Managing Forest Ecosystems

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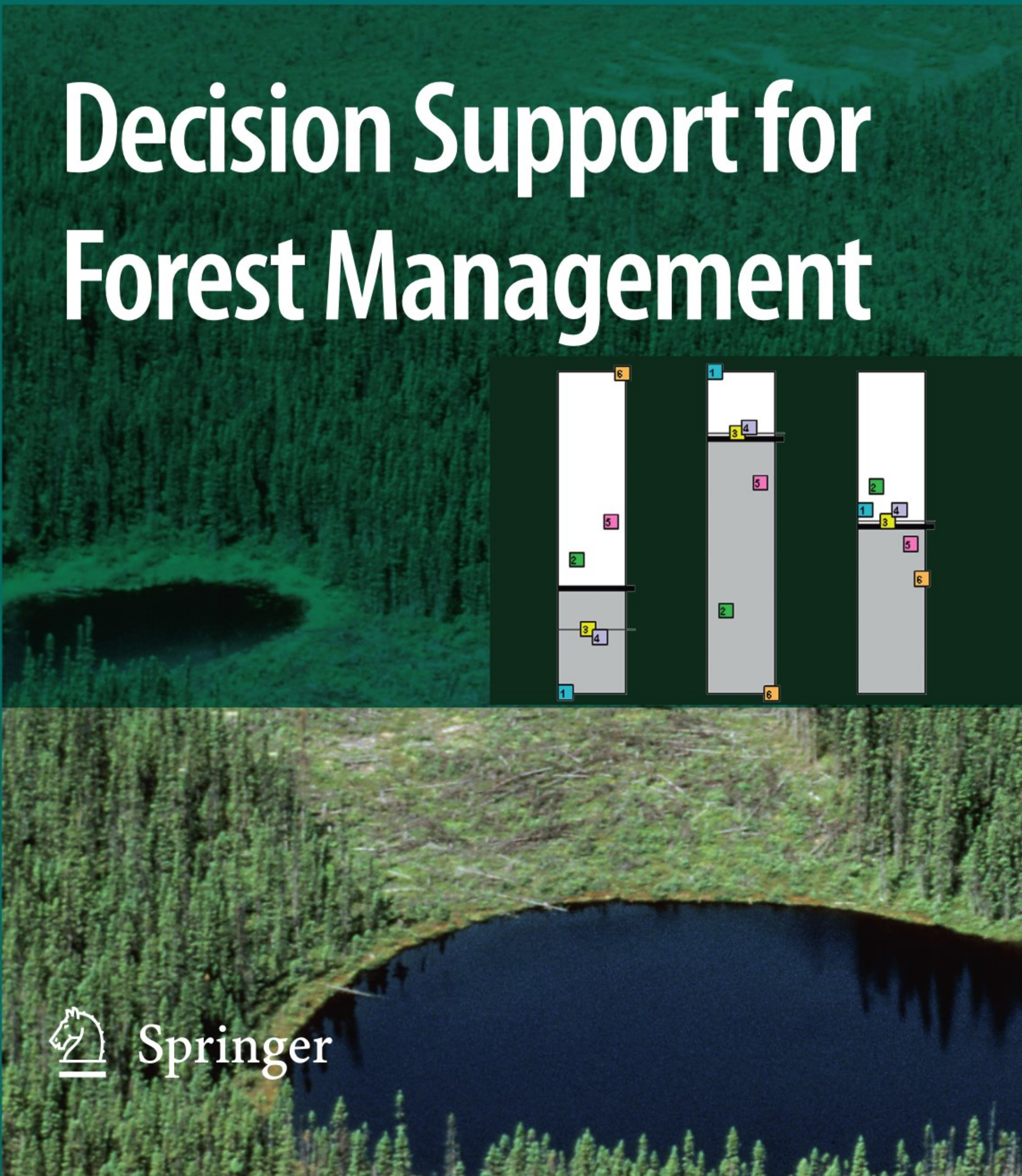
Decision Support for Forest Management



Springer

Decision Support for Forest Management

Managing Forest Ecosystems

Volume 16

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Aims & Scope:

Well-managed forests and woodlands are a renewable resource, producing essential raw material with minimum waste and energy use. Rich in habitat and species diversity, forests may contribute to increased ecosystem stability. They can absorb the effects of unwanted deposition and other disturbances and protect neighbouring ecosystems by maintaining stable nutrient and energy cycles and by preventing soil degradation and erosion. They provide much-needed recreation and their continued existence contributes to stabilizing rural communities.

Forests are managed for timber production and species, habitat and process conservation. A subtle shift from *multiple-use management* to *ecosystems management* is being observed and the new ecological perspective of *multi-functional forest management* is based on the principles of ecosystem diversity, stability and elasticity, and the dynamic equilibrium of primary and secondary production.

Making full use of new technology is one of the challenges facing forest management today. Resource information must be obtained with a limited budget. This requires better timing of resource assessment activities and improved use of multiple data sources. Sound ecosystems management, like any other management activity, relies on effective forecasting and operational control.

The aim of the book series ***Managing Forest Ecosystems*** is to present state-of-the-art research results relating to the practice of forest management. Contributions are solicited from prominent authors. Each reference book, monograph or proceedings volume will be focused to deal with a specific context. Typical issues of the series are: resource assessment techniques, evaluating sustainability for even-aged and uneven-aged forests, multi-objective management, predicting forest development, optimizing forest management, biodiversity management and monitoring, risk assessment and economic analysis.

The titles published in this series are listed at the end of this volume.

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ISBN 978-1-4020-6786-0 e-ISBN 978-1-4020-6787-7

Library of Congress Control Number: 2007940856

Printed on acid-free paper

9 8 7 6 5 4 3 2 1

springer.com

Preface

This book has been developed as a textbook of decision support methods for students and can also serve as a handbook for practical foresters. It is based on the research we have carried out and lectures we have given over the past years. We have set out to present all the methods in enough details and examples that they can be adopted from this book. For researchers who need more details, references are given to more advanced scientific papers and books.

In this book, theories of decision making and the methods used for forestry decision support are presented. The book covers basics of classical utility theory and its fuzzy counterparts, exact and heuristic optimization method and modern multicriteria decision support tools such as AHP or ELECTRE. Possibilities of analyzing and dealing with uncertainty are also briefly presented. The use of each method is illustrated with examples. In addition to decision aid methods, we present the basic theory of participatory planning. Both hard and soft methods suitable for participatory or group decision analysis are presented, such as problem structuring method and voting. The criticism towards decision theory is also covered. Finally, some real-life examples of the methods are presented.

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Acknowledgements

Many researchers and students have helped us by reviewing chapters, suggesting improvements and even checking our example calculations. We would like to acknowledge these reviewers, Ms. Anu Hankala, M.Sc. Teppo Hujala, M.Sc. Annu Kaila, Dr. Juha Lappi, Dr. Pekka Leskinen, Dr. Lauri Mehtätalo and Mr. Mikael Wathén for their efforts to improve our work. The errors remaining are nevertheless attributable entirely to the authors. We would also like to thank our co-authors in many research articles, especially professor Juha Alho, Dr. Tero Heinonen, Dr. Joonas Hokkanen, Dr. Eija Hurme, Dr. Miika Kajanus, Professor Osmo Kolehmainen, Professor Risto Lahdelma, M.Sc. Sanna Laukkanen, Dr. Leena Leskinen, Dr. Pekka Leskinen, Dr. Teppo Loikkanen, Dr. Jukka Matero, Dr. Lauri Mehtätalo, Lic.Sc. Eero Muinonen, Professor Mikko Mönkkönen, Professor Teijo Palander, Dr. Mauno Pesonen, Professor Timo Pukkala, Dr. Jouni Pykäläinen, Professor Pekka Salminen, Lic.Sc. Ron Store, and Dr. Jukka Tikkanen. Their co-operation has made this book possible.

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Chapter 1
Introduction

1.1 Planning and Decision Support

Decision means choosing from at least two distinct alternatives. Decision making, on the other hand, can be defined to include the whole process from problem structuring to choosing the best alternative (e.g. Kangas 1992). Most decisions we face every day are easy, like picking a meal from a restaurant menu. Sometimes the problems are so complex, however, that decision aid is needed.

Decision making can be considered from at least two points of view: it can be analyzed, how the decisions should be made in order to obtain best results (prescriptive approach), or, it can be analyzed, how people actually do decisions without help (descriptive approach) (e.g. von Winterfeldt and Edwards 1986). The first approach is normative; it aims at methods that can be used to aid people in their decisions. These decision-aid methods are usually based on an assumption that decisions are made rationally. There is evidence that people are not necessarily rational (e.g. Simon 1957). However, this is not a problem in decision aid: it can realistically be assumed that decisions actually were better, if people were instructed to act rationally. Decision-aid methods aim at helping people to improve the decisions they make, not mimicking human decision making.

The planning situation can be characterized with three dimensions: the material world, the social world and the personal world (Mingers and Brocklesby 1997; Fig. 1.1). The material world dictates what is possible in a planning situation, the personal world what we wish for, and the social world what is acceptable to the society surrounding us. All these elements are involved in decision making, with different emphasis in different situations.

The decisions can be made either under certainty or uncertainty, and the problem can be either unidimensional of multidimensional. In addition, the problem can be either discrete (i.e. the number of possible alternatives is limited) or continuous (i.e. there is an infinite number of possible alternatives), and include either one or several decision makers.

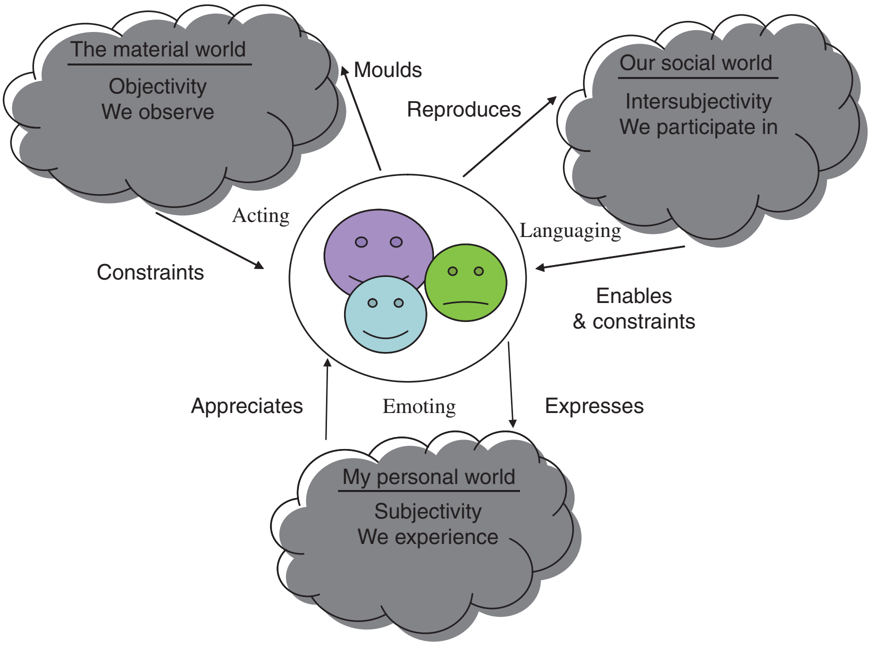

Fig. 1.1 Three dimensions of problem situation (Modified from Mingers and Brocklesby 1997)

If the problem is unidimensional problem with certainty, the problem is straightforward to solve. If the alternatives are discrete, the best is chosen. If the decision has to be made under uncertainty, also the discrete unidimensional case is of interest. Modern utility-theoretic studies can be considered to begin with the works of Ramsey (1930) and von Neumann and Morgenstern (1944) dealing with the unidimensional case under risk.

In a multidimensional case under certainty, the problem is to define the tradeoffs between the attributes or criteria. Such tradeoffs are subjective, i.e. there are no correct tradeoff values that the decision makers should use (Keeney and Raiffa 1976). The most challenging problems are those with multiple dimensions including uncertainty. There may be uncertainty in all parameters of decision analysis, for instance, the future consequences of different actions or the preferences of the decision maker with respect to different criteria may be uncertain. There exist, therefore, several applications of decision-support tools accounting for the uncertainty.

Another complication is that there may be several decision makers or other stakeholders involved. In such cases the problems may be messy: it is not clear what are the alternatives among which to choose from, or what are the criteria with respect to which the alternatives should be compared. For such situations, there exist several problem structuring methods (Mingers and Brocklesby 1997).

A rational decision maker chooses an alternative which in his opinion maximizes the utility (Etzioni 1986; von Winterfeldt and Edwards 1986). For this, one has to have perfect knowledge of the consequences of different decision alternatives, the goals and objectives of the decision maker and their weights, in other words of the preferences. Accordingly, the basis of decision making can be divided into three elements: alternatives, information and preferences (Bradshaw and Boose 1990). The basis has to be solid with respect to all elements so that one is able to choose the best alternative. Keeney (1982) divided the decision analysis into four phases which all are necessary parts of the modelling of decision making:

1. Structuring a decision problem
2. Defining the consequences of decision alternatives
3. Eliciting out the preferences of the decision maker
4. Evaluating and comparing the decision alternatives

Generally, in decision-making processes, decision makers are assumed to rank a set of decision alternatives and choose the best according to their preferences. To be able to rank, they select the criteria that are relevant to the current problem and that are of significance in their choice (e.g. Bouyssou et al. 2000). The criteria used in ranking are standards or measures that can be used in judging if one alternative is more desirable than another (Belton and Stewart 2002). Each alternative needs to be evaluated with respect to each criterion.

Belton and Stewart (2002) (Fig. 1.2), on the other hand, divided the decision-aid process to three phases, namely problem structuring, model building and using the model to inform and challenge thinking. This definition emphasises using decision aid as a help in thinking, not as a method providing ready-made solutions. According to Keeney (1992), decision-makers should focus on values, and on creating creative

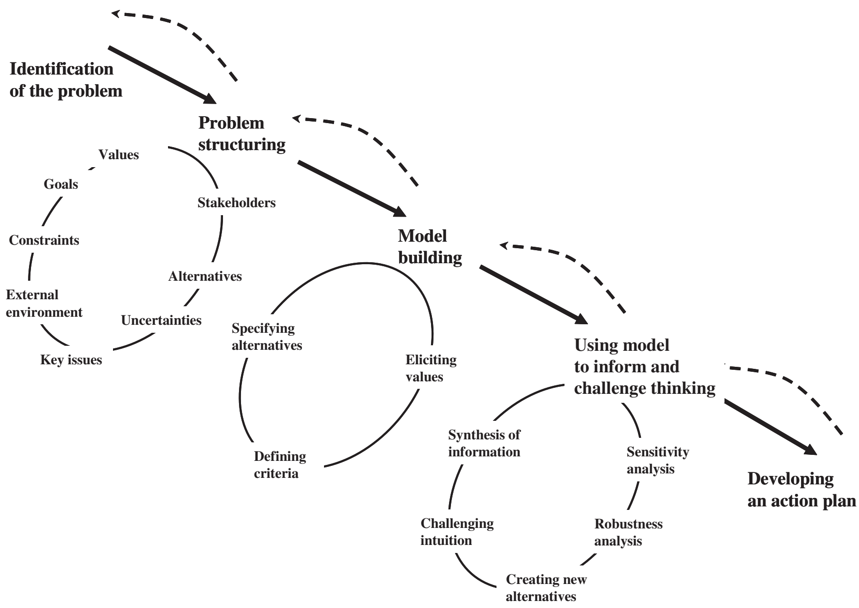

Fig. 1.2 The process of MCDA (Belton and Stewart 2002)

new alternatives based on their values, rather than ranking existing alternatives. He argues that creating the alternatives is the most crucial phase of all in the decision-making process, and it is not dealt with at all in the traditional decision science. Both these perspectives reflect the current view of decision analysis. Some of the older ideas and definitions have been strongly criticized for treating decision makers as machines (e.g. French 1989, p. 143).

As the name suggests, Multiple Criteria Decision Support [MCDS, or MCDA (MCD Aid), or MCDM (MCD Making)] methods have been developed to enable analysis of multiple-criteria decision situations. They are typically used for dealing with planning situations in which one needs to holistically evaluate different decision alternatives, and in which evaluation is hindered by the multiplicity of decision criteria that are difficult to compare, and by conflicting interests. For more fundamental descriptions of MCDS, readers are referred to Keeney and Raiffa (1976), von Winterfeldt and Edwards (1986), French (1989), Bouyssou et al. (2000), Vincke (1992) or Belton and Stewart (2002).

Decision problems can, however, be complex even if there is only one objective. For instance, the case could be such that the decision-maker needs to allocate the resources (e.g. money and land) to competing forms of production (e.g. what tree species to plant) in order to get the best profit. In such cases, the decision-aid methods typically used are mathematical optimization methods. These methods produce exact optimal solutions to decision problems. The most commonly applied of these methods is linear programming LP (see, e.g. Dantzig 1963; Dykstra 1984; Taha 1987; Hillier and Lieberman 2001). There are also many modifications of this basic approach, such as integer programming and goal programming. Optimization methods can also be used in cases where there are an infinite number of possible actions and several criteria (Steuer 1986).

In many cases the real problems are too complicated for these exact methods. Then, either the problem is simplified so that it can be solved with exact methods, or the solution is searched using heuristic methods (e.g. Glover 1989; Glover et al. 1995; Reeves 1993). These methods can produce a good solution with fairly simple calculations, but they cannot guarantee an optimal solution. The benefit in these methods is that the true decision problems can be described better than with exact methods, where the problems often have to be simplified in order to fit to the requirements of the methods. It is more useful to get a good solution to a real problem, than an exact solution to a misleadingly defined one.

1.2 Forest Management Planning

Forest management planning is a tool of central importance in forestry-related decision making. The aim in forest planning is to provide support for forestry decision making so that the mix of inputs and outputs is found that best fulfils the goals set for the management of the forest planning area. The current use of forests is typically multi-objective. Ecological, economic and social sustainability is aimed for. Forests should produce reasonable incomes while at the same time promoting conservation and recreational considerations. In other words, forests are being used simultaneously for multiple purposes (e.g. Kangas 1992; Davis et al. 2001).

Forestry decision making often includes numerous decision-makers or other stakeholders. They could be owners of the forests, local inhabitants, people connected with tourism and recreation services, private persons or officials concerned with nature conservation, or personnel of forestry enterprises. Each of them can have different objectives concerning the use of forests or other natural resources, which further complicates the evaluation.

Forest planning problems are typically described so that each stand in the forest has several different treatment schedules that are possible alternatives for it. For instance, harvests with two different rotation times produces two different schedules for one stand. Each schedule may include several treatments with a different timing. It may be that the schedule for one stand includes one or two thinnings before the final harvest, and planting after it. The development of the stand is then predicted, with respect to all relevant criteria. The predictions are typically based on forest simulators including growth and yield models for forest.

With different combinations of standwise treatment schedules, a huge number of different production programmes for the whole area could be obtained. Among these programmes, those that are efficient with respect to the criteria involved are worth further investigations. This means that programmes dominated by some other programme should be excluded from the analysis. Normally, the end result of forest planning is a management plan, which presents a recommended production programme for the forest area, with predictions of the consequences of implementing the plan.

Briefly, the main phases in a forest planning process are:

(i) Forest data acquisition and assessing the present state of the forests
(ii) Clarifying the criteria and preferences of the decision maker(s) regarding the use of forests and, in participatory planning, clarifying the criteria and preferences of other interested parties
(iii) Generating alternative treatment schedules for forest stands within the planning area and predicting their consequences
(iv) Producing efficient production programmes for the forest area
(v) Choosing the best production programme from among those deemed to be efficient with respect to the criteria and preferences as clarified in phase (ii)

These phases do not necessarily proceed in this order, and they can be applied iteratively, interactively, and/or simultaneously.

Forest planning can be either strategic, tactical or operational planning. In strategic planning, the basic idea is to define what is wanted from forest, and in tactical planning to define how these goals are obtained. In forest context, strategic planning typically means time horizons from 20 years upwards. Long horizons are especially needed when assessing the sustainability of alternative decisions. Strategic plans are usually prepared to cover fairly large areas, from woodlot level in private forests to regional level in the forestry of big organizations. For practical reasons, there planning calculations are not very detailed.

In tactical forest planning, on the other hand, the time horizon is typically 5–20 years. The number of alternative forest plans, each consisting of a combination of forest-stand treatment schedules, can be considerable, practically infinite. It also means that the resulting plans are detailed, typically including standwise recommendations. In operational planning, carrying out these standwise recommendations is planned in great detail. In practise, strategic and tactical planning are often integrated so that both strategic and tactical solution are produced at the same time. Planning is continuous work, and whenever the planning environment or needs of decision maker(s) change, the plan is updated.

1.3 History of Forest Planning

The earliest forest management planning methods for large areas were based on the concept of fully regulated even-aged forests (e.g. Kilkki 1987; Davis et al. 2001). Fully regulated forest is an ideal state of forests. It means that a forest area has a steady-state structure and conditions, and a stable flow of outcomes. The growth is equal to annual harvest, and harvest is the same each year. The area harvested each year can be calculated simply by dividing the total area A by the selected rotation time R. Thus, it ensures a sustainable yield, which has been an important objective of forestry.

Real forests, however, do not fulfil the requirements of fully regulated forests. Yet, it must be decided how large an area and how much volume to cut. Traditional methods of forest planning provide two different types of methods: those based on area control and those based on volume control (Recknagel 1917; Davis et al. 2001, p. 528).

Area control method is the simplest way to regulate the harvests. If a constant area A/R is harvested each year, the forests are fully regulated after R years. On the other hand, the harvested volume may vary a lot between years. This method assumes a constant site quality, but it is also possible to utilise different rotation times for different sites.

The oldest volume control method is the Austrian formula, first published already in 1788 (Speidel 1972),

$$C_t = I + [(V_c - V_f)/a] \tag{1.1}$$

where C_t is the annual cut, I is the annual increment of forests, V_c is the current volume of the growing stock, V_f is the volume of the desired state (i.e. fully regulated forest) and a is the adjustment time. This means that the harvest is the growth of the area, corrected so that the volume of fully regulated forests is achieved after the adjustment period. This method ensures a constant harvest level in short term. Yet, the method does not necessarily ensure the fully regulated condition on longer term (Davis et al. 2001, p. 545). Later on, these methods were developed to more advanced cutting budget methods, which enable controlling both area and volume at the same time (e.g. Lihtonen 1959; Kuusela and Nyyssönen 1962; Davis 1966).

In single stands, planning has been concentrated in defining an optimal rotation time (e.g. Gregory 1972; Johansson and Löfgren 1985). There are several criteria for selecting the rotation time. The simplest of them is to select the rotation, which maximizes the mean annual increment (MAI) of forests (rotation of maximum sustained yield). This is achieved by harvesting the stand when MAI is equal to current volume increment. The most famous of the rotation calculation methods is, however, the Faustmann formula (Faustmann 1849). In this formula, the value of land is maximized over infinite number of rotations (the rotation of maximum land rent). In continuous form the formula is (Viitala 2002)

$$\underset{\{u\}}{Max} L = \sum_{i=0}^{\infty} (pV(u)e^{-ru} - c)e^{-iru} = \frac{pV(u)e^{-ru} - c}{1 - e^{-ru}} \tag{1.2}$$

where p is the price of timber (no assortments assumed), $V(u)$ is the volume at the end of rotation time u (only clearcut assumed), r is the rent and c defines the costs of regeneration (no other costs assumed). This rotation time is the economically optimal rotation for any given stand. In continuous form, the optimization problem can be analytically solved, and general results, i.e. cutting rules, can be produced. In this form, however, thinnings cannot be included. In a discrete form, thinnings can be included, but the problem can no more be analytically solved. The discrete form is (Viitala 2002)

$$\underset{\{u\}}{Max} L = \frac{\sum_{i=0}^{u} (R_i - C_i)(1+r)^{u-i}}{(1+r)^t - 1} \tag{1.3}$$

where R denotes the revenues and C costs in year i.

The next phase for large area planning was the introduction of linear programming and complex models that were developed to predict forest development under different scenarios (e.g. Duerr et al. 1979; Clutter et al. 1983; Kilkki 1987; Buongiorno and Gilles 2003). The first applications of linear programming to forest planning were published in the 1960s (e.g. Curtis 1962; Kilkki 1968). In the next decades, forest planning models based on linear programming were developed in many countries, for instance, the FORPLAN model in USA (Johnson 1986; Johnson et al. 1986; see also Iverson and Alston 1986), and MELA model in Finland (Siitonen 1983, 1994). Also models based on simulation were generated in many countries, i.e. models that were not used to find an optimal solution but more to make if-then calculations of different cutting scenarios. Such models were, for instance, HUGIN in Sweden (Hägglund 1981) and AVVIRK in Norway (e.g. Eid and Hobbelstad 2000). Many of these models have been developed until recent years, but new ones have also been published. These models have, however, also been criticized. For instance, the approaches based on LP were not regarded as sufficient with respect to ecological considerations (e.g. Shugart and Gilbert 1987). There were also problems due to the spatial dimensions of the problems, non-linearities and uncertainty. To alleviate these problems, methods for spatial and heuristic optimization were adopted to the forestry calculations (Pukkala 2002).

Any optimization method, however, cannot answer the question of how to value the different criteria in planning. This is because the values are inherently subjective. The criteria are often contradictory, and need to be carefully weighted in order to find the best solution. To deal with the valuation problems, in the last 10 years multi-criteria decision aid has also been adopted in forestry decision making (Pukkala 2002; Kangas and Kangas 2005). However, as optimization methods provide efficient solutions located in different parts of the production possibility frontier, and MCDA methods can be used to analyse the values and preferences, these methods complement rather than compensate each other.

Nowadays, numerous decision makers or other stakeholders are often involved in forest planning. Each of them can have different objectives concerning the use of forests or other natural resources, which further complicates the evaluation. Multi-criteria decision-aid methods can often be used also in these situations (e.g. Kangas 1994). However, methods based on social choice theory have also been developed for participatory planning and group decision making.

References

Belton, V. and Stewart, T.J. 2002. Multiple criteria decision analysis: an integrated approach. Kluwer, Dordrecht, 372 pp.

Bouyssou, D., Jacquet-Lagrez, E., Perny, P., Slowinski, R., Vanderpooten, D., and Vincke Ph. (Eds.), 2000. Aiding decisions with multiple criteria. Essays in honour of Bernard Roy. Kluwer, Dordrecht, 274 pp.

Bradshaw, J.M. and Boose, J.H. 1990. Decision analysis techniques for knowledge acquisition: combining information and preferences using Aquinas and Axotl. International Journal of Man-Machine Studies 32: 121–186.

Buongiorno, J. and Gilles, J.K. 2003. Decision methods for forest resource management. Academic, New York, 439 pp.

Curtis, F.H. 1962. Linear programming of the management of a forest property. Journal of Forestry 60: 611–616.

Clutter, J.L., Fortson, J.C., Pienaar, L.V., Brister, G.H., and Bailey, R.L. 1983. Timber management: a quantitative approach. Wiley, New York, 333 pp.

Dantzig, G.B. 1963. Linear programming and extensions. Princeton University Press, Princeton, NJ, 630 pp.

Davis, K.P. 1966. Forest management: regulation and valuation. 2nd edn. McGraw-Hill, New York, 519 pp.

Davis, L.-S., Johnson, K.N., Bettinger, P.S., and Howard, T.E. 2001. Forest management – to sustain ecological, economic and social values. 4th edn. McGraw-Hill, New York, 804 pp.

Duerr, W.A., Teeguarden, D.E., Christiansen, N.B., and Guttenberg, S. 1979. Forest resource management. W.B.Saunders, Philadelphia, 612 pp.

Dykstra, D.P. 1984. Mathematical programming for natural resource management. McGraw-Hill, New York, 318 pp.

Eid, T. and Hobbelstad, K. 2000. AVVIRK-2000 – a large-scale forestry scenario model for long-term investment, income and harvest analyses. Scandinadian Journal of Forest Research 15: 472–482.

Etzioni, A. 1986. The case for a multiple-utility conception. Economics and Philosophy 2: 159–183.

Faustmann, M. 1849. Berechnung des Wertes welchen Waldboden, sowie noch nicht haubare Holzbestände für die Waldwirtschaft besitzen. Allgemeine Forst- und jagdzeitung 25: 441–455.

French, S. 1989. Readings in decision analysis. Chapman & Hall, London, 210 pp.

Glover, F. 1989. Tabu search – part I. ORSA Journal of computing 1: 190–206.

Glover, F., Kelly, P., and Laguna, M. 1995. Genetic algorithms and tabu search: hybrids for optimization. Computers in Operations Research 22:111–134.

Gregory, G.R. 1972. Resource economics for foresters. Wiley, New York, 477 pp.

Hägglund, B. 1981. Forecasting growth and yield in established forests – An outline and analysis of the outcome of a subproject within the HUGIN project (Rep 31). Department of Forest Survey, Swedish University of Agricultural Sciences, Sweden.

Hillier, F.S. and Lieberman, G.J. 2001. Introduction to operations research. 7th edn. McGraw-Hill, New York, 1214 pp.

Iverson, D.C. and Alston, R.M. 1986. The genesis of FORPLAN: a historical and analytical review of Forest Service planning models. General Technical Report. INT-214. USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT, 37 pp.

Johansson, P-O. and Löfgren K-G. 1985. The economics of forestry and natural resources. Basil Blackwell, Oxford, 292 pp.

Johnson, K.N. 1986. FORPLAN version 1: an overview. USDA Forest Service, Land Management Planning Section, Washington, DC, 85 pp.

Johnson, K.N., Stuart, T.W., and Crim, S.A. 1986. FORPLAN version 2: an overview. USDA Forest Service, Land Management Planning Section, Washington, DC, 110 pp.

Kangas, J. 1992. Metsikön uudistamisketjun valinta – monitavoitteiseen hyötyteoriaan perustuva päätösanalyysimalli. Summary: choosing the regeneration chain in a forest stand, a decision-model based on multi-attribute utility theory. Joensuun yliopiston luonnontieteellisiä julkaisuja 24, 230 pp.

Kangas, J. 1994. An approach to public participation in strategic forest management planning. Forest Ecology and Management 70: 75–88.

Kangas, J. and Kangas, A. 2005. Multiple criteria decision support in forest management – Fundamentals of the approach, methods applied, and experiences gained. Forest Ecology and Management 207: 133–143.

Keeney, R.L. 1992. Value-focused thinking. A path to creative decision making. Harvard University Press, Cambridge, MA, 416 pp.

Keeney, R.L. 1982. Decision analysis: an overview. Operations Research 30: 803–838.

Keeney, R.L. and Raiffa, H. 1976. Decisions with multiple objectives: preferences and value trade-offs. Wiley, New York, 569 pp.

Kilkki, P. 1968. Tulotavoitteeseen perustuva hakkuulaskelma. Acta Forestalia Fennica 91, 54 pp.

Kilkki, P. 1987. Timber management planning. Silva Carelica 5: 1–160. Joensuun yliopisto. Metsätieteellinen tiedekunta.

Kuusela, K. and Nyyssönen, A. 1962. Tavoitehakkuulaskelma. Acta Forestalia Fennica 74, 34 pp.

Lihtonen, V. 1959. Metsätalouden suunnittelu ja järjestely. WSOY, 355 pp.

Mingers, J. and Brocklesby, J. 1997. Multimethodology: towards a framework for mixing methodologies. Omega, International Journal of Management Science 5: 489–509.

von Neumann, J. and Morgestern, O. 1944. Theory of games and economic behaviour. Wiley, New York, 641 pp.

Pukkala, T. (Ed.). 2002. Multi-objective forest planning. Managing Forest Ecosystems, Vol 6. Kluwer, Dordrecht, 207 pp.

Ramsey, F.P. 1930. The foundations of maths and other logical essays. Humanities Press, New York, 280 pp.

Recknagel, A.B. 1917. Theory and practise of working plans. 2nd edn. Wiley, New York.

Reeves, C.R. (Ed.) 1993. Modern heuristic techniques for combinatorial problems. Blackwell, Oxford, 320 pp.

Shugart, H.H. and Gilbert, B.J. 1987. An ecological evaluation of FORPLAN in national forest planning. In: Hoekstra, T.W., Dyer, A.A., LeMaster, D.C. (Eds.). FORPLAN: an evaluation of a forest planning tool. General Technical Report RM-140. USDA Forest Service, Rocky Mountain Forest and Range Experiment Station, Fort Collins, CO, pp 105–121.

Siitonen, M. 1983. A long-term forestry planning system based on data from the Finnish national forest inventory. Proceedings of the IUFRO subject group 4.02 meeting in Finland, September 5–9, 1983. University of Helsinki, Department of Forest Mensuration and Management, Research Notes 17, pp 195–207.

Siitonen, M. 1994. The MELA system as a forestry modelling framework. Lestnictvi-Forestry 41: 173–178.

Simon, H.A. 1957. Models of man: social and national. Wiley, New York, 247 pp.

Speidel, G. 1972. Planung im Forstbetrieb. Verlag Paul Parey, Hamburg/Berlin, 267 pp.

Steuer, R.E. 1986. Multiple criteria optimization: theory, computation, and application. Wiley, New York, 532 pp.

Taha, H.A. 1987. Operation research. Macmillan, New York, 876 pp.

Viitala, E.-J. 2002 Metsän optimaalinen kiertoaika: lähestymistavat ja niiden talousteoreettinen perusta. Research notes of Finnish Forest Research Institute. Report 848, 128 pp.

Vincke, Ph., 1992. Multi-Criteria decision aid. Wiley, New York.

von Winterfeldt, D. and Edwards, W. 1986. Decision analysis and behavioral research. Cambridge University Press, Cambridge.

Part I
Discrete Problems

Chapter 2
Unidimensional Problems

2.1 Decisions Under Risk and Uncertainty

From the viewpoint of decision theory, the decision problems including uncertainty can be presented according to a decision table

$$\begin{array}{cc} & \begin{array}{cccc} \omega_1 & \omega_2 & \cdots & \omega_m \end{array} \\ \begin{array}{c} d_1 \\ d_2 \\ \vdots \\ d_n \end{array} & \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{bmatrix} \end{array} \tag{2.1}$$

The components of a decision table are the decision alternatives $(d_i,\ i = 1,\ldots n)$, the states of nature $(\omega_j,\ j = 1,\ldots m)$, and the consequences $(c_{ij},\ i = 1,\ldots n,\ j = 1,\ldots m)$. The consequence of an action is determined by the action, and by a number of external factors which are beyond the control of the decision maker. A state of nature is a particular set of values that these external factors might assume.

If the state of nature that will actually occur and the consequences associated with the decision alternatives are known, a decision is made under certainty. Under risk and uncertainty, the state of nature that would prevail is not known with certainty. Under risk, the probability of each state of nature occurring and, correspondingly, the probability distribution of consequences are known; otherwise, the decision is made under uncertainty.

The probabilities of the states of nature are rarely known, but it is often possible to estimate these probabilities. If objective probabilities can not be determined, subjective ones, based, for example, on expertise, may be used. This being the case, risk management methods can be applied also to support decision making under uncertainty. Therefore, the distinction between risk and uncertainty is not always clear. In addition to the future states of nature, uncertainty may be related to other elements of the decision making as well. These sources of uncertainty are dealt with in later chapters.

Different decision-makers can take different attitudes towards risk and uncertainty, which may lead to different priority orders among choice alternatives. People can search for good profits, although their probability is not great (risk-seeking person), or settle with lower profits that have great probability if there is risk of large losses (risk-averse person). Decision maker can also be risk-neutral.

Maximization of expected utility is a risk-neutral decision strategy for supporting risky choices (e.g. von Winterfeldt and Edwards 1986). Assume a problem where there are m possible consequences of a decision d_i, $c_{i1}, c_{i2}, \ldots, c_{im}$ that have probabilities of realization $p_1, p_2, \ldots, p_m$. Then, the expected utility from decision d_i is

$$E(u(d_i)) = p_1u(c_{i1}) + p_2u(c_{i2}) + \cdots + p_mu(c_{im}) = \sum_{j=1}^{m} p_ju(c_{ij}). \qquad (2.2)$$

For decision support under uncertainty, several different decision strategies or rules have been developed (see, e.g. Miller and Starr 1969; Lee and Moore 1975; Cook and Russell 1981). For example, according to Maximin- or Wald-criterion, alternatives are ranked according to the worst possible consequences (risk avoiding behaviour), and the alternative with the best worst-case consequence is chosen. According to Maximax-criterion, alternatives are ranked according to the best possible consequences (risk taking behaviour), and the alternative with the best best-case consequence is chosen. Hurwicz-criterion is a combination of these two categorical rules; the alternative with the greatest weighted mean of the worst and the best possible outcomes is chosen. Here, the weights for the worst and the best possible outcomes reflect the attitude towards risk; e.g. for a risk neutral decision maker the weights are equal.

A more general criterion, which produces the above mentioned criteria as special cases, has been developed by Kangas (1992, 1994). In this approach, the decision-maker determines the importance of three priority measures in decision-making: (i) the worst possible outcome, (ii) the expected outcome, and (iii) the best possible outcome associated with the decision alternative. The alternatives can then be ranked based on the weighted average of these three outcomes. Then, if the weight of the worst outcome, bw, is one, one speaks of the maximin-criterion. Correspondingly, if the weight of the best outcome, bb, is 1, alternative is chosen according to the maximax-criterion. If the weight of the expected outcome, be, is 1 alternative is selected from a risk neutral decision maker's point of view.

If $bb > be > bw$ the decision maker can be classified as a risk seeker. In general, if bb is greater than bw, one can speak about risk seeking behaviour. Correspondingly, if $bb < be < bw$, or, more generally, if $bb < bw$, the decision maker can be classified as a risk avoider. The decision strategy can be changed flexibly by weighting the coefficients using different weighting schemes. Sensitivity analysis can be made, for example, of the meaning of the attitude towards risk in the choice of the forest plan.

2.2 Measuring Utility and Value

2.2.1 Estimating a Utility Function

All methods for estimating the utility (or value) functions are based on certain axioms. Eilon (1982) presented three basic axioms that are needed in estimation:

2.2.1.1 Connectivity

The decision maker is able to say from two alternative outcomes A and B, if he/she prefers A to B, B to A or if he/she is indifferent between these outcomes.

2.2.1.2 Transitivity

If the decision maker prefers outcome A to B and outcome B to C, then he/she also prefers outcome A to C.

2.2.1.3 Comparability

If the decision maker has three outcomes, A, B and C, and he/she prefers A to B and B to C, he/she can choose a coefficient x such that utility of $xA + (1-x)C = B$.

The first of these axioms may be violated, if the decision maker cannot make his/her mind. In practical work, it has often been noted that axioms 2 and 3 may not hold (e.g. Eilon 1982; Knowles 1984; Bell and Farquhar 1986). Furthermore, the last axiom only makes sense if the outcomes that are compared are quantitative, such as money.

Estimating the utility function at unidimensional scale is typically based on indifference methods (von Winterfeldt and Edwards 1986, p. 217). In practise it means, that decision maker needs to match two outcomes or pairs of outcomes to meet indifference relation. In essence, it means estimating the utility function based on the comparability axiom above.

As the utility is relative, the utility of two consequences can be arbitrarily assigned, and the rest of the utilities are assessed relative to these (Keeney and Raiffa 1976, p. 140). It is assumed that the most preferred consequence is defined as c^* and the least preferred as c^0. The utilities provided by these consequences can be scaled to $u(c^*) = 1$ and $u(c^0) = 0$, respectively. In the next stage, the consequences c_i are compared to lotteries, where the consequence is c^* with probability π and c^0 with probability $(1-\pi)$. Such lotteries are defined with $(c^*,\ \pi,\ c^0)$. The decision-maker is required to state, which is the probability π with which he/she is indifferent between the certain consequence c_i and the lottery. Because of the indifference, the utility $u(c_i)$ must be equal to the expected utility of the lottery.

It follows that

$$u(c_i) = \pi u(c^*) + (1-\pi)u(c^0) = \pi 1 + (1-\pi)0 = \pi. \tag{2.3}$$

When several such comparisons are made, the utility function can be fitted to the expressed probabilities. This approach is called variable probability method (von Winterfeldt and Edwards 1986).

The other possibility is to use a constant probability, say 0.5, and to change the consequence c_i to such amount that the utility it provides would be indifferent with the lottery. This approach is called variable certainty equivalent method.

The well-known von Neumann–Morgestern utility function was already based on such comparisons. In their approach, risk attitudes are dealt with implicitly; form of the utility function describes the decision maker's attitude towards risk (von Neumann and Morgestern 1947). In many cases, the certainty equivalent c_i, which gives the same utility as the lottery, is actually larger or smaller than the expected payoff of the lottery. For instance, the decision-maker may say that 80€ is the certainty equivalent for lottery (200, 0.5, 0). Then, the difference between the expected payoff and certainty equivalent, 100€–80€, is the risk-premium. This is the amount a risk-avert decision maker is willing to "give up" in order to avoid uncertain lottery. If the risk premium is negative, the decision maker is a risk-seeker.

The utility function of risk-neutral person is according to this theory linear, and that of risk-seeker convex. This result has, however, been criticized, since a concave utility function can also be reasoned based on an assumption of decreasing marginal utility (e.g. Sarin 1982; Sheng 1989; Kangas 1992). The estimation of Neumann–Morgenstern type utility function is also considered to be too complicated for practical decision-making processes (Leung 1978; Kirkwood and Sarin 1985; Butler and Loomes 1988). Therefore, risk is not accounted for in most real applications.

Example 2.1. Certainty equivalent method

Assume a game with the best possible outcome being a gain of 10,000€ and the worst outcome a loss of 10,000€. The decision maker is asked what amount of money obtained for certain is indifferent (i.e. giving the same utility) as game

Table 2.1 The obtained utility data

Income	Utility
−10,000	0
−8,400	0.125
−6,400	0.25
−4,400	0.375
−2,000	0.5
400	0.625
3,200	0.75
6,000	0.875
10,000	1

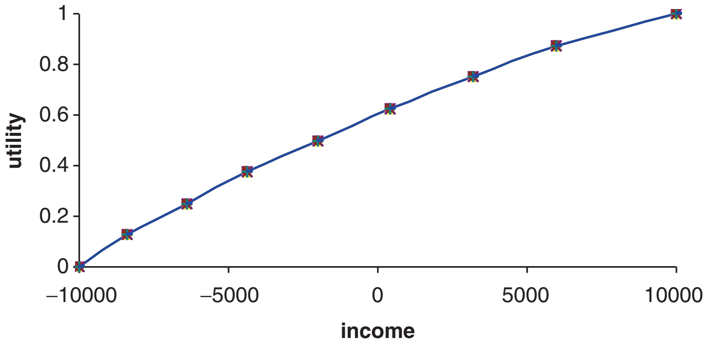

Fig. 2.1 Utility function

(10,000, 0.5, −10,000). If the DM answers −2,000, the risk premium is (0 − −2,000)€ = 2,000€, which means that the decision maker is risk – avoider.

The next question is, what certain outcome is indifferent to game (−10,000, 0.5, −2,000) and game (−2,000, 0.5, 10,000). If the answers were, for instance, −6,400€ and 3,200€, next games to be analyzed are (−10,000, 0.5, −6,400), (−6,400, 0.5, −2,000), (−2,000, 0.5, 3,200) and (3,200, 0.5, 10,000). When the answers to these games are obtained, and $\mathrm{u}(-10{,}000) = 0$ and $\mathrm{u}(10{,}000) = 1$, utility of −2,000 is calculated with $\mathrm{u}(-2{,}000) = 0.5 \cdot 0 + 0.5 \cdot 1.0 = 0.5$. The rest of the utilities can be calculated in the same way. Finally, the utility function can be fitted to the obtained data (Table 2.1) and the utility of income can be drawn (Fig. 2.1). The function in example 2.1 is concave, which describes a risk-avoider according to theory of von Neumann and Morgestern (1947).

2.2.2 Estimating a Value Function

Unidimensional value functions – or utility functions for no-risk situations – are formed based on comparisons between alternatives, but without lotteries. There exist several methods for estimating value function, of which only a few are presented in this book.

One possibility is to utilize the natural scale with which the performance of alternatives is measured, for instance, money, and scale it to range 0–1 (Keeney 1981). The most popular scaling approach is the maximum score based approach

$$v_i = c_i / \max(c), \tag{2.4}$$

That is, the criterion values c_i are divided with the maximum value among alternatives. The best alternative is assumed to have value one. Rest of the alternatives are relative to that and zero value is only given to an alternative also having zero value in natural scale. Then, the values follow a ratio scale. Another possibility is to scale the natural scale values with score range procedure

$$v_i = (c_i - \min(c))/(\max(c) - \min(c)) \tag{2.5}$$

The best alternative is assumed to have a value one also in this case, and the worst the value zero. In this case, if $\min(c) > 0$, the alternatives do not follow a ratio scale, but an interval scale. In ratio scale, it is meaningful to compare the ratios between values, in interval scale only the differences. In interval scale, ratio comparisons simply do not make sense: all the alternatives are infinitely better, when compared to the worst alternative. Interval scale can be interpreted as local scale, the length of which depends on the specific planning situation (e.g. Kainulainen et al. 2007). If $\min(c) = 0$, these cases are equal.

The scaled scores obtained with (2.4) and (2.5) are often interpreted as value function. Such interpretation is quite common in practical decision support tools, as it is not necessary to ask decision makers any questions to form this kind of value function. Another interpretation is that the different variables and measurement scales are just standardized to the same scale.

If the scaled values are interpreted as a value function, it means that the analysis is based on an assumption of a linear value function. The value function may, however, be assumed to follow a certain type of non-linear function. In such a case, the decision-maker can choose the shape from a few predefined ones (e.g. exponential function). Then, a function of that type is fitted to the values presented in natural scale, but no more questions concerning the value function are asked from the decision-maker.

A group of methods useful for estimating value function are the so-called direct rating methods. In these methods, the decision maker is assumed to be able to rank the alternatives from best to worst. The best alternative and/or the worst alternative are given some arbitrary number of points, for instance 100 points for the best alternative and 0 for the worst alternative. Decision maker is then asked to give the rest of the alternatives points, related to the best and worst alternatives (von Winterfeldt and Edwards 1986, p. 229). These points are then scaled to 0–1 interval.

Example 2.2. Assume five alternatives, which all produce different amounts of money. It is assumed that the natural scale is in linear relationship with the value scale. The alternatives are scaled to value scale both utilising a ratio scale and an interval scale. The alternatives and different versions of scaling are presented in Table 2.2. In Fig. 2.2, the ratio scale value function is presented with diamonds and the interval version with squares.

Example 2.3. The decision maker was first asked to rank the alternatives from best (1) to worst (5). After that, decision maker was asked to give points between

Table 2.2 Scaling from original scale to utility scale

Alternative	Money	Ratio scale	Interval scale
1	250	1	1
2	124	0.496	0.427
3	76	0.304	0.209
4	55	0.22	0.114
5	30	0.12	0

Table 2.3 Points given to the alternatives

Alternative	Money	Order	Points	Value
1	250	1	100	1
2	124	2	60	0.6
3	76	3	35	0.35
4	55	4	20	0.2
5	30	5	0	0

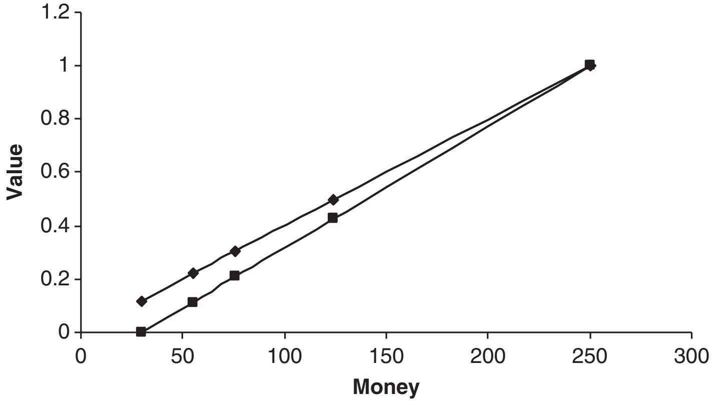

Fig. 2.2 Scaled utilities

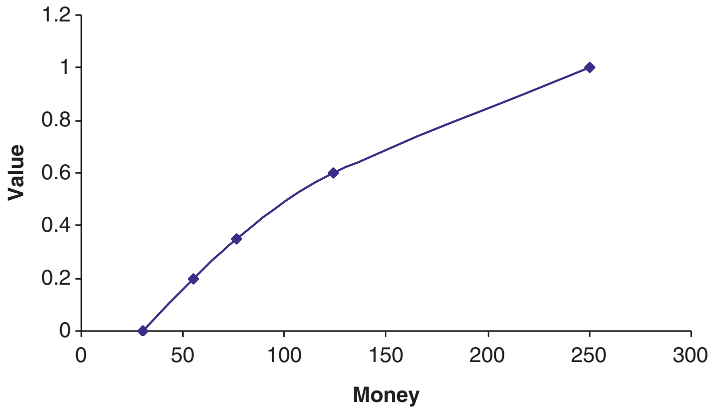

Fig. 2.3 Value function obtained from given points

Table 2.4 Indifferent changes

i	x_i	x_{i+1}	z_{i+1}	Points
0	0	30	30	1
1	30	70	40	1
2	70	120	50	1
3	120	180	60	1
4	180	250	70	1

0 and 100 to the three middle alternatives of the example 2.2. The obtained data is presented in Table 2.3 and the resulting value function is presented in Fig. 2.3.

Methods based on indifference are also used for estimating value functions, not only utility functions. In the case of value functions, decision makers are not asked to select a certain amount of money equal in utility to some lottery, but for selecting an outcome or difference in outcome that is indifferent to another outcome or difference in outcomes. One example of the indifference methods is the difference standard sequence method. In this approach, first a zero level x_0 is defined, i.e. the level which is least preferred. Then, a small but meaningful improvement z_1 from this level x_0 to a better level $x_1 = x_0 + z_1$ is selected. Then, the decision maker is asked, which improvement z_2 from level x_1 to level $x_2 = x_1 + z_2$ is equally preferred to the improvement z_1 from level x_0. After that, the decision-maker is asked which improvement z_3 from level x_2 is equally preferred to the improvement z_2 from level x_1 and so on. Thus, decision maker has to compare changes, the utility of which is assumed to depend on the level achieved so far. Since all these improvements $z_1 \ldots z_n$ are equally preferred, they can all be given same amount of points, say 1. Then, the points at each level can be calculated, so that $v(x_0) = 0,\ v(x_1) = 1,\ v(x_n) = n$, and the value function can be calculated by dividing the points at each level by n.

If the change z_i is smaller than the equally preferred change z_{i+1}, the value function is concave and shows marginally decreasing value (von Winterfeldt and Edwards 1986, p. 233). Thus, a concave utility function can be due to decreasing marginal value, not just the sign of risk-aversion.

Table 2.5 Resulting values

Money	Points	Value
0	0	0
30	1	0.20
70	2	0.40
120	3	0.60
180	4	0.80
250	5	1.00

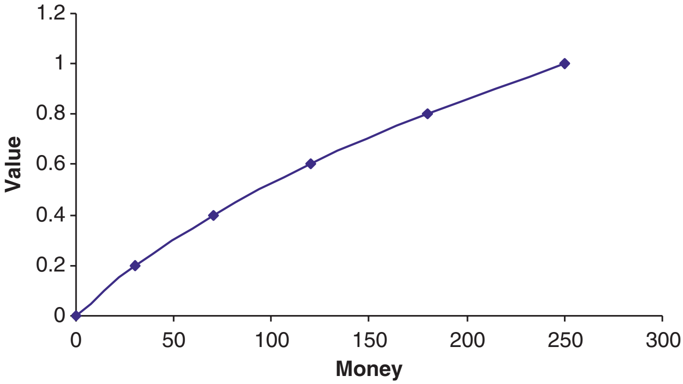

Fig. 2.4 Utility function resulting from indifferent changes

Example 2.4. The situation is the same as in the above examples. In this case the zero level x_0 is set to 0€, and the first improvement step z_1 is 30€. Then the decision maker evaluates that a change $0 \rightarrow 30$ is equally preferred to a change $30 \rightarrow 70$, and a change $30 \rightarrow 70$ is equally preferred to change $70 \rightarrow 120$ and so on. All the equally preferred changes are given in Table 2.4., the resulting values in Table 2.5., and the obtained value function is presented in Fig. 2.4.

References

Bell, D.E. and Farquhar, P.H. 1986. Perspectives on utility theory. Operations Research 34: 179–183.

Butler, D. and Loomes, G. 1988. Decision difficulty and imprecise preferences. Acta Psychologica 68: 183–196.

Cook, T.M. and Russell, R.A. 1981. Introduction to management science. Prentice-Hall, New Jersey, 763 pp.

Eilon, S. 1982. Control and utility. Omega 10: 223–231.

Kainulainen, T., Leskinen, P., Korhonen, P., Haara, A. 2007. A statistical approach to assess interval scale preferences in discrete choice problems. Manuscript.

Kangas, J. 1992. Metsikön uudistamisketjun valinta monitavoitteiseen hyötyteoriaan perustuva päätösanalyysimalli. Summary: choosing the regeneration chain in a forest stand: adecision model based on multi-attribute utility theory. University of Joensuu. Finland.

Kangas, J. 1994. Incorporating risk attitude into comparison of reforestation alternatives. Scandinavian Journal of Forest Research 9: 297–304.

Keeney, R.L. 1981. Measurement scales for quantifying attributes. Behavioral Science 26: 29–36.

Keeney, R.L. and Raiffa, H. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Wiley, New York, 569 pp.

Kirkwood, C.G. and Sarin, R.K. 1985. Ranking with partial information: a method and an application. Operations Research 33: 38–48.

Knowles, G.J. 1984. Some econometric problems in the measurement of utility. American Journal of Agricultural Economics 66: 505–510.

Lee, S.M. and Moore, L.J. 1975. Introduction to decision science. Petrocelli/Charter, New York, 589 pp.

Leung, P. 1978. Sensitivity analysis of the effect of variations in the form and parameters of a multiattribute utility model: a survey. Behavioral Science 23: 478–485.

Miller, D.W. and Starr, M.K. 1969. Executive decisions and operations research. Prentice-Hall. New Jersey, 607 pp.

von Neumann, J. and Morgestern, O. 1947. Theory of games and economic behaviour. Wiley, New York, 641 pp.

Sarin, R.K. 1982. Strength of preference and risky choice. Operations Research 30: 982–997.

Sheng, C.L. 1989. Some quantitative concepts of value and utility from a utilitarian point of view. Theory and Decision 26: 175–195.

von Winterfeldt, D., Edwards, W. 1986. Decision analysis and behavioral research. Cambridge University Press, Cambridge.

Chapter 3
Multi-Criteria Decision Problems

3.1 Theoretical Aspects

The basis for decision making is that given two objects, say A and B, people can meaningfully say whether they prefer A to B, B to A or whether they are indifferent (von Winterfeldt and Edwards 1986). Usually, it is assumed that people can also state the strength of this preference. The strength could be expressed either in ordinal terms, or in cardinal terms. If the decision maker can say that change from A to B is preferable to change from B to C, then the judgment is ordinal. If the decision maker can say by how much, the judgment is cardinal.

Multi-Attribute Utility Theory, where the utility of the decision maker is considered to consist of several attributes, is usually shortened with MAUT. In different contexts, concepts 'objectives' and 'criteria' are used instead of 'attributes'. Malczewski (1999, p. 85) defines multi-criteria decision making as a broader class, which includes both multi-attribute decision making for discrete decision problems and multi-objective decision making for continuous problems. He defines attributes as measures of performance of an object, and objects as statements about the desired state of a system. In this book, the attributes and criteria are used as synonyms, and multi-objective is only used in the context of optimization.

In many cases also the term MAVT, Multi-Attribute Value Theory, is used. The difference between MAUT and MAVT is that the value functions do not include the risk preferences of the decision maker but the utility function does. von Winterfeldt and Edwards (1986, p. 215) think this difference is spurious, however. A utility function is also a value function, while a value function is not necessarily a utility function.

The problem is formulated with a set of distinct alternatives $d_i,\ i = 1,\dots,n$ and a set of decision criteria $c_j,\ j = 1,\dots,m$ so that c_{ij} represents the performance of alternative i with respect to criterion j. It is simply not possible to independently maximize or minimize several criteria at the same time: you cannot maximize the gross incomes while at the same time minimizing the costs, or maximize the yield and minimize the risks (Keeney and Raiffa 1976, p. 66).

Therefore, the big issue in multi-criteria decision making is that of tradeoffs: how much is the decision maker willing to give up in one criterion, in order to improve the performance with respect to another criterion by some fixed amount. For instance, the decision maker needs to decide, how much more risk of beetle outbreak she/he will tolerate in order to improve net incomes by 100€, or how much incomes is she/he willing to give up in order to reduce the risk by 10%.

The tradeoffs decisions are about personal values, and thus, they require subjective judgment of the decision maker. This means that there are no correct or wrong answers to the value questions; people may have very different preference structures. The tradeoffs problem can be solved in two ways: (1) the decision maker can informally weigh the tradeoffs is his/her mind or (2) the decision maker can formalize his/her preferences to a multi-criteria utility function and use it to solve the problem (Keeney and Raiffa 1976). Either way, the tradeoffs are inevitable in any multiple-criteria decision.

There are a few choice procedures that do not require utility functions in order to make choices. One of these is dominance. We can say that alternative i dominates alternative i', if

$$
\begin{aligned}
&c_{ij} \geq c_{i'j}, \ \forall j = 1, \ldots, m \\
&c_{ij} > c_{i'j}, \ \text{for some } j = 1, \ldots, m
\end{aligned}
$$

It means that alternative i is at least as good as alternative i' for all criteria j, and, in addition, alternative i is strictly better than alternative i' with respect to at least one criterion j. If an alternative is dominated by some other alternative, it can be left out from the analysis: it can never be chosen as the best alternative, whatever the preference structure. If there is one alternative among the n alternatives that dominates all other alternatives, the choice would then be easy. However, such is the case only rarely. It may, however, be that some of the alternatives can be eliminated before further analysis.

What is important in the non-dominated alternatives, is that they form the efficient frontier or the Pareto optimal set among the alternatives (Fig. 3.1).

One possible way of choosing among a set of alternatives, without considering the tradeoffs, is to utilize a lexicographic ordering (Keeney and Raiffa 1976). In this method, the decision maker first ranks the criteria with respect to their importance. Then, the most important criterion is c_1 and the least important criterion is c_m. Then, alternative i is preferred to alternative i', denoted by $i \succ i'$, if and only if

(a) $c_{i1} > c_{i'1}$ or

(b) $c_{ij} = c_{i'j}, \ j = 1, \ldots, k$

$c_{i(k+1)} > c_{i'(k+1)}$, for some $k = 1, \ldots, m-1$

It means that the choice is made only based on the most important criterion. If there are several alternatives that are equal with respect to that criterion, then the second most important criterion is considered and so on.

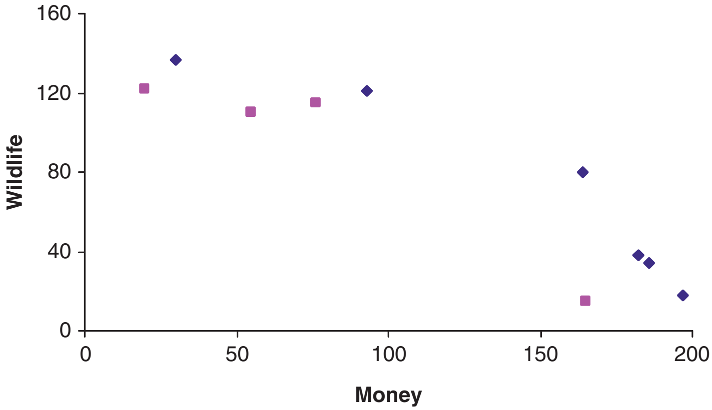

Fig. 3.1 Dominated alternatives are presented with squares, and non-dominated with diamonds. The non-dominated alternatives form the efficient frontier of the problem

3.2 Multi-Attribute Utility Functions

3.2.1 Function Forms

In a case of multi-attribute utility function, it is assumed that there are m criteria, and a unidimensional utility (or value) function is evaluated or can be evaluated for each of these criteria. The task is now to aggregate these utility functions to describe the overall utility of the alternatives. This aggregation is done by weighting the different criteria in the utility function with respect to their importances. The relations between the weights of different criteria describe the tradeoffs between the criteria.

The most applied multi-attribute utility function is the linear additive utility function

$$U_i = \sum_{j=1}^{m} a_j c_{ji} \tag{3.1}$$

where U_i describes the overall utility of alternative i (or priority of alternative i) and c_{ij} is the performance of the alternative i with respect to criterion j and a_j is the importance weight of criterion j. In this equation, it is assumed that the criteria values c_{ij} are already in utility scale or are scaled to a utility scale with Formula (2.4) or (2.5), for instance.

Typically, it is required that

$$\sum_{j=1}^{m} a_j = 1, \tag{3.2}$$

otherwise the utility could always be increased by increasing the weights. The trade-offs between criterion k and k' can be calculated from the ratio of the weights $a_k/a_{k'}$.

In general, the marginal rate of substitution between criteria k and k' can be calculated as a ratio of partial derivatives of the utility function as

$$\lambda = \frac{U'_k}{U'_{k'}} = \frac{a_k}{a_{k'}} \tag{3.3}$$

This means that the decision maker is willing to give up λ units of criterion k' in order to increase the value of criterion k by one.

Example 3.1. Assume a utility function with $U_k = 0.67c_{1k} + 0.33c_{2k}$, where c_1 denotes units of money and c_2 the number of animals in some wildlife species. Then, the decision maker is willing to give up one animal in order to increase the incomes with $0.67/0.33 = 2$ units of money.

