Pergamon

Omega, Int. J. Mgmt Sci. Vol. 25, No. 6, pp. 691–706, 1997
© 1997 Published by Elsevier Science Ltd. All rights reserved
Printed in Great Britain
PII: S0305-0483(97)00040-6
0305-0483/97 $17.00 + 0.00

Multi-attribute Utility Methods in Group Decision Making: Past Applications and Potential for Inclusion in GDSS

UTPAL BOSE

Texas A M University, Corpus Christi, TX, USA

ANNE M DAVEY

Northeastern State University, Tahlequah, OK, USA

DAVID L OLSON

Texas A&M University, College Station, TX, USA

(Received February 1997; accepted after revision July 1997)

This paper reviews a variety of studies in which multi-attribute utility theory (MAU) has been used successfully to aid group decision processes and discusses the incorporation of MAU in Group Decision Support Systems (GDSS). GDSS of various levels of automation have been proposed to aid group decision making. A number of commercial GDSSs are available which are capable of aiding generation of alternatives, their evaluation, and selection. Many authors have promoted the incorporation of quantitative decision making models in GDSS. The most appropriate quantitative tool for GDSS is MAU, but MAU has rarely been utilized. The cases reviewed illustrate that the use of MAU techniques is not prohibitively difficult or complex. **© 1997 Published by Elsevier Science Ltd. All rights reserved**

Key words—group decisions, multi-criteria, utility, decision making/process

1. INTRODUCTION

GROUP DECISION SUPPORT SYSTEMS (GDSS) have become a popular research topic [1–4] due to the growing importance of group participation in decision making and the increasing capabilities of hardware and software to respond to the needs of decision makers. DeSanctis and Gallupe [2] proposed three levels of GDSS. Their first level included support to the group processes of generating ideas (brainstorming), evaluating alternatives generated, and voting to reach consensus. A second level GDSS was considered that would include model support. The third level added rules of order that would control the use of level 1 and 2 features.

Of interest to this paper are level 2 GDSSs that include multiple objective models of various kinds, particularly those which would include the use of such models to aid the aggregation of individual preferences. Several of these systems have been described in the literature [5–7] and a number of commercially available GDSSs have been developed [8, 9]. In a recent survey of GDSS research, Iz and Gardiner [10] provide descriptions and comparisons of GDSSs which incorporate a variety of multiple criteria decision methodologies to

reflect group preference. Most of these systems have not had multi-attribute utility (MAU) models included, possibly because of the perceived complexity of these models. Their survey found only three systems (of about 30) which proposed to use multi-attribute utility theory to analyze and or aggregate preference information [11–13]. Of the three systems only one had actually been implemented on a computer and used in a simulated decision-making situation [13].

The aggregation of individual preferences into a group utility function (i.e. a mathematical relationship combining individual preferences or utilities) has been studied by economists since the eighteenth century [14, 15]. MAU methods decompose the complex overall evaluation problem into smaller subproblems that can be better managed in terms of scaling, weighting, and combining criteria or objectives. Reintegration typically occurs within MAU through the application of utility functions and relative importance weights. MAU methods let us obtain the values of alternatives that have more than one useful attribute, thus involving evaluation on more than one criterion. A MAU model shows the decision makers how to aggregate the value or satisfaction derived from each of the various attributes into a single measure of the overall value of the multi-attribute alternative [43]. A group utility function, determined by aggregating the utility of each alternative over each attribute, incorporating the relative importance to each decision maker, might reflect the preferences and trade-offs among group members and would serve as an effective tool in group decision making when multiple objectives exist.

The purpose of this paper is to review some applications of MAU methods reported in the literature, to discuss the benefits of applying MAU methods, and to suggest how they may be incorporated into GDSS. A thorough scan of the management science and management information science literature was performed with the objective of including all relevant papers. Certainly some were missed. Included were those that reported the use of MAV or MAU techniques in a group decision-making situation. The review demonstrates that MAU theory has proven useful in group decision-making situations. It seems a logical step to design GDSS to help support this process.

We have categorized MAU cases into three types:

(1) Cases where a group utility function was determined;
(2) Cases where voting, sum of ranks, or an equivalent method was used;
(3) Cases where consensus was achieved informally.

Conclusions are drawn about the ability of MAU methodology to improve and increase the use of group decision support systems.

2. CASES WHERE A GROUP UTILITY FUNCTION WAS DEVELOPED

Table 1 summarizes some aspects of five cases where a group utility function was developed. These examples demonstrate that aggregated group utility functions can be successfully developed.

2.1. Dyer and Miles (1976)

Dyer and Miles [17] used a two phase process, based on von Neumann–Morgenstern utility theory [21] to generate utility functions to compare trajectories for the Mariner Jupiter/Saturn 1977 Project. Ten teams of scientists were charged with choosing a trajectory pair by consensus. Thirty-two trajectory pairs, which spanned a wide range of criteria achievement, were identified as potential candidates for the project.

In the first phase, these alternatives were ordinally ranked, in order of decreasing preference, by the teams of scientists. The second phase determined the preferences on a cardinal scale through the use of von Neumann–Morgenstern lotteries. First, each team compared each trajectory pair to a lottery between the most preferred and the least preferred pairs. Then, because the relative strength of preference between the least preferred trajectory pair and the most preferred trajectory pair could vary considerably from team to team, a normalization step to obtain inter-team comparability for the least preferred trajectory pair was used. This process resulted in a set of cardinal utility function values for the 32 alternatives from each team.

A combination of collective choice rules, normalization method, and weights yielded nine

Table 1. Cases where a group value function was developed

Authors	Decision context	Elicitation of individual preferences	Aggregation of individual preferences into group preferences	Final decision
Dyer and Miles (1976) [17]	Evaluation of trajectories for the Mariner Jupiter/Saturn 1977 Project	(Teams) ordinally ranked alternatives Utilities determined by lottery comparisons between alternative pairs	Used several collective choice rules: Rank sum, maximin, additive, and multiplicative collective choice	Three alternatives were ranked highest by all methods—discussion used to make a choice from amongst the 3
Golabi *et al.* (1981) [16]	Selection of a portfolio of solar energy projects for DOE	Standard utility assessment procedures.	Used the mean ratings of each attribute.	Projects were rated by utility scores and scores used to determine project. portfolios.
Dyer and Lund (1982) [18]	Definition and evaluation of strategies to merchandise gasoline and car products	Questionnaires to determine weights and partial utilities	Expert judgments to determine objective weights Group discussions to arrive at final weights and utilities	Highest utility option implemented Firm satisfied with results
Thomas *et al.* (1989) [19]	Evaluation of options for installation of a computer system	Nominal Group Technique used to generate criteria and alternative. Individual managers scored alternatives on each criteria and specified importance weights for criteria	Individual utilities calculated—then discussed, adjusted. Ratings done again by upper management and organizational utilities scores calculated	Highest utility alternative was adopted
Reagan-Cirincione *et al.* (1991) [20]	Generation and evaluation of policy options for New York State Insurance Department	Task force members scored policy options on 45 criteria, determined weights as stakeholders	Criteria listed hierarchically under stakeholders, different weights assigned to each stakeholder	Two options were equally scored—a hybrid was generated and recommended

