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불명확한 상황에서의 다중속성 경영의사결정을 지원하기 위한 지능적 의사결정지원시스템

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An Intelligent DSS to Assist in Multi-Attributed Managerial Decision Under Fuzziness

This paper develops a new approach to dealing with qualitative reasoning processes involved in managerial decisions, drawing upon choice strategies that have been developed within the general framework of multi-criteria decision making. Issues such as choices under uncertainty and preference formulation are addressed. An MCDM DSS intended to assist in high-level management decisions must focus on helping the decision maker to properly define the problem by providing a structure to it and to dynamically evaluate the alternative courses of action. A conceptual architecture is developed and presented to propose a general model for designing decision support systems specifically designed to assist in MCDM in a managerial context. A commercial loan approval judgment case is described to illustrate the real-world situation where decisions are made under fuzziness and usually require a high degree of intuition and subjective judgment. Development of a prototype system intended to partially represent application of the architecture is described.

1) 중앙대학교 경영대학

I. INTRODUCTION

In recent years, there has been a surge of interest among decision theorists in the cognitive processes involved in decision making. Understanding the decision process has been recognized as a key step in providing decision aids for various management activities. As many organizational decisions must be made within a given set of constraints, decision research has particularly centered around the problem of choosing among competing alternatives, within the general framework of multi-criteria decision-making (MCDM). In an organizational context, MCDM has been an issue of central concern to managers who make decisions. This is particularly true when an organization is viewed as an entity that constantly strives to solve problems in order to adapt to environmental changes [Pfeffer & Salancik, 1978]. To make appropriate decisions that will lead to possibly favorable conditions and thus solve organizational problems, managers have to address a wide spectrum of factors that are considered important in arriving at a final decision.

Mintzberg et al. [1976] argue that "it is at the top levels of organizations where better decision-making methods are most needed." In fact, past approaches to computerized decision support for organizations have mainly focused on low-level or middle-level management decisions. Quantitative analysis methods developed in the OR/MS area such as goal programming have been useful only for decision problems where the analysis involves the use of quantitative data and models. With the recent emergence of DSS concepts, there have been developed computerized systems designed to provide support to semi-structured decisions such as bond trading or capital acquisition analysis [Keen & Scott-Morton, 1978]. Nevertheless, these systems could hardly lend effective support to highly unstructured choice problems that often form the basis of many top management decisions. A shift in emphasis from quantitatively-oriented to qualitatively-oriented decision tools seems imperative in order to better address the fuzziness and uncertainty issues faced by today's managers.

As technological advances made it possible to apply artificial intelligence techniques to multi-criteria decision problems, some authors suggested the design of knowledge-based DSS for specific applications such as consumer product selection

[Widmeyer & Lee, 1986] or for generalized MCDM problems [Jarke et al., 1984; Hong & Vogel, 1991]. These authors focus, as an area of AI application, on either preference elicitation or data/model management. However, they do not yet address such issue as support for qualitative reasoning processes involved in complex decisions. We need a methodology designed to aid the decision maker in solving qualitatively-oriented multi-criteria decisions under uncertainty. Application of AI techniques must be extended to include facilitation of high-level management decision processes that typically require a large degree of human intuition and personal analysis.

This paper develops and presents a conceptual architecture for designing a knowledge-based DSS that facilitates structuring and solving MCDM problems characterized by uncertainty for an organization. The present approach combines MCDM theories with the DSS technology in order to assist in the qualitative reasoning process involved in many multi-attributed managerial decisions. In the paper, strategies for making choices among alternatives are briefly discussed that have been modeled after human choice making processes. Then, a method is developed for providing computerized support to complex & uncertain multi-criteria decisions using theories of MCDM. A system architecture for an MCDM DSS design is presented that shows how expert knowledge and data can be accessed and used by the system to help the decision maker solve intricate multi-criteria decision problems. Development of a prototype intended to partially represent the architecture will be described. Finally, we describe a real-world case on a bank's commercial loan approval judgment.

Ⅱ. THE MCDM LITERATURE

Research on MCDM to date has produced literature in two main arenas. One arena has approached MCDM from operations research and management sciences disciplines, resulting in optimization methods for choice making. The other arena is concerned with descriptive research pertaining to human choice behavior. Our literature review will focus on the latter, examining what knowledge has been compiled on the way people make choices. We will be allowed to gain a perspective on it, as we review choice models for evaluating decision alternatives.

Solving problems through MCDM involves choice of one or more alternatives by evaluating the alternatives according to criteria. The MCDM literature suggests that there are a host of choice strategies, or choice rules, that allow the decision maker to arrive at a decision. It is widely accepted notion that MCDM consists of two categories: MADM (multiple attribute decision making) and MODM (multiple objective decision making) [Hwang & Masud, 1979; Hwang & Yoon, 1979; Cohon, 1978]. MADM is concerned with choice, while MODM {{) MODM methods such as MOLP (multiple objective linear programming) or goal programming are not to be discussed in this article. They are fully described in [Cohon, 1978].}} relates to design (for more details on this dichotomy of MCDM, see [Hwang & Masud, 1979]). Our main concern in this paper is MADM that involves choosing among available options based on multiple attributes, hence we will use the term MCDM to primarily refer to MADM. These MCDM models include not only the models that describe human choice behavior but also the models that specify methods for making optimal choices. This descriptive/ prescriptive classification of choice models represents two major approaches to choice making, which we will describe in this section.

The choice strategies are classified into two categories depending on the level of cognitive processing demanded on the decision maker: compensatory (high processing) strategies and noncompensatory (reduced processing) strategies [Klayman, 1982; Minch & Sanders, 1986]. The compensatory/ noncompensatory distinction is made on the basis of whether the same information is searched for each alternative, so that advantages of one dimension are traded against disadvantages of another dimension. A choice strategy is compensatory if inter-dimensional compensation of attributes values can be made (i.e., commensurability exists across dimensions), and it otherwise is noncompensatory. Therefore, compensatory strategies are cognitively more demanding but may lead to more optimal decision outcomes than noncompensatory strategies. Compensatory strategies include normative, linear models such as the additive model and the additive-difference model. Noncompensatory strategies include descriptive, non-linear models such as the dominance model, the conjunctive model, the disjunctive model, the lexicographic ordering model, and the elimination-by-aspects model. Below we briefly discuss the general characteristics of each choice model.

Additive Model: The additive model, together with the additive–difference model, demands a high degree of cognitive processing. Search is exhaustive, and the goal is to arrive at an optimal solution through normative linear models. In the additive model, overall worth" indices are developed for each alternative, and then a final ordinal comparison of these indices is made to pick the best [Anderson, 1973; Klayman, 1982]. These worth indices represent weights assigned to different dimensions in accordance with their relative importance. The value of an alternative on a dimension is multiplied by the corresponding weight across all dimensions, and the multiplied values are summed up to arrive at an overall value of that alternative. This is repeated over all alternatives, and alternative–by–alternative comparisons are made to find the alternative with the highest total [Klayman, 1982].

