Helsinki University of Technology

Systems Analysis Laboratory Research Reports A86, June 2003

LIFE CYCLE IMPACT ASSESSMENT BASED ON DECISION ANALYSIS

Jyri Seppälä

Dissertation for the degree of Doctor of Science in Technology to be presented with due permission for public examination and debate in Auditorium E at Helsinki University of Technology (Espoo, Finland) on the 29th of August, 2003, at 12 o'clock noon.

Helsinki University of Technology
Department of Engineering Physics and Mathematics
Systems Analysis Laboratory

Distribution:
Systems Analysis Laboratory
Helsinki University of Technology
P.O.Box 1100
FIN-02015 HUT, FINLAND
Tel. +358-9-451 3056
Fax +358-9-451 3096
systems.analysis@hut.fi

This report is downloadable at
www.sal.hut.fi/Publications/r-index.html

ISBN 951-22-6592-3
ISSN 0782-2030

Otamedia Oy
Espoo 2003

Title: Life cycle impact assessment based on decision analysis

Author: Jyri Seppälä
Finnish Environment Institute
Mechelininkatu 34 a
P.O.Box 140, 00251 Helsinki
jyri.seppala@ymparisto.fi

Date: June 2003

Status: Systems Analysis Laboratory Research Reports A86, June 2003

Abstract: Life cycle assessment (LCA) is a popular tool for evaluating environmental impacts of products and services. However, the methodological choices and framework to assess environmental impacts in LCA are still under discussion. Despite intensive development worldwide, few attempts have been made hitherto to systematically present the theoretical bases of life cycle impact assessment (LCIA). In this study, the decision analytic foundations for LCIA are illustrated. It is shown that the typical aggregation equation used in LCIA for calculating indicator results can be derived from multiattribute value theory (MAVT) if certain simple assumptions hold. The decision analysis framework presented in this work offers additional values for all the phases of LCIA. A value tree, a tool used for structuring multicriteria decision making problems, can be helpful for selection of impact categories and classification. MAVT can clarify the debate concerning marginal and average approaches in the determination of characterisation factors. On the basis of MAVT, normalisation is needed before weighting. The methods and experiences of preference elicitation derived from the field of decision analysis can be utilised in the determination of subjective characterisation factors and impact category weights. Furthermore, experiences and techniques for the sensitivity analysis of multi-criteria decision models can be utilised in LCIA. In addition, MAVT assists in the calculation of impact category indicator results and total impact indicator results according to the appropriate aggregation equations. The decision analysis framework presented in this work is flexible and suitable for different impact assessment approaches developed in LCIA and it can help the methodological development with which the non-linearity aspects of impact assessment are taken into account. It is shown in the work that site-dependent characterisation methods can easily be fitted into the framework. In a case study of the Finnish forest industry a Finland-specific impact assessment model utilising the results of other tools, such as air quality and transport models and even expert judgements, was developed. In addition, the so-called ratio estimation method for the elicitation of impact category weights was applied and developed so that interval-valued ratio judgements could be used in the uncertainty analysis of the model. In the case of the Finnish metals industry, decision analysis impact assessment was applied to produce a solution in which global, regional and local environmental problems were assessed in the same framework. In both case studies, experts working with the environmental issues valuated impact category weights with the help of decision analysis techniques. In the work it was shown that MAVT provides a foundation for a logical and rational approach to impact assessment in LCA. In the future, there is a need to demonstrate quantitatively the differences between LCIA conducted according to MAVT and according to current practices. Furthermore, there is a need for research to study the strengths and weaknesses of the different decision analysis methods for LCIA purposes.

Keywords: life cycle impact assessment, LCA, decision analysis, valuation, environmental impact assessment, forest industry, metals industry, models, theories.

Academic dissertation

Systems Analysis Laboratory
Helsinki University of Technology

Life cycle impact assessment based on decision analysis

Author:	Jyri Seppälä
Supervising professor:	Professor Raimo P. Hämäläinen Helsinki University of Tehcnology
Preliminary examiners:	Dr. Reinout Heijungs University of Leiden, The Netherlands
	Dr. Mari Hjelt Gaia Group Oy, Finland
Official opponent:	Professor Anne-Marie Tillman Chalmers University of Technology, Sweden

Publications

This study consists of the following publications, which are referred to by their Roman numerals. The author's contribution in each article is described below. In addition, some previously unpublished results are presented.

I Seppälä, J. 1999. Decision analysis as a tool for life cycle impact assessment. In: Klöpffer, W. & Hutzinger, O., *LCA Documents* 4. Eco-Informa Press, Bayreuth (Also published in *The Finnish Environment* 123. Finnish Environment Institute, Helsinki).

II Seppälä, J. & Hämäläinen, R.P. 2001. On the meaning of the distance-to-target weighting method and normalisation in life cycle impact assessment. *International Journal of Life Cycle Assessment* 6(4): 211-218.

III Seppälä, J., Koskela, S., Melanen, M. & Palperi, M. 2002. The Finnish metals industry and the environment. *Resources, Conservation and Recycling* 35: 61-76.

IV Seppälä, J., Basson, L. & Norris, G. A. 2002. Decision analysis frameworks for life-cycle impact assessment. *Journal of Industrial Ecology* 5(4): 45-68.

Contribution of the author

I J. Seppälä is fully responsible for this paper.
II J. Seppälä planned the study, compared different life cycle impact assessment methods to the theoretical basis of multiattribute value theory and wrote the paper, which was commented by R.P. Hämäläinen.
III J. Seppälä was responsible for the structures of the paper and life cycle impact assessment. All authors wrote the improvement analysis jointly.
IV The paper was initiated, planned and written jointly by J. Seppälä and L. Basson. The paper was commented by G. Norris. Seppälä was in particular responsible for findings concerning multiattribute value theory and life cycle impact assessment.

Acknowledgements

A starting point for this study was an application of LCA to the Finnish forest industry, carried out by the Finnish Environment Institute (SYKE) in 1995-1997. The project team was led by Lea Kauppi. The project was a learning process for us all and it gave me the opportunity to develop my thoughts about links between environmental impact assessment, LCA and decision analysis. I express my warm thanks to the team and the numerous persons involved in the project. Especially, I would like to express my thanks to Antero Honkasalo from the Ministry of the Environment for encouragement to start the study and to continue to apply the methodology in the other sectors in order to produce new data for environmental policy.

My contacts with several colleagues and institutes in Finland and abroad have played an important role in different stages of the work. I am greatly indebted to Juha Grönroos, Jyrki Tenhunen, Sirkka Koskela, Asta Reinikainen and Kimmo Silvo from SYKE for collaboration with different LCIA applications. Especially, Matti Johansson has contributed to my thoughts about impact assessment methodology of regional impact categories. Encouragement given by Juha Kämäri, Mikael Hildén, Veli-Matti Tiainen and Alec Estlander had important role in completing the thesis. Numerous other colleagues in SYKE and experts involved in different LCIA applications deserve my thanks for their support. My deepest thanks are due to Matti Melanen from SYKE, who has provided invaluable support in reviewing of manuscripts of articles and the summary of this thesis.

The involvement in the SETAC-Europe working groups on life cycle assessment concerning global and regional impact categories and normalization, grouping and weighting has created for me an inspiring community of colleagues throughout Europe and across the Atlantic. The co-operations with Mark Huijbregts and José Potting from the Netherlands have encouraged me to continue in the field of site-specific impact assessment in LCIA. On the other hand, the co-operation with Lauren Basson from Australia and Greg Norris from USA, in particular, has provided me a forum for creative debates about decision analysis impact assessment framework.

The summary paper was greatly improved due to the comments of the pre-examiners Mari Hjelt and Reinout Heijungs. I would like to thank them for their valuable comments and careful reading of the manuscript. The research was supervised by Prof. Raimo P. Hämäläinen from Helsinki University of Technology. I would like to thank him for his encouragement. He has been an important person to me in deepening my understanding on decision analysis. I also thank Michael Bailey for checking the English of the manuscript.

Finally, I want to express my warmest thanks to my wife and my sons for their patience and understanding while I was concentrating more on my thesis than on my family. Without their support the task would never have been completed.

This thesis is dedicated to the memories of my father and my grandparents.

Järvenpää, May 2003 Jyri Seppälä

Contents

1 Introduction

1.1 Life cycle impact assessment as part of LCA

Production and consumption of goods and services are primary factors causing harmful effects on the environment. For this reason, the management of production and consumption is a key area in order to achieve sustainable development in our society. There is a need for decision-making tools for evaluating environmental options particularly in relation to goods and services. In this field life cycle assessment (LCA) appears to be a valuable tool and its use has increased dramatically in recent years. Life cycle assessment is a method for assessing the environmental considerations of a product or service throughout its entire life cycle. A complete life cycle includes everything from raw material extraction, processing, transportation, manufacturing, distribution, use, re-use, maintenance and recycling to final disposal (Consoli et al. 1993).

The overall framework for LCA is well established. The works of Fava et al. (1993) and Consoli et al. (1993) outlined LCA as a four-step process (Fig. 1). It is initiated with goal definition and scoping, followed by life cycle inventory and life cycle impact assessment. In goal and scope definition, the problem and the aims of the study are defined. In this step, a functional unit of the work (e.g. one tonne hot rolled steel bar) is chosen, for which the inventory and impact assessment results will be presented. In inventory analysis, data about environmental interventions (emissions, resource extractions and land use) during the life cycle of the product or service is collected. In impact assessment, the inventory data is compared and aggregated from the point of view of environmental impacts. In the last step, interpretation (formerly called improvement analysis), the inventory and impact assessment results are analysed against the aim of the study, including an assessment of uncertainties and key assumptions as well as recommendations for actions. Although the carrying out of an LCA follows the sequence described above, in practice, LCA is a highly iterative tool. Findings in any step of LCA can lead to changes in the other steps (see the two-way arrows in Fig. 1).

