or 2) use of default budgets might seriously misrepresent the actual farm situation. However, the data elicitation procedures were again viewed as quite valuable to structure the decision and stimulate farm managers to base their decisions on data.

Once the probability elicitation procedure was explained, probability distributions of yields and prices for several crops were elicited with little difficulty. However, most distributions were relatively 'tight', more symmetric and had higher minimum levels than those of the other agents. For yield distributions, this might simply be a real reflection of differences in soil and climate conditions. It could also indicate potential bias in the elicitation technique. However, questions to the agent concerning these points indicated that subjective beliefs about variability of prices and yields were not well formed, and that the elicitation technique seems to accurately represent beliefs which are not well thought out. This indicates a need to encourage the agent to focus carefully on his opinions about the specific random process in question.

Framing a decision problem with multiple objectives was reasonable to the agent, and he could name other decisions in which farm operators pursue multiple objectives. Treating return and risk as competing objectives was also reasonable to the agent. However, the GOALDIR operational formulation of return and risk objectives was not well understood, primarily because of the agent's lack of knowledge about probability. An intuitive definition of risk to this agent reflects primary concern for avoiding low yields. He understood the purpose of the aid as quantifying tradeoffs between the competing objectives, and focussed principally on the graphics display to determine desired relative changes in the objectives. No questions were asked concerning the model structure or functional relationships. In general, the agent was willing to accept on faith the validity of the model procedures to determine best/worst objective function values. However, a clear preference was expressed for alternative procedures which would allow more detailed analysis of individual cause and effect relationships. For example, he would like to examine the effects on risk and return objectives caused by varying expected prices of particular crops.

This session lasted over three hours. Two hours were spent in demonstrating elicitation software and estimating probability distributions for three crop yields and three crop prices.

5.7.4 Interview of First Operator

The first farm operator is a partner with several other family members in a large (6000 acres) cash grain operation. The crops raised are corn, wheat, soybeans and dry beans. Beside cropping enterprises, the partnership also operates a certified seed operation and has close business connections with other non-farm firms.

This operator is an unusually well educated (university degree) and knowledgeable operator with over four decades of farming experience. His management style is innovative and dynamic, as demonstrated by the steady growth and diversification of business operations. Although he was somewhat less familiar with and knowledgeable of probability concepts than the agents, he was more comfortable with computer operations than two of the three agents.

Although the session lasted three hours, considerable time was spent discussing the rental decision process in general. This partnership rents no land on a yearly basis. Instead, all land is leased for at least three years on a cash basis. There is an agreement with most landlords to adjust the rental price according to harvest time cash price. The partnership rents twelve farms. The operator considered that in his area very few farms are available for rent each year. If a parcel is available, the operator usually makes the rental decision on the basis of labor availability, government base acreage of the land, and the price outlook for the next several years. It should be noted that most important decisions in the operation are made with the participation of all active partners. Therefore, communication between partners and discussion based on facts are essential when decisions are made.

This operator had no clearly defined concept of business risk, although from his perspective risk for the operation has its source primarily in unexpected interest rate increases and secondarily in price fluctuations. The operation uses forward pricing to protect itself from price fluctuations. The concept of a target income level was quite natural to the operator, and he was able to state a value almost immediately.

Not enough time was available to elicit complete budget and rental information, but the templates were demonstrated and some budgets elicited. The business keeps quite detailed records, and the operator was able to give very precise variable cost information from memory without difficulty.

The operator expressed considerable interest in the probability elicitation procedure, asking for a copy for his operation. Only a few minutes were necessary to explain the process, and after the first distribution was elicited the operator became quite comfortable with the procedure. Somewhat more time was necessary to obtain each distribution than with the extension agents. Because of limited time, yield distributions were elicited for three crops on only a single soil type. Price distributions were also elicited for three crops.

The operator decided by himself that the interval range would affect his estimates, and asked that an interval range chosen by the researcher be reduced. There was some evidence from the operator's comments that conviction weights stated for the distribution tails may have been confused with historical frequencies. It appeared somewhat more difficult to the operator to anchor weights on the modal range as elicitation proceeded to the distribution tails. Reminding the subject that the weights should be stated relative to the most likely interval should be done at frequent intervals so that errors are not committed. There was also a tendency to smoothly decrease conviction weights as elicitation progressed from the modal range towards the tails. This may reflect use of an ad hoc smoothing rule to reduce cognitive effort, or may simply reflect imprecise beliefs. The operator had difficulty with probability concepts, and was not able to interpret the difference between the most likely and expected values of distributions. More extensive explanations of simple probability concepts using graphics procedures would likely be rewarded by more understanding of terms and concepts and more carefully considered subjective probabilities. The only conclusions that can be made with confidence are that the operator found the procedures easy to master, that he agreed with the resulting probabilities, and that those distributions were similar to distributions which could be calculated from historical data.

Evaluating decisions based upon tradeoffs between competing objectives was not difficult for the operator. Although the operational definition of returns as used in the model was understood by the operator, he had difficulty understanding the definition of risk. The land rental decision may be primarily considered a production decision, and risk associated with land rental appears to be closely associated with expectations of low yield. Price risk may not be explicitly considered in rental decisions, probably because of relative price stability provided by government feed grain programs.

The operator had considerable difficulty in understanding the decision process of choosing an implied set of activities according to explicit tradeoffs between risk and return. The best/worst solutions presented in the aid appeared to confuse the operator, and did not improve comprehension of model operation. The graphical output was a focus of tradeoff decisions, with relatively little attention to numeric output.

5.7.5 Interview of Second Operator

The second operation visited is a single family, mixed crop-livestock farm. Sugar beets, dry beans, soy beans and corn are raised on the owned land and five rented farms. Although there have been several opportunities to rent additional land, the family has not changed rental properties in the past three years. Individual rental parcels are evaluated by estimating expected returns given various rental arrangements which might be negotiated with the landlord.

One son has assumed primary responsibility for the livestock operation, and the record keeping is handled jointly by the husband and wife. Several family members participate in important decisions, and a multi-person management unit can be identified.

The operator's time was very limited, and relatively less data was elicited than with the previous operator. He did not find the probability elicitation procedure difficult, but comments indicated that the elicited distributions may not have been careful or accurate expressions of belief. The concept of a target income was reasonable to him, as were the risk and return concepts used in the model. However, search by objectives was definitely not a comfortable procedure. The operator stated a clear preference for a procedure which would allow him to select farm plans and then calculate the impacts on risk and return objectives.

5.7.6 General Observations

Certain observations common to several interviews should also be mentioned. The agents were in general more comfortable with production issues rather than the economic issues treated in the decision aid. This is not surprising, since all are agricultural production specialists. Although the agents interviewed were selected for their reputations as innovators, it is unlikely that they are qualified without further training to instruct farmers in risk analysis and associated probability concepts. Neither are they sufficiently comfortable with computer operations to instruct operators in use of programs of more than moderate complexity.

Tabular probability values were not well understood by most subjects, and verbal summaries of the information such as, "According to your stated estimates, there is one chance in five of corn price between $1.70 and $1.80 at harvest time ", were generally necessary to interpret the tabular data. A tendency to 'smooth' conviction weights for some intervals from the modal range towards the distribution tails was observed in some cases. As noted above, it is unclear whether this procedure accurately reflects beliefs, or is instead a technique to reduce the difficulty of carefully examining beliefs for each interval.