In the linear additive utility function, the tradeoff between the criteria is constant. It means, that the willingness of the decision maker to change one unit of criterion k' to λ units of criterion k does not change, even if there is only a few units left of criterion k', or even if there is already plenty of criterion k. If a decreasing marginal utility is assumed, this does not hold. In this case, a more general function, namely the additive utility function needs to be used. It is of the form

$$U_i = \sum_{j=1}^{m} a_j u_j(c_{ij}) \tag{3.4}$$

where $u_j(c_{ij})$ is the partial utility due to criterion j. It is described with the unidimensional utility function for this criterion. In this function, the marginal rate of substitution is a function of the current values of criteria j.

The additive utility models are compensatory at nature. In this respect, this utility function differs from other forms of utility functions. It means that even if some criteria assume their lowest possible levels, this can be compensated if some other criterion or criteria assume very good values. The compensation is dictated by the marginal rate of substitution.

Example 3.2. Let us consider six non-dominant alternatives from Fig. 3.1. The overall utility function is assumed to be

$$U_i = a_1 \cdot 0.00506 \cdot c_{i1} + a_2 \cdot 1.55251 \cdot \exp(-60.2556/c_{i2})$$

and the resulting utilities are presented in Table 3.1. The weights of these two criteria are assumed to be equal, i.e. 0.5, and the greatest overall utility is observed for alternative 2, with 164 units of money and 80 animals. If the number of wildlife were 1, this could be fully compensated with 309 units of money, i.e. such an alternative would get the largest overall utility, 0.782. On the other hand, if the amount of money were 10 units, this could be compensated with 2,100 animals, giving overall utility 0.780. The marginal utility of additional animals is very small, when the number of animals is high.

The partial derivatives of these functions are $a_1 \cdot 0.00506$ with respect to criterion c_1, money, and a_2 $1.55251 \cdot \exp(-60.2556/c_{i2})(60.2556/c_{i2}^2)$ with respect to criterion c_2, number of wildlife animals. Thus, the marginal rate of substitution does not

Table 3.1 Overall utilities of the alternatives

Alternative	Money	Wildlife	Overall utility
1	197	18	0.526
2	164	80	**0.780**
5	30	137	0.576
8	186	34	0.603
9	182	38	0.619
10	93	121	0.707

depend on money, but it depends on the amount of animals. When the number of wildlife animals varies from 30 to 530, the marginal rate of substitution varies from 0.36 to 17.02 animals: the more animals there are, the more the decision maker is willing to give up for additional unit of money. The partial derivatives and the resulting λ are presented in the Table 3.2.

In addition to these two utility functions, there exist a number of different functions. One example is the multiplicative model (von Winterfeldt and Edwards 1986, p. 291)

$$1 + aU_i = \prod_{j=1}^{m} [1 + aa_j u_j(c_{ij})] \tag{3.5}$$

which can also be presented in a form of an additive utility function with interaction terms

$$U_i = \sum_{j=1}^{m} a_j u_j(c_{ij}) + a \sum_{j=1}^{m} \sum_{k>j}^{m} a_i a_j u_i(c_{ij}) u_k(c_{ik}) + \cdots + a^{m-1} \prod_{j=1}^{m} a_j u_j(c_{ij}). \tag{3.6}$$

In this function, the interaction between the partial utility of different criteria is presented using products of each pair of alternatives, products of each group of three criteria, and finally the product of all criteria. The interactions are dealt with

Table 3.2 Ratio of partial derivatives

Wildlife	Money	Wild	λ
30	0.00253	0.00697	0.3628
80	0.00253	0.00344	0.7352
130	0.00253	0.00174	1.4531
180	0.00253	0.00103	2.4493
230	0.00253	0.00068	3.7184
280	0.00253	0.00048	5.2589
330	0.00253	0.00036	7.0704
380	0.00253	0.00028	9.1527
430	0.00253	0.00022	11.5057
480	0.00253	0.00018	14.1293
530	0.00253	0.00015	17.0234

using one parameter, a, with a power of $p-1$, where p is the number of terms in the product. It means, that for two-term interactions $p=1$, and for m-term interactions $p=m-1$. This parameter a must lie between -1 and ∞. As the value of a increases, the amount of interaction increases, for $a=0$ this formula simplifies to additive utility function. In a two-dimensional case a can be calculated from (von Winterfeldt and Edwards 1986)

$$a = \frac{1-a_1-a_2}{a_1 a_2} \tag{3.7}$$

It means that if $a_1+a_2=1$, a is 0, and if $a_1=a_2=0$, a is infinite.

Using this function, the degree of compensation cannot be calculated as neatly as with the previous additive models. Furthermore, also the interpretation of the model is more complicated, as the level of any one criterion affects to the utility obtained from a fixed level of another criterion.

Example 3.3. Assume the criteria in the example 3.2 have an interaction, i.e. the level of money affects to the utility obtained from wildlife. Both criteria have equal weight, 0.4, and thus the interaction term $a = \frac{1-0.4-0.4}{0.4 \cdot 0.4} = 1.25$. The partial utilities are calculated with the same functions as in example 3.2 and the resulting utilities are presented in Table 3.3. In this case, as the alternative 2 has the most even distribution of the criteria, it is the best alternative also with this utility model.

Since all the interactions are dealt with the same parameter, this function is fairly inflexible. In principle, it would be possible to estimate separate interaction term for each interaction pair of criteria, but this would require a lot of data from decision makers: each parameter requires at least one observation in order to be estimated, and the number of observations increases very fast as m increases.

Another common utility function form is the conjunctive function

$$U_i = \prod_{j=1}^{m} (u_j(c_{ij}))^{a_j} \tag{3.8}$$

This model is non-compensatory at nature. If the utility due to one of the criteria assumes zero value, the overall utility is also zero. It favours alternatives having fairly similar partial utility values for all criteria (e.g. Tell 1976).

Table 3.3 Overall utilities with interaction term

Alternative	Money	Wildlife	Overall utility
1	197	18	0.431
2	164	80	**0.746**
5	30	137	0.491
8	186	34	0.532
9	182	38	0.554
10	93	121	0.654

One example of utility functions is also the distance function (Tell 1976; Tell and Wallenius 1979)

$$U_i = \sqrt{\sum_{j=1}^{m} a_j^2 \left(c_j^{opt} - c_{ij}\right)^2} \tag{3.9}$$

where c_j^{opt} defines the optimal state of each criterion. This model needs to be scaled so that the optimal value of criterion is given value 1 and the least preferred value of that criterion is given zero value.

The weights a_j have throughout the chapter been interpreted as importances of the different criteria. However, this approach has also been criticized. For instance, Keeney and Raiffa (1976) consider the weights to be simple rescaling method which is necessary to match the units of one unidimensional utility function with another. Since it is possible to obtain very different value functions from the same data for any one criterion (e.g. Formulas 2.4 and 2.5) this needs to be kept in mind. For instance, when Formula 2.4 is used, the weights can be interpreted to describe the importance of change from 0 level in natural scale to the maximum level, and when Formula 2.5. is used, the same weights should describe the importance of change from the minimum value at natural scale, i.e. 0 at utility scale, to the maximum value at both natural and utility scale.

Example 3.4. In the data of the example 3.2, also a conjunctive utility function can be used. The partial utilities are calculated with the same functions as in example 3.2. The criteria are assumed to be equally important also in this example, and the resulting utilities are presented in Table 3.4. In this case, as the alternative 2 has the most even distribution of the criteria, it is the best alternative also with this utility model.

3.2.2 Basis for Estimating the Weights

There exist a large amount of methods that can be used for estimating the weights in the utility function. Generally, they can be divided to two main categories: direct and indirect methods. In indirect methods, the estimation may be based on the earlier, true decisions. These revealed preferences are commonly utilised for evaluating

Table 3.4 Overall utility assuming a conjunctive utility function

Alternative	Money	Wildlife	Overall utility
1	197	18	0.233
2	164	80	**0.779**
5	30	137	0.390
8	186	34	0.498
9	182	38	0.541
10	93	121	0.666

non-market values. In direct methods, the estimation is based on direct questions concerning the importances of criteria in the decision situation at hand.

It has been claimed that the old decisions are the only reliable way to estimate the true utility function. Such utility function is true only with respect to the old decision, however. The preferences and situation of the decision maker may have totally changed after that old decision was made, and thus, the model may not be at all useful in a new decision situation. The estimated utility model may also be incorrect for the old decision, if it was made based on imperfect information on the alternatives. Therefore, studying the old decisions and the preferences implied by these decisions are mainly useful in descriptive studies. When aiming at decision support, direct methods can be assumed more useful.

Direct estimation methods can be further divided to two groups, statistical and subjective methods (Schoemaker and Waid 1982). In statistical methods, the decision makers are asked to holistically evaluate some decision alternatives, and the utility function is estimated based on these values. In subjective methods, the decision problem is divided to several criteria, and preferences are asked regarding these criteria.

Different estimation method for utility functions, have been tested, for instance by Eckenrode (1965), Fishburn (1967), Tell (1976), Tell and Wallenius (1979), Eliashberg (1980), Jacquet-Lagreze and Siskos (1981), Schoemaker and Waid (1982), Horsky and Rao (1984), and Laskey and Fischer (1987). In this sub-chapter, only one group of subjective direct methods of estimation are presented, namely SMART. Later in the chapter, some additional techniques like the pairwise comparisons of Analytic Hierarchy Process are presented. These can also be used for estimating a utility function. However, these methods do not necessarily belong under the MAUT, and therefore they are dealt with separately.

3.2.3 Smart

SMART (Simple Multi-Attribute Rating Technique) is a decision support method developed at the close of the 1960s and early 1970s in the field of multi-attribute utility theory (von Winterfeldt and Edwards 1986). In fact, several methods based on direct evaluation are involved in the family of SMART methods, of which various researchers have developed new versions over the years. Generally, in SMART, additive models are applied.

Direct rating in SMART means, for example, that criteria are directly assigned numerical values depicting their importance. The least important criterion is first given 10 points and the points of other criteria are related to that. Then, the points are summed, and the final weights are the points of each criterion divided by the sum.

$$a_j = \frac{p_j}{\sum\limits_{i=1}^{m} p_i} \tag{3.10}$$

The same principles can, of course, also be used for estimating the value function with respect to each criterion (Chapter 2).

When the importance of the individual criteria and the priorities of each of the alternatives with respect to each of the criteria have been determined, the overall utility of alternatives can be calculated. SMART methods have been applied in natural resources management by Reynolds (2001) and Kajanus et al. (2004), for instance.

Another version of SMART, namely SMARTS (SMART using Swings) also exists. In SWING weighting, it is first assumed that all criteria are their lowest possible values, e.g. at utility function value 0. Then it is asked, which criteria is most important to change from its minimum level to its maximum level. This criterion is given 100 points. After that, the rest of the criteria are evaluated relative to that criterion. This approach has the advantage that the importance weights explicitly depend on the range of criteria values on the problem at hand, while the former SMART weighting does not necessarily do so.

Example 3.5. The case example presented next is applied throughout the book to illustrate different MCDM tools. The data comes from a real-life case of strategic planning in a 320.9 ha area in northern Finland, owned by state and managed by the Finnish State Forest Enterprise Metsähallitus. It has been used in many planning studies. The data consists of three criteria and six alternatives (see Kangas et al. 1992). The problem was to assess the priority of the forest plans generated for the area. The plans were

Continue natural growth with no cuttings (NAT)
Optimize scenic beauty index (SCEN)
Normal forestry guidelines (NORM)
Optimize game values (GAME)
Modest regeneration (MREG)
Maximize income (INC)

The decision criteria in this problem were timber production, scenic beauty, and game management. Each of the criteria was further decomposed into several sub-criteria. In order to keep the example as simple as possible, only timber production and scenic beauty of the main criteria were used here. The timber production was divided to two sub-criteria, namely net incomes during first 10 years and stumpage value after 20 years. The decision hierarchy is presented in Fig. 3.2.

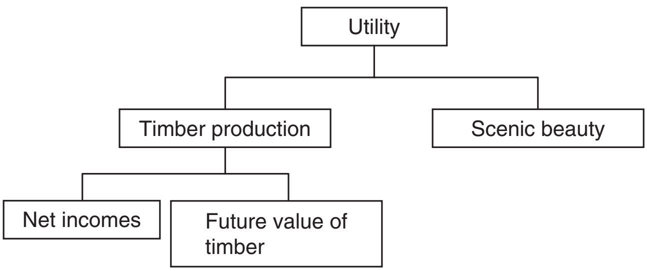

Fig. 3.2 The decision hierarchy in SMART example

Table 3.5 Net incomes, stumpage values and scenic beauty index of the six alternative plans

	Net incomes 1000€	Stumpage value million€	Scenic beauty index
NAT	0.00	0.71	5.5
SCEN	79.6	0.28	5.7
NORM	38.0	0.60	5.4
GAME	33.0	0.61	5.5
MREG	102.3	0.51	5.2
INC	191.7	0.13	4.9

Table 3.6 Cutting schemes of the example alternatives

	Regeneration 1st period (ha)	Per cent Clear-cut	Regeneration 2nd period (ha)	Per cent Clear-cut
NAT	0	0	0	0
SCEN	55.1	0	104.3	0
NORM	14.9	81	15.6	81
GAME	17.0	0	17.2	0
MREG	50.3	96	44.5	11
INC	109.6	68	87.2	29

Table 3.7 Sub-utility function values

	Net incomes	Stumpage value	Scenic beauty
NAT	0.000	1.000	0.750
SCEN	0.631	0.546	1.000
NORM	0.360	0.954	0.625
GAME	0.319	0.959	0.750
MREG	0.740	0.893	0.375
INC	1.000	0.000	0.000

Table 3.8 Global and local utilities

	Global utility	Timber production	Scenic beauty
NAT	0.350	0.200	0.150
SCEN	0.688	0.488	**0.200**
NORM	0.532	0.407	0.125
GAME	0.533	0.383	0.150
MREG	**0.697**	**0.622**	0.075
INC	0.600	0.600	0.000

Table 3.9 Weights based on ranking

	Rank reciprocal	Rank sum	Rank Exponent with $z = 1.6$	ROC
Timber production	0.67	0.67	0.75	0.75
Scenic beauty	0.33	0.33	0.25	0.25

Net incomes describe the timber harvesting income during the first half of the 20-year planning period, and stumpage value describes the monetary value of the remaining trees at the end of the 20-year period. Scenic beauty is an index describing scenic beauty after 20 years, calculated with MONSU software (see Pukkala 2006). The data for the example is presented in Table 3.5. From the alternatives, NAT means that there are no cuttings at all. In SCEN and GAMES alternatives, regeneration is carried out, but no clear-cuts are allowed. In INC alternative, the area of clear-cutting is largest: in MREG the regeneration area is only half of that, although most of the regeneration is carried out with clear-cutting (Table 3.6.).

In SMART analysis, an exponential utility function (of the form $a \cdot \mathrm{e}^{-b/x}$) was assumed for net incomes and stumpage value, and a linear utility function (Formula 2.5) for Scenic beauty. The utility functions were calculated with WebHIPRE program (http://www.hipre.hut.fi). The utility function values for each alternative and each criterion are given in the Table 3.7.

The criteria were next weighted. Since the criteria form a decision hierarchy, the lowest-level criteria were first weighted. The least important criterion, stumpage value, was given 10 points and the most important, net incomes, was given 30 points. Then, the weight of net incomes becomes 0.75 and that of stumpage value 0.25. The higher-level criteria were compared in the same way: the scenic beauty was given 10 points and the timber production was given 40 points, which gave weights 0.2 for scenic beauty and 0.8 for timber production. Then, the global weights of net incomes and stumpage value were calculated as $0.8 \cdot 0.75 = 0.6$ and $0.8 \cdot 0.25 = 0.2$. With these weights, the priorities of the alternatives could be calculated. In Table 3.8. the priorities of each alternative with respect to both higher-level criteria, and the global priorities are shown.

It is also possible to use the importance ranks of the criteria to calculate the weights a_j for the alternatives. This approach is called SMARTER (Simple Multi-Attribute Rating Technique Exploiting Ranks). One possible approach for calculating the weights from ranks are the so-called Rank Order Centroid or ROC weights (Edwards and Barron 1994)

$$a_j = (1/m) \sum_{i=j}^{m} 1/i, \tag{3.11}$$

where the criteria are assumed to be arranged from most important $(j = 1)$ to least important $(j = m)$. von Winterfeldt and Edwards (1986; also Stillwell et al. 1981) presented three other formulas that can be used for calculating weights from

Table 3.10 Global utilities with ROC weighting

	Global utility
NAT	0.375
SCEN	**0.707**
NORM	0.538
GAME	0.547
MREG	0.677
INC	0.563

importance ranks of criteria, namely the rank reciprocal rule,

$$a_j = \frac{1/r_j}{\sum\limits_i 1/r_i} \tag{3.12}$$

the rank sum – rule

$$a_j = (m+1-r_j)\Big/\sum_{i=1}^{m} r_i \tag{3.13}$$

and the rank exponent rule

$$a_j = (m+1-r_j)^z\Big/\sum_{i=1}^{m} r_i^z, \tag{3.14}$$

where z is estimated with

$$\frac{a_j}{a_i} = \frac{(m+1-r_j)^z}{(m+1-r_i)^z} \tag{3.15}$$

where r_j is the rank of criterion j.

In the last formula, the decision maker needs to give a preference ratio (3.15) for one pair of weights, in order to calculate the rest of them. This ratio could, for instance, be the weight ratio of the most and least important criteria.

All three of the formulas can be considered ad hoc procedures (Stillwell et al. 1981; Edwards and Barron 1994). Yet, they could be useful if the decision maker does not want to evaluate the magnitude of his/her preferences.

Example 3.6. In the example above, in the higher hierarchy level there are two criteria. In this case, the weights for these two criteria, calculated with the formulas based on ranks are in Table 3.9. Using ROC weighting, the global priorities of the alternatives are presented in Table 3.10., SCEN alternative being the most preferred one.

3.3 Even Swaps

Even swaps, originally developed by Hammond et al. (1998a, b), is a method for making tradeoffs among criteria across a range of alternatives. The method is based on direct comparison of the preferences of each pair of decision elements: one criterion is valued in terms of another criterion. The criteria can be qualitative as well as quantitative. The method goes on in four steps (Hammond et al. 1998a, b).

Step 1. The consequence matrix is created. Each row represents an alternative, and each column a criterion. Each cell contains the consequence of the given alternative with respect to the given criterion.

Step 2. Dominated alternatives are eliminated. For instance, if alternative A is better than alternative B on one or more criteria, and no worse on all other criteria, then alternative B can be eliminated. Also such alternatives that are practically dominated (i.e. have only a slight advantage in one criterion and are dominated in other criteria) can be removed.

Step 3. Criteria, which have equal rating for each alternative, can be ignored in decision making. Therefore, the criteria are made equivalent by making tradeoffs. This is carried out with the following steps (Kajanus et al. 2001):

- Determining the change necessary to eliminate one criterion
- Assessing what change in another objective would compensate for the needed change
- Making the even swap in the consequence table by reducing the one objective while increasing the other
- Cancelling out the now irrelevant objective

Step 4. Steps 2 and 3 are repeated until there is only one objective left. Then, the dominant alternative is selected.

Example 3.7. The original table of consequences is the same as in example 3.5

	Net incomes 1000€	Stumpage value million€	Scenic beauty index
NAT	0.00	0.71	5.5
SCEN	79.6	0.28	5.7
NORM	38.0	0.60	5.4
GAME	33.0	0.61	5.5
MREG	102.3	0.51	5.2
INC	191.7	0.13	4.9

From this table, the swaps are made in order to get either some alternatives dominated, or either some criteria irrelevant. The example was carried out with the SMART-SWAPS program (http://www.smart-swaps.hut.fi, Mustajoki and Hämäläinen 2005; Mustajoki and Hämäläinen 2006). The SMART-SWAP program actively proposes swaps for the decision maker, to make the analysis easier.

The first swap was to compensate a change $5.4 \rightarrow 5.5$ in NORM's scenic beauty with a decrease of incomes $38 \rightarrow 33$. The resulting table shows that NORM is now dominated by GAME, and can be removed.

	Net incomes 1000€	Stumpage value million€	Scenic beauty index
NAT	0.00	0.71	5.5
SCEN	79.6	0.28	5.7
~~NORM~~	~~33.0~~	~~0.60~~	~~5.5~~
GAME	33.0	0.61	5.5
MREG	102.3	0.51	5.2
INC	191.7	0.13	4.9

The second swap was to compensate a change 4.9 → 5.5 in INC's scenic beauty with a decrease of incomes 191.7 → 170

	Net incomes 1000€	Stumpage value million€	Scenic beauty index
NAT	0.00	0.71	5.5
SCEN	79.6	0.28	5.7
GAME	33.0	0.61	5.5
MREG	102.3	0.51	5.2
INC	170.0	0.13	5.5

The next swap was to compensate a change 5.2 → 5.5 in MREG's scenic beauty with a decrease of incomes 102.3 → 90

	Net incomes 1000€	Stumpage value million€	Scenic beauty index
NAT	0.00	0.71	5.5
SCEN	79.6	0.28	5.7
GAME	33.0	0.61	5.5
MREG	90.0	0.51	5.5
INC	170.0	0.13	5.5

and the next swap was to compensate a change 5.7 → 5.5 in SCEN's scenic beauty with a increase of stumpage value 0.28 → 0.38. Now, SCEN alternative is dominated and can be removed from the table. In addition, scenic beauty is irrelevant and can be removed from the table.

	Net incomes 1000€	Stumpage value million€	~~Scenic beauty index~~
NAT	0.00	0.71	~~5.5~~
~~SCEN~~	~~79.6~~	~~0.38~~	~~5.5~~
GAME	33.0	0.61	~~5.5~~
MREG	90.0	0.51	~~5.5~~
INC	170.0	0.13	~~5.5~~

The next swap was to compensate a change 0.61 → 0.71 in GAME's stumpage value with a decrease of incomes 33 → 28, resulting NAT being a dominated alternative that can be removed.

	Net incomes 1000€	Stumpage value million€
~~NAT~~	~~0.0~~	~~0.71~~
GAME	28.0	0.71
MREG	90.0	0.51
INC	170.0	0.13

The next swap was to compensate a change 0.51 → 0.71 in MREG's stumpage value with a decrease of incomes 90 → 80, resulting GAME being a dominated alternative that can be removed

	Net incomes 1000€	Stumpage value million€
~~GAME~~	~~28.0~~	~~0.71~~
MREG	80.0	0.71
INC	170.0	0.13

Then, the final swap was to compensate a change 0.13 → 0.71 in INC's stumpage value with a decrease of incomes 170 → 145, resulting MREG being a dominated alternative, and INC the recommended one

	Net incomes 1000€	Stumpage value million€
~~MREG~~	~~80.0~~	~~0.71~~
INC	145.0	0.71

3.4 Analytic Hierarchy Process

3.4.1 Decision Problem

The Analytic Hierarchy Process (AHP), originally developed by Saaty (1977, 1980), is a widely used MCDS method and perhaps the most popular in many application fields, including natural resource management. Mendoza and Sprouse (1989),

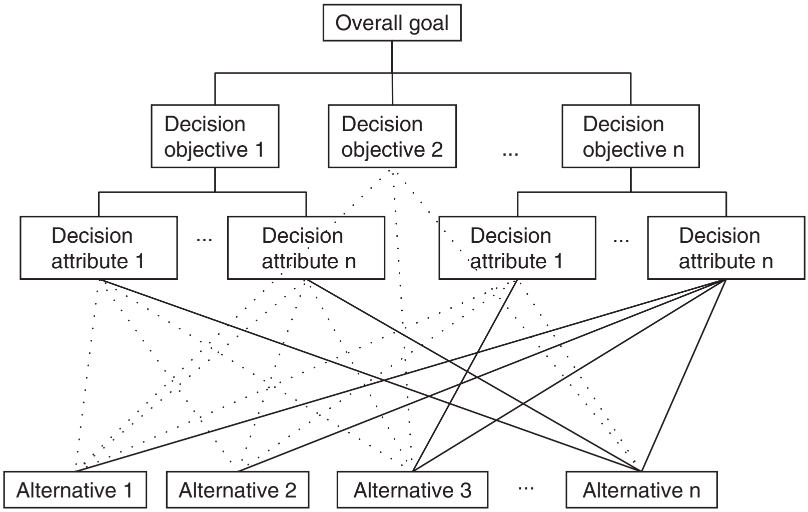

Fig. 3.3 The decision hierarchy

Murray and von Gadow (1991), and Kangas (1992), among others, have used AHP in forestry applications, and the number of applications is continuously increasing (e.g. Rauscher et al. 2000; Reynolds 2001; Vacik and Lexer 2001). AHP has also gained interest among forestry practitioners. The Finnish State Forest Enterprise Metsähallitus, which governs the vast majority of state-owned lands in Finland, has used AHP, or more precisely the HIPRE software, in practical natural resource planning (Pykäläinen et al. 1999). For a review of AHP forestry applications, readers are referred to Kangas (1999), and to Schmoldt et al. (2001) for extensions and for AHP-related development.

Basically the AHP is a general theory of measurement based on some mathematical and psychological principles. In the method, a hierarchical decision schema is constructed by decomposing the decision problem in question into decision elements – goals, objectives, attributes and decision alternatives. The general goal is at the top of a decision hierarchy, and decision alternatives constitute the lowest level (Fig. 3.3).

The branches of the decision hierarchy are assumed to be independent of each other. It means that the decision criteria are not supposed to measure the same values from the decision maker's point of view. For instance, if scenic beauty measures, for instance, the recreational value of the forest estate, but has no intrinsic value besides that, it should not be included as a criterion of its own, but as a sub-criterion for recreational value. Defining the decision hierarchy is important, as splitting the criteria in different ways has been noted to affect their weight in the decision analysis (e.g. Pöyhönen and Hämäläinen 1998; Pöyhönen et al. 2001). This does not mean, however, that the decision criteria should not be correlated. On the contrary, it often happens that, for instance, criteria describing biodiversity and recreation value may be correlated.

On the other hand, the independency means that the criteria should not have interactions. It is possible that the incomes in the different alternatives also affect the importance of aesthetic or ecological values (e.g. Leskinen et al. 2003). In basic AHP this is not allowed, but in regression AHP context (e.g. Leskinen and Kangas 2005a) and in ANP such interactions can be accounted for.

The importances or preferences of decision elements are compared in a pairwise manner with regard to each element above in the hierarchy. Based on these comparisons, an additive model on a ratio scale describing the preferences of the decision maker and priorities of decision alternatives with respect to the objectives or attributes is estimated. The model is called a priority function. The decision alternative which produces the greatest global priority is considered the "best" and most satisfactory.

Differences in measurement scales and units do not present any difficulty when the AHP is used, because the method is based on straight comparison between the significance and preference of each pair of decision elements without using any physical unit. Thus, AHP can deal with qualitative attributes as well as those which are quantitative.

3.4.2 Phases of AHP

The four basic steps involved in using the AHP to address decision problems are:

1. The decision hierarchy is constructed by decomposing the original decision problem into a hierarchy of interrelated decision elements.
2. Pairwise comparisons are made at each level of the hierarchy. In making the comparison, the question is, which of the two factors has a greater weight in decision making, and how much greater, or which of the two decision alternatives is more preferred with regard to a certain decision attribute.
3. Using the pairwise comparisons as input, the relative weights (importance/preference) of elements at each level are computed using the eigenvalue method. The resulting weights or priorities represent the decision maker's perception of the relative importance or preference of the elements at each level of the hierarchy.
4. The ratings for the decision alternatives are calculated based on the relative weights of the decision elements.

Pairwise comparisons give the decision maker a basis on which to reveal his/her preferences by comparing two elements at a time. The importances or preferences of decision elements are compared in a pairwise manner with regard to each element above in the hierarchy. First, each of the alternatives from 1 to n is compared to each other alternative with respect to decision attribute 1. These comparisons, with respect to one decision element, form one comparison set. Then, each of the alternatives is compared to each other alternative with respect to rest of the decision attributes, one by one. After that, the decision attributes are compared pairwisely with respect to each decision objective above them, and finally, the decision objectives are compared in a pairwise manner with respect to the goal.

In the standard method presented by Saaty (1977, 1980), the decision maker has the option of expressing preferences between the two elements as:

(i) Equal importance or preference of both elements
(ii) Weak importance or preference of one element over another
(iii) Essential or strong importance or preference of one element over another
(iv) Demonstrated importance or preference of one element over another
(v) Absolute importance or preference of one element over another

These preferences are then translated into numerical values of 1, 3, 5, 7 and 9, respectively, with 2, 4, 6 and 8 as intermediate values. Many other variations of the scale have been presented (see Leskinen 2001). It is also possible to carry out comparisons by using a continuous scale, e.g. by making use of graphical bars in the computer interface (e.g. Pukkala and Kangas 1993).

For estimating the priorities, the matrix of pairwise comparisons **A** is constructed for each set of comparisons. The elements of the matrix, a_{ij}, describe the comparison of alternative (or attribute or objective) i to j. The matrix is required to be reciprocal, i.e. in the matrix the element $a_{ij} = 1/a_{ji}$. It means that if alternative i is twice as good as j, then j has to be half as good as i. Each alternative is then indifferent with itself, i.e. when $i = j$, $a_{ij} = 1$.

If there were no inconsistencies in judgements, matrix **A** has unit rank since every row is a constant multiple of the first row, and all the eigenvalues of the matrix are zero except one. (Rank of a matrix is the number of mutually independent rows in it). Based on a consistent matrix **A**, relative weights can be determined by solving the equation

$$\mathbf{A}\mathbf{w} = \lambda \mathbf{w}, \tag{3.16}$$

where λ is the only nonzero eigenvalue of a consistent matrix **A**, and **w** is its right eigenvector. The solution **w** of this problem is any column of **A**. These solutions differ only by a multiplicative constant. Thus, the same relative weights are got based on any column of the matrix. In human decision making, some inconsistencies can be expected: people's feelings and preferences are not always consistent. Furthermore, as the largest value used in the comparison matrix is 9, and there are only nine possible answers, in many cases it may be impossible to compare the decision elements consistently using this scale.

Example 3.8. If the comparisons were such that decision maker considers alternative 1 to be twice as good as 2, alternative 2 three times as good as 3, and alternative 1 six $(= 2 \cdot 3)$ times as good as alternative 3, (i.e. $a_{12} = 2$, $a_{23} = 3$ and $a_{13} = 6$), the decision matrix is considered to be consistent. The matrix **A** would then be

$$\begin{bmatrix} 1 & 1/2 & 1/6 \\ 2 & 1 & 1/3 \\ 6 & 3 & 1 \end{bmatrix}$$

In this case, the weights can be obtained simply by dividing each column with the sum of its cell values, giving weights

$$\begin{bmatrix} 0.111 \\ 0.222 \\ 0.667 \end{bmatrix}$$

When **A** contains inconsistencies, the estimated weights can be obtained using the eigenvector equation.

$$(\mathbf{A} - \lambda_{\max}\mathbf{I})\mathbf{q} = 0 \tag{3.17}$$

where λ_{max} is the largest eigenvalue of matrix **A, q** its right eigenvector and **I** the identity matrix. The right eigenvector, **q**, constitutes the estimation of relative weights. It is the first principal component of the matrix of pairwise comparisons. The first principal component of a matrix is a linear combination of the variables (i.e. comparisons with respect to one alternative) that describes the largest part of the variation in the matrix. It gives the relative weights to the compared elements, which best fit to the made comparisons. If the matrix does not include any inconsistencies, i.e. the judgements made by a decision maker have been consistent, **q** is an exact estimate of the priority vector.

Each eigenvector is scaled to sum to one to get the priorities. The form of priority functions is the same as the form of additive linear utility functions without interaction terms.

Global priorities of decision elements are calculated downwards from the top of the hierarchy by multiplying the local priorities by the priority of their corresponding decision element at the level above. Global priority of an element is then used to weight the local priorities of elements at the level below and so on down to the bottom level. Global priorities at each level sum up to one.

It has been shown that λ_{max} of a reciprocal matrix **A** is always greater or equal to n (= number of rows = number of columns) (e.g. Saaty 1977). If the pairwise comparisons do not include any inconsistencies, $\lambda_{max} = n$. The more consistent the comparisons are, the closer the value of computed λ_{max} is to n. Based on this property, a consistency index, *CI*, has been constructed

$$CI = (\lambda_{max} - n)/(n-1). \tag{3.18}$$

CI estimates the level of consistency with respect to the entire comparison process. A consistency ratio, *CR*, also measures the coherence of the pairwise comparisons. To estimate the *CR*, the average consistency index of randomly generated comparisons, *ACI*, has to be calculated ($CR = CI/ACI$). *ACI* varies as a function of the size of matrix (e.g. Saaty 1980). As a rule of thumb, a *CR* value of 0.1 or less is considered to be acceptable. Otherwise, all or some of the comparisons must be repeated in order to resolve the inconsistencies of pairwise comparisons.

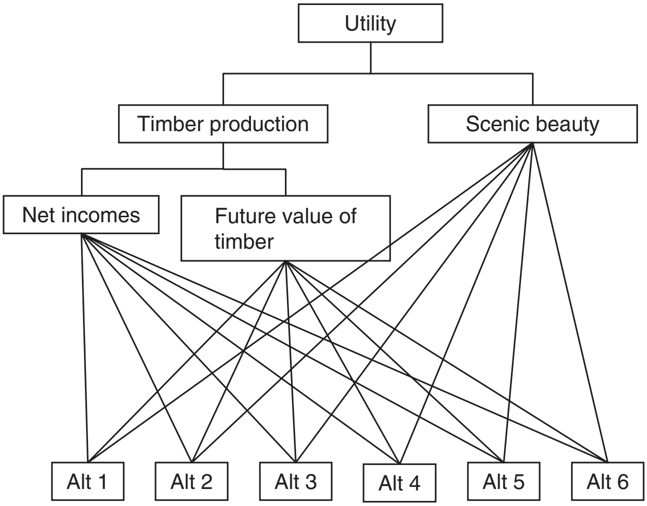

Fig. 3.4 The decision hierarchy of the AHP example

Example 3.9. The problem of example 3.5 is analysed using AHP. There are six decision alternatives and three criteria. They form a decision hierarchy (Fig. 3.4). The alternatives were compared pairwisely with respect to each criterion, namely net incomes, value of timber and scenic value (Table 3.11). The obtained CR results mean that the comparisons were a bit too inconsistent for a good analysis, and it would be recommendable to make some of them again. After comparing the alternatives, the criteria were compared. First, the second-level criteria, net incomes and value of timber, were compared to each others and then the higher level criteria were compared (Table 3.12)

The priorities and the consistency rations were calculated with webHIPRE program (http://www.hut.hipre.fi/). The priorities were first calculated at the level of decision attributes and objectives (Table 3.13). Then, INC is the best alternative with respect to net incomes, NAT with respect to stumpage value and SCEN with respect to scenic beauty. The local weight of net incomes was 0.75 and that of stumpage value 0.25, the local weights of scenic beauty was 0.2 and that of timber production 0.8. Thus, the global weight of net incomes was $0.8 \cdot 0.75 = 0.6$ and that of stumpage value $0.25 \cdot 0.8 = 0.2$. The global priorities of the alternatives with respect to decision attributes were obtained by multiplying the priorities at the decision objective level with the global weights (Table 3.14). Global priorities with respect to timber production were obtained by adding together the global priorities with respect to net incomes and stumpage value, and the overall priorities by adding the priorities of timber production and scenic beauty together (Table 3.14). It can be noted that INC is the best alternative with respect to timber production as a whole, since the weight of stumpage value is quite low, and also its overall priority was the best.

To illustrate the notion of inconsistency, the priorities of the alternatives were calculated from each column in matrix 3.11 (Table 3.15). It means that six

Table 3.11 Pairwise comparisons

	NAT	SCEN	NORM	GAME	MREG	INC
(a) with respect to net incomes						
NAT	1/1	1/4	1/2	1/2	1/7	1/9
SCEN	4/1	1/1	2/1	2/1	1/3	1/5
NORM	2/1	1/2	1/1	1/1	1/4	1/7
GAME	2/1	1/2	1/1	1/1	1/5	1/7
MREG	7/1	3/1	4/1	5/1	1/1	1/2
INC	9/1	5/1	7/1	7/1	2/1	1/1
CR = 0.099						
(b) with respect to value of timber						
NAT	1/1	6/1	3/1	3/1	4/1	8/1
SCEN	1/6	1/1	1/4	1/4	1/3	3/1
NORM	1/3	4/1	1/1	1/1	2/1	6/1
GAME	1/3	4/1	1/1	1/1	2/1	6/1
MREG	1/4	3/1	1/2	1/2	1/1	4/1
INC	1/8	1/3	1/6	1/6	1/4	1/1
CR = 0.159						
(c) with respect to scenic beauty						
NAT	1/1	1/2	1/1	1/1	3/1	5/1
SCEN	2/1	1/1	3/1	5/1	5/1	6/1
NORM	1/1	1/3	1/1	1/1	2/1	4/1
GAME	1/1	1/5	1/1	1/1	2/1	4/1
MREG	1/3	1/5	1/2	1/2	1/1	3/1
INC	1/5	1/6	1/4	1/4	1/3	1/1
CR = 0.146						

Table 3.12 Pairwise comparisons between the criteria

	Net incomes	Value of timber
Net incomes	1/1	3/1
Value of timber	1/3	1/1
CR = 0.000		
	Timber production	Scenic beauty
Timber production	1/1	4/1
Scenic beauty	1/4	1/1
CR = 0.000.		

Table 3.13 Local utilities with respect to different criteria

	Net incomes	Stumpage value	Scenic beauty
NAT	0.036	0.421	0.186
SCEN	0.113	0.057	0.382
NORM	0.064	0.188	0.155
GAME	0.061	0.188	0.155
MREG	0.272	0.114	0.081
INC	0.455	0.031	0.04

Table 3.14 Overall utility and global utility with respect to timber production criterion and scenic beauty

	Overall utility	Timber production	Scenic beauty
NAT	0.143	0.106	0.037
SCEN	0.156	0.079	**0.076**
NORM	0.107	0.076	0.031
GAME	0.105	0.074	0.031
MREG	0.202	0.186	0.016
INC	**0.287**	**0.279**	0.008

different priority estimates were obtained. It can be noted that these priority estimates have a lot of variation among them, for instance, the priority of INC with respect to net incomes varies from 0.360 to 0.509 (0.455 in eigenvalue analysis, Table 3.13), and that of NAT from 0.024 to 0.053 (0.036 in eigenvalue analysis).

3.4.3 Uncertainty in AHP

Many decision scientists have criticized the AHP method. Perhaps the two foremost problems with the application of AHP have been that the original comparison scale does not allow for the expression of any hesitation regarding a single comparison, and that the AHP itself does not provide tools for in-depth analyses of the comparisons, particularly of the uncertainty inherent in the data (e.g. De Jong 1984; Crawford and Williams 1985; Alho et al. 1996). The only means to analyse the uncertainty in AHP is to calculate the inconsistencies. Moreover, part of the inconsistencies in the pairwise analysis may be due to the scale, not the answers given by the people (Leskinen 2001).

In basic AHP the number of comparisons increases rapidly as the number of alternatives and criteria increases. Large numbers of comparisons may be too costly

Table 3.15 Priorities calculated by scaling each column of pairwise comparisons matrix separately

	1	2	3	4	5	6
NAT	0.040	0.024	0.032	0.030	0.036	0.053
SCEN	0.160	0.098	0.129	0.121	0.085	0.095
NORM	0.080	0.049	0.065	0.061	0.064	0.068
GAME	0.080	0.049	0.065	0.061	0.051	0.068
MREG	0.280	0.293	0.258	0.303	0.255	0.238
INC	0.360	0.488	0.452	0.424	0.509	0.477

and tedious, especially for participatory planning problems. However, eigenvalue technique requires a full comparison matrix in order to be carried out.

Finally, rank reversal occurring when using the AHP may cause problems (e.g. Belton and Gear 1983). This means that if new alternative is included in the analysis, it is possible that the rank of the previously considered alternatives changes, although the preferences do not change. For instance, if the preferences originally are so that A is preferred to B, and B to C, after including a new alternative D the situation may change so that B is preferred to A. The rank reversal may be partly due to the arithmetic aggregation rule applied in the basic AHP, and partly due to inconsistencies in the pairwise comparisons (Leskinen and Kangas 2005b). According to, rank reversal is acceptable if it is due to inconsistencies (i.e. new alternatives give new information concerning the preferences), but not acceptable if it is due to the method itself. Using geometric aggregation rule, the rank reversal problem can be avoided (Barzilai and Golany 1994; Leskinen and Kangas 2005b). The problem of rank reversal does not only apply to AHP, but also, for instance, SMART, if the sub-utility functions are calculated using interval scale.

To alleviate these problems, different modifications of AHP have been developed. In these, the concept of decision hierarchy and the pairwise comparisons may be similar to the basic AHP, but the techniques are different. The number of comparisons can be reduced by the use of regression techniques for estimating preferences instead of the eigenvalue technique (Alho et al. 1996, 2001; Leskinen 2001). The pairwise comparisons are denoted with $r_{ij} = v_i / v_j \exp(\varepsilon_{ij})$, where $\exp(\varepsilon_{ij})$ describes the uncertainty in each pairwise comparison. Since all the values of items i, v_i are positive, with no loss of generality, it can be expressed as

$$v_i = \exp(\mu + \alpha_i) \tag{3.19}$$

where μ and α_i are parameters. Then, the ratio can, in turn, be expressed as

$$v_i / v_j = \exp(\alpha_i - \alpha_j) \tag{3.20}$$

and the model can be expressed as

$$\log(r_{ij}) = y_{ij} = \alpha_i - \alpha_j + \varepsilon_{ij} \tag{3.21}$$

Thus, expressing the values v_i as exponents and using a logarithmic transformation enables using a linear model. The parameters α_i, $i = 1, \ldots, n-1$ are then estimated using standard regression tools, for instance SAS program. The parameter α_n related to the item n is assumed to be zero for definiteness, i.e. otherwise there would be an infinite number of solutions to this model. The minimum number of observations in regression analysis is the number of parameters to be estimated, i.e. it would be enough to include only one row or column from the pairwise matrix in the analysis. In that case, however, it would not be possible to estimate the inconsistency involved. For that, additional observations are needed.

In this model, the distribution of the error term, ε_{ij}, describes the uncertainty of the analysis. With this formulation, the error variance describes the inconsistency of the comparisons: if the variance is 0, the comparisons are consistent and the higher the variance, the more inconsistency there is.

The priorities of the alternatives that sum up to one are finally calculated as

$$q_i = \frac{\exp(\alpha_i)}{\sum_{i=1}^{n} \exp(\alpha_i)} \tag{3.22}$$

With this formula, the scale is transformed from logarithmic scale back to original one (value scale). The division by the sum of transformed values scales the sum of priorities to one. Finally, if the weight for each criterion j is denoted by a_j, the utility of each alternative i can be calculated with geometric aggregation rule as

$$U_i = \prod_j q_{ij}^{a_j} / \sum_i \prod_j q_{ij}^{a_j}. \tag{3.23}$$

Example 3.10. The pairwise comparisons of example 3.9 with respect to net incomes were analyzed with regression AHP. In Table 3.16 are the data used in the analysis. The explanatory variables are just zeros and ones. They describe, which alternative has been compared to which, according to model 3.21. Since the parameter for the last alternative is set to 0, INC is not included in the data. The parameters were calculated using SAS, and the priorities of the alternatives with respect to net incomes could be calculated (Table 3.17).

The standard error of the model is 0.19 and R^2 is 0.9863. They indicate that the pairwise comparisons are not quite consistent, but the consistency is fairly high. These comparisons were consistent enough also with respect to CR criterion.

Table 3.16 Pairwise comparison data for a model

NAT	SCEN	NORM	GAME	MREG	r	y
1	−1	0	0	0	0.25	−1.38629
1	0	−1	0	0	0.5	−0.69315
1	0	0	−1	0	0.5	−0.69315
1	0	0	0	−1	0.143	−1.94491
1	0	0	0	0	0.111	−2.19823
0	1	−1	0	0	2.0	0.693147
0	1	0	−1	0	2.0	0.693147
0	1	0	0	−1	0.33	−1.10866
0	1	0	0	0	0.2	−1.60944
0	0	1	−1	0	1.0	0
0	0	1	0	−1	0.25	−1.38629
0	0	1	0	0	0.143	−1.94491
0	0	0	1	−1	0.2	−1.60944
0	0	0	1	0	0.143	−1.94491
0	0	0	0	1	0.5	−0.69315

Table 3.17 Estimated priorities of alternatives

	α	Exp(α)	q
NAT	−2.55106	0.077999	0.035316
SCEN	−1.38936	0.249235	0.112846
NORM	−1.95364	0.141757	0.064183
GAME	−1.99083	0.136582	0.06184
MREG	−0.50575	0.603053	0.273044
INC	0	1	0.45277
	Sum	2.208626	1

Another example of accounting for uncertain preferences in AHP framework is interval AHP (Leskinen and Kangas 1998; see also Arbel 1989; Salo and Hämäläinen 1992). In interval AHP, the decision makers are asked the probability that the preference lies in a certain interval, or the interval the preference lies in with a certain probability.

The regression approach to AHP can also be reformulated to Bayesian framework (e.g. Alho and Kangas 1997; Basak 1998). Bayes theorem is then used to derive the conditional distributions of the parameters. Then, it is easy to calculate the probabilities that one plan is better than all the others, for example.

Yet another example of accounting for uncertainty in AHP context is the fuzzy AHP. In fuzzy AHP, preference ratios of criteria or alternatives are described by membership functions (e.g. Mendoza and Prabhu 2001).

3.4.4 ANP

The Analytic Network Process (ANP) is an extension of the AHP (Saaty 2001) that answers some of the development challenges of the basic AHP methodology. Basically, the ANP is a general theory of ratio scale measurement of influence, with a methodology that deals with dependence and feedback. The comparisons are made using pairwise comparisons like in original AHP, but the relations between the criteria are included in the comparisons. The main idea is to avoid the assumption of independence among criteria of the standard AHP.

ANP model can be designed either using a so-called control hierarchy (i.e. a hierarchy of subsystems with inner dependencies) or as a non-hierarchical network, which includes both decision criteria and alternatives as clusters (e.g. Wolfslehner et al. 2005). The clusters are connected with arrows that describe the flow of influence. Thus, each criterion can have an interaction with other criteria (outer dependence), and each sub-criterion can have interaction with other sub-criteria in the same cluster (inner dependence).

A hypothetical example of ANP network is presented in Fig. 3.5. In the example, decision objective 1 influences to objectives 2, 3 and 6, and objective 3 is also influencing objective 1. In addition, there is a feedback loop back to the objective

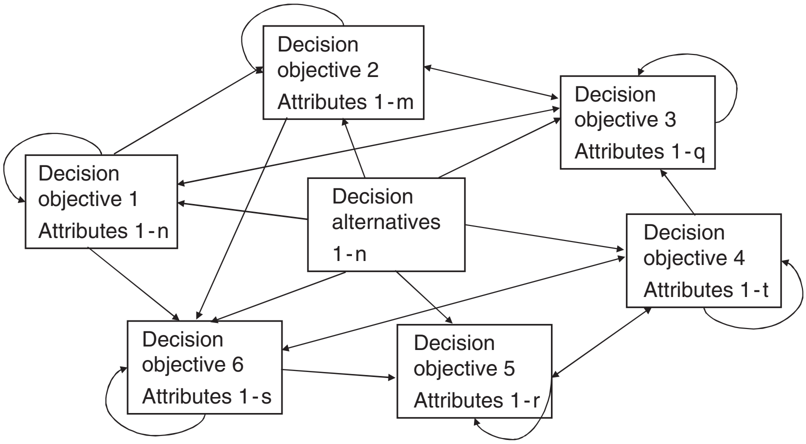

Fig. 3.5 An example of ANP network

itself. The influence means that instead of comparing decision attributes of objective 2 in pairwise manner, the influence is accounted for. Thus it is asked, for instance, "With regard to decision objective 1, decision attribute 1 is how many times more important than decision attribute 2?". For a forestry example concerning criteria and indicators of sustainable management, readers are referred to Wolfslehner et al. (2005).

The ANP utilises a so-called supermatrix calculation in order to deal with interactions among the network of criteria and decision alternatives. Saaty (2001) stated that, generally taken, the ANP is more objective and more likely to capture what happens in the real world than the AHP. However, applying the ANP is much more laborious and time-consuming. Obviously the ANP has potential application in forest management, where different kinds of interdependencies between decision elements are usual.

3.5 A'WOT

In the so called A'WOT method (Kurttila et al. 2000; Pesonen et al. 2001a) the Analytic Hierarchy Process (AHP) and its eigenvalue calculation framework are integrated with SWOT analysis. SWOT is a widely applied tool in strategic decision support. In SWOT, the internal and external factors most important for the enterprise's future are grouped into four categories: Strengths, Weaknesses, Opportunities, and Threats. By applying SWOT in a strategic planning process, the aim usually is to develop and adopt a strategy resulting in a good fit between these internal and external factors. When used properly, SWOT can provide a good basis for strategy formulation. However, SWOT could be used more efficiently than normally has been the case in its applications. The most crucial problem with SWOT is

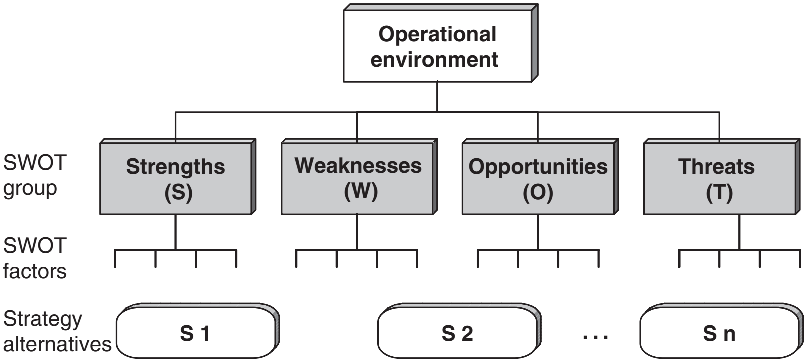

Fig. 3.6 A'WOT framework (Kurttila et al. 2000)

that it includes no means of analytically determining the importance of factors or of assessing the fit between SWOT factors and decision alternatives.

The aim in applying the hybrid method is to improve the quantitative information basis of strategic planning processes. AHP's linking with SWOT yields analytically–determined priorities for the factors included in SWOT analysis and makes them commensurable (Fig. 3.6). In addition, decision alternatives can be evaluated with respect to each SWOT factor by applying the AHP. So, SWOT provides the basic frame within which to perform an analysis of the decision situation, and the AHP assists in carrying out SWOT more analytically and in elaborating the analysis so that alternative strategic decisions can be prioritised.

The main phases of A'WOT are as follows:

1. The SWOT analysis is carried out. The relevant factors of the external and internal environment are identified and included in SWOT analysis.
2. Pairwise comparisons between the SWOT factors are carried out separately within each SWOT group. When making the comparisons, the issue at stake is which of the two factors compared is more important and how much more important. With these comparisons as the input, the mutual priorities of the factors are computed.
3. The mutual importance of the SWOT groups is determined by applying pairwise comparisons. There are several possibilities as how to do this. For instance, it is possible to compare the groups as such or the most important factors in each group pairwisely.
4. The strategy alternatives are evaluated with respect to each SWOT factor by using pairwise comparisons and the eigenvalue technique.
5. Global priorities are calculated for the strategy alternatives.

In the earliest A'WOT applications (Kurttila et al. 2000; Pesonen et al. 2001a), only steps (1)–(3), as listed above, were carried out in an early stage of a strategic planning process. A'WOT strengthens the decision basis also in the case where the result is only the quantification and commensuration of SWOT factors. However, the final goal of any strategic planning process as a whole is to develop and propose a strategy resulting in a good fit between internal and external factors. When steps (4) and (5) are included in the A'WOT process, the initial SWOT analysis might not always be applicable as such (Pesonen et al. 2001b).

The reason for this is that the SWOT factors could have been formulated so that strategy alternatives can not be evaluated with respect to them. This being the case, SWOT factors need some value-focused modification and fine-tuning (e.g. Leskinen et al. 2006). For A'WOT, SWOT factors should be determined by asking, which are the internal and external factors of the operational environment that should be taken into account in choosing the strategy for the enterprise. Then it is possible to compare strategy alternatives with respect to strengths, weaknesses, opportunities, and threats as listed in SWOT. To take an example of the pairwise comparisons: which of the two strategy alternatives compared (when implemented) makes it possible to better exploit a certain opportunity, and how much better? According to the experiences of A'WOT applications and tests, the combined use of the AHP and SWOT analysis is a promising approach in supporting strategic decision-making processes (Kurttila et al. 2000; Pesonen et al. 2001a, b).

References

Alho, J. and Kangas, J. 1997. Analysing uncertainties in experts' opinions of forest plan performance. Forest Science 43: 521–528.

Alho, J., Kangas, J., and Kolehmainen, O. 1996. Uncertainty in the expert predictions of the ecological consequences of forest plans. Applied Statistics 45: 1–14.

Alho, J.M., Kolehmainen, O., and Leskinen, P. 2001. Regression methods for pairwise comparisons data. In: Schmoldt, D.L., Kangas, J., Mendoza, G.A., Pesonen, M. (Eds.). The analytic hierarchy process in natural resource and environmental decision making. Kluwer, Dordrecht, pp. 235–251.

Arbel, A. 1989. Approximate articulation of preference and priority derivation. European Journal of Operational Research 43: 317–326.

Barzilai, J. and Golany, B. 1994. AHP rank reversal, normalization and aggregation rules. INFOR 32: 57–64.

Basak, I. 1998. Probabilistic judgments specified partially in the analytic hierarchy process. European Journal of Operational Research 108: 153–164.

Belton, V. and Gear, T. 1983. On a short-coming of Saaty's method of analytic hierarchies. Omega 11: 228–230.

Crawford, G. and Williams, C. 1985. A note on the analysis of subjective judgment matrices. Journal of Mathematical Psychology 29: 387–405.

De Jong, P. 1984. A statistical approach to Saaty's scaling method for priorities. Journal of Mathematical Psychology 28: 467–478.

Eckenrode, R.T. 1965. Weighting multiple criteria. Management Science 12: 180–192.

Edwards, W. and Barron, F.H. 1994. SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. Organizational Behaviour and Human Decision Process 60: 306–325.

Eliashberg, J. 1980. Consumer preference judgments: an exposition with empirical applications. Management Science 26: 60–77.

Fishburn, P.C. 1967. Methods of estimating additive utilities. Management Science 13: 435–453.

Hammond, J.S., Keeney, R.L., and Raiffa, H. 1998a. Even swaps: a rational method for making trade-offs. Harvard Business Review, March–April, pp. 1–11.

Hammond, J.S., Keeney, R.L., and Raiffa, H. 1998b. Smart choices: a practical guide to making better decisions, Harvard Business School Press. Boston. MA.

Horsky, D. and Rao, M. R. 1984. Estimation of attribute weights from preference comparisons. Management Science 30: 801–821.

Jacquet-Lagreze, E. and Siskos, J. 1981. Assessing a set of additive utility functions for multicriteria decision-making, the UTA method. European Journal of Operational Research 10: 151–164.

Kajanus, M., Ahola, J., Kurttila, M., and Pesonen, M. 2001. Application of even swaps for strategy selection in a rural enterprise. Management Decision 39: 394–402.

Kajanus, M., Kangas, J., and Kurttila, M. 2004. The use of value focused thinking and the A'WOT hybrid method in tourism management. Tourism Management 25: 499–506.

Kangas, J. 1992. Multiple-use planning of forest resources by using the analytic hierarchy process. Scandinavian Journal of Forest Research 7: 259–268.

Kangas, J. 1999. The analytic hierarchy process (AHP): standard version, forestry application and advances. In: Helles, F., Holten-Andersen, P., and Wichmann, L. (Eds.). Multiple use of forests and other natural resources. Kluwer, Dordrecht. Forestry Sciences 61. pp. 96–105.

Kangas, J., Kangas, A., Leskinen, P., Pykäläinen, J. 2001a. MCDM methods in strategic planning of forestry on state-owned lands in Finland: applications and experiences. Journal of Multi-Criteria Decision Analysis 10: 257–271.

Kangas, J., Matero, J., and Pukkala, T. 1992. Analyyttisen hierarkiaprosessin käyttö metsien monikäytön suunnitteluun – tapaustutkimus. Metsäntutkimuslaitoksen tiedonantoja 412, 48 pp.

Kangas, J., Pesonen, M., Kurttila, M., and Kajanus, M. 2001b. A'WOT: Integrating the AHP with SWOT analysis. In: Dellman, K. (Ed.). Proceedings of the Sixth International Symposium on the Analytic Hierarchy Process ISAHP 2001, August 2–4, 2001, Kursaal Bern, Berne, Switzerland, pp. 189–199.

Keeney, R.L. and Raiffa, H. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Wiley, New York, 569 pp.

Kurttila, M., Pesonen, M., Kangas, J., and Kajanus, M. 2000. Utilizing the analytical hierarchy process (AHP) in SWOT analysis – A hybrid method and its application to a forest – certification case. Forest Policy and Economics 1: 41–52.

Laskey, K.B. and Fischer, G.W. 1987. Estimating utility functions in the presence of response error. Management Science 33: 965–980.

Leskinen, P. 2001. Statistical methods for measuring preferences. Publications in Social Sciences 48. University of Joensuu. Doctoral thesis.

Leskinen, P., Kangas, A., and Kangas, J. 2004. Rank-based modelling of preferences in multicriteria decision making. European Journal of Operational Research 158: 721–733.

Leskinen, P. and Kangas, J. 1998. Analysing uncertainties of interval judgement data in multiple-criteria evaluation of forest plans. Silva Fennica 32: 363–372.

Leskinen, P. and Kangas, J. 2005a. Multi-criteria natural resource management with preferentially dependent decision criteria. Journal of Environmental management 77: 244–251.

Leskinen, P. and Kangas, J. 2005b. Rank reversals in multi-criteria decision analysis with statistical modelling of ratio scale pairwise comparisons. Journal of the Operational Research Society 56: 855–861.

Leskinen, P., Kangas, J., and Pasanen, A-M. 2003. Assessing ecological values with dependent explanatory variables in multi-criteria forest ecosystem management. Ecological Modelling 170: 1–12.

Leskinen, L.A., Leskinen, P., Kurttila, M., Kangas, J., and Kajanus, M. 2006. Adapting modern strategic decision support tools in the participatory strategy process – a case study of a forest research station. Forest Policy and Economics 8: 267–278.

Malczewski, J. 1999. GIS and Multicriteria decision analysis. Wiley, New York, 392 pp.

Mendoza, G.A. and Prabhu, R. 2001. A fuzzy Analytic Hierarchy Process for assessing biodiversity conservation. In Schmoldt, D., Kangas, J., Mendoza, G.A., Pesonen, M. (Eds.). The

Analytic Hierarchy Process in Natural Resource and Environmental Decision Making. Kluwer, Dordrecht. Managing Forest Ecosystems 3, pp. 219–235.

Mendoza, G.A. and Sprouse, W. 1989. Multiobjective programming for generating alternatives. Forest Science 33: 458–468.

Murray, D.M. and von Gadow, K. 1991. Prioritizing mountain catchment areas. Journal of Environmental Management 32: 357–366.

Mustajoki, J. and Hämäläinen, R. 2005. A preference programming approach to make the even swaps method even easier. Decision Analysis 2: 110–123.

Mustajoki, J. and Hämäläinen, R. 2006. Smart-swaps – decision support for the PrOACT process with the even swaps method. Manuscript.

Pesonen, M., Ahola, J., Kurttila, M., Kajanus, M., Kangas, J. 2001a. Applying A/WOT to forest industry investment strategies: case study of a Finnish company in North America. In: Schmoldt, D., Kangas, J., Mendoza, G.A., and Pesonen, M. (Eds.). The analytic hierarchy process in natural resource and environmental decision making. Kluwer, Dordrecht, pp. 131–148.

Pesonen, M., Kurttila, M., Kangas, J., Kajanus, M., Heinonen, P. 2001b. Assessing priorities using A/WOT among resource management strategies at Finnish forest and park service. Forest Science 47: 534–541.

Pöyhönen, M. and Hämäläinen, R.P. 1998. Notes on the weighting biases in value trees. Journal of Behavioral Decision Making 11: 139–150.

Pöyhönen, M., Vrolijk, H., and Hämäläinen, R.P. 2001. Behavioral and procedural consequences of structural variation in value trees. European Journal of Operational Research 134: 216–227.

Pukkala, T. 2006. Monsu-metsäsuunnitteluohjelmisto. Versio 5. Ohjelmiston toiminta ja käyttö. Mimeograph, 53 pp.

Pukkala, T. and Kangas J. 1993. A heuristic optimization method for forest planning and decision making. Scandinavian Journal of Forest Research 8: 560–570.

Pykäläinen, J., Kangas, J., and Loikkanen, T. 1999. Interactive decision analysis in participatory strategic forest planning: experiences from State owned boreal forests. Journal of Forest Economics 5: 341–364.

Rauscher, H.M., Lloyd, F.T., Loftis, D.L., and Twery, M.J. 2000. A practical decision-analysis process for forest ecosystem management. Computers and Electronics in Agriculture 27: 195–226.

Reynolds, K.M., 2001. Prioritizing salmon habitat restoration with the AHP, SMART, and uncertain data. In: Schmoldt, D., Kangas, J., Mendoza, G.M., Pesonen, M. (Eds.). The analytic hierarchy process in natural resources and environmental decision making. Kluwer, Dordrecht, pp 199–218.