During the 1990s the steps of LCA were assigned their detailed contents on the basis of co-operation between investigators in several countries, especially in the Society of Environmental Toxicology and Chemistry (SETAC) and the International Organization for Standardization (ISO). Life cycle assessment is documented in the form of ISO standards 14040-14043, giving instructions for LCA practitioners to conduct LCA applications according to “good practice”.

Inventory data, environmental interventions representing a “cradle-to-grave” perspective, are the core of LCAs. However, from the point of view of a decision maker, the inventory results are usually not sufficient for decision-making. It is difficult to give answers to the question whether intervention X should be regarded as more severe than intervention Y in the product system P. In comparative studies it may be found that alternative A is better than alternative B in some interventions, but poorer in others. In such cases, the impact assessment phase is used in LCA. Life cycle impact assessment (LCIA) enables us to interpret the results of the inventory and furthermore to draw the correct conclusions concerning improvement approaches (Saur et al. 1996). The consideration of environmental effects as a consequence of environmental interventions provides additional information, which is not covered by the inventory step. However, a life cycle study does not always need to use impact assessment. In some cases conclusions can be drawn and judgements and valuations are possible on the basis of the results of the inventory phase.

In LCIA the values of environmental interventions assessed in the inventory analysis are interpreted on the basis of their potential contribution to environmental impact. The term “potential contribution” indicates that the result of LCIA is not an absolute value, and that LCIA is a relative approach to environmental assessments. The idea is that comparative studies do not need such detailed data on temporal and spatial aspects as do the more absolute methods such as environmental risk assessment. The strength of LCA is its focus on an overall impact.

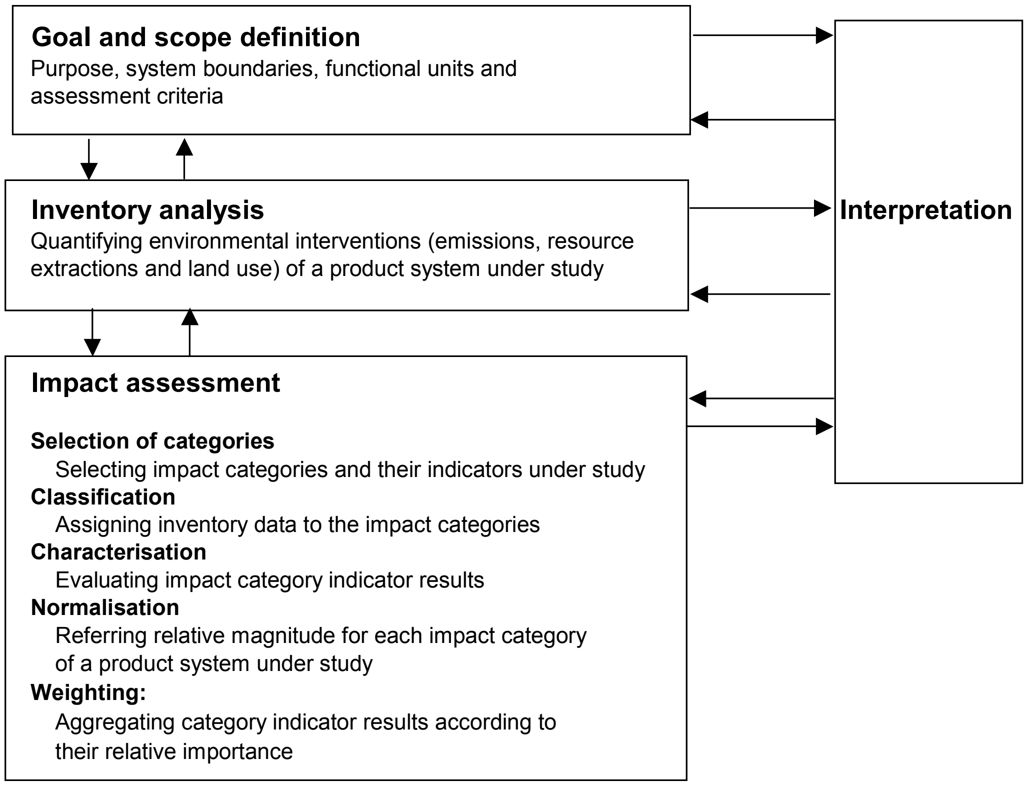


Fig. 1. Phases of LCA according to ISO (1997) and typical phases in life cycle impact assessment (LCIA).

LCIA is typically divided into five phases: selection of impact categories, classification, characterisation, normalisation and weighting. In the selection of impact categories (e.g. climate change and acidification), indicators for the categories (e.g. radiative forcing in climate change, H^+ release in acidification) and models to quantify the contributions of different environmental interventions to the impact categories are selected. The second phase, classification, is an assignment of the inventory data to the impact categories. In characterisation the models make an aggregation of interventions possible within each impact category. Values of interventions are changed to impact category indicator results by characterisation factors, and thereby the number of factors taken into account in the interpretation of results can be reduced from tens or even hundreds to about 10 to 15. From a decision maker's perspective, impact category indicator results are more manageable forms than interventions but due to their proxy characteristics they are difficult to interpret. In order to obtain a more comprehensive view of impact category indicator results, normalisation can be conducted. This phase relates the magnitude of the indicator results in the different impact categories to references values. A reference value is the impact indicator result calculated on the basis of an inventory of a chosen reference system (e.g. all society's activities in a given area and over a specified period of time) (Consoli et al. 1993, Wenzel et al. 1997, Finnveden et al. 2002).

Normalisation can further help the interpretation of impact category results but in practice comparative evaluations require data about trade-offs between different category indicator results in order to choose the best alternative. The trade-offs are determined as weighting factors (weights) in the weighting phase. Furthermore, in the LCA terminology weighting includes aggregation of indicator results (i.e. results from characterisation and normalisation) into a single value representing an overall impact value. For this reason, weighting is desirable in many LCA applications (e.g. Hansen 1999, Bengtsson 2000), although determination of weights is based on value choices.

The framework and terminology described above are in accordance with the International Organization for Standardization (ISO 1997, 2000a), with the exception that there is also a new phase, grouping, between normalisation and weighting in the ISO standards. Grouping is the assigning of impact categories into one or more sets without weighting; it may involve sorting and/or ranking (Finnveden et al. 2002). According to the ISO standards, LCIA is divided into mandatory and optional phases. Characterisation is considered as the last mandatory step due to its scientific character; in characterisation different interventions should be aggregated to impact category indicator results on the basis of the relevant environmental processes. However, some authors (e.g. Owens 1998, Hertwich et al. 2000) have pointed out that all phases of LCIA starting from the selection of impact categories include value choices (see Sections 3 and 8.2).

Although there is an approximate consensus on the procedural framework of LCIA, the methods may vary in LCA applications. Different methods can easily produce different results. The results depend among other things on the coverage of impact categories, the chosen impact category indicators and the models chosen for characterisation factors. Furthermore, a reference system used in normalisation can affect the interpretation. When the aim of a study is to combine different impact category indicator results into a single value, the results are highly sensitive to changes in the impact category weights (as pointed out in article I). Because there is no clear consensus among the LCA community for the determination of weights (see e.g. Finnveden et al. 2002), the LCA community has been reluctant to use single value scores in LCA case studies (Barnthouse et al. 1997). According to the International Organisation for Standardization (ISO 2000b), weighting shall not be used for comparative assertions disclosed to the public due to its subjective character.

In summary, LCIA is a useful phase in LCA, but the results of LCIA are not generally considered reliable due to the coarse methodology. For this reason, there is an on-going development including different methodological choices of LCIA. The scientific and methodological framework for LCIA has been under discussion in several international forums (e.g. Bare et al. 1999, 2000, Udo de Haes 1996, Udo de Haes and Wrisberg 1997, Udo de Haes et al. 1999).

1.2 Approaches used in life cycle impact assessment

The main point in the criticism of LCIA methodology is that LCIA does not (yet) have an acceptable way to model environmental impacts (Hofstetter et al. 2000a). This is due to the facts that information on time and spatial detail in current LCIA is still very limited (Hertwich et al. 2002) and that there are no practical methods for assessing local and long-term effects.

In practice, “less is better” has been the only approach in LCIA since the late 1990s. This approach assumes that all amounts of same kinds of interventions lumped together cause harmful effects on the environment on the basis of their intrinsic hazard characteristics, regardless of where and when they take place and whether the amounts are above or below certain thresholds (White et al. 1995). A threshold means that there is zero damage below an amount of intervention j that is greater than zero.

It is a well-known fact that the “less is better” approach is suitable for emissions causing global problems such as climate change and ozone depletion. However, in local environmental problems, where scale refers to distances from about one kilometre to some tens of kilometres, the situation is different. For example, emissions of hazardous substances will have an environmental effect only if the concentrations exceed the No-Observable-Effect-Concentration (NOEC). The argument is valid from the point of view of environmental science. For this reason, White et al. (1995) pointed out the alternative approach, called “only above threshold”, where only the emissions predicted to exceed the thresholds are taken into account.

