MULTIPLE CRITERIA DECISION MAKING IN ACCOUNTING EXPERT SYSTEMS

Daniel E. O'Leary
School of Accounting
University of Southern California
Los Angeles, California 90089-1421
USA
213-743-4092

Abstract

The purpose of this paper is to analyze the use of multiple criterion decision making (MCDM) in accounting expert systems (AES). Focusing on the MCDM nature of expert system evaluation functions leads towards a partial taxonomy of AES and a further understanding of "intelligence" in AES. The focus on the MCDM nature of the evaluation functions also serves to highlight the limitations of some of the expert system shells that are inherently designed for single criteria decision making.

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"Any idiot system can maximize a single function."
(Paraphrase of a quote from the Dean of the
Columbia Business School, 1975)

1. Introduction

For the past decade or so, extensive general research has evolved in the area of knowledge-based expert systems. More recently, accounting researchers have focused on developing knowledge-based expert systems for accounting applications.

Virtually all those accounting expert systems have used a single criteria evaluation functions or have no evaluation function. Since most decision making involves multiple criteria, the approach of those systems maybe at a disadvantage when compared to the approach of human decision makers or the problems maybe highly limited in scope. There are even some that may argue that these systems are not "intelligent."

The purpose of this paper is to analyze the use of multiple criteria decision making (MCDM) evaluation functions in accounting expert systems (AES), investigate the evaluation functions in some AES (and their focus on single criterion decision making (SCDM)) and review the potential MCDM methods which can be used in AES.

In accomplishing this purpose, this paper elicits a partial taxonomy for AES and moves towards defining "intelligence" in AES by focusing on the MCDM nature of the evaluation function in expert systems. The focus on the MCDM nature of the evaluation function also serves to highlight the limitations of some of the expert system shells that are inherently designed for SCDM.

1.3 The Plan Of This Paper

This paper proceeds as follows. Section 2 defines artificial intelligence and expert systems. Section 3 develops the modes of decision making that form the basis of the analysis of the AES. Section 4 reviews MCDM, the MCDM nature of accounting decisions and the implementation of MCDM by humans. Section 5 relates MCDM to decision support systems and expert systems. Section 6 analyzes some previous AES and discusses the MCDM and SCDM nature of the AES that have been developed. Section 7 develops some extensions of the use of MCDM in AES. Section 8 summarizes the paper.

2. Artificial Intelligence and Expert Systems

Artificial Intelligence (AI) is that part of computer science aimed at developing computer programs that perform tasks that take intelligence and which for the moment humans are better than computers (Barr and Feigenbaum [1982] and Rich [1983]).

Expert Systems (ES) is a branch of AI. ES's are computer programs that are designed to perform a task in a specific task domain as well as a human expert would perform the same task (Barr and Feigenbaum [1982] and Hayes-Roth et al. [1983]).

Functionally, ES's may have one or more of the following characteristics. An ES can perform an intellectually demanding task rather than a mechanical one. The ES may effectively interact with the user, e.g., the system may request more information from the user, if necessary. Or conversely, the user may request a trace of the reasoning of the ES. Although these functional characteristics are implemented in many ES's, none of them is necessary for an ES.

2.1 ES Structure

Structurally, ES's usually consist of three major components: database, knowledge base and inference engine. The database contains the data used by the ES.

The knowledge base contains the knowledge that the ES uses to process the data. Typically, this is the domain-specific knowledge that an expert would use to solve the problem. Generally, this knowledge is symbolic rather than numeric, e.g., natural language.

There are a number of different ways of representing knowledge. Two of the primary methods are rule-based and frame-based knowledge representation. The rule-based form of knowledge representation generally takes the form of "if... (condition) then... (consequence/goal/subgoal)." Often there is a weight associated with the probability or strength of a rule. The frame-based form of knowledge representation uses a "frame" to capture the characteristics associated with a given entity.

The characteristics define the knowledge about the entity that is of interest in the application.

The inference engine is the approach used in the program to process the knowledge base. There are usually at least two processes represented in the inference engine: choosing the set of alternatives for evaluation and evaluating the alternatives. For example, in rule-based systems the inference engine typically uses either forward or backward chaining to find the feasible alternatives. Forward chaining is a way of reasoning toward a goal. Whereas, backward chaining starts with the goal and determines the approach necessary to accomplish the goal. It also uses the weights on the rules to evaluate the strength or probability of the sequence of rules.