Saaty, T.L. 1977. A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology 15: 234–281.

Saaty, T.L. 1980. The Analytic hierarchy process. McGraw-Hill, New York.

Saaty, T.L. 2001. Decision making with dependance and feedback. The analytic network process. 2nd ed. RWS Publications, Pittsburgh.

Salo, A.A. and Hämäläinen, R.P. 1992. Preference assessment by imprecise ratio statements. Operations Research 40: 1053–1061.

Schoemaker, P.J. and Waid, C.C. 1982. An experimental comparison of different approaches to determining weights in additive utility models. Management Science 28: 182–196.

Schmoldt, D., Kangas, J., Mendoza, G.A., Pesonen, M. (Eds.), 2001. The analytic hierarchy process in natural resource and environmental decision making. Kluwer, Dordrecht.

Stillwell, W.G., Seaver, D.A., Edwards, D. 1981. A comparison of weight approximation techniques in multiattribute utility decision making. Organizational Behavior and Human Performance 28: 62–77.

Tell, B. 1976. A comparative study of some multiple-criteria methods. The Economic Research Institute at the Stockholm School of Economics, 203 pp.

Tell, B. and Wallenius, J. 1979. A survey of multiple-criteria decision methods and applications: utility theory and mathematical programming. Liiketaloudellinen aikakauskirja 28: 3–22.

Vacik, H. and Lexer, M.J., 2001. Application of a spatial decision support system in managing the protection forests of Vienna for sustained yield of water resources. Forest Ecology and Management 143: 65–76.

von Winterfeldt, D. and Edwards, W. 1986. Decision analysis and behavioral research. Cambridge University Press, Cambridge.

Wolfslehner, B., Vacik, H., and Lexer, M.J. 2005. Application of the analytic network process in multi-criteria analysis of sustainable forest management. Forest Ecology and Management 207: 157–170.

Chapter 4
Uncertainty in Multi-Criteria Decision Making

4.1 Nature of Uncertainty

Often, word uncertainty has been equated with random variability (Ferson and Ginzburg 1996). In decision making, the uncertainty is traditionally connected to the unknown or uncertain future states of nature: the consequences of alternative actions are not known, which makes choices risky.

Probability theory demands that probabilities should fulfil the Kolmogorov axioms. It means that the probability of each event has to be greater than or equal to zero (i.e. negative probabilities are not allowed), the probability of the entire set of events has to be one (i.e. some event in the whole set of events will occur with probability 1) and that the probability of a union of disjoint events is the sum of their individual probabilities (e.g. Williams 1991). It also means that the probability of a union of an event and its negation must add up to one.

Probabilities can be either objective or subjective. Objective probabilities can be calculated for events that can be repeated infinitely many times; for instance, the probabilities of obtaining heads or tails when tossing a coin. Subjective probabilities describe beliefs of persons; for instance, someone may believe that a certain sports team will win with 0.7 probability. The Bayesian probability theory may be the best known example of utilising subjective probabilities.

Additivity requirement in probability theory means that if the decision maker has no idea of the probability of some event, like whether there is life on Mars of not, both alternatives (there is and there is not) need to be assigned a 0.5 probability. Assigning so high a probability to either option may seem counterintuitive in the case of complete ignorance. There exist theories, in which also non-additive subjective beliefs can be dealt with, for example the possibility theory (Dubois and Prade 1988) and the evidence theory (Schafer 1976; Klir and Harmanec 1997). These theories were developed to deal with situations, where the classical or Bayesian probability theory was deemed too normative. They are argued to be suitable especially in cases where human opinions, judgement and decisions are involved (Zimmermann 1985; Dubois and Prade 1988).

In decision analysis, people may be uncertain about their preferences. People do not know, for instance, which alternative they prefer with respect to a certain criterion, or they do not know exactly how much they prefer a certain alternative. Furthermore, there may be uncertainty concerning the performances of the alternatives with respect to the criteria. One way to reflect such uncertainty is to present the uncertain preferences and/or performances using linguistic scales. For instance, the criterion values with respect to some characteristics, like the recreational value of a certain area may be evaluated as "low", "medium" or "high". In another occasion, one alternative may be "slightly preferred", "strongly preferred" or "extremely preferred" when compared to another alternative.

In decision analysis, all judgments, numerical or linguistic, need to be transformed to numbers in order to make a recommendation. In different decision support tools, different approaches have been developed to deal with these uncertainties (for a review see Kangas and Kangas 2004). One commonly used approach for dealing with linguistic uncertainty is to use the fuzzy set approach (Zimmermann 1985).

4.2 Fuzzy Set Theory

4.2.1 Membership Functions and Fuzzy Numbers

Fuzzy set theory was first presented by Zadeh (1965). The basis of the fuzzy set theory is a membership function $\mu(x)$, which describes the degree by which a certain statement is true (Zimmermann 1985). For example, a statement 'a tree is defoliated' can be more or less true. If we had a crisp definition, like 'a tree is defoliated if it has lost at least 50% of its needles or leaves', the membership function would only have values 0 and 1, and fuzzy sets would not be needed.

Otherwise, a membership function (Fig. 4.1) for a fuzzy set $\tilde{A}$ could be

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < 20\% \\ \dfrac{x-20}{60-20}, & 20\% \leq x \leq 60\% \\ 1, & x \geq 60\% \end{cases} \tag{4.1}$$

where x is the percentage of needles lost (in this case), and $\mu_{\tilde{A}}(x) \in [0,1]$. The membership function needs not to be linear. Then, the fuzzy set $\tilde{A}$ is defined as

$\tilde{A} = \{(x, \mu_{\tilde{A}}(x))\,|x \in X\}$, where X is the set of possible values of x (0–100% in this case) (e.g. Niskanen 2003).

Fuzzy numbers can also be defined. Fuzzy numbers are such membership functions, which are convex (Chen and Hwang 1992; Cox 1994; Malczewski 1999). The membership function should be piecewisely continuous, and given four real

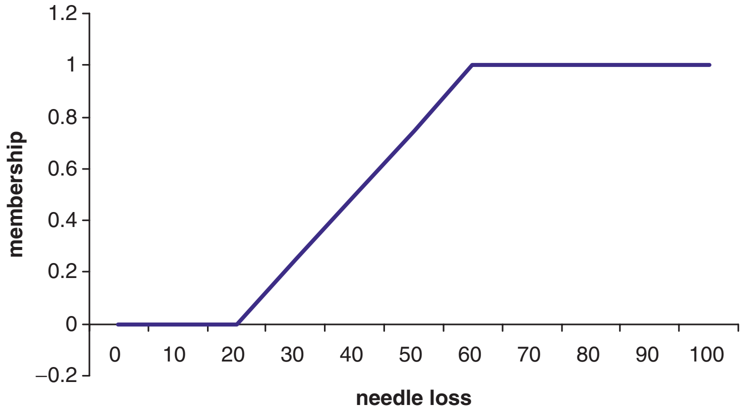

Fig. 4.1 Example of a membership function

numbers, $a \le b \le c \le d$,

$$\mu_M(x) = 0, \quad \forall x \le a$$
$$\mu_M(x) \text{ is increasing in } [a, b], \text{ decreasing in } [c, d]$$
$$\mu_M(x) = 1, \quad x \in [b, c]$$
$$\mu_M(x) = 0, \quad \forall x \ge d$$

The fuzzy numbers can be, for instance, triangular or trapezoidal in shape (Fig. 4.2). The triangular and trapezoidal fuzzy numbers are presented based on the numbers a, b, c, and d above, i.e. fuzzy number $M = (a, b, c, d)$. In triangular form $b = c$. These fuzzy numbers can also be presented as so-called L–R fuzzy numbers $M' = (b, c, (b-a), (d-c)) = (b, c, \alpha, \beta)$, i.e. α and β describe the deviation from the peak values b and c to left and right, respectively (e.g. Chen and Hwang p. 89).

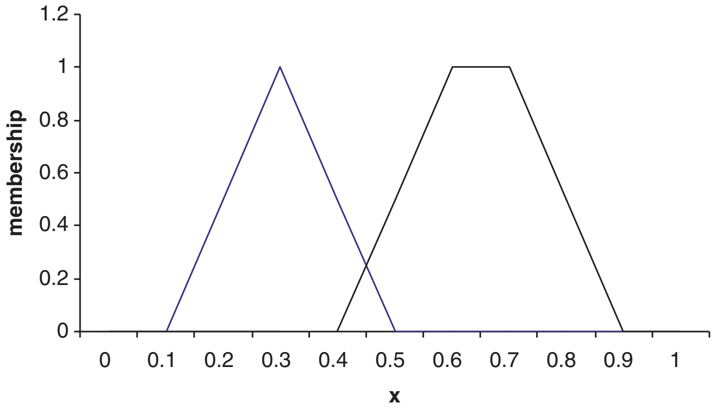

Fig. 4.2 Two examples of fuzzy numbers, triangular and trapezoidal

In order to utilize fuzzy numbers, they require arithmetic rules. For instance, the sum of two trapezoidal fuzzy numbers M and N is (e.g. Chen and Hwang 1992, p. 93; Mattila 2002)

$$M+N=(a,b,c,d)+(e,f,g,h)=(a+e,b+f,c+g,d+h) \tag{4.2}$$

and their product is

$$M\cdot N=(a,b,c,d)\cdot(e,f,g,h)=(a\cdot e,b\cdot f,c\cdot g,d\cdot h). \tag{4.3}$$

A subtraction of two fuzzy numbers is

$$M-N=(a,b,c,d)-(e,f,g,h)=(a-h,b-g,c-f,d-e) \tag{4.4}$$

and their division is

$$M/N=(a,b,c,d)/(e,f,g,h)=(a/h,b/g,c/f,d/e). \tag{4.5}$$

In products and divisions these formulas apply only if both fuzzy numbers are positive, i.e. $\mu_M(x)=0, \forall x<0$. Otherwise, different formulas need to be applied.

Furthermore, rules based on which the fuzzy numbers can be ranked are needed. Usually the first and foremost method for ranking fuzzy numbers is just to look at the drawn curves and use intuition (Cheng 1999). If this fails, different rules can be used. A number of such rules have been presented in the literature (see, e.g. Chen and Hwang 1992; Chang et al. 2006). Since the fuzzy numbers can have overlapping areas, their ranking is not self-evident, and different rules may give different answers (Fig. 4.3). Moreover, one rule may not produce a clear ranking, and therefore several rules may be needed.

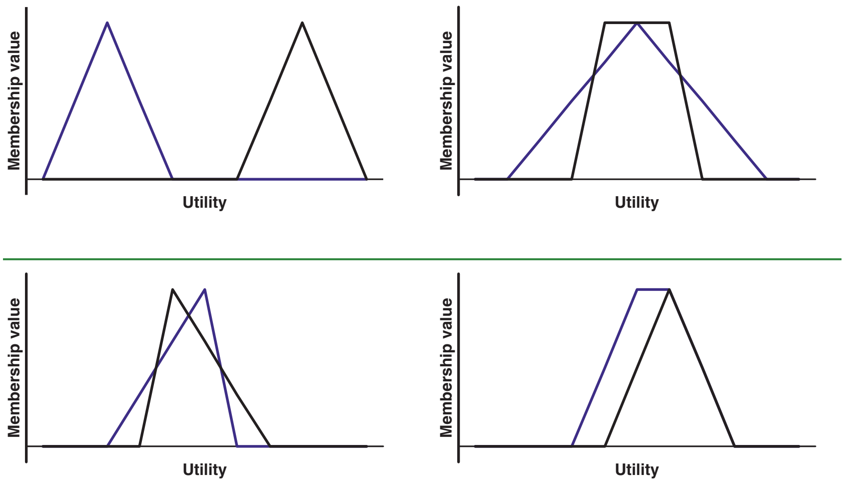

Fig. 4.3 In the upper left figure, ranking of the fuzzy numbers is obvious, but in the later three examples it is not

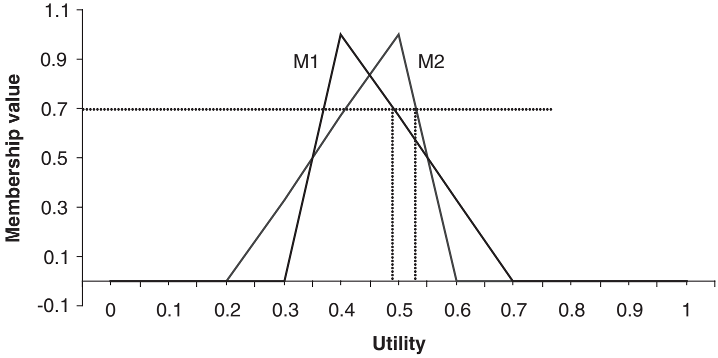

Fig. 4.4 Ranking of fuzzy numbers M1 and M2 with α-cut level 0.7

One possible solution is to rank the numbers based on so-called α-cut (Adamo 1980; Chen and Hwang 1992). It means that the decision maker defines an acceptance threshold α for the fuzzy number. Then, a line is drawn on the figure on that level of membership value (Fig. 4.4), and the fuzzy number having greater maximum value at that level is deemed better. In Fig. 4.4, number M2 is better at the α-cut level 0.7. If the α-cut level were smaller than 0.5, e.g. 0, M1 would be deemed better. Thus, this rule may produce controversial results in some cases.

Many rules for ranking fuzzy numbers are based on so-called defuzzification, i.e. calculating crisp measures from the fuzzy numbers. Many methods have been proposed for defuzzification, but the most commonly used methods are (e.g. Hellendoorn and Thomas 1993; Yager 1996; Rondeau et al. 1997)

mean of maximum (MOM)

$$m_1 = \frac{b+c}{2} \tag{4.6}$$

and center of area/gravity (COA)

$$m_2 = \frac{\int_a^d x\mu(x)dx}{\int_a^d \mu(x)dx}. \tag{4.7}$$

The MOM criterion can be criticized because it does not take into account the divergence of the fuzzy number. The COA criterion is better in the sense that it accounts for all the possible solutions, but it does not necessarily choose a solution having the maximum membership value (Rondeau et al. 1997). They produce similar results, however, in the case of symmetric fuzzy numbers. The difference is notable only if the fuzzy numbers are more complicated.

It may be that neither of these criteria can produce a ranking for two fuzzy numbers. Then, the divergence or spread $(d-a)$ of the fuzzy numbers can be used in ranking. From two fuzzy numbers otherwise similar, the fuzzy number with smaller spread is considered better.

Example 4.1. The MOM criterion in the fuzzy numbers of Fig. 4.4 are 0.4 for M1 and 0.5 for M2. Thus, based on MOM, M2 is easily seen to be better. The COA criterion for M2 is calculated as

$$\frac{\int_{0.3}^{0.4} x\frac{x-0.3}{0.1}dx + \int_{0.4}^{0.7} x\frac{0.7-x}{0.3}dx}{\int_{0.3}^{0.4} \frac{x-0.3}{0.1}dx + \int_{0.4}^{0.7} \frac{0.7-x}{0.3}dx} = \frac{0.018+0.075}{0.05+0.15} = \frac{0.093}{0.2} = 0.465$$

and for M1 as

$$\frac{\int_{0.2}^{0.5} x\frac{x-0.2}{0.3}dx + \int_{0.5}^{0.6} x\frac{0.6-x}{0.1}dx}{\int_{0.2}^{0.5} \frac{x-0.2}{0.3}dx + \int_{0.5}^{0.6} \frac{0.6-x}{0.1}dx} = \frac{0.059+0.026}{0.15+0.05} = \frac{0.085}{0.2} = 0.425$$

which would also give M2 as better.

4.2.2 *Fuzzy Goals in Decision Making*

In decision making, the membership function may describe degree of satisfaction with respect to some goal (or some constraint). It can be given, for instance, with a function

$$\mu_{\tilde{A}}(x) = \mu_{ij}(x) = \begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & x \geq b \end{cases} \tag{4.8}$$

where a is the lower border and b is the upper border for the satisfaction, i.e. the satisfaction is zero when $x < a$ and it reaches its maximum when $x \geq b$. The borders a and b, defining the membership function, can be given by the decision maker.

For decision making, the different goals need first to be aggregated describing the overall desirability of each alternative, and second, the alternatives need to be ranked according to these aggregated values (Bellman and Zadeh 1970; Zimmermann 1985). In a traditional way of fuzzy decision making (e.g. Bellman and Zadeh 1970; Malczewski 1999; Ducey and Larson 1999; Kangas et al. 2006b), a logical 'and' operator would be used to make a combination. An intersection of two fuzzy sets, $\tilde{A} \cap \tilde{B}$, is then defined as a minimum of their membership functions as

$$\mu_{\tilde{A}}(x) \wedge \mu_{\tilde{B}}(x) = Min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)) \tag{4.9}$$

Then, the recommendation would be the alternative, for which the minimum satisfaction value is the largest (Bellman and Zadeh 1970). However, this procedure allows for no compensation or tradeoffs between the criteria in the sense of utility theory (e.g. Dubois et al. 1996). A bad degree of satisfaction with respect to one criterion cannot be compensated by a good satisfaction level on another. In fact, it models soft constraints more than soft goals (Dubois et al. 1994).

The ‘min’ aggregation is one example of the so-called t-norms, which all are non-compensatory in nature (e.g. Eastman and Jiang 1996; Choi and Oh 2000). Another example of t-norms is the product aggregation, $\tilde{A} \cdot \tilde{B}$, which is simply the product of the membership functions $\mu_{\tilde{A}}(x) \cdot \mu_{\tilde{B}}(x)$ (Zimmermann 1985, p. 29).

Another possibility for aggregating is the logical ‘or’ procedure (from the family of t-conorms). In this procedure, the union of two sets is described with the maximum of their membership functions as

$$\mu_{\tilde{A}}(x) \vee \mu_{\tilde{B}}(x) = Max(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)). \tag{4.10}$$

This approach, on the other hand, could be too liberally compensating (e.g. Eastman and Jiang 1996; Malczewski 1999). When at least one of the criteria reaches the maximum level 1, the aggregation also gets value 1. Another aggregation method of the same family is the algebraic sum $\tilde{A} + \tilde{B}$ with aggregation

$$\mu_{\tilde{A}}(x) + \mu_{\tilde{B}}(x) = 1 - (1 - \mu_{\tilde{A}}(x))(1 - \mu_{\tilde{B}}(x)). \tag{4.11}$$

Unfortunately, neither ‘and’ nor ‘or’ type aggregations behave in a way needed in decision analysis. Therefore, aggregations that are in the middle of these extremes have been searched for. One group of these is formed by different mean operators, such as arithmetic average. In ordered weighted average (OWA), the membership functions are weighted based on their ranks (Yager 1988). For instance, largest membership function value gets the largest weight and smallest the smallest weight and so on. This is used to define the degree of compensation among the criteria, the so-called ‘andness’ and ‘orness’ of the aggregation (see, e.g. Eastman and Jiang 1996; Despic and Simonovich 2000). The larger weight is given to the largest membership function value, the greater the ‘orness’, and the larger weight is given to the smallest membership function value, the greater the ‘andness’.

Another important aggregation method is the γ-norm (Zimmermann and Zysno 1980; Zimmermann 1985), in which the algebraic sum and product aggregation methods are combined. The aggregation is

$$\mu_{\tilde{\theta}} = \left(\prod \mu_i\right)^{1-\gamma} \left(1 - \prod (1 - \mu_i)\right)^{\gamma} \tag{4.12}$$

where γ is a parameter [0, 1] defined by the decision maker defining the degree of ‘andness’ and ‘orness’. The larger this parameter, the greater the degree of ‘andness’ is.

None of these aggregation methods acknowledges the possible differences in the importances of the criteria, which is one of the basic concepts in decision analysis and Multi-Attribute Utility Theory (MAUT). However, weighting the criteria is quite possible also in fuzzy decision analysis. For instance, Bellman and Zadeh

Table 4.1 Data from example 3.5

Alternative	Net income 1,000€	Stumpage value (million euros)	Scenic beauty (index)
NAT	0	0.71	5.5
SCEN	79.6	0.28	5.7
NORM	38	0.6	5.4
GAME	33	0.61	5.5
MREG	102.3	0.51	5.2
INC	191.7	0.13	4.9

(1970) proposed a weighted mean aggregation method

$$\mu_\theta = \sum \alpha_i \mu_i \tag{4.13}$$

with weights similar to traditional utility functions and scaling to one as $\sum \alpha_i = 1$.

In addition to this mean operator, weights can be applied also in other aggregation methods. For instance, Yager (1978) proposed using exponential weight in 'min' operator, so that important criteria would have weight greater than zero, making the membership grade smaller, and less important criteria would have weights smaller that zero, making the membership grade larger. Then, the minimum of membership grades is more likely to be defined by the important objectives. The γ-norm can also be weighted, giving (e.g. Despic and Simonovich 2000)

$$\mu_{\tilde{\theta}} = \left(\prod \mu_i^{\alpha_i}\right)^{1-\gamma} \left(1 - \prod (1-\mu_i)^{\alpha_i}\right)^{\gamma} \tag{4.14}$$

In the following examples, the weights have been assumed to be non-fuzzy.

Example 4.2. The data used in the example is from example 3.5. (Table 4.1). It is assumed, that for each criterion the full satisfaction is obtained, if the criterion value is at least 95% of the maximum value (parameter *b* in Eq. 4.8). The lower border for satisfaction (parameter *a* in Eq. 4.8) was set to 20% (38.34), 50% (0.355) and 80% (4.56) of the maximum criterion value for net incomes, stumpage value and scenic beauty, respectively. Then, the degrees of satisfaction for each alternative and each criterion are in Table 4.2. With different aggregation rules, the results are presented in Table 4.3.

Table 4.2 Degrees of satisfaction

Alternative	Net income 1,000€	Stumpage value	Scenic beauty
NAT	0	1	1
SCEN	0.29	0	1
NORM	0	0.77	0.98
GAME	0	0.8	1
MREG	0.44	0.49	0.75
INC	1	0	0.4

Table 4.3 Results with different aggregation rules

Alternative	Min	Product	Max	Sum	Mean	Mean weighted	γ-norm $\gamma = 0.5$
NAT	0	0.000	1	1	**0.667**	0.400	1.000
SCEN	0	0.000	1	1	0.430	0.374	1.000
NORM	0	0.000	0.98	1	0.583	0.350	0.998
GAME	0	0.000	1	1	0.600	0.360	1.000
MREG	**0.44**	**0.162**	0.75	0.93	0.560	0.512	**1.366**
INC	0	0.000	1	1	0.467	**0.680**	1.000

The mean rule selected the NAT alternative. In example 3.5, incomes were assumed to be the most important criterion, but when weights were not used, its bad degree could be compensated by the good degrees of two other criteria. If similar weights were used also in this example, namely incomes 0.6, and stumpage value and scenic beauty weight 0.2 each, INC would be the choice, when the original choice was MREG. This is because the satisfaction level of net incomes is quite low for alternatives other than INC. It means that the defined satisfaction level also emphasises the importance of the most important criterion. The t-conorms Max and Sum could not select one best alternative. The non-compensative t-norms 'Min' and product selected clearly a compromise value, MREG.

Example 4.3. The same problem was then solved using the OWA analysis. For this, the satisfaction levels were ordered from largest to smallest. Weight 0.1 was then given to the largest value, 0.3 to the middle one, and 0.6 to the smallest value. It means that the 'andness' level in this analysis is great, i.e. the minimum levels of satisfaction are emphasised in the analysis. Then, again, MREG is the selected alternative, as it is the only alternative having satisfaction level greater than zero for all criteria (Table 4.4).

When the degree of satisfaction is expressed as one number, it can be argued that the information is no fuzzier than in classical MCDM methods (Hannan 1983). Only the form of scaling the original scale to utility (or satisfaction) scale is different. Otherwise, the satisfaction levels could as well be interpreted as sub-utility function values.

Table 4.4 Results with OWA aggregation

Alternative	Largest	Middle	Smallest	OWA
NAT	1	1	0	0.400
SCEN	1	0.29	0	0.187
NORM	0.98	0.77	0	0.329
GAME	1	0.8	0	0.340
MREG	0.75	0.49	0.44	**0.486**
INC	1	0.4	0	0.220

Table 4.5 The example 3.5 with linguistic performance expressions

Alternative	Net income	Stumpage value	Scenic beauty
Importance	High	Moderate	Low
NAT	VL	VH	M
SCEN	M	L	H
NORM	L	H	M
GAME	L	H	M
MREG	H	M	L
INC	VH	VL	VL

Table 4.6 Performance values as fuzzy numbers

Criteria values	
VL	(0.05, 0.2, 0.2, 0.35)
L	(0.2, 0.35, 0.35, 0.5)
M	(0.35, 0.5, 0.5, 0.65)
H	(0.5, 0.65, 0.65, 0.8)
VH	(0.65, 0.8, 0.8, 0.95)

Table 4.7 Importances as fuzzy numbers

Importances	
Low	(0.1, 0.25, 0.25, 0.4)
Moderate	(0.35, 0.5, 0.5, 0.65)
High	(0.6, 0.75, 0.75, 0.9)

Table 4.8 Fuzzy criteria numbers multiplied by criterion weights

Alternative	Net incomes	Stumpage value	Scenic beauty
NAT	0.03, 0.15, 0.15, 0.32	0.23, 0.40,0.40, 0.62	0.04, 0.13, 0.13, 0.26
SCEN	0.21, 0.38, 0.38, 0.59	0.07, 0.18, 0.18, 0.33	0.05. 0.16, 0.16, 0.32
NORM	0.12, 0.26, 0.26, 0.45	0.18, 0.33, 0.33, 0.52	0.04, 0.13, 0.13, 0.26
GAME	0.12, 0.26, 0.26, 0.45	0.18, 0.33, 0.33, 0.52	0.04, 0.13, 0.13, 0.26
MREG	0.3, 0.49, 0.49, 0.72	0.12, 0.25, 0.25, 0.42	0.02, 0.09, 0.09, 0.20
INC	0.39, 0.6, 0.6, 0.86	0.02, 0.10, 0.10, 0.23	0.01, 0.05, 0.05, 0.14

Table 4.9 Overall fuzzy utility

Alternative	Overall utility	m_1
NAT	0.29, 0.68, 0.68, 1.19	0.68
SCEN	0.33, 0.71, 0.71, 1.23	0.71
NORM	0.33, 0.71, 0.71, 1.23	0.71
GAME	0.33, 0.71, 0.71, 1.23	0.71
MREG	0.44, 0.83, 0.83, 1.34	**0.83**
INC	0.41, 0.75, 0.75,1.22	0.75

4.2.3 Fuzzy Additive Weighting

Fuzzy decision analysis can also be based on linguistic criterion values and fuzzy weights. For such a situation, fuzzy additive weighting method has been proposed (Bonissone 1982; Chen and Hwang 1992; Malczewski 1999, p. 230; Kangas et al. 2007). The fuzzy utility is of form

$$F_i = \sum_{j=1}^{m} a_j^- c_{ij}^- \tag{4.15}$$

where a$^-$ denote the fuzzy weight and c$^-$ the fuzzy criterion value. In this method, both the weights and the criteria can be linguistic variables, i.e. variables that are evaluated with vague terms, which are then presented using fuzzy numbers. For instance, the criteria could be "slightly important" or "highly important" and one criterion, for instance the risks caused to environment, could be presented with "low risk", "medium risk" and "high risk". Many other procedures have also been presented for utilising fuzzy numbers in decision analysis, but this method is the simplest.

Example 4.4. In the data of the previous example, the criteria are assumed to be linguistic variables having five levels, very low, low, medium, high, and very high with respect to each criterion (Table 4.5). The criteria, on the other hand, were having importance evaluated using scale low, moderate, and high. Then, if the linguistic variables were given values as in Table 4.6 and the importances as in Table 4.7, the fuzzy criteria values times the fuzzy importance weights can be calculated as fuzzy numbers (Table 4.8). The fuzzy numbers representing the overall utility are obtained as a fuzzy number calculated from the sum of these fuzzy numbers (Table 4.9). The recommended alternative is selected based on the mean of maximum m_1. In this case, the selected alternative is the MREG alternative. The resulting fuzzy numbers are also presented in the Fig. 4.5.

4.3 Possibility Theory in Decision Making

Fuzzy sets form the basis also for the possibility theory. The possibility theory was first presented by Zadeh (1978). It is also related to the evidence theory and to degrees of belief and plausibility. Possibility theory utilises two measures attached to one event, namely 'necessity measure' and 'possibility measure'. Both of them are membership functions, which can take values between zero and one. If an event is completely possible, then its possibility is 1. If it is completely impossible, then its possibility is 0. Similarly, if an event is certain, then its necessity measure is 1, if it is not at all certain, then its necessity measure is 0.

These two measures are related to each others. If an event A is certain, i.e. completely necessary $(N(A) = 1)$, then its complement event is impossible, and its possibility is $\Pi(\bar{A}) = 0$. Similarly, if an event is completely possible $(\Pi(A) = 1)$

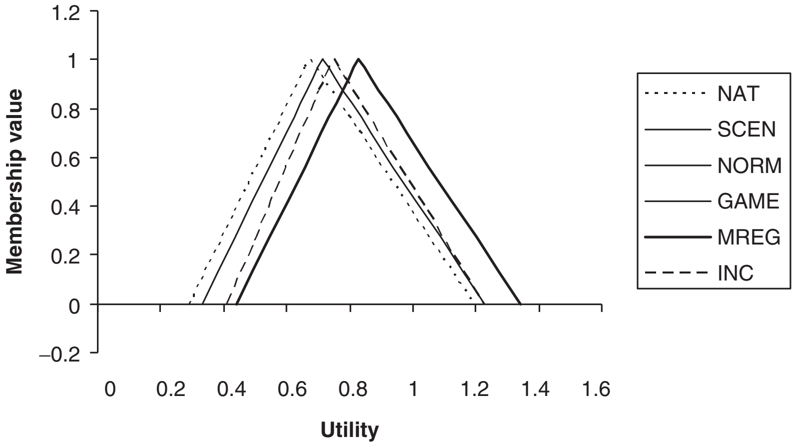

Fig. 4.5 The fuzzy numbers that describe the membership in relation to utility values

then its complement event's necessity measure is zero $(N(\bar{A}) = 0)$. Generally, $N(A) = 1 - \Pi(\bar{A})$. In all cases, an event's possibility measure needs to be larger than its necessity measure.

For example, if an expert thinks it is absolutely sure that abundance of game birds will decrease in the future, then the possibility of increasing abundance is zero. Similarly, if decreasing abundance is completely possible, then the necessity of increasing abundance is zero. However, also the possibility of increasing abundance in this situation may well be larger than zero.

Unlike in probability theory, the sum of necessity measure or possibility measure of an event and its complement needs not equal one, i.e.

$$\begin{cases} N(A) + N(\bar{A}) \leq 1 \\ \Pi(A) + \Pi(\bar{A}) \geq 1 \end{cases} \tag{4.16}$$

However, if an event is at least a bit certain $N(A) > 0$, then it has to be completely possible, and if it is not at all certain $N(A) = 0$, then it can only be relatively possible.

Therefore, to characterize uncertainty of an event A, both these measures are needed. Necessity degree describes the indications supporting the event, and one minus the possibility degree describes the indications weighting against it (i.e. its complement event's necessity) (Dubois and Prade 1988).

The classical decision rules, such as Wald criterion, can be redefined for a case of qualitative expressions of uncertainty (Dubois et al. 2001). For this purpose, the possibilities $\pi(\omega)$ of the states of nature ω and the utilities $u(x) = u(d(\omega))$ from consequence x of decision d in state ω (normalised to range [0, 1]) need to be combined as

$$v_*(d) = \inf_{\omega \in \Omega} \max(n(\pi(\omega)), u(\omega)) \tag{4.17}$$

where n is an order-reversing mapping from possibility to utility scale. This order reversing mapping n can be, for instance, the necessity of an opposite event, $1 - \pi(\omega)$.

Thus, utility value of any decision is compared to the necessity of not achieving it, and the larger of these two values is a decisive characteristic for that decision. For instance, if the possibility of the considered state of nature (e.g. 0.4) is smaller than the utility (e.g. 0.5), the order-reversed value $1 - \pi(\omega)$ is larger (0.6). In this case, the possibility of achieving the utility is so low that it is considered more important in the decision than the utility. Thus, if the possibilities are low compared to utility, decisions are based on the possibility rather than utility. Similarly, if the event's possibility is high compared to the utility, then the decision is based on utility rather than possibility.

The final rating for each alternative is the infinum (the lower bound) among all the possible states of nature. Then, a decision is rated low if there is a highly possible consequence that has low utility value (Dubois et al. 2001). In contrast to typical Maximin criterion, highly unlikely unwanted consequences are neglected. This decision rule expresses an aversion for a lack of information. An important assumption in this rule is the assumption of commensurability of the utilities and the degrees of certainty. Also the counterpart to usual Maximax-criterion can be defined using order-preserving mapping m instead of n (Dubois et al. 2001).

Example 4.5. Assume a case with two possible states of nature, ω_1 "the prices will increase in future" and ω_2 "the prices will decrease in the future" and two possible decisions, namely d_1 "sell now" and d_2 "sell later". The utilities produced by these two options in the two states are presented in Table 4.10. If possibility of the state ω_1 were 0.6, then necessity of state ω_2 would be 0.4, and if possibility of state ω_2 were 1.0, necessity of state ω_1 would be 0.0. Thus, the possibility of decreasing prices as well as the necessity of it is larger. Then,

$$v_*(d_1) = \min(\max(0.4, 0.6), \max(0.0, 1.0)) = \min(0.6, 1.0) = 0.6$$
$$v_*(d_2) = \min(\max(0.4, 0.8), \max(0.0, 0.2)) = \min(0.8, 0.2) = 0.2$$

and we would choose action one, to sell now. As the order-reversing mapping (necessity of the opposite event) was used, the resulting strategy is for a risk-averse person. The same decision would have resulted also from classical Maximin criterion: the utility of decision 1 in the worst case is higher. In this case, the necessities of the opposite events were so low that they were not decisive in the analysis.

Table 4.10 The data for possibility theory example

	ω_1	ω_2
u(d1)	0.6	1.0
u(d2)	0.8	0.2
$\pi(\omega)$	0.6	1.0
$1-\pi(\omega)$	0.4	0.0

4.4 Evidence Theory

The evidence theory was first developed by Dempster in the1960s (1967a, b). His work was later extended and refined by Schafer in the 1970s (Schafer 1976). Therefore, this theory is also called the Dempster–Schafer theory (Klir and Harmanec 1997). The theory also deals with subjective beliefs.

In the evidence theory, a number between zero and one is used to describe degree of support a certain source of evidence provides for a certain proposition, i.e. the degree of belief (Schafer 1976). This is called a belief function (Bel). However, the degrees of belief are not probabilities. For example, they do not necessarily add up to one. It is possible to give low degree of support both to a proposition (e.g. price of timber will increase) and its negation (price of timber will decrease). This situation represents ignorance about the subject issue.

If $m(A)$ is defined as the basic probability assignment of a set A in T, a set of all possible outcomes, and if it is defined that

$$\begin{aligned} m(\emptyset) &= 0 \\ \sum_{A \subset T} m(A) &= 1 \end{aligned} \tag{4.18}$$

where $m(A)$ measures the belief assigned exactly to A, total belief assigned to A is defined as a sum of beliefs assigned to subsets of A as (e.g. Ducey 2001)

$$Bel(A) = \sum_{B \subset A} m(B) \tag{4.19}$$

To fully describe the beliefs concerning proposition A, doubt concerning it also needs to be known. The degree of doubt, $Dou(A)$, is defined as the degree of belief to the negation of A, $Bel(\bar{A})$. Since $Dou(A)$ and $Bel(A)$ need not add up to one, $Pl(A) = 1 - Dou(A)$, the so-called upper probability of proposition A, is larger than or equal to $Bel(A)$. It describes plausibility of A. The plausibility can also be defined as the total probability assigned to outcomes that do not exclude A as (e.g. Ducey 2001)

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B) \tag{4.20}$$

The difference between the belief and the plausibility of a set A describes the ignorance about the issue (Schafer 1976).

Using a Bayesian decision rule (e.g. Ducey 2001), decision making is based on a number of decision alternatives $d_i \in D$, and a number of possible states of nature $\omega_j \in \Omega$. The value of a pair (d_i, ω_j) to a decision maker is expressed as a loss function $L(d_i, \omega_j)$. Uncertainty concerning the states of nature is expressed as a probability distribution for ω. Since the decisions may affect the probabilities, a conditional probability distribution $p(\omega_j|d_i)$ is used (e.g. Ducey 2001). The decision that minimizes the expected loss

$$L(P)_i = \sum_j p(\omega_j|d_i)L(\omega_i, s_j) \tag{4.21}$$

given the observed data is selected.

The Bayesian decision rules can be extended to the context of the evidence theory. For example, Dempster and Kong (1987) have suggested a so-called mini-upper decision criterion. Assume the probability of the states of nature ω_j given the decision d_i can be defined as any p satisfying

$$\begin{aligned} &Bel(\omega_j \mid d_i) \leq p(\omega_j \mid d_i) \leq Pl(\omega_j \mid d_i) \\ &\sum_j p(\omega_j \mid d_i) = 1 \end{aligned} \tag{4.22}$$

This set is called P_{bel}. Then, the upper expected loss would be

$$L_i^* = \sup_{P \in P_{bel}} L(P)_i \tag{4.23}$$

That is the greatest loss that is possible given the plausible probability range. The mini-upper decision rule then chooses the decision that minimizes the upper expected loss (Dempster and Kong 1987; Ducey 2001). This rule is similar to the classical Minimax rule, which minimizes the maximum loss, and it converges to the Bayesian decision rule, when P_{bel} becomes more precise (Ducey 2001; Caselton and Luo 1992).

Example 4.6. Assume a planting decision to a site with a risk of disease caused by snow blight. There are two alternatives, to plant pine or spruce. If no damages occur, planting pine is more profitable. If damages occur, planting spruce is more profitable. There are two possible states of nature (1 = damages occur, 2 = damages do not occur), and two possible decisions (1 = pine and 2 = spruce), and the losses obtained from each decision are presented in the Table 4.11. The losses are negative, i.e. the utilities are positive. The probability of damage occurring is assumed to be $0.1 < p_{damage} < 0.7$.

In this case, the upper expected loss is the loss occurring using the greatest possible probability for damages

$$\begin{aligned} L^*(d_1) &= 0.7 \cdot -200 + 0.3 \cdot -600 = -320 \\ L^*(d_2) &= 0.7 \cdot -400 + 0.3 \cdot -450 = -415 \end{aligned}$$

and spruce should be planted. However, if the plausibility of snow blight damage were 0.4, then the upper expected loss would be

$$\begin{aligned} L^*(d_1) &= 0.4 \cdot -200 + 0.6 \cdot -600 = -440 \\ L^*(d_2) &= 0.4 \cdot -400 + 0.6 \cdot -450 = -430 \end{aligned}$$

Table 4.11 The data for evidence theory example

	ω_1 damages occur	ω_2 damages do not occur
L(d_1) pine	−200	−600
L(d_2) spruce	−400	−450

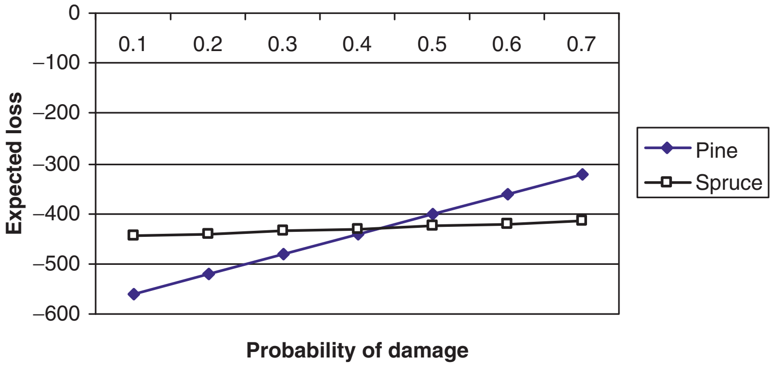

Fig. 4.6 The expected loss as a function of damage probability

and pine should be planted. The dependence of the loss on the probability is presented in Fig. 4.6.

4.5 Outranking Methods

4.5.1 Outline

Outranking methods serve as one alternative for approaching complex choice problems with multiple criteria (e.g. Bouyssou et al. 2001). Outranking indicates the degree of dominance of one alternative over another (e.g. Rogers and Bruen 1998b). The outranking methods enable the utilisation of incomplete value information and, for example, judgments on ordinal measurement scale (e.g. Rogers and Bruen 1998b). They provide the (partial) preference ranking of the alternatives, not a cardinal measure of the preference relations.

In outranking methods, strong assumptions concerning the "true" preference structure of the decision maker are avoided. It is not necessary to assume that a utility function exists, or that it can be described with some certain function form. The question is, whether there is enough information to state that one alternative is at least as good as another. The outranking approach, consequently, concentrates on comparing the alternatives in a pairwise manner.

In each case, the problem is formulated with a set of distinct alternatives a_i, $i = 1, \ldots, n$ and a set of decision criteria $g_j, j = 1, \ldots, p$ so that $g_j(a_i)$ represents the performance of alternative i with respect to criteria j. These criteria may be ordinal or even descriptive, on the contrary to most decision-aid methods. The decision problem is assumed not to be hierarchical like in AHP, for example. This, however, is not a problem since all hierarchical problems can also be presented as "flat" ones, i.e. use only the lowest level criteria. Thus, similar decision problems can be analysed using either AHP or outranking, the hierarchical presentation in the former serves as a tool for designing the problem.

The outranking methods have been used, for example, for choosing the solid waste management system (Hokkanen and Salminen 1997a, c), for locating the waste treatment facility (Hokkanen and Salminen 1997b), for nuclear waste management (Briggs et al. 1990), for irrigation system evaluation (Raju and Pillai 1999) and other Environmental Impact Analysis (EIA) projects. In forestry, outranking has been tested in a few cases (e.g. Kangas et al. 2001a, b).

The families of ELECTRE and PROMETHEE are the most widely known outranking methods. The ELECTRE methods have originally been developed by Bernard Roy (1968). Several versions of the ELECTRE method have been presented for different situations: ELECTRE I and IS are designed for selection problems, ELECTRE TRI for sorting problems and ELECTRE II, III and IV for ranking problems (see Roy 1991; Yu 1992; Rogers et al. 2000). In this book, only the ELECTRE III method of this family is presented. The PROMETHEE methods were developed in the 1980s (see Brans et al. 1986).

In PROMETHEE I and II and ELECTRE III outranking methods, the criteria are treated as so-called pseudo-criteria (Brans et al. 1986; see, e.g. Hokkanen and Salminen 1997c). This means that a threshold model is applied to the original criteria value. If the criteria values are sufficiently close to each other, they are indifferent to the decision maker, and if the difference between the criteria values is sufficiently large, there is no doubt which alternative is better according to that criterion. In between, there is an area, in which the decision maker is assumed to hesitate between indifference and strict preference.

The uncertainty is dealt using pseudo-criteria (e.g. Vincke 1992). This means that two thresholds, namely indifference and preference thresholds, are defined. The indifference threshold for criterion $j,\ q_j$, is a difference beneath which the decision maker is indifferent between two management alternatives a_k and a_l, i.e.

$$a_k \mathrm{I} a_l \Leftrightarrow \left| g_j(a_k) - g_j(a_l) \right| \leq q_j, \tag{4.24}$$

where I denotes indifference and $g_j(a_k) - g_j(a_l)$ denotes the difference between alternatives k and l with respect to criterion j. The preference threshold for criterion $j,\ p_j$, is a difference above which the decision maker strongly prefers management alternative a_k over a_l, i.e.

$$a_k \mathrm{P} a_l \Leftrightarrow g_j(a_k) - g_j(a_l) > p_j, \tag{4.25}$$

where P denotes preference. Between these two thresholds there is a zone where the decision maker hesitates between indifference and strong preference, i.e. the zone of weak preference.

$$a_k \mathrm{Q} a_l \Leftrightarrow q_j < g_j(a_k) - g_j(a_l) \leq p_j. \tag{4.26}$$

However, the zone of weak preference does not make sense if the criteria are ordinal or descriptive. In such a case, the preference and indifference thresholds could be set to zero. This means that if one alternative is considered better in ordinal scale, this alternative is strictly preferred.

The indifference threshold can be defined either with respect to the uncertainty of the criteria values or as a threshold at which the differences become perceptible to decision makers (Rogers and Bruen 1998b). Maystre et al. (1994) defined the indifference threshold as the minimum margin of uncertainty and the preference threshold as the maximum margin of uncertainty with respect to different criteria. Thus, the preference threshold implies that there is no doubt that a certain alternative is better than the other. However, there are no right values for the thresholds or a right way to define them.

4.5.2 PROMETHEE Method

In PROMETHEE I and II, the outranking degree $\Pi(a_k,\ a_l)$, describing the credibility of the outranking relation that 'alternative a_k is better than alternative a', for each pair of alternatives $(a_k,\ a_l)$ is calculated as

$$\Pi(a_k, a_l) = \sum_{j=1}^{p} w_j F_j(a_k, a_l), \tag{4.27}$$

where $F_j(a_k,\ a_l)$ is the preference function and w_j are the weights of the criteria. In (4.27), it is assumed that the weights are scaled to add up to one. In outranking, the weights are not interpreted as importances of the criteria in the same sense as in MAUT or AHP, but more like votes given to different criteria. The weights can be obtained, for example, by giving scores from 1 to 7 to the criteria, with 1 given to the least important criteria (Hokkanen and Salminen 1994). However, the weights could also be obtained from pairwise comparisons as in the AHP method.

In PROMETHEE outranking method, the threshold values are assumed to be constant (see Salminen et al. 1998). The value of preference function $F_j(a_k,\ a_l)$ for a pair of alternatives a_k and a_l with respect to criteria j are calculated using thresholds p_j and q_j as

$$F_j(a_k, a_l) = \begin{cases} 1, \text{ if } g_j(a_k) - g_j(a_l) \geq p_j \\ 0, \text{ if } g_j(a_k) - g_j(a_l) \leq q_j \\ \dfrac{(g_j(a_k) - g_j(a_l)) - q_j}{p_j - q_j}, & \text{otherwise} \end{cases} . \tag{4.28}$$

This formula can be interpreted to give a fuzzy degree of preference of one alternative over another.

In this formula, the linear threshold function is utilised (Fig. 4.7). Six different forms of the threshold function can be applied. Three of them can be derived

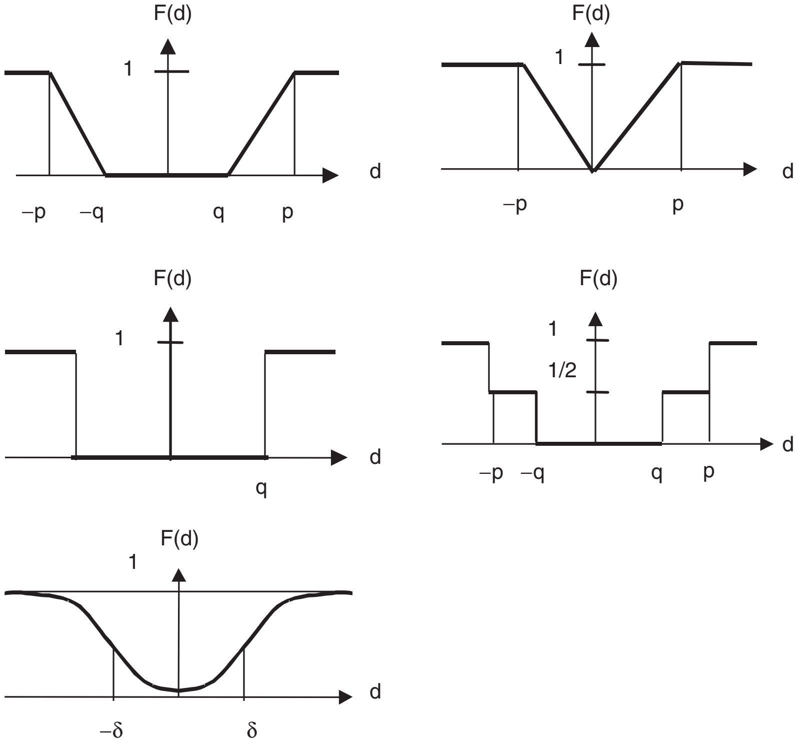

Fig. 4.7 The preference F as a function of difference $(d = g_j(a_k) - g_j(a_l))$ between alternatives with respect to some criterion with different options

from the linear threshold function, by setting $q = 0$, $q = p$, or $q = p = 0$. The two other forms are the step function and the non-linear or Gaussian function (Fig. 4.7, see Brans et al. 1986). These, however, have a slightly different interpretation than the others. The criteria and threshold values together constitute the pseudo-criteria.

The outranking degrees Π are used to calculate for each alternative the leaving flow

$$\Phi^+(a_k) = \sum_{l \neq k} \Pi(a_k, a_l)/(n-1), \tag{4.29}$$

the entering flow

$$\Phi^-(a_k) = \sum_{l \neq k} \Pi(a_l, a_k)/(n-1), \tag{4.30}$$

and the net flow

$$\Phi(a_k) = \Phi^+(a_k) - \Phi^-(a_k). \tag{4.31}$$

Table 4.12 Weights and threshold values

	w	q	p
Net incomes (1,000€)	0.6	5	20
Future timber value (million euros€)	0.2	0.05	0.2
Scenic value (index)	0.2	0.1	0.2

In PROMETHEE I the alternatives are ranked based on both the leaving and entering flow. These rankings are then used to calculate a partial preorder, where certain alternatives may remain incomparable. If one alternative is better than another with respect to both negative and positive flow, then it is determined better. In a case where one alternative is better according to positive flow and another with respect to negative flow, these two alternatives are interpreted as incomparable.

In PROMETHEE II the net flow is used, which leads to complete ranking (Hokkanen and Salminen 1997a, b). This ranking method utilises the 'cardinal' properties of the valuations, while PROMETHEE I utilised the 'ordinal' properties (Bouyssou and Perny 1992; Bouyssou 1992).

Example 4.7. The data is the same as in example 3.5 (see also Table 4.1). The values used for the weights, and preference and indifference thresholds are given in Table 4.12. It means that alternatives differing less than by 5,000€ are considered as indifferent, but 20,000€ means a clear preference difference. Then, a matrix containing the preference function (F) values for each pair of alternatives k and j, for the first criterion, namely the net incomes is calculated (Table 4.13a). In this case, the differences between the alternatives were clear so that INC is clearly better than any other alternative, and MREG is better than all the others except INC. Alternatives NORM and GAME are indifferent.

The same analysis is then done with respect to the future timber value (4.13b) and with respect to scenic beauty (4.13c). With respect to scenic beauty, the differences are again clear, but for stumpage value some of the differences are in the weak preference zone. For instance, SCEN is weakly preferred to INC. In that case, $\mathrm{d} = 0.28 - 0.13$, giving $\mathrm{F} = (0.28 - 0.13 - 0.05)/(0.2 - 0.05) = 0.67$. The credibility matrix Π is calculated as their weighted average (Table 4.14). For instance, credibility for statement that INC outranks NAT is calculated with $0.6 \cdot 1.0 + 0.2 \cdot 0.0 + 0.2 \cdot 0.0 = 0.600$. Finally, the positive and negative flows are calculated from the credibility matrix (Table 4.15). The alternatives are ranked here both according to Net flows, Negative flows and Positive flows into decreasing order. MREG alternative is best with respect to net flow. Since INC and MREG cannot be separated based on the positive flow, their rank is indetermined according to PROMETHEE I. In this case, the ranking is fairly clear, but this is not the case generally.

Table 4.13 Preference function values

	NAT	SCEN	NORM	GAME	MREG	INC
			(**a**) with respect to net incomes			
NAT	0.0	0.0	0.0	0.0	0.0	0.0
SCEN	1.0	0.0	1.0	1.0	0.0	0.0
NORM	1.0	0.0	0.0	0.0	0.0	0.0
GAME	1.0	0.0	0.0	0.0	0.0	0.0
MREG	1.0	1.0	1.0	1.0	0.0	0.0
INC	1.0	1.0	1.0	1.0	1.0	0.0
			(**b**) with respect to future timber value			
NAT	0.0	1.0	0.39	0.33	0.99	1.0
SCEN	0.0	0.0	0.0	0.0	0.0	0.67
NORM	0.0	1.0	0.0	0.0	0.27	1.0
GAME	0.0	1.0	0.0	0.0	0.33	1.0
MREG	0.0	1.0	0.0	0.0	0.0	1.0
INC	0.0	0.0	0.0	0.0	0.0	0.0
			(**c**) with respect to scenic beauty			
NAT	0.0	0.0	1.0	0.0	1.0	1.0
SCEN	1.0	0.0	1.0	1.0	1.0	1.0
NORM	0.0	0.0	0.0	0.0	0.0	1.0
GAME	0.0	0.0	1.0	0.0	1.0	1.0
MREG	0.0	0.0	0.0	0.0	0.0	1.0
INC	0.0	0.0	0.0	0.0	0.0	0.0

4.5.3 ELECTRE Method

The ELECTRE III method, can be considered as a non-compensatory model (Rogers and Bruen 1998a). It means, that a really bad score of any alternative with respect to any one criterion cannot necessarily be compensated for by good scores in other criteria.

In ELECTRE III method, a concordance index $C(a_k,\ a_l)$ for each pair of alternatives is computed, describing the strength of a claim that alternative a_k is at least as good as alternative a_l, utilising pseudo-criteria in a similar fashion as in

Table 4.14 Credibility matrix

	NAT	SCEN	NORM	GAME	MREG	INC
NAT	0.000	0.200	0.280	0.067	0.400	0.400
SCEN	0.800	0.000	0.800	0.800	0.200	0.333
NORM	0.600	0.200	0.000	0.000	0.053	0.400
GAME	0.600	0.200	0.200	0.000	0.267	0.400
MREG	0.600	0.800	0.600	0.600	0.000	0.400
INC	0.600	0.600	0.600	0.600	0.600	0.000

Table 4.15 Positive and negative and net flows

	Positive flow	Negative flow	Net flow
MREG	0.600	0.304	0.296
INC	0.600	0.387	0.213
SCEN	0.587	0.400	0.187
GAME	0.333	0.413	−0.080
NORM	0.251	0.496	−0.245
NAT	0.269	0.640	−0.371

PROMETHEE method. The concordance index is calculated as

$$C(a_k, a_l) = \sum_{j=1}^{p} w_j c_j(a_k, a_l), \tag{4.32}$$

where w_j are the relative importance of the different criteria (scaled to add up to one in the formula) and $c_j(a_k,\ a_l)$ is the local concordance index, defined as

$$c_j(a_k, a_l) = \begin{cases} 0, \text{ if } g_j(a_l) - g_j(a_k) \geq p_j \\ 1, \text{ if } g_j(a_l) - g_j(a_k) \leq q_j \\ \dfrac{p_j - (g_j(a_l) - g_j(a_k))}{p_j - q_j}, \text{ otherwise.} \end{cases} \tag{4.33}$$

In Formula (4.33), constant threshold values are applied. However, in ELECTRE III, the thresholds may be either constant, proportional to the criterion value, or they could be expressed with a linear model as a function of the criterion value (e.g. Rogers and Bruen 1998b).

The concordance index is interpreted a bit differently than the preference relations F in PROMETHEE. Here, it is analysed if there is evidence against the claim that alternative a_k is at least as good as a_l, and if a_l is clearly preferred to a_k, no such evidence can be found. If the alternatives are indifferent, or $g_j(a_l) - g_j(a_k) < 0$, then such evidence can be found (Fig. 4.8). In PROMETHEE, the evidence supporting the claim that a_k is better than a_l is searched for.

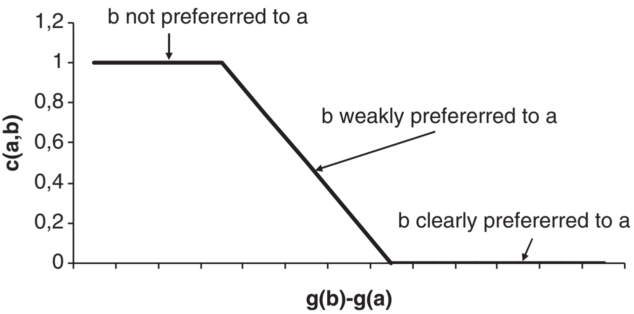

Fig. 4.8 Support of the local concordance index for claim that a is at least as good as b

If the decision were based on the concordance indices of alternatives, weighted with the importance of different criteria, the approach would basically be based on an additive utility function similarly as in PROMETHEE method given suitable values for g_i and p_i (see Salminen et al. 1998). Then, the ratios of weights of different criteria would represent the substitution rates between the different criteria. However, in ELECTRE III there is also a so-called veto threshold v_j, which is used to compute the discordance index for the alternatives. The discordance index is used to model the degree of incompensation between the criteria. This means, that an alternative with a very poor value of any one criterion cannot be chosen irrespective of the values of the other criteria. It also means that the weights of the criteria cannot be interpreted as substitution rates, but they represent votes for the criteria (Miettinen and Salminen 1999). The discordance index is defined for each criterion as

$$d_j(a_k, a_l) = \begin{cases} 0, \text{ if } g_j(a_l) - g_j(a_k) \leq p_j \\ 1, \text{ if } g_j(a_l) - g_j(a_k) \geq v_j \\ \dfrac{(g_j(a_l) - g_j(a_k)) - p_j}{v_j - p_j}, \quad \text{otherwise.} \end{cases} \tag{4.34}$$

The discordance indices of different criteria are not aggregated using the weights, since one discordant criterion is sufficient to discard outranking. In environmental planning the veto threshold is appropriate in a sense that some alternatives may not be found acceptable at all with respect to some criteria (Rogers and Bruen 1998b). The closer the veto threshold v_j is to the preference threshold p_j, the more important the criterion j can be considered (Roy 1991).

Finally, the degree of outranking is defined by $S(a_k,\ a_l)$ as

$$S(a_k, a_l) = \begin{cases} C(a_k, a_l), \text{ if } J(a_k, a_l) = \emptyset \\ C(a_k, a_l) \displaystyle\prod_{j \in J(a_k, a_l)} \frac{1 - d_j(a_k, a_l)}{1 - C(a_k, a_l)}, \quad \text{otherwise,} \end{cases} \tag{4.35}$$

where $J(a_k,\ a_l)$ is a set of criteria for which $d_j(a_k,\ a_l) > C(a_k,\ a_l)$ (Miettinen and Salminen 1999).

In basic ELECTRE III method, a descending (Z_1) and ascending (Z_2) preorder is constructed using the outranking degrees S. The final partial order $\mathrm{Z} = \mathrm{Z}_1 \cap \mathrm{Z}_2$ is constructed based on these two complete orders. The preorders Z_1 and Z_2 are constructed using a descending and ascending distillation.

In descending distillation procedure, first the maximum credibility value is searched for, $\lambda_{\max} = \max S(a_k, a_l)$. Then, a quality matrix is formed such that only values that are sufficiently close to that are considered. Sufficiently close means here $S(a_k, a_l)$ values that are greater than $\lambda_{\max} - s(\lambda)$, where $s(\lambda) = 0.3 - 0.15\lambda_{\max}$ (Belton and Stewart 2002, p. 246). The quality matrix $\mathrm{T}(a_k, a_l)$ is defined as

$$T(a_k, a_l) = \begin{cases} 1, \text{ if } S(a_k, a_l) > \lambda - s(\lambda) \\ 0, \qquad\qquad \text{otherwise} \end{cases} \tag{4.36}$$

Ranking is then based on the number of alternatives outranked by each alternative minus the number of alternatives which outrank it, i.e. row sum minus the column sum for each alternative. The set of alternatives having the largest qualification is the first distillate D_1. If this distillate contains only one alternative, the procedure is continued in the set of alternatives A, excluding that one alternative, i.e. in group $A\backslash D_1$. If there are more alternatives in D_1, the distillation procedure is applied to alternatives inside it. When the whole group of alternatives is distillated this way, the first preorder Z_1 is ready. Ascending distillation is carried out in the same way, except the alternatives with smallest qualification are searched for first (for details, see, e.g. Maystre et al. 1994; Buchanan et al. 1999; Rogers et al.2000; Belton and Stewart 2002).

The two distillations are then combined to form a partial preorder. This is carried out so that an alternative is ranked higher in the final order, if it is ranked higher in both these distillations. If the alternatives are indifferent in both distillations, they are deemed indifferent. In the obtained partial preorder some alternatives may be incomparable, i.e. their performance order cannot be determined. This is the case, if one alternative is better with respect to one distillation but worse with respect to another.

This possibility of incomparability was, at first, deemed an important quality of ELECTRE method. However, it is quite inconvenient in practical decision aid situations. A complete ranking may be obtained using, for example, the 'min' procedure (see Pirlot 1995). In the 'min' procedure, the alternatives are ranked according to the minimum outranking degree of each alternative. The alternative having the highest minimum is ranked first, and so on (see Miettinen and Salminen 1999). The 'min' procedure utilises the ordinal properties of the valuations (Pirlot 1995). Another possibility is to utilize the so-called median ranking (Roy et al. 1986), where the incomparabilities are removed by comparing the ranks of the two alternatives in the two distillations.

The PROMETHEE II method includes an indifference threshold and a preference threshold, but not a veto threshold as ELECTRE III. Also the method by which the alternatives are ranked differs, and, thus, these methods may not always produce similar results.

The outranking methods are often used for group decision making situations. In group decision making, the analyst typically chooses the values for the thresholds, and the decision makers only choose the weights of the criteria. Usually, each decision maker gives his/her own weights, and in the analysis the median or mean values for the weights are used (Roy 1991). However, it is also important to study the effect of the extreme values to the weights in a sensitivity analysis.