Additive–Difference Model: The additive–difference model is a compensatory choice strategy requiring high cognitive processing like the additive model, but it differs from the additive model in that for each weighted dimension a difference is computed between the values of a pair of alternatives. In this model, two alternatives are considered at once, dimension by dimension [Klayman, 1982]; thus the intra–dimensional rather than inter–dimensional information is utilized. The weighted differences are summed for each alternative. Now, comparisons are made between pairs of options in terms of distance; the better of the first two alternatives is compared to the next alternative. This is repeated over the remaining options, until one best alternative is chosen.

Dominance Model: The dominance model is the simplest form of noncompensatory choice strategies, and it is usually used for the initial screening of alternatives. An alternative is said to be dominated if and only if there is another alternative which is better than that in one or more dimensions and is equal to that in the remaining dimensions [Yu, 1973]. In the dominance method, dominated alternatives are all eliminated from the set of existing alternatives, and the result of this elimination process is a set of non–dominated alternatives that can be further evaluated by other non–compensatory choice rules. In this sense, the dominance model is not a stand-alone decision method. But, the power of a decision method can be expanded when the dominance method is used together with other MCDM methods.

Conjunctive Model: With the conjunctive model, the decision maker starts with specifying a set of cutoff values on different dimensions. Instead of computing each alternative's overall score, the decision maker relies on alternative reduction based on cutoff values. The decision rule to use is to select the alternative that will exceed the specified cutoff values on all dimensions, by eliminating all alternatives that do not meet the criteria (cutoffs) on one or more dimensions. This procedure continues until all unsatisfying alternatives have been eliminated; then, the options surviving the test are adopted as final choice. It will sometimes be possible for no alternative to be selected as final choice. In such a case, the initially set constraints can be relaxed to allow at least one alternative to be accepted as a decision.

Disjunctive Model: Like the conjunctive model, the disjunctive model requires the decision maker to establish cutoff values for the attributes. An alternative is chosen if and only if it exceeds a minimal cutoff on one or more dimensions [Klayman, 1982] and if all the aspects of the other alternatives should fall below or be equal to the criterion values [Svenson, 1979]. In other words, selection of an alternative is based on a disjunctive combination of values; an alternative satisfies the rule as long as its values exceeds cutoffs on one or more dimensions. Klayman [1982] suggests that the disjunctive model bases a choice on quick 'acceptance' of an alternative, whereas the other noncompensatory models focus on quick 'elimination' of alternatives. Hence, a suboptimal decision is typical of the disjunctive model. As with the conjunctive model, relaxation of constraints is sometimes necessary when the search cannot reach a decision.

Lexicographic Ordering Model: The lexicographic ordering model demands that the decision maker assign weights to the attributes in order of relative importance. It does not involve the use of dimensional cutoff values, but rather it relies on alternative-by-alternative comparisons. The attributes are lexicographically ordered, and the different weights of dimensions are taken into account in choosing an alternative. The decision rule is to select an alternative that contains values closest to the best values across all dimensions. Starting with the most important dimension, alternatives are ordinally compared to the alternative with the "best" value for that dimension, and the alternatives that have values distant from the best value are eliminated; this process is repeated on next important dimensions until one alternative is left.

Elimination–By–Aspects Model: Developed by Tversky as a choice theory, the elimination–by–aspects (EBA) model uses the cutoff values on dimensions specified by the decision maker to eliminate less attractive alternatives in a sequential manner. The model starts by selecting an aspect on a significant dimension, and eliminates all alternatives that do not include the aspect [Tversky, 1972]. If more than one alternatives pass the test on that dimension, only those passing alternatives are tested against the criterion on the next important dimension. If no alternative qualifies for the test on the dimension, either can the constraint be relaxed or can the dimension be ignored to search the alternatives on the next dimension. This process is continued until only one alternative remains. As has been previously mentioned, an aspect is a value on an attribute. When an aspect is picked as a baseline or standard, its role is as a criterion or a cutoff value.

The seven choice models described above represent how an expert decision maker would structure and solve problems at least for suboptimization of his/her goal. In a crude sense, compensatory models are based on linear algebraic models, whereas noncompensatory strategies are based on non–linear models. While they may not yield a rationally–grounded, optimal decision, they can provide a solution that is sound enough to satisfy the decision maker's needs.

These choice strategies can be applied to diverse real–world problems. However, successful application of the models requires careful evaluation of the tradeoffs between strengths and weaknesses of each model. This necessitates an analysis of the problem to find a model that captures the characteristics of the given problem. In addition, the applicability of these models seems limited to situations where decision tasks are relatively well–structured. When decisions involve many qualitative attributes, it may be necessary to develop a special version of a choice model.

Ⅲ. A NEW APPROACH TO SUPPORTING COMPLEX MCDM DECISIONS

The traditional approach to helping the decision maker solve multi-criteria choice problems through a DSS is searching the data base, applying some quantitative models to the data, and presenting the solution to the decision maker. However, this method is not likely to work well for such complex choice problems as we previously discussed. To ensure effective support for behaviorally-grounded aspects of complex decisions, emphasis must be placed on a structural decomposition of the unstructured decision problem and on an effective manipulation of preference information. Such an emphasis will lead to a decision outcome that can be more convincing to the decision maker. In this section, we show how a decision problem can be hierarchically represented, and present a method for systematically evaluating alternatives.

1. Hierarchical Representation of a Decision Problem

To represent a choice problem into a hierarchy, we borrow the notion of structural criteria from the Saaty's analytical hierarchy process (AHP) method. The AHP is a multi-criteria decision method that uses hierarchic or network structures to represent a decision problem and then develops priorities for the alternatives based on the decision maker's judgments throughout the system [Saaty, 1987]. Because it is based on rank-ordering of alternatives for choice making that is different from our method, we will only discuss its problem representation scheme (for details on AHP, see [Saaty, 1987; Saaty, 1980]). In the AHP, the goal of a decision is decomposed into more specific criteria that are further broken down into lower levels as needed. At the lowest level of the hierarchy are the alternatives.

The structural criteria concept is useful in analyzing complex decision processes that involve highly aggregate (or abstract) criteria. An aggregate criterion is broken down to lower, more concrete levels until it is operationalized or it cannot be itemized any further. In this manner, it facilitates the structuring of complex decision problems. To illustrate a realistic example of using structural criteria, consider a marketing executive hiring problem. As can be seen in Figure 1, the decision goal of hiring a highly competent candidate is, for simplicity, decomposed into such criteria as leadership, marketing expertise, and judgmental ability. The leadership criterion can be divided into subcriteria that include experience in years at managerial positions, communication skills, and leadership potential. The marketing expertise may be explained by a combination of factors such as educational background and claimed expertise, and the educational background is further divided into the final degree program completed and the exposure to marketing courses. Finally, the judgmental ability criterion is indicated in two subcriteria such as intuitive skills and analytical skills. Information sources can be located for the lowest-level criteria. The application form may provide information for the experience in years at managerial positions and for the education background (the degree and the relevance of majors to marketing). The interview results tell about the communication skills and the claimed expertise. Recommendation letters or contacts with references may provide a basis for determining the leadership potential, the intuitive skills, and the analytical skills. Notice that the present method does not include the alternatives in the hierarchy as the AHP does.

