Comparison of AHP with Six Other Selection Aids

David L. Olson, Alexander I. Mechitov, and Helen Moshkovich
Department of Business Analysis, Texas A&M University
College of Business, University of West Alabama
Institute for Systems Analysis, Russian Academy of Sciences
dolson@tamvm1.tamu.edu

Abstract: AHP is one of a number of selection aids. This paper compares seven of these systems over the features of the types of problems they support, limitations with respect to problem dimensions, the specificity of the analysis, and cognitive effort required on the part of decision makers. AHP in its original form is specific to particular decisions (the results are a function of the choices available). However, the distributed form of AHP can be applied to many alternatives. AHP requires theoretically complex input on the part of decision makers, but has been found easy to use by human subjects tested.

Introduction

AHP is one of a number of tools to aid selection decisions. These systems include MAUT (Keeney and Raiffa, 1986; Fishburn, 1984; von Winterfeldt and Edwards, 1986; as well as the SMART version of Edwards, 1977; and Edwards and Barron, 1994), preference cones (Köksalan, 1989; Köksalan and Taner, 1992; Korhonen, Wallenius and Zionts,1984; Ramesh, Karwan and Zionts, 1988; and Taner and Köksalan, 1991), outranking procedures (Roy, 1978; Brans and Vincke, 1985; Brans, Vincke and Mareschal, 1986; and Brans and Mareschal, 1992), and the Russian system ZAPROS (Larichev and Moshkovich, 1991). There also have been systems seeking to support decision maker learning, such as *AIM* (Lotfi, Stewart and Zionts, 1992) and *VIMDA* (Korhonen and Laakso, 1986; Korhonen, 1988; and Korhonen and Wallenius, 1989).

This paper discusses some of the differences in method approaches, compares the kinds of problems where each of these techniques would be expected to have an advantage, and the kind of decision maker effort required. Techniques will be compared on the dimensions of task type, task dimensionality, task uniqueness, and cognitive effort required of decision makers.

Task Type

Possible task types for decision aids include identifying the best alternative from a given set, selecting a short list from that set (sorting the alternatives into a partial order of ranking), and providing a means to rank order all of the alternatives (full order ranking). The biggest divergence across methods is found in the outranking systems and in *ZAPROS*, where the emphasis is on providing decision makers with a partial order.

Partial Orders

A partial order is an incomplete ranking with many ties possible. This approach is popular in France, with Professor Roy as its primary exponent. While the conventional North American view is that a partial order is inferior to a full order, partial order proponents argue that minor differences in cardinal scores based on inaccurate input really don't establish superiority. The philosophical underpinning of the French approach is that the selection aid should filter a large list of multiattribute alternatives down to a short list for the decision maker to concentrate on. The *ELECTRE I* and *PROMETHEE I* approaches emphasize selection of those alternatives that have salient advantages on one or more attributes (or criteria), with corresponding disadvantages on one or more attributes. The *ZAPROS* system from Russia also adopts this partial order philosophy. *VIMDA* uses a similar approach, generating up to eight nondominated alternatives an iteration for decision makers to select from, although the intent of VIMDA is to identify the best alternative.

Roy and Vanderpooten (1996) describe multiple objective approaches as being descriptive or constructive. The descriptive approach (AHP and MAUT) are based on the philosophical concept that there is a best solution, and therefore the way to approach the analysis is to obtain an accurate measure of value. If there truly is a best solution, a precise measurement will map perfectly to a single scale of value (thus providing a cardinal measure that can be used for comparison). However, Schärlig (1996) argues that many management problems are not suitably dealt with by this approach, because they involve human choice. The constructive approach (the basis for the French school of MCDM) conversely develops working hypotheses of decision maker preference, based on concepts of incomparability, concordance, discordance, and thresholds of domination. Roy and Mousseau (1996) define incomparability as a fourth relationship in addition to the three basic relationships of choice A preferred to choice B, indifference between A and B, or B preferred to A. Two options are incomparable if they are so different that the decision maker cannot express preference between them without considerable thought.