Example 4.8. The example 4.7 is analyzed again with ELECTRE III, using the 'min' approach for ranking the alternatives. In this example, the same weights and preference and indifference thresholds are used as above. In addition, however, a veto threshold for each criterion is added. The values for these parameters are presented in the Table 4.16.

As the concordance index matrices c for each criterion are almost similar to those of PROMETHEE (except that alternatives at least as good are searched for,

Table 4.16 Weights and the threshold values

	w	q	p	v
Net incomes	0.6	5	20	200
Future timber value	0.2	0.05	0.2	2
Scenic beauty	0.2	0.1	0.2	2

Table 4.17 Resulting concordance matrix

	NAT	SCEN	NORM	GAME	MREG	INC
NAT	1.000	0.200	0.400	0.400	0.400	0.400
SCEN	0.800	1.000	0.800	0.800	0.200	0.400
NORM	0.720	0.200	1.000	0.800	0.400	0.400
GAME	0.933	0.200	1.000	1.000	0.400	0.400
MREG	0.600	0.800	0.947	0.733	1.000	0.400
INC	0.600	0.667	0.600	0.600	0.600	1.000

Table 4.18 Discordances with respect to

	NAT	SCEN	NORM	GAME	MREG	INC
			(**a**) net incomes			
NAT	0.000	0.331	0.100	0.072	0.457	0.954
SCEN	0.000	0.000	0.000	0.000	0.015	0.512
NORM	0.000	0.120	0.000	0.000	0.246	0.743
GAME	0.000	0.148	0.000	0.000	0.274	0.771
MREG	0.000	0.000	0.000	0.000	0.000	0.386
INC	0.000	0.000	0.000	0.000	0.000	0.000
			(**b**) the future timber value			
NAT	0.000	0.000	0.000	0.000	0.000	0.000
SCEN	0.128	0.000	0.067	0.072	0.017	0.000
NORM	0.000	0.000	0.000	0.000	0.000	0.000
GAME	0.000	0.000	0.000	0.000	0.000	0.000
MREG	0.000	0.000	0.000	0.000	0.000	0.000
INC	0.211	0.000	0.150	0.156	0.100	0.000
			(**c**) the scenic beauty			
NAT	0.000	0.000	0.000	0.000	0.000	0.000
SCEN	0.000	0.000	0.000	0.000	0.000	0.000
NORM	0.000	0.111	0.000	0.000	0.000	0.000
GAME	0.000	0.000	0.000	0.000	0.000	0.000
MREG	0.056	0.167	0.000	0.056	0.000	0.000
INC	0.222	0.333	0.111	0.222	0.056	0.000

Table 4.19 Final outranking matrix

	NAT	SCEN	NORM	GAME	MREG	INC
NAT	1.000	0.167	0.400	0.400	0.362	0.031
SCEN	0.800	1.000	0.800	0.800	0.200	0.326
NORM	0.720	0.200	1.000	0.800	0.400	0.171
GAME	0.933	0.200	1.000	1.000	0.400	0.153
MREG	0.600	0.800	0.947	0.733	1.000	0.400
INC	0.600	0.667	0.600	0.600	0.600	1.000

indicating that each alternative is at least as good as itself), only the resulting concordance matrix C is presented (Table 4.17).

The discordance matrices are next calculated (Table 4.18). For instance, the discordance of the claim that NAT is at least as good as INC with respect to net incomes is $(191.7 - 0 - 20)/(200 - 20) = 0.954$, i.e. fairly high (Table 4.18a). The other alternatives all have fairly high discordance with the claim that they are at least as good as INC alternative with respect to net incomes. When calculating the final degree of outranking for NAT over INC, the concordance is reduced because of the discordance with respect to net incomes, so that the final outranking degree is $0.4 \cdot (1 - 0.954)/(1 - 0.4) = 0.4 \cdot 0.046/0.6 = 0.031$. INC alternative also has some discordance with respect to claims that it is at least as good as other alternatives with respect to future timber value and scenic beauty. Since these discordances are smaller than the concordances of the same claims, they do not affect. The final outranking degree matrix S is presented in Table 4.19. When these outranking degrees for each alternative are ranked from smallest to largest, it is clear that the minimum outranking degree is the highest for INC alternative.

If the qualification matrix T is calculated from S, with the largest outranking degree being 1, then $s = 0.15$ so that only outranking degrees greater than 0.85 are counted. The resulting T matrix is presented in Table 4.20, and the row and column sums, as well as qualifications in Table 4.21. In the qualifications, GAME alternative has the best qualification, and it would be the first alternative in the descending preorder. The rest of the alternatives would be included in a similar analysis for defining the rest of the preorder.

Table 4.20 Qualification matrix T

	NAT	SCEN	NORM	GAME	MREG	INC
NAT	1	0	0	0	0	0
SCEN	0	1	0	0	0	0
NORM	0	0	1	0	0	0
GAME	1	0	1	1	0	0
MREG	0	0	1	0	1	0
INC	0	0	0	0	0	1

Table 4.21 Row and column sums and qualifications Q for each alternative

	Row sum	Column sum	Q
NAT	1	2	−1
SCEN	1	1	0
NORM	1	3	−2
GAME	3	1	2
MREG	2	1	1
INC	1	1	0

4.5.4 Other Outranking Methods

There are a wide range of related methods, but those do not have as wide international usage as the presented methods. For example, fuzzy PROMETHEE utilises fuzzy numbers in describing the performance of the alternatives with respect to certain criteria in addition to fuzzy relations (Goumas and Lygerou 2000). There are also attempts to include the uncertainty in the performance values using probability distributions (d'Avignon and Vincke 1988).

4.6 Probabilistic Uncertainty in Decision Analysis

4.6.1 Stochastic Multicriteria Acceptability Analysis (SMAA)

It is also possible to account for uncertainty in a probabilistic framework. The effect in both the weights of the criteria and the performance of the alternatives with respect to these criteria can be assumed stochastic. Then, it can be analysed with a Monte Carlo analysis what is the probability that a certain alternative beats all the other alternatives, or that a certain alternative beats another alternative. The distribution of utilities for each alternative with respect to all decision criteria simultaneously can be calculated by sampling the distribution of weights and the criteria values, and by calculating the utility obtained from each realization (e.g. Alho and Kangas 1997; Kangas et al. 2000, 2007). In these studies, the uncertainty involved in criteria weights was estimated using regression AHP.

Even in a case the decision makers cannot or do not wish to express their preferences concerning different criteria, or even provide a preference order, it is still possible to utilise some MCDS tools in decision support. In acceptability analysis, instead of considering which alternative is preferred using certain weights, the weights that support a certain alternative are considered. Charnetski and Soland (1978) presented the comparative hypervolume criterion for cases where only partial preference information is available. Bana e Costa (1986, 1988) presented an acceptability index, which was computed as the proportion of volume of the weight space that supports a certain alternative. Butler et al. (1997) simulated the effect of different weights on the results of the utility analysis and Lahdelma et al. (1998) introduced a stochastic version of acceptability analysis (SMAA), where both the weights and the criterion values were assumed stochastic.

In the original SMAA method by Lahdelma et al. (1998) the weight space analysis is performed based on an additive utility or value function. The SMAA-2 method by Lahdelma and Salminen (2001) generalized the analysis to a general utility or value function. The SMAA-O method by Lahdelma et al. (2003) extends SMAA-2 for treating mixed ordinal and cardinal criteria in a comparable manner. In addition, the SMAA family includes, among others, the methods ref-SMAA, SMAA-3 and SMAA-III. In ref-SMAA the analysis is based on ideal or reference points instead of utility function (Lahdelma et al. 2005). The SMAA-3 method (Lahdelma and Salminen 2002) is based on pseudo-criteria as in the ELECTRE III decision-aid and SMAA-III is a full SMAA version of ELECTRE III (Tervonen et al. 2007).

The SMAA analysis has been used for several real-life problems. Among them are, for instance, planning the development of Helsinki harbour (Hokkanen et al. 1999), searching for technology for cleaning polluted soil (Hokkanen et al. 2000) and for locating a waste treatment facility (Lahdelma et al. 2002).

The SMAA-2 method (Lahdelma and Salminen 2001) has been developed for discrete stochastic multicriteria decision making problems with multiple decision makers. SMAA-2 applies inverse weight space analysis to describe for each alternative what kind of preferences make it the most preferred one, or place it on any particular rank.

The decision problem is represented as a set of n alternatives $\{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n\}$ to be evaluated in terms of m criteria. The decision makers' preference structure is represented by a real-valued utility or value function $u(\boldsymbol{x}_i, \mathbf{w})$

$$U_i = \sum_{j=1}^{m} w_j u_j(x_{ij}). \tag{4.37}$$

The criterion values x_{ij} are usually scaled to value scale using (2.5), i.e.

$$u_j(x_{ij}) = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{4.38}$$

The value function maps the different alternatives to real values by using a weight vector $\mathbf{w}$ to quantify decision makers' subjective preferences. SMAA-2 has been developed for situations where neither criteria measurements nor weights are precisely known.

Uncertain or imprecise criteria are represented by a matrix of stochastic variables ξ_{ij} with joint density function $f(\xi)$ in the space $\mathbf{X} \subseteq \mathrm{R}^{n\times m}$. The observed criterion values x_{ij} are thus assumed to be realized values of a stochastic variable having a probability distribution. It is assumed that the observed values x_{ij} represent the expected value of this distribution, and the uncertainty involved in the criterion value is described with the variance of the distribution. The distribution could be, for instance, a uniform distribution, giving all values within range $[x_{ij} - \Delta_j, x_{ij} + \Delta_j]$ equally probable. More likely, the distribution could be a normal distribution so that small deviations from the expected value are more probable than large ones.

If the variation in each variable is described with a uniform or normal distribution this way, it is assumed that the uncertainty in any one variable is not related to the uncertainty in another variable. If the criterion values are based on same causal factors, the uncertainties may be dependent (e.g. Lahdelma et al. 2006). However, explanatory variables in production models are often the same: for example, the site index, volume of the growing stock, and age of the forest can be used to predict other forest products such as berry yields. The predicted berry crop might, for instance, be the bigger the larger the volume of the stand. Therefore, the errors in basic forest variables affect them, and there may be dependencies in the errors between different criteria measurements as well. In this case, a multivariate normal distribution could be used (Kangas et al. 2006a).

The decision makers' unknown or partially known preferences are represented by a weight distribution with joint density function $f(\mathbf{w})$ in the feasible weight space $\mathbf{W}$. This facilitates very flexible modelling of different kinds of preference information. For example, the decision makers can specify precise weights, a priority order for the criteria, weight intervals, intervals for weight ratios, or arbitrary linear or non-linear constraints for weights. Total lack of preference information is represented in 'Bayesian' spirit by a uniform weight distribution in $\mathbf{W}$, i.e. for each criterion j each weight from range [0, 1] is equally probable. This can be expressed with a joint distribution function for the weights

$$f(\mathbf{w}) = 1/vol(\mathbf{W}) \tag{4.39}$$

where $vol(\mathbf{W})$ is the volume of the weight space. The weight space can be defined according to needs, but typically, the weights are non-negative and normalized, i.e.

$$\mathbf{W} = \{\mathbf{w} \in R^m | w_j \geq 0 \text{ and } \textstyle\sum_{j=1}^{m} w_j = 1\}. \tag{4.40}$$

The feasible weight space is an $n-1$ dimensional simplex in n dimensional space. For instance with three criteria, the weight space is a plane and with two criteria a line (Fig. 4.9, Tervonen and Lahdelma 2007).

The value function is then used to map the stochastic criteria and weight distributions into value distributions $u(\xi_i,\ \mathbf{w})$. In practice, it means that the joint distributions of criteria values and weights are sampled for a large number of times, say K. From these, K different realizations of the problem are obtained. From the variation between the K realizations, the value distribution is obtained. The distribution is thus obtained numerically, an analytic solution would not be easy to calculate, as the weights need to be normalized.

Obtaining m weights adding up to one may seem a difficult task. It is not possible to sample m weights and scale them to one by dividing with the sum of obtained weights, since then it would never be possible to obtain high weight for any criterion. The task is, however, easy (see also Lahdelma and Salminen 1998). For obtaining the weights, $m-1$ random numbers r are sampled from the uniform distribution. These numbers are then ordered from smallest to largest and values 0 and 1 are included in the numbers as $0 < r_1 < \cdots < r_{m-1} < 1$. Then, m numbers summing up to one are obtained from differences $r_1 - 0,\ r_2 - r_1, \ldots, 1 - r_{m-1}$.

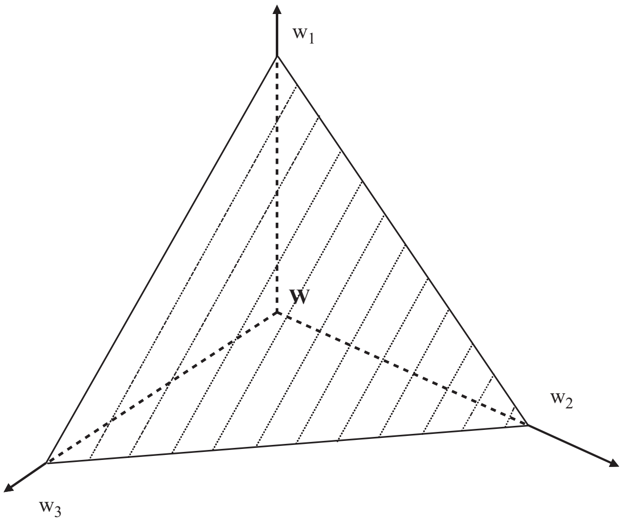

Fig. 4.9 The feasible weight space in a case of no information on weights, presented as a shaded triangle with corner points (1, 0, 0), (0, 1, 0) and (0, 0, 1)

If there is information concerning the priority order of weights, for instance, this can be used to order the obtained weights accordingly (Fig. 4.10). The decision maker may be able to define a complete importance order, or only the importance order of two groups of criteria, etc.

Example 4.9. Assume three criteria, from which the first one is known to be the most important, and the importance order of the two other criteria is undetermined. This can be denoted with $C_1 > C_2 ? C_3$. To obtain weights for these, two random numbers

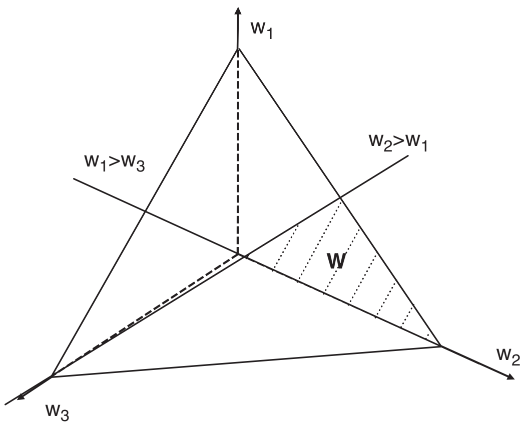

Fig. 4.10 The feasible weight space, when the importance order of criteria is $C_2 > C_1 > C_3$

Table 4.22 An example realization from the simulation

Δ	Net income ± 10	Stumpage value ± 0.2	Scenic beauty ± 0.1
NAT	−2.360	0.550	5.519
SCEN	87.582	0.434	5.792
NORM	28.290	0.563	5.473
GAME	25.772	0.508	5.409
MREG	92.948	0.376	5.144
INC	182.042	0.044	4.868

from a uniform distribution are sampled. These values were 0.112 and 0.308. From these, the weights are 0.112, $0.308 - 0.112 = 0.196$ and $1 - 0.308 = 0.692$. Since the first criterion was the most important, it was given the largest weight, 0.692 and since the priority of the others was undetermined, they were given values in the order of observation, 0.112 for C_2 and 0.196 for C_3.

Example 4.10. Assume the data set of example 3.5. It is assumed that all criteria values have a uniform distribution so that net incomes variate $\pm$ 10(1,000€), stumpage value ± 0.2 (million euros) and scenic beauty ± 0.1 units around the expected values (observed values). Random values for each variable are sampled from the uniform distributions with the given assumptions. These variables form one realization in the simulation. An example realization is presented in the Table 4.22 and the resulting sub-utilities are presented in Table 4.23.

Based on the value distributions, the rank of each alternative is defined as an integer from the best rank (=1) to the worst rank (=n) by means of a ranking function

$$rank(i, \xi, \mathbf{w}) = 1 + \sum\nolimits_{k=1}^{n} \rho(u(\xi_k, \mathbf{w}) > u(\xi_i, \mathbf{w})), \tag{4.41}$$

where $\rho(\text{true}) = 1$ and $\rho(\text{false}) = 0$. With a given realization of weights $\mathbf{w}$ and criteria value matrix ξ, this formula computes the rank of alternative $\mathbf{x}_i$, as one plus the number of alternatives $\mathbf{x}_k$ that are strictly better than $\mathbf{x}_i$. SMAA-2 is based on analyzing the stochastic sets of favourable rank weights

$$\mathbf{W}_i^r(\xi) = \{\mathbf{w} \in \mathbf{W} | rank(i, \xi, \mathbf{w}) = r\}. \tag{4.42}$$

Table 4.23 Sub-utilities resulting from simulated criterion values

	Net income	Stumpage value	Scenic beauty
NAT	−0.012	0.725	0.774
SCEN	0.457	0.524	1.115
NORM	0.148	0.746	0.716
GAME	0.134	0.652	0.636
MREG	0.485	0.424	0.305
INC	0.950	−0.148	−0.040

Any weight vector $\mathbf{w} \in \mathbf{W}_i^r(\xi)$ results in such values for different alternatives that alternative x_i obtains rank r.

The first descriptive measure of SMAA-2 is the rank acceptability index b_i^r, which measures the variety of different preferences that grant alternative x_i rank r. It is the share of all feasible weights $\mathbf{W}_i^r(\xi)$ that make the alternative acceptable for a particular rank, and it is most conveniently expressed in percent. Then, its acceptability is calculated as the expected volume of $\mathbf{W}_i^r$, proportional to total weight space volume as (Lahdelma et al. 1998; Lahdelma and Salminen 2001; Miettinen et al. 1999)

$$b_i^r = vol(\mathbf{W}_i^r)/vol(\mathbf{W}) \tag{4.43}$$

Generally b_i^r is computed numerically as a multidimensional integral over the criteria distributions and the favourable rank weights using

$$b_i^r = \int_{\mathbf{X}} f(\xi) \int_{\mathbf{W}_i^r(\xi)} f(\mathbf{w}) d\mathbf{w}\, d\xi. \tag{4.44}$$

The most acceptable (best) alternatives are those with high acceptabilities for the best ranks. Evidently, the rank acceptability indices are in the range [0, 1] where 0 indicates that the alternative will never obtain a given rank and 1 indicates that it will obtain the given rank always with any choice of weights (with the given information concerning weights). For comparing how different varieties of weights support each rank for each alternative, graphical examination of the rank acceptability indices is useful. Alternatives with high acceptabilities for the best ranks are taken as candidates for the most acceptable solution. On the other hand, alternatives with large acceptabilities for the worst ranks should be avoided when searching for compromises – even if they would have high acceptabilities also for fair ranks.

The first rank acceptability index is called the *acceptability index* a_i. The acceptability index is particularly interesting, because it can be used for classifying the alternatives into stochastically efficient ones ($a_i > 0$) and inefficient or "weakly efficient" ones (a_i zero or near-zero). The acceptability index not only identifies the efficient alternatives, but also measures the strength of the efficiency considering the uncertainty in criteria and decision makers' preferences.

If the applied weight distribution is assumed to represent accurately the distribution of multiple decision makers' (or other stakeholders') preferences, then the acceptability index is the share of votes that an alternative would receive in a voting situation. An alternative obtaining over 50% acceptability (or some other qualified majority) could then be chosen directly. In the general case, when the applied weight distribution cannot be assumed to represent the different preferences accurately, the acceptability indices should not be used for absolute ranking of the alternatives. This is due to the fact that an alternative with low support for first rank may well be the preferred one with suitable preferences.

If there is information available concerning the preferences, but it is not used in the analysis, the results may be highly misleading. For instance, in a simulation study where true preferences were assumed to exist but not used in decision analysis at all, the SMAA analysis did recommend the best alternative only in less than 50% of cases (Kangas 2006). If no information of the preferences is used, the SMAA analysis implicitly makes the recommendations as if the criteria had equal importance to the decision maker.

Often, it can be useful to calculate also cumulative acceptability of some alternatives. Instead of analyzing the acceptability for one given rank, it is analyzed what is the acceptability for at least a given rank k (k-best acceptability). For instance, the probability that alternative i is at least third, i.e. among the three most acceptable alternatives, can be analysed.

The *holistic acceptability index* can be computed for each alternative as a weighted sum of the rank acceptabilities

$$a_i^h = \sum_{r=1}^{n} \alpha_r b_i^r, \tag{4.45}$$

where suitable *meta-weights* (or rank weights) $1 = \alpha_1 \geq \alpha_2 \geq \ldots \geq \alpha_n \geq 0$ are used to emphasize the best ranks. The holistic acceptability index is thus in the interval [0, 1] and aims to provide a rough measure of the overall acceptability of the alternatives. The meta-weights can be, for instance, centroid weights

$$\alpha_r = \sum_{i=r}^{n-1} \frac{1}{i} \Big/ \sum_{i=1}^{n-1} \frac{1}{i} \tag{4.46}$$

Different meta-weights produce slightly different results, however, and the choice of the meta-weights is subjective. Different ways to choose the meta-weights are discussed in Lahdelma and Salminen (2001). The holistic acceptability indices have an important practical use: sorting the alternatives by their holistic acceptability index brings similar alternatives close to each other and makes the rank acceptability index graph and table much more descriptive.

The *central weight vector* $\mathbf{w}_i^c$ is the expected centre of gravity (centroid) of the favourable first rank weights of an alternative. $\mathbf{w}_i^c$ is computed numerically as a multidimensional integral over the criteria distributions and the favourable first rank weights using

$$\mathbf{w}_i^c = \int_X f(\xi) \int_{W_i^1(\xi)} f(\mathbf{w})\, \mathbf{w}\, dw\, d\xi / a_i. \tag{4.47}$$

In practise it means that a mean of weights is calculated from those realisations that give a certain alternative the first rank. The central weight vector represents the preferences of a hypothetical decision maker supporting this alternative. Of course, the actual preferences of the decision makers may be more or less incompatible with the central weight vectors. Still, presenting the central weights of different alternatives to the decision makers may help them to understand how different weights correspond to different choices with the assumed preference model. This information may also aid the decision makers to elicit their preferences in terms of weights.

The *confidence factor* p_i^c is the probability for an alternative to obtain the first rank when the central weight vector is chosen. The confidence factor is computed as a multidimensional integral over the criteria distributions using

$$p_i^c = \int_{\xi \in \mathbf{X}: \mathbf{w}_i^c \in \mathbf{W}_i^1(\xi)} f(\xi) d\xi. \tag{4.48}$$

Confidence factors can similarly be calculated for any given weight vectors. The confidence factors measure whether the criteria data are accurate enough to discern the efficient alternatives. The confidence factor can also be used together with the acceptability index for eliminating weakly efficient alternatives. If the acceptability index is very low (near-zero, $\ll 1/n$) and the confidence factor is low (less than, say, 5%), we can argue that such an alternative is very unlikely the most preferred by any decision maker. In contrast, a very high confidence factor (over 95%) indicates that with suitable preferences, the alternative is almost certainly the most preferred one.

The correlation among errors may considerably affect the results in the SMAA analysis. Generally, if there are positive correlations across the alternatives, within each criterion, the risks are less profound than in the case of independent errors (see Kangas et al. 2006). This is because high correlations retain the performance order of alternatives with respect to each criterion in the realizations. On the other hand, high positive correlations of criteria within alternatives may increase the risks involved in SMAA analysis. This is because the performance order of the alternatives is likely to change in the realizations, if the errors are to same direction with respect to several criteria, but to different directions across alternatives. These arguments can also be proven mathematically (see Lahdelma et al. 2006).

Example 4.11. The problem analyzed in Example 3.5 is analyzed again using SMAA-2. In the first analysis, it was assumed that the importance order or criteria is not known, denoted by C_1 ? C_2 ? C_3. The criteria values were assumed to be certain. Then, the rank acceptabilities are presented in Table 4.24. The rank probabilities are very similar for three alternatives, NAT, SCEN and INC, but NAT could be selected as most probable alternative. INC has also 65.8% probability of being the worst alternative.

The central weight vectors of alternatives describe what kind of preferences support these alternatives (Table 4.25). The results show that if large weight were given to incomes, INC would be the preferred alternative, if large weight were given to scenery SCEN would be the preferred alternative, and if large weight were given to stumpage value, NAT would be the preferred alternative. If all criteria had quite

Table 4.24 Rank acceptabilities and confidence factors assuming no information from criteria importances

	1st	2nd	3rd	4th	5th	6th	p_i^c
NAT	42.1	10.3	18.0	1.3	7.8	20.6	100
SCEN	32.2	8.7	20.6	12.3	19.9	6.3	100
NORM	0.0	0.2	34.3	37.4	20.9	7.3	100
GAME	3.9	60.5	13.4	17.8	4.3	0.0	100
MREG	0.1	15.5	12.4	30.2	41.7	0.0	100
INC	21.6	4.8	1.4	1.0	5.3	65.8	100

Table 4.25 Central weight vector assuming no information from alternatives

	Net incomes	Stumpage value	Scenic beauty
NAT	0.176	0.558	0.265
SCEN	0.290	0.138	0.571
NORM	0.491	0.502	0.007
GAME	0.427	0.369	0.204
MREG	0.499	0.465	0.036
INC	0.687	0.180	0.133

similar weights, GAME could be the best alternative. The confidence factors are 100% for each alternative, since the criteria values were assumed to be certain.

In the second analysis, it was assumed that the first criterion, net incomes, was the most important, and the priority order of stumpage value and scenic beauty is not known, denoted by $C_1 > C_2$? C_3. The rank acceptabilities for given ranks are presented in Table 4.26. It means that alternatives NAT and NORM are dominated and alternative MREG nearly dominated when it comes to the first rank. If the alternative were chosen based on the first rank probability a_i, INC would be the most preferred alternative.

The holistic acceptability index a_i^h for the alternatives are presented in Table 4.27. INC would be the most preferred one also with this score. The cumulative rank acceptability indices for the alternatives are presented in Table 4.28 and Fig. 4.11. The INC alternative is better than the others in the first two ranks, but if the alternative is required to get at least third rank, SCEN is slightly better.

The central weight vectors for the alternatives are given in Table 4.29. Since NAT alternative was dominated, it has no central weight vector, i.e. it cannot be the best if the net incomes are the most important criterion. Instead, MREG and NORM have central weight vectors. It means that also NORM has probability above zero being the best alternative, even though the probability is less than 0.1%. It can be seen that if scenic beauty is given fairly large weight (although net incomes as most important has larger), SCEN may be the best alternative, and NORM or MREG if stumpage values are given much weight.

Table 4.26 Rank acceptabilities and confidence factors assuming net incomes the most important criterion

	1st	2nd	3rd	4th	5th	6th	p_i^c
NAT	0.0	4.9	8.8	2.6	21.9	61.8	0
SCEN	31.8	26.3	29.4	2.0	3.4	7.2	100
NORM	0.0	0.0	4.5	19.2	55.8	20.5	100
GAME	7.3	14.1	10.2	58.3	10.2	0.0	100
MREG	0.3	36.4	43.8	15.5	4.0	0.0	100
INC	60.6	18.3	3.4	2.4	4.8	10.5	100

Table 4.27 Holistic acceptability

	NAT	SCEN	NORM	GAME	MREG	INC
a_i^h	10.2	59.8	14.9	35.8	43.3	**74.0**

Table 4.28 Cumulative rank acceptability indices

	1	2	3	4	5	6
NAT	0.0	4.9	13.7	16.3	38.2	100.0
SCEN	31.8	58.1	87.5	89.5	92.8	100.0
NORM	0.0	0.0	4.5	23.7	79.5	100.0
GAME	7.3	21.4	31.5	89.8	100.0	100.0
MREG	0.3	36.7	80.5	96.0	100.0	100.0
INC	60.6	78.9	82.3	84.7	89.5	100.0

Table 4.29 Central weight vectors assuming net incomes the most important criterion

	Net incomes	Stumpage value	Scenic beauty
NAT	0.000	0.000	0.000
SCEN	0.492	0.149	0.359
NORM	0.493	0.492	0.015
GAME	0.431	0.365	0.204
MREG	0.499	0.463	0.038
INC	0.696	0.151	0.154

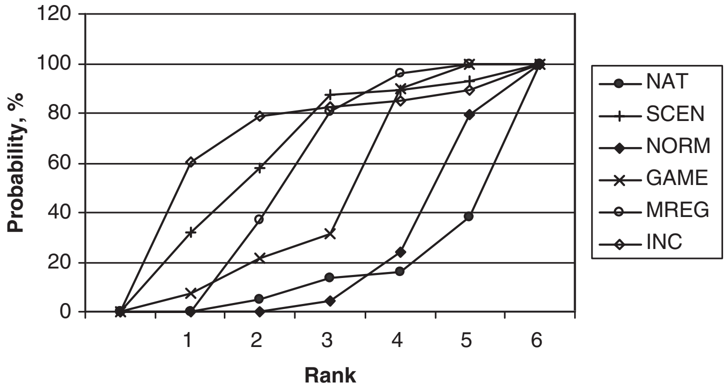

Fig. 4.11 The cumulative acceptabilities (k-best acceptability)

4.6.2 SMAA-O

SMAA-O is a version of SMAA, which can utilise also ordinal information concerning the performance of alternatives with respect to some criteria. Ordinal data are converted into stochastic cardinal data by simulating such values (in the [0, 1] interval) to the ordinal criteria that preserve the given rankings (Miettinen et al. 1999). It is assumed that the cardinal (ratio scale) utility values for a given criterion exist, but only their order is known. Similar ideas have been earlier presented by Rietveld and Ouwersloot (1992).

In practice, $m-2$ random numbers are sampled from a uniform distribution, and ordered together with zero and one, in order to obtain one realisation of the possible underlying cardinal criterion values. Although all values are random numbers sampled from uniform distribution, the method includes implicit assumptions concerning the distribution of ordinal values (see Leskinen et al. 2004). In this method, the order is assumed to be correct, but using a statistical approach deviations from the given order can be accepted with a certain probability.

Example 4.12. Assume that in the previous example the performance with respect to the last criterion, scenic beauty, is expressed as ordinal value. The ranks are in Table 4.30. It is also assumed that there is 10% standard deviation in the values of net incomes and stumpage value. In this case, the rank acceptabilities and confidence factors are presented in Table 4.31. When there is uncertainty in the criterion values, normally distributed for the first two criteria, and about the underlying cardinal criterion values of the ordinal criterion, the rank acceptabilities among the alternatives are somewhat more even: none of the alternatives is dominated any more. The confidence factors, on the other hand, are smaller. The INC alternative would be selected with 99.4% confidence using the central weight vector for it, but NORM and GAME would only occasionally be best even with these favourable weights.

4.6.3 Pairwise Probabilities

Another possibility to analyse the SMAA calculations is to calculate pairwise winning probability for all pairs of alternatives k and l (Leskinen et al. 2006). It

Table 4.30 Rank values for scenic beauty criterion

	Scenic beauty
NAT	2.
SCEN	1.
NORM	4.
GAME	3.
MREG	5.
INC	6.

Table 4.31 Rank probabilities and confidence factors

	1st	2nd	3rd	4th	5th	6th	p_i^c
NAT	5.3	8.5	11.0	13.8	15.6	45.8	48.4
SCEN	30.2	33.5	23.6	3.8	3.6	5.3	95.4
NORM	1.1	2.4	6.4	27.5	33.9	28.7	11.1
GAME	2.8	7.2	15.7	38.5	29.9	5.8	22.7
MREG	2.2	28.6	37.3	11.3	12.3	8.2	12.2
INC	58.3	19.9	5.9	5.1	4.7	6.1	99.4

describes the probability of alternative k beating another alternative l. It can be calculated as the proportion of realizations where one alternative is better than another, using the same realizations of the stochastic processes as for the original rank acceptabilities. Then, if a certain alternative has 100% winning probability against another, it is dominant, and 50% probability might indicate either a tie between the alternatives or conflicting criterion values for equally important criteria.

For analysing the pairwise winning probabilities, a rule that is widely accepted within social choice theory can be found, namely the Condorcet criterion (e.g. Bouyssou et al. 2000). The Condorcet winner is the candidate that in pairwise election gets the majority of votes against all other candidates. In the SMAA analogy, the Condorcet winner is the alternative which has more than 50% probability of winning against all other alternatives. Condorcet loser, on the other hand, has less than 50% probability of winning against all alternatives.

A measure obtained from voting theory which may give good insight into the problem is the Copeland score (e.g. Bouyssou et al. 2000). The Copeland score is calculated so that an alternative that gets a majority in a pairwise election, scores one point, and the alternative that loses the pairwise election loses one point

$$\text{Copeland}_k = \sum_{\substack{l=1 \\ k \neq l}}^{n} r_{kl}, r_{kl} = \begin{cases} 1, \ \text{if}\ p(a_k, a_l) \geq 0.5 \\ -1, \quad\quad \text{otherwise} \end{cases} \tag{4.49}$$

where $p(a_k,\ a_l)$ is the probability of alternative k beating alternative l and n is the number of alternatives. Then, the maximum score is $(n-1)$ for a Condorcet winner and minimum score is $-(n-1)$ for a Condorcet loser. This rule always finds the Condorcet winner, if it exists.

In some cases the elections may result in a situation where there is no Condorcet winner. For instance, there may be ties. In this case, another rule called Simpson score is useful (e.g. Martin et al. 1996). Simpson score is the minimum number of votes in pairwise elections a certain alternative gets against all other alternatives. In the SMAA context, it would be the minimum of pairwise winning probabilities for one alternative

$$\text{Simpson}_k = \min(p(a_k, a_l)), \quad l = 1, \ldots, n\ k \neq l. \tag{4.50}$$

Table 4.32 Pairwise winning probabilities

	NAT	SCEN	NORM	GAME	MREG	INC
NAT		10.8	33.6	0.0	13.2	15.5
SCEN	89.2		89.2	84.2	60.5	36.7
NORM	66.4	10.8		12.7	5.5	12.2
GAME	100.0	15.8	87.3		25.7	21.3
MREG	86.8	39.5	94.5	74.3		18.4
INC	84.5	63.3	87.8	78.7	81.6	

If a Condorcet winner exists, Simpson's score is larger than 50%. If no alternative wins against all others in pairwise competitions, Simpson's score chooses an alternative against which there is not a large majority.

From pairwise probabilities it is also possible to calculate a holistic index. The Positive Outranking Index (POI) is calculated as the mean of the observed pairwise probabilities of alternative k beating each of the other alternatives l

$$\mathrm{POI}_k = \frac{1}{n-1} \sum_{\substack{l=1 \\ k \neq l}}^{n} p(a_k, a_l). \tag{4.51}$$

This index has a clear interpretation: indices more than 50% indicate alternative above average, and less than 50% indicate an alternative below average. It also does not require arbitrary weights and the score only improves if an alternative has positive probability to win. In this approach, losing to some alternatives can be compensated, if the alternative beats the others by large enough an amount. This approach resembles the positive flow in PROMETHEE method (e.g. Vincke 1992).

The positive outranking index could also be calculated by counting only those probabilities that are over 50%, giving a second version of positive outranking index (POI II)

$$\mathrm{POI\ II}_k = \frac{1}{n-1} \sum_{\substack{l=1 \\ k \neq l}}^{n} r_{kl}\, p(a_k, a_l),\ r_{kl} = \begin{cases} 1, & \textit{if}\ p(a_k, a_l) \geq 0.5 \\ 0, & \text{otherwise.} \end{cases} \tag{4.52}$$

Then, the index would both penalize losing to another alternative quite hard (but not as much as Copeland score), and also take into account the amount by which it wins.

Table 4.33 Performance indices based on pairwise probabilities

	NAT	SCEN	NORM	GAME	MREG	INC
a_i^h	10.2	59.8	14.9	35.8	43.3	**74.0**
POI	14.6	71.9	21.5	50.0	62.7	**79.2**
POI II	0.0	64.6	13.3	37.5	51.1	**79.2**
Copeland	−5.0	3.0	−3.0	−1.0	1.0	**5.0**
Simpson	0.0	36.7	5.5	15.8	18.4	**63.3**

Example 4.13. In the problem above assuming net incomes as most important criterion (Example 4.11), the pairwise probabilities of each alternative beating the others are presented in Table 4.32 and the resulting scores in Table 4.33. The probability of an alternative beating itself is not considered. In this example, INC beats each alternative with probability greater than 50%, and it is best with all the indices.

References

Adamo, J.M. 1980. Fuzzy decision trees. Fuzzy Sets and Systems 4: 207–220.

Alho, J.M. and Kangas, J. 1997. Analyzing uncertainties in experts' opinions of forest plan performance. Forest Science 43: 521–528.

Bana e Costa, C. 1986. A multicriteria decision-aid methodology to deal with conflicting situations on the weights. European Journal of Operational Research 26: 22–34.

Bana e Costa, C.A. 1988. A methodology for sensitivity analysis in three criteria problems: a case study in municipal management. European Journal of Operational Research 33: 159–173.

Bellman, R. and Zadeh, L.A. 1970. Decision making in fuzzy environment. Management Science 17: B141–B164.

Belton, V. and Stewart T.J. 2002. Multiple criteria decision analysis: an integrated approach. Kluwer, Dordrecht, The Netherlands.

Bonissone, P.P. 1982. A fuzzy sets based linguistic approach: theory and applications. In: Gupta, M.M. and Sanchez, E. (Eds.). Approximate reasoning in decision analysis. North-Holland, Amsterdam, pp. 329–339.

Bouyssou, D. and Perny, P. 1992. Ranking methods for valued preference relations: a characterization of a method based on leaving and entering flows. European Journal of Operational Research 61: 186–194.

Bouyssou, D., Marchant, T., Pirlot, M., Perny, P., Tsoukiàs, A., and Vincke, P. 2000. Evaluation and decision models – A critical perspective. Kluwer, Dordrecht, The Netherlands.

Bouyssou, D., Jacquet-Lagrez, E., Perny, P., Slowinski, R., Vanderpooten, D., and Vincke Ph. (Eds), 2001. Aiding decisions with multiple criteria. Essays in honor of Bernard Roy. Kluwer Academic Publishers. Dordrecht, The Netherlands.

Brans, J.P., Vincke, Ph., and Mareschal, B. 1986. How to select and how to rank projects: the PROMETHEE method. European Journal of Operational Research 24: 228–238.

Briggs, Th., Kunsch, P.L., and Mareschal, B. 1990. Nuclear waste management: an application of the multicriteria PROMETHEE methods. European Journal of Operational Research 44: 1–10.

Buchanan, J., Sheppard, P., and Vanderpoorten, D. 1999. Project ranking using ELECTRE III. Research report 99-01, University of Waikato, Dept. of management systems, New Zealand.

Butler, J., Jia, J., and Dyer, J. 1997. Simulation techniques for the sensitivity analysis of multicriteria decision models. European Journal of Operational Research 103: 531–546.

Caselton, W.F. and Luo, W. 1992. Decision making with imprecise probabilities: Dempster-Schafer theory and application. Water Resources Research 28: 3071–3083.

Chang, J-R., Cheng, C-H., and Kuo, C-Y. 2006. Conceptual procedure for ranking fuzzy numbers based on adaptive two-dimension dominance. Soft Computing 10: 94–103.

Charnetski, J.R. and Soland R.M. 1978. Multiple-attribute decision making with partial information: the comparative hypervolume criterion. Naval Research Logistics Quarterly 25: 279–288.

Chen, S-J. and Hwang, C-L. 1992. Fuzzy multiple attribute decision making. Methods and applications. Lecture notes in economics and mathematical systems 375. Springer, New York, 536 pp.

Cheng, C-H. 1999. Evaluating weapon systems using raking fuzzy numbers. Fuzzy Sets and Systems 107: 25–35.

Choi, D-Y. and Oh, K-W. 2000. ASA and its application to multi-criteria decision making. Fuzzy Sets and Systems 114: 89–102.

Cox, E. 1994. The fuzzy systems handbook. Academic, Cambridge.
d'Avignon, G.R. and Vincke, Ph. 1988. An outranking method under uncertainty. European Journal of Operational Research 36: 311–321.
Dempster, A.P. 1967a. Upper and lower probabilities induced by a multivalued mapping. Annales of Mathematical Statistics 38: 325–339.
Dempster, A.P. 1967b. Upper and lower probability inference based on a sample from a finite univariate population. Biometrika 54: 515–528.
Dempster, A.P. and Kong, A. 1987. Probabilistic expert systems in medicine: practical issues in handling uncertainty – comment. Statistical Science 2: 32–36.
Despic, O. and Simonovich, S.P. 2000. Aggregation operators for soft decision making in water resources. Fuzzy Sets and Systems 115: 11–33.
Dubois, D. and Prade, H. 1988. Possibility theory. An approach to computerized processing of uncertainty. Plenum Press, New York, 263 pp.
Dubois, D., Fargier, H., and Prade, H. 1994. Propagation and Satisfaction of flexible constraints In: Yager, R.R. and Zadeh, L.A. (Eds.). Fuzzy Sets, Neural Networks and Soft Computing. Van Nostrand Reinnold, New York pp. 166–187.
Dubois, D., Fargier, H., and Prade, H. 1996. Refinements of the maximin approach to decision making in a fuzzy environment. Fuzzy Sets and Systems 81: 103–122.
Dubois, D., Prade, H., and Sabbadin, R. 2001. Decision theoretic foundations of qualitative possibility theory. European Journal of Operational Research 128: 459–478.
Ducey, M.J. 2001. Representing uncertainty in silvicultural decisions: an application of the Dempster-Schafer theory of evidence. Forest Ecology and Management 150: 199–211.
Ducey, M.J. and Larson, B.C. 1999. A fuzzy set approach to the problem of sustainability. Forest Ecology and Management 115: 29–40.
Eastman, J.R. and Jiang 1996. Fuzzy measures in multi-criteria evaluation. In: Proceedings of the 2nd International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Studies. Fort Collins, CO, May 21–23, pp. 527–534.
Ferson, S. and Ginzburg, L.R. 1996. Different methods are needed to propagate ignorance and variability. Reliability Engineering and System Safety 54: 133–144.
Goumas, M. and Lygerou, V. 2000. An extension of the PROMETHEE method for decision making in fuzzy environment: ranking of alternative energy exploitation projects. European Journal of Operational Research 123: 606–613.
Hannan, E.L. 1983. Fuzzy decision making with multiple objectives and discrete membership functions. International Journal of Man-Machine Studies 18: 49–54.
Hellendoorn, H. and Thomas, C. 1993. Defuzzification in fuzzy controllers. Journal of Intelligent and Fuzzy Systems 1: 109–123.
Hokkanen, J. and Salminen, P. 1997a. Choosing a solid waste management system using multicriteria decision analysis. European Journal of Operational Research 98: 19–36.
Hokkanen, J. and Salminen, P. 1997b. Locating a waste treatment facility by multicriteria analysis. Journal of Multi-Criteria Decision Analysis 6: 175–184.
Hokkanen, J. and Salminen, P. 1997c. ELECTRE III and IV decision aids in an environmental problem. Journal of Multi-Criteria Decision Analysis 6: 215–226.
Hokkanen J., Lahdelma, R., and P. Salminen. 1999. A multiple criteria decision model for analyzing and choosing among different development patterns for the Helsinki cargo harbour. Socio-Economic Planning Sciences 33: 1–23.
Hokkanen, J., Lahdelma, R., and Salminen, P. 2000. Multicriteria decision support in a technology competition for cleaning polluted soil in Helsinki. Journal of Environmental Management 60: 339–348.
Kangas, A. 2006. The risk of decision making with incomplete criteria weight information. Canadian Journal of Forest Research 36: 195–205.
Kangas, A. and Kangas, J. 2004. Probability, possibility and evidence: approaches to consider risk and uncertainty in forestry decision analysis. Forest Policy and Economics 6: 169–188.
Kangas, A., Kangas, J., and Pykäläinen, J. 2001a. Outranking methods as tools in strategic natural resources planning. Silva Fennica 35: 215–227.

Kangas, A., Kangas, J., Lahdelma, R., and Salminen, P. 2006a. Using SMAA methods with dependent uncertainties for strategic forest planning. Forest Policy and Economics 9: 113–125.

Kangas, A., Kangas, J., and Laukkanen, S. 2006b. Fuzzy multicriteria approval method and its application to two forest planning problems. Forest Science 52: 232–242.

Kangas, A, Leskinen, P., and Kangas, J. 2007. Comparison of fuzzy and statistical approaches in multi-criteria decision making. Forest Science 53: 37–44.

Kangas, J. and Kangas, A. 2004. Multicriteria approval and SMAA-O in natural resources decision analysis with both ordinal and cardinal criteria. Journal of Multi-Criteria Decision Analysis 12: 3–15.

Kangas, J., Store, R., Leskinen, P., and Mehtätalo, L. 2000. Improving the quality of landscape ecological forest planning by utilizing advanced decision-support tools. Forest Ecology and Management 132: 157–171.

Kangas, J., Kangas, A., Leskinen, P., and Pykäläinen, J. 2001b. MCDM methods in strategic planning of forestry on state-owned lands in Finland: applications and experiences. Journal of Multi-Criteria Decision Analysis 10: 257–271.

Kangas, J., Hokkanen, J., Kangas, A., Lahdelma, R., and Salminen, P. 2003. Applying stochastic multicriteria acceptability analysis to forest ecosystem management with both cardinal and ordinal criteria. Forest Science 49: 928–937.

Klir, G.J. and Harmanec, D. 1997. Types and measures of uncertainty. In: Kacprzyk, J., Nurmi, H., Fedrizzi, M. (Eds) Consensus under fuzziness. International series in intelligent technologies. Kluwer, Dordrecht, The Netherlands.

Lahdelma R. and Salminen, P. 2001. SMAA-2: stochastic multicriteria acceptability analysis for group decision making. Operations Research 49: 444–454.

Lahdelma, R. and Salminen, P. 2002. Pseudo-criteria versus linear utility function in stochastic multi-criteria acceptability analysis. European Journal of Operational Research 141: 454–469.

Lahdelma, R., Hokkanen, J., and Salminen, P. 1998. SMAA – Stochastic multiobjective acceptability analysis. European Journal of Operational Research 106: 137–143.

Lahdelma, R., Miettinen, K., and Salminen, P. 2003. Ordinal criteria in stochastic multicriteria acceptability analysis (SMAA). European Journal of Operational Research 147: 117–127.

Lahdelma, R., Miettinen, K., and Salminen, P. 2005. Reference point approach for multiple decision makers. European Journal of Operational Research 164: 785–791.

Lahdelma, R., Makkonen, S., and Salminen, P. 2006. Two ways to handle dependent uncertainties in multi-criteria decision problems. Omega (in press).

Leskinen, P., Kangas, A., and Kangas, J. 2004. Rank-based modelling of preferences in multi-criteria decision making. European Journal of Operational Research 158: 721–733.

Leskinen, P., Viitanen, J., Kangas, A., and Kangas, J. 2006. Alternatives to incorporate uncertainty and risk attitude into multi-criteria evaluation of forest plans. Forest Science 52: 304–312.

Malczewski, J. 1999. GIS and multicriteria decision analysis. Wiley, New York, 392 pp.

Martin, W.E., Schields, D.J., Tolwinski, B., and Kent, B. 1996. An application of social choice theory to U.S.D.A. Forest Service decision making. Journal of Policy Modelling 18: 603–621.

Mattila, J. 2002. Sumean logiikan oppikirja. Art House, Kustantaja, 289 pp.

Maystre, L.Y., Pictet, J., and Simos, J. 1994. Méthodes multicritères ELECTRE. Presses Polytechniques et Universitaires Romandes, Lausanne.

Miettinen, K. and Salminen, P. 1999. Decision-aid for discrete multiple criteria decision making problems with imprecise data. European Journal of Operational Research 119: 50–60.

Miettinen, K., Lahdelma, R., Salminen, P. 1999. SMAA-O – Stochastic multicriteria acceptability analysis with ordinal criteria. Reports of the Department of Mathematical Information Technology Series B, Scientific Computing B5. University of Jyväskylä, Finland.

Niskanen, V. 2003. Software computing methods in human sciences. Studies in fuzziness and soft computing. Springer. Heidelberg, Germany, 280 pp.

Pirlot, M. 1995. A characterization of ‘Min’ as a procedure for exploiting valued preference relations and related results. Journal of Multi-Criteria Decision Analysis 4: 37–56.

Raju, K.S. and Pillai, L.R.S. 1999. Multicriteria decision making in performance evaluation of an irrigation system. European Journal of Operational Research 112: 479–488.

Rietveld, P. and Ouwersloot, H. 1992. Ordinal data in multicriteria decision making, a stochastic dominance approach to siting nuclear power plants. European Journal of Operational Research 56: 249–262.

Rogers, M. and Bruen, M. 1998a. A new system for weighting environmental criteria for use within ELECTRE III. European Journal of Operational Research 107: 552–563.

Rogers, M. and Bruen, M. 1998b. Choosing realistic values of indifference, preference and veto thresholds for use with environmental criteria within ELECTRE. European Journal of Operational Research 107: 542–551.

Rogers, M., Bruen, M., and Maystre, L.-Y. 2000. ELECTRE and decision support: methods and applications in engineering and infrastructure investment. Kluwer, Dordrecht, The Netherlands.

Rondeau, L., Ruelas, R., Levrat, L., and Lamotte, M. 1997. A defuzzification method respecting the fuzzification. Fuzzy Sets and Systems 86: 311–320.

Roy, B. 1968. Classement et choix en présence de points de vue multiples (la méthode ELECTRE). Revue Française d'Informatique et de Recherche Opérationnelle 8: 57–75.

Roy, B. 1991. The outranking approach and the foundations of Electre methods. Theory and Decision 31: 49–73.

Roy, B., Présent, M., and Silhol, D. 1986. A programming method for determining which Paris metro stations should be renovated. European Journal of Operational Research 24: 318–334.

Salminen, P., Hokkanen, J., and Lahdelma, R. 1998. Comparing multicriteria methods in the context of environmental problems. European Journal of Operational Research 104: 485–496.

Schafer, G. 1976. A mathematical theory of evidence. Princeton University Press, Princeton, NJ, 297 pp.

Tervonen, T. and Lahdelma, R. 2007. Implementing stochastic multicriteria acceptability analysis. European Journal of Operational Research 178: 500–513.

Tervonen, T., Figueira, J.R., Lahdelma, R., and Salminen, P. 2007. Towards robust ELECTRE III with simulation: theory and software of SMAA-III. Submitted manuscript.

Williams, D. 1991. Probability with Martingales. Cambridge Mathematical Textbooks. Cambridge University Press, Cambridge, 251 pp.

Vincke, Ph. 1992. Multi-criteria decision aid. Wiley, New York, 154 pp.

Yager, R.R. 1978. Fuzzy decision making including unequal objectives. Fuzzy Sets and Systems 1: 87–95.

Yager, R.R. 1988. On ordered weigh averaging aggregating operators in multi-criteria decision making. IEEE Transactions on Systems, Man and Cybernetics 18: 183–190.

Yager, R.R. 1996. Knowledge-based defuzzification. Fuzzy Sets and Systems 80: 177–185.

Yu, W. 1992. Aide multicritère à la décision dans le cadre de la problématique du tri: méthodes et applications. Ph.D. thesis, LAMSADE, Université Paris-Dauphine, Paris.

Zadeh, L.A. 1965. Fuzzy sets. Information and Control 8: 338–353.

Zadeh, L.A. 1978. Fuzzy sets as a basis for theory of possibility. Fuzzy Sets and Systems 1: 3–28.

Zimmermann, H.-J. 1985. Fuzzy set theory – and its applications. Kluwer, Dordrecht, The Netherlands, 355 pp.

Zimmermann, H.-J. and Zysno, P. 1980. Latest connectives in human decision making. Fuzzy Sets and Systems 4: 37–51.

Part II
Continuous Problems

Chapter 5
Optimization

5.1 Linear Programming

5.1.1 Primal Problem

Linear Programming (LP) is the most common optimization method used in forest management planning (e.g. Davis et al. 2001; Buongiorno and Gilles 2003). The idea in LP is to allocate the limited resources optimally. In LP method the planning problem is described with an objective function which is to be maximized (or minimized)

$$\max z = \sum_{j=1}^{n} c_j x_j \tag{5.1}$$

subject to some constraints. The constraints can be either output constraints

$$\sum_{j=1}^{n} a_{ij} x_j \geq b_i, \quad i = 1, \ldots, q \tag{5.2}$$

or input constraints

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i, \quad i = q+1, \ldots, p. \tag{5.3}$$

Constraints are usually expressed as inequalities, but equality constraints (i.e. constraints with $=$ instead of $\leq$ or $\geq$) can also be used. In addition, LP formulation includes non-negativity constraints

$$x_j \geq 0, \quad \forall j = 1, \ldots, n. \tag{5.4}$$

In this formulation, each x_j is a decision variable to be solved. In forest planning problems decision variable x_j is usually area (ha) or the proportion of area treated with alternative (activity) j. The coefficients c_j tell how much this area produces or consumes the objective variable when treated with alternative j. For instance, if the objective is to maximize the revenues, and treatment alternatives are to harvest by clear-cutting or thinning, the coefficient c_j is the revenue per hectare (€/ha) from clear-cutting and thinning, respectively. If the decision variable is proportion, then c_{ij} is presented as euros per area available (€).

An LP problem usually also involves constraints, either output constraints (5.2) or input constraints (5.3). The right hand sides (RHS, b_i) of output constraints tell how much at least the decision maker requires some commodity i. An example of output constraints is a requirement that the volume of growing stock should be at least a certain amount (m^3). The RHS's of input constraints, on the other hand, tell how much at most the decision maker is able or willing to use a certain input. An example of the input constraints is the number of working hours the decision maker is willing to use on forest management. The coefficients a_{ij} tells how much the area treated with treatment j produces or uses commodity i.

The most obvious input constraint in forest management planning problems is the area available: the total area treated with different alternatives must not exceed the area available (or the sum of proportions can not exceed one). In the case of area constraints, the a_{ij} coefficients are ones, and b_i is the area in hectares (or one in the case of proportions). In this case, equality constraint is used instead of inequalities. Finally, all the decision variables are required to be non-negative. This means, however, no loss of generality of the method, as variables having negative values can be reformulated using, e.g., the difference between two non-negative variables.

Any solution that satisfies all the constraints is called a feasible solution. The feasible solutions are in a region restricted by constraints, a so-called feasible region. The best solution among the feasible solutions is the optimum. In LP, if there is a unique optimal solution, it always is a corner-point in the feasible region.

The following properties of the problem are assumed:

- Linearity
  - The objective function and all constraints need to be formulated so that the value of objective function (or constraint) is directly proportional to the value of decision variable.
  - It means, for instance, that the revenue and cost €/m^3 has to be the same irrespective of the level of the harvests.
- Additivity
  - The value of objective function has to be such that it can be calculated directly as a sum of the contributions of each individual decision variable.
  - It also means that the decision variables need to be independent of each others. For instance, an increase in the revenues of one treatment should not affect the revenues of other treatments.
- Divisibility
  - In LP, the constraints and the objective function need to be such that all the decision variables are continuous variables. This means, that if there are several treatment options for a single forest area, the solution may divide the area

to two or more parts with different treatment. The number of such parts is at most equal to the number of binding input and output constraints. If this cannot be allowed, integer programming needs to be used.

- Determinism
  - It is assumed that all coefficients *a, b* and *c* are known with certainty, for instance the future growth of the forests and future prices of timber. Thus, it may be useful to calculate the optimal solution with several assumptions of prices etc., i.e. to do sensitivity analysis.

The problem is usually solved with a Simplex algorithm (for a method description see, e.g. Dantzig 1951; Taha 1997; Hillier and Lieberman 2001). In this book, the examples are solved using the Solver in Excel. For details of using Solver in forestry problems the readers are referred to Buongiorno and Gilles (2003).

The possible results are:

1. No feasible solution is found
   - The constraints are too tight
2. One optimal solution
3. Infinite number of optimal solutions
   - The objective function is parallel to a constraint function, and the same objective function value can be obtained in all points between two corner-points
4. The optimum is infinite
   - The problem should be reformulated

Example 5.1. Assume a factory that produces two products, say toy trains and toy cars. Each train gives a revenue of 3€, and each car 2€. Both products require two kinds of material, say birch and spruce wood. Each train consumes $2\,\mathrm{dm}^3$ of birch and $1\,\mathrm{dm}^3$ of spruce, and each car $1\,\mathrm{dm}^3$ of birch and $2\,\mathrm{dm}^3$ of spruce. There is $6\,\mathrm{dm}^3$ of each species available. The decision variables are the number of produced trains (x_1) and cars (x_2).

The problem is to maximize the profits

$$\max\ \mathrm{z} = 3\mathrm{x}_1 + 2\mathrm{x}_2$$

subject to

$$\begin{aligned} 2\mathrm{x}_1 + \mathrm{x}_2 &\le 6 \text{ (birch wood consumption)} \\ \mathrm{x}_1 + 2\mathrm{x}_2 &\le 6 \text{ (spruce wood consumption)} \\ \mathrm{x}_1,\ \mathrm{x}_2 &\ge 0 \end{aligned}$$

This simple problem can be solved graphically (Fig. 5.1). The constraints are drawn to a figure to be able to see the feasible region. Then, the objective function is drawn though the origin (0, 0) and moved further and further away from origin. The furthest point where the objective function still is inside the feasible region is the optimal point.

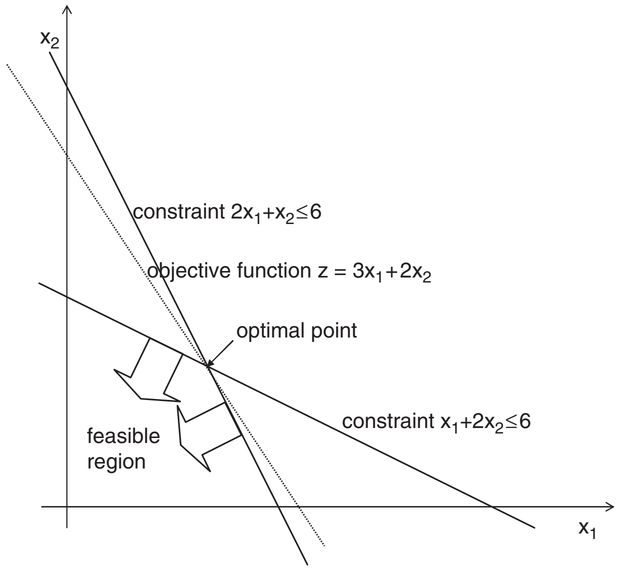

Fig. 5.1 Constraints as a function of decision variables define the feasible region

Example 5.2. Assume a pine forest area of 60 ha. The initial volume per hectare is 180 m^3/ha, i.e. the total volume in the area is 10,800 m^3. The harvest revenue is 30€/m^3. The problem is to maximize harvest revenues in a 30-year period so that the volume in the end would be at least the same as in the beginning, the harvest revenues in the first 10-year period would be at least 50,000, and that it would increase by 5,000€ in each of the later 10-year periods.

The decision variables in this problem are the areas (ha) of the four treatment alternatives, x_1, x_2, x_3 and x_4. The alternative treatments are: to harvest at the first period, harvest at the second period, harvest at the last period and not to harvest at all. The volume development in these four alternative treatments is presented in Table 5.1

Then, the objective function is

$$\max\ z = 5,250x_1 + 6,600x_2 + 7,950x_3 + 0x_4,$$

Table 5.1 Expected volume (m^3/ha) of the forest area treated with each of the alternatives in different periods

Alternative	Initial	2016	2026	2036
Harvest 1	180	5	17.5	52.5
Harvest 2	180	225	5	17.5
Harvest 3	180	225	270	5
No harvest	180	225	270	297

Table 5.2 Harvest revenues at each period in these four alternatives

Alternative	2016	2026	2036
Harvest 1	5,250	0	0
Harvest 2	0	6,600	0
Harvest 3	0	0	7,950
No harvest	0	0	0

describing the total harvest revenues over all periods in the area. The area constraint is

$$x_1 + x_2 + x_3 + x_4 = 60$$

the revenue constraints for the three periods are

$$\begin{aligned}
5250x_1 + 0x_2 + 0x_3 + 0x_4 &\geq 50{,}000 \\
0x_1 + 6600x_2 + 0x_3 + 0x_4 &\geq 55{,}000 \\
0x_1 + 0x_2 + 7950x_3 + 0x_4 &\geq 60{,}000
\end{aligned}$$

and the constraint for the volume in the end of the period is

$$52.5x_1 + 17.5x_2 + 5x_3 + 297x_4 \geq 10{,}800.$$

The non-negativity constraints can be either given implicitly or selected as an option. The result obtained with Solver is presented in Table 5.3. The resulting level of the constraints is exactly the given constraint for the area (60 ha), the first and second 10-year periods (50,000€ and 55,000€), and the final volume (10,800 m^3). Instead, in the last 10-year period the harvest revenue is greater (64,315€) than required (60,000€). Thus, this constraint was not binding, but there is a 4315€ slack. The rest of the constraints were binding. The resulting optimal total harvest revenues were then 169,315€.

5.1.2 Dual Problem

For each primal problem there is an analogous dual problem. If the primal problem is a maximization problem, then dual problem is a minimization problem. Vice versa, if the primal is a minimization problem, dual is a maximization problem. If the

Table 5.3 The solution

Alternative	Area (ha)
Harvest 1	9.52
Harvest 2	8.33
Harvest 3	8.09
No harvest	34.05

primal problem has a unique solution, so does the dual problem, and the solution to the dual problem is the same as to the primal problem. If the primal has no feasible solution (i.e. solution that would satisfy all the constraints), the solution of dual is infinite, and vice versa. The primal and dual problems are so tightly related that solving primal automatically produces the solution for dual and vice versa.