Although the advantage of the “only-above-threshold” approach is clear, its implementation in practice has been developed only slowly due to the complexity of applying it on a life cycle scale. First, the approach needs data on sites in relevant systems, which is not common for the LCA tradition. In inventory analysis interventions are typically summed up across the whole life cycle. Secondly, there are theoretical difficulties to determine thresholds and thirdly, the methods to link the surpassing of thresholds to the functional unit of the LCI in a quantitative way have not been available to LCA practitioners.

LCA is commonly considered as a tool for global and regional environmental problems because of its inability to describe local effects on the basis of the "less-is-better" approach. However, recent studies (e.g. Potting et al. 1998, Huijbregts et al. 2000, Krewitt et al. 2001) have shown that spatially derived characterisation factors can differ by orders of magnitude in the context of regional impact categories such as acidification, tropospheric ozone formation and terrestrial eutrophication. Against this background it is obvious that site-dependent characterisation factors are needed for calculations of impact category indicator results in order to produce realistic results in the non-global impact categories (see e.g. Potting et al. 2002). Thus, the site-generic vs. site-dependent characterisation factors have been under discussion in several international forums in recent years. The advantage of site-generic characterisation factors is their practicality, but their disadvantage is poor accuracy of assessment. In the case of site-dependent characterisation factors the situation is the opposite.

The aspect on the basis of which different LCIA approaches can be distinguished is how a quantifiable representation of impact category is chosen in the cause-effect chain (environmental mechanism) in order to calculate indicator results. The traditional approach is that the object of characterisation modelling is a "midpoint" in the cause-effect chain within each impact category (e.g. radiative forcing in climate change, H^+ release in acidification). Thus, the midpoint modelling is based on relatively accurate methods, but leads to many impact categories. On the other hand, many impact categories with proxy indicators are difficult to weight against each other in order to produce a total impact value for the alternative product systems. For this reason, an alternative approach was developed for choosing a point in the cause-effect chain. The so-called endpoint modelling (see Bare et al. 2000) refers to assessment describing observable environmental endpoints, such as years of life lost. Hertwitch and Hammitt (2001b) called this approach a damage function approach because it attempts to predict damage and then aggregates predicted damages in terms of an indicator that already includes explicit valuation. In practice, the approach needs more complex models, resulting in extensive uncertainty compared to midpoint modelling. On the other hand, impact categories can be reduced in this way from tens to only a few and their interpretation is clearer, i.e. the weighting task is easier for valuators (respondents). For this reason, endpoint-based approaches are gaining popularity in comparative LCIAs where trade-offs between impact categories are needed. The environmental priority system (EPS) (Steen and Ryding 1992, Steen 1999) and the Eco-Indicator 99 (Goedkoop and Spriensma 1999) methods are the best-known endpoint modelling methods.

Although the terminology in endpoint modelling is not consistent with the terminology adopted by ISO, the same phases can be applied in the midpoint and endpoint modelling approaches. In the endpoint modelling the "damage categories" (Human Health, Ecosystem Quality and Resources in Eco-Indicator 99) can be handled as impact categories in the midpoint modelling. Furthermore, so-called damage factors correspond to characterisation factors.

The approaches described above are mainly related to characterisation. One key issue between different methods is naturally the impact categories that they cover, i.e. for which impact categories there exist characterisation factors. Different LCIA methods differ from each other on the basis of areas of protection related to the impact categories. Areas of protection, also called "safeguard subjects", mean classes of endpoints which have some well recognisable value for society. Udo de Haes et al. (1999) distinguished four areas of protection: human health, natural resources, natural environment and man-made environment.

Various LCIA methods also differ from each other from the point of view of their aggregation level: Does a method include only characterisation, like CML (Heijungs et al. 1992), or can normalisation and weighting be conducted? Different reference systems in normalisation also cause variations among different methods. In the Ecoscarcity (Ahbe et al. 1991, Baumann and Rydberg 1994, BUWAL 1998) and Environmental Theme methods (Baumann and Rydberg 1994), reference systems have been country-specific, whereas many methods such as Eco-Indicator 1995 (Goedkoop 1995) and Eco-Indicator 99 use Western Europe or the whole of Europe as a reference area.

In LCA, terminology methods with weighting options are called weighting methods. The EPS-method does not include normalisation as a previous stage before the final aggregation into a single score, whereas the Eco-Indicator methods and EDIP (Hauschild and Wenzel 1998) do. The aggregation rule of the Ecoscarcity and Tellus (Tellus Institute 1992) methods are not in accordance with the ISO standards because interventions are directly aggregated without the characterisation phase.

Determination of weights has been a controversial issue in LCIA because of its subjectivity. For this reason, the ISO provides no examples of weighting. Outside the ISO, however, weighting methods have received extensive attention since 1992 (Guinée et al. 2002). In LCIA there are three commonly used groups of methods for the determination of weights (Finnveden 1997, Finnveden et al. 2002): the panel method, the monetary method and the distance-to-target method. Weighting according to the distance-to-target method, based on political targets, has been used in many popular LCIA methods (e.g. Ecoscarcity, Environmental Theme, EDIP) because there is no need to use valuators (respondents). An alternative distance-to-target approach was carried out in Eco-Indicator 95, where all damage weighting factors were set to 1 when the target values for impact categories were determined at the same damage level. In panel methods, valuators (respondents) are asked to give their trade-offs between different impact categories. There are several issues that affect differentiation between different panel methods, starting from who, how and what is asked (see Section 3.4.2). Monetary methods consist of all methods which measure environmental impacts on a monetary basis. There are a large number of different approaches for methods that are based on willingness to pay and methods that are not (see Finnveden et al. 2002).

Temporal aspects can be taken into account in the characterisation phase and in the determination of weights. Udo de Haes et al. (1999) proposed that characterisation factors should be calculated for infinite time with discounting. Long-term effects caused for example by the accumulation of persistent chemicals and greenhouse gases are usually handled by using a long time-period (e.g. 500 years for climate change). This time frame can be divided into shorter cut-off periods. This offers a basis for the calculation of different characterisation factors used in a sensitivity analysis (e.g. a 100 year period). Furthermore, the values of characterisation factors may depend on the changes of interventions over time. The method applied in LCIA is that the determinations of characterisation factors are based on both the past (or current) and the future (e.g. the year 2010) load situation (see e.g. Potting et al. 1998, Krewitt et al. 2001).

In summary, although there is an approximate consensus on the procedural framework of LCIA, there are many controversial issues concerning the spatial and temporal aspects required to keep LCIA as a practical and scientific tool at the same time. The development of LCIA is still in progress. It is evident that the methods will gradually include more spatial and temporal details, and that impact category indicators will be continuously more endpoint oriented.

1.3 Decision analysis and life cycle impact assessment

Decision analysis can be defined in different ways. Keeney (1982) described it as "a formalisation of common sense for decision problems which are too complex for informal use of common sense". A more technical definition of decision analysis is that it is a set of methods of systems analysis and operations research which can be applied in supporting extensive decisions (Bunn 1984). The key word is analysis, which refers to the process of breaking a decision problem down into its constituent components. After the decomposition of the problem, each smaller problem, component, is dealt with separately and evaluated by the decision maker. The individual components are then recomposed to give overall insights and recommendations on the original problem (Bunn 1984). This has been referred to as the “divide and conquer orientation” of decision analysis (Keeney 1982).

The purpose of decision analysis is not to replace judgment, but to help organise it and to provide a model of the problem which can lead to greater understanding of the situation. In a decision analysis process there are typically three parties: a decision maker, a decision analyst and experts. The decision maker is a single person or a group of persons who must solve a decision problem. The role of the decision analyst is to familiarize the decision maker and the expert(s) with the decision analytic method applied and to make sure that all the necessary information is available. The experts provide information on the specific problems of the analysis.

Although decision analysis comprises a set of techniques, its foundations are typically related to the roots of modern utility theory developed by von Neumann and Morgenstern (1947). Since then several authors have developed a number of different theories and algorithms for decision making, leading to a number of different methods (see e.g. Stewart 1992, Huang et al. 1995, Al-Shemmeri et al. 1997, Guitouni and Martel 1998).

LCA methodology has been developed with a weak link to decision analysis. In the early LCA literature, decision analysis was first mentioned in the context of weighting. In the first guide of LCIA, Heijungs et al. (1992) proposed multi-criteria analysis (MCA) as a tool for weighting. They presented a calculation rule for the total environmental index (category indicator results) based on a quantitative MCA; effect scores (category indicator results) are multiplied by the corresponding weighting factors and the results are summed up. However, the calculation rule was not referred to any specific methods used in the field of decision analysis.

In SETAC's workshops held in the early 1990s, decision analysis was considered as a convention and procedure for weighting different impacts. SETAC's book "A conceptual framework for life-cycle impact assessment" (Fava et al. 1993) based on the Sandestin workshop (Feb. 1992) contained short descriptions of two common decision analysis techniques, multiattribute utility theory (MAUT) and analytical hierarchy process (AHP). However, the texts did not include any examples of how to apply the techniques to weighting of impact categories. Furthermore, the guideline for LCA: "A code of practice" (Consoli et al. 1993) includes the following reference to future research needs in valuation (weighting): "Development of quantitative or science-based approaches (decision theory, statistical integration, analytic hierarchy processes etc.)".