methods for comparing both the ordinal rankings and the cardinal utility function values. Results were quite similar. Three of the trajectory pairs were consistently highly rated and further discussion among the teams led to selection of one of these trajectory pairs. Apparently ordinal rankings and the rank sum collective choice rule would have been sufficient to identify the final selection. Cardinal evaluation, however, tested the collective choice for sensitivity to different strengths of preference not revealed by the ordinal rankings.

Responses to post analysis questionnaires indicated that participating in the process increased decision makers' understanding of the relationship between criteria, characteristics of alternative pairs, and differences in preferences. This appears to have satisfied two of the goals of the process which were to "assist each team in gaining an in-depth knowledge of its preferences and to provide a language of preference to facilitate communication between teams." Participants indicated that the determination of utility functions enhanced communication of other scientists' understanding of the relationships involved. The exercise also speeded up the decision. Prior to the exercise no preferred trajectory had been identified, despite requests for such a choice. In addition, the exercise may have prevented a poor result. A trajectory that had been given serious consideration was ranked 28th by the rank sum collective choice rule, and thus found to be clearly inferior to the final choice. The cardinal utility evaluation contributed to the process by aiding selection from among the top three candidate pairs and also permitted a wider range of collective choice rules to be used.

There appear to be a variety of ways that use of a GDSS could have supported this decision-making situation. Input through a GDSS, designed to accept preference data, analyze and compile it and then communicate results to participants could be expected to eliminate the need for much of the human facilitators' time and effort and to speed the process along. There could also have been automatic checks for internal consistency of preference assignments. This additional support might have prompted the scientists to come to a decision earlier. As indicated above, despite previous requests for a choice, none was made before the utility analysis process was implemented.

2.2. Golabi, Kirkwood and Sicherman (1981)

Golabi *et al.* [16] used MAU in the selection of solar energy projects to be funded by the United States Department of Energy. They combined a multi-attribute utility approach with another approach to deal with different aspects of a portfolio selection problem. The multi-attribute approach was used specifically to evaluate the technical quality of individual proposals and the other procedure was applied to the portfolio aspects of the problems. The authors worked with technical personnel to establish 22 attributes to measure the technical value of each proposed project. Standard multi-attribute utility assessment procedures were carried out [22] and a utility function of the following form was developed:

$$u(x_1,x_2,\ldots,x_M) = \sum_{m=1}^{M} k_m u_m(x_m) \qquad (1)$$

where u is the von Neumann–Morgenstern utility function over the 22 attributes, $u_m(x_m)$ is a utility function over each individual attribute, and k_m is a constant. The authors report that use of the utility function avoided some assessment difficulties and was easily obtained. Five evaluators filled in an evaluation form with attribute levels for each proposal and the mean rating was used in computation of the utility function. Calculations were performed by a computer. In cases where the ratings among the evaluators were very different, the computer flagged the case so that evaluators could review and possibly revise their input. The computer also provided summary reports including the utility values for each proposal, a rank-ordered list of the proposals and some other data. The output from this MAU analysis was used as input to the second part of the analysis which was to select a portfolio of the proposals.

Although a computer was used in this case it could not be considered a GDSS. It does, however point out that the MAU analysis could easily be programmed and performed by a computer. Adding the interfaces for user input and links so the users could communicate with each other would be a relatively minor task.

2.3. Dyer and Lund (1982)

Dyer and Lund [18] applied MAU and judgmental modeling to define and evaluate strategies for merchandising gasoline and car products through full-facility service stations. The model covered manufacturing, distribution, and retail outlets with merchandising options at all three levels. The authors implemented the MAU model.

A merchandising event was described by the type of transaction i, the type of product j, the type of retail outlet k, and the type of marketing channel l. Each possible combination of these four dimensions was treated as a separate objective or criterion of the model. Variations in dimensions resulted in 660 objectives, too cumbersome to apply trade-off analysis to determine weights. Therefore, expert judgments were obtained to evaluate how a strategy would affect an objective on the four dimensions. These judgments were combined with quantitative data on product sales margins reflecting the contribution to profit generated by each objective in order to estimate weights w_{ijkl}. An additive utility function was developed to estimate overall value of each merchandising strategy or alternative. The overall utility of strategy a, $V(a)$, is expressed;

$$V(a) = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{l=1}^{L} w_{ijkl} v_{ijkl}(a) \qquad (2)$$

where i, j, k, and l are the four dimensions described above, w_{ijkl} are the estimated weights, and $v_{ijkl}(a)$ are conditional utility functions representing an evaluation of the performances of the merchandising strategy for a single 'objective' defined by i, j, k, and l.

Twenty-four separate decision areas, such as product line, price, sales promotion, etc., were identified as forming the basic merchandising strategy of the company. Various combinations of these 24 decision factors were used to identify 11 possible merchandising strategies. The conditional utility function $v_{ijkl}(a)$ for each strategy a depended on partial functions representing evaluation of the strategy on the 24 decision areas.

Seventy-two decision makers participated in group discussions of the questionnaires to arrive at values for w_{ijkl} and V_{ijkl}. The 11 strategies were evaluated using model (2) and a choice was made. Implementation of the strategy proved to be successful and the firm was satisfied with the application of the MAU model to its merchandising strategy problem.

Dyer and Lund [18] developed a very complex model by decomposing the system into simpler elements in order to get decision maker inputs. Essentially the method used subjective estimations of weights and partial utility functions. Extracting all of the necessary information through questionnaires, meetings, analysis, and model building took approximately two years. The model that resulted could be generalized to any industry with similar manufacturing-distribution-retail organization.

While the application was a successful implementation of decision theory, a GDSS could have helped speed the process by facilitating the collection, organization, and analysis of data. The Dyer and Lund [18] study involved an large number of decision makers (72) and interaction and coordination between them did take a lot of time. GDSSs can be operated in the mode of 'one time, different places' where decision makers don't necessarily have to gather in one meeting room to participate. This flexibility can make it easier for decision makers to fit meetings into their schedules, thus avoiding long waits before a group meeting can be arranged.