Some subjects determined historical frequencies for yields within some intervals, which then were transformed to express the desired conviction weights. Operators pay close attention to the random weather processes which affect yield variability, and appear to have more carefully considered expectations concerning yields. This may indicate that direct elicitation of yield probability distributions may be more efficient in some cases. It is likely that direct elicitation would be more successful with operators who keep production records and who have some familiarity with probability concepts, and for crops for which historical frequencies provide a reasonable estimate (to the operator) of expected yields in the current year.

Display of a default set of conviction weights for prices was expected to serve the purpose of a distributional reference for subjects with less clearly defined expectations for prices than for yields. On the other hand, blanket acceptance of the default weights may severely misrepresent the subject's price expectations. The interviews indicated that default weights did influence the elicited weights to some degree, but that subjects substantially modified the weights in accordance with their own beliefs. Although all subjects were encouraged to examine probabilities resulting from expressed conviction weights and to alter distributions which did not 'seem right' in their opinion, conviction weights were not modified in any interview. This could be attributed to lack of interest or ill-defined underlying beliefs. In any case, it tends to undermine the advantages of interactive elicitation procedures, since convenient modification was expected to be a major benefit of the interactive process.

Partial rental of a parcel was indicated in the hypothetical problem, but all subjects rounded or truncated solutions with little comment. Although it is entirely possible that such a practice could lead to decisions which are not optimal, it appears to create few operational problems for users.

Distinguishing risk and return as competing objectives was an intuitively reasonable framework for all subjects. There was evidence that crop rotation and soil fertility objectives are also important factors in some operators' rental decisions. However, quantification of objectives confuses some subjects. They are often more comfortable with ill-defined, intuitive formulations of objectives other than cash returns. Most subjects did not express full confidence in the suggested solution activities because they did not understand the procedures used to calculate solutions. Only the first agent inquired about the structure and functional relationships of the model, and he subsequently displayed a fuller understanding and more confidence in the solutions. Development of user confidence in complex procedures appears to be more difficult if the procedures are not in some way similar to existing decision practices. Graphic representations were carefully considered by all subjects in probability elicitation and solution evaluation, suggesting that many farm operators may find tabular data more difficult to interpret and utilize in these types of tasks.

CHAPTER VI

CONCLUSIONS AND PROPOSED RESEARCH AGENDA

6.1 Introduction

Keen and Scott Morton (1978) describe development of decision support systems as an iterative process, with repeated phases of design, implementation, evaluation followed by subsequent reformulation. The present research has examined issues of decision theory and decision support, designed and implemented a multiple objective decision aid, and conducted preliminary field testing with extension agents and operators. One decision support development cycle has been completed, and an assessment must be made of what has been learned from the literature, model development and field testing. A decision support research agenda is derived to continue the difficult task of expanding farm management researchers' capability to assist management decision making.

6.2 Conclusions from the Literature

Rationalist and behavioralist theories of individual decision making are in many ways alternative explanations of the same empirical phenomena. The former paradigm attempts to develop context-independent and objective decision making principles, while the latter describes actual decision processes from the perspective of subjective, cognitive elements. While rationalist decision theory claims to provide the framework for determining the best possible solution within the domain of defined problems (and hence the action that should be taken), behavioral theory attempts to reveal the largely hidden cognitive operations (what the individual is thinking during decision making). The rationalist perspective has relatively little consideration for the cognitive processes in decision making, while the behavioralist perspective provides no clear framework or standard for evaluating decisions.

Characteristics of the human information processing system have been described here, and limitations with respect to logical decision processes have been examined. Behavioralist research has documented persistent violations of rationalist assumptions in a wide range of decision contexts with subjects of varying skill, education and experience. Selective attention is paid to multiple objectives and multiple dimensions of choice alternatives. To avoid the time and complexity of finding the best alternative, individuals often choose alternatives with values that are only satisfactory. Decision rules are utilized which often guarantee sub-optimal outcomes, and errors are common in forming and manipulating judgemental beliefs. The general conclusion is inescapable that unaided individual decision making is prone to errors vis a vis rationalist principles because of the innate structure and operation of the cognitive apparatus.

But the behavioralist camp begs one question and leaves another hanging. Individuals generally do not make completely unaided decisions. They utilize a wide range of memory, representational and computational aids, and thus to an unknown extent avoid serious errors. Behavioral theory is largely silent on the issues of 'person-tool rationality'. Although a satisfactory basis for examining defects in existing decision processes, behavioral theory forms a very incomplete framework for designing procedures to aid decisions. The objective of management support is not only to detect biases, but to aid individuals to make better decisions. On the other hand, rationalist theory is often criticized as not providing a practical, workable basis for aiding decisions. Procedures recommended under the rationalist framework frequently assume data, computational and time resources which are not available to decision makers.

A working framework for decision support involves a synthesis of concepts and techniques from both decision paradigms. Hybrid decision aids would utilize rational decision procedures to the extent possible within the documented characteristics and constraints of human cognition. Similarly documented strengths of human information processing such as pattern recognition, inferential judgements and long term memory recall should be supported by such decision aids.

Multiple criteria decision models (MCDM) provide a mathematical structure for decision aids reflecting both behavioral and rationalist principles. All reflect the consideration of multiple dimensions of decision alternatives, yet provide powerful solution techniques utilizing either dominance or optimization procedures. Interactive multiple criteria models allow further opportunities for developing greater user confidence and learning about problem structure and preference tradeoffs. Interactive MCDM methods require articulation of only local preferences and iterate towards preferred solutions. Since the model is directed by user preferences, proposed solutions may have a better chance of being implemented.

Of the currently available interactive MCDM methods, the Interactive Multiple Goal Programming (IMGP) method best embodies many features of a desired hybrid analytical model. Articulation of local preferences, use of aspiration levels and flexible consideration of various functional formulations and decision rules are characteristics which recommend IMGP as a mathematical model for a decision aid.

6.3 Conclusions from Model Development

A two objective risk-return aid was developed on a microcomputer to assess feasibility and potential of IMGP-based aids. The principal conclusion is that interactive multiple objective modeling is feasible. However, limitations of current microcomputer software and hardware force severe compromises between realistic modeling of decision problems and timely operation of decision aids. The data and functional form requirements cause the resulting optimization models to press the limits of current microcomputer technology. It is expected that these restrictions will be alleviated as faster and more powerful microprocessors become available. However, it is unclear whether both faster operation and more realistic modeling can be accomplished with the next generation of technology.

A related design problem from both the analytical and programming perspectives involves user-specific and default data. Use of 'representative' data in the decision aid greatly simplifies model construction and improves turnaround time, but may seriously misrepresent the decision as perceived by the user. Compromise from the standpoint of aid design was reached by eliciting data that a farm operator might have in farm records or about which the operator is likely to have relatively well-formed opinions or expectations. Other data which the user could not be expected to provide were imposed from external, representative sources. Although the effects of these compromises on software development is tangible, effects on model solutions are unknown.

The LP solution procedure upon which the IMGP model is based depicts alternatives as infinitely divisible. Solutions may be indicated with fractional acreages or farms, an obviously unrealistic answer to the real problem. Although a mixed integer integer algorithm could be used to alleviate this problem, mixed integer programs are significantly slower (as much as fifteen times slower) than LP programs. Thus, size and realism of the decision model would again have to be traded off against speed of model operation. In addition, the IMGP procedure chosen for this implementation requires substantial modification for problems not characterized by a convex feasible set.

Simple graphical representations were utilized in the decision aid. Plans for more complex graphics were abandoned because of hardware-dependence of most graphics procedures, relatively slow operation and difficulty in integrating graphics routines with other software. However, both graphical and optimization procedures will become much more practical for real time decision support as faster microprocessors (as much as twenty times faster) and more sophisticated software (with complex but flexible 'toolkit' modules) become more widely available.