In the LCA symposium held at the fourth SETAC-Europe congress in Brussels, Heijungs (1994) and Tukker (1994a) presented the total environmental index model based on MCA, in which category indicator results could be transformed by a function. From a theoretical viewpoint, Heijungs (1994) referred to MAUT and demonstrated with the help of a simple example the relation between valuation and normalisation. In the first SETAC working document on life cycle impact assessment methodology, Tukker (1994b) proposed that determination of weighting factors for the MCA model can be carried out according to iso-utility functions. He also presented some findings about the relation between weight determination and normalisation in the model.

Despite the above mentioned findings concerning the relation between weighting and decision analysis, SETAC's "Towards a methodology for life cycle impact assessment" (Udo de Haes 1996) did not include any mention about decision analysis and its possibilities in the context of development of the LCIA methodology. In the book the typical calculation rule of LCIA was presented without any references to decision analysis (Heijungs and Hofstetter 1996), although it is consistent with the rule derived from the basis of decision analysis as can be seen in this thesis.

Since 1996 several authors have noted that decision analysis can be applied in the context of LCA. Most of the applications have been confined to weighting or to the use of LCIA results in the final decision context. The latter application field means that LCIA results are handled together with other criteria (e.g. economic aspects) in the decision making process. On the other hand, Miettinen and Hämäläinen (1997) pointed out that decision analysis can be used as early as during scope and goal definition in order to assist the choice of feasible alternatives and an appropriate set of impact categories. In addition, decision analysis can help to identify what is important for the LCA application.

Thus, decision analysis can also enhance gathering of “correct” data in the inventory analysis. Werner and Scholz (2002) also reported that a set of criteria for life cycle inventory derived from decision analysis can be used to determine relevant product systems for the purposes of an assessment problem.

In the context of LCA, applied decision analysis methods have been so-called multiple criteria decision analysis (MCDA) or - making (MCDM) methods. They have been developed to structure and model multidimensional decision problems in terms of a number of individual criteria where each criterion represents

a particular dimension of the problem to be taken into account.[1] Furthermore, MCDA methods can be divided into multiple attribute decision analysis (MADA) and multiple objective optimization (MOO) methods (e.g. Chen and Hwang 1992). MADA methods are developed for the sorting or ranking of a finite set of alternatives in decision making situations with multiple objectives, whereas MOO assists in the synthesis of a preferred solution when the potential solution set is described by continuous variables (or a mix of discrete and continuous variables). In the MOO methods the primary idea is to design a “most” promising alternative with respect to limited resources (Chen and Hwang 1992). Examples of the application of MOO in LCA or in conjunction with LCA-based environmental indicators include e.g. Azapagic (1996), Azapagic and Clift (1998), Stewart (1999) and Alexander et al. (2000). However, the focus of this thesis is on MADA methods due to the fact that MOO is not associated with the typical LCIA problems in which the alternatives have been predetermined.

In the field of MADA, there are three popular groups of methods: methods based on multiattribute utility theory, the analytical hierarchy process (AHP) and outranking methods. The multiattribute utility theory includes the multiattribute utility theory (MAUT) method itself and the multiattribute value theory (MAVT) method. MAVT is applied for value measurement when there are no uncertainties about consequences of the alternatives, whereas MAUT is used under conditions of uncertainty (Keeney and Raiffa 1976, von Winterfeldt and Edwards 1986, French 1988). The commonly used simple multiattribute rating technique (SMART) (Edwards 1977, von Winterfeldt and Edwards 1986) and weighted summation method (see e.g. Janssen 1992) are applications of MAVT. In the LCIA field there can be found at least the following examples of the application of MAVT in addition to the articles of this thesis: Hämäläinen and Miettinen (1997), Lundie (1999), Lundie and Huppes (1999).

AHP (Saaty 1980) has similarities with MAVT (see Salo and Hämäläinen 1997), but its main point is that it allows decision makers to use so-called pairwise comparisons between the alternatives with qualitative expressions connected to a 1-9 scale. A software tool called “BEES” for LCA has included an option to use AHP for weighting (National Institute of Standards and Technology 2000). The U.S. Environmental Protection Agency has used AHP in LCA case studies in order to provide a basis for the valuation step (Tolle et al. 1998). Ong et al. (2001) used AHP to calculate total environmental scores for product alternatives. AHP was used to determine weighting factors directly for interventions omitting the characterisation phase of LCIA. In addition, Khan et al. (2002) used AHP as a part of the MADA approach of fuzzy composite programming (FCP).

Application of MAUT requires that the decision maker is able to decide which of two alternatives he or she prefers. Thus, it is not permitted to say: “In this case, I really do not know” whereas in the context of outranking methods it is. The outranking methods include a number of methods, of which ELECTRE methods (e.g. Roy 1973, Roy and Hugonnard 1982; for a summary of ELECTRE methods, see Rogers et al. 1999) and PROMETHEE methods (Brans et al. 1984, Brans and Vincke 1985, Brans et al. 1986) are the most popular. Basson et al. (2000) applied the ELECTRE methods for LCIA purposes. Le Téno

[1] There is an abundance of terminology in decision analysis. The words *objectives* and *attributes* may be used synonymously with the word *criteria*. A useful distinction is to refer to more general statements about aspects that would be considered in the evaluation of alternatives as *objectives* when they explicitly have a direction of preference associated with them (e.g. minimise environmental impact) and as *criteria* when the direction of preference is not stated and merely implied. The term *attributes* is then reserved for that which is actually evaluated (qualitatively or quantitatively) about the performance of these alternatives relative to the more general *objectives*/*criteria*.

and Mareschal (1998), Le Téno (1999), Geldermann (1999) and Geldermann et al. 2000 used the PROMETHEE methods with fuzzy logic to interpret environmental interventions (without the characterisation phase) or impact category indicator results. Spengler et al. (1998) and Geldermann (1999) demonstrated the benefits of a PROMETEE decision support system for integrated technique assessment, considering technical, economic and ecological aspects of products.

In the report of the SETAC LCA impact assessment working group (composed of North American experts) there is a brief summary of the various valuation methods including MAUT, AHP and Lexicographic (a simple MADA method) (Barnthouse et al. 1997). The application area of decision analysis was restricted to the valuation (weighting) phase of LCIA.

Hertwich et al. (2000) studied a theoretical, philosophical foundation of LCA. Their central conclusion was that LCA can be justified by its use in decision making. The message was: "if LCA is to help decision makers reduce environmental impacts, its methods should be evaluated according to how well they fulfil this purpose." In their later studies, Hertwich and Hammitt (2001a, 2002b) showed how LCIA can be described and structured as an exercise in decision analysis. Their findings concerning attributes and objectives in LCIA were mainly based on the decision analysis work related to MAUT/MAVT (Keeney 1992).

In the operational guide to LCA in the ISO standards (Guinée et al. 2002), there is a section concerning theoretical foundations of LCA in which multi-criteria analysis, multi-objective decision making and decision theory are mentioned as tools for normative elements of LCA. Furthermore, the authors presented that multi-criteria analysis methods may be useful for grouping and weighting, but they did not refer to any of the above mentioned LCA case studies in which decision analysis methods were applied.

The report of the second SETAC-Europe working group on life cycle assessment includes a chapter concerning normalization, grouping and weighting in LCIA (Finnveden et al. 2002). The author of this thesis was a member of the working sub-group on normalization, grouping and weighting and was responsible for decision analysis issues related to normalisation and weighting. The work of this sub-group concluded that "findings and experiences from the MCDA field can be applied to LCIA, possibly forming a theoretical basis for (elements of) LCIA and also to help discern "good and bad" approaches to LCIA". The work included findings about the relation between normalization and weighting derived from articles I, II and IV. Furthermore, the texts about decision analysis techniques of preference elicitations for weighting of panel methods were derived from article IV. In addition, the work included a discussion of biases related to the elicitation process, referred to in article I.

1.4 Aims and structure of the thesis

Few attempts have been made hitherto to explore systematically the theoretical bases of different stages of LCIA and how these stages are related to each other. This thesis aims at illustrating the basic theoretical foundations for life cycle impact assessment on the basis of decision analysis.

In this thesis, multiattribute value theory (MAVT) was chosen as a theoretical basis for LCIA. There are two reasons for this. Firstly, MAUT and MAVT have well established theoretical foundations based on axioms compared with the outranking methods and AHP (see e.g. French 1988, Guitouni and Martel 1998). Secondly, in article I it was shown that the typically used calculation rule to aggregate data into a single value (total impact value) corresponds directly to MAVT.

In this thesis, a life cycle impact assessment framework based on MAVT is called decision analysis impact assessment (DAIA). The purpose is to present how to apply this framework for different stages of LCIA. The main research question of the study is: "What are the possibilities of decision analysis in LCIA, and what is the value addition of this approach compared to the current practice used in LCIA?"

In Section 2, the theoretical principles of MAVT are briefly reviewed. In Sections 3-8 it is shown how this theoretical foundation can be applied at the practical level of LCIA. In this summary the focus is on mathematical links between different elements of LCIA, whereas in article IV the framework is presented in a more general and descriptive way.

In Section 3, selection of impact categories and classification in LCIA is presented to correspond to a structuring phase of decision analysis. A value tree used in the case studies of articles I and III is pointed out as a valuable decision analysis tool to structure impact assessment. From the point of view of this structuring, characterisation is described as an exercise in which MAVT can be used to help to choose the appropriate characterisation factors and calculation rule for characterisation (Section 4). This is a central issue in the thesis because other authors have not presented the possibilities of decision analysis in characterisation. In this thesis, characterisation issues are presented according to the LCA terminology, which differs from the notation of decision analysis used in the original article I. In this way, the issue may be easier to understand for the LCA practitioners. A new feature in this summary is also that site-dependent characterisation in the decision analysis framework is handled more broadly than in articles I and III, where Finland-specific characterisation factors are used; in this paper the site-specific aspects are taken into account for several countries at once in order to provide a better basis for the future work of impact assessment toolboxes.