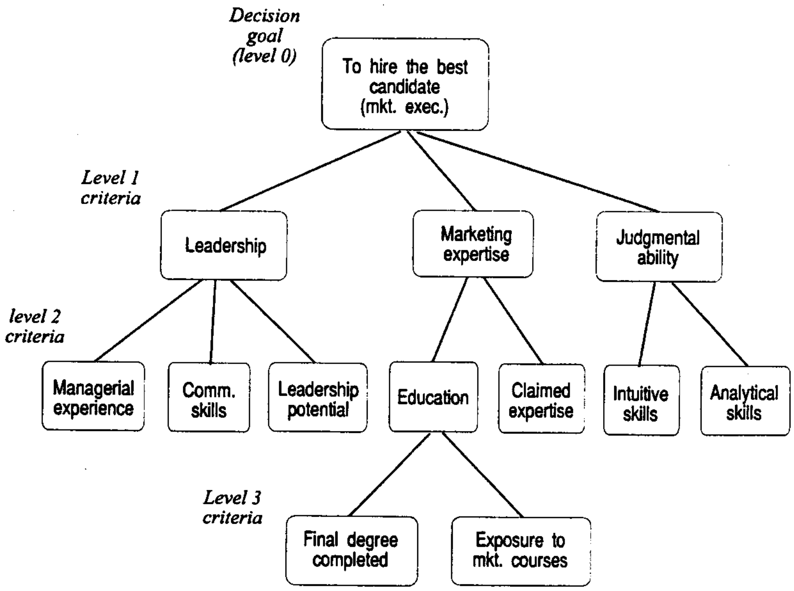

Figure 1. Hierarchical decomposition of the goal in a marketing executive hiring problem

2. Evaluation Methodology for Decision Alternatives

The seven choice strategies that we earlier discussed are theoretical models on descriptive MCDM. Thus they are not purely representative of how people actually make choices on multiple attributes. Empirical evidence suggests that people, in practice, use a combination of the choice models in arriving at a decision. In her experimental study, Corbin [Corbin, 1980] found that subjects would set cutoffs, but search a bit further than the first acceptable offer as long as that acceptable offer could be guaranteed available. Wright & Barbour [1977] examined phased decision strategies under an experiment. Their results revealed that in the first phase, people initially screened the options using multiple cutoffs and in the second phase, they adopted a new choice strategy based on the result of the initial screening. An implication to be drawn from these findings seems that the evaluation of options must start with the initial screening that then precedes the review of the remaining options on dimensions.

Insights that we can gain from these empirical findings help us to build a practically-oriented decision process model for solving managerial MCDM problems. This model is depicted in Figure 2. At the left of the boxes are listed important information that has to be determined during individual phases. Recognizing that people tend to solve a problem in an adaptive manner through several iterations, an arrow from report generation is pointing to the preference specification phase in order to show that the decision maker may want to reiterate the process by adjusting his or her preferences. Choosing a highest-priority option for multi-attributed managerial problems would necessitate a step-by-step evaluation of the alternatives in an adaptive, reiterative fashion. As Table 1 indicates, items shown in the Input column represent information that should be captured and used during each phase. In addition, appropriate choice models should be chosen and executed upon the alternative ratings. Below is examined each of the individual phases involved in the proposed decision process model.

Problem Definition: According to Buede [1992], problem definition should encompass three tasks including goal formation (GF), information processing (IP), and problem structuring (PS).

The GF task basically defines the deci-

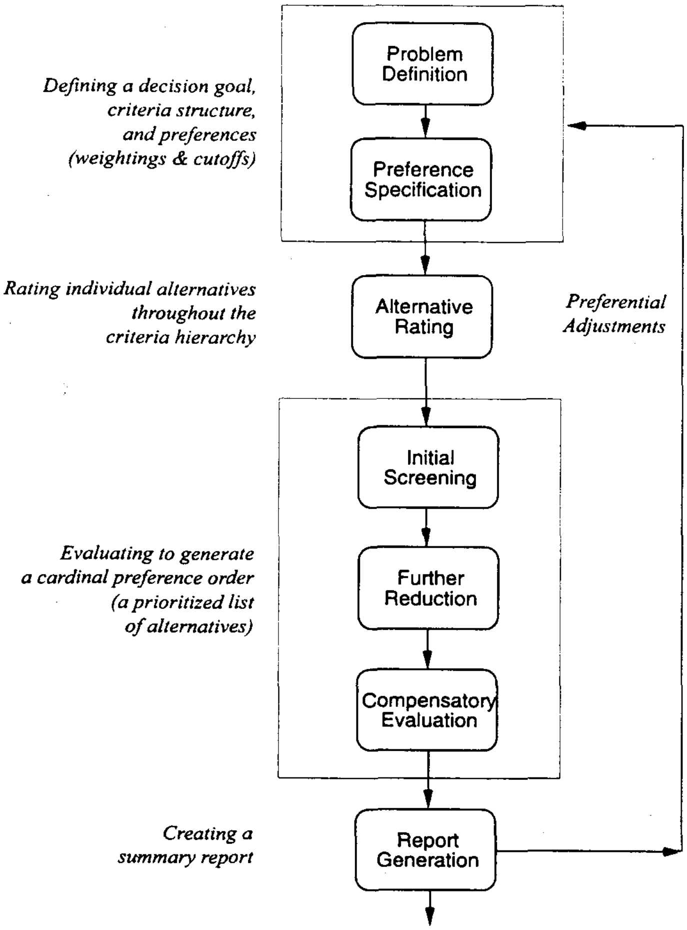

Figure 2. A decision process model for supporting managerial MCDM

Talbe 1. Models & inputs needed for each phase

Phase	Choice Models	Inputs
Problem Definition	–	Decision problem
Preference Specification	–	Policy & constraints
Alternative Rating	–	Criteria structure
Initial Screening	Dom	Alternatives set
Futher Reduction	Conj, Disj, EBA, Lex	Preferences
Compensatory Evaluation	Add, Add–Dif	Weightings
Report Generation	–	Model results

NOTE: Dom, Conj, Disj, EBA, Lex, Add, Add–Dif stand for the dominance model, the conjunctive model, the disjunctive model, the elimination–by–aspects model, the lexicographic ordering model, the additive model, and the additive–difference model respectively.

sion goal needing to be focused on under the given problem. The IP task is concerned with collecting and analyzing relevant data, and formulating the decision problem that is currently being examined. With the PS task, a criteria hierarchy is developed that incorporates important considerations for the focal decision problem. The way a decision problem can be decomposed into a hierarchical criteria structure has already been discussed in the preceding subsection. Through this process, an initially abstract, general goal will convert to more concrete, specific criteria.

Preference Specification: Preferences in general encapsulates not only a decision maker's personal preferences reflecting his/her expertise and experience but also the organizational policy and objectives. For example, the organizational policy may require that some criteria be treated more importantly than others; that is, it may often dictate priorities for the individual criteria being considered. In addition, preferences are formulated to include some constraints imposed by the task environment. More specifically, the resulting preferences should specify both the weightings for individual criteria and any cutoffs that need to be attached to some criteria. The weightings will have to be determined according to priorities given to individual criteria such that they will be compatible with the corporate management policy. Also, in many decision making instances, the decision maker will find himself faced with some constraints that would affect his decision. These constraints most commonly are imposed by the corporate policy. Such constraints are usually tied to a certain subset of criteria, and should be incorporated as cutoffs into the decision process. Examples include budget availability, time limit, resource availability, minimum rate of return on an investment, education standards required of managerial positions, etc. The role of these cutoffs during decision making is the elimination of candidates that do not meet the standards or cutoffs established.