Integration of the various functional routines that together constitute the decision aid is a serious obstacle to cost-effective development and implementation. This research used two generic commercial programs for elicitation and LP solver functions. Few such commercial programs are designed to be integrated into a larger software system, and these were no exception. Particular problems arise in passing data from one routine to another and in developing a reasonably consistent interface between the aid and the user. The former problem required rather intensive analyst input to operate the aid, while the latter problem was not resolved. An alternative design procedure is development of custom software for each decision aid, which unfortunately increases development costs and often does not approach the power and speed of commercial software.

6.4 Conclusions from Field Testing

Testing of the GOALDIR aid provided empirical evidence with respect to several decision-specific and general decision aid issues. Validity of the decision model, data elicitation procedures, multiple objective solution procedures and intermediary-user issues are discussed below.

6.4.1 The Rental Decision

Correspondence between the decision model and the real world rental decision is limited by necessary approximation of functional relationships and data measurements. In addition, characteristics of the real problem may differ from the model structure with respect to time horizon, relevant objectives, and organizational context. That is, the rental decision is not generally a portfolio analysis of all owned and potentially rented cropland, but is considered by farm operators as an evaluation of isolated rental tracts. Rather than evaluating rental arrangements on the basis of current year expected returns, operators make formal or informal multiple year committments for particular properties on the basis of expected returns over a longer time horizon.

In addition, rotational objectives should be treated explicitly in a rental decision model. Some operators will refuse to depart from a strict rotational cycle regardless of return prospects. Others are willing to plant a significant proportion of cropland according to expected relative returns. This behavior could be considered in a multiple objective decision aid.

Although this research has examined individual decision making, many farm businesses have multi-person management units. Decision aids could be designed as forums for discussion and decision making by relevant individuals in the firm. Formalization of the problem and interaction between differing individual perspectives may significantly improve decisions.

6.4.2 Data Elicitation

The data elicitation for a farm-specific model consumes much more time than initially estimated. Elicitation of rental arrangements and government program information for ten to fifteen potentially rentable parcels may require an hour. Another hour may be required for elicitation of variable cost budgets, particularly if such budgets are specified for all possible crops on each parcel. At some point, differences between variable cost budgets no longer have a significant effect on solutions, and the time requirements of additional specific variable cost budgets are no longer worth the effort. Gross figures, on the other hand, may destroy the very subtlety desired in modeling the rental decision.

Much the same conflict between specific data and time-effective data elicitation applies to probability elicitation procedures. At least one-quarter to one-half hour should be used to carefully explain the elicitation process and the specific random variable to be measured. Although not part of the procedures in this analysis, historical yield data used as a benchmark will probably facilitate more reliable encoding of probabilistic beliefs. If records are available and the procedure is well understood, each probability distribution can be elicited in less than fifteen minutes. If yields are elicited for each possible crop on each possible parcel, the total number of elicited distributions quickly multiplies. For example, three crops which can each be grown on fifteen parcels requires forty five distributions. Again it is unclear at what point additional investment in probability elicitation efforts no longer has a significant effect on the model solution.

At a minimum, it seems that a yield distribution should be elicited for each crop on each major soil type. However, one yield distribution per soil type combined with a price distribution for each crop still implies a significant amount of time consumed in price and yield elicitation. With only three crops and two major soil types, at least two hours could be required for this stage of elicitation, suggesting that the total time necessary for data elicitation may easily exceed four hours. It is questionable whether farm operators would be content to 'feed' data to the model for that amount of time without receiving any usable results or feedback. Investigation could be carried out to determine the effects of various aggregation or smoothing procedures to provide quick estimates rather than such intensive data elicitation. Perhaps if the elicited data could also be used in other decision procedures, such as fertilizer application decisions, the additional time might be more justifiable.

Critical issues related to probability elicitation include the reliability (freedom from random error) and validity (accurate representation of beliefs) of expressed probabilities. It is clear from this research and other field tests that the conviction weights procedure is operational. That is, probability distributions can be elicited with relative ease from individuals who have little knowledge of probability concepts. However, there is no documented evidence that such distributions elicited with the conviction weights method is free from random error or is an accurate representation of beliefs. Before much confidence can be placed in an aid purporting to support decisions, questions of reliability and validity of competing elicitation techniques must be addressed.

Within the context of this research, it is not possible to determine whether display of default budgets and price distributions helped subjects to more accurately express farm-specific data than would otherwise have been possible. The willingness of subjects to disagree with default price distributions elicited from a university price analyst was somewhat surpising. This behavior indicates that subjects consider the default information but express their own judgements.

Simple graphics representation of probability distributions was used by the subjects to compare beliefs with skewness implied by the elicited probabilities. A graphics-based conviction weights procedure would allow the user to manipulate bar graphs on a computer monitor rather than to express numeric weights. It is possible that a completely graphics-based elicitation procedure may be well accepted by operators, which could provide a more efficient and conceivably more accurate mapping of beliefs.

Decision aids to some extent will require farm-specific data. If records are not available or if operator expectations must be measured, interactive data elicitation is feasible and may contribute to more accurate measurement of desired variables. Visual feedback in probability elicitation procedures may stimulate more careful consideration of beliefs and expectations, and may have benefits which extend beyond the current decision. Although data elicitation was implemented with a spreadsheet program for this research, better software integration would require database functions usually available only with custom software.

6.4.3 Multiple Objectives and Optimization

Explicit incorporation of multiple objectives and optimization solution procedures are related decision support issues. As discussed in Chapter 4, evidence exists that farm operators seek multiple, sometimes incommensurable and often conflicting management objectives. The interviewed agents and operators reacted favorably to a multiple objective model framed as tradeoffs between risk and return objectives. However, the specific objective formulations were not well understood. The risk objective in GOALDIR is defined as probability-weighted deviations below the elicited target income level. Most subjects, however, expressed the opinion that a more intuitive of risk is the probability of returns below target, akin to Roy's (1952) 'safety-first' formulation.

Although subjects also reacted favorably to explanations of the target value concept, it is unclear whether preferences are accurately represented by the type of mean-risk below target model described by Fishburn (1977). Further questions involve the reliability of elicitation procedures for target values and the effects of errors in estimating target values. Can the operator state without assistance a specific value which reflects an abrupt change of preference for returns? If record keeping is poorly handled in the firm, the current decision aid assume that the operator has a clear subjective estimate of factors such as fixed costs and living expenses which may be used to formulate a target return value. The effects of estimation errors in target values on model solutions are also not well understood. Clearly, solution values in risk-return are altered by changes in target values (Tauer 1983), as are underlying activity variables. Tauer derives a set of simple crop plans while incrementing the target return by equal amounts from a benchmark value. Solutions for which expected return is constrained vary significantly from plans derived using a different target. The effect on returns of changes in target values results from the interaction of constraint functions and the 'hard' risk constraint, and does not appear amenable to analytic examination. Sensitivity analysis of target values in the LP formulation is not possible because the target value appears in several constraint functions.

As noted above, crop rotation and multi-year return objectives could also be formulated and explicitly incorporated in multiple objective models. Some operators may find that such an expanded model constitutes a significantly improved depiction of the real decision, while others may prefer to consider only current year risk-return objectives. Much simpler formulations are possible with only one or two objectives, but only the researcher's judgement can determine whether such a formulation reasonably describes the preference structure. On the other hand, simultaneous consideration of many objectives in a decision may violate information processing limitations of the decision maker. Structuring decision aids as tradeoffs between multiple objectives is reasonable to decision makers, but research must be conducted to examine the impacts of decision aids formulated with different numbers and types of objectives.