In Section 5, findings about the relations between normalisation, characterisation and weighting are presented with the help of mathematical formulation. In this section the findings derived from articles I, II and IV provide the new rules for the LCIA methodology and clarify the role of normalisation in LCIA.

Section 6 concerns weighting, which is typically recognised as an application area of decision analysis for LCIA. This section summarises from articles I, II and III the requirements of MAVT for determination of impact category weights and aggregation of all information into a single score.

In Section 6.2 factors affecting biases in the context of so-called panel methods are discussed from the viewpoint of experiences of the Finnish forest industry LCA application (article I). In addition, the latest works concerning biases in using MAVT in weight elicitation are referred to. In Section 6.4 there is an illustrative example from article III of how to combine local and global effects in weighting.

Although interpretation is not included in LCIA (see Fig. 1), it is the title of Section 7. This is due to the fact that in the decision analysis framework, sensitivity and uncertainty analyses are inseparable parts of the decision support process. In article I methodological solutions under conditions of incomplete information with respect to input data of LCIA models were developed. These and the latest findings in the literature are reviewed in this section.

In the first part of the discussion section (8.1), critical views on MAVT and the possibilities of other MADA methods for LCIA purposes are presented. In Section 8.2, criticism of the use of weighting in LCIA is handled from the point of view of decision analysis. In Section 8.3, the use of decision analysis impact assessment is discussed. After the discussion some general conclusions are finally presented (Section 9).

2 A decision analytic foundation for life cycle impact assessment

In this thesis, it is shown that LCIA can be considered as a general problem of decision making with multiple objectives. The task is to make a choice among alternatives which have consequences related to more than one attribute. Alternatives in the context of LCIA can be considered as issues such as different product systems[2], unit processes[3], life cycle stages[4] or interventions, which will be compared with each other. Furthermore, attributes which measure the degree to which the objectives are met are

[2] Product system is the collection of materially and energetically connected unit processes which performs one or more defined functions (ISO 1997).
[3] Unit process is the smallest portion of a product system for which data are collected when performing a life cycle assessment (ISO 1997).
[4] Life cycle stage consists of unit processes and covers a certain defined part of the product system.

either impact categories or environmental interventions (emissions, resource extraction, land use). Objectives indicate here the direction to move in order to minimise environmental impacts.

In this study, decision analysis impact assessment (DAIA) is based on multiattribute value theory (MAVT). Furthermore, the theoretical foundations of MAVT are based on value measurement (whereas the theoretical foundations of MAUT are based on utility measurement). In measurement theories, the objects and relations are considered as the primitive notations for measurement. In MAVT these objects are pairs of outcomes (values of attributes) and the relation is strength of preference. Furthermore, these outcomes are riskless (whereas gambles are used in utility measurement techniques and outcomes are risky).

In MAVT, measurement techniques are utilised when a number of assumptions about the decision maker's preferences have to be made in order to rank alternatives. These assumptions are regarded as the axioms of the method. They represent a set of postulates, which may be regarded as reasonable. If the decision maker accepts these axioms, and if he is rational (i.e. behaves consistently in relation to the axioms), then he or she should also accept the preference rankings indicated by the method.

There are several alternative axiom systems for value measurement. A good description of the axiom system can be found in the work of von Winterfeldt and Edwards (1986), which is one of the standard works on MAVT. The starting point for all the different axiom systems is that a decision maker is able to decide his preferences over any pair of consequences (*a*,*b*,*c*…) between which the decision maker's preferences are expressed. The decision maker's preference relations can be strict preference ("*a* is preferred to *b*"), indifference ("*a* is as preferable as *b*") or weak preference ("a is at least as preferable as b"). The decision maker is assumed to be transitive. In the context of strict preference this means that if he prefers *a* to *b* and *b* to *c* then he prefers *a* to *c*. The same holds for indifference and weak preference. Summation assumption requires that the result of adding two strengths of preference must be greater than the sum of the parts. For example, if the decision maker prefers *a* to *b* and *b* to *c*, then the strength of preference of *a* over *c* must be greater than the strength of preference of *a* over *b*. When the other required assumptions (cancellation, solvability and archimedean; see von Winterfeldt and Edwards 1986) of the axiom system are satisfied, it can be proved that there exists a measurable value function *v* for all possible consequences (Krantz et al. 1971, Dyer and Sarin 1979). It has the property

$$v(a) - v(b) \geq v(c) - v(d) \qquad (1)$$

if and only if the improvement from *b* to *a* is judged to be greater than the improvement from *d* to *c*. Thus, the measurable value function allows expressing strength of preference for different levels of consequence space *X*. Note that if v^* also satisfies Eq. 1, then there are real numbers $\alpha > 0$ and β such that $v^*(a) = \alpha v(a)+\beta$ (Dyer and Sarin 1979).

A cardinal value function describes the conversion from the "natural scale" of *X* to the value scale (Fig. 2) and it can be continuous or discrete. Value functions can be constructed according to the measurement techniques. In measurement techniques direct numerical judgements or indifference judgements are used. Direct numerical estimation methods such as direct rating, ratio estimation, category estimation and curve estimation are used only in the case of value measurement. In these methods the respondents are asked to make direct estimates of strengths of preferences on a numerical scale (see e.g. von Winterfeldt and Edwards 1986). In the indifference methods pairs of evaluation objects (e.g. NO_x emission for acidification) are varied until a match is established in their respective strengths of preference. Difference standard sequences and bisection are indifference methods used in MAVT, whereas variable probability and variable certainty equivalent methods are used in MAUT (von Winterfeldt and Edwards 1986).

A value function plays a central role in the breakdown of a decision problem with multiple objectives into its constituent components and the recomposition of the original problem. After the structuring phase (Section 3) it is known which alternatives and attributes are related to the decision problem. Consider an alternative that can be expressed by a vector, $\mathbf{x} = (x_1,x_2, \ldots,x_n)$ where x_i is a measurement of attribute X_i (i=1,..,n). In the multiattribute case $\boldsymbol{X}$ is a product set of attributes X_i. Assume that the assumptions of

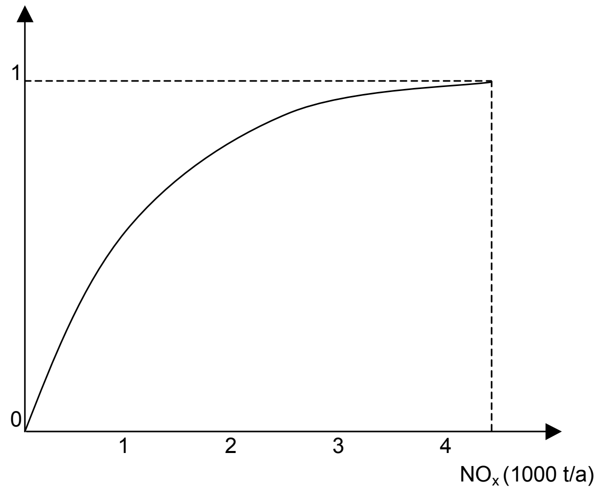


Fig. 2. A single-attribute value function for the attribute of nitrogen oxides within tropospheric ozone formation.

value measurement hold over the pairs of attributes $\boldsymbol{X} \times \boldsymbol{X}$ and that the single-attribute value functions have been determined. Then it may be possible to decompose the multiattribute value function into a function of single-attribute value functions

$$v(x_1,...,x_n) = f(v_1(x_1),...,v_n(x_n)) \tag{2}$$

where f is an overall aggregation function for single-attribute value functions $v_i(x_i)$.

There are three main forms of f to generate the decompositions of v over the X_i: additive, multiplicative and multilinear. The most commonly used form of the decompositions is the additive function

$$v(x_1,...,x_n) = k_1 \cdot v_1(x_1) + ... + k_n \cdot v_n(x_n) \tag{3}$$

where k_is are the weights of the single-attribute value functions, sometimes called the scaling constants or the attribute weights. In Eq. 3 single-attribute value functions are normalized onto a certain interval, e.g. [0,1].

In the MAVT framework it is important to understand that weights are needed for the cardinal single-attribute functions to commensurate in some way. Thus, in MAVT approaches, weights have no absolute or intrinsic meaning and there is no sense in attempting to derive them without reference to the single-attribute value functions (Bana e Costa et al. 1997).

Use of the additive model (Eq. 3) is only appropriate if the difference independence assumption holds. This means that the preference on the outcome of one attribute does not depend on the outcomes of the other attributes. This strong assumption describes sufficient conditions for the additive decomposition.

To check the difference independence assumption, consider two alternatives that differ only in attribute i (von Winterfeldt and Edwards 1986):

$\mathbf{x} = (c_1, c_2, \ldots, x_i, \ldots, c_n)$
$\mathbf{y} = (c_1, c_2, \ldots, y_i, \ldots, c_n)$

Now consider **x'** and **y'**, which have the same values x_i and y_i as **x** and **y** but different constant levels b_j in the other attributes:

$\mathbf{x'} = (b_1, b_2, \ldots, x_i, \ldots, b_n)$
$\mathbf{y'} = (b_1, b_2, \ldots, y_i, \ldots, b_n)$

The difference independence assumption (axiom) holds if for all $i = 1,2,\ldots,n$, x_i, $y_i \in X_i$; $c_j, b_j \in X_j$, $j \neq i$, the strength of preference of **x** over **y** is equal to the strength of preference of **x'** over **y'**,
i.e. $v(\mathbf{x}) - v(\mathbf{y}) = v(\mathbf{x'}) - v(\mathbf{y'})$.