Alternative Rating: Once the decision goal and the related criteria structure have been determined, the alternatives currently being considered must be rated. The alternative rating process requires a special instrument to help the decision maker systematically and consistently rate each alternative. The decision maker can rate each alternative under each criterion using one of the following three scaling systems.

(1) *The Numeric Scale:* The numeric scale is used to represent quantitative attributes with associated unit names. Examples of attributes for this category include consumed time (in hours, minutes, or seconds), annual sales volume (in dollars), number of occurrences (in count), GMAT scores (in percentile), length of industrial experience (in years), automobile's interior space (in cubic feet), and gas mileage (in miles per gallon). Selection of this scale will require specification of information on the unit name, the expected range of likely values (upper and lower bounds), whether a benefit attribute or a cost attribute (for normalization purpose), and whether judgmental or known. The unit name indicates the name of a unit with which an attribute can be quantified, such as dollars, years, hours, etc. The expected range of likely values is based on the decision maker's prediction on what range most of the values for the existing alternatives will fall in, and is needed to subsequently determine the interval equivalents (1 to 10) of the present values indicated in the numeric scale. A criterion is classified into either a benefit attribute or a cost attribute depending on whether the attribute positively contributes to the accomplishment of decision objectives. Finally, the decision maker must specify whether an attribute is judgmental or known; a judgmental attribute requires a personal judgment in rating an alternative, whereas data is already available for a known attribute.

(2) *The Interval Scale:* A majority of qualitative attributes are represented using the interval scale. The interval scale would be similar to the Likert scale, but uses 10 points in the range from 1 to 10. In the interval scale, 1 and 10 are assigned to least desirability and most desirability respectively, and any intangible characteristic of an alternative can be indicated on a 10-point continuum with a value between the two extremes (1 and 10).

(3) *The Aspect Scale:* The aspect scale is a substitute for the interval scale, which can also be used to indicate the characteristic of an alternative under a qualitative criterion. The aspect scale, however, employs a set of descriptive aspects to characterize an alternative. The aspect set being specified for a certain criterion should contain an exhaustive list of possible aspects. For example, the set of aspects for a criterion, the final degree completed, might be high school diploma, bachelor's degree,

masters degree, and doctorate. In another example, the set of aspects for a teaching effectiveness criterion might include highly effective, somewhat effective, average, somewhat ineffective, and highly ineffective. These are some of simplistic examples, and the decision-maker can design any sophisticated aspect scale in accordance with his needs. Once the aspect set is determined, rating an alternative under that criterion will be simply a matter of choosing one from the available aspects, facilitating the alternative rating process.

Initial Screening: We use the dominance rule to screen out absolute rejects in the initial screening phase. Absolute rejects in this phase are those alternatives that are dominated by non-dominated alternatives. As earlier discussed, a pair of alternatives are evaluated each time to check whether an alternative is dominated by the other. This phase produces a list of non-dominated alternatives. The initial screening phase eliminates the need for redundant information processing.

Further Reduction: The options that survived the initial screening test are further evaluated to eliminate less feasible candidates. Cutoffs on the lowest-level criteria established by the decision maker are used to determine the alternatives that exceed those cutoffs; either the conjunctive model or the disjunctive model may be used. The screening process is performed starting from the lowest up to the highest level of criteria. When a condition is detected where an option does not meet the threshold for a criterion, the process immediately stops and the option is excluded from further consideration. The further reduction phase may also utilize the lexicographic ordering strategy. As criteria at each level have been assigned priorities in the Preference Specification phase, the alternatives are now evaluated with respect to the criteria starting from most important to least important, and from lowest-level to highest-level. The alternatives are reduced to a smaller subset through this procedure.

Compensatory Evaluation: The compensatory evaluation stage is necessary to generate a rank-order of alternatives. The alternatives must be evaluated in a compensatory manner based on the overall computed utilities of the alternatives. This algorithm is based on MAUT (multi-attribute utility theory). Under this method, an additive utility function u(x) is used as shown below:

$$u(x) = p_1u_1(x_1) + p_2u_2(x_2) + p_3u_3(x_3) + \cdots + p_nu_n(x_n) \quad (1)$$

where there are n criteria. The partial utility functions ($u_1, u_2, \cdots, u_n$) included in this equation are specific to the individual criteria that exist for a given problem. The values of these partial utilities must individually fall in the range between 0 and 1. The variable p denotes the weighting factor for a criterion, signifying the relative importance of that criterion, and it is normalized between 0 and 1 such that the sum of p's in the equation equal 1. Using the above utility function at each of the multiple levels of the criteria hierarchy, the following procedure must be completed:

1. Compute the utility for each alternative: The additive model can be used to find th*e utilities. The utility for an alternative is obtained by multiplying attribute values by corresponding weights and adding up the results.
2. Generate a cardinal preference order: Once the utilities have been computed, the alternatives are rank-ordered based on the utilities of alternatives from the highest to the lowest. This rank-order is attached with computed utilities; i.e., the relative importance of each alternative is numerically expressed

Report Generation: In this phase of decision process, facts that have been gathered through the execution of choice models are presented to the decision maker through a summary report. This summary report basically contains a summary of model results. It should not only give a prioritized list of feasible alternatives (i.e., a cardinal preference order) according to the result of the compensatory evaluation, but also list the findings from model execution in a way to give the decision maker a comparative feel of strengths and weaknesses associated with the individual alternatives. In addition, the report needs to give a listing of alternative ratings data which would permit the decision maker to review his evaluations. This information may be valuable when the decision maker perceives inconsistencies between his decision outcome and his alternative ratings, in which case it would be imperative to reiterate the session with the system, as earlier shown in Figure 2. The key function of the summary report will be to help the decision maker enhance the understanding of the problem characteristics and to place the decision maker in a better position to make a final decision. This is particularly important, for oftentimes the decision maker may not be thoroughly cognizant of the situational aspects that he or she reviews due to the bottleneck of human information processing capability.

Ⅳ. A CONCEPTUAL ARCHITECTURE FOR AN MCDM DSS

Using as a basis the decision support approach described in the preceding section, we have developed an architecture that is intended to guide the design of an MCDM DSS. The underlying skeleton of the architecture was adapted from the Sprague's 3-area framework for DSS capability sets, which includes data management, model management, and dialog management [Konsynski & Sprague, 1987].

Figure 3 depicts the architecture proposed for the purpose of designing a knowledge-based DSS that specifically aims at helping the decision maker solve complex MCDM problems. This architecture includes five main software modules that comprise a generalized MCDM DSS. They are (1) the user interface, (2) the knowledge acquisition module, (3) the inference engine, (4) the model manager, and (5) the data manager. Links among the components are shown to indicate the flow of data and control during the decision-aiding process. As the system is initiated, rules and facts in the knowledge base are loaded onto the system. The model manager requests data to the data manager that in turn accesses data base files to search for needed alternatives data. Specified models are applied to the returned data, yielding data ready for processing. Using these values, the inference engine makes reasoning according to the rules prescribed by the knowledge base to deduce facts. There are two information bases for storage of relevant information, which are associated with the modules mentioned above. They include the knowledge base and the data base.