A closely related set of issues concerns the solution procedure of the decision aid. IMGP restricts choice to a subset of the feasible region bounded by efficient values of the relevant objectives, with best and worst values used to construct reference solutions. The procedure forces the user to select preferred tradeoffs between objectives, while alternative actions are implicit in model solutions (a 'top-down' approach). These characteristics place IMGP in the class of optimization (or dominance) models, and demonstrate the power of rationalist procedures to direct users towards unambiguously better solutions in terms of the model objectives. However, agents and operators found the process confusing and counter-intuitive.

Clear preferences were expressed for solution procedures which would permit selection of possible actions and subsequent evaluation of feasibility and consequences (a 'bottom-up' approach). GOALDIR utilizes an optimization procedure to incorporate powerful rationalist principles for decision support, but the least intelligible concept for the subjects was the top-down approach of the aid. This may be attributable to the subjects' slight understanding of the model structure, functions and implied causal relationships, or lack of confidence that the model adequately represents the real problem. The top-down approach as applied to some ill-structured decisions may also violate the manager's sense of control over the decision process. If key aspects of model structure and function are not understood and accepted, aids which allow design of individual alternatives may be preferred by managers.

Depending upon decision maker and problem characteristics, aids based on optimization procedures may not provide significant assistance for making better decisions. Further, optimization-based aids rarely provide a framework for user learning about the problem as described by Langley and Simon (1981, see Section 3.6). Perhaps the most effective contribution of decision aids is to be found in techniques to assist in achieving better comprehension of problem structure and effective search of the problem space, not in application of decision rules.

Graphics representations were beneficial for display of model solutions generated by GOALDIR. Subjects focussed intently on tradeoffs displayed as bar graphs, and paid relatively little attention to the objective function values. When pattern recognition or display of relative changes in values are sought in decision aids, graphics appear to convey information very efficiently and are preferred in many cases by operators.

6.4.4 Context of Management Assistance

None of the managers interviewed would be able to operate the aid without assistance, nor could agents serve as intermediaries for operation of the aid in its present form. Training for users and intermediaries in the technical and decision principles embodied in the aid may be a precondition for successful use of GOALDIR or any sophisticated decision aid. In the context of agricultural decision aids, most intermediaries are likely to be extension agents, credit officers or commercial technicians. Given current computer and decision skills of agricultural managers, it appears that the most beneficial applications of decision aids will be to complement other management assistance activities of technical specialists.

Many researchers contend that unassisted use of decision aids by the manager can increase comprehension and confidence in solutions, but little evidence exists on this issue. What does seem obvious is that unassisted operation is a more cost-effective approach when the scarce resource is the qualified management advisor. As personal computers become less expensive and more widely disseminated in the agricultural community, opportunities for assisting managers with decision aids will increase. Training and aids for learning computer operations and decision principles will be required before it can be expected that managers will utilize complex decision aids without assistance.

6.5 Elements of a Decision Support Research Agenda

Decision support research has to this point been almost exclusively problem- and action-oriented. Relatively little generalizable research has been conducted to examine interactions between characteristics of decisions problems, decision makers and decision tools, and consequent effects on chosen actions. The final sections of this chapter present issues which should be investigated in experimental and operational settings in order to accelerate progress in developing successful aids to assist managers.

Isolation of features and examination of their impacts is necessary to obtain generalizable research results for decision aid design. A number of experimental designs can be developed which focus on analysis of particular decision support issues. In order to provide valid generalizations to support farm manager use of decision aids, experiments must be designed which at some stage employ managers as subjects. This is not to say that other individuals such as college students should never be used, but the relevance of such results is open to question until confirmed in a farm context. In order to assess the effects of individual personality characteristics, managers with clearly distinct problem solving styles should be selected as subjects. The interaction of decision type with the feature investigated should generally be examined by testing effects across a range of decision types (although our knowledge of decision taxonomy is admittedly poor).

6.5.1 Probability Elicitation

Probability elicitation in some form will be a feature of many decision aids, since uncertainty at the firm level is typically poorly reflected in aggregate estimates. Lack of adequate historical records at the farm level often means that managers must provide relatively unsupported judgements of critical price and production parameters, which highlights the critical importance of the elicitation procedure to accurately encode the beliefs of the individual. A further management issue concerns the consistency of probability assessments with objective data.

Behavioral researchers have provided extensive evidence of errors in unaided probability judgements, but little research has examined probability elicitation aided by decision tools. Principal errors in assessing probabilities have been related by Kahneman et al. (1982) to heuristics used to reduce information processing requirements. Hogarth (1980) documents biases in probabilistic thinking, but claims that the most important human error observed in probability experiments is lack of consistency. If rules used to estimate uncertainty were applied consistently, decisions would be improved on average. Another particularly relevant observation is that estimates of probabilities differ depending on the elicitation method. Techniques vary in their capability to accurately measure beliefs.

Several questions must be answered with respect to probability elicitation with farm managers:

1. What are the relative operational advantages of competing elicitation techniques in a particular probability assessment?
2. How do techniques compare in terms of reliability, that is, are probability encodings repeatable, stable and consistent (Wallsten and Budescu 1983)?
3. How do techniques compare in terms of validity, that is, are they valid measurements of beliefs?
4. A broader and somewhat separate issue concerns whether probability estimates are 'correct'. Although the traditional concept of subjective probability allows no unambiguous determination of 'right' or 'wrong' judgements, from a management support perspective individuals can certainly be assisted to learn probability concepts and integrate information in such a manner that estimates are more accurate when evaluated after outcomes are known.

The current research has documented an implementation of the conviction weights technique, a relatively simple indirect procedure for eliciting probabilities. However, the elicitation issues discussed above can be addressed only by careful experimentation over time and between methods. An evaluation of information from farm records can also be used to assess the consistency of elicited distributions with historical data. A sample of farm managers should be identified who keep sufficient records to provide a basis for analyzing external validity of elicited probabilities. Principal competing elicitation techniques should be applied with each manager to assess probabilities for particular variables. Repeated interviews should be conducted over a reasonably long time period to determine the replicability and stability of assessments with each method. The benchmark used to evaluate the accuracy of such distributions would be detrended estimates obtained from farm records. Individuals would also be asked to rank and evaluate operational features of the techniques. The most accurate assessment technique may not be reasonable for management support if its application is tedious or other features are objectionable to managers.

6.5.2 Preferences

The simple objectives of risk and return have been assumed in the GOALDIR aid to be the only preferences of the decision maker in regard to rental decisions. Certainly this does not seem to be a completely unwarranted assumption. However, for decision support purposes, an examination should be made whether more efficient use of managers' time in decision making is possible by modeling a problem with one objective or a range of potential objectives. Deterministic LP models used as decision aids simplify problems by assuming profit maximization as the single objective, and sometimes achieve considerable success by highlighting solution sensitivity and bottlenecks or opportunities. Yet no one would suggest that the decision maker seeks only a single objective. It is often unclear that more complex models add significantly to problem comprehension or to better quality decisions.

