Multi-Criteria Decision Analysis (MCDA) in Forest Operations – an Introductional Review

Boško Blagojević, Rikard Jonsson, Rolf Björheden, Eva-Maria Nordström, Ola Lindroos

Abstract

Decision making in forestry is very complex and requires consideration of trade-offs among economic, environmental, and social criteria. Different multi-criteria decision analysis (MCDA) methods have been developed for structuring and exploring the decision-making process of such problems. Although MCDA methods are often used for forest management problems, they are rarely used for forest operation problems. This indicates that scholars and practitioners working with forest operations are either unaware of MCDA methods, or see no benefit in using these methods. Therefore, the prime objective of this review was to make MCDA methods more intelligible (compared with current level of understanding) to novice users within the field of forest operations. For that purpose, basic ideas as well as the strengths and limitations of selected MCDA methods are presented. The second objective was to review applications of MCDA methods in forest operations. The review showed that MCDA applications are suitable for forest operation problems on all three planning levels – strategic, tactical, and operational – but with least use on the operational level. This is attributed to: 1) limited availability of temporally relevant and correct data, 2) lack of time (execution of MCDA methods is time consuming), and 3) many operational planning problems are solved with regards to an economic criterion, with other criteria serving more as frames. However, with increased importance of environmental and social aspects, incorporating MCDA methods into the decision-making process on the operational planning horizon (e.g., by developing MCDA-based guidelines for forestry work) is essential.

Keywords: multi-criteria decision analysis, decision-making, forest operations

1. Introduction

The complexity of forestry decision making is associated with dimensions and categories, which range from: long term (strategic) to short term (operational) on a temporal scale, stand level to national level in a spatial scale, and individual to group decision making in a stakeholder scale (Segura et al. 2014). Previously, forestry decision making was often performed by a single, empowered decision maker (forest owner or forest officer) and, thus, the decision-making process was less complex than present-day processes. However, after the UN Conference on the Environment and Development in Rio (UNCED 1992), public participation through involvement of different groups of stakeholders gained relevance and wide acceptance (Mendoza and Martins 2006). In addition, forestry decision making is a very complex issue that requires consideration of trade-offs among economic (e.g., timber, forage, livestock, hunting), environmental (e.g., soil erosion, carbon sequestration, biodiversity conservation), and social criteria (e.g., recreational activities, level of employment, population settlement) (Diaz-Balteiro and Romero 2008). Another issue is that various stakeholders participating in the decision-making process can have different or opposite priorities, objectives, and goals, which may lead to conflicts.

The complexity of decision problems in forestry is ever increasing. Correspondingly, the difficulty faced by decision-makers in searching a solution that considers all criteria, examines tradeoffs, reduces conflicts, in an optimizing framework (Ananda and Herath 2009), without the help of decision support systems (DSS) has also increased. Segura et al. (2014) classified DSS for forest management problems into six groups: multiple criteria decision analysis (MCDA), optimization, simulation, economic models, statistical methods, and information systems. Usually, these groups are combined in DSS in a way such that simulations, information systems, statistical models and/or economic models provide input data for MCDA or optimization. For example, geographic information systems (GIS) and strengths, weaknesses, opportunities, and threats (SWOT analysis, economic model) are often used in conjunction with MCDA methods. Similarly, life cycle assessment (LCA) can be used to assess the environmental pillar in sustainability analysis, while MCDA covers more pillars (e.g., economic and social) and can be used to compare alternatives from a product to a policy level (Cinelli et al. 2014). Segura et al. (2014) reviewed 120 forest management problems; MCDA was used in 31%, while optimization appeared in 59% of the papers; the total number of operational problems (29) was less than the number of tactical (39) and strategic (52) forest management problems. Moreover, MCDA methods were more often used in strategic problems than in tactical and operational problems, but almost the opposite was true for forest management decisions concerned primarily with environmental questions. For example, for a total of 179 forest management problems with biodiversity objectives, MCDA, MCDA combined with voting methods, and optimization methods were applied in 41.9%, 52.7%, and 20.5% of the research papers, respectively (Ezquerro et al. 2016).

The trend of increasing MCDA application will most likely continue as today's forestry decision problems (with multiple criteria, functions, and stakeholders (typically) with conflicting interests) call for highly flexible and versatile DSS, which require tools complementary to simulation and optimization tools (Kangas and Kangas 2005). Belton and Stewart (2002) and Mendoza and Martins (2006) described several inherent properties that render MCDA appealing and practically useful for decision making in forestry, namely MCDA:

⇒ explicitly considers multiple, conflicting criteria
⇒ helps to structure the management problem
⇒ provides a model that can serve as a basis of discussion
⇒ offers a process that leads to rational, justifiable, and explainable decisions
⇒ can deal with mixed sets of data (quantitative and qualitative) including expert opinions
⇒ is conveniently structured to enable a collaborative planning and decision-making environment
⇒ provides a participatory environment that accommodates the involvement and participation of multiple experts and stakeholders (Mendoza and Prabhu 2003).

Overall, the framework of MCDA is supposed to aid in decision making and aims to integrate objective measurement with value judgment. By doing this explicitly, the inbound subjectivity of decision making can be managed in a more clear and precise way (than that achieved without MCDA applications). MCDA is intended for complex decisions and aims to aid in the decision-making process by providing decision-makers with tools for improved knowledge about their decisions. This means that the content will change only modestly, but the understanding of the process will increase, and their priority will be clarified. Therefore, at the time of decision making, the decision-maker will know more about the issue (than previously) but must still make one or several decision(s) (Belton and Stewart 2002). These useful properties of MCDA have recently been recognized by scholars and researchers worldwide. Indeed, whereas only a handful of scientific papers within the environmental field mentioned MCDA methods in the early 1990s, several hundreds of papers using MCDA methods were published annually in the late 2000s (Huang et al. 2011). In fact, in the last four decades, MCDA has been an efficient and often used approach for solving forest resource management problems (Ananda and Herath 2009) for both individual and group (participatory) context (Nordström et al. 2010, Acosta and Corral 2017).

However, some scholars have highlighted the weaknesses of applying MCDA in forestry. According to Kangas et al. (2006), MCDA methods are sometimes too complex, demand significant amounts of data, consist of excessive number questions to be answered by decision makers, and are usually time consuming. Decision makers may, therefore, struggle in understanding the principles underlying the ranking of various options, i.e., the method can seem like a »black-box« and this can lead to distrust (Gregory 2002). According to those authors, voting methods can be a credible alternative in forest decision making. Segura et al. (2014), as in the case of this paper, included voting methods in the MCDA group, since they are used more frequently than MCDA.

Although MCDA methods are often used for forest management problems, they are rarely used for forest operation problems. Therefore, the prime objective of this paper was to present and elucidate MCDA methods (together with Multi-criteria approval and Delphi voting methods) to novice users within the field of forest operations. For that purpose, basic ideas as well as the strengths and limitations of selected MCDA methods are presented. The second objective was to review existing applications of MCDA methods in forest operations.

2. General definition of time perspectives in forestry

Decision problems related to forestry are often divided into strategical, tactical, and operational time levels (Carlsson et al. 2006, Borges et al. 2013, Segura et al. 2014). However, the definitions of these three perspectives vary in the literature (Church 2007, Epstein et al. 2007, Gunn 2007). Moreover, the time perspectives may differ widely within an organization, as strategic planning may be performed on a 100 year-horizon for some organizational units and on a 10 year-horizon for others. Comparisons between such time perspectives must, therefore, account for these potential differences. Nevertheless, the focus within the planning perspectives is connected to the aim of the planning processes and could, hence, be considered common to most organizations and branches. Therefore, in this paper the perspectives have been defined as follows:

Strategic planning focuses on producing policies and organizational goals, as well as helping the organization to function and make decisions that are favorable to the organization. This level can and should include all parts of the organization and may include re-definition of these parts through financial adjustment. The perspective has no upper time limit, but border on the tactical planning stage at the lower end.