2.4. Thomas, McDaniel and Dooris (1989)

Thomas *et al.* [19] used MAU techniques to evaluate and combine information generated by managers using the Nominal Group Technique [23] for a computer system installation decision. MAU techniques allowed decision makers to define a structured decision making process and combine results from unit or division specific Nominal Group Technique (NGT) sessions to be combined into solutions applicable throughout the organization. The decision process was described in three phases. The authors conducted the meetings, compiled results, and presented this information to group participants.

The first phase involved using NGT to gather information, generate system alternatives, and identify criteria for judging alternatives. NGT encouraged participant involvement and open generation of ideas. Participants from five divisions contributed ideas, clarified these ideas, and ranked responses. Questions were designed to uncover evaluation criteria and perceptions about alternative solutions.

In the second phase, managers in each division group rated each alternative in terms of how well that alternative performed on each criterion. The alternatives were scored on a scale of 1–10. Then weights were elicited from managers reflecting the importance of each criterion on a scale of 1–100. Using a weighted additive utility function, the value of each alternative was calculated using each decision maker's weights. These results were presented to decision makers through on-line networked personal computers, allowing decision makers to change their weights and see the impact of these changes. Intradivisional differences were discussed and negotiated using the MAU model as a focal point.

The third phase moved to the organizational level. Divisional alternatives were combined into organization-wide alternatives, and evaluation criteria were adapted to relate to organizational needs. Each division manager rated the organizational-level alternatives on a scale of 1–10. The CEO rated the importance of criteria on a scale of 1–100. These scores and weights were then reviewed and discussed at an organizational meeting and used to produce a utility function for the overall organization. The feasibility of the preferred alternative was discussed, and a final decision made. The information system with the highest utility score was ultimately selected by the organization.

The effectiveness of this process was indicated by the positive opinions of the participants. Questionnaires were completed after the first phase of the process and at the end of the process. These questionnaires included questions concerning satisfaction with and commitment to the process and the final decision. In addition, although the selected system was substantially different from a system previously favored by the MIS staff, there was little resistance to change when the final decision was made.

In the study by Thomas *et al.* [19] a rudimentary GDSS was used, as personal computers were networked to display results of the analysis as inputs were compiled and tallied. Decision makers were allowed to change their inputs and see the results of these changes. The nominal group technique was used in the first phase of the analysis in this study. At least one commercial GDSS [9] includes nominal group technique support. Participants indicated their satisfaction with the process and with the decision that resulted. The firm retained the

technique for use in other decision-making situations, and were able to use it without decision analyst guidance. We view this as evidence that a GDSS incorporating MAU, available for use when needed, would be valuable even without technical guidance.

2.5. Reagan-Cirincione, Schuman, Richardson and Dorf (1991)

Reagan-Cirincione *et al.* [20] reported use of MAU and simulation to generate and evaluate policy options in resolving a medical malpractice crisis for the New York State Insurance Department. A task force was created consisting of members of the State Insurance Department aided by a consulting firm. A systems dynamics model, built by a group from the State University of New York, was used to aid the task force in examining the implications of various policy options. Three multifaceted options were generated to be evaluated by MAU. The systems dynamics simulation model enhanced understanding of the medical malpractice system, making it easier to develop the value model.

The MAU model was structured in a hierarchical manner. Six stakeholder groups were identified at the top level: health care consumers, hospitals, lawyers, malpractice victims, property and casualty insurers, and doctors. Forty-five specific criteria were identified under various stakeholders. For example, lawyers were assigned criteria of case merit, process, the role of lawyers, and compensation. Hospitals were assigned criteria of cost, reimbursement, malpractice visibility, and doctor selection. Task force members played the roles to assure the perspective of stakeholders were represented. The impact of each of the three policy options on each criterion were developed. Scoring on a 0–100 scale was used, with the worst option receiving a score of 0 while the best option received a value of 100. When task force members disagreed about the impact of an option, a midrange value was selected and the value noted to be tested during sensitivity analysis.

The next step was to assign relative weights to each stakeholder, and therefore to each criterion. The task force established normative estimates of the influence different stakeholders should have in policy evaluation. Overall scores for each option were calculated using the weighted linear additive MAU function:

$$V(x) = \sum_{i=1}^{N} w_i x_i \qquad (3)$$

where $V(x)$ is the overall evaluation for option x, w_i is the weight given to criterion i, and x_i is the rating for option x on attribute i, and N was 45 for the total number of criteria.

By using this function, the task force found two policy options to be equally rated as best. To test model assumptions and to gain further insight, sensitivity analysis was conducted. The same two policy options still scored highest. The MAU approach ensured a thorough and equitable evaluation of all policy options and enhanced accountability by making the criteria by which evaluations were made explicit. MAU also allowed task force members to more easily compare the strengths and weaknesses of policy options and to use this analysis to generate a stronger hybrid option.

The Reagan-Cirincione *et al.* [20] study also used a form of GDSS. There were three decision conferences, or computer supported meetings, during which group members examined the impacts of different policy options using a simulation model, evaluated options using a multi-attribute utility model, and developed a final recommendation. A computer software package called HIVIEW was used to perform the multi-attribute value analysis, and to calculate overall scores for each alternative. The task force was pleased with the speed and efficiency of the process. The multi-attribute utility model encouraged those participating to think in new, fresh and mind-stretching ways. Task force members found that constructing the MAU model helped them clarify the demands of different stakeholders and to develop better policy recommendations.

2.6. Discussion of aggregated utility functions

The examples of Dyer and Miles [17], Golabi *et al.* [16], Dyer and Lund [18], Thomas *et al.* [19] and Reagan-Cirincione *et al.* [20] showed how individual utilities could be aggregated.

Thomas *et al.* [19] also demonstrated how nominal group technique could be incorporated

into such a solution process. Dyer and Lund [18] demonstrated how to decompose complex problems to make them more workable.

In related work, Wang and Shen [24] propose a GDSS which aids a group in a three step process which includes developing an aggregate utility function. Wang and Shen [24] also discuss the importance of allowing decision makers to change preferences in response to becoming aware of the preferences and ideas of other participants. A GDSS approach where decision makers are able to input preferences, examine others preferences and the resulting aggregate rankings, and then revise and refine their own inputs will be of great value. This was demonstrated by the computer support in the Thomas *et al.* [19] study and in the Golabi *et al.* [16] case.