If the assumption of difference independence fails, it may be possible to apply multiplicative or multilinear models. Both models have a different version of independence axiom that must be fulfilled in order to use the model (see e.g. von Winterfeldt and Edwards 1986).

It is important to notice that the independence assumptions refer to judgements and preferences, not to physical relations between attributes in the environment. For this reason, in this report the term judgemental independence assumption is used where there is a need to emphasize this viewpoint.

When a multiple value function with the help of single-attribute value functions (e.g. Eq. 3) has been constructed in LCIA, the best alternative is found by minimizing the value function. Minimization is used due to the notation of value function in LCIA applications: the higher the value, the greater is the damage to the environment.

3 Selection of impact categories and classification

Structuring of the decision problem is the first phase of decision analysis which precedes the evaluation phase. According to Bana e Costa et al. (1997), structuring is a mixture of art and science which seeks to build a more-or-less formal representation integrating the objective environmental components of the decision context with subjective points of view.

In articles I and IV it is shown that structuring of the decision problem corresponds to selection of impact categories and classification in LCIA. From the decision analysis point of view, an important issue is also the selection of alternatives that may be carried out in the context of goal and scope definition in LCIA. For this reason, alternatives such as product systems, unit processes, life cycle stages or interventions can be inputs to the LCIA process.

The selection of impact categories includes a selection of impact category indicators. An impact category indicator is a quantifiable representation of an impact category, and therefore it is the object of characterisation modelling. In characterisation modelling different types of mathematical techniques can be used for predictions of physical, chemical and biological phenomena in environmental systems.

In the decision analysis framework, there are two approaches to arrange values of impact categories. The approach of type 1 used in LCIA is that impact category indicators or impact categories are considered as attributes. In this case impact category indicator results are values of attributes, i.e. the measurements of the attributes are indices that are calculated by using characterisation factors and data on interventions on the basis of scientific knowledge. In practice, this has been the situation in all MCDA-LCIA studies where characterisation has been included (see Section 1.3). In the second approach (applied in articles I and III), interventions are considered as attributes and impact categories are described as objectives in the first step. The values of the attributes are measured or assessed scores. The calculation of impact category indicator results on the basis of attribute values is a multiattribute assessment problem itself, and it produces values for impact categories. In the second step, the objectives (impact categories) measure the degree to which the higher-level objective (the total impact caused by different impacts) is met and they offer the basis for the new weighting task. Therefore, the selection of impact categories classification (where interventions are assigned to impact categories according to their cause-effect chain) can be included in decision analytic impact assessment in the second approach.

To be exact, the amounts of interventions are not the values of attributes in the second approach presented in article I, where the measurement of attribute $X_{i,j}$ is called rating, $x_{i,j}$ (intervention *j* within impact category *i*). It is an "effective" part of the amount of intervention *j* that causes harmful effects within impact category *i*. In this way, it is possible to apply site-dependent impact assessment (see Appendix 1).

From the point of view of decision analysis a useful tool in problem structuring is a value tree (e.g. von Winterfeldt and Edwards 1986). A value tree for an LCIA application of the second approach is composed of three elements: impact categories, attributes and alternatives (Fig. 3). On the left hand side the general objective behind the assessment is presented, i.e. the total impact caused by different impacts. The impacts caused by a product system are determined and divided into main categories *i* (*i=1,...,n*) which can be further divided into sub-categories. For example, acute aquatic, chronic aquatic and chronic terrestrial toxicity sub-categories can be included under ecotoxicological impacts. Finally, impact categories are divided into attributes, interventions *j* (*j=1,...,m*) (emissions, extractions and land use). Interventions caused by an alternative *a* are assigned to one or more impact categories *i* (*i=1,...,n*) on the basis of their cause-effect relationships.

Note that in article IV intervention attributes are considered as sub-attributes, whereas impact categories are main attributes. However, this presentation follows the above-mentioned terminology.

The elements of a value tree should be constructed and defined such that they have the required properties (completeness, operationality, decomposability, absence of redundancy and minimum size; see Keeney and Raiffa 1976), which are illustrated in article I. A checklist to fulfil these properties can be the following (modified from Keeney and Raiffa 1976 and from von Winterfeldt and Edwards 1986):

- Completeness: Can the decision maker think of any impact aspects of the alternatives that have not been captured? If so, the tree may not be complete.
- Operationality: Can the alternatives be located on each attribute easily? If not, the attribute may be ill-defined.
- Decomposability: Can the decision maker think of preferences for several levels of an attribute independently of the levels in other attributes? If not, the dimension may not be judgementally independent.
- Absence of redundancy: Are the attributes highly correlated across alternatives? If so, they may be redundant.
- Minimum size: Is the number of attributes too large to manage? If so, omit the attributes whose values do not differ among the alternatives.

Article IV includes illustrative examples concerning the meaning of the requirements. In addition, the case studies of the Finnish forest industry (article I) and metals industry (article III) show how these requirements can in practice be taken into account in LCIA. The fact is that the environmental intervention-effect network, including primary, secondary and tertiary effects etc. is a very complex issue to handle with the hierarchical structure. The construction of a value tree needs value judgements to decide what are important impacts and how these can be modelled in an appropriate way (selection of category indicators and characterisation modelling). To avoid double counting, determinations of impact categories are necessary. For example, in article I impact on biological diversity was included as one consequence under all ecological impact categories because emissions also have an impact on biological diversity. Consequently land-use issues were the only factors taken into account under the impact category called impact on biological diversity (see Fig. 3).

The decomposability criterion requires that attributes and impact categories are not judgementally independent. This feature must be taken into account in the structuring phase. In the case studies (articles I and III), the possible dependences were tested with the help of thought experiments according to the principles presented in Section 2. It is important to note that the decomposability criterion is not violated although intervention *j* can be involved in several impact categories (e.g. NO_x in Fig. 2). This is due to the fact that in each impact category *i*, specific effects are determined and only the effective part