Schärlig (1996) discusses the concept of weak preference, a fuzzy zone between indifference and preference. A state of weak preference arises. For instance, a salary of $80,000 per year clearly is greater than a salary of $79,500 per year on a continuous scale. However, the difference is very slight, and well within the range of differences in costs of living between various locations, and most decision makers would consider them equivalent. On the other hand, a salary of $80,000 is clearly preferable to a salary of $60,000. The range of salary over which the human has preference differential is the area of weak preference.

Weak preference can lead to intransitivity. In a three criteria problem, on the first criterion A has superior performance to B, which has superior performance to C. On the second criterion, C has superior performance to A and B, while A and B have equal performance. On the third criterion, C and B have equal performance, both superior to A. The first criterion is twice as important as either of the other two criteria. In this case, choice A could be preferred to B (A→B on criterion 1, which is more important than criterion 3, where B→A), and B preferred to C (B→C on criterion 1, which is more important than criterion 2, where C→B). But when A is compared to C, A→C on criterion 1, but C→A on both criterion 2 and criterion 3. Adding the relative weights results in a draw.

If the descriptive approach is adopted, the argument would be that the magnitude of advantage of A→B and B→C was not considered. For instance, a person might have three job options. Option A has a salary of $80,000 doing something boring in an unattractive location. Option B is doing something boring at $60,000 in a great location. Option C is doing what you want at $50,000 in a great location. Salary is considered to have a weight of 0.5, while type of work and location have weights of 0.25. On salary, A→B and B→C. On type of work, C→A, C→B, and A≡B. On location, B≡C while B→A and C→A. Really, one cannot apply a cardinal formula without knowing the value scales for salary, type of work, and location. Just how much is $80,000 better on a person's value scale than $60,000, or $50,000? AHP, MAUT, and SMART all provide such measures. The outranking proponents, who doubt the accuracy of such measures, and whose calculus allows for ranges of indifference, can find an intransitivity. They argue that minor differences are really nonexistent The constructive counterargument would be that the relative advantage of performance is not likely to be linear. For our purpose, the point is that the constructivist approach would argue that transitivity is NOT appropriate for many managerial decisions involving fuzzy preference.

Selection of Best Alternative

The preference cone method is unique among the techniques we have examined in that it is only capable of identifying the best alternative from the given set. The preference cone method operates using a process of elimination, identifying a tighter and tighter preference cone that can be used to mathematically eliminate alternatives on the basis of past preferences. This cone, along with the rejection of alternatives directly from the pairwise comparisons, finally ends up with one winning alternative. There is no inference made about the relative ranking of the rejected alternatives. The AIM and VIMDA learning methods operate in a similar manner, focusing on identifying the best solution.

Full Orders

The other techniques we consider provide some mechanism for obtaining a full order. This is done by using a value function, where a higher number indicates a better alternative. Like AHP, MAUT (and *SMART*) provide such a numeric value that can be used as the basis for full rank ordering. *ELECTRE II* and *PROMETHEE II* were developed to provide a similar full rank ordering capability for outranking systems, although the general philosophy of outranking methods focuses on partial order.

Those methods that provide cardinal value functions (Roy's descriptive approach) have the benefit of providing a formula that can be used for any of the tasks we consider. That has an apparent advantage. However, those supporting partial order methods would argue that the implied accuracy of the cardinal formula is misleading. Concepts like incomparability are the basis for questions of the validity of preference statements used as the basis for cardinal formulas.

Task Dimensionality

There are two basic dimensions to task dimensionality that we consider: the number of attributes and the number of alternatives.

Number of Attributes (or Criteria)

Hierarchical structures can be used to provide some means of organizing and therefore controlling the complexity of decisions involving many attributes. As with AHP, MAUT, the outranking methods, and *VIMDA* all are more complex when there are many attributes, simply because there are more coefficients to identify. Fischer (1979) concluded that the predictive validity of multiattribute models was adequate only when there were fewer than five attributes. However, the hierarchical structure as used in AHP and MAUT provides a mechanism to allow the decision maker to focus on specific subsets of these attributes sequentially. SMART, a simplified version of MAUT, uses the same hierarchy. However, Edwards (1977) argued that only a limited number of attributes could be cognitively balanced by humans, and suggested focusing on the most important (preferably seven or less).