Golabi *et al.* [16] also used computer support to calculate utilities although decision maker inputs were gathered on written forms and presumably keyed in by support staff. In addition to calculating utilities for individual proposals, the computer printed out results for review by decision makers, including utility values, a rank-ordered list of the proposal and some other information. Although they did not have the user interface and input capabilities that we normally associate with GDSS, they did have some of the MAU modeling tools that we are promoting in this paper. Golabi *et al.* [16] reported that the MAU procedures they developed had been applied to other funding decisions and concluded they would be useful in a variety of situations.

The implementation of MAU has been noted to require care and professional expertise in its application as indicated by the cases reported above and others [25, 26, 22]. The study by Dyer and Lund [18] found that the systematic analysis of their approach was useful, but noted that care should be taken to avoid extreme positions on the part of some group members. Lathrop and Watson [27] applied linear aggregation of group members to obtain group utilities. But those authors noted that there were some difficulties in implementation, and noted that no entirely satisfactory method for devising group utilities exists. Therefore we will discuss other approaches to the problem, beginning with cases where ordinal rather than cardinal aggregation has been applied.

3. CASES WHERE VOTING OR SUM OF RANKS WERE USED

If cardinal measures of group utility are too elusive to obtain without expert decision analysts, more fundamental aggregation methods might work. Two examples using ordinal aggregation methods are reviewed. Table 2 summarizes some of the features of these cases.

3.1. Lincoln and Rubin (1979)

Lincoln and Rubin [28] used a MAU approach to identify the preferred control strategy reflecting specific pollutant trade-offs in an environmental emissions model for a coal-fired power plant. Two individuals each from an electric utility, a state control agency, and an environmental group had the task of selecting an emission control scenario for three types of coals. A scenario consisted of an emission control technology and an emission standard. The selected scenario would define emission levels of six pollutants acceptable to all groups in light of trade-offs.

A computer model for coal-to-electric power systems was used to determine emission levels for each pollutant for a type of coal. Five of these scenarios reflected alternate systems and degrees of control for sulfur dioxide emissions. Single attribute utility functions for each of the six participants were identified following Keeney [29]. Five discrete points were fitted to equation (4) using the least squares method. Individual utility functions were constructed of the form:

$$V_i(x_i) = 1 + b_i(1 - e^{c_i(x_i - x_{\min})/(x_{\max} - x_{\min})} \quad (4)$$

where $i = 1$, 2, and 3 reflected air, land, and water pollution respectively, b_i and c_i coefficients are derived from the least squares analysis.

Total utility functions for each decision maker were constructed using the form:

$$1 + KV(x) = \sum_{i=1}^{3}[1 + Kk_iV_i(x_i)] \quad (5)$$

where $V(x)$ is overall total utility for alternative pollutant emission mix x, and K, and k_i are parameters empirically derived from test data.

Inputs from individual decision makers were obtained through interviews by researchers. Individual utilities were aggregated into three

Table 2. Cases where voting or sum of ranks were used

Authors	Decision context	Elicitation of individual preferences	Aggregation of individual preferences into group preferences	Final decision
Lincoln and Rubin (1979) [28]	Identification of optimal strategies for environmental emissions models for a coal-fired power plant	Individual utilities determined through interviews with researchers	Aggregation of individual utilities by: method of marks and majority rule	Same alternative was chosen by both rules
Edwards and von Winterfeldt (1987) [26]	Formulation of public policies for energy management in Germany and water control in Arizona	Interviews determined measurable values (decision criteria) and weights	Rank sums	Nearly dominant alternative was found

group values, one for each interest group, by developing a 'social utility preference' using both the method of marks and majority rule. The method of marks involved assigning a mark of '5' to the scenario with the greatest value and a mark of '1' to the scenario with the lowest value. Marks were equally distributed across ties. Rank scores were summed and normalized to a range of 1–5. The same alternative was selected by both the method of marks and by majority rule.

3.2. Edwards and von Winterfeldt (1987)

Edwards and von Winterfeldt [26] developed a process for structuring and clarifying public values and applied it to an energy policy decision in Germany as well as a water control decision in Arizona. The German study did not aggregate individual preferences, but the Arizona study used voting for that purpose. The objective was to formulate public policies by assisting stakeholder groups to articulate their values and concerns in a way that could be useful to both the regulator and to other stakeholders.

The proposed method involved five steps. First stakeholder groups were identified—a short list of 5–10 groups representing major points of view was suggested. Second, a set of decision options was identified. Third, stakeholder views about the problem were structured in terms of options for dealing with risk and in terms of the criteria used to evaluate the options. A tree structure was used to organize these values. Stakeholders were interviewed to determine their values and the tree was constructed to the approval of the stakeholders. Once each stakeholder group had their own value tree, the fourth step was to construct a common value tree. Discussions were held to ensure that the common tree satisfied every stakeholder and contained a subset of the values of every stakeholder. The lowest level of this tree was clearly defined so that the impact of each option was measurable. Finally, weights were assigned to criteria and quantitative value models were developed for each stakeholder group. The common tree was used by each stakeholder group, but with different weights. These models were then used to generate an overall numeric evaluation of each option, preference differences were identified, and these

findings were used to assist in conflict resolution.

The purpose of the Arizona water control study was to select a dam project to satisfy Arizona's water needs. Sixty stakeholder groups agreed to participate. The consultants who conducted the study identified eight alternatives. The consultants identified criteria because of the large number of stakeholders. Fourteen criteria were identified, including costs, net benefits, flood control, water quality, habitat, relocation, and recreation and measurements for each were developed. Six meetings of ten groups each were organized in order to simplify the process, with each meeting emphasizing a different subset of the fourteen criteria. Stakeholders were asked to pick which meeting they would attend. The meetings were used to determine relative weights for the fourteen criteria. Participants were provided with an unnumbered scale with endpoints labeled 'not important' and 'most important' and were asked to rank order the fourteen criteria on this scale. Weights obtained from individuals were averaged to determine a set of weights for each of the six meetings. Discussion and revision of the averages continued until participants agreed on the weight set. Overall desirability scores for each of the eight alternatives were obtained by multiplying each group's mean weight for each attribute by the technical performance score expected for that alternative on that attribute and then summing over the attributes. This resulted in six sets of scores for the eight alternatives. Rankings of alternatives based on these scores were summed and a nearly dominant alternative was identified. The preferred alternative was ranked first by three groups, second by two groups, and third by the sixth group.