Section 4.2 discussed the relevant research on multiple objectives in farm management. Much of the research consists of elaboration of relatively general objectives gathered from previous research or researcher experience followed by relative ranking of objectives by the manager-subject. Relatively few attempts have been made to extend this research to examine the impact of multiple objectives in the context of specific decisions (exceptions are more common in developing country agricultural research, e.g. Barnett et al. 1982). The social and psychological issues involved in analysis of multiple objectives of farm operators have received relatively little attention. A principal reason is that, "The setting for evaluating multiple goals is complex. It introduces a broader range of concepts than is commonly used in economic analysis, many of which are not designed to yield optimal or equilibrium conditions." (Robison et al. 1984: 28)

As noted by Robison et al. (1984), aspiration levels and time significance of objectives are also important features of preferences relevant to particular decisions. Before systematic examination can be made of the effects of multiple objectives for decision aids, descriptive research should be carried out to examine the ordering and composition of objectives sought by managers in important decisions. However, there is no tradition of descriptive research within the farm management field which examines individual managers at the level of detail necessary to describe specific decision processes and examine the complex effects of multiple objectives.

There is some descriptive research in related fields. In corporate management research, Mintzberg et al. (1976) examined decision processes by enlisting managers to keep detailed diaries of activities, and researchers spent long periods (as long as five years) gathering information about a single firm's decision processes. They were able to identify common procedures in decision making which could then be used as general references for intervention in management assistance for other firms. Bennett et al. (1982) studied farm management from a social perspective in longitudinal research lasting seventeen years. Adaptation to economic conditions was related to multiple values and objectives were affected by social relationships.

This type of longitudinal research is rare in farm management research principally for reasons of theoretical perspective and cost considerations. However, the methods of other social sciences could be adopted to better describe the objectives which motivate farm managers in particular decisions. The long term research effort of investigating managerial processes on individual farms would be rewarded by details of the objectives sought by managers in specific decision types over time. Many questions concerning the identification of good managers could be answered with more detailed descriptive information relating how good managers make their decisions. This can best be investigated in the format of longitudinal observation and interviews.

Does multiple objective modeling make any difference? Dobbins and Mapp (1983) selected six goals for a recursive goal programming model examining intergenerational transfers. The order of multiple objectives (goals) was found to significantly affect production plans. Barnett et al. (1982), on the other hand, concluded that their representative farm planning problem provided no evidence that multiple objective modeling was a significantly more accurate predictor of farm organization. Few research projects have attempted to investigate whether the quality of decisions made by individuals is affected by the assumed preference structure of the decision model. Management game experiments in a workshop environment would appear to be the best framework for investigation of these effects. Comparative evaluation can be made of single objective models, risk (two objective) models and more complex multiple objective models in a range of constructed problems. Given that there is no way to know a 'best' answer without information about individual preferences, evaluation would principally involve the relative demands of models on decision makers. Individuals would rank the procedures in terms of ease of use, information requirements, time requirements, usefulness of model output and confidence in the model.

6.5.3 Solution Procedures

Simon (1983) presents three ways to represent problem solving tasks:

1. <u>Search</u>, in which the focus concerns examination of the current state and selective, successive application of operators to move to another state until a solution is found.
2. <u>Reasoning</u>, in which a system of logic allows deduction of new statements from axioms and previously deduced statements. Thus, solving a problem consists of accumulating logical statements until the outcome is found.

3. <u>Constraint satisfaction</u>, in which a set of alternatives is defined by constraints. Solving the problem consists of narrowing down the set of alternatives that satisfy all constraints.

Simon indicates that these metaphors for problem solving are not mutually exclusive, and any problem solving algorithm may be viewed ". . . now as search, now as reasoning, now as constraint satisfaction." (1983: 7) The IMGP procedure can be examined with any of the metaphors. The reasoning of the optimization procedure depicts the accumulation of inductive and deductive knowledge about the farm planning problem, the constraints applied (including both 'hard' resource constraints and 'soft' goal constraints) allow giant steps towards solutions by eliminating whole classes of alternatives, and the analysis of a current state determines the search direction for the next step. Other decision models, such as regression models and stochastic budgeting, can be seen to reflect somewhat different types of problem solving metaphors. These models may not define problem solving tasks in a manner similar to the unaided decision maker's representation. Fundamental differences in problem representation and problem solving procedures may induce rejection of the decision model by the user. The particular question at issue here is the dispreference expressed by the individuals interviewed for the top-down solution procedure utilized in the decision aid. The more general question, of course, concerns the conditions under which optimization procedures are appropriate for decision aids.

Three factors which seem to influence acceptance of and confidence in the solution procedure of an aid are: 1) the model representation versus the unaided representation; 2) decision maker control of the procedure; and 3) opportunities for learning. These are examined below with reference to the current aid.

First, the decision aid assumes that the optimization model reasonably reflects the structure of the real world problem. There appear to be several plausible reasons why this may not be the case. The aid assumes that all objectives and relative preferences are well defined (even if unknown) before the decision aid session. The relevant variables, specific values of those variables, causal and functional relationships, and the extent of detail in those relationships are all factors which determine the model and real problem structure. If the individual understands the model but does not agree with the model representation, confidence is unlikely to develop. In addition, the decision maker and the model designer are often unlikely to be in complete agreement on the representation of uncertainty in the problem, or possible sequential choices, or the extent of decomposition necessary for decisions to be made. Any of these problems can occur even though the decision maker understands the model structure. The particular aid developed here has not been explained in any detail to decision makers, and thus cannot claim to be understood by them. Rather than rejection of model structure, this application was characterized principally by ignorance of structure. This also is unlikely to instill confidence. However, even if it were understood, problems could be expected in decision makers' acceptance of such factors as the operational definition of objectives and the restricted functional relationships dictated by the research objective of developing a microcomputer-based aid operating in real time.

The second factor which affects confidence in a decision model is the extent of user control. Since managers must bear responsibility for decisions, they demand justification for relinquishing control of the process to any decision model. An optimization model, with its focus on finding solutions implied by objectives, may not at first seem controllable to the decision maker. The normal decision process of intelligence, design and choice is automated in considerable part by the IMGP model, and the decision maker performs only the functions of data input and potential solution evaluation. The process is so different from the intuitive decision process that lack of control instills a subsequent lack of confidence. For the decision maker to feel in control of the model, 1) the model structure and procedures must be understood to some extent and accepted by the user (as would be the case with a professional user), 2) the model must have a track record for the user, or 3) the model can be accepted on faith. Since none of these conditions were satisfied in the current application, the lack of user control was probably the principal cause for rejection of the optimization procedure. It could be said that one cannot control or have confidence in something that is not understood, but this is not strictly true. Most individuals in the United States have considerable (perhaps too much) confidence in their ability to control an automobile, even though they understand very little of the mechanical and physical principles involved. Experience and faith seem to be very adequate substitutes for understanding in this case.

A final reason why optimization procedures are rejected by decision makers is the inherent diminished possibility for learning. It can be expected that inquisitive managers wish to learn facts, principles and procedures in one decision which may serve them in other, possibly unrelated decisions. This is particularly true if the decision must be made repeatedly or is not a 'life or death' decision. Six principles defining the conditions under which learning can take place were discussed in Chapter 3. They are: knowledge of results, generation of alternatives, causal attribution, hindsight (feedback), learning from instruction and automatization. It can be seen that optimization procedures such as used in the GOALDIR aid provide relatively weak conditions for learning which can be applied to new decision situations, particularly with respect to generation of alternatives, causal attribution and hindsight. Inquisitive decision makers who wish to gain new skills rather than merely solve the current problem may not place great confidence in the aid.

This feature of decision aids can be tested in a similar manner to that suggested for the multiple objective issue. To ensure valid comparison of contrasting procedures, risk programming and stochastic budgeting techniques should be compared in prepared problems presented to the manager-subjects. Managers would be assigned randomly to groups which make individual decisions with either the budgeting or programming aid. To provide a benchmark for evaluation, expected utility functions should be elicited prior to problem solving. Resulting solutions could be compared in terms of utility costs. Comparisons should also be made of the time necessary for competing techniques and the relative computational costs of the models.