ES's usually are developed using either an AI language or an ES shell. An AI language is a computer language that is aimed at processing symbolic information, such as natural language. Two of the primary AI languages are Prolog (Clocksin and Mellish [1984]) and Lisp (Whinston and Horn [1981]). Prolog is the language chosen by the Japanese for the fifth generation computer. Lisp has received extensive use in AI in the United States. An ES shell is software that is designed to aid the development of ES's. Typically, an ES shell makes the storage of knowledge easier and prespecifies the inference engine.

Two of the better known ES shells are EMYCIN (e.g., Buchanan and Shortliffe (1984)) and AL/X (e.g., Duda and Gaschnig (1981)). Both of these ES shells are rule-based and both use a weight on the rule to determine the strength or probability of the chosen sequences of rules.

2.2 Decision Support Systems

Decision Support Systems (DSS) are computer-based systems that are used to (Keen and Scott Morton [1978, p.1]):

1. Assist managers in their decision processes in semistructured tasks.
2. Support, rather than replace, managerial judgement.
3. Improve the effectiveness of decision making rather than its efficiency.

Some authors imply that ES's are a subset of DSS's (e.g., Keen and Scott Morton [1978]), while others argue that they are not (e.g., Turban and Watkins [1984]). That discussion is outside the scope of this paper.

2.3 Accounting Expert Systems

AES are expert systems developed to solve accounting-based problems. There apparently is only one AI-based system that will be in commercial use in accounting (Willingham and Wright (1985)). That proprietary system was developed to examine the collectability of term and collateral loans. The system was built using an expert system shell (Insight 2) and has over 1000 rules. The other AES that have been developed are prototypes. Those prototype systems are the primary focus of this paper. These systems are discussed in section 6.

3. Modes of Decision Making

Since ES perform decision making tasks of experts this implies that it is critical to understand decision making processes. In one theoretical approach, Thompson (1964) characterized four modes of decision making: computation, judgement, compromise and inspiration. These modes are summarized in table 1.

Table 1

Thompson's Modes of Decision Making

		(Criteria of Choice)	
		Single	Multiple
(Description of	Certain	Computation	Compromise
Alternatives)	Uncertain	Judgement	Inspiration

Source: J.D. Thompson (1964) as summarized in Zeleny (1982).

The greatest "intelligence" is required in "inspiration," whereas there is some question if "computation" requires "intelligence." "Compromise" and "Judgement" lie somewhere between those two extremes.

Computation is the typical mode of a highly structured numeric or symbolic problem. Numeric computation is the best known computation process. For example, solving the typical linear programming problem generally requires only computation. Symbolic computation can arise in many situations. Probably the most basic is a dictionary table look-up. However, a simple forward or backward chaining on a set of rules also is computation.

Judgement is the dominant concern of multiattribute utility theory. Judgement is usually defined by a single dimensional, clearly stated, but poorly measurable objective (Zeleny [1982]). Typical objectives include maximizing utility, minimizing employee dissatisfaction or maximizing the strength of a relationship between a set of rules.

Compromise is an MCDM process. Compromise involves trading off on competing objectives; for example a cost:time trade-off. The first step in compromise is to identify a set of alternatives and the second step is to reduce this set of alternatives.

Inspiration is the mode of decision making that is commonly attributed to executives. This approach includes both the processes of judgement and compromise.

4. Multiple Criteria Decision Making

As noted by Zeleny (1982, p. 1), "Multiple objectives are all around us." We may search for the shortest route home, but also want the least expensive, the most scenic or the fastest route. Virtually all decision making situations include multiple criteria/objectives. In addition, the objectives may be conflicting. The Dean of the Columbia Business School has said:

> As for conflicting objectives-quality vs. lower cost, better product vs. cheaper raw materials, for example-just about any idiot can maximize a single function. Anybody can increase sales. After all, if nothing else matters, you can decrease the price to zero. In fact, you don't have to stop there. If they won't take it at zero, you pay them to take it.[1]

Zeleny (1982, p. 23) concedes that in some cases decision makers may be able to express their preferences along a single dimension. However, Zeleny (1982) suggests that SCDM occurs primarily under extreme conditions of time pressure, emergency or crisis.