3.3. *Discussion of voting or sum of the ranks methods*

In these applications, pooled groups were used to assure that all views were represented at equal weights. Other voting schemes are possible, as proposed by Keeney and Kirkwood [30]. These include use of a benevolent dictator or honest broker to determine relative weights. These ordinal approaches are expected to be stabler and require less effort for accurate measurement than the cardinal approaches discussed in the previous section.

In the study by Lincoln and Rubin [28] interviews were conducted with participants following a pre-structured format developed from the work of Keeney *et al.* [31]. This procedure could be automated so that participants entered their preferences into a GDSS and the value function developed automatically.

The meetings used in the Edwards and von Winterfeldt [26] studies could have been conducted via GDSS facilitating easy input, display and revision of individual preference information—either rankings or weights. Some of these functions are available in current GDSS software.

While these ordinal methods may be easier to apply, there may be a desire to gain group consensus without voting or ranking. Voting and Ranking are considered to have weaknesses and may lead to inconsistent results [32]. One voter may have a very weak preference, while another has a very strong preference, but both votes count the same. The same applies to rankings. Ranking 1–2–3–4... implies equal spacing, while MAU provides a scale which considers finer differences. Reliance on the Japanese approach of consensus building may be a preferred approach, particularly in cooperative situations. Consensus building may also enhance implementation of the chosen solution because all participants have 'bought' into it. This approach has been used in the cases to follow.

4. CASES WHERE INFORMAL (OR NO) AGGREGATION WAS PERFORMED

The following three studies (summarized in Table 3) demonstrate cases where there was no formal attempt to combine the utility functions of group members. There was no effort made to have the analysis reach a conclusion. The focus was on aiding the group process so that some consensus would emerge.

4.1. *Ulvila and Snider (1980)*

Ulvila and Snider [33] developed a model of negotiation between countries seeking improved oil tanker safety and pollution prevention. The model was used to prepare US negotiators for an international conference and to ultimately develop a proposal acceptable to other nations. The objective was to use an additive multi-attribute value model to represent negotiations

Table 3. Cases where informal (or no) aggregation was used

Authors	Decision context	Elicitation of individual preferences	Aggregation of individual preference into group preferences	Final decision
Ulvila and Snider (1980) [33]	Negotiation among countries to improve oil-tanker safety and pollution prevention	Interviews/questionnaires used to assign weights to criteria	Used results to define an alternative that would be scored highly by safety and pollution prevention	Defined a package acceptable to a large number of countries and close to final conference agreement
Keeney *et al.* (1986) [31]	Determination of strategy for adding electric generating capacity at a plant site	Interviews—value-trade-off questions	No aggregation—one respondent's results were used because all were similar	A preferred strategy was clearly indicated by the individual utility function modeling software was transferred to the firm for future use
Jones *et al.* (1980) [34]	Development of UK energy policy options	Users rated relative importance of attributes. Each option was given a score for each attribute. Individual utilies were calculated.	No aggregation. Utilities scores were used for discussion and negotiation	Model was used as a tool to represent different viewpoints and framework for discussion

from the perspectives of many of the participants. Task teams of US Coast Guard personnel were used to represent different countries.

The process involved the following six main steps:

(1) Identify criteria that could be applied by each country to evaluate alternative sets of tanker construction and equipment standards.
(2) Define several possible alternative sets of tanker construction and equipment standards and score them on each criterion.
(3) Investigate whether any alternative was dominant.
(4) If no dominance existed, assess relative importance of the impacts of alternative standards on criteria and use these to evaluate the attractiveness of each alternative to the USA and to the other parties involved in negotiations. Assign weights to criteria, giving 100 points to the most important criteria and proportionately less to the others according to each parties' preferences.
(5) Examine the robustness of the conclusions to numerical assessments given.
(6) Use the model to explore for new alternatives exploiting possibilities for joint gains.

Eleven criteria were identified by analysts in a process of defining and redefining the problem in order to obtain a set of criteria that were representative of participant concerns as well as being at least nearly additive. Criteria included world oil outflow, oil in a country's own waters, safety, costs of various kinds, ease of passing cost to consumers, tanker surplus, shipyard activity, competitive advantage, and enforceability. Comprehensiveness and the use of standard terms allowed additive value functions to be used to assign weighted average scores to the alternatives. In addition, the criteria aided in emphasizing the differences in preferences and non-overlapping interests among interest groups.

Four alternatives, including the current safety standard, were evaluated on each criterion. Each score represented the impact of the alternative on the criterion relative to the status

quo. Scores were standardized on a 0–100 scale. For the world oil outflow and oil in a country's own waters criteria, hierarchical models were developed for alternative scoring. For other criteria direct assessment (i.e. $ for cost) was used. All measurements were rescaled to a 0–100 scale.

Relative importances of the impacts of alternatives were assessed on the 11 criteria by asking the task teams to compare the importance of the criteria and to assign weights. Analysts asked questions to refine weights to accurately reflect respondent preferences. Consensus within each task team was reached through group discussion. Each alternative was evaluated from the point of view of each task team (representing different countries) based on a weighted average score. The process helped delegates develop a useful structure for dealing with a complex negotiating situation by:

(1) aiding delegates in disaggregating the problem into manageable parts without losing sight of the overall problem;
(2) allowing delegates to use the model to analyze various parts of the problem;
(3) Identifying a system to evaluate the alternatives with respect to US interests;
(4) anticipating the evaluations and positions of other countries;
(5) incorporating technical data from a variety of sources into the evaluations.

The analysts were eventually able to define a package that was acceptable to a large number of countries and was very close to the final agreement reached at the conference. The model proved to be an effective vehicle for communication, strongly influencing the way delegates formulated and presented their arguments at the conference. It helped delegates to understand the situation, anticipate positions of others, create new alternatives, and facilitate and focus communications.

4.2. *Jones, Hope and Hughes (1990)*

Jones *et al.* [34] developed and operated a multi-attribute utility model to study energy policy options in the United Kingdom. Model development included identification of stakeholders, options for action, attributes, and empirical indicators. Model operation involved ranking of attributes, rating of attributes in importance preserving ratios, scaling of ratings, scoring options on each attribute, calculation of utilities, and decision. Decision analysts implemented the MAU model.

About 25 individuals from 16 stakeholder organizations were involved in the analysis of five energy policy options for the UK. An initial list of 30 attributes to be included in the analysis was gathered from publications of a variety of interested organizations. The list was presented to participants who were asked to select the 15 most important attributes. This limit was selected to reduce the time required to run the model, and to make the exercise more manageable. Participants were asked to identify an appropriate empirical indicator by which the performance of an energy policy on each attribute could be measured and a range of feasible values for that indicator. During this process a number of attributes were added to the list, bringing the total to 41 attributes. Participants were then asked to determine the relative importance of their 15 attributes on a 1–100 scale, and finally to evaluate the performance of the five options on each of the selected attributes. Each option was given a score for each attribute on a range of 0–10 with 0 indicating the worst outcome.