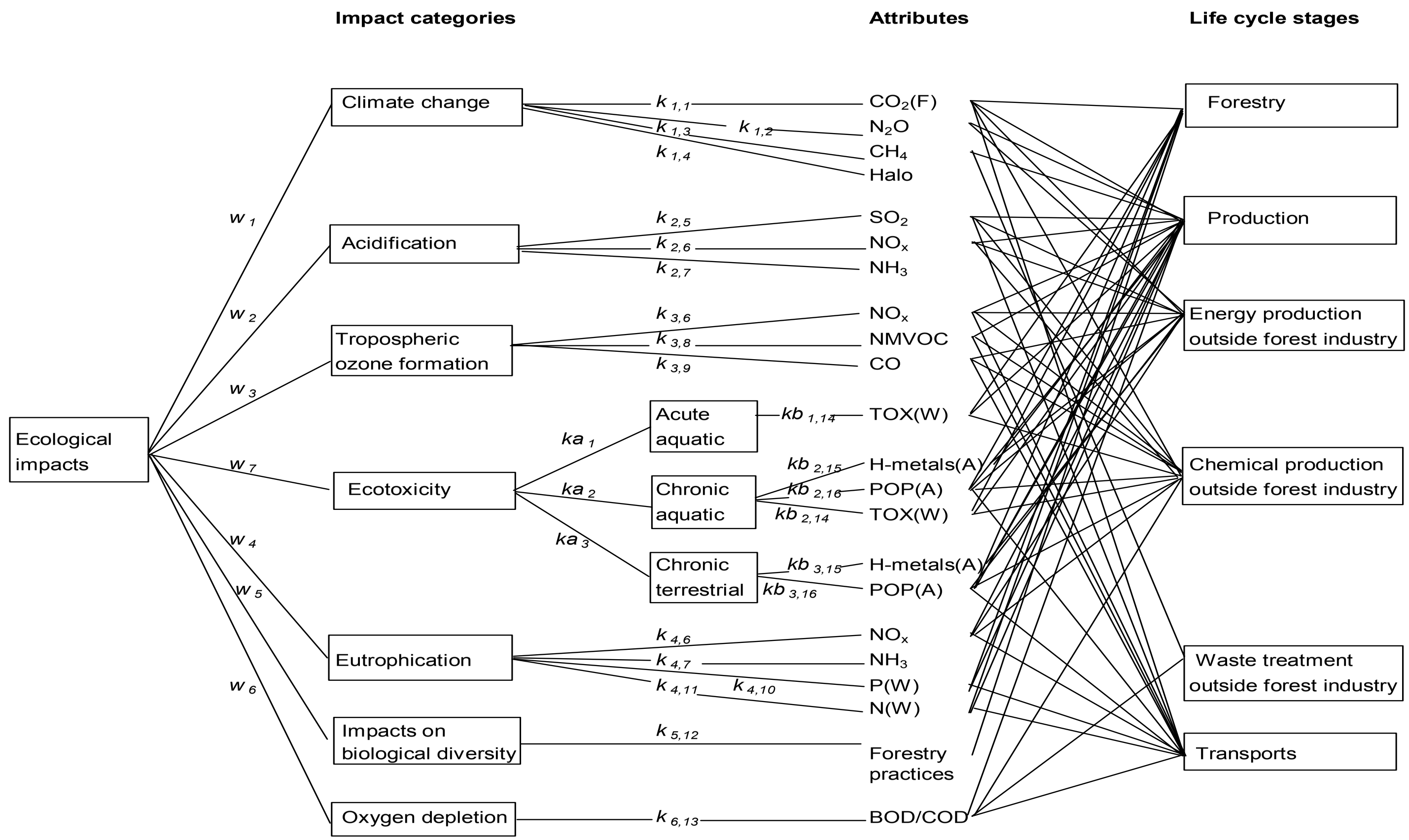


Fig. 3**.** The value tree of the ecological impacts in the LCIA case of the Finnish forest industry and notation of impact category weights (w_i), sub-category weights (ka_{SC}) and attribute weights ($k_{i,j}$ and $kb_{SC,j}$) (modified from article I). Legend: CO_2(F)=carbon dioxide (fossil), N_2O=nitrous oxide, CH_4=methane, Halo=halocarbons (CFCs, HCFCs and HFCs), SO_2=sulphur dioxide, NO_x=nitrogen oxides, NH_3=reduced nitrogen, NMVOC=non-methane volatile organic compounds, CO=carbon monoxide, TOX(W)=release of toxic compounds (e.g. heavy metals, phenols, organochlorine compounds, pesticides) into water, H-metals(A)=release of heavy metals (As, Cd, Cr, Cu, Hg, Ni, Pb, Se, Zn) into the atmosphere, POP(A)=release of persistent organic pollutants (e.g. PAHs, dioxins, pentachlorophenol) into the atmosphere, P(W)=phosphorus into water, N(W)=nitrogen into water, Forestry practices = harvesting (timber felling, pruning and topping), draining, soil preparation after final felling, wood fertilisation, BOD/COD= biological/chemical oxygen demand.

of intervention *j* related to the effects in this category *i* is included in the characterisation process. Although the same interventions within different impact categories are physically dependent on each other, they are not judgementally dependent on each other (see also Sections 4.2 and 6.3). Thus, the starting point that intervention *j* is included in the calculation of two or more impact categories is not an argument against the use of MAVT/MAUT models in LCA (cf. Le Téno and Mareschal 1998).

A value tree can be constructed according to top-down or bottom-up approaches. The former approach starts from an explication of the decision makers'/experts'/analysts' most general values (e.g. areas of protection in the context of LCA). The idea of the latter approach is to identify impact-relevant characteristics which distinguish the alternatives and to synthesize them in order to obtain higher order impact values.

In the case studies of the Finnish forest industry (article I) and metals industry (article III), the aims were to find the most significant life-cycle stages and interventions within the sectors. In both cases, the value trees were constructed according to bottom-up approaches.

As mentioned in Section 1.2, the local impact categories are not typically included in LCIA. However, in the case study of the Finnish metals industry (article III), local impact categories such as direct effects on flora (SO_2, NO_x, fluoride, dust), solids to water, thermal load, impacts on amenities (dust), wastes (different groups), noise, smell, and soil and ground water pollution (different interventions) were also taken into account. The decision analysis framework permits handling of these impact categories together with regional and global impact categories (see Section 6.4).

Structuring value trees is a cooperation process between a decision analyst and experts. For example, in the case of the forest industry the initial value trees were designed by the analyst. These were sent to 10-15 experts within the Finnish Environment Institute. On the basis of their comments the value trees were reformulated by the analyst and an open discussion session was held where the experts could discuss and reformulate the value trees until a consensus was reached. In the case of the Finnish metals industry, the initial value trees were constructed by co-operation between the analyst and an expert group of each metal factory. The expert group consisted of an environmental manager of the company and inspectors from the municipality and a regional environmental authority. In both case studies, there were no difficulties to reach consensus.

A value tree (or objectives hierarchy as Keeney and Raiffa (1976) called it) is a basic tool for structuring of MAUT/MAVT and AHP applications. Despite this it is poorly elaborated in the field of LCA. In the context of selection of impact categories and classification it is only mentioned in the articles of this thesis. Miettinen and Hämäläinen (1997) presented it in the decision situation where the other criteria such as economy and consumer issues are taken into account with LCIA results. Werner and Scholz (2002) pointed out in their study that these required criteria related to the value tree can be used to determine relevant inventory data of product systems. However, they did not refer to the value tree/objectives hierarchy or to selection of impact categories and classification. In principle, their approach may lead to the same result as that reached with the approach presented in this thesis. However, the first phase of LCIA appears to be a better place for conducting a value tree application because of the iteration character of LCA (see Section 1.1). Selection of impact categories and classification precede the evaluation phase, and findings made in this stage can cause changes in inventory analysis or even in goal and scope definition.

Hertwich and Hammit (2001a) discussed how decision analysis can be used to structure LCIA. They presented the idea of objectives hierarchy but they did not deal with its required properties. In order to construct meaningful attributes and objectives for LCIA they concentrated on a means-ends objectives network presented by Keeney (1992). This is a network based on causal relationships and its construction requires judgements about facts instead of value judgements. Hertwich and Hammit (2001a, 2001b) showed that this tool can help to define the point in the environmental mechanism at which the category indicators are defined. They suggested that these category indicators can be described as attributes, whereas safeguard subjects correspond to fundamental objectives. However, it is important to understand that a means-ends objectives network can help to construct a meaningful value tree. The purpose of the means-ends network is not to replace the use of a value tree in the context of hierarchical methods such as MAUT/MAVT and AHP. The value tree is needed for the construction of a value model (such as a value function) in order to quantify objectives and to rank the alternatives (Keeney 1992).

It is important to note that value judgements are required to construct value trees, and judgements about facts are required to construct means-ends networks. For this reason, Keeney (1992) pointed out that the construction of both the value tree and the means-ends network can clarify the facts and values of a decision situation. This approach is worthy of testing in LCIA because one of the main points of criticism is that LCA does not strictly separate the subjective from the objective elements (Hofstetter et al. 2000a).

4 Characterisation

The purpose of characterisation in LCIA is to estimate the potential contributions of different interventions (emissions, resource extractions and land use) to different impact categories and to sum the amounts of interventions into a single number within each impact category. According to the international standard for life cycle impact assessment, ISO 14042 (ISO 2000a), characterisation should be based on a scientific analysis of the relevant environmental processes, and for this reason, the results of characterisation may be considered as input for a decision analysis framework (approach 1 in Section 3). However, in articles I and III it was shown that characterisation can be considered as a multiattribute problem itself and that the rules of MAVT can assist the execution of characterisation. Thus, a starting point for the presentation in this section is the value tree of type 2 in Section 3, where interventions are described as attributes. In this section we gather different findings concerning relationships between characterisation and decision analysis rules from articles I-IV. In addition, in this context it will be shown how different site-dependent characterisation approaches can be carried out in the decision analysis framework.

The issues that will be presented in the next sections can be applied in the case of different impact assessment approaches (Section 1.2), unless stated otherwise.

4.1 Mathematical framework

In LCIA a basic rule to calculate an indicator result of impact category i is

$$I_i = \sum_{j=1}^{m} C_{i,j} \cdot x_j \qquad , i = 1,\ldots,n \tag{4}$$

where I_i = indicator result of impact category i
$C_{i,j}$ = characterisation factor for intervention j within impact category i
x_j = amount of intervention (emission, resource extractions or land use) j

In article I it was pointed out that according to MAVT, Eq. 4 can be interpreted as a simple additive weighted model:

$$I_i = v_i(x_1,\ldots,x_m) = \sum_{j=1}^{m} k_{i,j} \cdot v_{i,j}(x_j) \qquad , i = 1,\ldots n \tag{5}$$

where I_i = evaluation object (= indicator result of impact category i)
v_i = overall value function (= multi-attribute value function) within impact category i
$k_{i,j}$ = weight (=scaling constant) of attribute X_j within impact category i
$v_{i,j}$ = normalized single-attribute value function for attribute j within impact category i

x_j = measurement on attribute X_j

In MAVT, it is customary to normalize[5] values of value functions onto the [0,1] range. In the impact assessment the most preferred achievement levels (x_j^o) on the attributes are fixed to zero through $v_{i,j}(x_j^o) = 0$ for all *i* and *j*. Furthermore, the least preferred achievement levels (x_j^*) on the attributes are assigned to one, i.e. $v_{i,j}(x_j^*) = 1$ for all *i* and *j*. Thus, the idea is that the consequences of each intervention within impact categories are assessed by putting values x_j into the corresponding single-attribute functions $v_{i,j}(.)$, and that the results $v_{i,j}(x_j)$ within impact categories are in the [0,1] range.

To understand the elements in Eq. 5, the following illustration is presented. Suppose that the conditions for an additive numerical presentation (see Section 2) exist such that $v_i(x_1,...,x_m) = \sum_{j=1}^{m} v'_{i,j}(x_j)$ where the value function $v'_{i.j}(.)$ is un-normalized. By normalizing the component value functions into the [0,1] range, the additive presentation can be written as (Salo and Hämäläinen 1997):

$$
\begin{aligned}
I_i = v_i(x_1,...,x_m) &= \sum_{j=1}^{m} v'_{i,j}(x_j) \\
&= \sum_{j=1}^{m} [v'_{i,j}(x_j) - v'_{i,j}(x_j^o)] \\
&= \sum_{j=1}^{m} [v'_{i,j}(x_j^*) - v'_{i,j}(x_j^o)] \frac{v'_{i,j}(x_j) - v'_{i,j}(x_j^o)}{v'_{i,j}(x_j^*) - v'_{i,j}(x_j^o)} \\
&= \sum_{j=1}^{m} k_{i,j} \cdot v_{i,j}(x_j) \qquad , i = 1, ..., n \qquad (6)
\end{aligned}
$$

where $k_{i,j} = v'_{i,j}(x_j^*) - v'_{i,j}(x_j^0)$ is the weight of the *j*th attribute (intervention) and $v_{i,j}(x_j) \in [0,1]$ is the normalized score of the *j*th attribute within impact category *i*, i.e. $v_{i,j}(x_j) = [v'_{i,j}(x_j) - v'_{i,j}(x_j^o)]/[v'_{i,j}(x_j^*) - v'_{i,j}(x_j^o)]$.