In the *Tactical planning* stage, implementation of the strategic plan for the upcoming period (e.g., on a yearly basis) is considered. The strategic plan is enacted, using the resources required for accordance with the strategic plan. The tactical planning stage follows the strategic planning stage in the upper time end and precedes the operational planning in the lower end.

The *Operational planning* stage is aimed at executing the tasks defined in the tactical plan. Hence, planning on the operational level focuses on the use of the available resources.

The selected definition is expected to capture (at a resolution suitable for the objective of this paper) the nature of the planning and its dependence on the time perspective. A proper definition is considered crucial, as the suitability of MCDA methods and their applications may vary with the time perspective.

3. Forest operations and associated problems

Forest operation problems have been described in many ways. This paper focuses on forest operations, in general, with a broad view of the area. Thus, Sundberg's (1988, 110 p.) description of forest operations frames the area in focus rather well: »…the interaction of labour and machines with the forest. It involves an understanding of the relationships between labour, technology, the forest resource, forest industries, people and the environment«.

Forest operation problems may be categorized in many ways (Epstein et al. 2007, D'Amours et al. 2008, Rönnqvist et al. 2015). We have divided forest operations into five categories, depending on the type of operation and the influence of the time perspective. Categories 1–2 focus on cultivation, 3 on procurement till roadside and 4–5 on transportation issues from roadside to industry.

- ⇒ regeneration (site preparation, establishment of a new stand)
- ⇒ pre-commercial thinning, i.e., harvesting without extraction of trees
- ⇒ harvesting and extraction, i.e., harvesting with extraction and procurement of trees
- ⇒ access to forest stands (e.g., road construction and maintenance)
- ⇒ logistics.

The categories cover both methods and technology and are subsequently divided into the time perspectives (see the following paragraphs). The categories cover only some issues related to forest operations but serve as a basis for further interpretation of MCDA application to the field. A comparison of the categories on the basis of time perspectives yields clear patterns. The *strategic planning* stage typically includes the long-term plans necessary for the prolonged time perspectives (e.g., choice of silvicultural regimes and harvesting methods, such as whole-stem or cut-to-length, and suitable technology for implementation of these methods). *Tactical planning* typically includes investment in the technology necessary to execute the subsequent operational plans, and planning of specific actions (e.g., number of machines, in varied sizes, for meeting the strategic plan requirements). *Operational planning* consists of measures required for the execution of actions. For the sake of the MCDA review, the operational planning stage is divided into three levels:

⇒ scheduling of resources to planned actions (e.g., identifying machines that should be used for planned stands)

⇒ detailed planning of actions (e.g., pre-planning of the trees that should be harvested, where to drive the machines in the stand, and adjustment of the scheduling plan)

⇒ on-site and real-time planning in direct connection to the execution, which might include adjustments of pre-made plans or the execution of work according to routines (e.g., operator chooses the trees for thinning, how to buck stems, and how to prevent rutting).

4. MCDA

4.1 General MCDA methodology

Multi-Criteria Decision Analysis (MCDA) is described by Belton and Stewart (2002) »as an umbrella term to describe a collection of formal approaches, which seek to take explicit account of multiple criteria in helping individuals or groups explore decisions that matter«. In other words, MCDA handles the process of making decisions in the presence of multiple, usually conflicting, criteria. The methodology of MCDA can be classified into four basic phases:

⇒ structuring the decision problem

⇒ assessing the possible impact of each alternative

⇒ determining the preferences (values) of decision-makers

⇒ evaluating and comparing the alternatives (Raiffa 1968, Keeney 1982, Belton and Stewart 2002, Nordström 2010).

In the first phase, identifying decision makers and defining the criteria and alternatives of the decision-making problem are essential. This phase is essential for the quality of the decision-making process, because poor structuring of a decision-making problem will probably lead to poor decisions, irrespective of the MCDA method employed. Therefore, in this paper, the first phase (where the type of decision-making problem is identified as either an individual or a group problem) is described in more detail than the other phases. Most decisions, whether personal or organizational, may involve multiple stakeholders, i.e., those affected by a decision and those tasked with implementing this decision (Belton and Stewart 2010). Identifying stakeholders and selecting those who will be involved in the process as decision makers (DMs) are therefore necessary. In group decision making, the weights of DMs reflect their expertise and/or importance and must be defined. Should the vote of all DMs be considered equally important, and if not – how should they differ? Several methods, ranging from the decisions of one DM, the entire group or mathematical methods may be used to establish DM weights. In the first case, weights are defined by a specific DM (i.e., a supra decision-maker with supreme expertise or authority) who is given the power to decide the level of influence of the other DMs. Finding a supra decision-maker, who is accepted by everyone, can be difficult (Ishizaka and Nemery 2013). In contrast, the entire group can be involved in allocated DM weights, in what is referred to as a participatory approach. In that approach, each DM evaluates all other group members (including him- or herself) using pairwise comparisons (Ramanathan and Ganesh 1994) or by choosing a value between a lower and an upper limit (Lootsma 1997). This implies that the DM can tacitly judge the weights of certain members of the group to form a decisional coalition (Van Den Honer 2001). Other approaches, which are more mathematical than this approach, can be used to define the weight between DMs. For example, weights can be obtained on the basis of the: demonstrated individual consistencies of each DM (Chiclana et al. 2007, Cho and Cho 2008, Srdjevic et al. 2011), agreement between individual decisions made by a DM and the group decision (group consistencies) (Regan et al. 2006, Yue 2012, Ju and Wang 2013, Blagojevic et al. 2016), or on the basis of past performance of DMs (Cooke 1991).

Afterward, a decision hierarchy must be structured, where the goal or overall objective (statement of what DM(s) wants to achieve via the decision), criteria, sub-criteria (if any), and alternatives should be defined (Keeney, 1992). This is usually done by previously selected DMs (from above) with the help of a decision analyst. An alternative approach, although rarely applied, is to have one person with supreme expertise or authority who will define all content of the decision hierarchy. Selected criteria should fulfill several requirements; they should be essential, controllable, complete, measurable, operational, decomposable, independent, concise, and understandable (for more details see: Keeney 1992, Kangas et al. 2015). Hence, finding qualified DMs may be difficult and, therefore, the selected criteria may correspond to those easily managed by the analyst. Some criteria that DMs are interested in may be omitted due to lack of data or models, but a laissez-faire attitude to criteria selection can influence the decision process. For example, if criteria were non-independent, they would yield an over-evaluated weight in the decision (Ishizaka and Nemery 2013). Moreover, exploring and including all relevant decision alternatives in the analysis, especially when the decision space is represented by a continuous rather than discrete (i.e., unlimited vs. limited) set of alternatives, may be difficult. Lack of alternatives that perform at a satisfactory level on all criteria may create dissatisfaction and conflict among DMs, resulting in a need for further alternatives (Belton and Stewart 2010). Several methods, such as Strategic Options Development and Analysis (SODA) (Eden and Ackermann 2001), Soft Systems Methodology (SSM) (Checkland 2001), Strategic Choice Approach (SCA) (Friend 2001), Robustness Analysis (Rosenhead 2001), and Drama Theory (Bennett et al. 2001), can be used for problem structuring; a thorough description of these methods is beyond the scope of this paper. However, in this phase, DMs may be susceptible to many cognitive and motivational biases (Montibeller and von Winterfeldt 2015) that can be avoided, with the help of a decision analyst. For example, criteria with many sub-criteria tend to receive higher weights than criteria with few sub-criteria (Morton and Fasolo 2009), and *desirability bias* may lead to the exclusion of alternatives that compete with the preferred one.