The results were displayed in tables and graphs listing all attributes, their indicators, and the best and worst values and ratings. There was also a listing of attributes with scores for each option and weighted scores for each attribute. Weighted scores were calculated by multiplying scores times ratings and dividing by 100. Total weighted scores for each option consisting of the sum of weighted scores over each attribute were displayed. Bar graphs displayed weighted scores for each option on each attribute to clearly indicate the most preferred option, the contribution of each attribute to the total, and the relative performance of each option on each attribute.

Each individual participant could compare their value assignments with others. However, there was no aggregation of different viewpoints. The model was used as a tool to represent different viewpoints. It was suggested that this aided communication and understanding between participants.

4.3. Keeney, Lathrop and Sicherman (1986)

Keeney *et al.* [31] used MAU and decision analysis techniques to help determine the best strategy for adding electrical generating capacity at a plant site. Fifteen attributes were combined into an overall multi-attribute utility function incorporating value trade-offs between objectives and attitudes toward risk. The evaluation function was assessed in a series of interviews with members of the organization's executive following Keeney and Raiffa [22] and Keeney [35]. These value trade-offs were used to estimate a complete set of scaling weights on the attributes for each participating executive. Because of similarity of responses from all participants, one was selected as representative of collective values. No other aggregation method was used. The resulting function indicated the significance of various attributes in the choice of technology. Twenty options were evaluated by using the expected utility function and a preferred strategy was clearly indicated. Extensive sensitivity analysis was also performed.

Participants indicated that the process was at least as valuable as the outcome. The process gave them a means to structure the problem, to ensure that questions that needed to be asked were asked. The process also served as a framework for future analyses and for sensitivity analysis, and served as an effective means of documentation.

4.4. Discussion of cases where no aggregation was performed

These last examples demonstrate the appropriateness of the interactive approach in obtaining the preferences of a decision maker or a group of decision makers. There exists evidence of interaction between solutions of the model and the preferences of decision makers. The interactive methods demonstrated in these cases follow the definitions given by Despontin *et al.* [36] that an interactive method is an information procedure between solutions of a model in the objective space and the preferences of a decision maker, given the feasible region in the decision space and a set of objective functions. The information given to the decision maker includes trade-offs, attainable values of goal variables, and a set of efficient solutions. The preference-information required from the decision makers includes reference points, goal constraints, and subjective marginal rate of substitution. We see in all three cases that the feasible region or the set of objective functions changes during the sessions.

It is evident from the cases that the interactive approach helped decision makers learn about their preferences, which were initially sometimes vague and not exactly known. For instance, in the Jones *et al.* [34] study, the identification process generated additional attributes, some of which showed up in the final shortened list of attributes. Whether the information exchange procedure is progressive and convergent depends mainly on the capabilities of the decision maker. It is known that the human mind is limited in its information processing capability [37], due to which a decision maker is rarely able to analyze the whole system when formulating the problem domain [38]. A GDSS can be expected to fill the void by assisting with information processing and providing structure to the problem by quantifying and ordering the preferences among criteria and reducing the different individual preferences among criteria to a single collective preference.

It is noted that in the last set of cases presented, the interactive method concentrates the discussion on the critical issues of the decision problem. This leads to a reduction of the divergence of opinions assuming that all members of the group are willing to express their judgments. In practice, this is often difficult to achieve because members are apprehensive that an honest judgment may annoy their colleagues, or may be ridiculed by group members as being trivial or irrelevant. A GDSS overcomes such hurdles because the anonymity of participants in the communications provided by the GDSS encourages the participants to be more forth-right with their opinions. Finally, the examples in this section stress the use of utility models to better understand the decision making environment, especially the positions of stakeholder groups. The aim is to further the process rather than to have an efficient decision reaching system.

5. DISCUSSION

The type of task that confronts the group determines the need for a decision structuring tool and its type to be incorporated in GDSS

design [2]. One major goal in decision-related meetings is to choose alternatives, which has been exemplified in several of the studies discussed here. Tasks to be carried out in such meetings are intellective tasks that require selection of the correct alternative and preference tasks that require selection of an alternative for which there is no objective criterion or correct solution [39]. To support such tasks where alternatives are known and need to be evaluated by group members, the objectives of GDSS technology should be to assist in the selection of either the correct alternative or the socially preferred alternative. It has been suggested that GDSS used in these meetings should include features that prompt members on their preferences, combine these preferences and then display the results for discussion [2]. Bui and Jarke [40] have suggested that multi-criteria decision models could be particularly useful in these decision making situations. Reagan-Cirincione *et al.* [20] suggest that MAU is most applicable to certain types of problems, particularly those with a limited number of discrete options that are to be evaluated on multiple criteria or stakeholder perspectives. They also indicate that MAU techniques are valuable for examining the strengths and weaknesses of options and can be used to generate new options. In their study of the New York State medical malpractice crisis they were able to develop new options that combined the strengths of existing options. Our review of the research studies indicates that incorporation of MAU in GDSS has a great potential to aid the group decision making process. MAU provides a means for group members to better understand their own preferences, as well as the preferences of other group members.

Using MAU, individual decision makers can express their preferences in various ways. As in [28], once decision makers have developed their utility functions, each decision maker can evaluate alternatives and form a rank order of these alternatives, after which the ranks are summed. This type of representation has been the basis of the theory of social choice in welfare economics. If the group preference is represented by a cardinal utility function, as in Dyer and Miles [17], or cardinal values for a finite number of alternatives, then it more fully reflects individual preference attitudes towards the alternatives.

The approaches discussed have considered the measures of alternatives as given and found the group's preferred alternatives based on these measures. The result of aggregation was chosen as the final group preference. On occasion, the value of attributes and their weights are assessed by decision makers without their understanding the general nature of the alternative that is scored highest by their utility function. If this occurs the final selection may surprise the decision maker, who may then realize that attribute utilities and weights for certain attributes had been incorrectly assessed. Though it is normal that some decision makers will be pleased with group preference while others will be less satisfied, it is important that the level of satisfaction with the group decision should be based on a true understanding of the decision problem by the decision makers. Sometimes when a decision maker finds it hard to understand the nature of the alternatives, clarifications by fellow group members can help. However, individuals often hesitate to seek clarification because they do not want to reveal their ignorance, fearing ridicule from their colleagues. If the meeting is conducted with GDSS support, such situations can be avoided because the anonymous feature of the system hides the identity of the participants allowing them to freely ask questions.