Our architecture has been built around important issues arising in DSS design, such as reduction of cognitive burden, support for qualitative reasoning processes, and effective data and model management. In the next section, the development of a prototype that has been designed based on the above five major components of the proposed architecture is discussed.

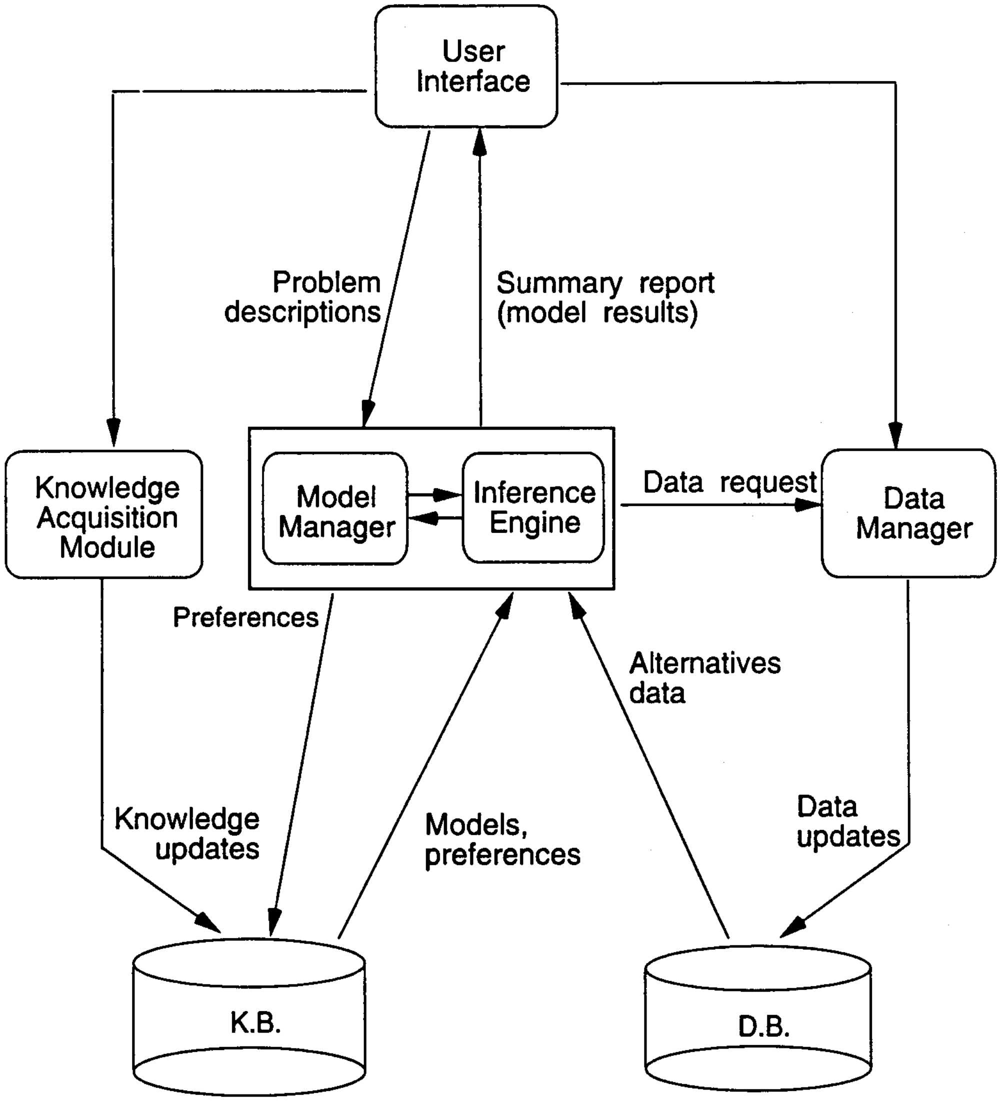

Figure 3. An architecture for a MCDM DSS

V. PROTOTYPE DEVELOPMENT

A prototype system, ISBIS (Integrated Spreadsheet–Based Inferencing System), implementing the current architecture has been developed at the University of Arizona Department of MIS. The ISBIS is intended to demonstrate the feasibility of designing a MCDM DSS based on the architecture presented in this paper. The prototype system is composed of the following five components

User Interface: The user interface module is a system shell that accesses and executes other modules existing in ISBIS. It is also used as a means for the system–user dialog where questions are asked by the system to determine problem characteristics and select appropriate models and where the results are presented. The decision maker interfaces with several functional modules which include the model manager, the data manager, and the knowledge acquisition module. The decision maker can update the database records via the data manager (SmartSheet program) and the knowledge base rules via the knowledge acquisition module. As a result of reasoning by the system, the user interface presents to the decision maker a summary report resulting from executing selected models. This report forms the basis for the decision maker's final judgment.

Knowledge Acquisition Module: The primary function of the knowledge acquisition module is to acquire, formulate, store, and edit knowledge necessary for the decision aiding process. Three types of knowledge are to be acquired or maintained via this module. The first type is preference knowledge that involves problem–specific information such as criteria structure, weightings, and cutoffs. The second type of knowledge is choice knowledge including a set of choice models implementing different human choice strategies. Acquisition or modification of choice knowledge is to be conducted by a knowledge engineer, because construction of production rules requires one to ensure consistency and completeness throughout the rules. The third type is model selection knowledge that can be used to determine an appropriate model to use for the decision maker. See [Hong & Vogel, 1991] for a discussion on model selection algorithm. The preference knowledge is represented using frames, whereas the other two types of knowledge are represented using production rules.

Inference Engine: Together with the knowledge base and the knowledge acquisition module, the inference engine forms an expert system subsystem for the system. It is used in conjunction with the model manager to help select and execute choice models and report a summary of their results. This is what directs the system's decision making behavior under the guidance of choice knowledge represented as rules. Facts are deduced using the data retrieved from the spreadsheet database and the rules from the knowledge base. The obtained facts are encoded in a system-generated report which summarizes what has been learned in the course of inferencing. This report plays an important role in helping the decision maker gain a better understanding of the structure of the problem, and also in narrowing the size of the problem down to a well manageable level.

The inference engine used for the ISBIS system was built using the forward-chaining algorithm. It starts with the initial states known only from the spreadsheet data, and moves forward to the final goal state which becomes the basis for a recommended choice. The inference engine functions as a control schema, i.e., an interpreter that controls the selection and activation of rules. Waterman and Hayes-Roth [1978] describes four key tasks involved in pattern-directed inference systems; they are selection, matching, scheduling, and execution of what they call pattern-directed modules. With ISBIS, the inference engine selects a choice rule to evaluate, checks to see if patterns match between the condition portion of the rule and the selected alternatives data, schedules rules to be triggered, and execute those rules to arrive at a conclusion.

Model Manager: The term, model management, has emerged with the recent recognition in the literature that a DSS consists of three components: dialog, data, and models. Models are regarded as instruments that transform data into information which can aid decision making [Dolk & Konsynski, 1984]. The major goal of model management is to free the decision maker of the burden of selecting and activating a model that usually requires a good understanding of technical aspects of the models.