In the second phase, performance data of alternatives with respect to all selected criteria must be obtained. This data can be quantitative – e.g., measured, calculated, estimated, simulated with a model – or qualitative (descriptive). Similarly, in the third phase, the importance (i.e., weights) of criteria must be defined. This definition can be made via several quantitative (statistical) methods, for e.g., the Entropy Method (Shannon and Weaver 1947, Srdjevic et al. 2004) or the Criteria Importance Through Inter-criteria Correlation (CRITIC) (Diakoulaki et al. 1995) method. Such methods are less frequently used than other methods, since they are *blind* to problem reality, i.e., weights are allocated based on the observed level of variation within each criterion (rather than on problem-related values). A common way to define criteria weights is to elicit preference values from decision makers. The preferences are subjective judgments (made by the decision maker), which can be expressed as cardinal values (e.g., the weight of criterion *j* is 0.300) or ordinal values (criterion *j* is ranked as second most important). They can be expressed either directly or in a pairwise manner. In group decision making, the criteria weights will be the sum of the weight preferences associated with each DM's criteria adjusted for the DM's individual weight within the group (established in the first phase). In the fourth and final phase, alternatives will be evaluated and compared using the selected MCDA method. The last two phases, which differ between the methods, are described in detail below.

4.2 MCDA methods

MCDA methods have been classified in several ways depending on the perspective and purpose of classification (Hajkowicz et al. 2000, Nordström 2010). The classification in this paper is based on the way the preferences are modeled (Belton and Stewart 2002), where all MCDA methods are divided into three different categories:

⇒ goal, aspiration or reference level methods

⇒ outranking methods

⇒ value measurement methods.

Goal aspiration or *reference level methods* rely on establishing desirable or satisfactory levels of achievement for each criterion (Linkov et al. 2004). All criteria should be quantitative, as these methods are aimed at minimizing the distance between a certain point and the actual achievement for each of several criteria under consideration (Romero et al. 1998). Methods from this group allow trade-off between criteria and are, therefore, compensatory. They are especially well-suited for problems with continuous or many alternatives and are non-demanding for DMs, who must only define weights of criteria and desired criteria level. Goal Programming (GP) (Charnes and Cooper 1961), Compromise Programming (CP) (Zeleny 1982), and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) (Hwang and Yoon 1981) methods represent three of the most widely used goal, aspiration or reference level methods. GP, which is used to handle multiple conflicting objectives, is an extension of Linear Programming (LP). In LP, an objective function is optimized (maximized or minimized) within the feasible region defined by the rigid LP constraints. These constraints can (indirectly) be more important than the objective, thereby leading to infeasibility problems (Kangas et al. 2015). In GP, this issue is resolved by considering an objective that is composed of several goals with hard and soft constraints. A goal with a soft constraint has a threshold that is an ideal point, which can be exceeded as solutions greater than this point are feasible even if they are undesirable (Ishizaka and Nemery 2013). Although there are various types of GP (Diaz-Balteiro et al. 2016), this continuous method is aimed at identifying an optimal solution from an infinite number of alternatives and can, hence, be very useful for generating alternatives. In contrast, CP and TOPSIS represent discrete MCDA methods aimed at selecting a solution from a finite number of alternatives. CP ranks alternatives according to their closeness to the ideal point (Zeleny 1982). The best alternative is the one occurring at the least distance from an ideal point in the set of efficient solutions. Similarly, in the TOPSIS method, the preferred alternative lies closest to the »ideal« solution, and farthest from the »negative-ideal« solution.

Outranking methods (or French school) are based on the pairwise comparison of alternatives along each selected criterion and the extent to which the preference for one alternative over the other can be asserted (Linkov et al. 2004). For each criterion, the preference function translates the difference between the two alternatives into a preference degree ranging from zero to one (Behzadian 2010). Outranking methods are non-compensatory and, hence, criteria weights are interpreted as votes given to different criteria (rather than as importance, as in compensatory methods). The weights can be obtained, for example, by assigning scores from 1 (least important) to 7 (most important) to the criteria (Hokkanen and Salminen 1997). However, the weights can also be obtained from pairwise comparisons, as in the AHP method (Kangas et al. 2015). Preference functions and threshold values must be selected and defined, respectively, for Outranking methods, which are therefore more demanding for DMs than Goal Aspiration methods. Furthermore, in outranking methods, complete ranking of alternatives is only achieved in some cases.

The PROMETHEE family (Brans et al. 1986) of outranking methods includes the PROMETHEE I and the PROMETHEE II methods for partial ranking and complete ranking, respectively, of the alternatives. Brans et al. (1986) proposed several criteria functions for measuring the difference between two alternatives associated with any criterion. For these measurements, decision maker(s) must select the type of criterion function and define the corresponding indifference and preference thresholds. Two alternatives are considered indifferent for a criterion if the difference between these alternatives is lower than the indifference threshold. A strict preference is revealed if the difference exceeds the preference threshold (Pohekar and Ramachandran 2004). Subsequently, positive and negative preference flows for each alternative are calculated using previously obtained outranking degrees. The positive flow quantifies the global preference for a given alternative compared with all the other alternatives, while the negative flow quantifies the global preference for a given alternative by all the other alternatives. In PROMETHEE I, if one alternative is better than another with respect to both negative and positive flow, then this alternative is determined to be better overall. If one alternative is deemed better according to positive flow and another is considered better with respect to negative flow, these two alternatives are interpreted as incomparable. In PROMETHEE II, the net flow is used and, hence, complete ranking of the alternatives is achieved (Hokkanen and Salminen 1997, Kangas et al. 2015).

The ELECTRE methods (Roy 1968) are similar to the PROMETHEE methods, in the sense that ELECTRE III uses both an indifference threshold and a preference threshold. However, a veto threshold, which is used to eliminate alternatives that perform excessively bad in any criteria, is also employed. Therefore, ELECTRE III can be considered a non-compensatory method (Rogers and Bruen 1998), where a bad score of any alternative with respect to one criterion cannot be compensated with good scores in other criteria. Nevertheless, given similar thresholds, and a sufficiently high veto threshold in ELECTRE III, these two methods (PROMETHEE II and ELECTRE) have produced identical results (Salminen et al. 1998). As previously mentioned, ELECTRE are non-compensatory methods and are, therefore, applicable to decision-making problems focused on environmental sustainability (Cinelli et al. 2014).

A third category, *Value Measurement* methods, may also be referred to as a full aggregation approach (or American school) (Ishizaka and Nemery 2013). This category consists of diverse methods, such as Multi-Attribute Utility Theory (MAUT), Simple Additive Weighting (SAW), Simple Multi-Attribute Rating Technique (SMART), Analytic Hierarchy Process (AHP), and Analytic Network Process (ANP). Multi-Criteria Approval (MA) and Delphi methods are considered more voting than MCDA methods but are also described here. Although these methods are based on diverse philosophies, most (except for MA) are compensatory, thereby allowing complete rankings of alternatives. Some of these methods (MAUT, AHP, ANP) are very demanding and time consuming for DMs, whereas others (AHP, SMART, MA, Delphi) are user friendly, more easily understandable, and likely to be used in group decision making.

In MAUT (Keeney and Raiffa 1976), the underlying assumption is that the decision maker's preferences for each criterion can be represented by a function, referred to as the sub-utility function. This sub-function(s) is usually unknown at the beginning of the decision process and, hence, must be constructed by the DM(s) (Ishizaka and Nemery 2013). Using utility sub-functions, diverse criteria (such as costs, risks, benefits, stakeholder values) are transformed into one common dimension-less scale (utility/value) (Linkov et al. 2004). These sub-utility functions are then aggregated to describe the overall utility of the alternatives. The relations between the weights of different criteria describe the trade-offs between the criteria (Kangas et al. 2015). The overall utility of each alternative is calculated by summing the products of the sub-utilities multiplied with the corresponding weights of the criteria. The SAW (Hwang and Yoon 1981) method, where the scores of alternatives with respect to the criteria are normalized to values of 0–1 rather than forming a utility function, is basically the simplest case of MAUT. In the SMART method (Edwards 1977), criteria and alternatives are both evaluated with a direct rating, on a scale ranging from 0 (alternative has no merit according to the given criterion) to 100 (ideal alternative). This rating incorporates all the criteria on the same units and, therefore, allows aggregation of all partial scores into a single score. For this aggregation, the weights of the decision criteria are also acquired on the 0 to 100 scale (Ishizaka and Siraj 2018). Once all the partial scores and criteria weights are obtained, the overall score for each alternative is calculated using the weighted sum.