Otherwise, Zeleny (1982) contends that no decision making occurs unless there are at least two decision making criteria. "If only one criterion exists, mere measurement and search suffice for making a choice (Zeleny [1982, p.74])." That is, there is no "intelligence" required unless multiple criteria are considered. Accordingly, it appears that Zeleny would contend that an "intelligent" expert system would have at least two choice criteria.

4.1 MCDM and Accounting Problems

Before promulgating MCDM for AES, we need to consider the question "Are accounting problems suitable for MCDM analysis?" There are a number of ways to answer this question.

One approach is to examine the literature to determine if there are any papers that relate MCDM and accounting problems. There are a number of applications summarized in, e.g., Ijiri (1965) and Lin (1979).

Another approach is to examine the decisions that accountants make to determine if they have multiple criteria. One way of classifying these decisions is based on the sub-disciplines of accounting, e.g., tax and management accounting.

Tax accountants face multiple criterion in a variety of environments. Zeleny (1982, p.2) summarizes some of the typical criteria for judging a good tax-shelter:

1. Current deductions from taxable income.
2. Future deductions from taxable income.
3. Capital gain after selling the investment.

Management accountants provide management with information to meet their decision making needs. As noted by Drucker (1974, p. 100), management needs to consider the multiple goals of the business:

> Much of today's lively discussion of management by objectives is concerned with the search for "one right objective." This search is not only likely to be as unproductive as the quest for the philosopher's stone; it does harm and misdirects.
>
> To manage a business is to balance a variety of needs and goals. And this requires multiple objectives.

Accordingly, since management have multiple objectives, so must management accountants.

Auditing also uses multiple objectives. There are a number of criteria in auditing including, e.g., error rate, materiality, etc.

This discussion suggests that rather than justifying the use of MCDM in accounting, the problem should be reversed. If SCDM is proposed for use in accounting then it should be justified.

4.2 MCDM Approaches

There are a number of approaches used by humans to implement MCDM. Probably the most frequent approach is to use a set of

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A second alternative is the use of an MCDM analytic procedure. These procedures include goal programming, linear multiple objective programming and compromise programming (Zeleny [1982]). These techniques have the advantage of finding optimal solutions to the specified problem, whereas, heuristic approaches find only a "satisfactory" solution.

5. The Relationship of MCDM to DSS and ES's

Since most decision processes are of an MCDM nature, their relationship to DSS and ES is analyzed.

5.1 MCDM and Decision Support Systems

Keen and Scott Morton (1978, p.48) indicate that " a marriage between MCDM and DSS promises to be practically and intellectually fruitful." There has been general systems research into this relationship (e.g., Haimes and Chankong (1985), but little work in accounting MCDM DSS.

5.2 MCDM and ES

There has been little research into the use of MCDM in ES. However, since many decision processes that require expertise also use multiple dimensions for the evaluation of alternatives, it is anticipated that MCDM will have a major impact on ES.

5.2.1 MCDM and ES Shells: SCDM

One of the potential limitations to the use of MCDM in ES is due to a limitation of some of the ES shells: the shells are inherently SCDM-oriented. For example, both of the rule-based systems EMYCIN and AL/X use a single dimension to evaluate the sequences of rules in the solutions found by the systems. EMYCIN ranks the alternatives by probability and AL/X ranks the alternatives by the strength of the relations. For those situations where a single dimension is appropriate there is no problem. However, this can lead to making the tool fit the situation and using an SCDM tool in an MCDM situation.

5.2.2 MCDM and ES: No Evaluation Function

A more extreme situation is the case where there is no evaluation function. This situation derives from the system using the symbolic processing nature of the AI language or the ES shell to "compute" the alternatives and not evaluating the quality or the feasibilty of the alternatives. This is analogous to providing the set of constraints to a linear programming problem and not having an objective(s); that is, this is computation and not judgement.

5.3 The Use of MCDM in a Taxonomy of AES

Each AES will either have an evaluation function or it will not have an evaluation function to analyze the quality of the

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solutions. If it has an evaluation function process then that process will either be an MCDM or an SCDM process.