The number of attributes has a more significant impact on the other systems. In preference cones, when there are a large number of attributes it becomes nearly impossible to find a cone that will eliminate any but dominated alternatives. There are too many dimensions so that the probability of an alternative performing in an inferior manner to another on at least one criterion becomes very high. With a large number of attributes (ten or more), almost all alternatives must be compared, resulting in no benefit of using preference cones. *ZAPROS* suffers from the same limitation with respect to the number of attribute categories.

The learning methods, *AIM* and *VIMDA*, require the decision maker to balance more attribute characteristics when there are many attributes. *VIMDA* limits the number of attributes to ten. In both *AIM* and *VIMDA*, attention is focused on those attributes whose aspiration levels are not satisfied. This feature alleviates the problem when larger number of attributes are present.

Number of Alternatives (Choices)

MAUT and AHP were intended for comparison of a small (seven or less) number of alternatives. Both approaches have been presented in a context where the relative ratings are a function of the alternatives being considered. In each of these systems, however, a formula is developed which could be applied to a data set of measurements reflecting any number of alternatives. In the original form of AHP, with each alternative a member of the bottom level of the hierarchy, the number of pairwise comparisons necessary grow exponentially with the number of alternatives considered. Therefore there is a practical limit on the size of problem that can be considered.

The absolute form of AHP (Saaty and Vargas, 1991: appendix B) provides a cardinal formula that can be applied to as many alternatives as there are to evaluate. MAUT provides a cardinal formula as well, which could also be applied to a large number of alternatives. SMART provides a similar formula. Thus in principle, all three of these methods could be applied to decisions with very large numbers of alternatives. However, such use would be based on preference elicitation information based on a partial set of alternatives, which has been argued as being inappropriate by some proponents of both MAUT and AHP.

Preference cones operate by eliminating all other alternatives by establishing the ultimate best choice as logically superior to each of the others. You would not want to use preference cones unless there were a large set of alternatives, because it operates by asking the decision maker to select the preferred alternative of two presented. This simple process of elimination could quickly yield the preferred choice in n-1 comparisons without going through the complexity of the mathematical programs used in preference cones. If **n** is small, there would be no point in identifying the cone.

ZAPROS is highly suitable to problems with large numbers of alternatives. The amount of input required in *ZAPROS* is a function of the number of attribute categories. Once the decision maker's preference mapping is identified, *ZAPROS* results could be applied to any number of alternatives.

The outranking methods, as well as the learning methods *AIM* and *VIMDA*, work with both large and small alternative sets. Both outranking and learning methods contribute more if there are large sets of alternatives to consider, although both approaches help the decision maker focus on key tradeoffs.

Task dimensionality is a very important factor in method appropriateness. AHP and MAUT are better when there are few alternatives. On the other hand, preference cones and *ZAPROS* are more suitable in the reverse case, where there are few attributes and many alternatives. The partial order idea of the outranking methods implies problems with large numbers of alternatives. *AIM* and *VIMDA* can be applied in either setting.

Task Uniqueness

Task uniqueness refers to the generalizability of the analysis. Specific analysis refers to the need to conduct new preference elicitation when faced with new alternatives. Conversely, universal analysis occurs when the original preference elicitation input can be used over many alternatives, whether they were considered in the original analysis or not. In AHP terminology, Saaty and Vargas (1991) refer to relative AHP as that analysis where ratio pairwise comparisons of preference are made within the context of the choices available. Saaty preferred relative AHP to absolute AHP, where a general formula was obtained for application over a large set of alternatives, or even for application to alternatives encountered in the future. Formulas obtained from MAUT and SMART could easily be applied over similar large sets of alternatives.