The AHP (Saaty 1980) method enables decomposition of a complex decision problem into a hierarchy, where the goal is at the top level, while criteria and alternatives occupy the lower levels. This method determines the preferences among a set of alternatives by employing pairwise comparisons of the elements comprising the hierarchy at all levels. Using Saaty's importance scale, the elements at a given level of the hierarchy are compared with the elements at a higher level (Table 1).

Table 1 Saaty's importance scale

Definition	Importance
Equal importance	1
Weak dominance	3
Strong dominance	5
Demonstrated dominance	7
Absolute dominance	9
Intermediate values	(2, 4, 6, 8)

Numerical values that are equivalent to linguistic values are placed in appropriate comparison matrices. The local priorities of the criteria and the alternatives are then calculated using one of the existing prioritization methods. In addition, the consistency of the decision maker judgments is calculated for each comparison matrix. Subsequently, the synthesis is performed by:

⇒ multiplying the criteria-specific priority vector of the alternatives with the corresponding criterion weight

⇒ appraising the results to obtain the final composite alternative priorities with respect to the goal. The highest value of the priority vector indicates the best-ranked alternative.

As previously mentioned, in AHP (as with the aforementioned MCDA methods), independent criteria must be employed. However, ANP provides a general framework for dealing with decisions without making assumptions about the independence of:

⇒ higher-level elements from lower level elements

⇒ elements within a level as in AHP hierarchy (Saaty 2004).

Decision elements in ANP are evaluated using pairwise comparisons (using the Saaty scale) and local priorities of compared elements are computed as in the original AHP. In contrast to AHP, ANP employs non-linear hierarchy consisting of a (non-linear) network of clusters (for example, cluster of criteria, cluster of alternatives), nodes (elements in a cluster), and dependencies (arcs) (Kadoic et al. 2017). Intra-cluster correlation of elements and inter-cluster correlation constitute dependency and outer dependency (or feedback), respectively. The computed local priorities are placed in a so-called supermatrix calculation that handles interactions among the network of criteria and decision alternatives. The main weaknesses of the ANP are related to the complexity of the method, duration of implementation, and uncertainty in making judgments, especially those on the cluster level (Kadoic et al. 2017). However, according to Saaty (2004), ANP is more objective than AHP and will provide a truer representation of real-world scenarios.

In the MA (Fraser and Hauge 1998), criteria are ranked according to their importance, and then approval limits or thresholds are defined for each criterion (Laukkanen et al. 2004). The threshold is usually defined as the average evaluation of the alternatives with respect to the criterion considered, although other threshold values can be used. For example, in maximization problems, each alternative is approved with respect to each criterion, if the criterion value is above average, and disapproved otherwise (Kangas et al. 2006). Five classes of voting result are possible, namely: unanimous, majority, ordinally dominant, deadlocked, and indeterminate. The voting result is unanimous if only one alternative has been approved with respect to all criteria. The majority result occurs when one alternative has been approved with respect to the majority of the most important criteria. If one alternative has been deemed superior based on the order of the criteria and the dichotomous preferences, the result is ordinally dominant (for more details see Fraser and Hauge 1998). The result is deadlocked if two or more alternatives are approved and disapproved with respect to the same criteria and, hence, determination of a single superior alternative is impossible. Similarly, if one alternative is approved with respect to the most important criterion, but another is approved with respect to more criteria, the voting result is indeterminate. In that case, further preference information is needed (Fraser and Hauge 1998, Kangas et al. 2006).

The Delphi method (Dalkey and Helmer 1963) is used to obtain consensus from a group of experts (Okoli and Pawlowski 2004) and is primarily used in situations where expert judgments are required. The answers from the experts are gathered via two or more rounds of questionnaires and group feedback is obtained between the rounds. The process is stopped when the stop condition (usually the number of rounds or consensus) is achieved. A key advantage of the Delphi method is that direct confrontation with the experts is avoided. Correspondingly, these experts are encouraged to revise their previous answers in light of the replies of other group members. A detailed description of methodology (e.g., guidelines for data collection, data analysis, reporting of results) is provided elsewhere (Schmidt 1997).

Fundamental and practical descriptions of MCDA methods are provided by Belton and Stewart (2002), Ishizaka and Nemery (2013), and Kangas et al. (2015). Ishizaka and Nemery (2013) have provided examples of the software available for all MCDA methods, which may be of interest to new users.

5. MCDA in forest operations – literature review

Scientific peer-reviewed papers with MCDA methods applied to forest operation problems were found through a literature search. Most of the literature was found in previous reviews (Diaz-Balteiro and Romero 2008, Segura et al. 2014, Ezquerro et al. 2016), as well as in the Web of Knowledge and Google Scholar databases or as a result of the snowballing approach also applied. Considering only papers published in English (regardless of publication year) yielded 23 papers about MCDA in forest operations. Several aspects of these papers, such as time perspectives as well as the type of problems, criteria, and MCDA methods employed, were analyzed (Table 2). The selection of a timber harvesting system was a common type of problem, and the choice of MCDA methods, as solutions, aided in decision situations with conflicting objectives (where gut feeling would have otherwise sufficed). The harvesting and extraction category were clearly dominant, probably owing to the large amount of resources used and the value created by these activities.

From the data presented in Table 2, all three types of sustainability criteria (economic, environmental, and social) were addressed in 15 of 23 (65%) of the papers. AHP (most used MCDA method), MAUT, ANP, MA, and PROMETHEE were employed in 52% (i.e., 12), 22%, 13%, 13%, and 9% of the studies, respectively.

As Table 2 shows, group decision making occurs frequently in studies (i.e., in 16 (70%) of the papers) focused on forest operation applications of MCDA. Geographically, most of the studies (65%) were applied in Europe (Table 2), and considering time perspectives, six, fifteen, and nine papers addressed operational, tactical, and strategic issues, respectively. Some of the papers contained two perspectives and have thereby been counted twice. Practitioners in collaboration with researchers have found MCDA applications suitable for forest operation issues in all three planning levels, but the operational level was associated with the fewest papers. Indeed, within the operational time perspective, most papers addressed the longest time horizon (L1), whereas no paper addressed the on-site and real-time decision process in direct connection to the execution (i.e., L3) stage.

6. Discussion

6.1 Is there a »best« MCDA method that can be used?

Different authors have tried to answer this question from a theoretical perspective (Guitouni et al. 1998, Roy and Słowiński 2013) and in relation to particular application areas (Cinelli et al. 2014, Mulliner et al. 2016, Diaz-Balteiro et al. 2017). Selection of an appropriate MCDA method for a given problem is itself an MCDA problem and, hence, this selection creates a meta-problem, which is difficult to resolve (Triantaphyllou 2000, Mulliner et al. 2016). Guitouni et al. (1998) and Roy and Słowiński (2013) proposed questions that may help an analyst choose a MCDA method well-adapted to the decision context. We agree with Ishizaka and Nemery (2013) that this approach is intended for experienced researchers and may be too complex for forest practitioners. Practitioners should still be familiar with at least basic properties of different MCDA methods.