Finally, a user evaluation of features such as described for the multiple objective issue should be undertaken.

6.5.4 Graphics

A prevalent feature of decision support techniques for management is graphical representations to communicate information and to summarize and analyze data. Because of information processing limitations in cognition, behavioral researchers (among others) have been strong proponents of graphics use in decision support. Recognition, memory, interpretation accuracy and comprehension are sometimes improved by visual stimuli. Responding to this argument, decision aid designers have increasingly incorporated graphical capability in their products.

Recently some researchers have suggested that, ". . . the extravagant claims favoring graphic presentation formats may be considerable overstated." (Ives 1982: 21) There is now some dispute whether users interpret graphic formats more accurately than tabular data and whether graphics improves the quality of decisions. DeSanctis (1985) reviews research on the role of graphics in human information processing. Some support is found for the premise that the ability to use graphics effectively is related to individual characteristics or cognitive style. Information search and memory recall seems to function differently if graphics displays are used. However, for a range of dependent variables such as interpretation accuracy and speed, recall and user confidence, there is little support for better performance with graphics than with tabular data. There is virtually no research on the effects of different graphic types or features on decision making. DeSanctis (1985) proposes that future research investigate the interaction of graph characteristics, individual user characteristics and decision context in their effect on decision strategy, problem comprehension and decision making.

There appears to be no research examining the relative advantages of graphic displays on farm management decision making, despite considerable effort to include such capability in decision support software. Some evidence would seem necessary to justify this effort, since real costs are involved in designing such features. In addition, if both graphic and other data representations are displayed in a decision aid, the cumulative result of cluttered displays may be to actually diminish the effectiveness of decision making.

At a minimum, two types of experiments can be designed to examine the issue of graphics representations. First, the specific question of 'graphics versus tables' can best be investigated with a gaming experiment based on a standard design described by Remus (1984). A production scheduling problem is designed with implied costs for changes in workforce level, idle time and excess inventory. Optimal rules for scheduling are a function of the previous period's workforce size and inventory and forecasts for future periods. Each subject makes repeated scheduling decisions based upon either tabular or graphic data. The difference in costs incurred by tabular or graphics users can then be compared. A similar design could be applied to farm managers in a workshop environment. A marketing game which requires storage and pricing decisions based on inventory levels and price forecasts could be designed. Optimal marketing rules would provide a benchmark for establishing decision costs.

Another analysis should examine wider issues of graphics support for farm manager decision making. Particular issues which should be addressed are the impacts of different graphics features such as color and form on comprehension, and preferences of decision makers for graphics features in varying problem contexts. Experiments can be also designed which test comprehension and which measure relative preference for alternative graphics features.

6.5.5 Evaluation

Relatively little is to be learned in terms of effective decision aid design from evaluation research which only attempts to measure the impacts of an aid on the decision process of a particular individual in a unique decision situation. A decision aid cannot be regarded as a homogeneous entity, but instead is a composite of design features, each of which makes a contribution to the observed consequences. Some of these features may be related to decision theory principles - the combination of beliefs (probabilities) and preferences (utilities), optimization techniques and the like. Other features may be more closely related to the behavioral issues discussed in this research - multiple objectives, graphical display, aspiration values or flexible decision rules. Evaluation of the impacts of a decision aid thus examines effects of the specific combination of features embodied in the aid. This combination may not be relevant or feasible in another situation for which a decision aid is designed.

Characteristics of the decision or of the individual also interact with those of the support technique. For example, Davis and Olson (1985) suggest that graphical display has beneficial impacts for inventory decisions. The same techniques may not be effective in decisions for which pattern recognition or data summarization are a less important part of the decision process. In terms of personal characteristics, the cognitive or problem solving style of the individual also interacts with characteristics of the aid. An analytical thinker may wish to use an optimization technique while a more intuitive thinker may prefer to 'hunt and peck' for acceptable solutions. Similarly, the substantive knowledge and problem solving skills of the individual will interact with and have considerable effect on the decision process.

Results from analysis of the separate decision support issues discussed above can provide a thorough basis for design and evaluation of decision aid features. Examination of individual decision features in a variety of decision types and with subjects of differing problem solving style is a more justifiable and generalizable research perspective for decision support. Nevertheless, evaluation methodologies must be improved to determine benefits of particular decision aids. The complexity of such evaluations has hindered development of decision support principles. Most decision support researchers simply recommend a 'smorgasbord' of evaluation methodologies ranging from user assessment of aid features to traditional cost-benefit analysis (Keen and Scott Morton 1978). Most decision support evaluations have consisted of case studies with a very small group of subjects. Hobbs (1985) contends that decision support research (and multicriteria research in particular) has suffered from ill-controlled experiments and poorly constructed frameworks for interpreting results. He states that 'ideal' MCDM experiments have the following characteristics:

1. Methods are tested which represent features of distinctly different approaches to decision making or are claimed to represent significant methodological improvements
2. Well-controlled experiments are designed and implemented with a large sample so that treatment-effect relationships are unambiguous
3. Methods are tested across a range of problem types
4. Experiments are designed to be as similar as possible to real decisions with respect to problem characteristics and motivational features

Of course, no single experiment is likely to satisfy all criteria simultaneously. Nevertheless, they are appropriate guidelines for designing decision aid evaluation.

Relative advantages and disadvantages of alternative decision aids is emphasized by Hobbs (1985). The value of a decision aid can only be evaluated with respect to alternative feasible procedures. Alternatives may be unaided decision processes or may be other aids developed with a different perspective for support. The contrast offered by simulation and optimization procedures is an obvious example of possible comparative evaluation of decision aids. Other examples can also be developed which compare and evaluate distinctly different decision aids for the same problem.

APPENDICES

APPENDIX A

GOALDIR MODEL VARIABLES AND EQUATIONS

A.1 Variables Derived Outside the Model

GM_{rh} =

$REV_{rh} - VC_h$

(Revenue per acre minus variable costs per acre for crop **h** in state of nature r.)

REV_{rh} =

$YLD_{rh} * PRICE_{rh}$

(Expected yield per acre times expected price for crop **h** in state of nature r.)

YLD_{rh} =

Draw from multivariate normal yield distribution, described by elicited expected values and standard deviations, and covariance matrix constructed from external data. Yields are estimated for optimal planting/harvesting period kl^*, and adjusted by a penalty matrix to reflect the effect of timeliness on yield.

$PRICE_{rh}$ =

Draw from multivariate normal price distribution, described by elicited expected values and standard deviations, and covariance matrix constructed from external data.

VC_h =

Estimated variable cost per acre for crop h. Variable cost is sum of direct cash costs including fertilizer and chemicals, fuel, lubrication and repairs, seed, hired labor, irrigation fuel, drying and hauling.

PLT_h =

Estimated hours/acre for planting operations of crop $_h$ with available equipment, calculated as implement width times speed times efficiency factor.

HAR_h =

Estimated hours/acre for harvesting operations of crop $_h$ with available equipment, calculated as implement width times speed times efficiency factor.

PLT_HOURS_k =

Estimated hours available in period k for planting operations, such that the probability that actual hours falls below this level is less than .2.

HAR_HOURS_k =

Estimated hours available in period k for harvesting operations, such that the probability that actual hours falls below this level is less than .2.

TARGET =

Operator-specified target return level.

A.2 Model Variables

The following section defines the variables of the GOALDIR model.

A.2.1 Activity Variables

$ACRES_{ijkl}$:

Acres of crop h on tract i, feed grain program status j, planted in period k and harvested in period l.