Three key roles played by the ISBIS model manager include selecting appropriate models, executing the selected models, and facilitating the data retrieval process. The model selection knowledge stored in the knowledge base determines what models to be used based on known problem characteristics, and the chosen models are passed onto the inference engine where the models are applied to the retrieved data. The ISBIS model manager facilitates data retrieval through communication with the SmartSheet module that we will discuss subsequently. This communication represents data flows that consist of dynamic requests from the models for information

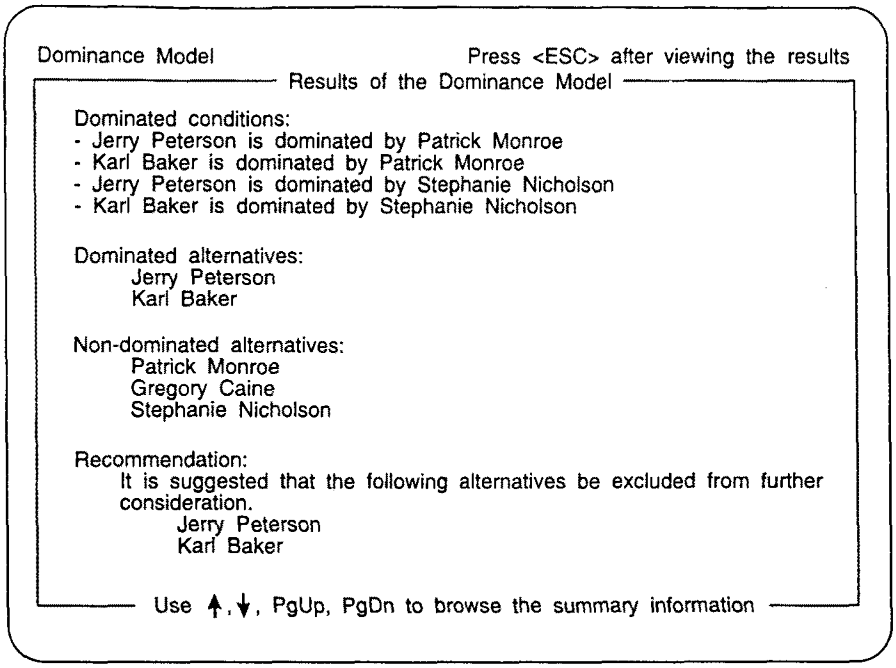

Figure 4. A sample screen displaying the results of the dominance model

and the corresponding responses from the database manager [Jarke et al., 1984].

As earlier shown, the application of choice models to fuzzy managerial decision problems should be based on the seven-phase normative MCDM process model. The model manager implements that process, where each phase selects an appropriate model to use. As a model is activated, the results are displayed on the screen and also stored in a separate file for later use in generating a summary report; see Figure 4 for a sample screen displaying the model results from ISBIS.

SmartSheet Program: This spreadsheet program not only provides fundamental computational capabilities like conventional spreadsheet programs, but also is specifically designed to support multiple criteria decision problems. Each dimension is represented in a column of the spreadsheet, and each alternative in a row. The spreadsheet-based data base may accommodate a large number of alternatives, the values of which are stored with respect to specific attributes. The storage of alternatives is analogous to the way that relational data base stores relations. SmartSheet accesses and searches the data base to furnish data to the inference engine.

SmartSheet can be regarded as a vehicle for alternative management. It enables the decision maker to generate and store any number of MCDM alternatives. The underlying idea of using a spreadsheet program to manage alternatives data has been presented by some authors [Blanning, 1986; Codd, 1970]. This concept stems from the relational data base theory. Viewing each of the multi-attributed alternatives as a tuple, one can regard a relation as a subset of alternatives since each relation is a subset of the Cartesian product of a set of domains corresponding to the key and content attributes of a file [Codd, 1970]. Because the MCDM alternative evaluation is based on two-dimensional representation of data, storage of data in a spreadsheet form is an intuitively appealing approach to maintaining the data base. For the ISBIS, the spreadsheet program was chosen over a relational database program because not only did we intend to exploit the computational power of a spreadsheet program but also was its role to support the user-system dialog. When organizing the MCDM data into the data base, one often finds it necessary to extract new pieces of information from the already existing data; for example, use of a formula can yield a value for another dimension over all alternatives.

One additional feature of SmartSheet is its role as an effective dialogue tool. The matrix-form representation of alternatives in SmartSheet allows for effective manipulation of data and also enhances the decision maker's interpretation of the alternatives to be evaluated. The spreadsheet-based data base is managed in accordance with a "What you see is what you get" principle, for one can browse it through while making changes to it. Dimensions can also be freely added or deleted as needed.

Powerful data manipulation is facilitated through the capability of storing the alternatives in a multiple of spreadsheet files by partitioning and allocating dimensions to separate files. For example, in a commercial loan judgment problem, the data base may consist of the capacity file, the collateral file, the capital file (e.g., the balance sheet), and so forth. Depending on the need of a search, different spreadsheet files can be accessed for evaluation of the alternatives.

It must be stressed that the above five modules constitute the core components that must be included in a knowledge-based MCDM DSS. They are specifically geared to supporting the key functions of a DSS which include dialog management, data management, and model management. In addition, they free the decision maker of much of cognitive burden involved in many complex decision processes because qualitative support is built into the DSS.

Ⅵ. THE COMMERCIAL LOAN APPROVAL JUDGMENT CASE

In this section, we describe a case pertaining to the commercial loan approval judgment problem. This case was prepared through a series of interviews with two loan officers at a bank who are in charge of commercial loan approval judgments. The chief objective of the case is to illustrate a real-world situation where the decision problem is intricate and unstructured to a large extent. Then, we demonstrate the use of ISBIS in assisting in the commercial loan approval judgment.

1. Case Illustration

ABC Bank is a large financial institution based in the West coast area of the U. S. It offers two major categories of loans to its customers: personal loans and commercial loans. The personal loans are provided to individuals, and the commercial loans to business corp orations. Personal loan approvals are made at the low level of the hierarchy. They are mostly handled by personal loan officers at each local branch. To the contrary, commercial loan decisions are highly centralized. They are all handled in the main office. The personal loan decision processes are beyond the scope of this paper. We will focus on the commercial loan approval decisions.

Presently, the bank has two loan officers designated to be responsible for analyzing and making decisions regarding approval of commercial loans requested by local private corporations of varying size. According to one of the two loan officers, "Determining the approvability of a commercial loan is indeed a holistic process." This statement highlights the nature of commercial loan approval judgment in which so many decision factors are interwoven together that choice making is truly sophisticated and intricate, necessitating personal analyses & judgments during the decision process.