Outranking methods (*ELECTRE* and *PROMETHEE*) focus on criteria independent of the number of alternatives available (much the same as *VIMDA* and *ZAPROS*). But the results are a function of the alternatives evaluated. The outranking relationships will change if additional alternatives are considered. Therefore, the analysis is specific rather than universal. *VIMDA* is also specific, in that the decision maker directly selects an alternative from the nondominated set presented by the system.

Preference cones and *ZAPROS* also develop the decision maker's preference structure. Preference cones operate by making inferences based on selections from available alternatives. The resulting preference cone may eliminate new alternatives without additional analysis, although there is the prospect that additional comparisons would be required. *ZAPROS* makes inferences based on selections from all possible alternatives, and would therefore be insensitive to additional alternatives. *AIM* includes a preference cone module as an optional method of reaching a decision, although the same learning approach as is used in *VIMDA* could also be used.

Decision Maker Cognitive Effort

This section will consist of two evaluations. The first is based on the theoretical work of Larichev (1992), followed by general comments based on experience with student subjects.

Larichev published a view of psychological validity of elementary operations required of decision makers by various multicriteria decision aids. Larichev felt that the scientific validity of multicriteria methods depends upon the kinds of input demanded of decision makers. Elementary operations were classified as complex, admissible, admissible for small dimensions, and uncertain (due to either admissibility or to complexity). An operation was classified as complex if psychological research indicates that in performing such operations the decision maker displays many inconsistencies and makes use of simplified strategies. An operation was classified as admissible if psychological research indicated that people were capable of performing these operations with minor inconsistencies, and if they could employ complex strategies. Operations that are admissible but for small dimension are those that research indicates can be performed with minor inconsistencies given that the number of criteria, alternatives, or multiattribute estimates are small enough that they can be dealt with without major inconsistencies. Those operations classified as uncertain were those where insufficient psychological research had been conducted in order to evaluate admissibility or complexity.

Each of the techniques we have discussed include some elementary operations classified by Larichev. We identify Larichev's classifications for operations that apply.

Analytic Hierarchy Process

AHP includes hierarchical structuring of criteria. Larichev rated this as a complex task. AHP involves assignment of quantitative equivalents for qualitative concepts, reflecting subjective comparisons through ratio values. Larichev classified this activity as uncertain in complexity. AHP can also be viewed as the qualitative comparison of two estimates taken from two criteria scales, which Larichev rates as admissible. Saaty's 17-point scale provides a simple way of quantifying qualitative concepts. However, Larichev would respond that this is an heuristic activity. Therefore, while AHP is not relatively complex relative to decision maker tasks, it is viewed by Larichev as heuristic, because placing a cardinal number on a subjective ratio pairwise comparison is expected by him to be an inaccurate measure of true preference.

Multiattribute Utility Theory

MAUT includes the elementary operations of decomposing complex criteria into simple ones during hierarchical structuring, as in AHP. As stated above, Larichev rates this activity as complex. MAUT also involves determination of quantitative equivalents of a lottery during the phase where criteria are compared with each other. Larichev rates this operation as complex. MAUT includes the step of identifying the quantitative value for attainments on criteria, which Larichev rates as uncertain relative to complexity. Therefore, Larichev would rate MAUT as challenging the cognitive capabilities of human decision makers.

The *SMART* method places less burden on decision makers, who can directly assign both weights and scores of alternatives on attributes. Larichev argued that this was a complex task for decision makers, but swing weights provide a means to improve the accuracy of these assessments. Nonetheless, the accuracy of the resulting cardinal formula obtained in *SMART* is questioned by Larichev.

Outranking Methods

Both *ELECTRE* and *PROMETHEE* involve assignment of quantitative criteria weights, which Larichev rates as complex. Outranking methods involve assignment of quantitative equivalents for qualitative estimates during the definition phase, where the decision maker is given a number of alternative means of scaling values for criterion attainment levels. This is rated as uncertain relative to complexity by Larichev. This same step can involve assignment of satisfactory levels by criterion, which Larichev rates as uncertain relative to admissibility. The most complex task involved in outranking methods is the assignment of criteria weights by decision makers as initial inputs. This is the output for most of the other techniques.