Y_r:

Shortfall of total net revenue below target for state of nature r.

EXP_DP_i:

Expected deficiency payment for farm i.

$RENT_i$:

Cash rental payment for farm i.

A.2.2 Objective Function Coefficients

EXP_GM_{hijkl}:

Expected gross margin of crop h on tract i, feed grain program status j, planted in period k and harvested in period l, in dollars per acre.

s:

Number of sample years or states of nature.

A.2.3 Technical Coefficients

PLT_h:

Expected field time necessary for planting operations of crop h, in hours per acre.

HAR

GM r

A.

LA

PL

HA

TAR

CORN

WHEAT

HAR_h:

Expected field time necessary for harvesting operations of crop h, in hours per acre.

GM_{rhijkl}:

Gross margin of crop h on farm i, feed grain program status j planted in period k and harvested in period l for state of nature r, in dollars per acre.

A.2.4 Constraints

$LAND_{ij}$:

Total tillable acres of farm i, government status j.

PLT_HOURS_k:

Estimated field time available in planting period k, such that the probability that actual field time is less than this value is .2 or less, in hours.

HAR_HOURS_l:

Estimated field time available in harvest period l, such that the probability that actual field time is less than this value is .2 or less, in hours.

TARGET:

Target gross margin, in dollars.

$CORN\_BASE_i$:

Corn base acreage for those farms in government program.

$WHEAT\_BASE_i$:

Wheat base acreage for those farms in government program.

A.3 Multiobjective Rental/Crop Mix Model

$$\text{MAX} \quad \Sigma\Sigma\Sigma\Sigma_{ijkl}\ \text{EXP\_GM}_{ijkl} * \text{ACRES}_{hijkl} \ + \ \text{EXP\_DP}_i \ - \ \text{RENT}_i$$

(h= 1..NUM_CROPS)

$$\text{MIN} \quad \Sigma_r \ Y_r \ / \ s$$

subject to:

$$\Sigma\Sigma\Sigma\Sigma_{hjkl}\ \text{ACRES}_{ijkl} \quad \leq \quad \text{LAND}_i$$

(i= 1..NUM_FARMS)

$$\Sigma\Sigma\Sigma_{hij}\ (\text{PLT} * \text{ACRES}_{ijkl}) \ \leq \ \text{PLT\_HOURS}_k$$

(k=1..NUM_PLT)

$$\Sigma\Sigma\Sigma_{hij}\ (\text{HAR} * \text{ACRES}_{ijkl}) \ \leq \ \text{HAR\_HOURS}_l$$

(l=1..NUM_HAR)

$$\Sigma\Sigma\Sigma\Sigma\Sigma_{hijkl}\ (\text{GM}_{rhijkl} * \text{ACRES}_{ijkl} \ +$$

$$\Sigma_i\ \text{EXP\_DP}_i - \Sigma_i\ \text{RENT}_i + Y_r \quad \geq \ \text{TARGET}$$

(r= 1..s)

$$\Sigma\Sigma_{kl}\ \text{ACRES}_{hijkl} \qquad \leq \quad \text{CORN\_BASE}_i$$

(h = <corn>)
i = 1..NUM_FARMS,
j = 1,3)

$$\Sigma\Sigma_{kl}\ \text{ACRES}_{hijkl} \qquad \leq \quad \text{WHEAT\_BASE}_i$$

(h = <wheat>
i = 1..NUM_FARMS,
j = 1,3)

APPENDIX B

SPREADSHEET TEMPLATES FOR GOALDIR DATA ELICITATION WITH PROTOCOLS FOR YIELD AND PRICE ELICITATION

B.1 Protocol for Yield Elicitation

The subject is first presented with screen 1 (Figure B.4), which displays a template for identification information, yield ranges and conviction weights. The interviewer selects with the subject a reasonable starting yield (not necessarily zero) and interval range which are calculated and displayed by the program. The total range should be wider than the subject is likely to consider possible.

Interviewer- "For this particular farm/soil type, and assuming that you were able to plant and harvest in a timely manner, in which of these ranges would yield be most likely to fall?"

When the subject indicates a range:

Interviewer- "I'll give that range a score of 100. Now for each of the other yields that are possible here, I'd like you to put a number from 1 to 100 indicating how likely that yield range is compared to the most likely range. A yield range that is just as likely would have a score of 100, while one that is only 1/10 as likely would be given a score of 10. You might want to think of it this way - if you always planted the same varieties, for every ten years that you might get yield in the most likely range, you would expect six years of yields in the range which you gave a score of 60. If you prefer, let's set the scores of the highest and lowest possible yields first. You may never have gotten these yields in years past, but what we're looking for is what yields you think are possible to get in very bad or very good conditions. How likely is this low (high) yield compared to the most likely yield?"

(Subject gives weights for lowest and highest ranges).

"Now let's fill in the scores between the lowest (highest) yield and the most likely yield. For each yield range, tell me a score from 1 to 100 that represents how likely you think that particular yield is compared to the most likely range."

(Subject fills in scores).

After all weights are filled in to the subject's satisfaction:

Interviewer- "Do you consider yields above the most likely range just as likely as yields below?" (If the response is not consistent with weights given, then point this out to the subject and adjust weights.)

It should be repeatedly emphasized to the subject that weights can be changed at any time the subject determines that they do not reflect their judgements about likelihood of yields in the range. Screen 2 (Figure B.5) is then displayed to the subject:

Interviewer- "Based on the scores you gave for each yield range, the program has calculated probabilities for each yield. In other words (indicating the probability density function), according to your scores these numbers represent the chances out of 100 that yields will fall in each of these yield ranges. The graph (indicating the graph) shows one asterisk for each 1 percent of probability, and the numbers here (indicating the cumulative table) show the probability that yields will fall below the upper limit of that yield range."

Interviewer - "Let's look first at the graph. The shape indicates in relative terms how likely are yields above the most likely yield as below. The fatter it is above (below), the more likely you've indicated yields are above (below) compared to below (above). Does that general shape seem right to you?" (If not, then return to screen 1 to adjust weights.)

Interviewer-"Now, according to the scores you gave, there is approximately a 1 in (truncate 1.0 divided by modal probability) chance of getting the most likely yield. Does that seem right?" (If not, then return to screen 1 to adjust weights.)

Interviewer-"Chances are approximately (truncate 10 times sum of probabilities of 2-3 most probable ranges) out of ten of getting between (low boundary of lowest interval) and (high boundary of highest interval). Does that seem right?" (If not, then return to screen 1 to adjust weights.)

Interviewer-"There are approximately (truncate 10 times sum of probabilities of 1-3 lowest intervals)) chances out of ten of falling below (high boundary of highest of these intervals). Does that seem right?" (If not, then return to screen 1 to adjust weights.)

Interviewer-"On the other end, there are approximately (truncate 10 times sum of probabilities of 1-3 lowest intervals)) chances out of ten of getting yield above (low boundary of lowest of these intervals). Does that seem right?" (If not, then return to screen 1 to adjust weights.)

Interviewer-"If we weight your yields by the probabilities, the weighted average yield is (expected yield). Does this seem right to you? Are any of the probabilities out of line with what you would expect?" (If so, return to screen 1 and adjust weights. If the subject accepts the probabilities as correct, the weights, yield interval and starting point are saved, and the process continues to the next crop or soil type/farm. Note that the standard deviation and coefficient of variation are not displayed or stated to the subject.)