Whether to approve a commercial loan largely depends on the requesting company's ability to pay back the loan. Analyzing the repayment ability, however, is not as easy as it might look. A detailed loan analysis is preceded by information gathering based on a variety of credit review factors. A general outline of the credit review factors is given in Table 2. These factors collectively represent different categories of information. The review items listed in Table 2 therefore can be mapped onto 5 main categories of attributes, commonly known as the 5 C's[3)] to provide a better conceptual interpretation of the financial strengths and weaknesses regarding the borrowing company. The five categories of attributes include capacity, capital, character, condition, and collateral. Although the 11 items of Table 2 serve the basis for information collection, the actual credit analysis is conducted along these five attributes. Capacity means the company's potential capacity for production. A good indicator of capacity is cash flow. Capital is the size of plant and equipment owned by the company. It is indicative of how strong a company is in terms of assets. For example, software companies are usually weak in this aspect. Character implies the history, the business which the firm is in, and other firm-related information that will characterize the organization. Condition includes all the aspects related to the organization's performance, such as the market share, the level of competition, current ownership, and banking relationship. Condition also relates to the external business environment like industrial trends that may potentially affect the firm's performance. Finally, collateral indicates what has been taken as collateral and in what terms. These five attributes represent key dimensions used for commercial loan multi-criteria choice problems. The major problem, however, is that all these five attributes are more qualitative than quantitative variables that cannot readily be described in numeric measures.

When all the information has been collected and thoroughly analyzed with regards to the 5 C's attributes, the loan officers prepare a credit review report based on the results of the analysis. Preparation of the report requires highly intuitive skills and sometimes involves subjective opinions. The credit review report is, the loan officers suggest, a comprehensive summary in which the results of the credit analysis are described. The purpose of the credit review report is not to provide a final decision, but rather to supply concentrated background information to the credit review committee for their finalized judg-

Table 2. Factors considered in a credit review

Review items	Credit analysis categories
Source of repayment	supplementary requirements
Collateral and line mechanics	collateral
Yield	supplementary requirements
Organization and management	character/condition
Plant and equipment	capacity/collateral
Operations	capacity
Balance sheet	capital
Debt servicing ability	capacity
Financial forecasting	supplementary requirements
Guarantors	supplementary requirements
Loan agreement covenants	supplementaly requirements

ment. The committee will review the report and either approve or disapprove the loan.

2. How ISBIS Can Assist in Commercial Loan Approval Judgment

ISBIS supports the commercial loan approval problem through a series of steps. It will first acquire and formulate the preference knowledge from the decision maker, building a knowledge base file that stores the structural criteria of this particular problem in a frame-based format. Knowledge acquisition is facilitated through a template that is intended to get information on a criterion, weight, cutoff, and lower-level criteria. Figure 5 lists the criteria hierarchically decomposed into more specific, operationalizable dimensions. The first level criteria such as character, condition, capacity, collateral, and capital are qualitative variables that need to be expressed on a ratio or interval scale. Other qualitative variables include concentrating business, key management, level of competition, and banking relationship. Again those qualitative variables can be indicated on a 10-point scale (e.g., 1-very poor, 10-excellent). For the rest of the dimensions, quantitative measures can be used such as dollars, percentage, etc.

Once the preference knowledge file has been constructed, the decision maker accesses the SmartSheet module to provide

Table 3. Alternatives data as recorded in a SmartSheet worksheet

Firm	C11	C12	C13	C21	C22	C23	C24	C31	C321	C322
A	3yrs	3	6	23%	6	20%	3	50%	$2.1%	$3.2M
B	30yrs	5	7	10%	4	90%	5	35%	$5.0%	$2.4M
C	15yrs	2	4	30%	9	65%	7	20%	$1.6%	$0.6M
D	9yrs	8	5	12%	3	30%	4	65%	$2.5%	$2.0M
E	9yrs	9	6	3%	10	50%	8	80%	$3.5%	$6.6M

[Cont'd]

Firm	C323	C324	C41	C42	C43	C44	C51	C52	C53
A	$1.6M	1.5	0.4	0.6	0.4	1mo	$8.0M	$1.0M	$3.5K
B	$1.0M	1.3	0.2	0.15	0.85	6mo	$6.9M	$1.8M	$4.9K
C	$0.3M	0.9	0.8	0.9	0.1	1yr	$2.7M	$0.5M	($4.0K)
D	$1.2M	1.1	0.45	0.2	0.8	1mo	$4.0M	$1.0M	$6.5K
E	$3.0M	1	0.55	0.5	0.5	1mo	$2.5M	$0.6M	$0K

data on the alternatives to the system. An empty spreadsheet appears on the screen, and the decision maker can rate each alternative under dimensions identified earlier. Table 3 shows a sample worksheet completed through this procedure. Values shown in the table are expressed on a 10-point interval scale or on an aspect scale (for qualitative dimensions) or as numeric measures (for quantitative dimensions). Other types of information such as income statement and balance sheet can also be recorded in SmartSheet spreadsheets for the decision maker's subsequent reference when needed. The created spreadsheets are stored in the SmartSheet data base.

Then, ISBIS interacts with the decision maker to elicit information necessary to determine what particular choice models should be activated in what sequence. If the dominance model needs to be executed, production rules specific to this model are retrieved from the knowledge base for use with the system. At the same time, the preference knowledge is retrieved to provide the system with the information on the criteria, weights, and cutoffs that must be incorporated into the loan approval decision. Execution of the dominance model results in a smaller number of alternatives that are non-dominated to one another. If the decision maker is willing to run a conjunctive model on the data, the conjunctive model is retrieved and executed to produce a new list of alternatives that is more manageable for the decision maker. Compensatory evaluation of the alternatives across different dimensions can also be performed via the additive model using the dimensional weights. The result is displayed on the screen in a tabular format as shown below. Ranks based on the utilities enable the decision maker to gain a picture of the ranks of the alternatives.

Firm	Computed	Rank
A	46	2
B	34	3
C	52	1

From the computed utilities shown, we can tell not only the relative positions of the firms but also the distance between one firm and the next. For example, Firm C excels Firm A by a difference of 6, while Firm A outscores Firm B by a difference of 8. The last step for ISBIS is to generate a summary report that lists the results of choice models executed and the alternatives ratings data. From the report, the decision maker will be able to arrive at a more concrete idea as to whether each borrowing company should be granted the loan.

Ⅶ. DISCUSSION OF THE PRESENT APPROACH

1. Key capabilities of an Intelligent DSS

Drawing upon our discussions concerning the architecture and prototype development, we herein point out four aspects that we believe important in providing computer-based support to managerial decision making. They represent benefits we might expect from using the prototype system, ISBIS.

Cognitive support for unstructured managerial decisions: As our architecture demonstrates, an MCDM DSS must be designed in ways that extract and provide useful information for weighing options, in the form of summary report, for example. That is, the system should be capable of providing an effective decision environment that will enhance the decision maker's perception of strengths and weaknesses of each option.

- Loan approvability (C0)
  - Character (C1)
    - Length of history of the firm (C11)
    - Concentrating business (C12)
    - Key management (C13)
  - Condition (C2)
    - Market share (c21)
    - Level of competition (C22)
    - Current ownership/control (C23)
    - Banking relationship (C24)
  - Capacity (C3)
    - Production capacity (C31)
    - Operation (C32)
      - Cash flow (C321)
      - Sales volume (C322)
      - Profit (C323)
      - Liabilities-to-assets ratio (C324)
  - Collateral (C4)
    - Portion of plant/equipment in collateral (C41)
    - Percentage of advance on collateral (C42)
    - Percentage of payback (C43)
    - Frequency of interest collection (C44)
  - Capital (C5)
    - Current assets (C51)
    - Fixed assets (C52)
    - Net working capital (C53)

Figure 5. A criteria structure for the commercial loan approval iudgment problem

Evaluation of intangible variables: A key problem arising in developing a computerized system for assisting in organizational multi–criteria decisions is the difficulty in operationalization of variables used in ill–structured decision processes. Qualitative variables present a problem in terms of measurability. This problem renders it impractical to directly apply theoretical choice strategies to unstructured choice problems. The present approach offered a solution to this problem, by introducing three different types of scaling systems, including numeric, interval, and aspect, designed to systematically rate alternatives under various decision criteria. Of these three, the aspect scale was discussed as a useful method for rating options when there is the lack of precision or certainty in the necessary information.