Preference Cones

Preference cones require decision makers to compare two alternatives viewed as a set of estimates by criteria and select the preferred of the two. Larichev rates this as an admissible operation for small dimensions. In other words, if there are two criteria varying (as in *ZAPROS*), this is considered an admissible operation. However, if there are three or more criteria varying, this task becomes increasingly difficult.

Learning Methods

VIMDA and *AIM* require decision makers to make the same selection as is made with preference cones, only instead of selecting the preferred combination of attainments from two alternatives, the decision maker is presented with up to eight choices (on up to ten criteria). Larichev rated this as a more difficult task. Users of *VIMDA* and AIM are also required to set aspiration levels, or targets, a task Larichev considered humans to be unreliable at. Overall, the selection of a preferred choice based on the performance of two alternatives over a large number of attributes is considered to be a complex task, and therefore of dubious accuracy.

ZAPROS

ZAPROS is designed specifically to require only those tasks of the decision maker that can be performed without introducing inconsistencies or requiring complex strategies. All that is asked of the decision maker is to select from pairs of alternatives differing on only two criteria. Transitivity is not allowed by this method, which checks the consistency of each new preference choice with all prior input. If inconsistency is encountered, it is resolved through a series of additional preference questions. Each criterion's performance is measured on a categorical scale. This makes *ZAPROS* less precise than methods using cardinal formulas, but the producers of *ZAPROS* argue that fine differences in performance on a specific attribute are not significant.

Based on Larichev's evaluation of psychological validity, *ZAPROS* is based on the most dependable human input. Preference cones are considered a little less reliable if more than two criteria are present (most likely the case), because decision makers are asked to compare two things that vary on more than two dimensions. The outranking methods involve tasks easily within human decision maker ability to be accurate except for the assignment of weights. MAUT involves even more challenging tasks in identification of lottery tradeoffs and value identification. AHP and *SMART* are easy for humans to use, but not necessarily accurate.

Comparison

The decision aids we have looked at all seek to help decision makers select multiattribute choices that best matches the decision maker's preference function. But we have seen that these methods vary in the types of problems they deal with, to include various dimensions of problem size, and the specificity of the analysis. The methods also vary in the inputs required from decision makers.

There also is a difference in theoretical expectations and what users perceive in actual practice. The entries in the following table are based on Larichev (1992) for theoretical rankings, focusing on cognitive effort. Subject rankings are based on our experiments as reported in Larichev, et al. (1993) and Larichev, Olson, Moshkovich, and Mechitov (1995). Subject comments and questionnaire rankings are the source documents for subject rankings of AHP, MAUT, *SMART*, prefcone, and *ZAPROS*. Outranking methods and learning methods were evaluated based on casual exposure to subjects.

	AHP	MAUT	SMART	prefcone	outrank	ZAPROS	learning
Task Type	pick best	pick best	pick best	pick best	partial order (full rank)	partial order	pick best
Task Dimension							
alternatives	few (absolute >)	few (formula)	few (formula)	many	either	either	either
criteria				few		few	≤10
Task Uniqueness	specific (absolute)	specific (formula)	specific (formula)	universal	specific	universal	specific
Cognitive Effort							
theoretical rank	7	6	5	2	4	1	3
subject rank	3	5	1	7	6	4	2

In this table, AHP represents Analytic hierarchy process, outrank represents *ELECTRE* and *PROMETHEE*, and learn represents *AIM* and *VIMDA*.

While AHP does not rank well on Larichev's theoretical scale, subjects found it more useful than many of the other techniques. In general, these subjects best appreciated methods that they understood well. That is the primary advantage of *SMART*. It is very easy to understand. AHP is also very easy to understand, with the exception of eigen value calculations. The primary criticism of AHP was that it often involved many pairwise comparisons. The learning methods are easy to understand, but involve balancing all attributes (criteria) simultaneously in making pairwise selections between alternatives. Subjects did not seem to mind this, probably focusing on a few attributes they considered the most important, or where the two alternatives differed the most. MAUT, outranking methods, and preference cone methods involved activities the subjects felt were less understandable. This led to little confidence in the alternatives recommended by those methods.