Methods such as SAW, SMART, AHP, and MA are simple to use and, more importantly, easier to understand than other methods, which are more mathemat-

Table 2 Summary of MCDA in forest operation papers, ordered by time perspective, forest operations category, type of problem and MCDA method used

Paper	Time	Forest operations category	Type of problem	MCDA method	Type and number of DMs	Number and type of criteria	Number of sub-criteria	Number of alternatives	Country of case study
Huth et al. (2005)	Strategical	Harvesting and extraction	Selection of harvesting system	PROMETHEE	Single	3; EC, EN, S	–	64	Malaysia
Dimou and Malivitsi (2015)	Strategical	Harvesting and extraction	Selection of harvesting system	Delphi	Group	3; EC, EN, S	15	5	Greece
Kühmaier et al. (2014)	Strategical	Logistics	Identification of energy wood terminal locations	AHP	Group (15)	8; EC, EN, S	15	–	Austria
Ghaffariyan and Brown (2013)	Strategical and tactical	Harvesting and extraction	Selection of harvesting system	PROMETHEE	Group (30)	5; O, EN	10	4	Australia
Horodnic (2015)	Strategical and tactical	Harvesting and extraction	Selection of harvesting system	AHP	Group (17)	7; EC, EN, S	28	4	Romania
Jaafari et al. (2015)	Strategical and tactical	Harvesting and extraction	Selection of harvesting system	ANP	Group (7)	3; EC, EN, S	10	4	Iran
Gerasimov and Sokolov (2014)	Strategical and tactical	Harvesting and extraction	Selection of harvesting system	HL rule	Group (51)	12; ER	–	14	Russia
Ghajar and Najafi (2012)	Strategical and tactical	Harvesting and extraction	Selection of harvesting method	ANP	Group	3; EC, EN, S	8	3	Iran
Kühmaier and Stampfer (2012)	Strategical and tactical	Logistics	Selection of energy wood supply	AHP and MAUT	Group	3; EC, EN, S	8	48	Austria
Stampfer and Lexer (2001)	Tactical	Harvesting and extraction	Selection of harvesting system	AHP and MAUT	Single	3; EC, EN, S	4	2	Austria
Kühmaier and Stampfer (2010)	Tactical	Harvesting and extraction	Selection of harvesting system	AHP, SMART and MAUT	Group	3; EC, EN, S	7	10	Austria
Wang (1997)	Tactical	Harvesting and extraction	Selection of skidding technology	AHP	No data	4; EC, EN, S	–	3	China
Ghaffarian (2008)	Tactical	Harvesting and extraction	Selection of skidding technology	AHP	Single	3; EC, EN, S	18	3	Iran
Synek and Klimánek (2015)	Tactical	Harvesting and extraction	Selection of skidding technology	AHP	Single	4; EN	–	5	Czech Republic
Talbot et al. (2014)	Tactical	Harvesting and extraction	Selection of excavator-based yarder technology	AHP	Group (40)	3; O	10	4	Norway
Melemez (2015)	Tactical	Harvesting and extraction	Risk analysis	AHP	Group	5	4	4	Turkey
Enache et al. (2013)	Tactical	Access to forest stands	Selection of forest road types	MAUT	Group	4; EC, EN, S	15	4	Romania
Diaz Balteiro et al. (2016)	Tactical and operational (L1)	Regeneration	Selection of forest plantations	AHP and GP	Group (12)	3; EC, EN, S	11	30	Spain
Laukkanen et al. (2004)	Operational (L1)	Harvesting and extraction	Selection of harvesting plan	MA	Group (7)	7; EC, EN, S	–	9	Finland
Laukkanen et al. (2005)	Operational (L1)	Harvesting and extraction	Selection of harvesting plan	MA	Group (3)	5; EC, EN, S	–	30	Finland
Palander and Laukkanen (2006)	Operational (L1)	Harvesting and extraction	Selection of harvesting system	MA	Group (3)	5; EC, EN, S	–	18	Finland
Coulter et al. (2006)	Operational (L1)	Access to forest stands	Prioritizing forest road investments	AHP	Single	3; EC, EN	12	20	USA
Olsson et al. (2017)	Operational (L2)	Regeneration	Spatial evaluation of stump suitability for harvesting	MAUT	Single	2; EC, EN	–	–	Sweden

EC – economic; EN – environmental; S – social; O – operational; ER – ergonomic;
L1 – scheduling of resources to planned actions; L2 – detailed planning of the action; L3 – real-time planning

ically complex. In addition, SAW requires minimal input parameters from decision makers. Conversely, in MAUT, ELECTRE, and ANP, DMs must define more input data (including utility functions, preference functions, indifference, preference, veto thresholds, pairwise comparisons), which is complicated and time consuming. The use of simple methods prevents the concealment of value judgments and promotes trust in the method, which is very important, especially in group decision making (Howard 1991). However, SAW (for example) assumes linearity of preferences, which may differ from the decision maker's preferences, and is therefore unrefined (Ishizaka and Nemery 2013). For example, can we assume that a forest company profit of $2M is twice as good as a profit of $1M?

Diaz-Balteiro et al. (2017) stated that characteristics, such as number of criteria and DMs, of the problem under consideration are crucial for the selection of a method. For example, the MAUT method may be suitable if the aim is to solve a problem with a small number of criteria and a few well-prepared DMs. Conversely, more pragmatic methods (compared with MAUT), such as AHP or Outranking methods, should be considered if there are many criteria and a set of DMs without any specific training in decision analysis (Diaz-Balteiro et al. 2017). Similarly, AHP, SMART, MA or Delphi are (compared with other methods) better suited for group decision making, as they are user friendly and more easily understandable. These comparisons suggest that non-complex methods should be employed for large non-expert groups. As previously explained, for problems where complete ranking of alternatives is required, outranking methods should be avoided in favor of methods with a compensatory nature. In addition, ANP should be used for decision-making problems involving dependent criteria.

There is no a »golden« MCDA method that suits all types of forest operations problems. Therefore, a general recommendation to practitioners is to concentrate on the selection of criteria and definition of alternatives, which will be essential for the outcome from all methods. If all relevant criteria and alternatives are included, with reliable data, then the output of most MCDA methods will yield substantial reduction in the risk of making decisions that lead to undesired outcomes.

6.2 Can MCDA methods be further used at operational levels?

The literature review indicates that a few publications have addressed MCDA application in forest operations. The MCDA methods used were similar to those employed in similar fields. A review of studies within the environmental field revealed that AHP, MAUT, PROMETHEE, ELECTRE, and TOPSIS were used in 48%, 16%, 8%, 5%, and 2% of the studies, respectively. The remaining papers were reviews and combinations of several MCDA methods (Huang et al. 2011). Diaz-Balteiro and Romero (2008) reported similar ranking for MCDA applications to forestry problems in the last 30 years, with AHP (22%), MAUT (17%), and GP (17%) representing the most commonly used methods. Hence, AHP is the dominant MCDA method for problems associated with environmental, forest management, and forest operation decisions. This is attributed to the fact that AHP is understandable and user-friendly, easy to use in group settings, and has the ability to combine qualitative and quantitative data in an effective manner.

Few publications address MCDA application in forest operations, which indicates that most of the forest scholars and practitioners working with forest operations have limited knowledge about MCDA methods. This paper can help fill the knowledge gap regarding these methods. However, scholars and practitioners may be aware of MCDA, but simply avoid using these methods. For example, a survey of information technology (IT) companies (Bernroider and Schmollerl 2013) reported that 71.9% of those companies were aware of MCDA methods, but only 33.3% used these methods (Ishizaka and Siraj 2018). There are no similar data for forestry, but the results may be similar. In general, the use of MCDA methods may be limited by several factors (Davis 1989, Venkatesh and Bala 2008, Giannoulis and Ishizaka 2010, Ishizaka and Nemery 2013, Ishizaka and Siraj 2018), including:

- ⇒ practitioners lack a clear perception of the added value (perceived usefulness)
- ⇒ non-experts struggle with understanding the MCDA methods
- ⇒ different MCDA methods may result in different solutions for the same problem, which adds to the confusion about which method to choose for a particular type of problem (Ishizaka and Siraj 2018).

MCDA can be subject to several behavioral and procedural biases (Montibeller and von Winterfeldt 2015), which can occur in all phases of the decision-making process, leading to incorrect recommendations (Marttunen et al. 2018).

The review also reveals that MCDA methods are less often used to address applications on the operational level, especially on the levels close to the execution of a decision (L2 and L3), than on other levels. This may be attributed to several factors. First, operational problems (in general) and everyday type problems, which are solved through routines and rules of thumb, occur more frequently than strategic problems (i.e., the one-off type, which are perceived as more complex). These strategic problems represent the »classical« MCDA problem setting. Second, on the operational level the need for concrete, precise, and updated data, is greater than on the strategic and tactical levels. For example, consider the selection of the most appropriate route for forestry machines in the terrain. Detailed and up-to-date data on factors related to soil damage (e.g., soil type, moisture content, slope, streams, daily precipitation data) are required if one of the criteria is aimed at minimizing soil damage. In contrast, descriptive or qualitative data (which can be less precise than quantitative data) is sometimes sufficient for the strategic level. Third, scholars may be more motivated and interested to write papers, which consider strategic and tactical problems as they might be perceived as *bigger* and more *important* issues (than other issues). Fourth, structuring a MCDA problem is a complex task (see Section 4), which requires certain methodological knowledge. The MCDA applications are, however, case-specific, and conditions may differ substantially on the operational level, possibly preventing the transfer of results from such case studies into general practice (Erler 2017). Fifth, many operational planning issues, such as planning of logging operations, are solved with one key criterion (economic) and the rest of the criteria serve more as frames. Therefore, the problem may be seen more as a profit-optimization problem (with environmental and social constraints) than a MCDA problem.