The objective function of dual problem is formulated from RHS's of the primal problem constraints and so-called shadow prices v_i. In the dual problem, the shadow prices are the decision variables, and objective function and all constraints are expressed as a function of them. Thus, the number of decision variables in the dual problem is the same as number of constraints in the primal problem.

In the dual problem, the constraints are formed from the original decision variables, i.e. there are as many constraints as there were decision variables in the primal. The right hand sides of the dual constraints are obtained from the coefficients of the primal objective function. For the problem presented in Formulas (5.1–5.4), the corresponding dual problem is

$$\min w = \sum_{i=1}^{p} b_i v_i \tag{5.5}$$

subject to

$$\sum_{i=1}^{p} a_{ij} v_i \geq c_j, \quad j = 1, \ldots, n \tag{5.6}$$

Thus, if the primal is a maximization problem, the constraints of dual problem are always $\geq$ type constraints. If the primal is a minimization problem, then the dual constraints are of $\leq$ type, i.e. (Taha 1997, p. 113)

$$\sum_{i=1}^{p} a_{ij} v_i \leq c_j, \quad j = 1, \ldots, n. \tag{5.7}$$

The shadow prices, v_i $i = 1, \ldots, p$, for output constraints are always non-positive and for the input constraints the shadow prices are always non-negative. For area constraints (i.e. equality constraints), the shadow prices are unrestricted, meaning that they can be either positive or negative. For constraints that are not binding, the shadow prices are zero.

The shadow prices measure, how much the objective function value changes, if the RHS of one constraint is changed by one unit, and all other things remain equal. Then, the shadow price for area, for instance, measures the value of one unit of land in the production. The properties can be derived from the equality

$$z = \sum_{j=1}^{n} c_j x_j = \sum_{i=1}^{p} b_i v_i = w \tag{5.8}$$

if z is revenue, and b_i is the area available, then v_i must be the worth of unit area. In a non-optimal solution $\sum_{j=1}^{n} c_j x_j < \sum_{i=1}^{p} b_i v_i$, i.e. the revenues are less than worth of the land. Thus, optimal solution is obtained when all resources are completely exploited. The shadow prices can also be used to calculate the reduced cost of an activity. The reduced costs are calculated as

$$rc_j = c_j - \sum_{i=1}^{p} a_{ij} v_i \tag{5.9}$$

The reduced cost can be calculated to all activities that are included in the solution and those that are not in the solution and also for new activities that have not been considered at all. If the activity is in fact in the solution, the reduced cost is always zero. If the activity is not in the solution, the reduced cost is negative: the costs (calculated using shadow prices) of the alternative are higher than the profits. If the reduced cost of the new activity is positive, it can profitably be included in the solution.

Example 5.3. In the example 5.2 the problem was

$$\max\ z = 175x_1 + 220x_2 + 265x_3 + 0x_4$$

subject to

$$\begin{aligned}
x_1 + x_2 + x_3 + x_4 &= 60\\
5250x_1 + 0x_2 + 0x_3 + 0x_4 &\geq 50{,}000\\
0x_1 + 6600x_2 + 0x_3 + 0x_4 &\geq 55{,}000\\
0x_1 + 0x_2 + 7950x_3 + 0x_4 &\geq 60{,}000\\
52.5x_1 + 17.5x_2 + 5x_3 + 297x_4 &\geq 10{,}800.
\end{aligned}$$

The dual problem for this is

$$\min w = 60\ v_1 + 50{,}000\ v_2 + 55{,}000v_3 + 60{,}000v_4 + 10{,}800v_5$$

subject to

$$\begin{aligned}
v_1 + 5250v_2 + 0v_3 + 0v_4 + 52.5v_5 &\geq 175\\
v_1 + 0v_2 + 6600v_3 + 0v_4 + 17.5v_5 &\geq 220\\
v_1 + 0v_2 + 0v_3 + 7950v_4 + 5v_5 &\geq 265\\
v_1 + 0v_2 + 0v_3 + 0v_4 + 297v_5 &\geq 0
\end{aligned}$$

Thus, the objective is to minimize the shadow price over the five constraints. Each shadow price refers to one constraint. For all constraints except for the area constraint, the shadow prices need to be non-positive, as the constraints are output constraints. For the area constraint (i.e. an equality constraint), the shadow price is unrestricted. The solver result for this is presented in Table 5.4. For the harvests in period 3, the shadow price is 0, as the constraint is not binding. For the area constraint, the shadow price is 8086.13€/ha. It means that the optimal harvest revenues could be increased with this amount, if there were one more unit of land, i.e. it is

Table 5.4 The solver solution for the dual problem

Constraint	Value	Shadow price
Area	60	8086.13
Period 1	50,000	−0.27
Period 2	55,000	−0.15
Period 3	64315,00734	0
End	10,800	−27.23

the value of one additional hectare of land. The shadow prices for the harvests in the first two periods are negative. It means that the optimal harvest level could be increased by 0.27 or 0.15 m^3 if the RHS of these constraints were reduced by 1 m^3, or, how much decision maker would need to give up in the optimal harvest level, if the constraint were increased by 1 m^3. The shadow price of the last constraint, the final volume, is −27.23. It means that the optimal harvest level could be increased by 27.23€, if the constraint were reduced by one m^3. In this example the reduced costs for all the activities are zero, as all the activities are in the final solution, i.e. all treatments have an area. If a new alternative, thinning at second period, were considered with harvest revenues 4050€/ha, and volume in each period as

Alternative	Initial	2016	2026	2036
Thinning	180	225	135	202

the reduced cost for this alternative would be

$$4050-(1\cdot 8086.13+0\cdot -0.27+4050\cdot -0.15+0\cdot 0+202\cdot -27.23)=2071.83,$$

meaning that this new alternative would be included in the optimal solution, if it were included in the analysis. When it was included in the analysis, the result would be such that harvesting with clear-cut in second period is no more in the solution (Table 5.5). Now, its reduced cost is also negative meaning that it is not profitable. Also the optimal value is better, 216,613€. The shadow prices for the new constraints are presented in Table 5.6. With the new treatment included, the shadow price of the land has increased. Thus, it relates to the value of land in the production, not necessarily to the market value of land.

Table 5.5 The new solution and the reduced costs

Alternative	Area (ha)	Reduced cost
Period 1	9.52	0.00
Period 2	0.00	−5378.57
Period 3	7.55	0.00
No harvest	16.60	0.00
Thinning	26.32	0.00

Table 5.6 The new shadow prices

Constraint	Value	Shadow price
Area	60.00	12728.57
Period 1	50,000	−0.99
Period 2	106613.78	0
Period 3	60,000	−0.57
End	10,800	−42.86

5.1.3 Forest Planning Problem with Several Stands

When there are m stands, with $\mathrm{n_k}$ alternatives for each stand, the problem can be formulated with

$$\max z = \sum_{k=1}^{m} \sum_{j=1}^{n_k} c_{kj} x_{kj} \tag{5.10}$$

subject to

$$\sum_{k=1}^{m} \sum_{j=1}^{n_k} a_{kji} x_{kj} \geq b_i, \quad i = 1, \ldots, q \tag{5.11}$$

and

$$\sum_{k=1}^{m} \sum_{j=1}^{n_k} a_{kji} x_{kj} \leq b_i, \quad i = q+1, \ldots, p \tag{5.12}$$

$$\sum_{j=1}^{n_k} x_{kj} = 1, \;\; k = 1, \ldots, m \tag{5.13}$$

and

$$x_{jk} \geq 0 \quad \forall k = 1, \ldots, m, \quad j = 1, \ldots, n_k \tag{5.14}$$

where n_k is the number of treatment alternatives, p is the number of constraints, b_i is the RHS value of constraint for criterion variable i, and x_{kj} is the proportion of the area of stand k on which treatment alternative j is applied. In this case, a separate area constraint is required for each m stands.

The formulation above is not, however, the only possibility for forestry problems. A frequently referred classification of forestry LP approaches is the one presented by Johnson and Scheurman (1977). They divided the various LP problem formulations applied to harvest scheduling into two basic types. With Model I, each activity variable is associated with a particular treatment schedule alternative that covers the whole planning horizon. The example above follows this Model I formulation. In Model II, instead, each individual treatment option forms a separate activity variable. It means, for instance that all stands that are clear-cut at the same time, can be combined into one calculation unit. This means, generally taken, that optimization problems formulated according to the Model II typically are greater, and, thus, need more calculation capacity to be solved in the same time as the same problem formulated by Model I. Nevertheless, according to Clutter et al. (1983), some harvest-scheduling problems might be handled more efficiently through a Model II formulation.

For example, the FORPLAN harvest-scheduling system, applied by the USDA Forest Service, enables both model types (e.g. Johnson 1977). Instead, in the Nordic Countries, for instance, LP problems applied in widely used forest planning packages MELA in Finland and GAYA in Norway can be classified as belonging to the Model I type approach.

5.1.4 JLP Software

In MELA and GAYA, an LP technique specially tailored for large Model I type optimization problems is used. The program is called JLP (Lappi 1992) and its later version J (http://www.metla.fi/products/J/index.htm). It uses so-called generalized upper bound technique rather than basic SIMPLEX algorithm in solving the problem. Both in the problem formulation and in solving the problem, the special features of a forest planning problem are applied.

In JLP it is assumed that a plan is made simultaneously for several treatment units, e.g. stands. For each stand, one or more treatment schedules are generated. The model is presented as

$$\max z = \sum_{k=1}^{p} a_{0k}\, x_k + \sum_{k=1}^{q} b_{0k} z_k \tag{5.15}$$

subject to

$$c_t \le \sum_{k=1}^{p} a_{tk} x_k + \sum_{k=1}^{q} b_{tk} z_k \le C_t, \quad t = 1, \ldots, r \tag{5.16}$$

$$x_k - \sum_{i=1}^{m} \sum_{j=1}^{n_i} x_k^{ij} w_{ij} = 0, \quad k = 1, \ldots, p \tag{5.17}$$

$$\sum_{j=1}^{n_i} w_{ij} = 1, \quad i = 1, \ldots, m \tag{5.18}$$

$$w_{ij} \ge 0, \quad \forall i, j \tag{5.19}$$

$$z_k \ge 0, \quad \forall k \tag{5.20}$$

The objective function is a sum of p interesting input and output variables x_k and q other decision variables z_k. Thus, this formulation allows for maximizing with respect to several criteria at the same time, using fixed constants a_{0k} that can be given by the decision maker. The other decision variables in the objective function include, for instance, slack variables used for goal programming (see Section 5.2).

The objective function (5.15) and constraints (5.16) are formulated so that explicit summation across the separate stands is not needed. The output and input variables are directly presented at forest estate level variables x_k, which should be fairly intuitive to the decision makers. Instead, the summation is carried out automatically by the system in the constraint (5.17). There, it is set that the aggregated value of x_k is the sum of x_k^{ij}, (i.e. the amount of variable k produced or consumed by unit i if schedule j is applied) over m treatment units and the n_i treatment schedules in these treatment units, weighted with the proportion of area in each unit i treated according to schedule j, w_{ij}. It should be noted that x_k^{ij} is expressed in a stand level, not per hectare (RHS of 5.18 is 1).

The coefficients c and C denote the lower and upper bounds given to the utility constraints. In usual LP formulation, these kinds of constraints need to be presented using two separate constraints for the upper and lower bound. In JLP, these are dealt with the knowledge that only one of the bounds can be binding at a time.

The constraint that the proportions of the treatment schedules in each stand must equal one is also made automatically. The constraint is embedded to constraints of the form (5.17) using the generalized upper bound technique (Lappi 1992, p. 108) so that the number of active constraints in the problem can be effectively reduced.

This formulation can be used for exactly the same problems as the earlier formulation, and it produces identical solutions. However, this formulation is more general than the one presented earlier. For instance, it is possible to formulate a constraint that the harvesting level at period 2 must be greater than that in the first period, and the difference can be set to greater or equal than zero using constants a and b in the constraint (5.16). In the earlier formulation, the difference variable needs to be explicitly formulated.

5.2 Goal Programming

Goal programming (GP) is a special case of linear programming. It was first described by Charnes and Cooper (1961). A forestry application of GP was first presented by Field (1973). After that, several applications of GP to forest management planning have been presented (e.g. Díaz-Balteiro and Romero 2001, 2003). Mendoza (1987) provided an overview of GP formulations and extensions with special reference to forest planning. Tamiz et al. (1998) provided a more general overview of GP elaborations and applications. By using goal programming, some crucial problems of standard linear programming (LP) can be avoided. However, the GP problem is solved similarly as in standard linear programming.

In standard linear programming, a single overriding management goal is assumed, which is represented by the objective function. For interpretational purposes, it is recommendable to use a single-valued objective function, the variables of which are commensurable and compatible. Other objectives are taken into account through constraints. The description of management goals by standard LP constraints may be unsatisfactory for several reasons. The selection of the goal to be handled as the objective function is arbitrary. The objective function is optimized within the feasible region defined by the rigid LP constraints; thus, the constraints may, in fact, receive a greater weight than the objective. Rigid constraints may also cause infeasibility problems.

In comparison to standard LP, GP facilitates the incorporation of decision maker's preferences into optimization problems. In addition, GP formulations may better reflect the multicriteria nature of forest management. However, GP does not solve all the problems related to LP. For example, proportionality, divisibility and additivity assumptions of LP also hold with GP and may be problems.

In GP, all the objectives are handled in the same manner: they are expressed by goal constraints. A goal constraint includes goal variables that measure the amount by which the contribution of all activities to the goal in question falls short or exceeds the goal level (i.e. the right hand side of the constraint). The objective function of a GP problem is to minimize the sum of the (weighted) deviations from all target levels associated with the management goals. When goal variables are included in a constraint, the problem of infeasibility linked to the constraint is avoided.

The general formulation of a GP problem is

$$\min \sum_{i=1}^{p} w_i^- D_i^- + w_i^+ D_i^+ \tag{5.21}$$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j + D_i^- - D_i^+ = G_i, \quad i = 1, \dots, p \tag{5.22}$$

$$\sum_{j=1}^{n} a_{ij} x_j \leq (or = or \geq) b_i, \quad i = p+1, \dots, P \tag{5.23}$$

$$x_j,\ D_i^-,\ D_i^+ \geq 0 \forall i, j \tag{5.24}$$

where (5.21) is the goal programming objective function, (5.22) is a goal constraint, (5.23) is an ordinary LP constraint, p is the number of goals represented by goal constraints and P is the total number of constraints.

In the objective function and in the goal constraints D_i^- is the underachievement deviation variable and D_i^+ is the overachievement deviation variable. Both of the deviation variables are required to be non-negative (5.24). Minimizing the differences ensures that one of these deviation variables is always zero, and the other can deviate from zero. If the underachievement variable is greater than zero, then amount D_i^- needs to be added to $\sum_{j=1}^{n} a_{ij} x_j$ in order to achieve the target level G_i for goal i, and if D_i^+ is greater than zero, this amount needs to be subtracted from it to achieve the goal.

The deviations can be weighted according to their importance, in the objective function w_i^- is the weight given to each unit of underachievement deviation; w_i^+ is the weight given to each unit of overachievement deviation. The weights can be interpreted to have two separate roles in the problem. As scaling factors, weights w_i^+ and w_i^- reduce deviations expressed in different measurement units to a common unit of measurement. As importance weights, they describe the relative importances of the goal variables. Because of these intermingling roles, the interpretation of weights as relative importances of goals, respectively, is not unambiguous.

Other definitions are the same as before, x_j is the jth activity variable; a_{ij} is the contribution to goal i made by each unit of activity j and n is the number of activity variables. Standard LP constraint may be used if any deviation from a goal target level is unacceptable. Also, constraint with only one deviation variable, either D_i^+ or D_i^-, can be applied.

Crucial issues when utilizing GP include: (i) specifying the target levels of the goals, (ii) determining the weights used in the objective function, and (iii) making goals measured with different units commensurable. Any mathematical programming problem has to be formulated so that the solution is as well as possible in line with the preferences of the decision maker. Prior information on the preferences of the decision maker is needed to formulate the problem appropriately.

Specifying a set of a priori relative weights for the goals is often found to be difficult. Several methods for estimating the weights through an interactive process have been presented. Unfortunately, for most decision makers it is difficult to supply the right information concerning his preferences, required to determine the search direction and the step-size in this direction. The better the first problem formulation, the faster the optimal solution can be found. In the very first problem formulation, some a priori weights are always required.

Kangas and Pukkala (1992) presented a decision theoretic approach to formulating a forestry goal programming problem. It differs from normal GP procedures with respect to the determination of the goal target levels and weights of deviations from these desired achievement levels. In their application it was assumed that the greatest possible sub-utility with respect to each objective included in the objective function is obtained at its maximum or minimum level.

First, the greatest or smallest attainable target level of each goal constraint was solved. This target level $(G_{u-max\ i})$ was considered to represent the greatest possible sub-utility, referring to the objective in question. The goal objective was to minimize the weighted sum of relative deviations from the maximum or minimum attainable target levels, referred to as aspiration levels. Weights were determined using the Analytic Hierarchy Process (Saaty 1980).

Thus, the formulation of the GP model was

$$\min \sum_{i=1}^{p} w_i D_i \big/ G_{u-\max i} \tag{5.25}$$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j + D_i^- = G_{u-\max i}, \quad i = 1, \ldots, k \tag{5.26}$$

$$\sum_{j=1}^{n} a_{ij} x_j - D_i^+ = G_{u-\max i}, \quad i = k+1, \ldots, p \tag{5.27}$$

$$\sum_{j=1}^{n} a_{ij} x_j \leq (or \geq) b_i, \quad i = p+1, \ldots, P \tag{5.28}$$

$$x_j,\ D_i^-,\ D_i^+ \geq 0 \,\forall i, j \tag{5.29}$$

Table 5.7 The forest development

Alternative	Initial	Period 1	Period 2	Period 3
Thinning 1	180	90	153	229.5
Thinning 2	180	225	135	216
Harvest 3	180	225	292.5	5
No harvest	180	225	292.5	351

where $D_i = D_i^-$ when it is a question of an objective producing the greatest sub-utility at its maximum level; $D_i = D_i^+$ when it is a question of an objective producing the greatest sub-utility at its minimum level; k is the number of objectives producing the greatest sub-utility at their maximum levels; $p-k$ is the number of objectives producing the greatest sub-utility at their minimum levels; $G_{u-max\ i},\ i = 1, \ldots, k$ is the maximum attainable value of a goal variable; $G_{u-max\ i},\ i = k, \ldots, p$ is the minimum attainable value of a goal variable.

Example 5.4. Assume again a forest area of 60 ha with initial volume 180 m^3/ha. The planning horizon is 30 years, and divided to three 10-year periods. Four treatment options are considered for this area, thinning at the first period, thinning at second period, clear-cut at third period and no harvests. The forest is assumed to develop according to Table 5.7 and the resulting incomes according to Table 5.8. The decision maker has set goals for the incomes from the three periods, as well as for the volume at the third period. The goals are, 60,000€ for each period and 14,000 m^3 for the final volume. The problem is formulated as

$$\text{Min}\, z = D_1^- + D_1^+ + D_2^- + D_2^+ + D_3^- + D_3^+ + D_e^- + D_e^+,$$

describing the deviations from the four goals. The area constraint is the same as in earlier example,

$$\mathrm{x}_1 + \mathrm{x}_2 + \mathrm{x}_3 + \mathrm{x}_4 = 60$$

the revenue constraints for the three periods are now

$$2{,}700\mathrm{x}_1 + 0\mathrm{x}_2 + 0\mathrm{x}_3 + 0\mathrm{x}_4 + D_1^- - D_1^+ = 60{,}000$$
$$0\mathrm{x}_1 + 4{,}050\mathrm{x}_2 + 0\mathrm{x}_3 + 0\mathrm{x}_4 + D_2^- - D_2^+ = 60{,}000$$
$$0\mathrm{x}_1 + 0\mathrm{x}_2 + 8{,}625\mathrm{x}_3 + 0\mathrm{x}_4 + D_3^- - D_3^+ = 60{,}000$$

Table 5.8 The incomes from these alternatives

Alternative	Period 1	Period 2	Period 3
Thinning 1	2,700	0	0
Thinning 2	0	4050	0
Harvest 3	0	0	8,625
No harvest	0	0	0

and the constraint for the volume in the end of the period is

$$5x_1 + 351x_2 + 229.5x_3 + 216x_4 + D_e^- - D_e^+ = 14,000.$$

The result is to thin 6.96 ha in the first period, 16.01 in the second period, clear-cut 22.22 ha in the third period and leave 14.81 ha not harvested.

All the income goals for three periods are achieved, so that corresponding deviation variables are zero. The only deviation variable not at a zero level is that of underachievement of end volume, which has value 46.96. Thus, the end volume is 13953.04 m^3. This is mostly due to the fact that the goals are in different units, and thus goals with larger numbers are given implicitly more value. If a weight 30 is given to the deviations of the end volume, i.e. minimizing

$$\text{Min}\, z = D_1^- + D_1^+ + D_2^- + D_2^+ + D_3^- + D_3^+ + 30D_e^- + 30D_e^+,$$

the results would be a bit different. Then, the optimal solution would be to thin 6.96 ha in the 1st period, 16.39 in the 2nd period, clear-cut 21.84 ha in 3rd period and to leave 14.81 ha not harvested. It can be interpreted that 30 is then the price given to the standing volume, which is the same as the price of harvested volume. In this case, the deviation D_1^- from the goal would be nonzero, namely 1043.47€ for the 1st period. Thus, if the goals cannot be expressed in the same units, they should be weighted appropriately (e.g. Kangas and Pukkala 1992).

5.3 Integer Programming

In some cases the decision variables can only have integer values, for instance the number of employees in an enterprise is an integer variable. Such problems can be solved using Integer Programming (IP). In some cases part of the variables can have integer values while the rest of them are continuous. Such problems call for Mixed Integer programming (MIP). A special case of integer variables is a case, where only binary values (0 and 1) are allowed. Examples of binary variables are, for instance, transportation routes. It is not possible to take a part of any one route, but one needs to follow one route from beginning to end. The problems caused by divisibility (e.g. division of calculation units for different treatment options) may also be avoided by applying Integer Programming IP.

Example 5.5. In example 5.1, the problem is clearly an integer problem: one can only produce whole toys. The solution to problem 5.1 was an integer solution, but if the other constraint were slightly changed, so that there is 7 dm^3 of spruce available, the optimal solution would not be an integer solution anymore. In this problem, the optimal integer solution can also be found graphically. In Fig. 5.2 all the possible integer solutions are presented with dots. In the example, the optimal solution is to produce 1.67 trains and 2.67 cars, with revenue 10.33€. The optimal integer solution is to produce two pieces of both trains and cars, with revenue 10€, i.e. less than the optimal revenue in the original problem.

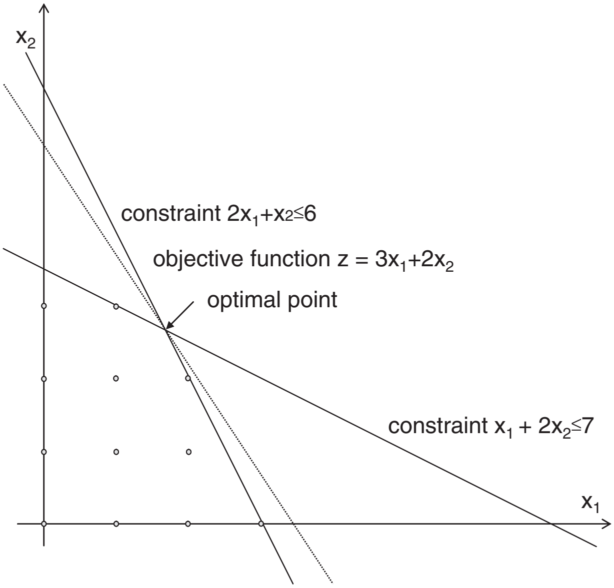

Fig. 5.2 The possible integer solutions

The optimum of the integer problem can at best be as good as the solution of the ordinary LP problem. Thus, the IP solution is always bounded by the original LP solution. This can be used when solving the IP problems.

There are two popular ways of solving the integer problems, namely the branch-and-bound algorithm and cutting plane method (Taha 1997). These algorithms exploit normal Simplex algorithm and computing power. The strategy includes three steps (Taha 1997, p. 384):

1. Relax the solution space of the ILP by replacing any binary value y with the continuous range $0 \leq y \leq 1$, and deleting the integer restrictions on all the integer variables. The result of the relaxation is a regular LP.
2. Solve the LP problem, and identify its continuous optimum.
3. Starting from the continuous optimum point, add special constraints that iteratively modify the LP solution space in a manner that will eventually give an optimum point that satisfies the integer requirements.

In branch-and-bound, the special constraints are two additional constraints. They are such that if an optimal solution to integer variable x_1 was 0.5 in the solution, it is in the next phase required to be either $x_1 \leq 0$ or $x_1 \geq 1$. As both of these constraints cannot be satisfied at the same time, two new LP problems are formed from the original one, with one additional constraint in both of them. Then, both these new problems are solved, i.e. the problem is branched to two. If needed, the problem is branched further and further, and the best solution found this way is finally selected. Thus, integer problems can be much harder to solve than ordinary LP problems.

However, the optimal solution to the original problem can only be the solution of one of these new problems. In some cases it is possible to determine that the search

Table 5.9 The problem data

	Variable	No harvest	Thinning	Clear-cut
Stand 1	Harvest volume	0	559	1,260
	End volume	1,281	798	21
Stand 2	Harvest volume	0	762	1770
	End volume	1,800	1,098	18
Stand 3	Harvest volume	0	585	1,170
	End volume	1,170	702	8

needs not to be continued in one of the branches, since better results can be obtained from other branches. Then it is possible to intelligently reduce the work needed.

Example 5.6. In the example 5.5, the optimal solution to the original problem was to produce 1.67 trains and 2.67 cars with revenue 10.33. As the problem is an integer problem, in the first branching of branch-and-bound technique x_1 is required to be either $x_1 \leq 1$ or $x_1 \geq 2$. The resulting two solutions are:

LP1: $x_1 = 1,\ x_2 = 3$ and objective function value is 9.
LP2: $x_1 = 2,\ x_2 = 2$ and objective function value is 10.

As both of these branches produced an integer solution, no further branching is needed. Then, the better of these solutions is selected, namely the solution LP2.

Example 5.7. Assume a forest area with three different stands and three management options for each of them; not harvesting, thinning and clear-cutting. The problem is to maximize the harvested volume while the growing stock volume needs to be at least $2,300\,m^3$. The harvesting volumes and remaining growing stock volumes for the three stands and three alternatives are presented in Table 5.9. Note that in this example both these volumes are given in m^3 per whole stand area, not per hectare.

As a normal LP problem, this problem can be presented as

$$\text{Max } z = 0x_{11} + 559x_{12} + 1260x_{13} + 0x_{21} + 762x_{22}$$
$$+ 1770x_{23} + 0x_{31} + 585x_{32} + 1170x_{33},$$

where x_{ij} is the proportion of stand i managed with treatment alternative j subject to

$$x_{11} + x_{12} + x_{13} = 1$$
$$x_{21} + x_{22} + x_{23} = 1$$
$$x_{31} + x_{32} + x_{33} = 1$$

indicating that in each stand, the sum of proportions must be equal to one and

$$1281x_{11} + 798x_{12} + 21x_{13} + 1800x_{21} + 1098x_{22}$$
$$+ 18x_{23} + 1170x_{31} + 702x_{32} + 8x_{33} \geq 2,300$$

Table 5.10 Proportions of treatment alternatives

	No harvest	Thinning	Clear-cut
Stand 1	0	1	0
Stand 2	0	0.72	0.28
Stand 3	0	1	0

is the constraint for end volume. The resulting harvest volume is 2184.3 m^3, and the proportions of the treatments in each stand are presented in Table 5.10. The solution is an integer solution in stands 1 and 3, but stand 2 is divided. If an integer solution is made by rounding this solution, i.e. thinning the stand 2, the resulting harvest volume is $1,906\,m^3$, and the corresponding end volume is $2,598\,m^3$. Thus, the end volume is much larger than required and the harvesting volume is clearly worse than in LP result.

If the decision variables x_{11}–x_{33} are required to have binary values, the resulting harvest volume is 1,932 m^3, and the corresponding end volume is 2,387 m^3. The MIP result is clearly more efficient than the solution obtained from rounding. The resulting treatment recommendations are also different: in MIP solution stand 1 is not harvested, stand 2 is thinned and stand 3 is clear-cut.

5.4 Uncertainty in Optimization

Mathematical programming, especially linear programming (LP), is still perhaps the most often applied approach to optimisation calculations of forest management planning at forest area level. When numerical optimisation is applied in forest planning, however, uncertainty about forest development is often ignored and the optimization is done as if under certainty. This can lead to two kinds of results. First, a nonoptimal alternative may be chosen. This being the case the realised objective function value is less than the optimal objective function value. This loss is called "regret" (Bell 1982). Second, the true worth of the optimal solution may be overestimated. This kind of loss is called "disappointment" (Bell 1985).

Effect of uncertainty on forest planning has been studied rather widely in the context of LP (e.g. Thompson and Haynes 1971; Hoganson and Rose 1987; Pickens and Dress 1988; Pickens et al. 1991; Gove and Fairweather 1992; Hof et al. 1992, 1996; Weintraub and Abramovich 1995; Boyschuk and Martell 1996; Forboseh et al. 1996). In an LP problem, there may be uncertainty concerning the objective function, the values of the right hand sides of the constraints and in the technical coefficients (coefficients describing how the actions affect the objectives).

It has been noted that uncertainty about coefficients of the objective function causes optimization to be optimistically biased. It means that the gains of the optimal solution will be overestimated, if there are errors in the objective function coefficients (Hobbs and Hepenstal 1989). Errors in the right hand sides of constraints have the opposite effect (Itami 1974). Uncertainty about the production coefficients causes exaggeration of the gains of the optimal solution. The obtained solutions may even be infeasible due to the uncertainty (Pickens and Dress 1988). The above mentioned problems concern also other optimization methods than LP, for instance heuristic methods or non-linear programming (e.g. Kangas and Kangas 1999).

The usual LP method does not consider the underlying uncertainty. Then, the obtained solutions may not be feasible. The decision maker may, for example, give a constraint that the population size should be at least the minimum viable population size. However, it is possible that the population size in the chosen solution is not viable due to the uncertainty concerning the value of the constraint. This can be prevented, if the uncertainty is taken into account using chance-constrained optimization, by formulating the constraint $\sum_{j=1}^{n} a_{ij}x_j \geq b_i$ as (Hof and Pickens 1991)

$$P = \left(\sum_{j=1}^{n} a_{ij}x_j \geq b_i \right) \geq \varphi_i \tag{5.30}$$

In this formula the probability of the solution to be feasible is set to ϕ_{i}, which may be, for instance, 95%. This problem can be solved with the usual LP method, by taking a new constraint level $\tilde{b}_i$ from the 95% percentage point of the cumulative distribution of b_i. Thus, the value of the constraint is increased in order to choose a solution that is on the safe side despite the uncertainty. If a critical population size is used as a constraint, the actual population size needs to be the larger the more uncertainty there is about the critical value (Haight and Travis 1997).

Uncertainty about the parameters a, i.e. in how the population reacts to the treatment, can also be considered using chance-constrained optimization. If the coefficients a are assumed to be normally distributed, constraint $\sum_{j=1}^{n} a_{ij}x_j \geq b_i$ can be presented as (Hof et al. 1992)

$$\sum_{j=1}^{n} \alpha_{ij}x_j + \delta_i \sqrt{\sum_{j=1}^{n} \sum_{h=1}^{n} x_j x_h \sigma_{ijh}^2} \geq b_i \tag{5.31}$$

where α_{ij} is the mean of a_{ij} and σ_{ijh}^2 is the covariance of a_{ij} and a_{ih}, and δ_i is the standard normal deviate corresponding to the required probability. This formulation follows from $\sum_{j=1}^{n} a_{ij}x_j$ being normally distributed with mean $\sum_{j=1}^{n} \alpha_{ij}x_j$ and variance $\sum_{h=1}^{n} \sum_{j=1}^{n} x_j\, x_h\, \sigma_{ijh}^2$. If the constraints are assumed to be mutually independent, any number of this type of constraints can be included in the problem formulation. The problem is a non-linear optimization problem, which can be solved, for example, with simulation (Pickens et al. 1991) or with a so-called cutting plane algorithm (Weintraub and Abramovich 1995).

It can be required that not only each constraint is met with a given probability, but that a set of constraints is met with a given probability (joint probability chance constraint). Also, it is possible to maximize the probability for meeting the constraints instead of using a constant probability (Hof and Pickens 1991; Hof et al. 1992).

The above mentioned formulation is suitable, if the uncertainty involved is random variation. If the uncertainty is due to ignorance or ambiguity, this formulation does not apply. If the value of critical threshold, for example, is an expert opinion, the threshold may be given as an interval value. Then, fuzzy linear programming may be utilised (e.g. Mendoza and Sprouse 1989; Bare and Mendoza 1992; Mendoza et al. 1993). The applications based on fuzzy linear programming and fuzzy goal programming are also numerous (e.g. Duckstein et al. 1988; Mendoza and Sprouse 1989; Pickens et al 1991; Bare and Mendoza 1992; Mendoza et al. 1993; Tecle et al. 1994; Hof et al. 1995; Ells et al. 1997). Even one LP application involving possibility theory has been published (Krcmar et al. 2001).

5.5 Robust Portfolio Modelling

5.5.1 Principles of the Method

Robust Portfolio Modelling (RPM) is a decision support methodology for analyzing large-scale project portfolio problems (Liesiö et al. 2007a). Portfolio problems refer to decision situations, where only a subset of possible projects can be implemented with available resources in recognition of multiple criteria. Examples of these kinds of situations are different funding decisions and, in forestry context, selection of the cutting areas among the forest stands that can be cut during the specific time period subject to, e.g., sustainable cutting level and labour constraints.

The RPM method includes the following phases (see also Fig. 5.3):

(i) Weight information, i.e. loose statements concerning the importances of the decision criteria is produced
(ii) Project performances and possible uncertainties related to them are defined
(iii) Constraints are defined
(iv) Efficient (non-dominated) portfolios are generated
(v) The performance measures for projects and portfolios that help to analyze their robustness are calculated

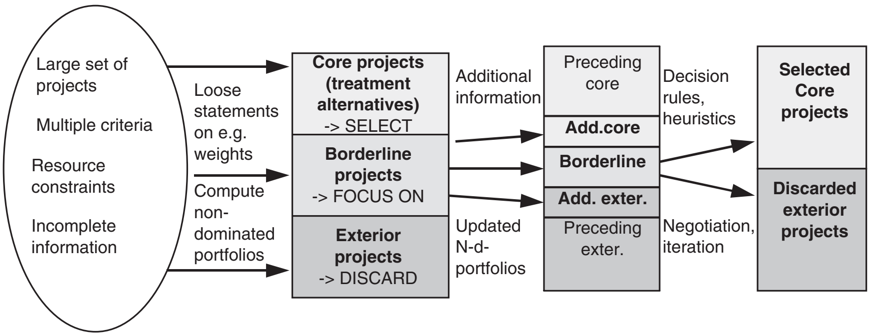

Fig. 5.3 RPM-decision support process (Liesiö et al. 2007a)

In phase (i) the decision makers' uncertain preferences are included in the specified additive weighting function (see Chapter 3). Incomplete information about criterion weights can be captured through linear inequalities (e.g. Salo and Punkka 2005) and also by statistical models that measure the uncertainties of the preference information (Alho et al. 2001; Leskinen 2001). For example, the decision maker may be able to define only that criterion i is the most important one, but she is not able to define the importance order of other criteria. In phase (ii) the uncertain project performances are defined, e.g., through intervals (Liesiö et al. 2007a). Both uncertainty sources affect the overall values of the individual projects and therefore the contents of the efficient portfolio. If the prevailing uncertainties increase, also the number of potentially efficient portfolios increases. In addition, also the defined constraints or project costs (iii) may be uncertain (Liesiö et al. 2007b).

The above listed uncertainties may result in extremely large number of potential non-dominated portfolios. Liesiö et al. (2007a, b) present dynamic programming based formulations for determining all potential non-dominated portfolios. The algorithms are supported by examinations concerning the efficient use of resources and whether the portfolio belongs to the non-dominated set.

Difficulties in obtaining complete and correct preference and project performance information suggest that robust solutions that perform reasonably well across the full range of different parameter values should be found and examined more carefully. For this purpose, RPM includes a calculation of a core index (Liesiö et al. 2007a). If the core index of a project is 1, the project is included in all non-dominated solutions and it is called as a core project. If the value of the core index is 0, the project has not been included in any non-dominated solution and it is called as an exterior project. If the value of the core index is between 0 and 1, the project has been included in some portfolios and it is called a borderline project. In this phase, the decision maker should concentrate on examining these borderline projects aiming to decrease their number. If the decision maker is able to express her preferences or project performance measures more accurately after she has inspected the results, and if the made changes only narrow the initial variation, the number of non-dominated portfolios and borderline projects decreases and the amount of core and exterior projects increases. This is one way to proceed towards more robust solution in phase (v). In addition, the decision maker may apply different project and portfolio level decision rules, interactive decision support and subjective elicitation in final selection phase (Liesiö et al. 2007a).

5.5.2 Use of RPM in Forest Planning

The effects of uncertainties in, e.g., forest owner's preferences or stand inventory data from the viewpoint of the resulting forest plans may be twofold. Firstly, the stand-level and planning-area level outcomes (e.g. harvestable timber volume) are incorrect, but the treatment recommendations for the stands are correct. As a result, the "correct" outcome from the stand will be realized when the treatment is carried

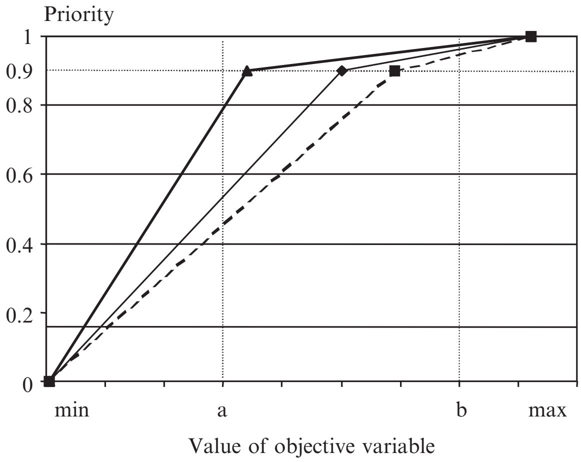

Fig. 5.4 An example of three different aspiration levels between values a and b that were defined by the forest owner (Muinonen et al. 2007)

out. Secondly, the stand-level and planning area level outcomes are incorrect and also the treatment recommendations for some stands (e.g. timing of thinning) are incorrect.

RPM like approaches that utilize optimisation, Monte Carlo simulations and calculations of the robustness measures can be rather directly adopted to many kinds of forest management related decision problems. Muinonen et al. (2007) examined the effects of forest owner's preference uncertainties in a way that has similarities with the RPM. Their analysis included uncertainties that were generated from the inconsistent pairwise comparison data and uncertain aspiration level that concerned the amount of cuttings during the first planning period.

Example 5.8. Uncertainties in the cutting amount goal

Forest owner may not be able to define exactly e.g., the cutting amount she wants to achieve during certain time-period. One possibility to overcome this problem is to use multi-attribute utility function and sub-utility functions as the objective function. The uncertainty related to the aspired amount of certain objective variable can be taken into account by varying the point where the sub-utility reaches the value of 0.9 or 1.0. In the Fig. 5.4, these points have been drawn randomly from a uniform distribution between the values a and b, which describes the decision maker's uncertain aspiration zone. Thousand realizations were derived between the defined values and they were included in the objective function that was optimized. Note however, that reaching the aspiration point depends, e.g. on the relative weights of the used objective variables. In addition, exceeding the aspiration point is in this example not penalized, only the marginal utility is smaller.

After the preference uncertainties have been included in the objective function, optimization calculations are carried out and efficient forest plans can be produced by utilizing techniques described earlier in this chapter and Chapter 6.

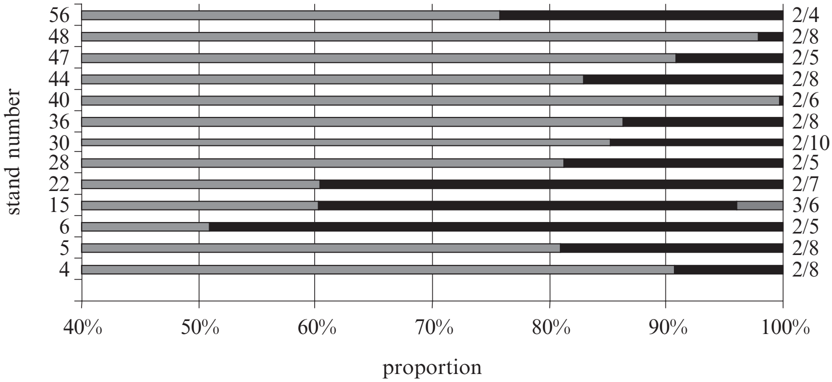

Fig. 5.5 The stand-level result from optimisation calculations for 13 uncertain stands. At the right side of the figure, e.g. the number 2/4 means that four treatment alternatives were simulated for the stand and only two of them became selected in the created forest plans. The proportion refers to the core index of the selected treatment alternative

In addition to the described example, the RPM based approach can be utilized in several other forestry related decision problems. For example, it is suitable for operational harvest scheduling problems, funding decisions concerning voluntary biodiversity protection (e.g. Punkka 2006) and many other selection problems where, e.g. budget constraints cause that all projects can not be carried out at the same time.

Example 5.9. The result of recognizing the uncertainties in the owner's aspiration level

The 1,000 uncertain aspiration levels were included in the objective function and 1,000 efficient forest plans were produced by utilizing simulated annealing heuristic technique (Chapter 6) in the optimization. The result was that the uncertainties affected only 13 stands (the total amount of stands was 62). In addition, only two or three treatment alternatives became selected for these stands (Fig. 5.5).

References

Alho, J.M., Kolehmainen, O., and Leskinen, P. 2001. Regression methods for pairwise comparisons data. In: Schmoldt, D.L., Kangas, J., Mendoza, G.A., and Pesonen, M. (Eds.). The analytic hierarchy process in natural resource and environmental decision making, Kluwer, Dordrecht, pp. 235–251.

Bare, B.B. and Mendoza, G.A. 1992. Timber harvest scheduling in a fuzzy decision environment. Canadian Journal of Forest Research 22: 423–428.

Bell, D.E. 1982. Regret in decision making under uncertainty. Operations Research 30: 961–981.

Bell, D.E. 1985. Disappointment in decision making under uncertainty. Operations Research 33: 1–27.

Boychuk, D. and Martell, D.L. 1996. A multistage stochastic programming model for the analysis of risks in forest management and silvicultural investments. Forest Science 42: 10–26.

Buongiorno, J. and Gilles, J.K. 2003. Decision methods for forest resource management. Academic, San Diego, CA, 439 pp.

Charnes, A. and Cooper, W.W. 1961. Management models and industrial applications of linear programming, Vol 1. Wiley, New York.

Clutter, J.L., Fortson, J.C., Pienaar, L.V., Brister, G.H., and Bailey, R.L. 1983. Timber management. A quantitative approach. Wiley, New York.

Dantzig, G.B. 1951. Maximization of a linear function of variables subject to linear inequalities. In: Koopmans, T.C. (Ed.). Activity analysis of production and allocation. Wiley, New York.

Davis, L.-S., Johnson, K.N., Bettinger, P.S., and Howard, T.E. 2001. Forest management – to sustain ecological, economic and social values. 4th edn. McGraw-Hill, New York, 804 pp.

Díaz-Balteiro, L. and Romero, C. 2001. Combined use of goal programming and the analytic hierarchy process in forest management. In: Schmoldt, D.L., Kangas, J., Mendoza, G., and Pesonen, M. (Eds.). The analytic hierarchy process (AHP) for natural resource and environmental decision making. Managing Forest Ecosystems, Vol. 2. Kluwer, Dordrecht, pp. 81–95.

Díaz-Balteiro, L. and Romero, C. 2003. Forest management optimization models when carbon captured is considered. A goal programming approach. Forest Ecology and Management 174: 447–457.

Duckstein, L., Korhonen, P., and Tecle, A. 1988. Multiobjective forest management: a visual, interactive, and fuzzy approach. In. Kent, B.M. and Davis, L.S. (Eds.). The 1988 Symposium on Systems Analysis in Forest Resources. USDA Forest Service. General Technical Report RM-161, pp. 68–74.

Ells, A., Bulte, E., and van Kooten, G.C. 1997. Uncertainty and forest land use allocation in British Columbia: Vague priorities and imprecise coefficients. Forest Science 43: 509–520.

Field, D.B. 1973. Goal programming for forest management. Forest Science 19: 125–135.

Forboseh, P.F., Bragee, R.J., and Pickens, J.B. 1996. A strategy for multiproduct stand management with uncertain prices. Forest Science 42: 58–66.

Gove, J.H. and Fairweather, S.E. 1992. Optimizing the management of uneven-aged forest stands: a stochastic approach. Forest Science 38: 623–640.

Haight, R.G. and Travis, L.E. 1997. Wildlife conservation planning using stochastic optimization and importance sampling. Forest Science 43: 129–139.

Hillier, F.S. and Lieberman, G.J. 2001. Introduction to operations research. 7th edn. McGraw-Hill, New York, 1214 pp.

Hobbs, B.F. and Hepenstal, A. 1989. Is optimization optimistically biased? Water Resources Research 25: 152–160.

Hof, J.G., Kent, B.M., and Pickens, J.B. 1992. Chance constraints and chance maximization with random yield coefficients in renewable resource optimization. Forest Science 38: 305–323.

Hof, J.G. and Pickens, J.B. 1999. Chance-constrained and chance-maximizing mathematical programs in renewable resource management. Forest Science 37: 308–325.

Hof, J.G., Pickens, J.B., and Bartlett, E.T. 1995. Pragmatic approaches to optimization with random yield coefficients. Forest Science 41: 501–512.

Hof, J.G., Bevers, M., and Pickens, J. 1996. Chance-constrained optimization with spatially autocorrelated forest yields. Forest Science 42: 118–123.

Hoganson, H.M. and Rose, D.W. 1987. A model for recognizing forestwide risk in timber management scheduling. Forest Science 33: 268–282.

Itami, H. 1974. Expected objective value of a stochastic linear program and the degree of uncertainty of parameters. Management Science 21: 291–301.

Johnson, K.N. and Scheurman, H.L. 1977. Techniques for prescribing optimal timber harvest and investment under different objectives – discussion and synthesis. Forest Science Monographs 18.

Kangas, A. and Kangas, J. 1999. Optimization bias in forest management planning solutions due to errors in forest variables. Silva Fennica 33: 303–315.

Kangas, J. and Pukkala, T. 1992. A decision theoretic approach applied to goal programming of forest management. Silva Fennica 26: 169–176.

Krcmar, E., Stennes, B., van Kooten, G.C., Vertinsky, I. 2001. Carbon sequestration and land management under uncertainty. European Journal of Operational Research 135: 616–629.
Lappi, J. 1992. JLP: A linear programming package for management planning. Finnish Forest Research Institute. Research Notes 414.
Leskinen, P. 2001. Statistical methods for measuring preferences. University of Joensuu, Publications in Social Sciences 48.
Liesiö, J., Mild, P., Salo, A. 2007a. Preference programming for robust portfolio modeling and project selection. European Journal of Operational Research 181: 1488–1505.
Liesiö, J., Mild, P., Salo, A. 2007b. Robust portfolio modelling with incomplete cost information and project interdependencies. European Journal of Operational Research (in press).
Mendoza, G.A. 1987. Goal programming formulations and extensions: An overview and analysis. Canadian Journal of Forest Research 17: 575–581.
Mendoza G.A. and Sprouse, W. 1989. Forest planning and decision making under fuzzy environments: An overview and illustration. Forest Science 33: 458–468.
Mendoza, G.A., Bare, B.B., and Zhou, Z. 1993. A fuzzy multiple objective linear programming approach to forest planning under uncertainty. Agricultural Systems 41: 257–274.
Muinonen, E., Kurttila, M., Leskinen, P., Kilpeläinen, H., and Pykäläinen, J. 2007. Examining the stand-level effects of preferential uncertainty in forest management planning. Manuscript.
Pickens, J.B. and Dress, P.E. 1988. Use of stochastic production coefficients in linear programming models: objective function distribution, feasibility, and dual activities. Forest Science 34: 574–591.
Pickens, J.B. Hof, J.G., and Kent, B.M. 1991. Use of chance-constrained programming to account for stochastic variation in the A-matrix of large-scale linear programs. A forestry application. Annales of Operations Research 31: 511–526.
Punkka, A. 2006. Luonnonarvokaupan tukeminen monikriteerisillä päätösmalleilla. Systems Analysis Laboratory, Helsinki University of Technology (in Finnish).
Saaty, T.L. 1980. The analytic hierarchy process. McGraw Hill. New York. 287 pp.
Salo, A. and Punkka, A. 2005. Rank inclusion in criteria hierarchies. European Journal of Operational Research 163: 338–356.
Taha, H.A. 1997. Operation research. An introduction 6th edition. PrenticeHall 915 p.
Tamiz, M., Jones, D., and Romero, C. 1998. Goal programming for decision making: an overview of the current state-of-the-art. European Journal of Operational Research 111: 569–581.
Tecle, A., Duckstein, L., and Korhonen, P. 1994. Interactive multiobjective programming for forest resources management. Applied Mathematics and Computing 63: 75–93.
Thompson, E.F. and Haynes, R.W. 1971. A linear programming-probabilistic approach to decision-making under uncertainty. Forest Science 17: 224–229.
Weintraub, A. and Abramovich, A. 1995. Analysis of uncertainty of future timber yields in forest management. Forest Science 41: 217–234.

Chapter 6
Heuristic Optimization

6.1 Principles

"A heuristic is a technique which seeks good (i.e. near-optimal) solutions at a reasonable computational cost without being able to guarantee either feasibility or optimality, or even in many cases to state how close to optimality a particular feasible solution is" (Reeves 1993). In the context of forest planning, the used heuristic techniques iteratively search for optimal combination of treatments for compartments. Thus, the treatments of compartments are the actual decision variables in the search process and the quality of the solution is usually measured by the value of the planning area level objective function.

Forest planning problems often have an integer nature, i.e. the compartments should not be split into parts. In addition, management activities in certain compartment may influence adjacent compartments through, e.g., increased wind damage or drainage risks. In addition, too large open areas certainly change the far-view scenery. These are reasons for adding spatial constraints upon harvesting activities of adjacent compartments to forest planning problems (Brumelle et al. 1997; Tarp and Helles 1997; Baskent and Keles 2005). These kinds of problems are called dispersion problems (Öhman 2002). On the other hand, clustering of certain types of compartments has been found beneficial from the viewpoint of species viabilities (e.g. Harrison and Fahrig 1995; Kurttila 2001; Öhman 2002; Nalle et al. 2004). In addition, sometimes it is beneficial to cluster harvesting areas, at least when the size of the compartments is small (Lu and Eriksson 2000; Heinonen et al. 2007). These clustering problems that prevent fragmentation of, e.g., old forest have become more common during the last decade. In forest planning, the above described planning problems where the solution is a set of integers are hard, even impossible, to solve using mathematical programming based techniques. Instead, heuristic techniques can solve these kinds of problems (see Kurttila 2001; Borges et al. 2002; Baskent and Keles 2005 for reviews on the use of spatial objectives and heuristic techniques in forest planning). The integer nature of planning problems and the use of spatial objectives are the most important reasons for the increased popularity of heuristics in forest planning.

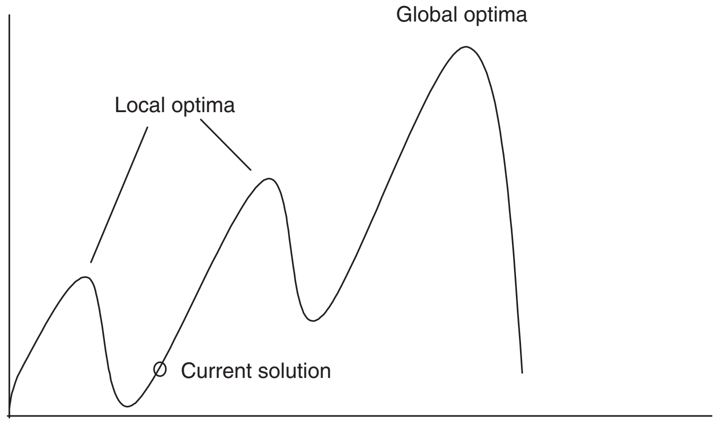

Fig. 6.1 Concepts of global and local optima (Adopted from Burke and Kendall 2005)

The operational principles of heuristic techniques are usually rather easy to understand and there can be an interaction between the optimization model and the decision maker, or planner. Furthermore, heuristics do not set very strict rules for the planning problem formulation, i.e. they typically enable the formulation of the optimization problem better in line with the multiple objectives and preferences of the decision maker (e.g. Kangas 1999). Although they do not necessarily find the technical global optimum of the given complicated problem, solutions nearer to the real-life optimum might be found by using them than by LP, for instance, if the preferences of the decision maker can be described more realistically (e.g. Kangas 1999).

Some heuristic techniques are deterministic, i.e. from the same initial solution they return always the same final solution (e.g. direct search phase of HERO, see the description below) (Burke and Kendall 2005). Some other techniques are stochastic (e.g. simulated annealing, threshold accepting, tabu search, genetic algorithms), which means that from the same initial solution they return different final solutions due to the random characteristics of their search processes. These random characteristics allow, e.g., the techniques to perform moves that decrease the objective function value or, the techniques utilize some other mechanism that enable them to move to a new location in a solution space. As a result, they have an ability to escape from the local optima (Fig. 6.1).

Particularly in the case of deterministic methods, a large number of different initial solutions should be examined to increase the probability for finding good solutions. Of course it could be possible to carry out exhaustive search, i.e. explore the whole solution space. However, the solution space in forest planning is usually enormous. Even for a very small forest of 20 compartments each having four treatment alternatives the total amount of alternatives is already $4^{20} = 1.099 \times 10^{12}$.

One difference between different heuristic techniques is also the number of solution candidates the techniques simultaneously process. While many techniques process only one solution at the time, genetic algorithms, for example, maintain and process a population of solutions. In this chapter, after presenting the typical objective function forms, the above mentioned and commonly used heuristic techniques are presented. This is followed by a brief discussion on possibilities to improve the heuristic search processes.

6.2 Objective Function Forms

Heuristic optimization techniques do not demand any specific objective function form, which means that the design of the objective function can be case-specific. According to Pukkala (2002), there are four basic alternatives to formulate the objective function for a multi-objective forest planning situation:

1. One objective is minimized or maximized via the objective function and the other goals are expressed as strict constraints.
2. The objective function measures the deviations of several objective variables from their target levels. These levels are given in other equations of the problem formulation. Strict constraint can also be included in the problem formulation.
3. A single objective is included in an objective function which is augmented with a penalty function. The penalty function measures how much additional objective variables deviate from their target values. The penalty function has the same unit as the single objective variable.
4. A multi-attribute utility function is developed and used as the objective function.

Although the formulation 1 (in linear case) corresponds to the typical LP problem, and formulation 2 to the GP formulation, all four formulations can be solved with heuristic optimization techniques.

The penalty function tries to minimize the deviations from the target values that have been specified for certain objective variables, usually at planning area level. For example, the maximization of NPV cutting income from the whole planning area may be augmented with a certain core-area demand (e.g. 10% of the forests of the planning area should be old-forest core-areas, i.e. old-forest area that has at least a pre-defined distance to the edge of the forest) for each sub-period through a penalty function (e.g. Öhman and Eriksson 1998)). Alternatively, the whole objective function includes only penalty functions, e.g. costs from deviating from planning area level harvest volume target, costs from harvested area with low volume per compartment area ratio, cost of violated adjacency constraints, or costs of harvest blocks violating the harvest block size constraint (Lockwood and Moore 1993).

In the former case, the total amount of core area is evaluated for each of the tested solutions and if the core area target is not met, the penalty decreases the maximized NPV so much that the probability for accepting such solution is low. In the latter case, the value of the objective function is minimized, and the function corresponds to the GP formulation. The penalty functions can be also designed so that small deviations from the target values are penalized relatively less than values more distant from the targets.

In the case of a multi-attribute utility function, different function forms can be used. The use of additive utility function enables the presentation of objective variables in a hierarchical manner (see Chapters 2 and 3). In an additive utility function, total utility U is calculated so that the weights, i.e. relative importance a_i, of the objective variables are scaled to sum equal to one

$$U = \sum_{i=1}^{p} a_i u_i(q_i) \tag{6.1}$$

where U is the total utility; p is the number of objectives; u_i is the sub-utility function of objective variable i getting values between 0 and 1; q_i is the quantity that the current solution produces or consumes objective variable i at the planning area level. Objectives are either forest products and values, such as timber, amenity and biodiversity, or resources, such as costs and labour requirement.

The sub-utility function depicts the change in the utility as the value of the objective variable changes (for more details see Section 3.2). The sub-utility function is estimated separately for each objective variable. When estimating the sub-utility function, first the maximum and minimum values that can be achieved for the objective variable from the planning area are computed (as single objective optima). The minimum value of the objective variable gets sub-utility zero and the maximum value of the objective variable gets a sub-utility of one (i.e. utilities in interval scale are used). The desirability of the intermediate values is estimated and the values are given relative priorities, which define the sub-utility function. A sub-utility function can be linear, non-linear, or piece-wisely linear. Estimation can be based equally well on subjective preference evaluations, expertise, objective measurements or information produced by empirical research. One advantage of the method is that it operates with case-specific production possibilities.

Also multiplicative parts or interactive terms can be added to the utility model. Multiplicative parts are useful when the objective variables are not interchangeable; i.e. if a good gain in one variable can not compensate for an inferior result in another. The general form of the utility model that includes multiplicative parts is:

$$U = \left(\sum_{i=1}^{p} a_i u_i(q_i) \right) \prod_{j=p+1}^{P} u_j(q_j) \tag{6.2}$$

The latter part of the function includes the objectives that are not interchangeable with the other objectives. It would also be possible to apply a purely multiplicative utility model.

6.3 Hero

The HERO heuristic optimization method is a direct ascent method. It has been especially developed for tactical forest planning mainly at area of non-industrial private forest holding level (Pukkala and Kangas 1993; Kangas et al. 2001). The optimization phase of HERO may be divided into two stages: random search for creating initial solutions and direct search phase for improving the best initial solution.

In the beginning of the optimization process, the random search phase assigns one treatment schedule for each compartment. The values and the sub-priorities of the objectives are computed, as well as the total utility. Several initial candidate solutions are usually produced and the best of them is used in the second phase. In this direct search phase, one compartment at a time is examined to see whether some other of its treatment schedules, which is not in the current solution, would increase the total utility. If the utility increases, the current treatment alternative is replaced by the one that increases the total utility. Once all the treatment schedules of all the compartments have been studied in this way, the process is repeated again until no more schedules increasing the utility can be found. In order to improve the probability for finding a good-quality solution, the whole process is repeated several times (say, 100–1,000 times), and the solution with the greatest utility value is taken as the optimal solution. In this way, the optimization phase of HERO combines random and systematic search components.

Example 6.1. Altogether 191 treatment alternatives were simulated for a 70 ha forest holding that had been divided into 75 compartments. The planning period included two 10-year sub-periods. MONSU forest planning software was used in the planning calculations (Pukkala 2006). The objective function was an additive utility function and it included the following objectives (and relative weights): cutting income during the 1st sub-period (0.4), cutting income during the 2nd sub-period (0.3) and standing timber volume at the end of the whole planning period (0.3). For standing timber-volume at the end of the planning period, the sub-utility reached a value 1.0 when the initial standing timber volume of the holding $(10,500\,\mathrm{m}^3)$ was reached. The sub-utility function of cutting-income from the first period was linear between its minimum and maximum value, and the sub-utility of cutting income from the 2nd planning period was formulated so that it reached the value of 0.9 at the point, where the cutting income was the same as the initial value growth per year in the holding multiplied by the number of years $(10 \times 18,000€)$. Three different parameter definitions were defined for the HERO and the achieved results are presented in Table 6.1.

The total utility measures directly the technical quality of the solution. As the number of random solutions and number of optimisation increases, also the total utility increases. Note that the aspiration level concerning standing timber level is always met, but the aspiration level for cutting income during the 2nd period is not reached.

Table 6.1 The results from three different heuristic searches

Number of initial random solutions	Number of optimisations	Total utility U	Cutting income 1st period	Cutting income 2nd period	Standing timber volume
1	1	0.63119	83,401	115,685	10,508
1,000	5	0.64833	64,315	150,765	10,518
1,000	500	0.65344	78,305	137,004	10,509

6.4 Simulated Annealing and Threshold Accepting

Simulated annealing (SA) is a variant local optimization method and it attempts to avoid getting trapped in local optima by allowing random deteriorations in the objective function value (e.g. Dowsland 1993). SA is originally based on the cooling process of liquid material, and the terminology of the method follows the terms of the physical cooling process (Kirkpatrick et al. 1983). Thus, the starting temperature defines the starting conditions of the process. The speed of the cooling process (defined through the cooling multiplier) affects the temperature and change the stage of the material so that as the material cools and becomes more solid the random elements can not change the solution as easily any more. The cooling process continues until the freezing temperature is reached and the material is solid. The search process of SA can continue until the current solution, i.e. the combination of treatments, can not be improved any more, and if the user-specified stop-rule has not been met earlier.