Fischer stated that MAUT lost its validity with five or more criteria. Actually, the same argument could be made for all of the methods, in that the accuracy of the technique would be suspect with more criteria. However, the mechanics of some of these methods are adversely affected by more criteria. There is a growth in the number of required comparisons in AHP when more criteria are present. *ZAPROS* is also affected, but on a different scale. The number of pairwise comparisons required grows exponentially with the number of criteria, as well as the number of categories upon which each criterion is graded. Preference cones also involve more decision maker pairwise comparisons with more criteria.

Task uniqueness refers to the ability to extend the analysis to alternatives not considered during preference elicitation. Specific applications are valid to those alternatives that were considered in the preference development. Universal applications would involve identification of a formula that can be applied to any alternative described by its attributes. Expert systems are an example of a universal application. Of the methods considered, only *ZAPROS* was designed for universal application. The other techniques are argued to be specific, although those that generate value formulas could be applied universally, given a means to objectively measure the performance of each alternative on each attribute (as in SMART).

Conclusion

Decision aids are very useful tools to aid decision makers. There are a number of diverse software products that have been developed to deliver these techniques. These techniques vary significantly in the type of problems they are suitable for, in the amount of information required, and in the type of conclusion reached.

The clearest distinction is on task type. AHP, MAUT, and preference cones are meant to select a best choice. *ZAPROS* and outranking methods are meant to focus the decision maker's attention on a short list of alternatives from an initial large set. This distinction is clouded by the fact that MAUT and AHP can and have been used to deal with large sets of alternatives.

AHP is theoretically difficult to use, but in practice users find it easy to express subjective preference through AHP. This is especially true relative to MAUT. The primary complaint we have encountered with AHP is when the number of pairwise comparisons requested exceeds 30 or so. Unfortunately, that is not an uncommon number of comparisons required in an analysis.

References

Brans, J.P. & Mareschal, B. (1992), "PROMETHEE V: MCDM Problems with Segmentation Constraints," *INFOR*, **30**:2, 85-96.

Brans, J.P. & Vincke, Ph. (1985), "A Preference Ranking Organization Method, The PROMETHEE Method," *Management Science*, **31**, 647-656.

Brans, J.P.; Vincke, P. & Mareschal, B. (1986), "How to Select and How to Rank Projects: The PROMETHEE Method," *European Journal of Operational Research* **24**, 228-238.

Edwards, W. (1977), "How to Use Multiattribute Utility Measurement for Social Decisionmaking," *IEEE Transactions on Systems, Man, and Cybernetics*, **SMC-7**:5, 326-340.

Edwards, W. and Barron, F. H. (1994), "SMARTS and SMARTER: Improved Simple Methods for Multiattribute Utility Measurement," *Organizational Behavior and Human Decision Processes* **60**, 306-325.

Fischer, G.W. (1979), "Utility Models for Multiple Objective Decisions: Do They Accurately Represent Human Preferences?" *Decision Sciences* **10**, 451-479.

Fishburn, P.C. (1984), "Multiattribute Nonlinear Utility Theory," *Management Science* **30**:11, 1301-1310.

Goicoechea, A., Stakhiv, E.Z. and Li, F. (1992). "Experimental Evaluation of Multiple Criteria Decision Models for Application to Water Resources Planning," *Water Resources Bulletin* **28**:1, 89-110.

Hobbs, B.F. (1986). "What Can We Learn from Experiments in Multiobjective Decision Analysis?" *IEEE Transactions on Systems, Man, and Cybernetics* **SMC-16**:3, 384-394.

Keeney, R.L. & Raiffa, H. (1976). *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*, New York: John Wiley & Sons.

Köksalan, M.M. (1989). "Identifying and Ranking a Most Preferred Subset of Alternatives in the Presence of Multiple Criteria," *Naval Research Logistics* **36**, 359-372.