Conformation to the ongoing transformation of forestry (environmental and social aspects have become increasingly important) requires further development and incorporation of MCDA methods into decision-making on the operational planning horizon of forest operations. For example, one possible future direction could be to develop and use general MCDA models for certain types of forest operation problems. Erler (2017) described a general DSS for the selection of harvesting system with characteristics that can be transferred to local conditions. This DSS lacks the precision and detail required to fit the diverse conditions in normal forestry. However, this DSS can be considered a compromise solution between a complex DSS, which requires practitioners with high MCDA skills, and decision making through routines and rules of thumb. Moreover, with potential technological innovation (i.e., capture of Big data) in timber harvesting (see Lindroos et al. 2017), relevant and correct data would be expected. The use of MCDA, even for real-time operational problems, may then be required.

Furthermore, the addition of other criteria and application of MCDA yield a rather cumbersome process of structuring the decision problem, assessing the possible impact of each alternative, determining the preferences of DMs, and evaluating and comparing alternatives. Performing this process is, therefore, easier at lower operational levels (L1), where the decisions are further away from execution, than at higher operational levels. Indeed, there is no possibility for an operator to implement a full MCDA method for each decision of which tree to harvest and which to leave in thinning. However, the operator would benefit from a DSS in the form of a work-methodology that has been developed with MCDA methods. The operator would then assess the alternatives and determine the decisions required under certain well-defined conditions, without having to execute the MCDA methods. This is similar to well-established concepts, such as eco-driving, where fuel consumption, costs, and/or travel time are combined and a DSS is presented to drivers in the form of behavioral guidelines (Barkenbus 2010). Therefore, we see a future need for incorporating MCDA into forest operations on operational level L3 (i.e., real-time planning immediately preceding execution via MCDA incorporation in the development of new work methods). Future guidelines for conducting forest work should benefit from the use of MCDA, which would provide operators with rules that incorporate possibly conflicting goals related to economic, environmental, and social factors. The challenge will be to develop rules that are accepted by the operators. The acceptance of (new) rules and the corresponding behavioral change are often difficult to achieve (e.g., Barkenbus 2010), irrespective of the methods used to develop those rules. With MCDA, the rule-development process will be rather transparent and may in fact facilitate acceptance, if the work is performed with appropriate criteria and weights, as well as engagement of suitable DM.

7. References

Acosta, M., Corral, S., 2017: Multicriteria decision analysis and participatory decision support systems in forest management. Forests 8(4): 116–131.

Ananda, J., Herath, G., 2009: A critical review of multi-criteria decision making methods with special reference to forest management and planning. Ecological economics 68(10): 2535–2548.

Barkenbus, J.N., 2010: Eco-driving: An overlooked climate change initiative. Energy Policy 38(2): 762–769.

Behzadian, M., Kazemzadeh, R.B., Albadvi, A., Aghdasi, M., 2010: PROMETHEE: A comprehensive literature review on methodologies and applications. European journal of Operational research 200(1): 198–215.

Belton, V., Stewart, T., 2002: Multiple criteria decision analysis: an integrated approach. Springer Science & Business Media, Norwell, MA, USA, 372 p.

Belton, V., Stewart, T., 2010: Problem structuring and multiple criteria decision analysis. In: Trends in multiple criteria decision analysis, Springer Boston MA, 209–239 p.

Bennett, P., Bryant, J., Howard, N., 2001: Drama theory and confrontation analysis. In: Rational Analysis for a Problematic World Revisited. John Wiley and Sons Ltd., Chichester, UK, 384 p.

Bernroider, E.W., Schmöllerl, P., 2013: A technological, organisational, and environmental analysis of decision making methodologies and satisfaction in the context of IT induced business transformations. European Journal of Operational Research 224(1): 141–153.

Blagojevic, B., Srdjevic, B., Srdjevic, Z., Zoranovic, T., 2016: Deriving Weights of the Decision Makers Using AHP Group Consistency Measures. Fundamenta Informaticae 144(3–4): 383–395.

Borges, J.G., Nordström, E.M., Garcia Gonzalo, J., Hujala, T., Trasobares, A., 2014: Computer-based tools for supporting forest management. SLU, Umea, Sweden [https://pub.epsilon.slu.se/11417/].

Brans, J.P., Vincke, P., Mareschal, B., 1986: How to select and how to rank projects: the PROMETHEE method. European Journal of Operations Research 24(2): 228–238.

Carlsson, D., D'Amours, S., Martel, A., Rönnqvist, M., 2006: Supply chain management in the pulp and paper industry. Working paper DT-2006-AM-3, Interuniversity Research Center on Enterprise Networks, Logistics and Transportation (CIRRELT), Universite Laval, Quebec, Canada, 39 p.

Charnes, A., Cooper, W.W., 1961: Management models and industrial applications of linear programming (Vol. I), John Wiley and Sons, New York, NY, USA, 471 p.

Checkland, P., 2001: Soft systems methodology. In: Rational Analysis for a Problematic World Revisited, John Wiley and Sons Ltd., Chichester, UK, 384 p.

Chiclana, F., Herrera-Viedma, E., Herrera, F., Alonso, S., 2007: Some induced ordered weighted averaging operators and their use for solving group decision-making problems based on fuzzy preference relations. European Journal of Operational Research 182(1): 383–399.

Cho, Y.G., Cho, K.T., 2008: A loss function approach to group preference aggregation in the AHP. Computers and Operations Research 35(3): 884–892.

Church, R.L., 2007: Tactical-level forest management models. In: Handbook of operations research in natural resources, Springer Science + Business Media LLC, New York, NY, USA, 343–363.

Cinelli, M., Coles, S.R., Kirwan, K., 2014: Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. Ecological Indicators 46: 138–148.

Cooke, R., 1991: Experts in uncertainty: opinion and subjective probability in science. Oxford University Press on Demand, New York, NY, USA, 336 p.

Coulter, E.D., Coakley, J., Sessions, J., 2006: The analytic hierarchy process: A tutorial for use in prioritizing forest road investments to minimize environmental effects. International journal of forest engineering 17(2): 51–69.

Dalkey, D., Helmer, O., 1963: An experimental application of the Delphi method to the use of experts. Management science 9(3): 458–467.

Davis, F.D., 1989: Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13: 319–340.

D'Amours, S., Rönnqvist, M., Weintraub, A., 2008: Using operational research for supply chain planning in the forest products industry. INFOR: Information Systems and Operational Research 46(4): 265–281.

Diakoulaki, D., Mavrotas, G., Papayannakis, L., 1995: Determining objective weights in multiple criteria problems: The critic method. Computers and Operations Research 22(7): 763–770.

Diaz-Balteiro, L., Romero, C., 2008: Making forestry decisions with multiple criteria: a review and an assessment. Forest ecology and management 255(8): 3222–3241.

Diaz-Balteiro, L., Alfranca, O., González-Pachón, J., Romero, C., 2016: Ranking of industrial forest plantations in terms of sustainability: A multicriteria approach. Journal of environmental management 180: 123–132.

Diaz-Balteiro, L., González-Pachón, J., Romero, C., 2017: Measuring systems sustainability with multi-criteria methods: A critical review. European Journal of Operational Research 258(2): 607–616.

Dimou, V., Malivitsi, Z., 2015: Strategic decision model for the evaluation of timber harvesting systems. International journal of forest engineering 26(2): 146–157.