B.2 Protocol for Price Elicitation

Screens 1 and 2 (Figures B.6 and B.7, respectively) are virtually identical, except that the only identification information necessary is the name of the crop. For screen 1, default price ranges and weights are displayed to the subject which are elicited from a price analyst. It is stated emphatically to the subject that everyone has their own beliefs about expected prices, and that they need not agree with the default values. If the subject thinks the total range should be broader than the default, new ranges are calculated, but the interval width should remain equal so that the default weights are not misleading.

Subsequent questions and explanations are identical to yield elicitation, except that probabilities are always expressed in "chances out of ten" rather than in "years out of ten".

Land Information

Name:

Farm No.	
Farm Description	
Principal Soil Type	
Total Acres	
Total Cultivable Acres	
Rented?	
Rent per acre	
Feed Grain Program?	
Corn Base Acreage	
Corn Base Yield	
Wheat Acres	

* Completed for each rented or owned farm.

FIGURE B.1 LAND ELICITATION TEMPLATE*

CASH EXPENSE PER ACRE FOR CROP:

Name:

Soil:

Farm(s):

	Typical Expense	Your Cost
Seed		
Fertilizer		
Chemicals		
Fuel, lubrication, maintenance		
Drying		
Hauling		
Hired Labor		
Other		
Total =>		

FIGURE B.2 VARIABLE COST ELICITATION TEMPLATE--SCREEN 1

CORN	SOY	WHEAT	NAVY	OATS	BARLEY	CORN SILAGE
19.6	8.4	10.8	20	6.4	13	17.5
27.1	7.9	37.3	11.5	9.7	22.6	30.8
15.2	18.15	2.35	14	.65	.65	14
32.9	19	23	26.1	24.4	24	14
30	8.9	0	0	0	0	0
21	6.3	12.6	5	6.6	12.6	0
0	0	0	0	0	0	0
0	0	1.5	1.5	1.5	1.5	0
145.8	68.65	87.55	78.1	49.25	74.35	76.3

* Budgets are not displayed until costs for the crop are elicited.

FIGURE B.3 VARIABLE COST ELICITATION TEMPLATE--SCREEN 2 *

	Yield Range	Weights
Name:	-	
	-	
	-	
Crop:	-	
	-	
	-	
Yield Unit:	-	
	-	
Farm No.:	-	
	-	
Soil Type:	-	
	-	
Interval:	-	
	-	
	-	
	-	
	-	
	-	

FIGURE B.4 YIELD PROBABILITY ELICITATION TEMPLATE--SCREEN 1

Yield Range	Probability That Yield: In Range	Equal or Less Than Range
-		
-		
-		
-		
-		
-		
-		
-		
-		Standard
-		Deviation
-		
-		Coeff. of
-		Variation
-		
-		Expected
-		Value
-		
-		

FIGURE B.5 YIELD PROBABILITY ELICITATION TEMPLATE--SCREEN 2

Crop:
Name:

	Price Range	Default Weights	Your Weights
	-		
	-		
	-		
	-		
	-		
	-		
	-		
	-		
	-		
	-		
	-		
Interval:	-		
	-		
	-		
	-		
	-		
	-		

FIGURE B.6 PRICE PROBABILITY ELICITATION TEMPLATE--SCREEN 1

Price Range	Probability That Price: In Range	Equal or Less Than Range
-		
-		
-		
-		
-		
-		Standard
-		Deviation
-		
-		
-		Coeff. of
-		Variation
-		
-		Expected
-		Value
-		
-		
-		
-		

FIGURE B.7 PRICE PROBABILITY ELICITATION TEMPLATE--SCREEN 2

APPENDIX C

PASCAL PROGRAM LISTING--MULTIVARIATE NORMAL RANDOM NUMBER GENERATOR

```
Procedure Mvnorm;
                    (Generates DRAWS vectors of VARIATES number of
                    correlated, jointly normal distributed variables
                    in the matrix MULTI_RND.
                    This program written by Dr. J. Roy Black,
                    Department of Agricultural Economics, Michigan
                    State University.)

  Const
    variates = 50;  (number of random variates desired)
    draws    = 35;  (number of vectors of random variates)

  Type
    all_arrays    =  array[1..variates] of real;
    sqr_mat       =  array[1..variates] of all_arrays;
    rnd_mat       =  array[1..draws] of all_arrays;

  Var
    x,means       :  all_arrays;
    c,covar       :  sqr_mat;
    multi_rnd     :  rnd_mat;
    i,j           :  integer;

  Procedure Get_data(var covar: sqr_mat;
                     var means: all_arrays);
   (*This is a dummy procedure.  Any data input procedure to enter
     the COVAR covariance matrix and MEANS mean values array can be
     used*)
   begin
   end;

  Procedure Ltm(     covar    :  sqr_mat;
                 var c        :  sqr_mat);
             (COVAR is covariance matrix, C is the calculated
              lower triangular matrix used to compute random variates)

    Var
      sum       :  real;
      i,j,k     :  integer;
```

```
Begin
  fillchar(c,sizeof(c),0);      (Initialize matrix)

                        (first diagonal element equal to square
                        root of corresponding covariance element)
  c[1,1] := sqrt(covar[1,1]);
  for j := 2 to variates do
                        (rest of 1st col. equal to
                        corresponding COVAR element divided
                        by 1st diagonal element)
    c[j,1] := covar[j,1] / c[1,1];
                        (this loop determines lower triangular)
                        ( elements of columns > 1)


  for i := 2 to variates-1 do
    begin

     sum := 0;
                        (diagonal elements from 2 to 2nd to last)
                        (equal to the square of corresponding)
                        (COVAR element of that row minus)
                        (the sum of squares of that row)
     for k := 1 to i-1 do
       sum := sum + sqr(c[i,k]);
     c[i,i] := sqrt(covar[i,i] - sum);
     sum := 0;
                        (off-diagonal elements of C equal to
                        (corresponding COVAR element minus the
                        (product of elements J and i of column k,)
                        (all divided by diagonal element)
     for j := i+1 to variates do
       begin
         for k := 1 to i-1 do
           sum := sum + c[j,k] * c[i,k];
         c[j,i] := (covar[j,i] - sum) / c[i,i];
       end;

    sum := 0;
                        (last diagonal element equal to square root)
                        (of the corresponding COVAR element minus)
                        (sum of squares of off-diag. elements)
    for k := 1 to variates-1 do
      sum := sum + sqr(c[variates,k]);
      c[variates,variates] := sqrt(covar[variates,variates] - sum);

end; (procedure Ltm)
```

```
Procedure Normal (     c        : sqr_mat);
     (computes one vector of variates)
                       means    : all_arrays;
                   var x        : all_arrays);

  Const
    twoxpi   =   6.283185;

  Var
    i,j       :  integer;
    z1,z2     :  real;
    z         :  all_arrays;

  Begin
    z2 := random;
    for i := 1 to variates do
             (computes VARIATES number of standard normal elements)
      begin
        z1 := random;
        z[i] := sqrt(-2.0 * ln(z1) * cos(twoxpi * z2));
        z2 := z1;
      end;
    x := means;
    for i := 1 to variates do
             (computes variates number of normal,)
             (correlated elements)
      for j := 1 to i do

        x[i] := x[i] + c[i,j] * z[j];
  End; (procedure normal)

Begin (main procedure)

  get_data(covar,means);
             (dummy data entry procedure not shown here)
  Ltm(covar,c);
             (create lower triangular matrix)
  for i := 1 to draws do
    begin
      Normal(c,means,x);
             (create one sample vector)
      multi_rnd[i] := x;
             (pass each vector to a DRAWS by VARIATES matrix)
    end;

end; (Procedure Mvnorm)
```

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