Köksalan, M.M. and Taner, O.V. (1992). "An Approach for Finding the Most Preferred Alternative in the Presence of Multiple Criteria," *European Journal of Operational Research* **60**, 52-60.

Korhonen, P.; Wallenius, J.; and Zionts, S. (1984). "Solving the Discrete Multiple Criteria Problem Using Convex Cones," *Management Science* **30**:11, 1336-1345.

Korhonen, P. (1988). "A Visual Reference Direction Approach to Solving Discrete Multiple Criteria Problems, *European Journal of Operational Research* **34**:2, 152-159.

Korhonen, P. and Laakso, J. (1986). "A Visual Interactive Method for Solving the Multiple Criteria Problem," *European Journal of Operational Research* **24**:2, 277-287.

Korhonen, P. and Wallenius, J. (1989). *A Visual Multiple Criteria Decision Support System*, Helsinki: NumPlan.

Larichev, O.I. (1992). "Cognitive Validity in Design of Decision-Aiding Techniques," *Journal of Multi-Criteria Decision Analysis* **1**:3, 127-138.

Larichev, O.I. and H.M. Moshkovich (1991). "ZAPROS: A Method and System for Ordering Multiattribute Alternatives on the Base of a Decision-Maker's Preferences," preprint, Moscow: All-Union Research Institute for Systems Studies.

Larichev, O.I., Moshkovich, H.M., Mechitov, A.I. and Olson, D.L. (1993). "Experiments Comparing Qualitative Approaches to Rank Ordering of Multiattribute Alternatives," *Journal of Multi-Criteria Decision Analysis* **2**:1, 5-26.

Larichev, O.I., Olson, D.L., Moshkovich, H.M. and Mechitov, A.I. (1995). "Numerical vs. Cardinal Measurements in Multiattribute Decision Making: (How Exact is Enough?)," *Organizational Behavior and Human Decision Processes* **64**:1, 9-21.

Lotfi, V., Stewart, T.J. and Zionts, S. (1992). "AnAspiration-Level Interactive Model for Multiple Criteria Decision Making," *Computers and Operations Research* **19**:7, 671-681.

Ramesh, R. Karwan, M.H. and Zionts, S. (1988). "Theory of Convex Cones in Multicriteria Decision Making," *Annals of Operations Research* **16**,131-148.

Roy, B. (1978). "ELECTRE III: Un Algorithme de Classement Fonde sur une Representation Floue des Preferences en Presence de Criteres Multiple," *Cahiers du Centre Etudes Recherche Operationelle* **20**, 3-24.

Roy, B. and Mousseau, V. (1996). "A Theoretical Framework for Analysing the Notion of Relative Importance of Criteria," *Journal of Multi-Criteria Decision Analysis* **5**, 145-159.

Roy, B. and Vanderpooten, D. (1996). "Response to F.A. Lootsma's Comments on our Paper 'The European School of MCDA: Emergence, Basic Features and Current Works," *Journal of Multi-Criteria Decision Analysis* **5**, 165-166.

Saaty, T.L. and Vargas, L.G. (1991). *The Logic of Priorities: Applications of the Analytic Hierarchy Process in Business, Energy, Health & Transportation*. Pittsburgh: RWS Publications.

Schärlig, A. (1996). "Letter to the Editor: The Case of the Vanishing Optimum," *Journal of Multi-Criteria*

Decision Analysis 5, 160-164.

Taner, O.V. & Köksalan, M.M. (1991). "Experiments and an Improved Method for Solving the Discrete Alternative Multiple-Criteria Problem," *Journal of the Operational Research Society*, 42:5, 383-391.

Vanderpooten, D. (1990). "The Interactive Approach in MCDA: A Technical Framework and Some Basic Conceptions," *Mathematical and Computer Modelling* 12, 1213-1220.

von Winterfeldt, D. & Edwards, W. (1986). *Decision Analysis and Behavioral Research,* Cambridge University Press: Cambridge, England.