If the system does not have an evaluation function then that suggests that the system is only a computational system. Some authors suggest that virtually all decision problems have an MCDM evaluation function. Accordingly, the existence of the evaluation function and the type of evaluation functions (MCDM or SCDM) serve to distinguish between characteristics of alternative systems. This indicates that these two characteristics can be part of a taxonomy of AES.

6. Accounting Expert Systems

This section summarizes and categorizes the existing prototype AES's into the categories of table 1. The results are summarized in table 2.

Table 2

AES by Mode of Decision Making

		(Criteria of Choice)	
		Single	Multiple
(Description of	Certain	TAXADVISOR	FINSTA
Alternatives)	Uncertain	AUDITOR EDP AUDITOR	N/A

6.1 TAXADVISOR

One of the best known AES's is TAXADVISOR. TAXADVISOR is a rule-based system that was built using EMYCIN. However, the system does not use the certainty factor capabilities inherent in EMYCIN.

TAXADVISOR (Michaelsen [1982]), is an AES designed to make recommendations concerning estate planning. The system recommends a set of actions based on a set of conditions.

The system functions as an reference source. The system provides the user with a "dump" of its knowledge base given a set of conditions. The resulting set of actions may be economically feasible or the set of actions may be economically infeasible or the set of actions may contain contradictory recommendations (Michaelsen [1982, pp. 166-170]).

Accordingly, one of the major limitations of TAXADVISOR is that it does not know if the actions it recommends are economically feasible or if the actions are contradictory. The system has no evaluation function to analyze the recommendations. Accordingly, this system is categorized in the "computation" decision mode of table 1.

The system could be extended to include the use of the certainty factor. However, as noted above, a ranking of actions based on the certainty factor is an SCDM process.

6.2 <u>AUDITOR and EDP AUDITOR</u>

AUDITOR (Dungan [1983]) is a rule-based system that was built using AL/X. AUDITOR was developed to make diagnostic judgements concerning the adequacy of a firm's allowance for bad debts.

EDP AUDITOR (Hansen and Messier [1985]) also is a rule-based system built using AL/X. EDP AUDITOR was developed to assist in the audit of computerized accounting systems.

Since both AUDITOR and EDP AUDITOR are rule-based systems built using AL/X, both of the systems use the AL/X evaluation function. This function measures the strength of a rule and derives a single "strength" measure associated with each solution. These SCDM systems each make use of this probabilistic devise. Accordingly, these systems are categorized in the "judgement" section.

6.3 <u>FINSTA</u>

FINSTA (Munakata and O'Leary [1985]) was developed to aid in the design of accounting information systems by developing aggregated financial statements from a set of accounts in order to improve management decision making. The system uses Prolog to model the judgements of a management consultant.

The inference engine was developed to meet the specific needs of the problem. The first phase of the program developed a set of alternative aggregations of the financial statements. The second phase chooses from among those alternatives based on two different criteria. Since this system uses multiple criteria but does not use probability its mode of decision making is categorized as "compromise."

7. Extensions of MCDM in AES

If an ES shell is used then the inference engine is prespecified. Accordingly, in those cases the evaluation process is a function of the inference engine. As a result, whether an SCDM or an MCDM process is used is dependent on the ES shell's inference engine. If the evaluation process is an MCDM process, then the user must ensure the ES shell has an MCDM evaluation process.

However, if an AI language is used to develop the system then the knowledge base can be interfaced with an arbitrary MCDM process. In particular, the inference engine can use the knowledge base to develop the feasible set of alternatives or the feasible region for MCDM evaluation. For example, in FINSTA the inference engine used the knowledge base to develop the alternatives that were later evaluated using a heurístic approach that was based on two different criteria. Another alternative is to use an MCDM optimization method (e.g., linear multiobjective programming or goal programming) to generate an optimal solution to the established problem.

If a technique such as goal programming is used then there is another step that can be taken: An expert system can be developed to analyze the dual variables, etc. Understanding the

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output is an important part of any mathematical programming problem, since, as noted by Geoffrion (1976, p.444), "the purpose of mathematical programming is insight not numbers." The process of developing an expert system for use in analyzing a mathematical program is discussed in more detail in O'Leary (1985).