Group preferences obtained by applying various aggregation methods are truly effective only when there is consensus within the group about what measures are to be used. This means that the multi-attribute hierarchy for the decision problem has to be constructed in such a way that is accepted by all members of the group. Kersten [7] argued that utility functions are non-stationary and in group decision making, concessions and negotiations among group members will cause changes in individual (and therefore group) utilities. Kersten [7] indicated that even though a solution might maximize utility value, it may not be acceptable to all group members because of perceptions concerning the relative positions of each individual decision maker. For instance, if the position of only one member is improved, others perceive that their positions have worsened. Using GDSS technology is likely to provide improved communication channels, supported by graphics and charts, that will go a long way in clearing up misplaced perceptions.

For example, an anonymous bar chart indicating the relative importance of attributes assessed by all individual decision makers, along with those for the group, is likely to make an objective impression on the decision makers and remove any misconceptions. Another situation where we can use this approach is where we have individual decision makers' utility functions. Distances or differences between decision makers can be identified on the basis that each decision maker's preference is expressed as a vector whose components are his values over attributes. The distances, when displayed anonymously with the help of a GDSS graphic module, are expected to help in understanding each decision maker's location in the entire group, which in turn helps the group to move towards a consensus.

Watabe *et al.* [41] presented discussion of alternative means to weight individual utility functions in order to reach a consensus acceptable to all participants. The Japanese approach is to discuss the options and trade-offs until a consensus is reached. To improve the probability of consensus, alternatives could be selected based upon a weighted score. Approaches used included a democratic weighting, where each participant had an equal vote; weighting including individual influence; and weighting reflecting the difficulty of persuading an individual. Those authors stated that all of these weighting methods had been observed in Japanese decision making, although weighting by individual influence seemed to be the most common. If a consensus is not possible, other means of reaching a decision need to be implemented. Dyer and Forman [42] discussed four group decision contexts, with conflict resolution strategies suggested for each (they suggested the analytic hierarchy process as a means of identifying individual and group value). If the members of the group held very similar objectives, shared development of criteria and evaluation was suggested, much as in the Japanese approach of Watabe *et al.* [41]. If, however, consensus was not attainable on a particular issue, voting or compromise could resolve the conflict. Calculation of the geometric mean of value functions was recommended if the group members were unwilling to vote or compromise. Finally, if group members held significantly different objectives or outlooks, it was suggested that each group member make individual judgments separately, which could then be shared, as in the Delphi method. By using a GDSS, the voting and calculation of the geometric mean of value functions can be automated, speeding up the decision-making process. The Delphi method, which is a time consuming process, can be accelerated considerably with the use of a GDSS.

Consensus can be obtained only after sufficient mutual understanding among group members has occurred. This aspect has been given considerable priority in Edwards and von Winterfeldt's [26] approach as applied to German energy policy where the goal was to have different stakeholders construct hierarchies and then combine them so that criteria involved in selecting an energy policy could be discussed by the public in a more effective manner. Group discussion and feedback, when used, helps modify the decision situation so that it is better understood and group consensus is facilitated. Progress can be gained by modifying the set of alternatives as in [33] or modifying the attribute hierarchy as in [26]. Iz and Jelassi [6] stated that combination of individual preferences into a group utility function requires explicit interpersonal comparison of utilities. In most of the cases examined here, this was done. Discussion and evaluation of participant preferences and their differences was part of the process in most of the cases examined. Since extensive communication plays an important role within the MAU method in these approaches, it seems reasonable to use a GDSS to make effective use of its communication and information storage modules and when the MAU module is added on we are likely to have a very effective decision aid.

6. CONCLUSIONS

In this paper we have tried to categorize the various ways group decision making has been approached when applying MAU and have argued that a GDSS containing a MAU based model can be a valuable asset to aid in group tasks which require selection from among alternatives. We have described some applications which appear in the literature and can be categorized on this basis. Existing MAU models have focused on identifying individual utility values. The best way to aggregate these values has not been totally resolved. Aggregation of

individual preferences has been accomplished by construction of group utility functions, through other collective choice rules, or through informal means. In some cases aggregation has not been attempted at all.

Several propositions that are expected to help in MAU-assisted group decision making have appeared. Quantified identification of individual preferences followed by aggregation of these individual preferences into a group preference is a very effective means for representing and understanding the situation objectively. However, a two-step process consisting of identification of individual preferences immediately followed by aggregation of those preferences may not produce true consensus. More communication between decision makers to help them better understand the decision problem will help them identify their preferences more correctly. Feedback of group preferences will provide them the opportunity to assess where they stand with respect to other members of the group and give them the option to revise their preferences. GDSSs are well suited to assist here.

We conclude that MAU models can be useful in GDSSs as a means for group members to better understand the positions of other group members. This should lead to broader examination of factors bearing on the decision problem. We expect the usefulness of such models to be primarily in the process of group members learning more about the decision problem, to include the desires and expectations of other members of the group. Group decisions are inherently time consuming as it is. It appears to us that the extra time required for development of cardinal measures of individual utility, or even ordinal measures of such functions, may not be necessary. The procedures outlined by Edwards and von Winterfeldt [26] appear to offer a useful structure that would lead to better understanding on the part of group members. Hopefully, consensus might emerge making voting superfluous. If voting is necessary to ultimately reach conclusion, a simple system accepted by group members would appear best.