SA starts its search process from a randomly selected initial solution. In the search process, randomly assigned neighbouring solutions are evaluated. In forest-planning context, the neighbourhood usually means that the treatment schedule of one randomly selected management unit is changed at a time (Bettinger et al. 2002). In SA the moves that improve the value of the objective function are always accepted. To avoid being trapped to a local optimum, the method accepts moves that do not improve the objective function value with a probability that decreases as the temperature gets cooler. The probability for accepting the non-improving moves is calculated as follows

$$p = exp((U_{New} - U_{Old})T_i^{-1}) \tag{6.3}$$

where T_i is the current temperature, and U_{Old} is the current objective function value and U_{New} is the new smaller objective function value. During the optimization process, the temperature cools, according to a user-specified cooling schedule. At high temperatures the probability for accepting inferior moves is high (the melted metal moves easily), but as the temperature decreases (the metal solidifies), the probability decreases. Parameters that the user has to specify when using SA are starting and stopping temperature, cooling schedule and the number of iterations at each temperature. The number of iterations can change during the cooling process, for example it can increase when the temperature cools. This is also a user-specified characteristic.

Threshold accepting (TA) (Dueck and Scheuer 1990) is a deterministic version of SA. TA has shown to be able to produce solutions as good, or even better, than SA (Dueck and Scheuer 1990; Bettinger et al. 2002; Pukkala and Heinonen 2004). In TA, moves that improve the solution are always accepted. Moves not improving the current solution are accepted when they result in an objective function value greater than the current value minus the threshold. In the beginning of the search the threshold value can be large, which enables wider movements in the solution space. The threshold is gradually decreased and finally only improvements are accepted. The search is stopped when the threshold becomes very small (freezing

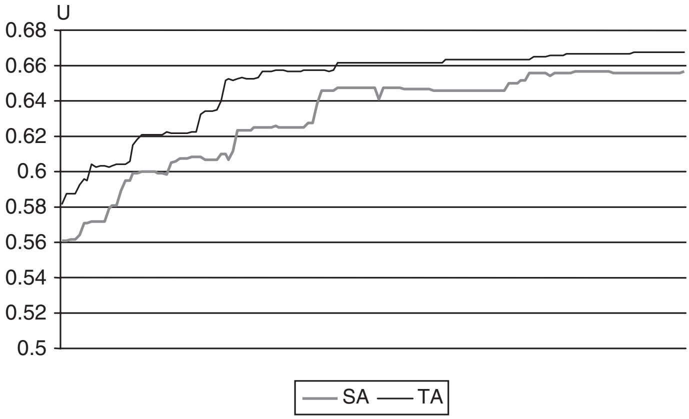

Fig. 6.2 Development of the total utility in SA and in TA during the first 150 moves

threshold) or when several consecutive thresholds are tested without any change in the solution.

Example 6.2. The planning data are the same as in example 6.1. In this example SA and TA were the used optimization techniques. For both techniques, the number of initial iterations, iteration multiplier and number of initial random solutions had same values. For SA, the initial temperature was 0.0013, the cooling multiplier which is used to reduce the temperature after the specified number of iterations was 0.9, and the stopping temperature was 0.000065. For TA, the initial threshold value was 0.0013, the threshold value multiplier was 0.9 and the stopping threshold was 0.0001.

Figure 6.2 illustrates the basic difference between SA and TA. The total utilities develop slightly differently in SA and in TA. SA allows some quite big deteriorations in the utility value, whereas they are smaller than the defined threshold in TA.

6.5 Tabu Search

Search memory in the form of tabu lists is the key characteristics of tabu search (TS). The lists direct and diversify the search process for instance by prohibiting the repetition of recent moves. The user-specified tabu tenure determines the number of iterations during which the treatment schedules that participated in a move may not be included in or removed from the solution.

As in previous techniques, the search process of TS starts from a random initial solution. Then, several candidate moves are produced. The user should define the number of candidate moves (at minimum one and at maximum all the neighbouring solutions) and how they are produced. The candidates may be produced by selecting randomly both the compartment and one of its treatment schedules that is not in the current solution. Alternatively the candidate moves can be produced systematically. Among these candidate moves, the move that produces an elite solution (the best solution so far) is always accepted even if it is tabu. Among the non-tabu moves, the move that produces the largest improvement (or the smallest deterioration) to the objective function is made. If non-tabu moves are not available, the move with smallest tabu-tenure (the treatment alternative that would next become non-tabu) is made. The duration of tabu tenure can be longer for moves that have entered the solution than for moves that have been removed from the solution (for more details, see, e.g. Glover and Laguna 1993; Richards and Gunn 2003).

Since the TS may concentrate in a small area in the solution space, the search can be further diversified by purposefully selecting rarely considered treatments options. For example, Boston and Bettinger (1999) diversified the search by using the long-term memory (frequency that each treatment alternative has been entered in the solution) so that after 3,000 repetitions, the algorithm developed a new solution using the least selected treatment alternatives. The TS routine was started again from this new solution, and the best solution so far was saved.

Example 6.3. This example illustrates the functioning of the short term tabu tenure. The example data consists of nine compartments, which have a varying number of simulated treatment alternatives as follows:

Compartment	1	2	3	4	5	6	7	8	9
Number of simulated treatment alternatives	4	5	2	3	4	5	4	5	4

In the optimization, the first move changes the solution in compartment 2. The tabu tenure for the alternative that has been removed from the solution is 10 and for the alternative that entered solution the tabu tenure is 2.

Compartment	1	2	3	4	5	6	7	8	9
The treatment alternative that is in the initial solution	1	2	1	3	4	4	1	2	3
Solution 2	1	5	1	3	4	4	1	2	3
Treatment alternative/Tabu Tenure		2/10							
		5/2							

The second move changes the solution in compartment 9. The tabu tenures of the previously changed treatment alternatives as well as the treatment alternatives that were changed during the current move are updated.

Compartment	1	2	3	4	5	6	7	8	9
The treatment alternative number that is in the current solution	1	5	1	3	4	4	1	2	3
Solution 3	1	5	1	3	4	4	1	2	1
Treatment alternative/Tabu Tenure		2/9							3/10
		5/1							1/2

6.6 Genetic Algorithms

Unlike the heuristic optimization techniques described above, genetic algorithms (GA) process simultaneously certain population of solution alternatives. This population is then evaluated and bred in the search process. The terminology of GA has correspondence to natural selection and genetics (Table 6.2). The alternative solutions are called chromosomes, which are processed by crossing over and by mutation and evaluated through fitness function. These operations result in new generation of chromosomes.

The GA starts from the initial population that can be created through random processes or by utilizing other heuristic optimization techniques. In the following step, the initial population is bred. It is possible to replace the whole initial population (i.e. change all forest plans in the population) or it can be replaced incrementally so that only part of the initial population is replaced by new chromosomes. New chromosomes can be created by using crossover or mutation. The selection of parent chromosomes for these operations can be random or the selection probability can depend on the chromosomes' fitness values. For example, the selection of the other parent can be based on the probability proportional to its ranking, and the other parent can be selected randomly. Also the mechanisms concerning the breeding process (number of crossovers, the length and location of crossovers, number and generation principles of mutations) must be defined. In addition, the user must also define the principles concerning the removal of chromosomes. It can be based on the fitness value so that the probability of removal is the highest for chromosomes that have a low fitness value. The new chromosomes form the new generation of chromosomes and the GA process ends when a certain number of generations have been produced or when a certain amount of generations have been produced without improvement (for more details, see, e.g. Reeves 1993 and Sastry et al. 2005).

Example 6.4. By using the data from example 6.3, different crossover methods (e.g. Sastry et al. 2005) are illustrated. Crossovers are performed to two parent chromosomes by applying one point crossover, two point crossover and uniform crossover, which can be considered as generic crossover techniques. In one point

Table 6.2 Terminology of GA with respect forest planning terminology

GA term	Forest planning term
Population	User defined number of forest plan alternatives
Chromosome	Forest plan
Gene	Forest stand/compartment
Allele	Treatment alternative
Crossover	An exchange of parts between two parent forest plan alternatives
Mutation	Random change in the stand's treatment alternative
Fitness value	Objective function value
Offspring	New generation of forest plan alternatives from breeding

crossover, one crossover point is randomly selected and the alleles on one side of the point are exchanged between the parents. In two point crossover, two points are randomly selected. In uniform crossover, every allele is exchanged between randomly selected two chromosomes with a certain probability, p_e. known as the swapping probability (which is usually taken to be 0.5).

One-point crossover

Parent 1	1	2	1	3	4	4	1	2	3
Parent 2	2	2	2	4	3	6	4	2	3
New chromosome 1	1	2	1	3	3	6	4	2	3
New chromosome 2	2	2	2	4	4	4	1	2	3

Two-point crossover

Parent 1	1	2	1	3	4	4	1	2	3
Parent 2	2	2	2	4	3	6	4	2	3
New chromosome 1	1	2	2	4	3	6	1	2	3
New chromosome 2	2	2	1	3	4	4	4	2	3

Uniform crossover

Parent 1	1	2	1	3	4	4	1	2	3
Parent 2	2	2	2	4	3	6	4	2	3
New chromosome 1	2	2	1	4	3	4	1	2	3
New chromosome 2	1	2	2	3	4	6	4	2	3

The principle of mutation is also illustrated below. The mutation probability has been defined to be 0.3, which means that at the treatment alternative changes at maximum in 30% of forest stands. In this example, the mutation takes place in the New chromosome 1 that was created through two point crossover. The mutation occurs in two alleles as follows:

New chromosome 1	**1**	2	2	**4**	3	6	1	2	3
After mutation	**2**	2	2	**1**	3	6	1	2	3

6.7 Improving the Heuristic Search

6.7.1 Parameters of Heuristic Optimization Techniques

The problem with heuristic optimization techniques is that although they can produce feasible solutions within a relatively short time, the quality of the solution remains unknown, especially in complex or large problems. The selected technique has an effect both on the time needed to find the solution as well as on the objective function value (Bettinger et al. 2002; Pukkala and Kurttila 2005). However, even if the technique would be suitable for the planning problem at hand, the user has to define several technique-specific parameter values, which also affect the performance (Baskent and Jordan 2002). In addition, the user has to decide how the initial solution(s) is produced. In practice, it is impossible to determine the single optimal set of parameters for a certain technique, because the planning situations vary much (Pukkala and Heinonen 2006).

Pukkala and Heinonen (2006) presented a method for optimizing the search process of three heuristic techniques (SA, TA and TS). The method optimizes the values of parameters that the applied heuristic optimization techniques need for quick and slow convergence requirement. In addition, the obtained solution with the best parameter set is simultaneously produced and displayed to the user. However, due to long computing times the everyday use of the method is impractical, but it is a valuable technique when heuristic techniques are developed and compared with each others. For improved practical usability, the method could be used to develop some practical rules concerning good technique-specific parameter values. It would be logical to try to relate these rules on the number of compartments, number of treatment schedules or on the size of the neighbourhood (Park and Kim 1998; Pukkala and Heinonen 2006).

6.7.2 Expanding the Neighbourhood

In forest planning and particularly in situations where spatial objectives are employed, it may be beneficial to examine two or more simultaneous treatment alternative changes (e.g. Bettinger et al. 1999). For example, if the treatment alternatives are changed simultaneously in two compartments, the values of non-spatial objective variables may remain practically unchanged but the spatial objective may be improved significantly. For this reason, so called two compartment neighbourhood moves may allow wider exploration of the solution space and more refinements to the solution (e.g. Bettinger et al. 2002; Heinonen and Pukkala 2004). In the study of Bettinger et al. (1999) TS with 2-opt moves gave good results when applied to a forest planning problem with even-flow and adjacency constraints. Also Bettinger et al. (2002) found out that the same technique performed very well in three different forest planning problems. More recently, the study of Heinonen and Pukkala (2004) compared one and two compartment neighbourhoods in local neighbourhood search based heuristics (SA, TS, HERO and random ascent). The two compartment neighbourhood was found to be clearly better than one compartment neighbourhood (Heinonen and Pukkala 2004). In addition to two compartment neighbourhood, it is possible to further develop the neighbourhood structure for example by using three compartment neighbourhoods and also by taking into account the relative locations of the compartments in neighbourhood definition.

Another possibility to enlarge the local search neighbourhood is the use of strategic oscillation (SO) in TS (Glover and Laguna 1993). SO is suitable for forest planning problems that include different constraints concerning, e.g. even-flow and adjacent cuttings. The constraints create barriers in the search space, i.e. they make it disjoint, which (see also Bettinger and Zhu 2006) reduces the search possibilities. For example, suppose that a 10 ha compartment, *j*, is adjacent to 45 ha area consisting or one or more compartments that would be cut during the period 2. The 10 ha compartment's ideal harvest time is also period 2. However, scheduling the cutting of this compartment to period 2 would increase the opening size greater than 50 ha, which in this case is the maximum allowed opening size. Therefore, some other compartments must be removed from the 45 ha opening before compartment *j* can be harvested in period 2. However, if the current volume harvested in period 2 is near the minimum constrained level, then removing other compartments from this opening will violate the harvest flow constraint. Thus, finding a sequence of feasible moves that add compartment *j* to harvest period 2 is difficult or impossible if constraints are constantly enforced (Richards and Gunn 2003). The basic idea of SO is to enlarge and smooth the constrained search neighbourhood by allowing infeasible moves. The search is carried out near constraint boundaries so that the solution visits both feasible and infeasible regions. The solution is forced back to feasible region by using penalty terms that increasingly penalize the objective function as the violations of the constraints increase. In the study of Richards and Gunn (2003) SO was found to be the most important design factor for constrained planning problem that was solved by different TS versions.

6.7.3 Combining Optimization Techniques

In order to improve the performance of the heuristic search processes, combining heuristic techniques with other heuristic technique or with LP has been examined also in forest planning context. Examples of combining heuristics include the study of Kurttila and Pukkala (2003). They combined SA and HERO so that the idea of cooling and that of accepting inferior solutions were applied in the same way as in SA, whereas the neighbourhood was searched in the same way as in the Hero, i.e. sequentially. All moves that improved the objective function value were accepted. At every temperature, all schedules for all compartments were inspected once and sequentially after which the temperature was changed and the same process was repeated until a stopping temperature was reached. Thus, also some inferior moves were accepted during the direct search phase of HERO, but as the temperature decreased, the probability of accepting these moves was decreased.

In the study that compared the performance of six heuristic techniques (Pukkala and Kurttila 2005) the performance of this technique was rather good. It was always faster than TS, SA and GA. In spatial planning problems only GA gave clearly better objective function values than the combination of SA and HERO. In another study (Hurme et al. 2007) SA and HERO were combined so that after the search process of SA terminated the direct search phase of the HERO was ran through once, which guaranteed that the current local optimum was certainly found. In addition, simple and fast technique like HERO can be used to produce initial solutions for

GA and for other heuristics as well (Pukkala and Heinonen 2006). Also Falcão and Borges (2002) combined two heuristics so that other of them applied systematic search and other random search. The developed sequential quenching and tempering technique first applies systematic search rather similarly as HERO to all stands in the forest. After all stands have been inspected and local optimum has been found, the technique makes a random perturbation. This means that a new treatment alternative is randomly assigned for a certain number of stands. After this, the systematic search phase is resumed.

In the study of Öhman and Eriksson (2001) LP was integrated with SA. SA was used for solving the spatial dimension of the planning problem, whereas LP was used for solving the non-spatial dimension. Two alternatives to combine these techniques were tested. In the first alternative, SA was used first to solve the spatial part of the planning problem, where the aim was to cluster old forests by applying two different measures related to core-area, namely the amount of core-area and the amount of edge habitat. The SA solution was used to prohibit such stand-level treatment schedules from the LP problem that did not produce old forest areas to same extent as the treatment schedule that had been selected for the optimal SA solution. In the second alternative, the procedure began with LP problem formulation. From the LP solution, the shadow prices were utilized in the SA problem. The results indicated that the combination of these two techniques produced more effective results than the approach that used SA alone.

Bettinger et al. (2002) in their study tested a hybrid of TS and GA. The hybrid utilized 1-opt and 2-opt moves and the diversification routine of the TS. After these phases, the two best solutions (one from the 1-opt process and one from the 2-opt process) were used as parent chromosomes and a crossover routine of GA was performed so that two new chromosomes were created. The new chromosome with the highest objective function value was then taken as a starting solution of the new TS process. This hybrid together with seven other heuristic techniques were compared in three different forest planning problems (one non-spatial and two spatial planning problems). In the comparison, this algorithm was classified according to its performance to a group "very good" as were also SA, TA, great deluge and TS with 1-opt and 2-opt moves.

References

Baskent, E.Z and Jordan, G.A. 2002. Forest landscape management modelling using simulated annealing. Forest Ecology and Management 165: 29–45.

Baskent, E.Z. and Keles, S. 2005. Spatial forest planning: a review. Ecological Modelling 188: 145–173.

Bettinger, P. and Zhu, J. 2006. A new heuristic method for solving spatially constrained forest planning problems based on mitigation of infeasibilities radiating outward from a forced choice. Silva Fennica 40: 315–333.

Bettinger, P., Boston, K., and Sessions, J. 1999. Intensifying a heuristic forest harvest scheduling search procedure with 2-opt decision choices. Canadian Journal of Forest Research 29: 1784–1792.

Bettinger, P., Graetz, D., Boston, K., Sessions, J., and Woodam C. 2002. Eight heuristic planning techniques applied to three increasingly difficult wildlife planning problem. Silva Fennica 36: 561–584.

Borges, J.G., Hoganson, H.M., and Falcão, A.O. 2002. Heuristics in multi-objective forest planning. In: Pukkala, T. (Ed.). Multi-objective forest planning, Kluwer, Dordrecht, pp. 119–151.

Boston, K. and Bettinger, P. 1999. An analysis of Monte Carlo integer programming, simulated annealing, and tabu search heuristics for solving spatial harvest scheduling problems. Forest Science 45: 292–301.

Brumelle, S., Granot, D., Halme, M., and Vertinsky, I. 1997. A tabu search algorithm for finding good forest harvest schedules satisfying green-up constraints. European Journal of Operational Research 106: 408–424.

Burke, E.G. and Kendall, G. 2005. Search methodologies. Introductory tutorials in optimization and decision support techniques. Springer Science + Business Media, New York, USA. 620 pp.

Dowsland, K.A. 1993. Simulated annealing. In: Reeves, C.R. (Ed.). Modern heuristic techniques for combinatorial problems. Blackwell, Oxford, pp. 20–69.

Dueck G. and Scheuer T. 1990. Threshold accepting: a general purpose optimization algorithm appearing superior to simulated annealing. Journal of Computer Physics 90: 161–175.

Falcão, A. and Borges, J.G. 2002. Combining random and systematic search heuristic procedures for solving spatially constrained forest management scheduling models. Forest Science 48: 608–621.

Glover, F. and Laguna, M. 1993. Tabu search. In: Reeves, C.R. (Ed.). Modern heuristic techniques for combinatorial problems. Blackwell, Oxford, pp. 70–150.

Harrison, S. and Fahrig, L. 1995. Landscape pattern and population conservation. In: Hansson, L., Fahrig, L., and Merriam, G. (Eds.). Mosaic landscapes and ecological processes. IALE Studies in Landscape Ecology, Vol. 2, Chapman & Hall, London, pp. 293–308.

Heinonen, T. and Pukkala, T. 2004. A comparison of one- and two-compartment neighbourhoods in heuristic search with spatial forest management goals. Silva Fennica 38: 319–332.

Heinonen, T., Kurttila, M., and Pukkala, T. 2007. Possibilities to aggregate raster cells through spatial objectives in forest planning. Silva Fennica 41: 89–103.

Hurme, E., Kurttila, M., Mönkkönen, M., Heinonen, T., and Pukkala, T. 2007. Maintenance of flying squirrel habitat and timber harvest: a site-specific spatial model in forest planning calculations. Landscape Ecology 22: 243–256.

Kangas, J. 1999. The analytic hierarchy process (AHP): standard version, forestry application and advances. In: Helles, F., Holten-Andersen, P., and Wichmann, L. (Eds.). Multiple use of forests and other natural resources. Kluwer, Dordrecht, Forestry Sciences 61, pp. 96–105.

Kangas, J., Pukkala, T., and Kangas, A.S. 2001. HERO: Heuristic optimization for multi-criteria forestry decision analysis. In: Schmoldt, D., Kangas, J., Mendoza, G.A., Pesonen, M. (Eds.). The analytic hierarchy process in natural resource and environmental decision making, Kluwer Academic Publishers. Dordrecht. Managing Forest Ecosystems 3. pp. 51–65.

Kirkpatrick, S. Gelatt, C.D, Jr., and Vecchi, M.P. 1983. Optimization by simulated annealing. Science 220: 671–680.

Kurttila, M. 2001. The spatial structure of forests in the optimization calculations of forest planning - a landscape ecological perspective. Forest Ecology and Management 142: 129–142.

Kurttila, M. and Pukkala, T. 2003. Combining holding-level economic goals with spatial landscape-level goals in the planning of multiple ownership forestry. Landscape Ecology 18: 529–541.

Lockwood, C. and Moore, T. 1993. Harvest scheduling with spatial constraints: a simulated annealing approach. Canadian Journal of Forest Research 23: 468–478.

Lu, F. and Eriksson, L. O. 2000. Formation of harvest units with genetic algorithms. Forest Ecology and Management 130: 57–67.

Nalle, D.J., Montgomery, C.A., Arthur, J.L., Polasky, S., and Schumaker, N.H. 2004. Modeling joint production of wildlife and timber. Journal of Environmental Economics and Management 48: 997–1017.

Öhman, K. 2001. Forest planning with consideration to spatial relationships. Doctoral dissertation. Department.of Forest Resource Management and Geomatics, SLU. Acta Universitatis Agriculturae Sueciae, Silvestria, Vol. 198, 32 pp.
Öhman, K. and Eriksson, L.O. 1998. The core area concept in forming contiguous areas for long term forest planning. Canadian Journal of Forest Research 28: 1032–1039.
Öhman, K. and Eriksson, L.O. 2002. Allowing for spatial consideration in long term forest planning by linking linear programming and simulated annealing. Forest Ecology and Management 161: 221–230.
Park, M.-W. and Kim, Y.-D. 1998. A systematic procedure for setting parameters in simulated annealing algorithms. Computers and Operations Research 25: 207–217.
Pukkala, T. 2002. Introduction to multi-objective forest planning. In: Pukkala, T. (Ed.). Multi-objective forest planning. Kluwer, Dordrecht, pp. 1–20.
Pukkala, T. 2004. Monikäytön suunnitteluohjelma Monsu. Ohjelmiston toiminta ja käyttö. University of Joensuu Faculty of Forestry, 72 pp (in Finnish).
Pukkala, T. and Heinonen, T. 2006. Optimizing heuristic search in forest planning. Nonlinear Analysis: Real World Applications 7: 1284–1297.
Pukkala, T. and Kangas, J. 1993. A heuristic optimization method for forest planning and decision-making. Scandinavian Journal of Forest Research 8: 560–570.
Pukkala, T. and Kurttila, M. 2005. Examining the performance of six heuristic search techniques in different forest planning problems. Silva Fennica 39: 67–80.
Reeves, C.R. 1993. Genetic algorithms. In: Reeves, C.R. (Ed.). Modern heuristic techniques for combinatorial problems. Blackwell, Oxford, pp. 151–196.
Reeves, C.R. 1993. Modern heuristic techniques for combinatorial problems. Blackwell, Oxford, 320 pp.
Richards, E.W. and Gunn, E.A. 2003. Tabu search design for difficult forest management optimization problems. Canadian Journal of Forest Research 33: 1126–1133.
Sastry, K, Goldberg, D., and Kendall, G. 2005. Genetic algorithms. In: Burke, E.G. and Kendall, G. (Eds.). Search methodologies. Introductory tutorials in optimization and decision support techniques, Springer Science + Business Media, New York, USA, pp. 97–125.
Tarp, P. and Helles, F. 1997. Spatial optimization by simulated annealing and linear programming. Scandinavian Journal of Forest Research 12: 390–402.

Part III
Cases with Several Decision Makers

Chapter 7
Group Decision Making and Participatory Planning

7.1 Decision Makers and Stakeholders

Environmental problems are typically messy and complex. There may be high risks involved and/or lack of scientific agreement on the cause of problems. The problems may be ill defined, and the goals may not be clear. In addition, numerous decision makers or other stakeholders are often involved in environmental planning.

The stakeholders are defined to be "any group or individual who can affect, or is affected by, the achievement of a corporation's purpose" (Freeman 1984). They could be persons like forest owners, farmers, forest workers or local inhabitants, or stakeholder groups such as tourism and recreation services, organizations concerned with nature conservation, rural communities, hunters associations, sporting and recreation associations or wood and forest industry (International Labour Office (ILO) 2000). Each of them can have different objectives concerning the use of forests or other natural resources, which further complicates the evaluation.

Group decision making is inevitable, for example, when dealing with forest planning of forest holdings owned by several people. In addition, group decision making is commonly used in business decision making, for instance wood procurement organizations. In group decision making, the total utility to be maximised can be taken as a combination of utilities of the persons belonging to the group. In group decision making typically at least some agreement among participants can be found, due to the organizational culture (Hjortsø 2004).

Public participation means that citizens are involved in the environmental or natural resource decision making that has an effect on them. Public participation is also seen as part of sustainable development. This is further underlined by the UNECE (1998) convention on access to information and access to justice in environmental matters. In the case of public participation, the views of participants are often fundamentally different and even conflicting (Hjortsø 2004). In such situations people often focus on protecting their own interests so that conflicts are an inherent part of public participation (Susskind and Cruishank 1987; Hellström 1997).

The most distinct difference between these two cases is the actual power to make the decisions. The group typically withholds all the power to make the actual decisions, but in participatory planning this is not the case, but usually the managing agency holds all the power. Thus, the level of participation may vary from mere informing the public to total control of public, depending on how much power the managing organization is willing to give up.

In most cases, organizing a participatory planning process is voluntary for the managing organization. In some cases, however, the use of participatory planning is required by law. Such is the case in many Environmental Impact Assessment (EIA) processes. In Finnish forestry, participatory planning has been used for instance in the decision making of Metsähallitus (formerly Forest and Park Service, e.g. Wallenius 2001) and municipalities owning forest, such as Raahe, Helsinki and Tampere (e.g. Tikkanen 1996; Sipilä and Tyrväinen 2005). Participatory approach has also been used for many policy programmes, like the National Forestry Programme and its regional counterparts (e.g. Tikkanen 2003; Primmer and Kyllönen 2006). In addition, participation has been used in defining nature conservation programmes, such as NATURA 2000 (Metsien suojelun … 2006).

There are several reasons for promoting public participation. The specific purposes may depend on the issues involved, the perspectives and interests of participants, and the existing cultural, political and organizational contexts. It can be assumed that the final decisions are made with more competence, when local knowledge is included and expert knowledge is scrutinized by the public (Webler et al. 1995). Furthermore, the legitimacy of the final decision may be better, when the citizens whose interests the project has an effect on are involved in the decision making.

In relation to forestry, ILO (2000; see also Hjortsø 2004) has identified seven purposes:

1. Increase awareness of forestry issues and mutual recognition of interests
2. Gather information and enhance knowledge on forests and their use
3. Improve provision of multiple forest goods and services
4. Stimulate involvement in decision making and/or implementation process
5. Enhance acceptance of forest policies, plans and operations
6. Increase transparency and accountability of decision making
7. Identify and manage conflicts and problems together, in a fair and equitable way

According to Heberlein (1976), the reason why people want to participate in the decision making is that people feel there is a discrepancy between the values held by agency personnel and the public. This may be the case especially in decision making concerning the environment, as the values in the society have been fast evolving. Public participation is not, however, the only way to involve public opinion in decision making regarding natural resources. The public views and values probably have their influence on the missions of the agencies doing the planning. Similarly, the views of public affect through the agency personnel. Moreover, public opinion also affects the democratic decision making system, which supervises the work of agencies making the actual decision.

Group decision making can often be aided with the same kind of methods as the decision making of one decision maker. In addition, group decision making might benefit from problem structuring methodology, if the process is ill-defined. The same methodology can also often be used in a public participation process (e.g. Kangas 1994; Pykäläinen et al. 1999; Kangas and Store 2003). However, there are many other aspects that also need to be accounted for, such as equity and equality.

7.2 Public Participation Process

7.2.1 Types of Participation Process

The public participation process can be divided in many ways. First, it can be seen either as a method, a mean to an end; or as an approach or ideology (Buchy and Hoverman 2000). It can vary from passive participation organized by an agency to self mobilization of local people at the face of some decision of interest to them. Participation processes can also be divided to open (every interested citizen can attend the process) and closed (only people invited by the managing organization can attend); or to combined (all interest groups participate at the same time) and separated (each interest group have their own process) (Tikkanen 2003).

One important division is division with respect to power given to the participating people (e.g. Arnstein 1969; Tikkanen 2003). Germain et al. (2001) divide the process to six levels:

1. Informing
2. Manipulation
3. Consultation
4. Collaborative decision making
5. Delegated power
6. Total control by participants

In the first case the managing agency informs the public about their future plans, but there is no public avenue for feedback or negotiation. The process may aim at educating people and/or changing their attitudes. It may be that the managing agency truly believes that if the public knew what the professionals know, they would think the same way (Daniels and Walker 1996). Such thinking can, however, also apply to the participants (Webler et al. 2001).

In the second case, participation is organized but it is illusory in the sense that public has no true power on the outcome. The purpose of the process may be to engineer support for the project (Germain et al. 2001). This kind of participation process may have a co-optation function, meaning that people can complain about the project, although the agency is not responding; or, the process can have a ritualistic function, meaning that the participation is required by law, but there is no direct need for the participation (Heberlein 1976).

In the third case, people can also express their own opinions about the project, but the managing agency retains the power to make the decisions (Germain et al. 2001). In this case, public cannot be sure if their opinions are accounted for or not (Heberlein 1976). It often places the public to a situation where they only can react to the decision the agency has made (Germain et al. 2001). Thus, although majority of studies have found that the public meeting influence the decisions of the managing agencies (Chess and Purcell 1999), people may feel that they are not adequately heard. And, at the same time, the personnel of the managing agency may feel that the public is never satisfied, whatever they do (Buchy and Hoverman 2000). In this level, public participation is usually carried out using public hearings, conferences and formation of advisory groups (Hjortsø 2004).

In the fourth case, the public is partly responsible for the resulting plan (Hytönen 2000). The aim in this level is to build consensus through collaborative problem solving, negotiation, conciliation and mediation, and joint decision making (Hjortsø 2004).

In the last two levels, the public has a dominant role in the decision making.

It has often been noted that a problem in public participation is the resistance of the managing agencies (e.g. Garcia Pérez and Groome 2000). On the other hand, it has also been noted that people usually avoid participating in the decision making (Riedel 1972). Even if the people want to participate, it may be that they are only interested in one or two issues. The silent majority may be satisfied with the work of the managing organizations, so that those participating have the most extreme views.

7.2.2 Success of the Participation Process

The success of public participation can be viewed from two different viewpoints: outcome and process (Chess and Purcell 1999). They also relate to specific concepts of justice, namely distributive justice and procedural justice (Smith and McDonough 2001).

Some people may evaluate the public participation only with respect to the outcome of the process. The criteria for the outcome include better accepted decisions, consensus, education, and improved quality of decisions (e.g. English et al. 1993). It may, however, be difficult to say whether the outcome is favourable or not: people may use the participation process to delay difficult decisions or to block unwanted proposals. It is also not easy to say how much the outcome is due to the participation process and how much due to some other factors (Chess and Purcell 1999).

The process also has an effect to the success. It has been noted that a fair procedure make people react less negatively to unfair outcome (Brockner and Siegel 1996) and that fair outcome could make people think more positively about the process (Van den Bos 1997). On the other hand, people may raise questions concerning the process if the outcome is not to their liking (Webler and Tuler 2001).

Although researchers and practitioners agree on the importance of the process, there still is no agreement on what the process should be like (Tuler and Webler

1999). There exist several criteria given to the participation process. Some of them may be theoretical, such as ‘fairness’, ‘competence’ and ‘reasonableness’, some may be based on participants’ goals and satisfaction (Chess and Purcell 1999). The participants’ goals, on the other hand, may vary according to culture, environmental problem, historical context, etc.

Tuler and Webler (1999) studied the opinions of participants concerning a good process. They found seven normative principles that emerged from the interviews.

1. Access to the process
2. Power to influence process and outcomes
3. Structural characteristics to promote constructive interactions
4. Facilitation of constructive personal behaviours
5. Access to information
6. Adequate analysis
7. Enabling of social conditions necessary for future processes

Access to the process means getting people present and involved in the participation process. It also means that in order to succeed, organization have to actively reach out to people (Chess and Purcell 1999).

Structural characteristics to promote constructive interactions emphasise the structure of social interaction: the time, location, availability and structure (e.g. seatings) of the meetings. The time and location needs to be such that not only experts who work on the case can attend (Heberlein 1976). Facilitation of constructive personal behaviour, on the other hand, emphasises the behaviour of the people involved. Respect, openness, understanding and listening are required. For instance, the process may be good in every other respect, but if people feel they have not been treated with dignity, the process does not feel fair (Smith and McDonough 2001).

With respect to access to information, people feel that both the knowledge and experiences of layman and experts should be heard. Adequate analysis means that people want to be able to understand the scientific reasoning behind the plans (Tuler and Webler 1999).

Finally, enabling the social conditions necessary for future processes emphasises that participatory process should not fuel the conflicts. On the contrary, it should build better relationships between the interest groups in the region.

One task of planning is to uncover common needs and understanding (Webler et al. 1995). According to McCool and Guthrie (2001), especially managers stress learning as an important aspect of successful participatory planning process. In the review made by Chess and Purcell (1999), the managing agencies could enhance the success of the participatory process also by (i) holding public meetings in addition to other forms of participation, (ii) providing significant technical assistance to participants, (iii) conducting vigorous outreach, (iv) discussing social issues, and (v) fielding questions adequately. On the other hand, the unsuccessful participation in their review was characterized by (i) poor outreach to potential participants, (ii) limited provisions of technical information, (iii) procedures that disempower citizens, (iv) unwillingness to discuss social issues, and (v) timing of hearings after the decisions have been made or otherwise late in the decision-making process.

Good examples of unsuccessful planning processes are presented by Garcia Pérez and Groome (2000).

While these general criteria for successful participatory process were clear, different people emphasise different issues. For instance, Webler et al. (2001) found five different perspectives emphasising different issues and Webler and Tuler (2001) found four differing perspectives in two different participatory processes. The perspectives in the latter were (a) a good process is credible and legitimate, (b) a good process is competent and information-driven, (c) a good process fosters fair democratic deliberation, and (d) a good process emphasises constructive dialogue and education. In the former case, the perspectives were a bit different: (a) a good process should be legitimate, (b) a good process should promote a search for common values, (c) a good process should realize democratic principles of fairness and equality, (d) a good process should promote equal power among all participants and viewpoints, and (e) a good process should foster responsible leadership.

Thus, some people emphasise discussion among the participants, some high quality information, some emphasise fairness and some leaders taking the responsibility. The differences may be due to both participation situations, and the participating people, and their occupation and previous experiences in participatory processes (Webler and Tuler 2001; Webler et al. 2001). For instance, being a politician or a proponent of property rights had a significant effect on the preferred way of participation. The good process also depends on the planning context (Webler and Tuler 2001).

7.2.3 Defining the Appropriate Process

In participatory planning, the problem setting phase includes: (i) analyzing the planning situation, (ii) identifying the people affected by the decisions, (iii) assessing if there is a conflict and the severity of the possible conflicts, (iv) defining the level of power given to the participants, and (v) gaining internal commitment in the managing agency for the participatory process (Kangas et al. 1996).

There exist several handbooks and guides for planning a participatory process (e.g. Bleiker and Bleiker 1995; ERM 1995; English et al. 1993; ILO 2000; see also Webler 1997). In more detail, the participatory planning process can be planned, for instance, using the list of questions presented by English et al. (1993):

- What is the goal of the participation process?
- Who counts as affected party?
- Who should participate in the process?
- Where should participation occur in the decision making process?
- What should be the roles and responsibilities of the participants?
- How to handle ethical principles?
- How to balance technical and value issues?
- How much influence on the decision should the process have?
- How long should the process last?
- How should the process relate to other decision making activities?

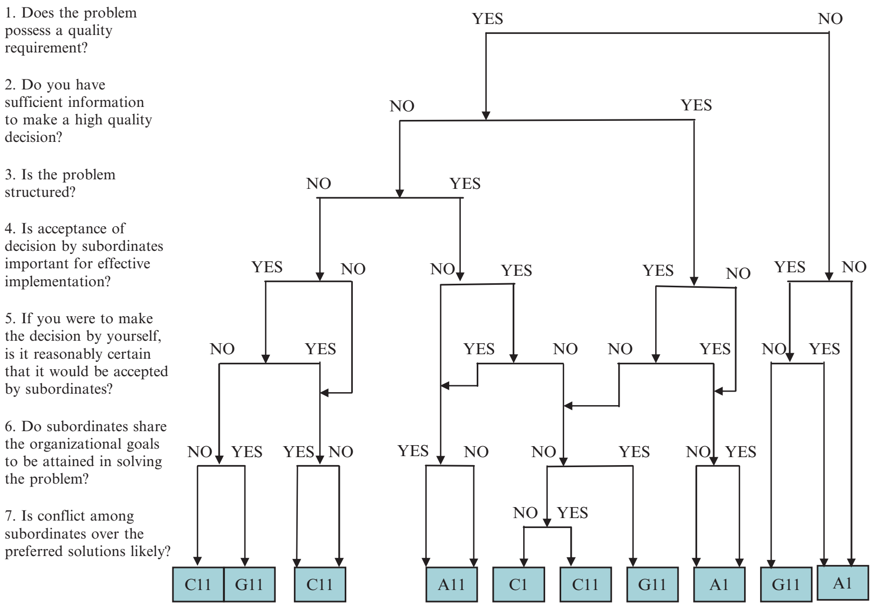

Fig. 7.1 Original Vroom–Yetton model (Vroom and Yetton 1973; Lawrence and Deagen 2001)
A1: The manager solves the problem alone using information presently available to the manager
A11: The manager obtains any necessary information from subordinates and then decides on a solution alone
C1: The manager shares the problem with relevant subordinates individually without bringing them together as a group, gets their ideas and suggestions, and then makes decision alone
C11: The manager shares the problem with subordinates in a group meeting, getting their ideas and suggestions, and then makes a decision that might or might not reflect the subordinates' influence
G11: The manager shares the problem with subordinates as a group, and together manager and the subordinates attempt to reach agreement on a solution

One possibility to analyze the level of participation is to use the so-called Vroom–Yetton approach (see Vroom and Jago 1988). The Vroom–Yetton model is a set of questions that lead to the different levels of participation in a decision making of an organization (Fig. 7.1) It has been later developed to better suit a public participation situation (Lawrence and Deagen 2001; Tikkanen 2003).

This approach may, however, be too simple, as there is evidence that only a few people are willing to commit themselves to very intensive planning (e.g. Riedel 1972). Instead, they would like to have many different channels for participation, varying from low to high intensity: some people will only want to have information concerning the project, some would like to be consulted in the projects and some would also like to participate in the decision making (ERM 1995). People would also like to be able to choose the level of participation suitable for them. The ERM (1995) manual advises planners to provide possibilities for participating at all these levels.

Participation includes many phases, and in each of these phases several different tools can be used. Janse and Konijnendijk (2007) present a set of tools for urban

Table 7.1 Categorization of individual tools (Janse and Konijnendijk 2007)

Tool categories	Tool sub-categories	Tools
Information Provision	Information Distribution	• Newsletter • Website • Contact and information office
	Public events	• Information meetings • Public exhibitions • Information stands • Public sensitization/ awareness raising events • Events dedicated to the presentation of project Vision documents
Information collection	Social surveys/interviews	• Social surveys • Interviews while walking through the forest
	Other surveys/inventories	• Land-use surveys • Botanical surveys • Forest inventory
Involvement of experts and the public at large	Involvement of the public at large/interest groups	• "Sounding board" group • Public workshops • Thinking days with the public
	Expert analysis/connoisseur approach	• Connoisseur approach – "future managers meeting local connoisseurs" • Expert analysis of urban woodland design • Expert interviews • Thinking days with experts
	Involvement of children and youths	• Youth work-play happening • Design of a play-forest with children • Education activities • Communication with children and teenagers though participation in practice • Youth round table
Processing and use of information	Assessment and analysis of information GIS tools	• Working group sessions • Visioning processes • Multi-Criteria analysis • Thematic maps/GIS mapping • Mapping of social values and meanings of urban green areas • Assessing the recreational potential of urban forest areas by means of GIS

forest planning, but this set of tools can be used also for other types of participatory processes (Table 7.1). For instance, the information required for participatory planning can be obtained with several different ways, for instance using public hearings, surveys, or different group decision support methods (see also Heberlein 1976; Hytönen 2000). Each of these methods has its own drawbacks and benefits. Glass (1979) states that none of the methods used for participatory planning is able to satisfy all the objectives of participation. Thus, the best technique depends on the planning situation. Moreover, it also means that using several different methods may be advisable.

There exist also several methodologies that are intended to cover the whole participatory planning process. The readers interested are referred to a thorough review by Tippett et al. (2007).

7.3 Tools for Eliciting the Public Preferences

7.3.1 Surveys

Surveys provide representative information on the population. A random sample of people is selected and their opinions are asked using a questionnaire. The sample can also be quite large, so that it is possible to investigate the opinions of larger number of people than with any other method. In surveys, the questions are usually structured and therefore easy to analyze quantitatively. On the other hand, this also means that the questionnaires are rigid.

The response rates in questionnaires are usually quite low (around 40–58%, Hytönen 2000), and the high rate of non-response may cause bias to the results. This may happen, if some groups respond more than others (e.g. Janse and Konijnendijk 2007). There may also be a trade-off between the length of the questionnaire and the response rate.

One potential problem with surveys is that the public responding may be uninterested and uninformed so that their preferences may be based on false (or nonexistent) information of the consequences of the alternative actions (e.g. Lauber and Knuth 1998). Thus, the preferences might be different if people had more information on the subject.

Another potential problem is that the questions asked in surveys may be too general to provide information that is directly useful for decision making in a particular case (e.g. Satterfield and Gregory 1998). For instance, the general environmental values may seem quite similar among people, but the reactions of people to an actual planning situation may still vary a lot. Therefore, the results of surveys can best be used as background information in a certain decision situation (Hytönen 2000). On the other hand, it is often possible to form the survey specifically for a certain planning situation (e.g. McDaniels and Thomas 1999).

The data presented and the questions used for preference gathering in the decision support methods may, however, be too difficult for the public to understand (e.g. Heberlein 1976). Moreover, small differences in the wordings may produce different results.

One promising method for public participation surveys is the social values mapping (Tyrväinen et al. 2007). In this method, the participants are provided a map, and they assign (pre-defined) areas with values according to their preferences. The values may include beautiful sceneries, space and freedom, or peace and tranquillity. This approach is easily comprehended by the public and also provides the planners spatially located information on the preferences of public. The participants could also themselves delineate the areas they value, but this approach is by far more laborious to the planners (Kangas et al. 2007).

The information provided along the questions may also influence the public opinion (e.g. McComas and Scherer 1999). It is possible that those who carry out the survey may manipulate the information to serve their needs. On the other hand, it may be that ‘overly’ positive information may not seem credible to participants. It has been noted that one-sided positive information had the most persuasive influence on those people, who already had positive assertions to the plan, and two-sided balanced information for those persons, who initially opposed the plan (Hovland et al. 1965). Furthermore, one-sided information had greatest effect on uneducated people, and two-sided to educated people. All in all, information has least effect when people already have well-formed opinions about the subject (e.g. McComas and Scherer 1999).

Due to all these problems, Heberlein (1976) argues that opinions of public gathered through survey may be poor indicators of the true preferences of public.

7.3.2 Public Hearings

In public hearings it is possible to consider the opinions of smaller groups. In hearings people typically can express their opinions in a non-structured way, so that the questions asked do not affect to the result. This way, they can also provide information that the organizers have not thought of asking. However, the problem is that the unstructured responses are much harder to analyze than structured surveys (for an example see Hytönen et al. 2002). They need to be analyzed using qualitative procedures, usually by classifying the answers in some way. It may also be that much of the information received is not useful in the planning process. For instance, people may state facts concerning the area rather than their preferences.

As the hearings are not based on sampling, there is no guarantee on how well the attending group represents the society at large. It may be that the hearing only reflects the well-known views of well-identified interest groups, or that only opponents of the propositions attend to the meetings (Heberlein 1976). In the worst case, the public hearings may represent the opinions of those dominating the discussion, not even the persons in the meeting (Hytönen 2000). However, there is also evidence that the opinions gathered with public hearings have been “in most respects” similar to the results of survey (O’Riordan 1976).

On the other hand, people attending the hearings are likely to have more information on the issues than people at large (e.g. Lauber and Knuth 1998). They may also be more interested on the issues at stake. The difficult question is how much the opinion of persons, who do not have adequate information and who are even not interested on it, should be accounted for in the planning.

It may also be that although ordinary people attend to the meeting, they do not actually participate. It may be very intimidating to present ones opinion at public, so that the opinions shared in the meetings are those of experts, people most severely affected by the decisions or people who are not intimidated by behavioural norms of the meetings (Heberlein 1976).

7.4 Problem Structuring Methods

7.4.1 Background

Problem structuring is an unavoidable phase of any decision support process. The MCDM methods presented so far do not provide enough tools for efficient problem structuring. Therefore, specific problem structuring techniques or so-called "Soft OR" have been developed. They may be useful for exploring the situation in such a way that formal MCDM methods can be successfully applied in later phases. Problem structuring methods are useful especially when the problem is complex and/or ill-defined (see Rosenhead 1989; Belton and Stewart 2002). Ill-defined problem means that people are attempting to take some purposeful action that will improve the current situation, but the possible actions to improve it are unknown, and the goals undetermined. Problem structuring methods are intended to (Mingers and Rosenhead 2004)

- Pay attention to multiple objectives and perspectives
- Be cognitively accessible to a broad range of participants
- Operate iteratively so that the problem representation adjusts to reflect the discussions among the participants
- Permit partial or local improvement to be identified

The problem structuring approaches vary in their scope and complexity, but they all aim at supporting problem structuring and problem solving. They all require a lot of time and commitment from participants, when compared to public participation using, for instance, public hearings. These methods are suitable when workshops are used as a form of participation. Usually also a facilitator (i.e. person guiding the decision makers in the use of analysis method) is needed to aid the work in groups.

One simple and popular way in problem structuring is to ask the participants to write their ideas and views on Post-It notes, and then distribute them to the walls. This way, a lot of detailed ideas can be generated by individuals; they are directly recorded; and also easily seen by other participants (e.g. Belton and Stewart 2002, p. 41). In the beginning, the ideas appear in an unstructured format, but as it is easy to move the Post-Its around, structure can eventually emerge, when similar ideas are clustered together. Clustering of the ideas together will further stimulate discussion and improve mutual understanding.

According to Belton and Stewart (2002) the main benefits of this approach is that all people have an equal chance to contribute with their ideas, there is a degree of anonymity involved and the process cannot be dominated by more powerful or eloquent persons.

Many researchers have developed specific, more formal methods for problem structuring (for a review see Mingers and Rosenhead 2004). In this book, two of these are presented, namely Strategic Options Development and Analysis (SODA, e.g. Eden and Simpson 1989) and Soft Systems Methodology (SSM, e.g. Checkland 1981, 1989). In its further developed form SODA is also called JOURNEY making (JOintly Understanding, Reflecting, and NEgotiation strategy, Eden and Ackermann 2001).

7.4.2 Strategic Options Development and Analysis

SODA is based on cognitive mapping (Eden 1988). It was developed as a way to represent individuals' 'construct systems' based on Kelly's personal construct theory (Kelly 1955). SODA aims at presenting the problem as the decision maker sees it, as a network of means and ends, or options and outcomes. The concepts linked to the network are action-oriented, which makes it a suitable approach for strategy development (e.g. Belton and Stewart 2002, p. 49). The cognitive maps can be done in paper, but there exists also software for doing them, for instance Decision Explorer (Eden and Ackermann 1998). Using computer enables a thorough analysis of the maps.

In the map, alternatives or contrasting ideas can be expressed as pairs or words connected with dots like 'saw mill … paper mill'. Concepts are linked with arrows to other concepts that they imply like 'employment' or 'deterioration of water quality'. The arrows can also be marked with minus signs to imply counter-effects, like 'loss of agriculture' may imply negative effects on 'quality of life' (Fig. 7.2). The (desired) outcomes or ends are concepts where the arrows lead ('e.g. quality of life') and strategic options or means are the concepts from which the arrows lead to outcomes (e.g. 'pulp mill … saw mill').

One cognitive map typically presents the cognition of one individual. In order to utilise cognitive mapping in group work, these individual maps need to be merged. This is what the SODA method is about. The idea is to structure multiple conflicting aspects and put the individual views into context. Giving the individual views anonymously, through software, may help in reducing conflicts, as people can concentrate on ideas rather than on persons (Ackermann and Eden 1994). It is, however, also possible to make a group map from the start (Ackermann and Eden 2001).

According to Eden (1989, 1990), SODA includes the following phases (all of which do not have to be included in the process):

1. Initial individual interviews and cognitive mapping
2. Feedback interview where the initial maps are verified

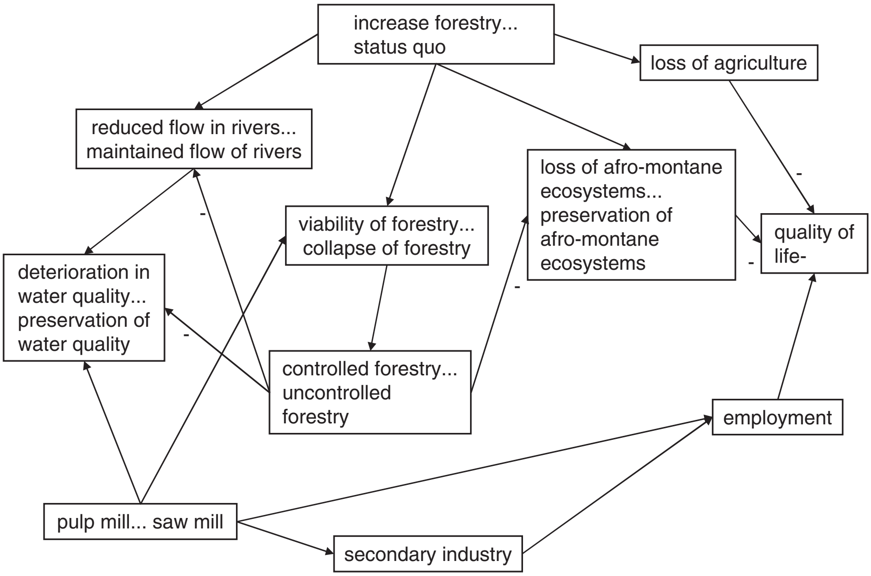

Fig. 7.2 An example of cognitive map for a problem of allocating land to exotic forest plantations (Modified from Belton and Stewart 2002)

3. Analysis for key issues
4. Refinement of issues
5. A workshop focusing on awareness
6. A workshop focusing on orientation
7. A workshop focusing on action portfolios

In the initial interview, participants express their view of the problem situation, and the facilitator or consultant aims at capturing the ideas on the map. In the second phase, the facilitator goes through the map with the participant, either exploring the goals and then working gradually down to the options, or exploring the options and then gradually working up to the goals. The idea is to make sure the map really expresses the view of that participant.

In phase three, the individual maps are first merged. This group map contains all the concepts of each member of the group, but in the group map they can be seen in the context of all other ideas (Eden 1990). Then, the key issues are identified with formal research. First, clusters of material that are closely linked to each others are searched for. Each cluster represents a problem within which there are problem-related goals and strategic options (Eden and Ackermann 2001). The clusters are re-arranged so that the goals are at the head of the cluster, and options in the tail of the cluster (Fig. 7.3). The clusters are linked to other clusters so that goals of one cluster lead to options of another, and options of one problem are consequences of a sub-ordinate problem. The issues best describing each cluster are the key issues. In phase four the resulting model is further refined, using interviews with experts. It means that issues missing are searched for, or orphan issues are included to the

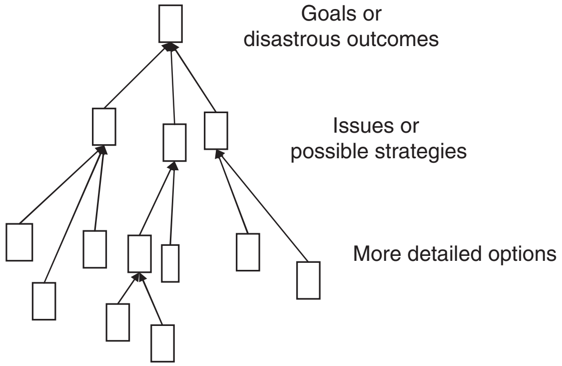

Fig. 7.3 A cluster rearranged as a 'tear-drop' (Modified from Ackermann and Eden 2001)

groups and so on. In phases from five to seven, it is used as a device facilitating negotiations within the group.

The cognitive map resulting from merging can be analysed using concepts such as domain, centrality and criticality (Eden and Ackermann 1998; see also Mendoza and Prabhu 2003). The idea is that these concepts help in finding important items from the maps.

Domain reflects the number of items linked to a particular item, irrespective of the causal directions (direction of the arrows). High domain values indicate a large number of items directly affecting or affected by this particular item. In Fig. 7.2, item pulp mill … saw mill has fairly high domain with four connections, and loss of agriculture fairly low with two connections.

Centrality reflects not only the direct impacts of an item to other items, but also the indirect impacts, through indirect connections to other items downstream the impact chains. The central score can be calculated as

$$C_i = \frac{S_1}{1} + \frac{S_2}{2} + \ldots + \frac{S_n}{n} \tag{7.1}$$

where S_j describes the j-level connections and n is the number of connections considered. The contribution of direct connections (S_1) is higher than that of the connections further away. In Fig. 7.2, loss of agriculture has two direct connections, four second-level connections thus its central score with $n = 2$ would be four.

Criticality reflects the number of critical items linked to a particular item, where the critical items are defined by the decision makers. It can be calculated how many critical items affect a particular item, and how many items are affected by it. The former is related to the number of different paths to a particular item and the latter is related to the number of paths from it. For calculating the criticality of an item, all paths to it or from it are counted, and the critical items in these paths are summed.

For instance, in Fig. 7.2 there is a path from increase forestry…status quo to quality of life either through loss of agriculture or through loss of afro-montane ecosystems … preservation of ecosystems. If employment is a critical factor, it is in two backward paths from quality of life, and respectively in two forward paths

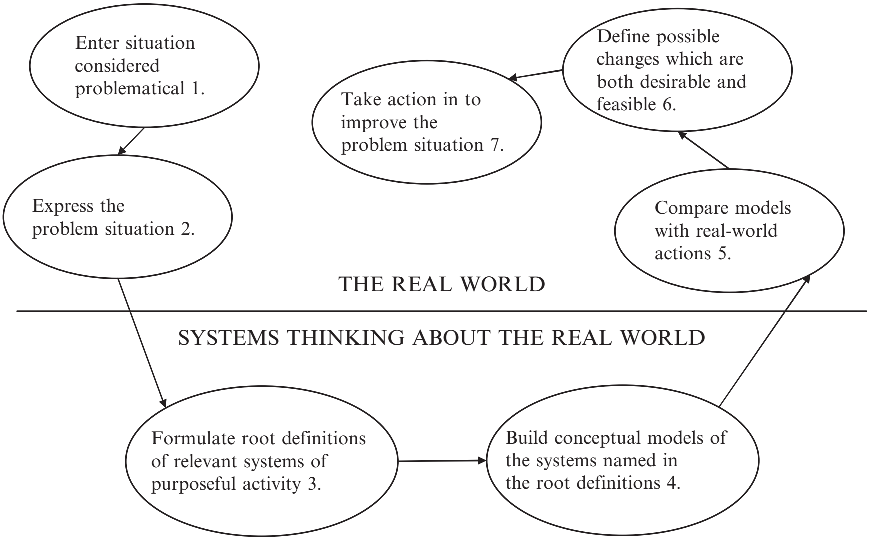

Fig. 7.4 The 7-stage representation of soft systems methodology (Modified from Checkland 2001)

from pulp mill . . . saw mill. For a more detailed example, see Mendoza and Prabhu (2003).

7.4.3 Soft Systems Methodology

Soft Systems Methodology (SSM) is a learning system that is developed to aid a system redesign. It is assumed that in any 'human activity system', i.e. in a system of people making decisions and taking actions, each person have their own way of thinking about the problematic situation (Checkland 2001). This is called 'Weltanschauung' or world view. For instance, the people who from one perspective are declared as terrorists, from another perspective are seen as freedom fighters. The SSM in its original form consists of seven stages (Fig. 7.4). These stages, however, need not to be rigidly followed and can be used more or less as an aid in the learning process.

In stages 1 and 2, the participants are supposed to find out what the problem is and express it. In the first versions of SSM the finding out was carried out with so-called 'rich pictures' (e.g. Khisty 1995). In the rich pictures, the participants are supposed to represent important relationships (e.g. between the citizens and city administration) and problem issues related to them (e.g. how can citizen impact the city to improve the recreation possibilities) as pictures.

In the later versions this finding out process was carried out with so-called analyses 1, 2 and 3 (Checkland 2001). In the first analysis the actors who have interest in the situation or could be affected by it are identified. In the second analysis it is analyzed what social roles are significant in the situation, what norms of behaviour are expected from role holders and what values are used to judge the role holders' behaviour, i.e. the culture of the social system. In the third analysis the situation is examined politically, by asking questions about the disposition of power. Thus, the method has also evolved in time (Checkland 1999).

The third stage is carried out by naming relevant systems for carrying out purposeful activity. Term 'relevant' here means that the system described is thought to help in exploring the problem situation. The system is analysed using the so-called CATWOE elements (Checkland 1985):

C 'customers'	Who would be victims or beneficiaries of this system were it to exist?
A 'actors'	Who would carry out the activities of this system?
T 'transformations'	What input is transformed into what output by this system?
W 'world view'	What image of the world makes this system meaningful?
O 'owner'	Who could abolish this system?
E 'environmental constraints'	What external constraints does this system take as given?

These questions are used to define the so-called 'root definitions' of the system. A different root definition is needed for each perspective. Examples of root definitions can be found, e.g. in Khisty (1995).

Example 7.1. A hypothetical example of root definition for a situation where citizen of a city would like to create a recreation area from a forested area could be as follows:

C Citizen of the city
A Committee chosen from among the citizen
T Transforming the forest area to a recreation area
W Improved recreation possibilities improve the well-being of all residents
O Committee chosen from among the citizen
E Budget constraints

From the city point of view the situation could be seen as a possibility to engage the citizen in the administration:

C City council members
A City staff
T Engaging the citizen more tightly to the city administration
W Improving the citizen activity would improve the mutual understanding and prevent conflicts
O The city council
E Time, staff and expertise

In the fourth stage, conceptual models (CM) of systems are built by participants using these root definitions as a basis. A different system is built for each relevant world view. Conceptual modelling of the system means assembling the verbs describing the activities that should be in the system named in the root definitions,

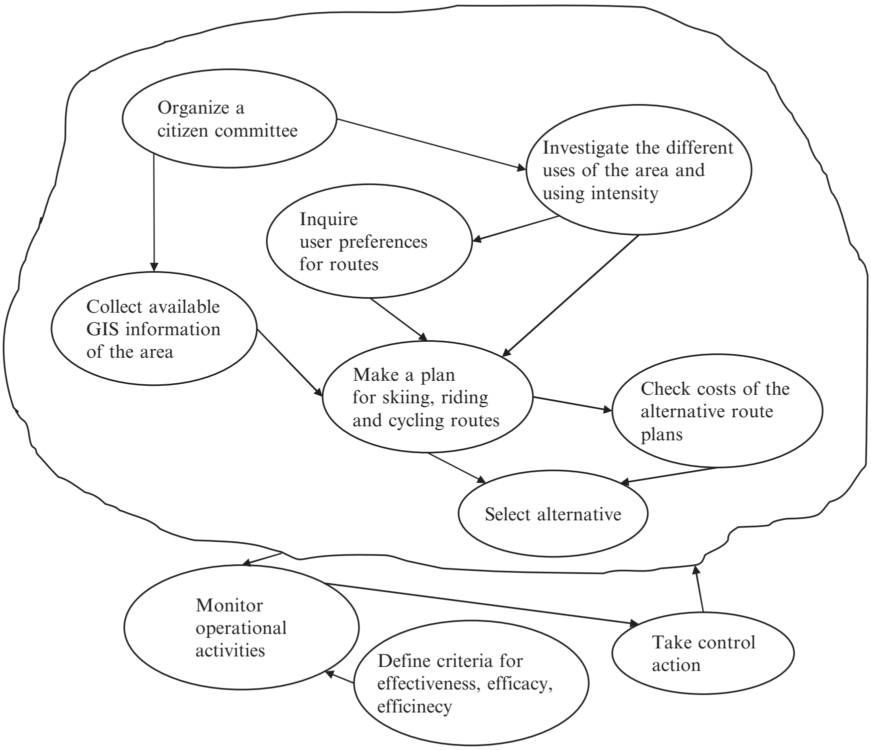

Fig. 7.5 A hypothetical example of a CM for creating a recreation area with facilities for different users

and structuring the verbs according to logical dependencies (Checkland 2001). For each system, also a sub-system for monitoring and controlling the system is added. It means defining criteria for effectiveness (is the proposed action the right thing to do), efficacy (do the selected means produce intended results) and efficiency (the ability to do the task without wasting resources) of the system.