8. Summary

This paper has focused on the nature of the evaluation functions in AES. This paper is the first to suggest the importance of MCDM in AES. This is substantiated by a review of some prototype AES's that found only one system that employs an MCDM evaluation function. There was no discussion in that paper relating to the MCDM nature of the system.

This focus has lead to four primary findings. First, it is feasible (as substantiated by FINSTA) and desirable to develop MCDM AES's. Second, the evaluation function appears to be a valuable characteristic in a taxonomy of AES. This is summarized in the characterization of the decision mode. Third, an "intelligent" AES must be in the decision mode of either judgement, compromise or inspiration. Purely computational AES do not appear to meet the requirements of intelligence. Fourth, many of the ES shells are of an SCDM nature. This can lead to formulation of MCDM problems as SCDM problems.

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FOOTNOTE

1. Hermes, vol. 3, no. 2, Spring-Summer 1975.

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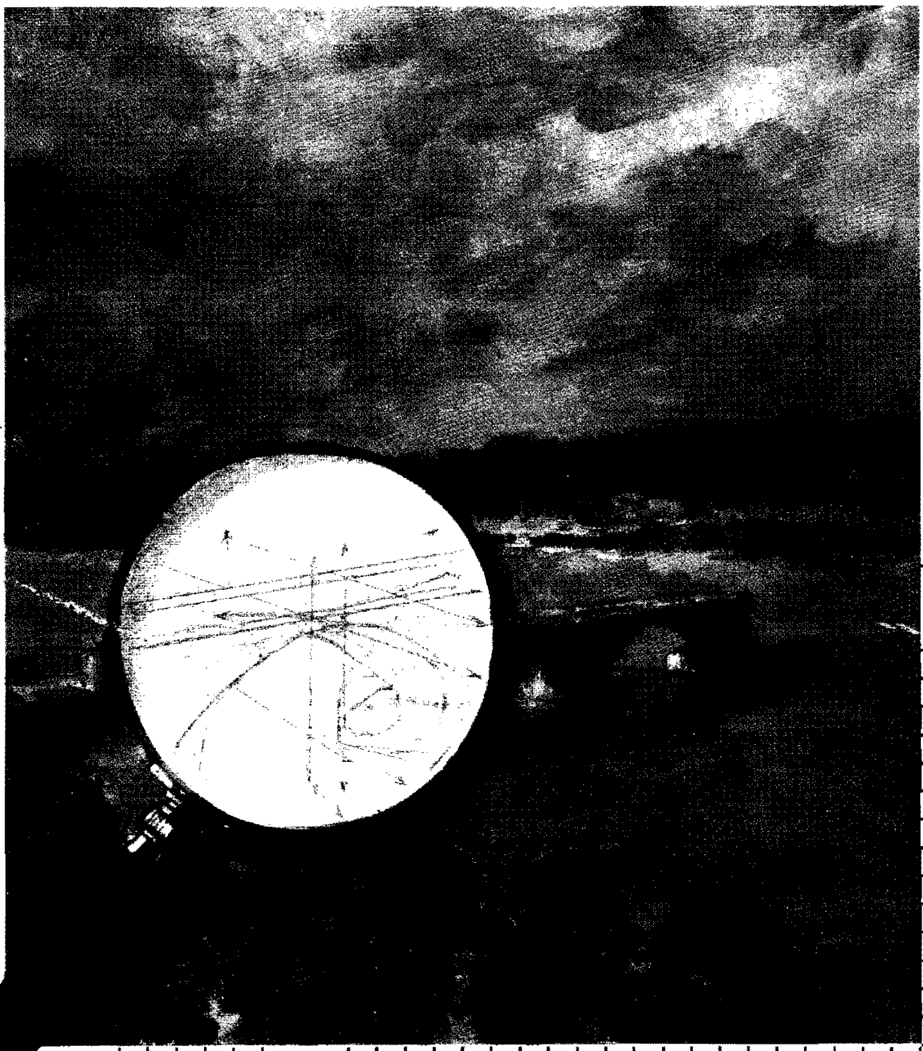

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