Eden, C., Ackermann, F., 2001: SODA – the principles. In: Rational Analysis for a Problematic World Revisited. John Wiley and Sons Ltd., Chichester, UK, 384 p.

Edwards, W., 1977: How to use multi attribute utility measurement for social decision making. IEEE Transactions on Systems, Man and Cybernetics 7(5): 326–340.

Enache, A., Ciobanu, V.D., Kühmaier, M., Stampfer, K., 2013: An integrative decision support tool for assessing forest road options in a mountainous region in Romania. Croatian Journal of Forest Engineering 34(1): 43–60.

Epstein, R., Karlsson, J., Rönnqvist, M., Weintraub, A., 2007: Harvest operational models in forestry. In: Handbook of operations research in natural resources, Springer Science + Business Media LLC, New York, NY, USA, 365–377.

Erler, J., 2017: Transfer System to Adapt Timber Harvesting Operations to Local Conditions. Croatian Journal of Forest Engineering 38(2): 197–208.

Ezquerro, M., Pardos, M., Diaz-Balteiro, L., 2016: Operational Research Techniques Used for Addressing Biodiversity Objectives into Forest Management: An Overview. Forests 7(10): 229–247.

Fraser, N.M., Hauge, J.W., 1998: Multicriteria approval: application of approval voting concepts to MCDM problems. Journal of Multi-Criteria Decision Analysis 7(5): 263–273.

Friend, J., 2001: The strategic choice approach. In: Rational Analysis for a Problematic World Revisited. John Wiley and Sons Ltd., Chichester, UK, 384 p.

Gerasimov, Y., Sokolov, A., 2014: Ergonomic evaluation and comparison of wood harvesting systems in Northwest Russia. Applied Ergonomics 45(2): 318–338.

Ghaffaryian, M.R., 2008: Selecting the best skidding system using AHP: A case study in Northern Iran. Nauka Gorata 45: 77–86.

Ghaffariyan, M.R., Brown, M., 2013: Selecting the efficient harvesting method using multiple-criteria analysis: A case study in southwest Western Australia. Journal of Forest Science 59(12): 479–486.

Ghajar, I., Najafi, A., 2012: Evaluation of harvesting methods for sustainable forest management (SFM) using the analytical network process (ANP). Forest policy and economics 21: 81–91.

Giannoulis, C., Ishizaka, A., 2010: A Web-based decision support system with ELECTRE III for a personalised ranking of British universities. Decision Support Systems 48(3): 488–497.

Gregory, R.S., 2002: Incorporating value trade-offs into community-based environmental risk decisions. Environmental Values 11(4): 461–488.

Guitouni, A., Martel, J.M., 1998: Tentative Guidelines to Help Choosing an Appropriate MCDA Method. European Journal of Operational Research 109(2): 501–521.

Gunn, E.A., 2007: Models for strategic forest management. In: Handbook of operations research in natural resources, Springer Science + Business Media LLC, New York, NY, USA, 343–363, 317–341.

Hajkowicz, S.A., McDonald, G.T., Smith, P.N., 2000: An evaluation of multiple objective decision support weighting techniques in natural resource management. Journal of Environmental Planning and Management 43(4): 505–518.

Hokkanen, J., Salminen, P., 1997: Choosing a solid waste management system using multicriteria decision analysis. European Journal of Operational Research 98(1): 19–36.

Horodnic, S.A., 2015: A risk index for multicriterial selection of a logging system with low environmental impact. Environmental Impact Assessment Review 51: 32–37.

Howard, A.F., 1991: A critical look at multiple criteria decision making techniques with reference to forestry applications. Canadian journal of forest research 21(11): 1649–1659.

Huang, I.B., Keisler, J., Linkov, I., 2011: Multi-criteria decision analysis in environmental sciences: ten years of applications and trends. Science of the total environment 409(19): 3578–3594.

Huth, A., Drechsler, M., Köhler, P., 2005: Using multicriteria decision analysis and a forest growth model to assess impacts of tree harvesting in Dipterocarp lowland rain forests. Forest Ecology and Management 207(1): 215–232.

Hwang, C.L., Yoon, K., 1981: Methods for multiple attribute decision making. In: Multiple attribute decision making, Springer Berlin Heidelberg, Germany, 58–191 p.

Ishizaka, A., Nemery, P., 2013: Multi-criteria decision analysis: methods and software. John Wiley & Sons, Chichester, United Kingdom, 310 p.

Ishizaka, A., Siraj, S., 2018: Are multi-criteria decision-making tools useful? An experimental comparative study of three methods. European Journal of Operational Research 264(2): 462–471.

Jaafari, A., Najafi, A., Melón, M.G., 2015: Decision-making for the selection of a best wood extraction method: An analytic network process approach. Forest Policy and Economics 50: 200–209.

Ju, Y.B., Wang, A.H., 2013: Projection method for multiple criteria group decision making with incomplete weight information in linguistic setting. Applied Mathematical Modelling 37(20–21): 9031–9040.

Kadoić, N., Ređep, N.B., Divjak, B., 2017: Decision Making with the Analytic Network Process. In: The 14th International Symposium on Operational Research in Slovenia, 27–29 September, Bled, Slovenia, 180–186 [http://bib.irb.hr/datoteka/888413.anp_sor17_nk_nbr_bd_finale.pdf]

Kangas, A., Kurttila, M., Hujala, T., Eyvindsin, K., Kangas, J., 2015: Decision support for forest management, second edition, Springer Berlin, Germany, 307 p.

Kangas, A., Laukkanen, S., Kangas, J., 2006: Social choice theory and its applications in sustainable forest management–a review. Forest Policy and economics 9(1): 77–92.

Kangas, J., Kangas, A., 2005: Multiple criteria decision support in forest management–the approach, methods applied, and experiences gained. Forest ecology and management 207(1): 133–143.

Keeney, R.L., 1982: Decision analysis: an overview. Operations Research 30(5): 803–838.

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

Keeney, R., Raiffa, H., 1976: Decision with multiple objectives: Preferences and value tradeoffs. Wiley New York, NY, USA, 569 p.

Kühmaier, M., Stampfer, K., 2010: Development of a multi-attribute spatial decision support system in selecting timber harvesting systems. Croatian journal of forest engineering 31(2): 75–88.

Kühmaier, M., Kanzian, C., Stampfer, K., 2014: Identification of potential energy wood terminal locations using a spatial multicriteria decision analysis. Biomass and Bioenergy 66: 337–347.

Laukkanen, S., Palander, T., Kangas, J., 2004: Applying voting theory in participatory decision support for sustainable timber harvesting. Canadian Journal of Forest Research 34(7): 1511–1524.

Laukkanen, S., Palander, T., Kangas, J., Kangas, A., 2005: Evaluation of the multicriteria approval method for timber-harvesting group decision support. Silva Fennica 39(2): 249–264.

Lindroos, O., La Hera, P., Häggström, C., 2017: Drivers of Advances in Mechanized Timber Harvesting–a Selective Review of Technological Innovation. Croatian Journal of Forest Engineering 38(2): 243–258.

Linkov, I, Varghese, A., Jamil, S., Seager, T.P., Kiker, G., Bridges, T., 2004: Multi-criteria decision analysis: a framework for structuring remedial decisions at contaminated sites. In: Comparative risk assessment and environmental decision making, Springer, Dordrecht, the Netherlands, 15–54.

Lootsma, F.A., 1997: Fuzzy Logic for Planning and Decision Making. Kluwer Academic Publishers, Dordrecht, the Netherlands, 192 p.

Kühmaier, M., Stampfer, K., 2012: Development of a multi-criteria decision support tool for energy wood supply management. Croatian Journal of Forest Engineering 33(2): 181–198.

Marttunen, M., Belton, V., Lienert, J., 2018: Are objectives hierarchy related biases observed in practice? A meta-analysis of environmental and energy applications of Multi-Criteria Decision Analysis. European Journal of Operational Research 265(1): 178–194.

Melemez, K., 2015: Risk factor analysis of fatal forest harvesting accidents: A case study in Turkey. Safety science 79: 369–378.