Spreadsheet as a device for alternative management: Electronic spreadsheet is conceived not only as an effective dialogue tool but also as a tool for alternative generation and storage. This aspect was amply discussed in the preceding section. In addition, the conceptual architecture developed in this paper shows how a spreadsheet program can be integrated with the model management subsystem for the successful application of choice models to alternatives data.

What-if capability: The what-if capability is a significant aspect that must be considered in a DSS design. It permits the simulation of the system's choice-making behavior under various possible scenarios. This feature is useful not only for the decision maker but also for the system developer, as he can test the knowledge base for consistency and completeness by observing the system results under many unique situations.

2. Other Approaches To Supporting Multi-Attribute Decisions

The idea of bringing the computer technology to the problems of decision analysis is not new. There exist software packages specifically designed to facilitate structuring and analysis of decision problems with multiple criteria. Herein, we like to have a comparative look at decision software packages that may resemble ISBIS on one of the following two central aspects: the spreadsheet analogy and the hierarchical criteria structure.

As aforementioned, our approach is using the spreadsheet to enhance the system-user dialog in rating and managing alternatives data. Decision support approaches using the spreadsheet analogy for information display can be found in some of recent commercial software packages, and they recognize that a spreadsheet would permit the display of a large amount of information [Buede, 1992]. According to Buede [1992], Value matrix packages (e.g., MAUD, Decision Pad, etc.) are software that assist the user in creating a matrix of options and criteria to compute weighted scores for individual options, and typically use one spreadsheet dimension for attributes and the other for options. Value matrix packages often fail to provide insights into the decision process when the number of options is large [Buede, 1992].

It was earlier indicated that our approach uses a non-linear, tree-like criteria structure in an attempt to more accurately represent potentially complex evaluation criteria and thereby to decrease problem complexity down to a manageable level. A representative software package based on such hierarchical structuring of evaluation criteria is Expert Choice that essentially is a software implementation of Saaty's AHP method. Expert Choice elicits weights & value scores using a specially designed interview-oriented process, and displays various graphs from its sensitivity analysis results [Buede, 1992]. Its features include mathematically derived priorities, numerical/verbal judgments made from pairwise option-comparisons, and computation of the inconsistency ratio in evaluation judgments [Expert Choice, Inc., 1993]. One problem that can be noted with this software is that some ratings data (such as work experience) need be normalized with arbitrary efforts on the part of the user. Other packages arranging criteria into a tree structure include Criterium, Treeval, and EXPERT87 [Buede, 1992].

In summary, three unique aspects can be pointed out that differentiate the present approach from others. The first is the incorporation of human choice strategies into ISBIS such that these choice strategies implemented as models can be freely selected and executed to meet the decision needs of the user. ISBIS therefore allows the user to 'simulate' decisions with different decision styles. The second way that ISBIS differs from others is that ISBIS provides three different modes of value elicitation, including the numeric scale, the interval scale, and the aspect scale, instead of a numeric-only scale. Other software programs designed to help solve multi-attribute problems rely mainly on numerical computations for utility analysis, and thus attempt to elicit solely numeric (or graphically quantified) values as indications of decision makers' preferences. In other words, the ISBIS's ability to rate the alternatives by choosing from a predetermined set of aspects (e.g., the aspect set for 'education' criterion: Doctorate, Masters, Bachelor, and High School) could importantly facilitate employing the elimination-by-aspects strategy. Thirdly and finally, the earlier discussed expert system subsystem in ISBIS also makes the present approach unique from other approaches; potentials for integrating ES with DSS are fully discussed in [Turban & Watkins, 1986]. It would help better meet the decision requirements, easing the potential cognitive demand for the decision maker.

Nevertheless, our approach has a few limitations, when compared with other decision software programs. One important feature that lacks in ISBIS is the capability of graphically displaying the information being processed. Especially, the graphical display of an evaluation criteria hierarchy would enhance the user's understanding of the problem structure and decision analysis. Secondly, ISBIS may not be suitable for decision problems where there are many, say over 20, options to evaluate; the option rating task under a complex criteria hierarchy could be highly demanding and time-consuming. Thirdly, ISBIS does not integrate the option generation function. Although few commercial software combines option generation and decision analysis, this function would potentially enrich decision support, linking decision options with the problem structure; i.e., the decision maker can flexibly reconfigure his decision case by adjusting/editing the options as well as his criteria structure, in a hope to resolve any potential mismatch between the system outcome and his expected outcome that reflects his personal insights into the problem. For a discussion of integrating option generation as a key component of decision support software, see Adelman [1987].

Ⅷ. CONCLUSION

This paper develops a multi-attributed decision support method to address qualitative aspects involved in fuzzy and complex managerial decision problems and presents a system architecture for designing a knowledge-based MCDM DSS, into which that method is incorporated. As the implications of such an intelligent DSS pointed out in the preceding section suggest, the present approach recognizes the need for, and places particular emphasis upon, decision aids for high-level management decisions for which the traditional, quantitatively-oriented decision support approach would not prove quite useful. Our architecture will provide DSS designers with insights into the fundamental issues pertaining to effective management of dialogue, models, and data in the design of an MCDM DSS. ISBIS demonstrates the usefulness of an intelligent decision support approach to assisting in unstructured managerial decision making via incorporation of an expert system component into DSS, hierarchical decomposition of a decision goal, facilitated preference formulation, and utilization of human choice strategies. Meanwhile, the present research has limitations. For example, it would have helped to validate the usefulness of the approach to offer some comparisons between system-supported loan decisions and manual ones.

The architecture presented in this paper entails continued research on the integration of MCDM theories with the DSS technology. Three prime issues can be articulated for future research. First, one needs to explore the differences in problem structures and characteristics between structured and unstructured MCDM, other than those discussed in the paper. Implications to be drawn from those differences should be very valuable for DSS designers, enabling them to highlight areas to focus on for decision support. Second, future research must place greater emphasis on extensive application of AI techniques to high-level managerial decisions. We need decision aids for top management that are far more supportive of cognitive processes involved in decision making than traditional DSS. Third, there needs to be more rigorous application of fuzzy set theory to managerial decision making in a more realistic way. While Bellman and Zadeh [1970] and more recently Zimmermann [1991] suggested a powerful method for using fuzzy sets to deal with fuzzy choices involved in decision making, their approach has been criticized by some researchers for the failure to incorporate the notion that the preferences of an individual decision maker are also fuzzy, incompletely formulated, incoherent, and conflicting (for example, see [Zeleny, 1980; Carlsson, 1982]).

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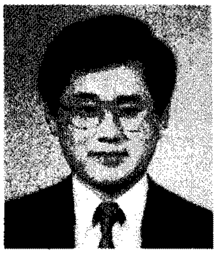
◇ 저자소개 ◇



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