REFERENCES

1. Beauclair, R. A. and Straub, D. W., Utilizing GDSS Ttchnology: Final report on a recent empirical study. *Information and Management*, 1990, **May 18,** 213–220.
2. DeSanctis, G. and Gallupe, R. B., A foundation for the study of group decision support systems. *Management Science*, 1987, **33,** 589–609.
3. Jessup, L. M. and Valacich, J. S., *Group Support Systems: New Perspectives*. Macmillan, 1993.
4. Poole, M. S., Holmes, M., Watson, R. and DeSanctis, G., Group decision support systems and group communication. *Communication Research*, 1993, **20,** 133–145.
5. Cohon, J. L., *Multiobjective Programming and Planning*. Academic Press, New York, 1978.
6. Iz, P. and Jelassi, M. T., An interactive group decision aid for multiobjective problems: An empirical assessment. *OMEGA*, 1990, **18,** 595–604.
7. Kersten, G. E., NEGO—group decision support system. *Information and Management*, 1985, **8,** 237–246.
8. Ayre, R. and Gottesman, B. Z., Group enabled: Workgroup computing. *PC Magazine*, 1994, **June 14,** 171–172.
9. Nunamaker, J., Vogel, D., Heminger, A., Martz, B., Grohowski, R. and McGoff, C., Experiences at IBM with group support systems: A field study. *Decision Support Systems*, 1989, **5,** 183–196.
10. Iz, P. and Gardiner, L. R., Analysis of multiple criteria decision support systems for cooperative groups. *Group Decision and Negotiation*, 1993, **2,** 61–79.
11. Vetschera, R., Integrating databases and preference evaluations in group decision support. *Decision Support Systems*, 1991, **7,** 67–77.
12. Nakayama, H., Tanino, T., Matsumoto, K., Matsuo, H., Inoue, K. and Sawaragi, Y., Methodology for group decision support with an application to assessment of residential environment. *IEEE Transactions on Systems, Man and Cybernetics*, 1979, **SMC-9,** 477–485.
13. Steeb, R. and Johnston, S., A computer-based interactive system for group decision making. *IEEE Transactions on Systems, Man and Cybernetics*, 1981, **SMC-11,** 544–552.
14. Borda, J. C., *Histoire de l'Academie Royale de Science*. Paris, Memoire sur les Elections au Scrutin, 1781.
15. Corener, J. L. and Kirkwood, C. W., Decision analysis applications in the operations research literature, 1970–1989. *Operations Research*, 1991, **39,** 206–219.
16. Golabi, K., Kirkwood, C. W. and Sicherman, A., Selecting a portfolio of solar energy projects using multi-attribute preference theory. *Management Science*, 1981, **27,** 174–189.
17. Dyer, J. S. and Miles, R. F., An actual application of collective choice theory to the selection of trajectories for the Mariner Jupiter/Saturn 1977 Projects. *Operations Research*, 1976, **24,** 220–244.
18. Dyer, J. S. and Lund, R. N., Tinker toys and christmas trees: Opening a new merchandising package for Amoco Oil Company. *Interfaces*, 1982, **12,** 38–52.
19. Thomas, J. B., McDaniel, R. R. Jr. and Dooris, M. J., Strategic issue analysis: NGT + decision analysis for resolving strategic issues. *The Journal of Applied Behavioral Science*, 1989, **25,** 189–200.
20. Reagan-Cirincione, P., Schuman, S., Richardson, G. P. and Dorf, S. A., Decision modeling:Tools for strategic thinking. *Interfaces*, 1991, **21,** 52–65.
21. von Neumann, J. and Morgenstern, O., *Theory of Games and Economic Behavior*. Princeton University Press, Princeton, NJ, 1947.
22. Keeney, R. L. and Raiffa, H., *Decisions with Multiple Objectives*. Wiley, New York, 1976.
23. Van de Ven, A. H. and Delbecq, A. L., Nominal versus interacting group processes for committee decision making effectiveness. *Academy of Management Journal*, 1971, **14,** 203–221.

24. Wang, H. F. and Shen, S. Y., Group decision support with MOLP applications. *IEEE Transactions on Systems, Man, and Cybernetics*, 1989, **SMC-19**, 143–153.
25. Bodily, S. E., A multi-attribute decision analysis for the level of frozen blood utilization. *IEEE Transactions on Systems, Man, and Cybernetics*, 1977, **SMC-7**, 683–694.
26. Edwards, W. and von Winterfeldt, D., Public values in risk debates. *Risk Analysis*, 1987, **7**, 141–158.
27. Lathrop, J. W. and Watson, S. R., Decision analysis for the evaluation of risk in nuclear waste management. *Journal of the Operational Research Society*, 1982, **33**, 407–418.
28. Lincoln, D. R. and Rubin, E. S., Cross-media environmental impacts of coal-fired plants: An approach using multi-attribute utility theory. *IEEE Transactions on Systems, Man and Cybernetics*, 1979, **SMC-9**, 285–289.
29. Keeney, R. L., Quantifying corporate preferences for policy analysis. In *Multiple Criteria Decision Making*, ed. H. Thiriez and S. Zionts. Springer-Verlag, New York, 1976, pp. 293–302.
30. Keeney, R. L. and Kirkwood, C. W., Group decision making using cardinal social welfare functions. *Management Science*, 1975, **22**, 430–437.
31. Keeney, R. L., Lathrop, J. F. and Sicherman, A., An analysis of Baltimore Gas and Electric Company's technology choice. *Operations Research*, 1986, **34**, 18–39.
32. Arrow, K., *Social Choice and Individual Values*. Wiley, New York, NY, 1963.
33. Ulvila, J. W. and Snider, W. D., Negotiation of international tanker standards: An application of multi-attribute value theory. *Operations Research*, 1980, **28**, 81–96.
34. Jones, M., Hope, C. and Hughes, R., A multi-attribute value model for the study of UK energy policy. *Journal of the Operational Research Society*, 1990, **41**, 919–929.
35. Keeney, R. L., The art of assessing multi-attribute utility functions. *Organizational Behavior and Human Performance*, 1977, **19**, 297–310.
36. Despontin, M., Nijkamp, P., and Spronk, J., Conflict analysis in macro-economic planning models. In *Macro-Economic Planning with Conflicting Goals, Lecture Notes in Economics and Mathematical Systems* 230, ed. M. Despontin, P. Nijkamp and J. Spronk. Springer, Berlin, 1984, pp. 1–19.
37. Simon, H. A., Rationality as process and as product of thought. *American Economic Review*, 1978, **68**, 1–16.
38. Axelrod, R. M., *The Structure of Decision: Cognitive Maps of Political Elites*. Princeton University Press: Princeton, NJ, 1976.
39. McGrath, J., *Groups: Interaction and Performance*. Prentice-Hall, Englewood Cliffs, NJ, 1984.
40. Bui, T. and Jarke, M., A DSS for cooperative multiple criteria group decision making. *Proceedings of the 5th International Conference on Information Systems*. 1984, pp. 101–113.
41. Watabe, K., Holsapple, C. W. and Whinston, A. B., Coordinator support in a Nemawashi decision process. *Decision Support Systems*, 1992, **8**, 85–98.
42. Dyer, R. F. and Forman, E. H., Group decision support with the analytic hierarchy process. *Decision Support Systems*, 1992, **8**, 99–124.
43. Huber, G. P., *Managerial Decision Making*. Scott-Foresman, Glenview, IL, 1980.

ADDRESS FOR CORRESPONDENCE: *Dr Anne Davey, College of Business and Industry, Northeastern State University, Tahlequah, OK 74464, USA*