Mendoza, G.A., Martins, H., 2006: Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest Ecology and Management 230(1–3): 1–22.

Mendoza, G.A., Prabhu, R., 2003: Qualitative multi-criteria approaches to assessing indicators of sustainable forest resource management. Forest ecology and management 174(1): 329–343.

Montibeller, G., Winterfeldt, D., 2015: Cognitive and motivational biases in decision and risk analysis. Risk Analysis 35(7): 1230–1251.

Morton, A., Fasolo, B., 2009: Behavioural decision theory for multi-criteria decision analysis: a guided tour. Journal of the Operational Research Society 60(2): 268–275.

Mulliner, E., Malys, N., Maliene, V., 2016: Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. Omega 59(part B): 146–156.

Nordström, E.M., 2010: Integrating multiple criteria decision analysis into participatory forest planning. Doctoral Dissertation, Swedish University of Agricultural Sciences, Umeå, Sweden, 70 p.

Nordström, E.M., Eriksson, L.O., Öhman, K., 2010: Integrating multiple criteria decision analysis in participatory forest planning: Experience from a case study in northern Sweden. Forest policy and economics 12(8): 562–574.

Okoli, C., Pawlowski, S.D., 2004: The Delphi method as a research tool: an example, design considerations and applications. Information and management 42(1): 15–29.

Olsson, B.A., Hannrup, B., Jönsson, M., Larsolle, A., Nordström, M., Mörtberg, U., Rudolphi, J, Strömgren, M., 2017: A decision support model for individual tree stump harvesting options based on criteria for economic return and environmental protection. Scandinavian Journal of Forest Research 32(3): 246–259.

Palander, T., Laukkanen, S., 2006: A vote-based computer system for stand management planning. International Journal of Forest Engineering 17(1): 13–20.

Pohekar, S.D., Ramachandran, M., 2004: Application of multi-criteria decision making to sustainable energy planning–a review. Renewable and sustainable energy reviews 8(4): 365–381.

Raiffa, H., 1968: Decision Analysis: Introductory Lectures on Choices under Uncertainty. Addision-Wesley, Reading, MA, USA, 300 p.

Ramanathan, R., Ganesh, L.S., 1994: Group preference aggregation methods employed in AHP: an evaluation and an intrinsic process for deriving members' weightages. European Journal of Operational Research 79(2): 249–265.

Regan, H.M., Colyvan, M., Markovchick-Nicholls, L., 2006: A formal model for consensus and negotiation in environmental management. Journal of Environmental Management 80(2): 167–176.

Rogers, M., Bruen, M., 1998: A new system for weighting environmental criteria for use within ELECTRE III. European Journal of Operational Research 107(3): 552–563.

Romero, C., Tamiz, M., Jones, D.F., 1998: Goal programming, compromise programming and reference point method formulations: linkages and utility interpretations. Journal of the Operational Research Society 49(9): 986–991.

Rosenhead, J., 2001: Robustness analysis: keeping your options open. In: Rational Analysis for a Problematic World Revisited. John Wiley and Sons Ltd., Chichester, UK, 384 p.

Roy, B., 1968: Classement et choix en présence de points de vue multiples (la méthode ELECTRE). Revue Française d'Informatique et de Recherche Opérationnelle 2(8): 57–75.

Roy, B., Słowiński, R., 2013: Questions guiding the choice of a multicriteria decision aiding method. EURO Journal on Decision Processes 1(1–2): 69–97.

Rönnqvist, M., D'Amours, S., Weintraub, A., Jofre, A., Gunn, E., Haight, R.G., Martell, D., Murray, A.T., Romero, C., 2015: Operations research challenges in forestry: 33 open problems. Annals of Operations Research 232(1): 11–40.

Saaty, T.L., 1980: The analytic hierarchy process. McGraw-Hill New York, NY, USA, 287 p.

Saaty, T.L., 2004: Fundamentals of the analytic network process–Dependence and feedback in decision-making with a single network. Journal of Systems science and Systems engineering 13(2): 129–157.

Salminen, P., Hokkanen, J., Lahdelma, R., 1998: Comparing multicriteria methods in the context of environmental problems. European Journal of Operational Research 104(3): 485–496.

Schmidt, R.C., 1997: Managing Delphi surveys using nonparametric statistical techniques. Decision Sciences 28(3): 763–774.

Segura, M., Ray, D., Maroto, C., 2014: Decision support systems for forest management: A comparative analysis and assessment. Computers and Electronics in Agriculture 101: 55–67.

Shannon, C.E., Weaver, W., 1947: The mathematical theory of communication. The University of Illinois Press, Urbana.

Srdjevic, B., Medeiros, Y.D.P., Faria, A.S., 2004: An objective multi-criteria evaluation of water management scenarios. Water resources management 18(1): 35–54.

Srdjevic, Z., Blagojevic, B., Srdjevic, B., 2011: AHP based group decision making in ranking loan applicants for purchasing irrigation equipment: a case study. Bulgarian Journal of Agricultural Science 17(4): 531–543.

Stampfer, K., Lexer, M.J., 2001: Multicriteria evaluation of thinning operations on steep terrain. Workshop Proceedings: New trends in wood harvesting with cable systems for sustainable forest management, 18–24 June, Ossiach, Austria, 73–79.

Sundberg, U., 1988: The emergence and establishment of forest operations and techniques as a discipline in forest science – An essay in honour of Ivar Samset. Communications of the Norwegian Forest Research Institute 41(8): 107–137.

Synek, M., Klimánek, M., 2015: Spatial Modeling of a New Technological Typification in Forestry Based on Multicriteria Evaluation of Skidding Technologies. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis 63(3): 841–852.

Talbot, B., Tarp, P., Nitteberg, M., 2014: Selecting an appropriate excavator-based yarder concept for Norwegian conditions through the analytic hierarchy process. International journal of forest engineering 25(2): 113–123.

Triantaphyllou, E., 2000: Multi-Criteria Decision Making Methods: A Comparative Study. Kluwer Academic Publishers, Dordrecht, the Netherelands, 290 p.

UNCED, 1992: United Nations Conference on Environment & Development. Rio de Janerio, Brazil, 3–14 June, AGENDA 21, 351 p. [https://sustainabledevelopment.un.org/content/documents/ Agenda21.pdf]

Van Den Honer, R.C., 2001: Decisional Power in Group Decision Making: A Note on the Allocation of Group Members' Weights in the Multiplicative AHP and SMART. Group Decision and Negotiation 10(3): 275–286.

Venkatesh, V., Bala, H., 2008: Technology acceptance model 3 and a research agenda on interventions. Decision Sciences 39(2): 273–315.

Wang, L., 1997: Assessment of animal skidding and ground machine skidding under mountain conditions. Journal of Forest Engineering 8(2): 57–64.

Yue, Z.L., 2012: Developing a straightforward approach for group decision making based on determining weights of decision makers. Applied Mathematical Modelling 36(9): 4106–4117.

Zeleny, M., 1982: Multiple Criteria Decision Making. McGraw-Hill New York, NY, USA, 563 p.

Authors' addresses:

Boško Blagojević, PhD *
e-mail: bosko.blagojevic@slu.se
Prof. Ola Lindroos, PhD
e-mail: ola.lindroos@slu.se
Swedish University of Agricultural Sciences
Department of Forest Biomaterials and Technology
Skogsmarksgränd 12
901 83 Umeå
SWEDEN

Rikard Jonsson, MSc
e-mail: rikard.jonsson@skogforsk.se
Rolf Björheden, PhD
e-mail: rolf.bjorheden@skogforsk.se
The Forestry Research Institute of Sweden – Skogforsk
Forest Operations Unit
Dag Hammarskjölds väg 36 A
751 83 Uppsala
SWEDEN

Eva-Maria Nordström, PhD
e-mail: eva-maria.nordstrom@slu.se
Swedish University of Agricultural Sciences
Department of Forest Resource Management
Skogsmarksgränd 12
901 83 Umeå
SWEDEN

*Corresponding author

Received: April 20, 2018
Accepted: August 26, 2018