The process is carried out in four steps (Checkland 1999):

1. Using verbs in imperative, write down the activities necessary to carry out T in CATWOE. Aim for 7 ± 2 activities.
2. Select activities which could be done at once.
3. Write those out on a line, then those dependent on these on line below, continue in this fashion until all activities are accounted for. Indicate the dependencies by arrows.
4. Redraw to avoid overlapping arrows where possible. Add monitoring and control.

In Fig. 7.5, a hypothetical example of a CM from citizen perspective for Example 7.1 is presented.

Then, the participants compare the real-world system with these ideal systems, and debate about the changes that are feasible and/or desirable, and the actions that need to be done (Fig. 7.4). The comparison is supposed to reveal the norms, standards and values among the participants. The idea is that when people compare the ideal models defined from different perspectives, their own way of perceiving the world also changes (Checkland 1989). Thus, they are supposed to learn from each others.

In example 7.2 a hypothetical example of the SSM methodology for improving a regional participation process is presented.

Example 7.2. by Teppo Hujala

Background: In Finland, forestry centres are statutory county-wide organisations, the duties of which include promoting sustainable forestry by means of law-enforcement, counselling of private forest owners and participating the development of regional forest-based economies.

Step 1: Problem definition

Problem: The Forestry Centre of "Deep Finland" (pseudonym) is claimed to have an inefficient impact on forestry sector's success and people's well-being in its region.

History: The Regional Forest Programme of Deep Finland, coordinated by the forestry centre, has been created in cooperation with regional forest council for period 2006–2010. The process gathered representatives of relevant interest parties to form a comprehensive strategic plan for forest-related issues. The plan is currently being implemented and monitored, and the new programme process will begin in 2009.

The owners: The development director of the forest centre (programme responsible), Secretary General of the National Forest Programme.

The actors: Members of the regional forest council (nominated by the Ministry of Agriculture and Forestry), decision-makers and employees of regional institutions related to forests, forest-related companies and entrepreneurs as well as forest owners in the region, researchers who act as consultants in the transformation process.

Internal need and pressure for change: Strategic objective of the forestry centre to achieve and strengthen the role as an acknowledged expert organisation which facilitates the sustainable success of the forest sector in Deep Finland Region.

External need and pressure for change: Societal needs for legitimacy and political pressures for more influential regional development and cost-effective activity. Diversified values of citizens. Agenda for following all-inclusively the National Forest Programme: "Sustainable welfare from diversified forests".

Step 2: Envisioning

What and where are we now? CATWOE

C = client/customer: Citizenry of the region in general, forest owners and people working within the forest-based sector in particular

A = actors: Members of the regional forest council

T = **transformation process**: A series of meetings where alternative futures are discussed and finally a suitable action strategy is agreed after.

W = **world view**: A constructive and collaborative planning process results in an outcome which is both desirable and feasible.

O = **owners**: The development director of the forest centre (programme responsible), Board of the forestry centre, Ministry of Agriculture and Forestry (Unit for Forestry Promotion), NGOs that were not invited for participation.

E = **environmental constraints**: Conflicting values, attitudes and interests among the participants, limited time resource for in-depth discussions, lack of information on which to base the decisions.

Core concept is formulated in the following form: The regional forest programme has been formulated through a participative process. However, the process has failed in reaching true collaboration, and thus, commitment to the plan is only partial. The decisions have been based on inadequate information on people's (citizens and stakeholders) perspectives. Additionally, the forestry centre lacks tools and money needed for monitoring and affecting the fulfilment of the plan.

Core vision: What do we want to be year 2012?: The Forestry Centre of Deep Finland administrates a comprehensive repertoire of tools for collaborative planning, which contributes to a constructive formulation of the forest programme, which is desirable and feasible. The programme process includes a monitoring system, with which the development actions can be adaptively modified. Thus, both the controllability and transparency of the programme have been improved, and the forestry centre is publicly regarded as an effective expert organisation for regional development.

Step 3: Analysis of the present and comparison with the vision

There seems to be a need for experimenting with different alternative collaboration methods, studying possible conflicting values regarding desirable participation methods, and most importantly, establishing a more thorough programme monitoring system.

The analysis of a subsystem: Programme monitoring system:

C = **client/customer**: The employees of the forest centre, members of the regional forest council.

A = **actors**: The same as above, as well as companies and entrepreneurs in the forest sector in the region, relevant public institutions providing statistics (e.g. municipalities, environment centre).

T = **transformation process**: Gathering relevant accumulative information flow into a special knowledge management system and deciding how to utilise the system in the meetings of the regional forest council.

W = **world view**: Statistics on activities in forest sector can be monitored in (almost) real time, and that will help the council to manoeuvre the developmental activities of the region.

O = **owners**: Companies or entrepreneurs not willing to join the information exchange scheme, employees of the forest centre who might not be ready for the change in working culture.

E = **environmental constraints**: Inflexibility of public agencies, incompatibility of information systems in different organisations, time schedule and functionality of national forest resource data system.

Core concept of the sub-system year 2006: The information needed in monitoring has been discussed in the meetings of the regional forest council.

Core vision of the sub-system year 2009: The requested information flow has been piloted and proven successful for contributing the council meetings.

Year 2012: The adaptive monitoring and management scheme is fully functioning as an essential part of the work of the regional forest council.

Analysis of the social system: Members of the current regional forest council are very interested in the new forms of participating the processes in forest sector, and they are a bit frustrated because of the slow progress of the project; the employees of forest centre possess some resistance for change, which brings some tension to the meetings: some consultancy to talk the issues through is needed

Analysis of the political system: The ministry pushes strongly to get the new up-to-date national forest resource data system work: along with new monitoring-based methods for acquiring and distributing money the forestry centre has to overcome its resistance as well as the doubts of losing power with allowing more open collaborating methods. Simultaneously, the forest programme is becoming a more legitimate tool for promoting regional economy among the public.

Step 4: Mission, i.e. changing the situation towards the direction stated in the core vision

Next Step 1: The regional forest council establishes a project for enhancing the process of composing and monitoring the regional forest programme.

Next Step 2: Decision-support researchers study the possible conflicting values regarding the desirable participation schemes.

Next Step 3: In the light of the study results, the researchers and the council jointly experiment with different alternative methods for collaborative planning (e.g. interactive utility analysis).

Next Step 4: Based on the experiences and the feedback of the experiments, guidelines for applying alternative collaboration approaches and methods in regional forest programme process are formulated.

Next Step 5: The enhanced programme process with guidelines, knowledge of values, and monitoring system is mobilised. The legitimacy and efficiency of the process increases, and the forest centre reaches the targeted reputation.

7.5 Decision Support for Group Decision Making

Decision analysis methods are often useful in a group decision making or participatory planning context. They force all the decision makers to systematically discuss all the important issues. Without a systematic analysis, it could be that some issues are addressed several times while other issues are not covered at all. It may be that people have already made their minds, and rather than learning from each other, the pros or favoured alternatives and cons of competing alternatives are repeated over and over again (Dyer and Forman 1992). Decision analysis methods are usually considered as most useful in fairly small groups.

There are two basic possibilities in using MCDS methodology in group decision making: (1) to do a combined analysis for all decision makers at the same time or (2) to do separate decision analyses for all decision makers and then either combine them to obtain priorities of the group, or use them as a basis for negotiation.

Combined decision analysis means that only one analysis is carried out, and it is supposed to capture the preferences of the group as a whole. In principle, for a combined analysis the group should have a consensus on every parameter needed in the analysis, in order to produce meaningful results. Decision makers should have, for instance, basically similar objectives.

In AHP, combined analysis means that each pairwise comparison should be made as a group. If a consensus cannot be reached, a good compromise is required. In such a case the individual pairwise judgments can be combined using a geometric mean of the pairwise comparisons to form one compromise value (Dyer and Forman 1992). A geometric mean is used instead of arithmetic mean to preserve the reciprocal property of the pairwise comparisons matrix (Aczel and Saaty 1983).

In other MCDS methods the group can, for example, vote to find the appropriate judgment. This kind of analysis is possible with any other MCDS method besides AHP, for instance with any of the outranking methods or multicriteria approval method.

The problem with the combined approach is that it is not possible to show the effect of each individual in the group on the analysis. It makes it easy for dominating participants to manipulate the results to their liking. Furthermore, the compromise value obtained by geometric mean or voting may not describe the preferences of any of the participants. On the other hand, it is possible that decision makers commit themselves more readily to a plan made together.

When the analyses are made separately for each decision maker in a group, it is possible to explicitly take each decision makers' preferences into account. If the separate analyses are combined, it is possible to show explicitly the effect each member has on the final result. For instance, the correlations between the result with and without one decision maker can be analysed (e.g. Vainikainen et al. 2008). Moreover, even if the analyses were not combined at all, learning more about the other participants' preferences might in itself help in building consensus.

One possibility for doing separate analyses for different decision makers is to calculate the mean of priorities (e.g. Forman and Peniwati 1998). This approach is possible for all decision analysis methods that provide global priorities for the alternatives. Such methods are, for instance SMART and AHP. Instead, methods such as outranking cannot be used this way. In a separate analysis, the decision models need not to be the same for all decision makers. For instance, each decision maker can include criteria that the other DMs do not consider as important.

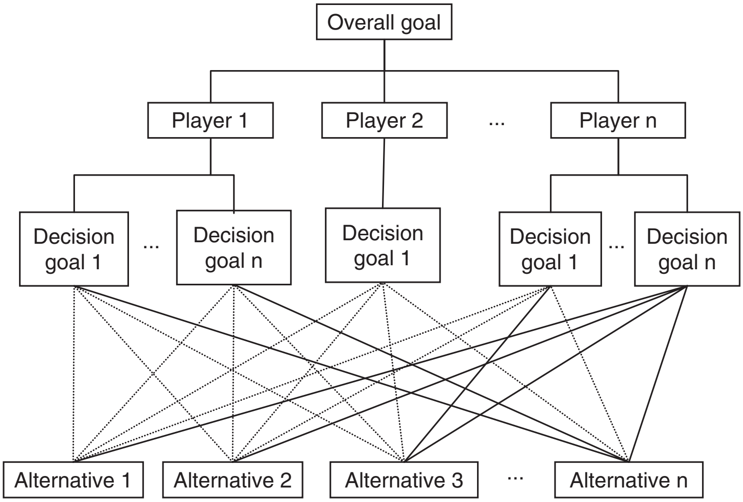

Fig. 7.6 AHP hierarchy including player level

Another way to make separate analyses is to include a separate player level to the analysis (Fig. 7.6). Then, the decision makers are included as one level in the decision hierarchy. Each decision maker can also in this case have his/her own decision model. Then, the players can also have different weights in the analysis, with respect to the size of the group they represent or years of experience on the matters handled or so on. If all the players have equal weights, the results of the player-level aggregation and mean of DMs' priorities are also equal. If the players have varying weights, a weighted mean of the priorities would produce the same results. Thus, the choice between these approaches is basically a matter of convenience. The selection of weights for the groups is, by no means, self-evident. Therefore, doing separate analyses for each group and using them as basis of negotiation may be a good option.

The use of MCDS methods can also be combined to a more general participatory planning context. The outline for such a situation using AHP is given by Kangas et al. (2001). The outline (slightly modified) is as follows:

(i) Description of the planning situation.
Preliminary identification of the relevant actors, interests, interested parties and institutions.
(ii) Detailed identification of the planning problem.
Starting an open participation process with traditional participation means and information gathering channels. Organising the first open meeting. Agreement on the need for the planning process with the public. Reproduction of problem images as stated by different actors and interested parties. Agreeing upon the rules to be followed if no compromise could be gained in the process.
(iii) General formulation of the problem
Explaining how the decision making process is intended to be carried out in the preliminary stage, and gaining commitment for the approach; modifying

the approach if necessary. Forming a planning group. The planning group might include a professional planner, representatives of interested parties, and other individuals. The tasks of the group include working as a link between all the interests and the organisation responsible of planning, taking part in the planning work on a voluntary basis, and controlling the process.

(iv) Creating decision models.
Each interest within the planning group creates its own decision model with AHP together with planners. The planner would help to analyse how the different objectives can be integrated or are in conflict with another. The planner together with the members or representatives of the interest parties can form an optimal solution from their point of view. Planning calculations are performed for each interest. As background information on the planning problem, calculations on the area's production possibilities as well as conventional cost-benefit analyses are presented to the participants. All the other information gained through the participatory process so far is analysed, too, especially that of qualitative nature. If found appropriate, the decision models are also derived representing that information mass.

(v) The planning group tries to negotiate a solution.
The planner's duty is to present possible compromise solutions and conduct the negotiations. Planning calculations and their results are interpreted, justified, and applied as background information in the negotiation process. New calculations, if necessary, are carried out interactively. AHP calculations are made using their multi-party options with differing weights of the participants so that participants can see the effects of different weighting schemes. Assessments are made on how well each interest's concerns are addressed in alternative solutions, and holistic evaluations and conditional conclusions are carried out. Especially those activities and goals, and their combinations, are carefully considered, which could not be included in the AHP calculations.

(vi) Presenting the results of the working group.
The results are presented in an open meeting and in different participation channels (such as newspapers, internet, open houses). Gaining feedback from the public. Also, alternative solutions with probable consequences might be presented to the public, especially if no initial consensus has been gained in (v). If a general agreement is achieved, proceed to the next phase. Otherwise, return to phase (v).

(vii) The planning group agrees on the follow-up procedure.
The planner writes a report including conclusions about the standpoints of every interest party. The plan is presented widely for the public.

(viii) Control of the actual implementation of the chosen plan, as agreed upon in (vii).
Assessing the need for continuous planning procedures according to principles of adaptive planning. Assessing the need for new planning processes.

Example 7.3. Assume three decision makers who have given their preferences with respect to net incomes (Example 3.5) using pairwise comparisons. The comparisons

Table 7.2 Preferences of the three DM with respect to net incomes

	NAT	SCEN	NORM	GAME	MREG	INC
(a)						
NAT	1	0.25	0.5	0.5	0.143	0.111
SCEN	4	1	2	2	0.333	0.2
NORM	2	0.5	1	1	0.25	0.143
GAME	2	0.5	1	1	0.2	0.143
MREG	7	3	4	5	1	0.5
INC	9	5	7	7	2	1
(b)						
NAT	1	0.5	1	1	0.333	0.25
SCEN	2	1	2	2	0.333	0.25
NORM	1	0.5	1	1	0.25	0.333
GAME	1	0.5	1	1	0.25	0.333
MREG	3	3	4	4	1	0.5
INC	4	4	3	3	2	1
(c)						
NAT	1	2	3	3	0.333	0.25
SCEN	0.5	1	2	2	0.333	0.2
NORM	0.333	0.5	1	1	0.25	0.2
GAME	0.333	0.5	1	1	0.2	0.2
MREG	3	3	4	5	1	0.5
INC	4	5	5	5	2	1

Table 7.3 Aggregate preferences

	NAT	SCEN	NORM	GAME	MREG	INC
NAT	1	0.630	1.145	1.145	0.251	0.191
SCEN	1.587	1	2	2	0.333	0.215
NORM	0.874	0.5	1	1	0.25	0.212
GAME	0.874	0.5	1	1	0.215	0.212
MREG	3.979	3	4	4.642	1	0.5
INC	5.241	4.642	4.718	4.718	2	1

Table 7.4 Priorities of the three decision makers, the arithmetic mean of them and the priorities based on the aggregate preferences

	DM 1	DM 2	DM 3	Mean priority	Aggregate priority
NAT	0.036	0.076	0.135	0.082	0.071
SCEN	0.113	0.126	0.088	0.109	0.11
NORM	0.064	0.077	0.056	0.066	0.067
GAME	0.061	0.079	0.054	0.065	0.066
MREG	0.272	0.279	0.265	0.272	0.276
INC	0.455	0.363	0.402	0.407	0.41

are presented in Tables 7.2a–c. The single preferences were combined at the level of single comparisons using the geometric mean (Table 7.3). Then, the aggregate preferences were used to calculate the aggregate priorities (Table 7.4). For comparison, the priorities of the single decision makers were also calculated from the preferences in Table 7.2 and their arithmetic mean was calculated. The obtained combined priorities from these two cases are almost identical, the difference being due to rounding.

References

Ackermann, F. and Eden, C. 1994. Issues in computer and non-computer supported GDSSs. Decision Support Systems 12: 381–390.

Ackermann, F. and Eden, C. 2001. SODA – Journey making and mapping in practice. In: Rosenhead, J. and Mingers, J. (Eds.). Rational analysis for problematic world revisited., Wiley, Chichester, pp. 43–60.

Aczel, J. and Saaty, T.L. 1983. Procedures for synthesizing ratio judgments. Journal of mathematical Psychology 27: 93–102.

Arnstein, S. 1969. A ladder of citizen participation. Journal of American Institute Planners 35: 216–224.

Belton, V. and Stewart T.J. 2002. Multiple criteria decision analysis: an integrated approach. Kluwer, Dordrecht.

Bleiker and Bleiker, H. 1995. Public participation handbook for officials and other professionals serving the public. 9th edn. Institute for participatory management and planning, Monterey, CA.

Brockner, J. and Siegel, P. 1996. Understanding the interaction between procedural and distributive justice: The role of trust. In: Kramer, R.M. and Tyler, T.R. (Eds.). Trust in organizations: frontiers of theory and research, Sage, Thousand Oaks, CA, pp. 390–413.

Buchy, M. and Hoverman, S. 2000. Understanding public participation in forest planning: a review. Forest Policy and Economics 1: 15–25.

Checkland, P. 1981. Systems thinking, systems practice. Wiley, Chichester.

Checkland, P. 1999. Soft systems methodology: a 30-year retrospective. In: Checkland, P. (Ed.). Systems thinking, systems practice. Wiley, Chichester.

Checkland, P. 1985. From optimizing to learning: a development of systems thinking for the 1990s. Journal of Operations Research Society 36: 757–767.

Checkland, P. 1989. Soft systems methodology. In: Rosenhead, J. (Ed.). Rational analysis for problematic world. Wiley, Chichester.

Checkland, P. 2001. Soft systems methodology. In: Rosenhead, J. and Mingers, J. (Eds.). Rational analysis for problematic world revisited. Wiley, Chichester, pp. 61–90.

Chess, C. and Purcell, K. 1999. Public participation and the environment: do we know what works? Environmental Science and Technology 33: 2685–2692.

Daniels, S.E. and Walker, G.B. 1996. Collaborative learning: improving public deliberation in ecosystem-based management. Environmental Impact Assessment Review 16: 71–102.

Dyer, R.F. and Forman, E.H. 1992. Group decision support with the analytic hierarchy process. Decision Support Systems 8: 99–124.

Eden, C. 1988. Cognitive mapping. European Journal of Operational Research 36: 35–43.

Eden, C. 1989. Using cognitive mapping for strategic options analysis (SODA). In: Rosenhead, J. (Ed.). Rational analysis for problematic world. Wiley, Chichester.

Eden, C. 1990. Strategic thinking with computers. Long Range Planning 23: 35–43.

Eden, C. and Ackermann, F. 1998. Making strategy: the journey of strategic management. Sage, Thousand Oaks, CA.

Eden, C. and Ackermann, F. 2001. SODA – The principles. In: Rosenhead, J. and Mingers, J. (Eds.). Rational analysis for problematic world revisited. Wiley, Chichester, pp. 21–42.
Eden, C. and Simpson, P. 1989. SODA and cognitive mapping in practise. In: Rosenhead, J. (Ed.). Rational analysis for problematic world. Wiley, Chichester.
English, M., Gibson, A., Feldman, D., and Tonn, B. 1993. Stakeholder involvement: open process for reaching decisions about future uses of contaminated sites. Final Report to the US Department of Energy. Waste management Research and Education Institute, University of Tennessee, Knoxville.
Environmental Resources Management (ERM) 1995. Manual on public participation for investors in Central and Eastern Europe and the Former Soviet Union. Final report to the European Bank for Reconstruction and Development. Environmental Resources Management, London.
Forman, E. and Peniwati, K. 1998. Aggregating individual judgments and priorities with the analytic hierarchy process. European Journal of Operational Research 108: 165–169.
Freeman, R.E. 1984. Strategic management: A stakeholder approach. Pitman, Boston, MA.
Garcia Pérez, J.D. and Groome, H. 2000. Spanish forestry planning dilemmas: technocracy and participation. Journal of Rural Studies 16: 485–496.
Germain, R.H., Floyd, D.W., and Stehman, S.V. 2001. Public perceptions of the USDA forest service public participation process. Forest Policy and Economics 3: 113–124.
Glass, J.J. 1979. Citizen participation in planning: the relationship between objectives and techniques. Journal of the American Planning Association 45: 180–189.
Heberlein, T.A. 1976. Some observations on alternative mechanisms for public involvement: the hearing, public opinion poll, the workshop and the quasi-experiment. Natural Resources Journal 16: 197–212.
Hellström, E. 1997. Environmental forest conflicts from a international comparative point of view. In Solberg, B. and Miina, M. (Eds.). Conflict management and public participation in land management. EFI Proceedings No. 14. European Forest Institute, Joensuu.
Hjortsø, N.C. 2004. Enhancing public participation in natural resource management using Soft OR – an application of strategic option development and analysis in tactical forest planning. European Journal of operational research 152: 667–683.
Hovland, C.I., Lumsdaine, A.A., and Sheffield, F.D. 1965. Experiences on mass communication. Wiley, New York.
Hytönen, L.A. 2000. Osallistamismenetelmät metsätalouden päätöksenteossa. Metsätieteen aikakauskirja 3/2000: 443–456.
Hytönen, L.A., Leskinen, P., and Store, R. 2002. A spatial approach to participatory planning in forestry decision making. Scandinavian Journal of Forest Research 17: 62–71.
International Labour Office 2000. Public participation in forestry in Europe and North America. Report of the FAO/ECE/ILO Joint Committee Team of Specialists on participation in Forestry. International Labour Office, Geneva.
Janse, G. and Konijnendijk, C.C. 2007. Communication between science, policy and citizens in public participation in urban forestry – experiences from the neighborwoods project. Urban Forestry and Urban Greening 6: 23–40.
Kangas, A., Haapakoski, R., and Tyrväinen, L. 2007. Integrating place-specific social values into forest planning – Case of UPM-Kymmene forests in Hyrynsalmi, Finland. Submitted manuscript.
Kangas, J. 1994. An approach to public participation in strategic forest management planning. Forest Ecology and Management 70: 75–88.
Kangas, J. and Store, R. 2003. Internet and teledemocracy in participatory planning of natural resource management. Landscape and Urban Planning 62: 89–101.
Kangas, J., Hytönen, L., and Loikkanen, T. 2001. Integrating the AHP and HERO into the process of participatory natural resources planning. In: Schmoldt, D., Kangas, J., Mendoza, G.A. and Pesonen, M. (Eds.). The analytic hierarchy process in natural resource and environmental decision making. Kluwer, Dordrecht, Managing Forest Ecosystems 3, pp. 187–197.
Kangas, J., Loikkanen, T., Pukkala, T., and Pykäläinen, J. 1996. A participatory approach to tactical forest planning. Acta Forestalia Fennica 251:24.

Kelly, G.A. 1955. The psychology of personal constructs. vol 1 and 2. Norton, New York.

Khisty, J. 1995. Soft systems methodology as learning and management tool. Journal of Urban Planning and Development 121: 91–107.

Lauber, B.T. and Knuth, B.A. 1998. Refining our vision of citizen participation: lessons from a moose reintroduction project. Society and Natural Resources 11: 411–424.

Lawrence, R.L. and Deagen, D.A. 2001. Choosing public participation methods for natural resources: a context-specific guide. Society and natural Resources 14: 857–872.

McCool, S.F. and Guthrie, K. 2001. Mapping the dimensions of successful public participation in messy natural resources management situation. Society and Natural Resources 14: 309–323.

McComas, K.A. and Scherer, C.W. 1999. Providing balanced risk information in surveys used as citizen participation mechanisms. Society and Natural Resources 12: 107–119.

McDaniels, T.L. and Thomas, K. 1999. Eliciting preferences for land use alternatives: a structured value referendum with approval voting. Journal of Policy Analysis and Management 18: 264–280.

Mendoza, G.A. and Prabhu, R. 2003. Qualitative multi-criteria approaches to assessing indicators of sustainable forest resource management. Forest Ecology and Management 174: 329–343.

Metsien suojelun osallistavat prosessit Suomessa. Sidosryhmien osallistuminen prosesseihin. 2006. Maa- ja metsätalousministeriön raportteja, 50 pp.

Mingers, J. and Rosenhead, J. 2004. Problem structuring methods in action. European Journal of Operational Research 152: 530–554.

O'Riordan, J. 1976. The public involvement program in the Okangan basin study. Utton, A.E., Sewell, W.R.D., and O'Riordan, T. Natural resources for a democratic society: public participation in decision-making. Westview, Boulder, CO.

Primmer, E. and Kyllönen, S. 2006. Goals for public participation implied by sustainable development, and the preparatory process of the Finnish National Forest Programme. Forest Policy and Economics 8: 838–853.

Pykäläinen, J., Kangas, J., and Loikkanen, T. 1999. Interactive decision analysis in participatory strategic forest planning: experiences from state owned boreal forests. Journal of Forest Economics 5: 341–364.

Riedel, J.A. 1972. Citizen participation: myths and realities. Public Administration Review 32: 211–220.

Rosenhead, J. (Ed.) 1989. Rational analysis for problematic world. Wiley, Chichester.

Satterfield, T. and Gregory, R. 1998. Reconciling environmental values and pragmatic choices. Society and Natural Resources 11: 629–647.

Sipilä, M. and Tyrväinen, L. 2005. Evaluation of collaborative urban forest planning in Helsinki, Finland. Urban Forestry and Urban Greening 4: 1–12.

Smith, P.D. and McDonough, M.H. 2001. Beyond public participation: fairness in natural resource decision making. Society and Natural Resources 14: 239–249.

Susskind, L. and Cruishank, J. 1987. Breaking the impasse: consensual approaches to resolving public disputes. Basic Books, New York.

Tikkanen, J. 1996. Taajametsien osallistava suunnittelu. Kokemuksia MetsäRaahe–suunnitteluprojektista. Metsäntutkimuslaitoksen tiedonantoja, 603.

Tikkanen, J. 2003. Alueellisen metsäohjelmatyön osallistamismenettely Pohjois-Suomen metsäkeskuksissa vuosina 1997–1998 ja 2000–2001. Metsätieteen aikakauskirja 3/2003: 321–344.

Tikkanen, J., Isokääntä, T., Pykäläinen, J., and Leskinen, P. 2006. Applying cognitive mapping approach to explore the objective structure of forest owners in a Northern Finnish case area. Forest Policy and Economics 9: 139–152.

Tippett, J., Handley, J.F., and Ravetz, J. 2007. Meeting the challenges of sustainable development – a conceptual appraisal of a new methodology for participatory ecological planning. Progress in Planning 67: 9–98.

Tuler, S. and Weber, T. 1999. Voices from the forest: what participants expect of a public participation process. Society and Natural Resources 12: 437–453.

Tyrväinen, L., Mäkinen, K., and Schipperijn, J. 2007. Tools for mapping social values of urban woodlands and other green areas. Landscape and Urban Planning.79: 5–19.
UNECE 1998. Convention on access to information, public participation in decision-making and access to justice in environmental matters. United Nations Economic Commission for Europe.
Vainikainen, N., Kangas, A., and Kangas, J. 2008. Empirical study on voting power in participatory forest planning. Forthcoming in Journal of Environmental Management.
Van den Bos, K. Lind, K.E.A., Vermunt, R., and Wilke, A.M. 1997. How do I judge my outcome when I do not know the outcome of others? The psychology of the fair process effect. Journal of Personality Social Psychology 72: 1034–1046.
Wallenius, P. 2001. Osallistava strateginen suunnittelu julkisten luonnonvarojen hoidossa. Metsähallituksen metsätalouden julkaisuja, 41.
Webler, T. 1997. Organizing public participation: a critical review of three handbooks. Human Ecology Review 3: 245–254.
Webler, T., Kastenholz, H., and Renn, O. 1995. Public participation in impact assessment: a social learning perspective. Environmental Impact assessment Review 15: 443–463.
Webler, T. and Tuler, S. 2001. Public participation in watershed management planning: views on process from people in the field. Human Ecology Review 8: 29–39.
Webler, T., Tuler, S., and Krueger, R. 2001. What is a good public participation process? Five perspectives from the public. Environmental Management 27: 435–450.
Vroom, V.H. and Yetton, P.W. 1973. Leadership and decision-making. University of Pittsburgh Press, Pittsburgh.
Vroom, V. and Jago, A. 1988. Managing participation in organizations. Prentice Hall, New Jersey, 239 pp.

Chapter 8
Voting Methods

8.1 Social Choice Theory

8.1.1 Outline

The basic task of social choice is to combine individual preferences into a collective choice. When individual utility functions are combined, the aggregation could be interpreted as a social welfare function (Martin et al. 1996). Social welfare can be interpreted to include monetary terms such as commodity consumption as well as other values such as collective activities, resource distribution, equity of generations, quality of life etc. (Arrow 1951). Sustainable forest management can be seen as maximizing the social welfare obtainable from the forests (Kant and Lee 2004).

The social choice situation can be described with four components or parts:

Voters or players
Choice alternatives
The information of voters' preferences over the alternatives
An aggregation device (voting model, voting procedure or voting method)

Throughout the history of democracy, voting has proved to be an efficient tool for making choices among decision alternatives, e.g. in different kinds of elections. It is also, in one form or another, known to everybody. It means that voting is also a reasonable approach for forest planning when multiple decision makers are involved (e.g. Kangas et al. 2006a).

In the voting theory, special attention has been paid to systems that are neutral and difficult to manipulate, although it can be shown that any non-dictatorial voting scheme is subject to manipulation (Gibbard 1973; Satterthwaite 1975). However, some methods require more information to manipulate an election than others (Nurmi 1987).

8.1.2 Evaluation Criteria for Voting Systems

There are several properties that are assumed to be reasonable requirements of a voting system (e.g. Martin et al. 1996; Bouyssou et al. 2000). These include:

- Unrestricted domain or universality: the preferences are not constrained and the system should be able to produce a definite result with all possible sets of preferences
- Non-dictatorship: no one person can dictate the result
- Non-imposition or citizen sovereignty: it should be possible to select any of the candidates with some preferences
- Monotonicity: if the relative rating of the other candidates does not change, voting a candidate higher should never lower the candidate in resulting ordering, nor should voting a candidate lower raise a candidate in the ordering
- Independence from irrelevant alternatives: the ranking of two candidates, x and y, should only depend on the ranking of x and y, and not on some other alternatives

It has been shown that there is no (deterministic) method of aggregating individual preferences over three or more alternatives that would satisfy these conditions for fairness and always produce a logical result (Arrow 1951). One of these requirements, monotonicity, can also be replaced by

- Unanimity (Pareto efficiency): if all voters prefer x to y, y should not be chosen.

Often at least one of the Arrow's conditions may be irrelevant (Kant and Lee 2004). Therefore, a suitable method can probably be found for most problems. In all, voting theory can be seen as a credible alternative in group decision making and participatory planning. However, it is not suitable to all problems: for instance, problems involving distribution of resources need to be solved with other methods (Sen 1997).

In addition to these requirements, many others have been set to voting systems. Among others, these include

- Consistency: if the voters in two arbitrary groups in separate elections select the same candidate, the result should not change if the groups are combined.
- Neutrality: the system itself does not promote any alternative. The rules in the case of ties, however, may violate this rule.
- Anonymity: the voter's name does not affect.

For a complete list of requirements, the readers are referred to Cranor (1996).

8.2 Positional Voting Schemes

8.2.1 Plurality Voting

Many voting systems have a lot to do with the utility theory. The most common of these, plurality voting (also called as first-past-the-post), takes into account the preference ordering of the voters, albeit only with respect to the best candidate. A major drawback of this method is that it is generally considered to be very easy to manipulate. It is often worthwhile for a voter to vote for some other alternative than the best choice, for instance, in order to avoid the worst choice.

The Block vote is the most common extension of the plurality to multi-seat elections (Reynolds and Reilly 1997). The voter must vote for the number of the candidates as to be elected, giving one vote to each. Majority voting is similar to plurality voting, except that the winning candidate must receive more than 50% of the votes. Plurality voting satisfies the monotonicity criterion.

Example 8.1. Assume 21 voters and three candidates, a, b and c. The preference orders of the voters are

– Ten voters has a preference order a > b > c
– Six voters has a preference order b > c > a
– Five voters has a preference order c > b > a

Thus, in plurality voting a has ten votes and wins the election. Yet, majority of voters, 11, thinks that candidate a is the worst possible selection.

8.2.2 Approval Voting

The approval voting method was independently proposed by several people in the 1970s (Brams and Fishburn 1983). It is a voting procedure in which each voter votes for as many candidates as she/he wishes. In other words, the voter votes for all candidates of whom she/he "approves". Each candidate approved by the voter receives one vote. The candidate receiving the greatest total number of votes is declared to be the winner.

This method is harder to manipulate by any one voter than plurality voting (Niemi 1984). This is because it requires information about the distribution of approvals of the alternatives in order to be manipulated (Nurmi 1987). Usually it is, however, a good strategy to vote sincerely. It can be shown that the optimal strategy in approval voting is to vote for all candidates that are better than average (e.g. Kim and Roush 1980). One drawback in approval voting is that it tends to promote moderate candidates, or candidates that no one has ranked to the last places. This voting system is also monotonic.

The approval voting is argued to be the best voting system, provided that the real preferences of voters are dichotomous (i.e. candidates are either approved or disapproved, Yilmaz 1999). This might not be the case except occasionally. Trichotomous or multichotomous preferences can, however, also be applied in modified voting schemes. For example, Yilmaz (1999) proposed a system where voters classify the candidates in three classes: Favourite, Acceptable and Disapproved. Then, the candidates are compared pairwisely so that a candidate scores a vote whenever it is ranked higher than the pair. It means that a favourite scores a point against acceptable and disapproved, while acceptable only scores a point against disapproved candidates. If one candidate has a majority against all others, it is chosen. Otherwise, the candidate with most disapproval votes is eliminated and the procedure is applied again until the winner can be found. Felsenthal (1989), on the other hand, proposed a method where voters can approve a candidate, disapprove it or abstain from voting.

Example 8.2. Assume the same 21 voters and three candidates, a, b and c as in example 8.1. The preference orders of the voters are also the same as above,

– Ten voters has a preference order a > b > c
– Six voters has a preference order b > c > a
– Five voters has a preference order c > b > a

Now, the result depends on how many candidates each voter approves. If each voter approves only the best alternative, candidate a wins, similarly as in plurality voting. If all voters approve the two best alternatives, a gets 10 votes, b gets 21 votes and c 11 votes. In this case, b wins. If only those preferring c vote approve also the second best candidate, b gets 11 votes and wins.

8.2.3 Borda Count

The Borda count, originally introduced by de Borda (l78l) takes into account the whole preference ordering: given n candidates, each voter casts n votes for the most preferred candidate, $n-1$ votes for the second most preferred one and finally 1 vote for the least preferred candidate (e.g. Saari 1994). Equivalent results can be obtained by giving $n-1$ votes for the preferred, $n-2$ for the second most preferred and finally 0 for the least preferred alternative. The winner is the candidate getting the most votes. It has been proved, among others by **?** (**?**), that the Borda count chooses the alternative which, on average, stands highest in the voters' preference orderings.

The problem with this method is that the result may be a function of the number of candidates (Riker 1982). The Borda count also fails to satisfy the independence of irrelevant alternatives criterion. This method has also been criticised because of its susceptibility to manipulation. The method can be manipulated, for example, by including irrelevant alternatives or by altering the preference ordering. However, it is more difficult to manipulate than many other methods: the voters would need to know the other voters' Borda scores before the voting in order to manipulate it (Nurmi 1987; Mueller 1989). Like other positional voting systems, Borda count is monotonic.

Also truncated forms of Borda count have been presented. Truncation means that not all alternatives need to be given a score: only the top set of the alternatives is given a score while the rest of the alternatives score zero points (Saari and van Newnhizen 1988). Such an approach may seem tempting, especially if there are many alternatives to be considered. However, this approach may give different results depending on how the ranking is truncated, although the preferences of the voters remain the same. It means that given three candidates, for example, any one of them can be elected, depending on whether only the best, the best two or all candidates are ranked. The same problem, however, applies to approval voting: the result depends on how many of the best alternatives are approved (Saari and van Newnhizen 1988).

Example 8.3. Assume the same 21 voters and three candidates, a, b and c as in example 8.1. The preference orders of the voters are also the same as above,

- Ten voters has a preference order a > b > c
- Six voters has a preference order b > c > a
- Five voters has a preference order c > b > a

In this case, the candidates get votes as

- A: $10 \cdot 2 + 6 \cdot 0 + 5 \cdot 0 = 20$
- B: $10 \cdot 1 + 6 \cdot 2 + 5 \cdot 1 = 27$
- C: $10 \cdot 0 + 6 \cdot 1 + 5 \cdot 2 = 16$

In this case, candidate b wins.

8.3 Pairwise Voting

Any voting system which chooses the Condorcet winner when it exists is known as a Condorcet method (Condorcet 1785). In this method, each voter ranks all candidates in order of preference. Candidates are then paired and compared in turn with each of the other candidates. The vote counting procedure then takes into account each preference of each voter for one candidate over another. The Condorcet winner is a choice which obtains a majority of votes against any other alternative in pairwise elections. The Condorcet winner does not always exist, but if it does, it can be found using Copeland rule or Simpson rule. Condorcet's method is said to eliminate the need for strategic voting.

Copeland's method is a variant of the Condorcet method in which the candidates are ranked on the basis of the pairwise victories (Copeland 1951). This method belongs to majoritarian procedures. Pairwise victories, defeats and ties are counted for each candidate, alternative a scores $+1$ points if a majority of voters prefers it to some other alternative b, and -1 if majority of voters prefer b to a. Sum of these scores gives the Copeland score and the candidate with the largest score is declared the winner. This method often leads to many ties.

In Simpson's voting rule, the number of voters preferring a to b, $N(a, b)$, is counted over all b distinct from a (Simpson 1969). The Simpson's score is the minimum of these values. Then, to win with Copeland score, an alternative must defeat all the other alternatives at least by a tiny marginal, but for winning with Simpson's rule it may be enough if any other alternative does not have a large majority against it.

Selecting the Condorcet winner is often perceived as an important property of the voting methods. The Condorcet criterion is, in fact, regarded as so important that voting schemes are evaluated with respect to how probable it is that the Condorcet winner is elected with the schemes if one exists. This probability is called the Condorcet efficiency (e.g. Gehrlein and Lepelley 2001). For example, neither plurality voting nor approval voting nor Borda count always chooses Condorcet winner. Except for Borda count, they even can choose the Condorcet loser, i.e. the alternative that loses to all the other alternatives in pairwise voting. However, Borda count is the most likely method to choose the Condorcet winner, when the number of alternatives is large (Mueller 1989). On the other hand, Condorcet criterion is also criticized, since it does not note the differences in the pairwise votes, i.e. preference intensities (Heckelman 2003).

Example 8.4. Assume the same 21 voters and three candidates, a, b and c as in example 8.1. The preference orders of the voters are also the same as above,

– Ten voters has a preference order a $>$ b $>$ c
– Six voters has a preference order b $>$ c $>$ a
– Five voters has a preference order c $>$ b $>$ a

The preferences of voters can be presented as a matrix giving the number of voters preferring row alternative to column alternative, i.e. the pairwise votes

	a	b	c
a		10	10
b	11		16
c	11	5	

In this case, b gets the majority against both a (11 votes) and c (16 votes) and it wins. With Copeland criterion, the results are

	a	b	c
a		−1	−1
b	1		1
c	1	−1	

With this criterion, a has a score -2, b 2 and c 0, and candidate b is the winner also with this criterion.

Example 8.5. If three new voters are included in the example above, with preferences c $>$ a $>$ b, and the preferences are otherwise similar than above, the pairwise votes would be

	a	b	c
a		13	10
b	11		16
c	14	8	

which means that a majority of voters think that a > b (13 voters), c > a (14 voters) and that b > c (16 voters). Thus, the preferences of majority are not transitive. In this case, Condorcet winner does not exist. With Simpson's score, however, alternative b is chosen, since it loses to a only by two votes.

8.4 Fuzzy Voting

The voting schemes can also be formed using fuzzy set theory. In fuzzy voting systems the preference relations of the alternatives are assumed fuzzy (Kacprzyk et al. 1992; Nurmi 1996; García-Lapresta and Martínez-Panero 2002). The simplest example of fuzzy voting is the fuzzy approval voting. The classic approval voting can be formalized to a formula

$$r_i^k = \begin{cases} 1, \text{if alternative } x_i \text{ is approved by voter } k \\ 0, \text{otherwise,} \end{cases} \tag{8.1}$$

and then, the final vote for alternative i is

$$r(x_i) = \sum_{k=1}^{m} r_i^k, \tag{8.2}$$

where m is the number of voters. A fuzzy version of approval voting is obtained simply by defining the approval of the alternatives $r_i^k \in [0,1]$, i.e. the degree of approval may vary from 0 to 1 (García-Lapresta and Martínez-Panero 2002). The final vote is achieved by summing the approvals of the alternatives i over voters k in a similar fashion as in classic approval voting.

The fuzzy approach can also be used for other voting schemes. For instance, the classic Borda Count voting can be formalized as a pairwise voting using a preference matrix R for each voter k as (García-Lapresta and Martínez-Panero 2002)

$$R_k = \begin{pmatrix} r_{11}^k & r_{12}^k & \cdots & r_{1n}^k \\ r_{21}^k & r_{22}^k & \cdots & r_{2n}^k \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1}^k & r_{n2}^k & \cdots & r_{nn}^k \end{pmatrix} \tag{8.3}$$

where n is the number of alternatives and

$$r_{ij}^k = \begin{cases} 1, \text{if alternative } x_i \text{ is preferred to alternative } x_j \text{ by voter } k \\ 0, \text{otherwise,} \end{cases} \tag{8.4}$$

Then, voter k gives alternative x_i score

$$r_k(x_i) = \sum_{j=1}^{n} r_{ij}^k \tag{8.5}$$

which equals the number of alternatives that are worse than alternative x_i. The final vote is obtained by summing the individual votes as

$$r(x_i) = \sum_{k=1}^{m} r_k(x_i) \tag{8.6}$$

The fuzzy relations can be defined, e.g., so that relation $r_{ij} = 0.5$ means that alternatives i and j are equally good, $r_{ij} = 0.0$ means that j is strictly preferred and $r_{ij} = 1.0$ means that i is strictly preferred to j. Values between 0.5 and 1.0 represent slight preference of i, values between 0.0 and 0.5 slight preference of j. Typically, a reciprocal property is assumed, giving $r_{ij} + r_{ji} = 1$. Furthermore, it is assumed that the preference relation of alternative i with itself is 0.5 (García-Lapresta and Martínez-Panero 2002). The fuzzy relation can also be defined so as to describe the certainty of the preference, not only the intensity of preference.

The vote of individual k for alternative x_i can be defined as the sum of preference intensities among the alternative and those worse than it as (García-Lapresta and Martínez-Panero 2002)

$$r_k(x_i) = \sum_{\substack{j=1 \\ r_{ij}^k > 0.5}}^{n} r_{ij}^k \tag{8.7}$$

The final vote is calculated similarly as in classic Borda. It would, however, be possible also to use other borderline than 0.5 for preference intensity.

The fuzzy approach gives more freedom to voters to give scores according to their real preferences. However, the greatest value of fuzzy voting schemes may be the fact that many of the famous results of voting theory, namely Arrow's impossibility theorem and the results of Gibbard and Satterthwaite can be done away (Nurmi et al. 1996). It means that by modifying the assumptions, it is possible to form aggregating rules that satisfy the Arrow's conditions. Another example of modified assumptions is the probability voting.

8.5 Probability Voting

In probability voting, the voters are asked to give the probabilities for voting any one candidate instead of strict preference relations. In probabilistic approval voting, on the other hand, the probability for approving any one candidate is required. These probabilities play the same role as the individual preference relations. They are to be interpreted so that the more likely an individual is to vote for a certain alternative, the more desirable that alternative is (Nurmi et al. 1996). The individual probabilities p_{ji} of individual j voting for alternative i can be aggregated to the probability of a group p_i simply by calculating the mean probability for alternative i among all the members of group. Even this simple voting scheme fulfils all the Arrow's conditions, but the results may be harder to interpret than in normal votes.

The actual decisions could even be calculated with a lottery. For instance, a probabilistic version of Borda count was presented by Heckelman (2003). In this system, a classic Borda count vote is first taken. However, the final decision is obtained by a lottery, where the probability of each alternative to win is its Borda score relative to the sum of all Borda points. In unique decision situations this might be a bit peculiar system (Nurmi et al. 1996). However, when a series of decisions is made, probability voting may give also a small interest group an influence which is in proportion to its size (Heckelman 2003).

8.6 Multicriteria Approval

8.6.1 Original Method

Fraser and Hauge (1998) presented an application of approval voting, called multicriteria approval (MA), which can be used in multicriteria decision making. Technically taken, in multicriteria approval the voters of social choice theory are substituted with multiple criteria. The standard version of MA has been developed for one decision maker, but if the decision makers can agree upon the importance order of the criteria and the border for approval for each criterion, the standard version suits also for group decision making.

Multicriteria approval method begins with the determination of the alternatives and the criteria. The criteria are ranked by their importance. The next step is to determine which of the alternatives will be approved for each criterion. Fraser and Hauge (1998) defined the border as the average evaluation of the alternatives with respect to the criterion considered. In other words, in maximization problems each alternative i, with respect to each criterion j, is approved if the criterion value is above average, and disapproved if otherwise. (in minimization problems, the direction is changed or the values are first multiplied by -1). With numerical criterion values $c_j(a_i)$, the border is the mean criterion value $\bar{c}_j = \sum_{i=1}^{m} \frac{c_j(a_i)}{m}$ of the m alternatives, with respect to each criterion j. This approval border is justified by the fact that according to approval voting theory, the optimal strategy for a voter is to vote for all the candidates that are above average (e.g. Kim and Roush 1980). When the criterion is evaluated in an ordinal scale, a middle rank has been used for approval (e.g. Laukkanen et al. 2002). The approval border could, however, be defined also in other ways.

There are five possible classes of voting results: unanimous, majority, ordinally dominant, deadlocked and indeterminate (Fig. 8.1). The voting result is Unanimous if one alternative has been approved with respect to all criteria while the other alternatives have not. Majority result occurs when one alternative has been approved with respect to the majority of criteria, in the importance order, starting with the most important one. If there are, for example, five criteria, for a majority result one alternative needs to be approved by at least the three most important of them.

If one alternative has been defined to be superior on the grounds of the order of criteria, the result is Ordinally Dominant. For instance, if two alternatives are approved by the same number of criteria, the one which is approved by the more

Unanimous	c1	c2	c3
a1	+	+	+
a2	+	+	–
a3	+	–	+

Majority	c1	c2	c3
a1	+	–	+
a2	**+**	**+**	**–**
a3	–	+	+

Ordinally dominant	c1	c2	c3
a1	–	+	+
a2	–	+	–
a3	**+**	**–**	**+**

Indeterminate	c1	c2	c3
a1	–	–	+
a2	+	–	–
a3	–	+	+

Fig. 8.1 The possible voting outcomes

important criteria, is better. Alternative k is classified to be ordinally dominant if (Fraser and Hauge 1998)

$$f\,(n^{*})_{ki} \geq 0\;\forall n^{*},\; 1 \leq n^{*} \leq n,\; \forall i \neq k \tag{8.8}$$

where

$$f_{\,(n^{*})_{ki}} = \sum_{j=1}^{n^{*}} g_{ijk}$$

and

$$g_{ijk} = \begin{cases} 1, & \mathit{if}\; c_j(a_k) > \bar{c}_j \wedge c_j(a_i) \leq \bar{c}_j \\ 0, & \mathit{if}\; c_j(a_k) > \bar{c}_j \wedge c_j(a_i) > \bar{c}_j \\ 0, & \mathit{if}\; c_j(a_k) \leq \bar{c}_j \wedge c_j(a_i) \leq \bar{c}_j \\ -1, & \mathit{if}\; c_j(a_k) \leq \bar{c}_j \wedge c_j(a_i) > \bar{c}_j \end{cases} \tag{8.9}$$

The process is based on the idea that approval with respect to a more important criterion can completely compensate disapproval with respect to a less important criterion (Fraser and Hauge 1998). However, approval with one more important criterion does not compensate disapproval with respect to two less important criteria.

The result is Deadlocked if there are two or more alternatives that are defined to belong to the above mentioned classes. These alternatives are approved and disapproved with respect to the same criteria, and so it is not possible to determine one single superior alternative. The result is Indeterminate if there is not enough information to determine one superior alternative. This is the case, for instance, if alternative A is approved by more criteria than B, but on the other hand, B is approved by more important criteria than A. In this case, more information is needed in order to make the recommendation.

Table 8.1 Original values

Alternative	Net income 1,000€	Stumpage value (million euros€)	Scenic beauty index
NAT	0	0.71	5.5
SCEN	79.6	0.28	5.7
NORM	38	0.6	5.4
GAME	33	0.61	5.5
MREG	102.3	0.51	5.2
INC	191.7	0.13	4.9

Example 8.6. The problem 3.5 was analysed with MA, using the average criterion value as the approval border. The approval borders for the criteria were 74.1 for net incomes, 0.47 for stumpage value and 5.36 for scenic beauty. The original values are presented in Table 8.1, and the alternatives that are approved and disapproved in Table 8.2. Net incomes are assumed to be the most important criterion, stumpage value the second and scenic beauty the least important one.

In all, three alternatives were approved with respect to net incomes, and four with respect to other criteria. None of the alternatives was approved with respect to all three criteria, but five of them were approved with respect to two criteria. Thus INC cannot be selected, since it is only approved by one criterion. Since MREG and SCEN were approved with respect to the most important criterion, they are better than NAT, NORM and GAME (the last three lose to first two in the comparison with $n^* = 1$ and $f(n^*) = -1$). Of the last two alternatives, MREG is approved with respect to stumpage value, and SCEN is not, so that SCEN has $f(n^*) = -1$ with $n^* = 2$. MREG alternative is the winner with a majority result.

8.6.2 Fuzzy MA

Fuzzy MA is based on a concept of fuzzy approval. In this case, the approval border with respect to each criterion is defined with a membership function $\mu(c_{ij})$ for a

Table 8.2 Approvals and disapprovals of the alternatives with respect to each criterion

Alternative	Net income 1,000€	Stumpage value (million euros)	Scenic beauty index
NAT	–	+	+
SCEN	+	–	+
NORM	–	+	+
GAME	–	+	+
MREG	+	+	–
INC	+	–	–

Table 8.3 Fuzzy approvals

Alternative	Net income 1,000€	Stumpage value (million euros)	Scenic beauty index
NAT	0	1	0.92
SCEN	0.36	0.1	1
NORM	0	1	0.71
GAME	0	1	0.92
MREG	0.56	0.76	0.29
INC	1	0	0

statement $\tilde{A}$ 'alternative i with criterion value c_{ij} is approved with respect to criterion j'. Thus, it describes a degree of approval.

The results of fuzzy MA can be calculated in the same way as the results of basic MA (Kangas et al. 2006b). In (8.8) it is required that $f(n^*)_{ki}$ always remains positive. However, as the values of g_{ijk} only have values -1, 0 and 1, the smallest negative value possible is in fact -1. Therefore, in fuzzy MA, the condition is given as

$$f\,(n^*)_{ki} > -1\ \forall n^*,\ 1 \leq n^* \leq n,\ \forall i \neq k \tag{8.10}$$

where

$$f_{(n^*)_{ki}} = \sum_{j=1}^{n^*} g_{ijk}$$

and

$$g_{ijk} = \mu(c_{kj}) - \mu(c_{ij}). \tag{8.11}$$

If the condition were not relaxed from (8.8), it would mean that all alternatives that are even slightly less approved than the best alternatives with respect to the most important criteria are immediately out of question. This is not in line with the concept of fuzzy approval. However, the relaxation does not affect to the results: given a crisp approval border, fuzzy MA gives the same recommendation as basic MA. Thus, basic MA is a special case of the fuzzy MA. In the fuzzy case, it is possible that there are several alternatives that have $f(n^*)_{ki} > -1$. Then, the one with greatest value is chosen. It also means that the possibility of ties is lower than in basic analysis.

Example 8.7. The approval borders in the problem above are defined to be fuzzy so that the minimum approval border is min $+0.2 \cdot (\max - \min)$ and the maximum approval border min $+0.8(\max - \min)$ for each criterion variable. Thus, to be at all approved, the alternative must have net incomes above 20% of the range of variation, and to be fully approved, above 80% of range of variation. In between, the alternatives are more or less approved. The fuzzy approvals are given in Table 8.3.

Then, the alternatives are compared pairwisely with respect to each criterion in turn, i.e. with n$^* = 1, 2, 3$. In the first comparison with respect to net incomes,

Table 8.4 Comparisons with respect to net incomes

	NAT	SCEN	NORM	GAME	MREG	INC
NAT		−0.36	0	0	−0.56	−1
SCEN	0.36		0.36	0.36	−0.2	−0.64
NORM	0	−0.36		0	−0.56	−1
GAME	0	−0.36	0		−0.56	−1
MREG	0.56	0.2	0.56	0.56		−0.44
INC	1	0.64	1	1	0.44	

(Table 8.4) alternatives NAT, NORM and GAME already obtain $f(n^*) = -1$, since they are not at all approved with respect to net incomes and INC is fully approved. Thus, these alternatives are out of question. In the next comparison, the comparisons based on stumpage value are added to these values (Table 8.5). In this time, no alternatives were excluded. However, the comparison between NAT and SCEN turned in favour of NAT. Thus, if INC alternative were not among the alternatives, NAT could be a good choice. When the final comparison with respect to scenic beauty is added, MREG is the winner (Table 8.6). Its worst value, -0.31, is better than the other alternatives left, SCEN (-0.46) and INC (-0.92).

The same information can be obtained from a cumulative approval sum. Whenever one alternative loses in cumulative approval at least 1 unit, this alternative is dropped from the analysis. In Fig. 8.2, the cumulative approval of NAT, GAME and NORM is 0 with respect to the first criterion, and they all lose 1 unit to the INC alternative. Thus, from the remaining alternatives, MREG has the best cumulative approval in the end.

8.6.3 Multicriteria Approval Voting

There exists also another version of MA, namely the Multicriteria Approval Voting MAV (Pasanen et al. 2005). In this approach, it is assumed that the importance order of criteria can be implicitly accounted for in MA. An implicit importance ordering can be assumed if the approval of alternatives is not dependent on the mean

Table 8.5 Comparisons with respect to stumpage value added

	NAT	SCEN	NORM	GAME	MREG	INC
NAT		0.54	0	0	−0.32	
SCEN	−0.54		−0.54	−0.54	−0.86	−0.54
NORM	0	0.54		0	−0.32	
GAME	0	0.54	0		−0.32	
MREG	0.32	0.86	0.32	0.32		0.32
INC	0	0.54	0	0	−0.32	

Table 8.6 Comparison with respect to scenic beauty added

	NAT	SCEN	NORM	GAME	MREG	INC
NAT		0.46	0.21	0	0.31	
SCEN	−0.46		−0.25	−0.46	−0.15	0.46
NORM	−0.21	0.25		−0.21	0.1	
GAME	0	0.46	0.21		0.31	
MREG	−0.31	0.15	−0.1	−0.31		0.61
INC	−0.92	−0.46	−0.71	−0.92	−0.61	

value of the criterion, but chosen by the decision makers (Pasanen et al. 2005). It is assumed that the chosen approval border carries all the information concerning the importance differences of criteria: the more important criterion, the higher the approval border. Thus, an importance order of criteria is not required.

The recommendation is based on the decision maker adjusting the approval borders until only one alternative is approved with respect to all criteria, and that is the recommended alternative. Another possibility would be to count, which of the alternatives is accepted with respect to largest number of criteria. In both cases, the approval borders really need to reflect the approval of the alternatives, so that the recommendation is not made based on the approval with respect to several criteria that are not important.

This approach has also been utilized in a real-life strategic planning case at Hetsähallitus (Hiltunen et al. 2007).

Example 8.8. In example 8.6, no alternative is approved with respect to all criteria. In order to have one alternative approved with respect to all criteria, the approval border of at least one criterion need to be lower. For instance, if the approval

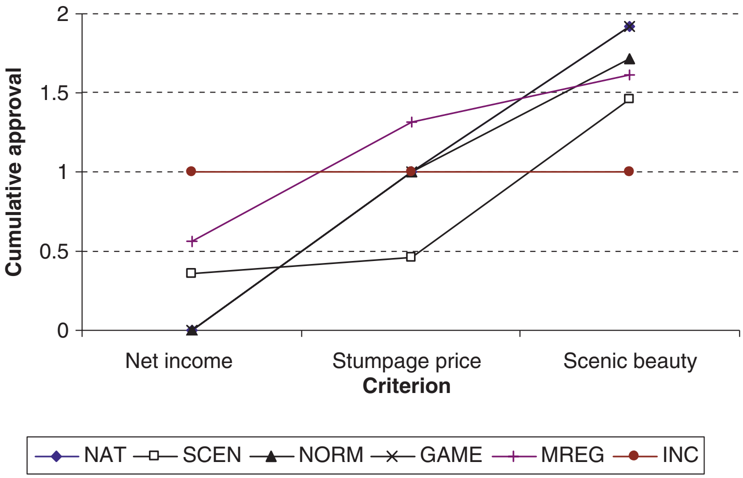

Fig. 8.2 Cumulative approvals of the alternatives

border of scenic beauty is reduced to 5.2, MREG is approved with respect to all criteria. If the approval border of stumpage value is reduced to 0.28, SCEN is approved with respect to all criteria, and it the approval border of net incomes is reduced to 38, NORM is approved with respect to all criteria. The choice, which approval border to reduce, depends on the importances of the criteria to the decision maker.

References

Arrow, K. 1951. Social choice and individual values. Wiley, New York.

de Borda, J-C. l78l. Mathematical derivation of an election system. Isis 44:42–51. English translation by A. de Grazia 1953.

Bouyssou, D., Marchant, T., Pirlot, M., Perny, P., Tsoukiàs, A., and Vincke, P. 2000. Evaluation and decision models – a critical perspective. Kluwer, Dordrecht.

Brams, S.T. and Fishburn, P. 1983. Approval voting. Birkhauser, Boston, MA.

Condorcet, M. de. 1785. Essai sur l'application de l'analyse à la probabilité des décisions rendues à la pluralité des voix (Essay on the Application of the Analysis to the Probability of Majority Decisions), Paris.

Copeland, A.H. 1951. A 'reasonable ' social welfare function, mimeographed, University of Michigan, Seminar on Applications of Mathematics to the Social Sciences, 1951.

Cranor, L.F. 1996. Declared-strategy voting: an instrument for group decision making. Academic dissertation. http://www.research.att.com/∼lorrie/pubs/diss/diss.html

Felsenthal, D.S. 1989. On combining approval with disapproval voting. Behavioral Science 34: 53–60.

Fraser, N.M. and Hauge, J.W. 1998. Multicriteria approval: application of approval voting concepts to MCDM problems. Journal of Multi-Criteria Decision Analysis 7: 263–272.

García-Lapresta, J.L. and Martínez-Panero, M. 2002. Borda count versus approval voting: a fuzzy approach. Public Choice 112: 167–184.

Gehrlein, W.V. and Lepelley, D. 2001. The condorcet efficiency of Borda rule with anonymous voters. Mathematical Social Sciences 41: 39–50.

Gibbard, A. 1973. Manipulation of voting schemes: a general result. Econometrica 41: 587–601.

Heckelman, J.C. 2003. Probabilistic Borda rule voting. Social Choice and Welfare 21: 455–468.

Hiltunen, V., Kurttila, M., Leskinen, P., Pasanen, K., and Pykäläinen, J. 2007. Mesta – Internet application for supporting discrete choice situations in strategic level participatory natural resources planning. Forthcoming.

Kangas, A., Laukkanen, S., and Kangas, J. 2006a. Social choice theory and its applications in sustainable forest management – a review. Forest Policy and Economics 9: 77–92.

Kangas, A., Kangas, J., and Laukkanen, S. 2006b. Fuzzy multicriteria approval method and its application to two forest planning problems. Forest Science 52: 232–242.

Kacprzyk, J., Fedrizzi, M., and Nurmi, H. 1992. Group decision making and consensus under fuzzy preferences and fuzzy majority. Fuzzy Sets and Systems 49: 21–31.

Kant, S. and Lee, S. 2004. A social choice approach to sustainable forest management: an analysis of multiple forest values in Northwestern Ontario. Forest Policy and Economics 6: 215–227.

Kim, K.H. and Roush, R.W. 1980. Introduction to mathematical consensus theory. Marcel Dekker, New York.

Laukkanen, S., Kangas, A., and Kangas, J. 2002. Applying voting theory in natural resource management: a case of multiple-criteria group decision support. Journal of Environmental Management 64: 127–137.

Laukkanen, S., Palander, T., and Kangas, J. 2004. Applying voting theory in participatory decision support for sustainable timber-harvesting. Canadian Journal of Forest Research 34: 1511–1524.

Laukkanen, S., Palander, T., Kangas, J., and Kangas, A. 2005. Evaluation of the multicriteria approval method for timber-harvesting group decision support. Silva Fennica 39: 249–264.

Martin, W.E., Schields, D.J., Tolwinski, B., and Kent, B. 1996. An application of social choice theory to U.S.D.A. Forest Service decision making. Journal of Policy Modelling 18: 603–621.

Mueller, D.C. 1989. Public choice II. Cambridge University Press, New York.

Niemi, R.G. 1984. Strategic behaviour under approval voting. American Political Science Review 78: 952–958.

Nurmi, H. 1987. Comparing voting systems. Reidel, Dordrecht.

Nurmi, H., Kacprzyk, J., and Fedrizzi, M. 1996. Probabilistic, fuzzy and rough concepts in social choice. European Journal of Operational Research 95: 264–277.

Pasanen, K., Kurttila, M., Pykäläinen, J., Kangas, J., and Leskinen, P. 2005. Mesta – Non-industrial private forest landowners' decision support for the evaluation of alternative forest plans over the Internet. International Journal of Information technology and Decision Making 4: 601–620.

Reynolds, A. and Reilly, B. 1997. The International IDEA Handbook of Electoral System Design. International Institute for Democracy and Electoral Assistance, Stockholm.

Riker, W.H. 1982. Liberalism against populism. Waweland Press, Inc, Prospect Heights.

Saari, D.G. 1994. Geometry of voting. Volume 3 of Studies in Economic Theory. Springer, New York.

Saari, D.G. and van Newnhizen, J. 1988. The problem of indeterminacy in approval, multiple and truncated voting systems. Public Choice 59: 101–120.

Satterthwaite, M.A. 1975. Strategy-proofness and Arrow's conditions: existence and correspondence theorems for voting procedures and social welfare functions. Journal of Economic Theory 10: 187–217.

Sen, A.K. 1997. On economic inequality. Oxford University Press, Oxford.

Simpson, P. 1969. On defining areas of voter choice: Professor Tullock on stable voting. Quarterly Journal of Economics 83: 478–490.

Yilmaz, M.R. 1999. Can we improve upon approval voting? European Journal of Political Economy 15: 89–100.

Part IV
Application Viewpoints

Chapter 9
Behavioural Aspects

9.1 Criticism Towards Decision Theory

9.1.1 Outline

Ever since the first publications of decision theory based on maximizing utility, there have also been researchers criticizing the theory. There have been arguments whether people actually do maximize utility in decision making, or are they simply aiming at satisfactory decisions. Similarly, there have been arguments concerning whether people just follow heuristic rules in their decision making, or do they behave rationally (e.g. Janis and Mann 1977; March 1994).

Furthermore, the decision makers having modern planning tools available have not always found them useful in real problems (Kasanen et al. 2000). This may partly be due to problems with interpretation of the results from MCDS. Partly the problem may be that not enough emphasis has been put in decision aid on important aspects such as structuring the problem and creating choice alternatives. Partly the problem may be the decision cost: making calculations and using planning procedures costs money, time and energy (Pingle and Day 1996). Even when planning procedures produce better decisions, the improvement also has to be large enough to cover this cost in order to make planning calculations worthwhile.

Partly the criticism may be due to misunderstandings concerning the aims of decision theory. For instance French (1989) says:

> How often have I heard decision analysis berated because it supposedly applies simplistic ideas to complex problems, usurping decision makers and prescribing choice!
>
> Yet I believe it does nothing of the sort. I believe that decision analysis is very delicate, subtle tool that helps decision makers explore and come to understand their beliefs and preferences in the context of the particular problem that faces them. Moreover, the language and formalism of decision analysis facilitates communication between decision makers. Through their greater understanding of the problem and the other's view of the problem, the decision makers are able to make a better informed choice. There is no prescription: only the provision of a framework in which to think and communicate.

Although part of the criticism may be unjustified, there still are problems that should be tackled when decision analysis is further developed. The decisions people actually do are often choices between two alternatives: status quo or a change of some sort. For instance, people decide to harvest a stand or not to harvest a stand. The decisions are also sequential: one small decision after another small decision is made, rather than solving big complex problems and so on (Beach and Mitchell 1987; Beach and Mitchell 1990). Lindblom (1959), for instance, discusses incremental decisions.

All this indicates that decision aid methods need to be developed also from behavioural point of view. Decision analysis has developed from the early days, often due to the justified criticism. For instance, the problem structuring methods are more often involved in the planning process (e.g. Belton and Stewart 2002). However, there is still more to do.

9.1.2 Satisficing or Maximizing?

When it is studied how people really make their decisions without the help of decision aid, it can be noted that the decisions have characteristics of satisficing rather than maximizing (e.g. March 1994). For instance, when deciding about a new person in an enterprise, the decision maker is said to be maximizing his utility, if he wants to hire the best person likely to be found, and satisficing, if he wants just to hire a person that meets the standards given.

It is clear that in real decision making, it is hardly ever possible to go through all the possible alternatives. In many everyday decisions it is not sensible to go through even a few alternatives. It is also never possible to know for sure all the consequences of the decisions made. From this respect, every decision is made in a satisficing fashion, as it can never be guaranteed that no better alternative is available.

On the other hand, it is hard to believe that people would be satisficing in a sense that they would select an alternative just fulfilling the given requirements, if they know a better option is available. For instance, how many decision makers would hire a person they know will do in a job, if they know that a superior alternative exists. In this respect, every decision is made in a maximizing fashion, given the knowledge available.

In experiments it has been noted that people actually tend to do better decisions if they know what is possible to attain, which gives support to this claim (MacLeod and Pingle 2005). On the other hand, this behaviour can also be explained from satisfying point of view: the level decision makers are satisfied with, the aspiration level, rises based on what is attainable and what other people have attained (Oechssler 2002).

There has been a passionate debate concerning whether people satisfy or maximize in the last 50 years, starting from Simon's famous papers (1955, 1957). However, the debate is pointless from the decision aid point of view. It is not important, how the people do their decisions unaided, what is important is whether they can do better when aided.

It is, however, possible that decision making has both satisficing and maximizing characteristics. According to March (1994), most decisions include some elements of satisficing, but it is rarely found in its pure form. It seems quite possible that a person first screens the alternatives available and leaves out every alternative that does not fulfil the standards, and selects the best alternative from among those alternatives that do. This is also what is assumed in the image theory (Beach and Mitchell 1987; Beach and Mitchell 1990). If people really do make decisions this way, it may be useful to acknowledge this also in developing decision aid.

9.1.3 Rules or Rational Behaviour?

When making decisions without aid, people often follow rules. The decision makers can ask themselves (March 1994):

1. What kind of situation is this? (The question of recognition)
2. What kind of person am I? What kind of organization is this? (The question of identity)
3. What does a person such as I, or an organization such as this, do in a situation such as this? (The question of rules)

The identities and rules, on the other hand, are shaped by the social roles of the decision makers, by culture and norms. The rules are also shaped by past experiences: certain actions lead to certain outcomes, and these are used to formulate decision rules and strategies (Einhorn 1982). When a certain strategy has yielded good results in earlier decisions, the same strategy is also used in future decisions. According to March (1994), rules formulate through several processes:

1. **Analysis**, through the anticipation and evaluation of future consequences by intentional decision makers.
2. **Bargaining**, through negotiation, conflict and compromise among decision makers having inconsistent preferences and identities.
3. **Imitation**, though copying of rules practices and forms used by others.
4. **Selection**, through differential birth and survival rates of unchanging rules and the decision making units using them.
5. **Learning**, through experience-based changes of routines and of the ways routines are used.

It has also been widely argued if people follow heuristic rules or if they make their decisions rationally by maximizing utility. The decisions can be explained from both perspectives. For those who favour the rule idea, maximizing utility is just one learned rule among others. For those favouring the idea of rational behaviour, rules are just constraints derived from rational action at a higher level (March 1994). In each decision, both aspects can often be seen. From the decision aid point of view, also this discussion is fruitless, unless understanding the rules people use somehow helps to develop decision aid tools.

People's experiences and perceptions of the world surrounding them may be biased in many ways. People for example interpret probabilities quite differently than the laws of probability dictate (Tversky and Kahneman 1982). For instance, people may think that when tossing a coin for heads and tails, a sequence H-T-H-T-T-H is more likely than the sequence H-H-H-T-T-T (which does not appear random) or sequence H-H-H-H-T-H (in which the coin does not seem fair). Biases may be due to availability of data (Tversky and Kahneman 1982). For instance, it may be that people assess the risk of damages in forest based on how often it has happened in their own or in their acquaintances' forests. Biases may also be due to anchoring to initial estimates (Tversky and Kahneman 1982). For instance, if people are given a number and asked to adjust it upwards or downwards to assess some value (like the percentage of unemployed people), they give the higher values the higher the initial value is.

Such biases may affect the rules by which the decisions are made. They also may have an effect on the results obtained from decision analysis. Such are the cases analyzed in prospect theory (Kahneman and Tversky 1979).

9.2 Image Theory

Image theory is a descriptive theory on decision making, but it can also be used in decision aid. Image theory is based on four types of images: self image, trajectory image, action image and projected image.

The self image consists of the personal beliefs, basic values, morals and ethics of a person (Beach and Mitchell 1987). The self image is shown in the principles a person uses in his decision making, and in goals he adopts. It is also applied to audit possible actions. When the decision maker is an organization, self-image consists of the organization's principles, which the individual decision maker's may or may not share, but which they usually regard as imperatives of the organization (Beach and Mitchell 1990).

The trajectory image consists of goals the decision maker has set concerning the future (Beach and Mitchell 1987). The goals may be concrete, such as obtaining a certain job, or an abstract state, like improving one's skills in languages. Action images are plans that the decision maker has for achieving the goals. The plans form a sequence that is meant to bring about progress towards a goal. The plan consists of tactics, the concrete actions with which the plan can be implemented (Fig. 9.1). The sequence of tactics may include clear actions, actions that have to be executed at the same time (1 and 2) or tactics that are alternative ways (3 and 4). To be adopted, a candidate plan must be compatible with the self image, and also provide means for achieving the goals.

The projected image represents the anticipated future, if (1) the decision maker adopts a certain plan or (2) if he continues with the plans that are currently being implemented. This anticipated future is then compared to the trajectory image or the

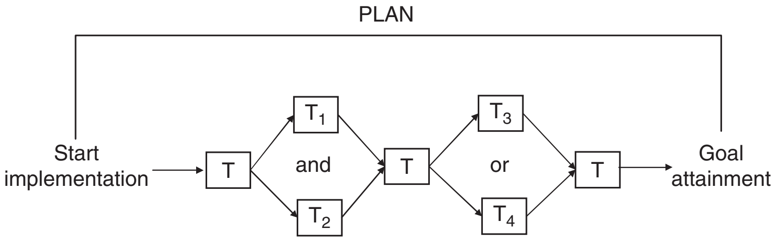

Fig. 9.1 A hypothetical plan with its component tactics (Modified from Beach and Mitchell 1987)

goals of the decision maker. The projected image of the plan currently implemented also enables the decision maker to evaluate the progress made so far.

According to image theory, there are two kinds of decisions: adoption decisions and progress decisions (Beach and Mitchell 1987). In adoption decision, candidates for

plans (or goals) are either adopted or rejected. An adoption decision requires that the candidate plan is at least compatible with the images. Progress decisions are made to decide whether to continue implementing a plan, if the compatibility of the projected image and trajectory image is not good. It means that if a plan does not seem to help in achieving the goals, it is first rejected and then a new plan is adopted.

The planning situation itself can be divided to two phases: screening and choice (Beach and Mitchell 1987). In the screening phase, alternatives that violate the self image are rejected, as well as such plans where the projection image violates the trajectory image. This is done using a so-called compatibility test. In the choice phase, the profitability of the remaining candidate alternatives are compared and the best alternative is chosen (Fig. 9.2).

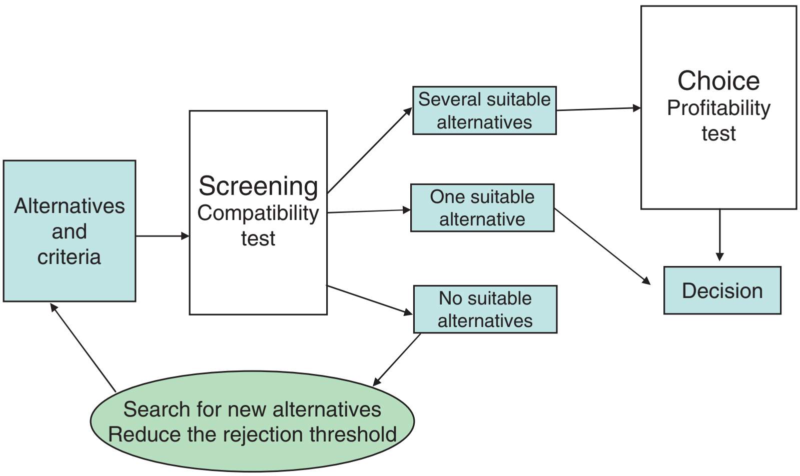

Fig. 9.2 Decision making process with image theory (Turunen 2003)

Table 9.1 Results from the screening phase

	Net incomes	Stumpage value	Scenic beauty
~~NAT~~	~~0.00~~	~~0.71~~	~~5.5~~
SCEN	79.6	0.28	5.7
NORM	38.0	0.60	5.4
GAME	33.0	0.61	5.5
MREG	102.3	0.51	5.2
~~INC~~	~~191.7~~	~~0.13~~	~~4.9~~

The screening phase is non-compensatory, i.e. alternatives that fail in one respect may be rejected, even if they are very good in other respects. Screening may be based on gut feeling: a certain alternative just does not feel right. The compatibility is measured with rejection thresholds (Beach and Mitchell 1987). Formally, the rejection threshold can be expressed as a weighted index of violations

$$I = \sum_{t=1}^{n} \sum_{p=1}^{m} W_p V_{tp}, \;\; V_{tp} \in \{0, 1\} \tag{9.1}$$

where W_p is the weight of principle p and V_{tp} is an indicator variable having value 1 if a certain tactics t in the plan violates the principle p and 0 otherwise. Then, a threshold value for I needs to be decided. It may mean, for instance that all forest plans that do not provide sufficient incomes are rejected, if the incomes have a large weight. Instead, a violation in the target number of game animals may not cause rejection of the whole plan, if the weight is sufficiently low. Of course, if $I = 0$, no violations at all are allowed. Thus, deciding the rejection threshold is very important, but it may also be very difficult for a decision maker. This phase represents the satisficing part of image theory.

The choice part, on the other hand is compensatory, so that good score in one respect can compensate a not-so-good score in another. This part can be carried out with usual decision support methods.

Example 9.1. Assume that in the example of 3.5, incomes should be at least 10,000€ and the stumpage value of timber at the end of the period should be at least 200,000€. Assume as well that the rejection threshold is 0 so that no violations are allowed.

In this case, two alternatives are rejected in the screening phase: the NAT and INC alternatives, due to violations from the targets. The rejected alternatives are stroke through (Fig. 9.1).

In the choice phase, the remaining alternatives are compared using additive utility function. The values in the natural scale are transformed to utility scale with Eq. (2.4). The global priority is then calculated using equal weights (0.33) for each criterion. The results are presented in Table 9.2. The best alternative in this case is MREG alternative.

Table 9.2 Local and global priorities of the remaining alternatives

	Net incomes	Stumpage value	Scenic beauty	Global priority
SCEN	0.78	0.46	1.00	0.74
NORM	0.37	0.98	0.95	0.76
GAME	0.32	1.00	0.96	0.75
MREG	1.00	0.84	0.91	0.91

9.3 Prospect Theory

It has been analyzed by experiments, how people make their decision when facing a risky situation. Usually it has been assumed that people tend to maximize expected utility, i.e. most of the people obey this norm most of the time. In the answers given, however, several types of deviations from this theory have been noted. Kahneman and Tversky (1979) presented three deviations, which they named to be certainty effect, reflection effect and isolation effect.

The certainty effect means that people tend to overweight (compared to maximizing expected utility) such outcomes that are certain, compared to outcomes that are merely probable (Kahneman and Tversky 1979). For example, if people have to choose from two prospects, A and B, where A includes probable incomes and B certain incomes, 80% chose alternative B although the expected utility EU of A is $0.8 \cdot 4{,}000 = 3{,}200$, i.e. greater than 3,000 in B. On the other hand, when people had to choose from prospects C and D, in which the probability of winning was one fourth of that in prospects A and B, the results were opposite. This result indicates that reducing the winning probability from certain to probable (from 1 to 0.25) reduces the utility more than reduction from probable to less probable (from 0.8 to 0.2). Over half of the people participating in the experiment violated expected utility theory.

Prospect	A: 4,000 with probability 0.8 0 with probability 0.2	B: 3,000 with certainty
EU	3,200	3,000
Choice percentages	20	80

Prospect	C: 4,000 with probability 0.20 0 with probability 0.80	D: 3,000 with probability 0.25 0 with probability 0.75
EU	800	750
Choice percentages	65	35

If, instead of winnings, losses are considered, the situation is different. If the winnings in the example above are changed to losses, people choose prospect A in 92% of cases, although the expected loss is greater than in prospect B, but prospect D rather than C. It means that people tend to avoid certain losses, and are ready to gamble with even bigger losses in order to avoid them (Kahneman and Tversky 1979). The result with negative prospects is the mirror image of those with positive prospects. This effect is called reflection effect.

Prospect	A:	B:
	−4,000 with probability 0.8 0 with probability 0.2	−3,000 with certainty
EU	−3,200	−3,000
Choice percentages	92	8

Prospect	C:	D:
	−4,000 with probability 0.20	−3,000 with probability 0.25
	0 with probability 0.80	0 with probability 0.75
EU	−800	−750
Choice percentages	42	58

Isolation effect means that if there are identical parts in prospects, they are discarded from the analysis, and the focus is on the part that distinguish two prospects (Kahneman and Tversky 1979). This may, however, lead to inconsistent preferences because the problems can be decomposed in several ways.

Assume a two-stage game. In the first stage, there is a 0.75 probability to end the game without winning anything, and a 0.25 probability to move to second stage. In the second stage, the choice is between winning 4,000 with probability 0.8 or winning 3,000 with certainty. The choice has to be made before the first stage. In this game, the choice is really between $0.25 \cdot 0.80 = 0.2$ probability of winning 4,000 (EU 800) and 0.25 probability of winning 3,000 (EU 750). Yet, 78% of people chose the second alternative with smaller EU. This is because the first stage was not considered in the choice.

These phenomena form the basis for prospect theory. In prospect theory, the choice process is divided to two phases: editing and evaluating. In the editing phase, the prospects are simplified. The editing can include several different operations. First, as people react differently to gains and losses, the prospects are presented as gains and losses with respect to a reference point (current assets). Prospects can sometimes also be simplified by combining probabilities with identical outcomes. It is also often possible to segregate the certain gains and losses from uncertain ones. For instance, if prospect is such that decision maker obtains 300 with probability 0.8 and 200 with probability 0.2, it can be simplified so that decision maker gets 200 certainly and 100 more with probability 0.8. Similarly, in a prospect where decision maker loses 400 with probability 0.6 and 100 with probability 0.4, the loss of 100 is certain, and in addition, decision maker can lose 300 with probability 0.6. In editing phase, also very unlikely outcomes are ignored and the probabilities are rounded from 0.99 to 1, or from 0.51 to 0.50. This editing is not, however, without problems: performing several editing tasks in different order may result in different prospects (Kahneman and Tversky 1979).

In the choice phase, the decision making situation under risk in described so that subjective weights π are added to the probabilities p of different outcomes, $\pi(p)$. It reflects the impact of p on the overall value of the prospect. The possible outcomes x are also weighted according to their subjective values, $v(x)$, measuring the value of the outcomes compared to a reference point.

The prospects analyzed are simple prospects with at most two non-zero outcomes. They are presented in the form $(x, p; y, q)$, where p is probability of outcome x and q is probability of y. If $p+q<1$ probability of zero outcome is $1-p-q$. The prospects are divided to two groups that are dealt with in different ways.

(1) If either $p+q<1$; or x is negative and y positive $(x \leq 0 \leq y)$; or y is negative and x is positive $(x \geq 0 \geq y)$, the value of the prospect can be calculated as

$$V(x,\ p;\ y,\ q) = \pi(p)\ v(x) + \pi(q)\ v(y)$$

where $\pi(0) = 0,\ v(0) = 0$ and $\pi(1) = 1$.

(2) If $p+q=1$; and both x and y are either positive $(x > y > 0)$ or negative $(x < y < 0)$, the value of the prospect can be calculated as

$$V(x,\ p;\ y,\ q) = v(y) + \pi(p)[v(x) - v(y)]$$

In the first formula, losses and gains are treated separately, and can have different subjective values. In the second case, where the prospect is either strictly positive or negative, the certain gain or loss $v(y)$ is separated from the additional gain or loss $(v(x) - v(y))$.

For instance, if one has to value prospect (400, 0.25; 100, 0.75), 100 is a certain gain and 300 more is obtained with probability 0.25. Then, the value of the prospect is V $(400,\ 0.25;\ 100,\ 0.75) = v(100) + \pi(0.25)[v(400) - v(100)]$.

In prospect theory it is assumed, that with respect to losses, the utility function is convex (i.e. utility function of a risk seeker) and with respect to gains the function

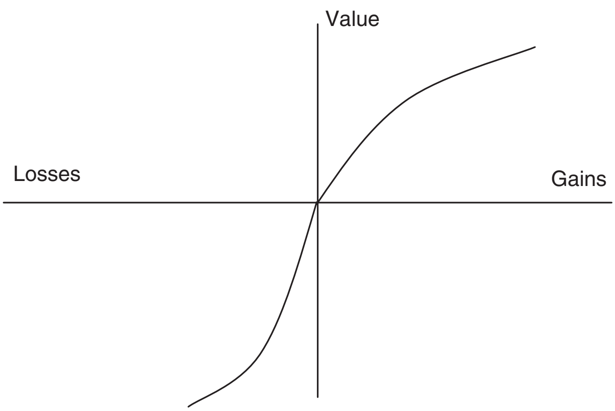

Fig. 9.3 Utility function derived from prospect theory

is concave (i.e. utility function of a risk avoider) (Fig. 9.3). It is also typical that the function is clearly steeper for losses than for gains (Kahneman and Tversky 1979). However, the behaviour of a person may markedly change when the gains and losses are very large when compared to the overall situation of the person. For instance, the possibility to lose one's apartment or the possibility to buy an apartment might be such cases.

References

Beach, L.R. and Mitchell, T.R. 1987. Image theory: principles goals and plans in decision making. Acta Psychologica 66: 201–220.

Beach, L.R. and Mitchell, T.R. 1990. Image theory: a behavioral theory of decisions in organizations. Research in Organizational Behavior 12: 1–41.

Belton, V. and Stewart T.J. 2002. Multiple criteria decision analysis: an integrated approach. Kluwer, Dordrecht.

Einhorn, H.J. 1982. Learning from experience and suboptimal rules in decision making. In: Kahneman, D., Slovic, P., and Tversky, A. (Eds.). Judgment under uncertainty: heuristics and biases, Cambridge University Press, Cambridge, pp. 268–286.

French, S. 1989. Readings in decision analysis. Chapman & Hall, London, 210 pp.

Janis, I.L. and Mann, L. 1977. Decision making. A psychological analysis of conflict, choice and commitment. Free Press, New York, 488 pp.

Kahneman, D. and Tversky, A.1979. Prospect theory: an analysis of decision under risk. Econometrica 47: 263–291.

Kasanen, E., Wallenius, H., Wallenius, J., and Zionts, S. 2000. A study of high-level managerial decision processes, with implications for MCDS research. European Journal of Operational Research 120: 496–510.

Lindblom, C. 1959. The science of "Muddling through". Public Administrative Review. pp. 79–88.

March, J. 1994. A primer on decision making – How decisions happen. Free Press, New York, 289 pp.

MacLeod, W.P. and Pingle, M. 2005. Aspiration uncertainty: its impact on decision performance and process. Journal of Economic Behaviour and Organization 56: 617–629.

Oechssler, J. 2002. Cooperation as a result of learning with aspiration levels. Journal of Economic Behaviour and Organization 49: 405–409.

Pingle, M. and Day, R.H. 1996. Models of economizing behavior: Experimental evidence. Journal of Economic Behaviour and Organization 29: 191–209.

Simon, H.A. 1957. Models of man: social and national. Wiley, New York, 247 pp.

Turunen, M. 2003. Mielikuvateoria säännöstelyn kehittämisessä. Diploma thesis. Helsinki University of Technology, Department of Water Resources Engineering.

Tversky, A. and Kahneman, D. 1982. Judgement under uncertainty. In: Kahneman, D., Slovic, P., Tversky, A. (Eds.). Judgment under uncertainty: heuristics and biases. Cambridge University Press, New York, pp. 3–20.

Chapter 10
Practical Examples of Using MCDS Methods

The examples given so far in this book are simple examples in the sense that in each case one MCDS tool is applied for a well-defined setting. In real life, using MCDS tools is not that simple. The whole planning process involves several phases, from creating the alternatives among which the recommendation is selected to selecting the possible participants to the MCDS approach used. In this chapter, we present three real-life cases in order to illustrate how the whole planning process is carried out, and what possible uses MCDS tools have. All these cases have been published before.

10.1 Landscape Ecological Planning

Kangas et al. 2000 For. Ecol. Manage. 132:157–171, Kangas et al. 2003 For. Sci. 49:928–937

The importance of landscape ecological planning in boreal forestry has been widely noted. It is necessary to examine forestry not only from the viewpoint of individual forest stands, but also to take into consideration area-level population dynamics and ecological considerations. From the ecological viewpoint, the greatest shortcomings of landscape ecological forest planning include lack of basic knowledge on population ecology and other ecological aspects. However, there may be expert knowledge available concerning the priority of treatment schedules in a forest area, and that can be used for landscape ecological planning. The example study presents an approach to landscape level forest planning applying regression AHP and SMAA for decision support. The focus is on multicriteria evaluation of alternative forest plans at area level.

The aim of the planning process was to support the choice of a tactical forest plan for the case study area, Kivalo forest estate of 2024 ha, owned by the State and administered by the Finnish Forest Research Institute METLA (now managed by Metsähallitus). The planning horizon was 10 years (1998–2007). The Kivalo forest estate is located in the Rural Commune of Rovaniemi, Finnish Lapland.

The process started by creating ecological networks of important areas for further comparison. The process of producing alternative ecological networks was assisted by employing GIS in two ways. First, different kinds of search operations were carried out utilizing the existing spatial and attribute data on the forest stands within the study area in order to find the ecologically important areas and to rank them (e.g. Store and Kangas 2001). Secondly, ecological corridors were generated among the ecologically important habitat patches, and buffer zones with differing widths were generated along and around habitat patches and other areas of special ecological values. With an eye to generating ecological networks, the original division of the area into compartments was refined on the basis of the information produced by spatial operations, e.g. by forming new compartments along brooks. New forest compartment maps could be produced by overlaying the corridors and buffer zones with the original compartment map.

Five different ecological networks were produced for the area as a starting point for elaborating alternative area-level plans. Ecological network 1 contained only those areas which should be conserved according to the Forest Act, and some other ecologically valuable compartments, namely, fertile tree stands along brooks, fragile summit areas, and two old-growth forest stands. In addition to the areas belonging to ecological network 1, ecological network 2 included more forest stands possessing ecological values, and some ecological corridors connecting key biotopes. Wider buffer zones were formed along brooks in network 2 than in network 1. Network 3 was formed by selecting areas next in the order of priority with respect to ecological considerations while taking into account the negative effects on revenues from wood production. In the case of network 3, also buffer zones along the forestry road in the southernmost part of the area were included. The reason for this was that the road area and its immediate surroundings were important habitat for northern bats living within the area. According to the same principle of including more areas of environmental value in the ecological solution, networks 4 and 5 were produced. In network 5, about half of the area belonged to the network (Fig. 10.1).

The MONSU forest simulation and optimisation software (Pukkala 1993) was applied in producing alternative forest plans for further evaluation. For each of the five ecological networks, two different forest plans were formed. These were generated by applying different objective functions. No treatments were recommended during the first 10 years for the forest stands belonging to the ecological network. Finally, there were ten different plans that were evaluated. Values for timber-production oriented criteria, such as ‘net incomes from timber production’ and ‘volume of the forest after the planning period outside the landscape ecological spots’ were calculated using MONSU. The ecological criteria were obtained using expert opinion.

With respect to timber production, there were three criteria, namely net income from timber cuttings, and volume of the growing stock outside conserved areas in the end of the period, and the area outside the ecological networks (Table 10.1). In the first study, there was only one ecological criterion based on expert judgment. The priorities of the plans with respect to ecological values were obtained from pairwise comparisons between the plans (Table 10.2). The decision hierarchy is presented in Fig. 10.2.

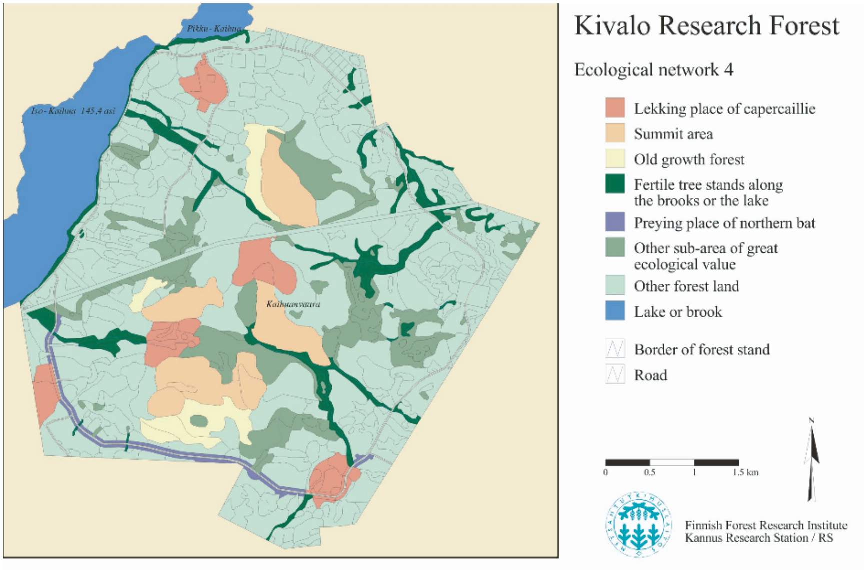

Fig. 10.1 Example of an ecological network (Kangas et al. 2000)

The relative weights of the elements in the decision hierarchy were assessed using a graphical comparison mode of pairwise comparisons. The weight for timber wood production was 0.6, and that for ecological considerations 0.4; weight of net revenues was assumed to be 0.62 and that of sustainability of wood production 0.38, respectively; and the total area of forest stands not belonging to an ecological network and the volume of the growing stock at the end of the planning period were 0.71 and 0.29, respectively. The resulting total and global priorities are presented in Table 10.3.

According to this analysis, alternative IX would be the best. In the second study, three socioecological criteria were considered, namely recreation, viability of rare species and risks to watercourse (Table 10.1). All of the socioecological criteria were measured in ordinal scale and thus, SMAA-O was used in analyzing the plans. In addition, the first two of the timber production criteria from the first study were used. Hierarchical structure was not assumed.

The importance order of the criteria was assumed to be Viability > Net incomes? Volume of growing stock > Recreation > Risks, the plan having the greatest overall acceptability was plan VIII (Table 10.4), but plan X was very close to it.

10.2 Participatory Planning

Pykäläinen et al. (1999) J. For. Econ. 5:341–364.

In this example, ideas of the HIPRE program developed by Hämäläinen and Lauri (1995) were used in an application of interactive decision analysis (IDA) on strategic

Table 10.1 Criterion values for each plan

Plan number	Net income from timber cuttings (10^6 euro)	Volume of the growing stock outside conserved areas in the end of the period ($1,000 m^3$)	Area belonging to ecological network (ha)	Recreation	Viability of rare species	Risks to watercourse
I	0.675	100	105	2	3	0
II	0.438	132	105	1	4	0
III	0.238	118	248	1	1	0
IV	0.546	143	248	2	5	0
V	0.361	125	369	1	2	0
VI	0.980	123	369	3	9	1
VII	0.806	106	469	2	6	1
VIII	1.126	133	469	3	10	1
IX	0.931	109	550	2	7	1
X	0.681	154	550	2	8	1

Table 10.2 Pairwise comparisons concerning the ecological value of the plans

Plan number	I	II	III	IV	V	VI	VII	VIII	IX	X
I	1	1/3	1/3	1/4	1/3	1/3	1/2	1/4	1/3	1/4
II		1	1	1/2	1/2	1/3	1/2	1/4	1/3	1/3
III			1	1/3	1/3	1/4	1/2	1/4	1/6	1/3
IV				1	1	1/2	1	1/3	1/2	1/3
V					1	1/3	1/2	1/5	1/4	1/4
VI						1	2	1/2	2	1/2
VII							1	1/2	1/2	1/3
VIII								1	1/2	1
IX									1	1/3
X										1

planning of state-owned natural resources. HIPRE allows the use of a modified version of AHP, utilizing sub-utility functions in the evaluation of choice alternatives. HIPRE program was chosen to be used by Metsähallitus (previously the Finnish Forest and Park Service FPS) governing the case study area.

The IDA application was part of a wider participatory planning project initiated by Metsähallitus in Kainuu, eastern Finland. The function of the IDA was to produce decision support for the formulation and selection of a forest strategy. Initially, four strategies following different scenarios were formulated in the planning project of Kainuu. The feasibility of land use allocations in general and their implications on producing forest outputs was mapped out by doing this. The impacts of the strategies were measured by numeric criterion variables and they were estimated through planning calculations. So called "Basic strategy" included the current

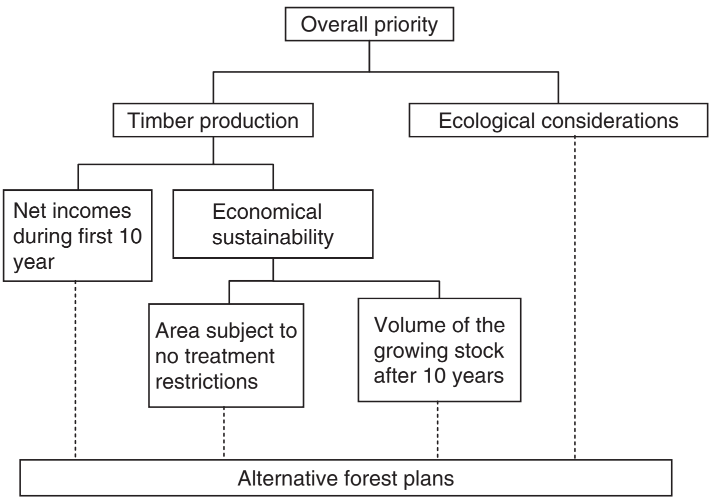

Fig. 10.2 The decision hierarchy (Modified from Kangas et al. 2000)

Table 10.3 Local and global priorities of the alternative plans

Plan number	Net revenues	Area not subject to treatment restrictions	Volume of the growing stock at the end of the period	Global priority
I	0.167	0.120	0.088	0.099
II	0.101	0.120	0.101	0.082
III	0.145	0.108	0.092	0.095
IV	0.081	0.108	0.104	0.085
V	0.137	0.098	0.093	0.097
VI	0.064	0.098	0.106	0.103
VII	0.119	0.090	0.097	0.095
VIII	0.053	0.090	0.108	0.108
IX	0.099	0.083	0.100	0.119
X	0.035	0.083	0.111	0.115

principles of land use allocation. The "Business strategy" emphasized the economic goals of Metsähallitus in Kainuu, and the "Forest recreation" and "Nature conservation" strategies emphasized the related goals.

The IDA was started with a decision hierarchy formulation (Fig. 10.3). The hierarchy consisted of six levels: the total utility, the parties (Metsähallitus by its former abbreviation FPS), the four main criteria for forest management, the sub-criteria, the criterion variables, and the alternative forest strategies.

The preferences of the parties involved (Metsähallitus, one regional and four local working groups including 10–12 interest groups each, and the public) were defined and included into planning in a form of an additive utility function

$$U_{tot} = \sum_{j=1}^{n} w_j U_j \tag{10.1}$$

where, U_{tot} is the total utility, w_j is the weight of party j, U_j is the utility of party j, and n is the number of parties involved. The utility of an individual party was

Table 10.4 Resulting rank acceptabilities and overall acceptability

Plan number	a^h	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
VIII	57	27	23	15	11	9	6	4	3	1	0
X	56	27	21	15	11	9	7	5	3	2	1
VI	44	14	15	15	16	13	9	7	5	3	1
IV	42	15	13	13	13	15	10	9	6	4	2
IX	35	6	11	18	17	14	11	9	7	5	2
II	27	7	8	8	8	9	10	12	15	13	9
VII	17	1	2	4	7	10	17	16	16	14	11
V	17	1	3	5	7	9	13	17	18	16	12
I	14	2	3	4	5	6	8	10	13	19	29
III	11	1	1	3	4	6	8	10	14	23	31

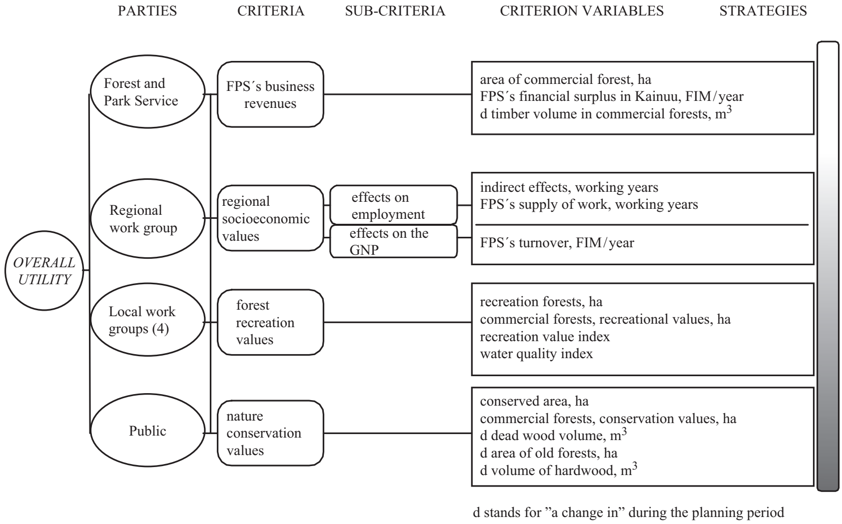

Fig. 10.3 The decision hierarchy (Pykäläinen et al. 1999)

calculated as follows:

$$U_j = \sum_{i=1}^{m_j} a_{ij} u_{ij}(q_{ij}) \tag{10.2}$$

where m_j is the number of criteria of party j, a_{ij} is the relative importance of criterion i, u_{ij} is the sub-utility function of criterion i, and q_{ij} is the quantity that the plan produces or consumes the criterion variable i of party j. Each sub-utility function was defined with respect to one upper level criterion or sub-criterion. By using the sub-utility functions, the values of criterion variables were converted to relative sub-utilities which were scaled on a fixed interval between 0 and 1. The differences between the worst and the best values of the variables were taken into account when defining the weights a_{ij}. The sub-utility functions and the weights of the criterion variables were defined by experts.

The problem included four main criteria, Metsähallitus's business revenues, regional socioeconomic values, forest recreation values and nature conservation values. Benefits related to Metsähallitus's business revenues were measured by using the area of commercial forests, Metsähallitus's financial surplus in Kainuu and the change in timber volume in commercial forests. The regional socioeconomic values were measured by the effect on employment (direct and indirect) and Metsähallitus's turnover. Forest recreation values were measured by the area of recreational forests, the area of commercial forests with recreational values, the recreation value index and the water quality index. The water quality index, in turn, was measured by the area of clearcut forest stands, the area of fertilised forests and the area of ditch network maintenance. The fourth main criterion was the nature conservation value, measured by the conserved area, the area of commercial forests with conservation

Table 10.5 Weights of main criteria given by the regional working groups

Working field	Metsähallitus's business revenues in Kainuu	Socioeconomic values	Forest recreation values	Nature Conservation values
Agriculture and forestry	0.261	0.372	0.213	0.154
Provincial Aadministration	0.205	0.470	0.218	0.107
Tourism	0.223	0.266	0.335	0.176
Forest industry	0.500	0.300	0.100	0.100
Small enterprises	0.268	0.357	0.217	0.158
Game husbandry	0.180	0.220	0.330	0.270
Research	0.192	0.301	0.235	0.272
Nature conservation	0.060	0.120	0.218	0.601
Mean	0.236	0.301	0.233	0.230

values, the change in dead wood volume, the change in the area of old forests and the change in the volume of hardwood.

The weights of the main criteria were defined interactively by the parties (Metsähallitus and regional working groups). With the interactive computer interface, the participants saw immediately how the current set of weights affected the strategy selection. For example, more weight could be given to the criterion not meeting the requirements of the party, and the consequences of this change could be

Table 10.6 Global priorities of the sub-criteria

Criterion variable	Global priority
Area of commercial forests	0.076
Metsähallitus's financial surplus in Kainuu	0.186
Change in timber volume in commercial forests	0.048
Effect on employment (direct)	0.084
Effect on employment (indirect)	0.084
Metsähallitus's turnover	0.072
Area of recreational forests	0.100
Area of commercial forests with recreational values	0.076
Recreation value index	0.043
Area of clearcut forest stands	0.014
Area of fertilised forests	0.003
Area of ditch network maintenance	0.008
Conserved area	0.103
Area of commercial forests with conservation values	0.031
Change in dead wood volume	0.010
Change in the area of old forests	0.052
Change in the volume of hardwood	0.010

Table 10.7 Global priorities of the alternatives

Strategy	Priority
Business	0.520
Basic	0.462
Forest recreation	0.440
Mixed 2	0.417
Mixed 1	0.376
Nature conservation	0.331

seen immediately. Interactive defining of the weights was continued until the participant accepted the plan. Each group had their own sessions. The weights given by the regional groups are given in Table 10.5.

The weights of the parties were defined by Metsähallitus (weights in brackets): Metsähallitus (0.5), regional work group (0.250), local work groups (0.125), and the public (0.125). By using these weights, the global weights (priorities) were calculated for the other decision elements in respect to the upper level elements related to them. The global weights of the criteria were: Metsähallitus's business revenues (0.310), regional socioeconomic values (0.239), forest recreation values (0.244) and nature conservation values (0.206). The global priorities of the lower level criteria are presented in Table 10.6.

Each strategy was considered to be a feasible one in the beginning of the planning process. However, the Finnish conservation program of old forests was constructed simultaneously with the natural resources strategy of Kainuu. In the conservation program of old forests, the area of conserved forests was to be increased from 28,000 to 62,000 ha. Also the landscape ecological planning in Metsähallitus called for restrictions in wood production on certain areas (92,000 ha). As a consequence of this, all the initial strategies were not feasible any more. That is why two new strategies were constructed: "Mixed 1" strategy and "Mixed 2" strategy. "Mixed 1" was the "Basic" strategy including the new nature conservation criteria. The "Mixed 2" strategy was a modified version of the "Business" strategy. The priorities of the initial and the mixed strategies are presented in Table 10.7.

10.3 Spatial Objectives and Heuristic Optimization in Practical Forest Planning

Hurme et al. (2007) Landscape Ecology 22: 243–256

This example shows how species-specific habitat suitability index, spatial objectives and heuristic optimisation were used in practical planning situation, where the land manager needed information from the production possibilities of the planning area's forests. Ecological and economic perspectives were included in these long-term forest planning calculations. Economic objectives referred to timber production (growing stock volume, cutting amounts and net present value of cutting

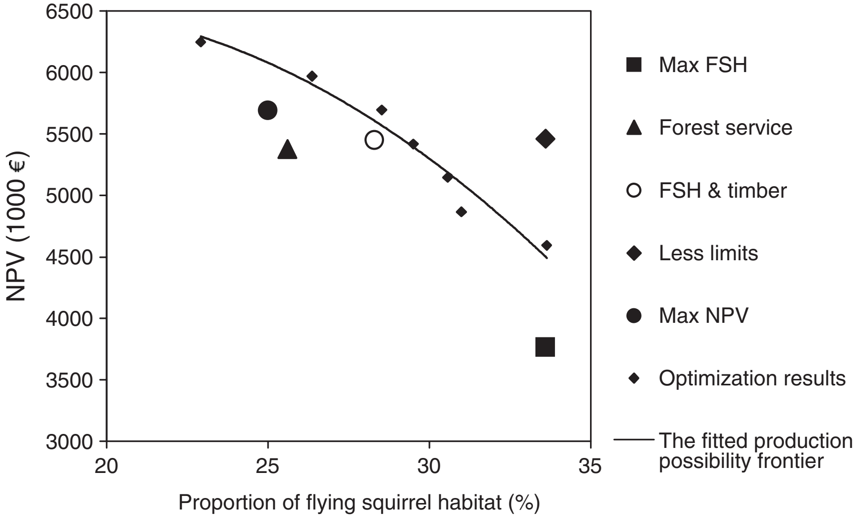

Fig. 10.4 Fitted production possibility frontier with respect proportion of FSH at the end of the planning period and the net present value of cutting income (Hurme et al. 2007)

income), whereas ecological objectives were based on suitable habitats for arboreal Siberian flying squirrel (*Pteromys volans*).

In the first phase, forest stands that were considered suitable for flying squirrel were defined using an empirical site-specific flying squirrel habitat (FSH) model. The model predicts the probability for the occurrence of the flying squirrel within a stand, and includes a spatial variable that describes the availability of suitable habitat within an activity area of an individual flying squirrel. The model building was based on existing knowledge of habitat preferences for the flying squirrel in NE Finland and on a total of 91 spruce-dominated stands that were surveyed. Thirty-five of them were found occupied by the flying squirrel. The explanatory variables in the model were area of a stand (ha) and growing stock volumes (m^3/ha) of spruce and birch. In addition, the area of a good quality habitat in the surrounding (500 m radius) of the stand was used as an explanatory variable of the model. Stands that had a probability of occurrence over 50% were assumed to be suitable for flying squirrel.

In the second phase, the estimated FSH-model was integrated into the MONSU forest planning system (Pukkala 2006), where it was then used as an objective variable in planning calculations. Due to the complexity of the planning calculations, heuristic technique based on simulated annealing with a two compartment neighbourhood (see Chapter 6; Heinonen and Pukkala 2004) was the used optimization technique. The length of the planning period was 60 years and it was divided into three 20-year periods. The planning area covered 10,215 ha of which 7,025 ha is productive forest land. The area was divided into 976 separate forest stands. However, 3,469 ha of the planning area included some restrictions on their use, based on protection of old forests, claimed areas or other limitations. At present, most of the areas suitable for flying squirrel were located in restricted areas.

In the third phase, five alternative forest plans were worked out with different objectives for flying squirrel habitat and timber production. In addition, the production possibility frontier was also worked out to define the interrelationship between net present value and flying squirrel habitat. The alternative plans were compared with respect to values of objective variables at the end of the planning period of 60 years and against a production possibility frontier (Fig. 10.4). In the “Max FSH” plan, the value of the FSH was maximized and in the “Max NPV” the net present value of cutting income was maximized, subject to growing stock volume constraint. In the “Forest service” plan, the cutting volumes during three sub-periods, growing stock at the end of the planning period, area of old forests and the volume of broad-leaved trees were the objective variables that were included in the additive utility function, which was the used objective function form. The resulting plan was intended to mimic the principles of the landscape ecological plan that had been created earlier for the area’s state owned forests. In plan “FSH & timber” the objective variables were FSH habitat, cutting volumes during the sub-periods and the growing stock volume at the end of the planning period. In “Less limits” plan, the used objective variables were exactly same as in the “FSH & timber” plan. However, in this plan, the production possibilities of the planning area were increased by releasing 2,024 ha of the forest area that was in restricted use in all other plans. These descriptions of plans are also visible from results presented in Fig. 10.4 where the “FSH & timber” is located reasonably close to the production possibility frontier, although NPV was not used as an objective variable in this plan. Plans “Max FSH” and “Less limits” are producing the maximal amount of FSH (approximately 34%)

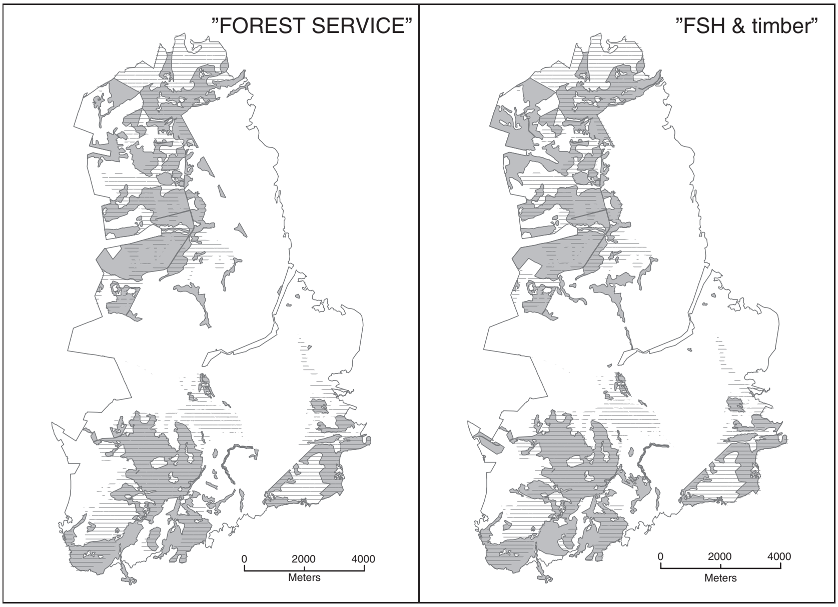

Fig. 10.5 Locations of flying squirrel habitats (gray) at the end of the planning period in plans “Forest service”, and “FSH & timber”. Striped areas have restrictions for use

although in both plans some cuttings also take place. In “Less limits” plan, released restrictions produce also about the same level of NPV as the plans “Max NPV” and “Forest service”. The use of FSH objective results in larger amount of flying squirrel habitat and a more clustered pattern of these habitats compared to the plan where this objective was not used (Fig. 10.5). The habitats are located near the areas that have restrictions for use.

References

Heinonen, T. and Pukkala, T. 2004. A comparison of one- and two-compartment neighbourhoods in heuristic search with spatial forest management goals. Silva Fennica 38: 319–332.

Hurme, E., Kurttila, M., Mönkkönen, M., Heinonen, T., and Pukkala, T. 2007. Maintenance of flying squirrel habitat and timber harvest: a site-specific spatial model in forest planning calculations. Landscape Ecology 22: 243–256.

Hämäläinen, R. and Lauri, H. 1995. Hipre3+ Users Guide. Helsinki University of Technology. Systems analysis Laboratory.

Kangas, J., Hokkanen, J., Kangas, A., Lahdelma, R., and Salminen, P. 2003. Applying stochastic multicriteria acceptability analysis to forest ecosystem management with both cardinal and ordinal criteria. Forest Science 49: 928–937.

Kangas, J., Store, R., Leskinen, P., and Mehtätalo, L. 2000. Improving the quality of landscape ecological forest planning by utilizing advanced decision-support tools. Forest Ecology and Management 132: 157–171.

Pukkala, T. 1993. Monikäytön suunnitteluohjelmisto MONSU. (Multiple-use planning package MONSU. In Finnish). Mimeograph. University of Joensuu, 45 pp.

Pukkala, T. 2006. Monsu metsäsuunnitteluohjelma. Versio 5. Ohjelmiston toiminta ja käyttö. Mimeograph.

Pykäläinen, J., Kangas, J., and Loikkanen, T. 1999. Interactive decision analysis in participatory strategic forest planning: experiences from State owned boreal forests. Journal of Forest Economics 5: 341–364.

Store, R. and Kangas, J. 2001. Integrating spatial multi-criteria evaluation and expert knowledge for GIS-based habitat suitability modelling. Landscape and Urban Planning 55: 73–93.

Chapter 11
Final Remarks

Planning situations and planning needs vary greatly case by case. Acquiring decision support for tactical planning is different from acquiring it for strategic planning; for non-industrial private forest planning compared to public or industrial forestry; for an individual decision maker compared to a consortium; for planning solely for wood production in comparison to ecosystem management planning; or when using quantitative criteria in comparison to qualitative criteria; etc. The decision support methods presented above have demonstrated that their properties vary greatly. It is therefore obvious that the different methods are at their best in different planning situations.

There is no method that is universally best or even applicable for all situations. On the other hand, every method can be used in forest planning for tasks for which it is especially suitable. The choice of best or simply suitable decision support method requires knowledge of many methods, consideration of case-specific requirements, and acquainting oneself with the planning situation – i.e. "planning of planning" (e.g. Kangas et al. 2001a; Kangas and Kangas 2002, 2005).

It may not be enough to select the one best planning method for one situation: the best option could be to select a combination of methods (Mingers and Brocklesby 1997). It could be wise to combine optimisation and MCDS, several MCDS methods, MCDS with problem structuring methods, or several different problem structuring methods. Some recent studies indicate that it would be useful to utilise more than just one MCDS method or hybrid approach in many planning situations, especially for behavioural reasons (e.g. Bell et al. 2001; Kangas et al. 2001a; Belton and Stewart 2002). One possible way is to think about the three worlds: material, personal and social, and select the method related to what components are emphasised in the planning situation (Fig. 11.1).

It is especially important to take into consideration what kinds of people are participating in the planning process. People differ in their knowledge and skills, and they are differently equipped for participating in decision analyses. Different methods, as well as applications of different measurement scales (i.e. ordinal versus cardinal, interval versus ratio) suit people differently when enquiring about their

	Appreciation of	Analysis of	Assessment of	Action to
Social	social practices, power relations	distortions, conflicts interests	ways of altering existing structures	generate empowerment and enlightenment
Personal	individual beliefs meanings emotions	differing perceptions and personal rationality	alternative conceptualizations and constructions	generate accomodation and consensus
Material	physical circumstances	underlying causal structure	alternative physical and structural arrangements	select and implement best alternatives

Fig. 11.1 A framework for mapping methods (Mingers and Brocklesby 1997)

preferences. On the other hand, the choice of the best MCDS method is also dependant on the quality of information that is available on preferences.

An important consideration for the selection of MCDS method is also the quality of the information available for evaluating the decision alternatives with respect to the decision criteria. A multiple criteria decision support method should be chosen so that all information that is available through a reasonable effort could be utilised as fully as possible. Exact information is used for criteria with exact values, and ordinal or dichotomous information is used for criteria with low quality data.

However, compromises must often be made when choosing the methods. Methods that enable deep analyses and complete exploitation of the available data are typically hard to use and understand. Conversely, very easy and simple methods, such as basic multicriteria approval, often lead to loss of information.

The behavioural viewpoint is important not only in choosing the method to be applied, but also when applying any decision support method. The planning process should be understandable and pedagogical, so that all the participants can fully understand the reasoning and results. Unfortunately, practical MCDS applications are often too technically oriented, and either simplify reality too much or are too difficult to use, understand, and interpret (e.g. Corner and Buchanan 1997).

A recommended approach, particularly in participatory or any other planning where ordinary people are involved, would be to use simple and straightforward MCDS methods. This is the case especially in planning via information networks (Kangas and Store 2003).

Another option would be to apply an easily understandable decision support method, or a method the participants have used before, in order to become familiar with the planning task and to understand the very nature of the decision problem. Using decision analysis tools might also be easier, if people have familiarized themselves with the situation using problem structuring methods such as SWOT, SODA or SSM. Voting methods may be a suitable starting point, when the problem has been clarified. After that, people may be ready to answer more demanding inquiries and, thus, to give higher-quality preference information. Then, detailed and in-depth analyses by more complicated methods would be possible.

However, in some cases, moving from an easily understood method to an in-depth analysis by more complicated methods might lead to a problem. Namely, people may be willing to produce similar results even with more complicated methods, after first obtaining results from the easily understood method. This being the case, it might be difficult to argue why there is a change in ranks (and in recommendations) when evaluating alternatives if uncertainties or probabilities are included, for instance. This puts additional requirements on the interpretation of the results.

In any planning process, it is also useful to perform as comprehensive a decision analysis as the data allows. Although complicated methods and calculations may not enhance people's involvement in planning processes, the methods often produce enlightening detailed results for the analysts and decision makers. Moreover, it often makes sense to invest in acquiring higher quality and more accurate information on both evaluation data and preferences, and to apply corresponding analysis methods (Kangas et al. 2001b). This is particularly the case in conflict management situations (Shields et al. 1999).

In real-life planning, it is typical that some criteria can be measured on cardinal scale, but it is difficult and sometimes even impossible to express all criteria in ratio or even in interval scale. As a consequence, there often are both ordinal and cardinal information in decision-making processes. Consequently, there is a need for decision support methods that can make use of ordinal and interval information. Another challenge is that in many decision support methods, the required inquiries are difficult for decision makers. It would often be easier to express ordinal than cardinal preferences for many decision makers, and for stakeholders in participatory approaches.

Forcing people to make priority comparisons in cardinal scales could, in some cases, lead to more biased estimates of true preferences than applying ordinal inquiries. Ordinal preferences can be taken as implicitly uncertain, as is often the case with stated preferences in actual decision processes. As a result, ordinal statements may reflect the true preferences better than exact cardinal values (e.g. Larichev 1992; Shepetukha and Olson 2001). This might sometimes also be the case with the evaluations of alternative decisions with respect to a single criterion, especially concerning forest functions evaluated on subjective preferences, such as the scenic beauty of forest landscape (Sugimura 1993).

In many forest and environmental planning processes, we have to contend with more or less incomplete information bases, with mixed data and sometimes even purely descriptive data that might allow only ordinal rankings. Thus, it can be concluded, that methods like Multicriteria Approval and SMAA-O have potential for wide application in today's forest and other natural resource management, and that their application potential will most probably increase in the future. However, applying cardinal information and ratio-scale methods allows for tradeoffs analyses. For that reason, it is always reasonable to employ such information and methods, if they are available. A further conclusion has been that whatever the planning task and the MCDS method, interactive use of the method greatly improve the efficiency of the process, as well as education and learning (e.g. Pykäläinen 2000).

MCDS methods need to be complemented with numeric simulation and optimization tools. Such tools especially contribute to the examination of future production possibilities and to the generation of alternative efficient forest plans, although they may fail to satisfactorily cover whole complex decision problems of multiple-purpose forestry. Simulation and optimization results can then be utilised together with other information sources, such as GIS analyses, expert judgments, subjective preferences and descriptive data, in an MCDS framework.

Research focusing on MCDS has been active in recent years in general, and increasingly so within the field of natural resource management. In addition, MCDS methods have gained interest not only of researchers in different disciplines, but also of decision makers and planners outside the scientific community. In the forestry practice, MCDS methods have been applied to better meet the many challenges of today's forest management. These challenges include providing decision support for multiple-purpose forestry and participatory planning, but also for managing risks and uncertainty and for making comprehensive use of different kinds of information from various sources. It is evident that the need and demand for MCDS applications in forestry and environmental planning will further increase in the future.

References

Bell, M.L., Hobbs, B.F., Elliott, E.M., Ellis, H., and Robinson, Z. 2001. An evaluation of multi-criteria methods in integrated assessment of climate policy. Journal of Multi-Criteria Decision Analysis 10: 229–256.

Belton, V. and Stewart, T.J. 2002. Multiple criteria decision analysis: an integrated approach. Kluwer, Dordrecht.

Corner, J. and Buchanan, J. 1997. Capturing decision maker preference: experimental comparison of decision analysis and MCDM techniques. European Journal of Operational Research 98: 85–97.

Kangas, J. and Kangas, A. 2002. Multiple criteria decision support methods in forest management: an overview and comparative analyses. In: Pukkala, T. (Ed.). Multi-objective forest planning, Kluwer, Dordrecht, pp. 37–70.

Kangas, J. and Kangas, A. 2005. Multiple criteria decision support in forest management – Fundamentals of the approach, methods applied, and experiences gained. Forest Ecology and Management 207: 133–143.

Kangas, J. and Store, R. 2003. Internet and teledemocracy in participatory planning of natural resource management. Landscape and Urban Planning 62: 89–101.

Kangas, J., Kangas, A., Leskinen, P., Pykäläinen, J. 2001a. MCDM methods in strategic planning of forestry on state-owned lands in Finland: applications and experiences. Journal of Multi-Criteria Decision Analysis 10: 257–271.

Kangas, J., Pesonen, M., Kurttila, M., and Kajanus, M. 2001b. A'WOT: Integrating the AHP with SWOT analysis. In: Dellman, K.S (Ed.). Proceedings of the Sixth International Symposium on the Analytic Hierarchy Process ISAHP 2001, August 2–4, 2001, Kursaal Bern, Berne-Switzerland. Bern. pp. 189–199.

Larichev, O.I. 1992. Cognitive validity in design of decision-aiding techniques. Journal of Multi-Criteria Decision Analysis 1: 127–138.

Mingers, J. and Brocklesby, J. 1997. Multimethodology: towards a framework for mixing methodologies. Omega, International Journal of Management Science 5: 489–509.

Pykäläinen, J. 2000. Interactive use of multi-criteria decision analysis in forest planning. University of Joensuu, Faculty of Forestry, Joensuu. Doctoral thesis.

Shepetukha, Y. and Olson, D.L. 2001. Comparative analysis of multiattribute techniques based on cardinal and ordinal inputs. Mathematical and Computer Modelling 34: 229–241.

Shields, D.J., Tolwinski, B., and Keny, B.M. 1999. Models for conflict resolution in ecosystem management. Socio-Economic Planning Sciences 33: 61–84.

Sugimura, K. 1993. Evaluation of forest functions by local people: development of a research method. Proceedings of the IUFRO Conference, Seoul, Korea, September 20–25, 1993. Forestry Research Insitute of the Republic of Korea.

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