Assuming linear single-attribute value functions $(v'_{i,j}(x_j) = \alpha_{i,j}x_j + \beta_{i,j})$ in Eq. 6 it can be shown that $v_{i,j}(x_j) = \alpha_{i,j} \cdot x_j$. Comparing the result with Eq. 4 we get $C_{i,j} = k_{i,j} \cdot \alpha_{i,j}$. Using the notation and normalization mentioned above, we get the following presentation

$$
C_{i,j} = k_{i,j} \cdot \alpha_{i,j} = k_{i,j} \cdot \frac{1}{x_j^* - x_j^o} = \frac{v'_{i,j}(x_j^*) - v'_{i,j}(x_j^o)}{x_j^* - x_j^o} \qquad , i = 1,...,n \text{ and } j = 1,...,m \qquad (7)
$$

Next it is shown that this equation for the determination of characterisation factors derived from the preference model corresponds to the equation derived from "objective" impact assessment models.

Suppose that there exists an impact assessment model that can describe cause-effect relationships between the interventions and an impact category indicator. For example, in the case of acidification, the unprotected area of an ecosystem is chosen as an acidification indicator and the RAINS model developed by the International Institute for Applied System Analysis (IIASA) is an impact assessment model (see Potting et al. 1998). This kind of model allows the following expression for calculation of the indicator result of impact category *i*:

[5] In this presentation a process in which the results are changed to dimensionless units within a certain range, e.g. [0,1] is called normalization. In the context of decision analysis the term is indicated by "z" instead of "s" in order to separate it from an LCIA step called normalisation. Normalisation has specific meaning in LCIA: it is a step in which the impact category indicator results are expressed relative to a well-defined reference system.

$$I_i = f_i(x_1, x_2, ..., x_m) = \sum_{j=1}^{m} f_{i,j}(x_j) \quad , i = 1,…,n \tag{8}$$

where function $f_i(.)$ identifies the overall impact assessment model within impact category i, and the damage function $f_{i,t}(.)$ for intervention t ($t \in j$) within impact category i can be calculated from $f_i(.)$ by decreasing amounts of intervention t from x_t^* to x_t^o and keeping the values of other interventions l ($l \in j$, $l \neq t$) at their worst levels (x_l^*). A damage function describes the shape of relationships between interventions and the indicator results within an impact category. In LCIA, characterisation factors can be interpreted as tangents at working points (Heijungs et al. 1992):

$$C_{i,j} = \frac{\partial f_{i,j}(x_j(R))}{\partial x_j} \quad , i = 1,…,n \text{ and } j = 1,…,m \tag{9}$$

where the working point is $((x_j(R), f_{i,j}(x_j(R)))$ representing the total load caused by all human activities of the reference system R. Eq. 9 forms a basis for the so-called marginal approach to determine characterisation factors (Heijungs et al. 1992, Udo de Haes et al. 1999).

Let $x_j(R) = x_j^*$ and assume that damage function $f_{i,j}(.)$ is linear at the $[x_j^o, x_j^*]$ interval, then

$$C_{i,j} = \frac{f_{i,j}(x_j^*) - f_{i,j}(x_j^o)}{x_j^* - x_j^o} \quad , i = 1,…,n \text{ and } j = 1,…,m \tag{10}$$

If we accept that the value function $v'_{i,j}(.)$ corresponds to the damage function $f_{i,j}(.)$, Eqs. 7 and 10 are the same. Thus, the "objective" principles for the determination of characterisation factors related to scientific impact assessment models are consistent with those derived from preference models. This leads to an important conclusion: the rules of MAVT can assist the determination of characterisation factors in LCIA.

Note that the calculation rule for the determination of characterisation factors is called the average approach (Udo de Haes et al. 1999) if characterisation factors are calculated according to Eqs. 7 or 10 at the "large" $[x_j^o, x_j^*]$ interval. (Usually this interval in the context of the average approach is represented as $[0, x_j^*]$). This concerns both linear and non-linear damage functions/value functions. From the point of view of MAVT, the average approach only produces the correct characterisation factor at the whole $[x_j^o, x_j^*]$ interval in the cases of linear damage functions. If linear damage functions pass X_j axes at intervention points x_j^{TH} and x_j^{TH} >0, these threshold points should be considered as x_j^o in Eq.10. In this case the use of zero value for x_j^o leads to incorrect characterisation factors as can be seen in article II.

If it is desirable that the characterisation can cover the large $[x_j^o, x_j^*]$ interval in non-linear conditions the correct way is to use Eq. 5, in which weighting factors and single-attribute value functions must be determined. However, this has not been applied in any LCIA applications. The applied practice is that the results of scientific impact assessment models are calculated either by increasing or decreasing the magnitude of interventions (e.g. 10%) in the working point (e.g. Potting et al. 1998, Krewitt et al. 2001). In this "incremental" way derived characterisation factors are directly used in Eq. 4 without testing the linearity in the chosen intervals.

4.2 Judgemental independence assumptions

It is important to note that the calculation rules of characterisation mentioned above are assumed to fulfil the assumption concerning difference independence between interventions within each impact category (see Section 2). This is the necessary assumption for using the additive model. However, if there exist judgemental dependences between interventions within impact categories, the calculation rules of characterisation will be changed from those presented in the previous section.

In article I it is shown how to check the difference independence assumption in the case of tropospheric ozone formation. The checking needs emission reduction results of each intervention under the impact category and joint reduction results which are calculated by reducing emissions of all interventions at the same time. In practice, difference independence does not hold if the joint reduction causes different decreasing in the impact category indicator result compared to the result derived from the sum of results caused by the separate reduction of each intervention (see Section 2).

If difference independence does not hold, but so-called multiplicative difference independence holds, the characterisation equation requires the determination of weights, the single-attribute value functions and an interaction constant. The interaction constant deals with interdependences among different intervention sets in the multiplicative model. The multiplicative model requires that the ordering of strengths of preferences among pairs of objects that vary only in a subset of attributes does not change if the constant levels on the remaining attributes are changed to some other constant levels (von Winterfeldt and Edwards 1986).

If the multiplicative model fails because of dependences, the multilinear model may still be appropriate. This requires that the multilinear difference independence assumption holds. This in turn means that the strength of preferences in any single attribute (intervention) is unaffected by constant values in other attributes (interventions). The model requires weighting factors, single-attribute value functions and many interaction parameters. In practice, if the number of attributes exceeds four, the assessment task becomes unfeasible (von Winterfeldt and Edwards 1986).

In practice, judgemental independence assumptions have not been studied in the context of characterisation. The users and developers of LCIAs are not familiar with the issue. However, many interventions related to regional and local impact categories may be judgementally dependent on each other in such ways that the additive model does not hold. For example, synergistic toxic effects due to two or more harmful substances indicate dependences between the harmful substances. It is important to note that if empirical environmental research or scientific impact assessment models can offer evidence about dependences between interventions within impact category i under study, the choice of characterisation model type (additive, multiplicative or multilinear) must be made according to the evidence. This holds although interventions are, for example, physically related to each other by the same source. Then the same abatement measures reduce the releases of all interventions at once. In this case the interventions are environmentally dependent, but they can still be judgementally independent from the point of view of a chosen impact category.

4.3 Characterisation based on judgements

In the case of no scientifically based characterisation factors, decision analysis offers the tools to conduct characterisation on the basis of judgements. The first task is to assess single-attribute value functions $v_{i,j}(.)$ according to the measurement techniques presented in Section 2. For this purpose, the ranges of attributes must be determined. In MAVT, it typically holds that the best and worst range values for each attribute are found on the basis of alternatives considered in the assessment. This is also a good starting point for case-specific LCA applications. However, if the aim is to construct a generic characterisation model, the range should be chosen to be large enough. In this way, there is no need to determine characterisation factors or characterisation models case by case, because attribute values related to different LCA application remain within the $[x_j^o, x_j^*]$ range.

If linear single-attribute value functions are assumed, the construction of value functions can be omitted and Eqs. 4 and 7 can be directly used in the case of additive models.

To assess attribute weights $k_{i,j}$ within impact category i, the decision maker's task is to imagine the strength of effects (damages) related to the $[v'_{i,j}(x_j^o), v'_{i,j}(x_j^*)]$ range. These subjective assessments of different interventions within impact category i are weighted against each other. To help this process, different elicitation techniques developed in decision analysis can be used.

Several methods have been developed for the elicitation of the scaling constants (weights) in the additive value function. The use of simple methods such as ratio estimation (Edwards 1977) and swing weighting methods (von Winterfeldt and Edwards 1986) is illustrated in article I. The trade-off method (Keeney and Raiffa 1976) is illustrated in article II. There are many other procedures for the determination of weights in the MAVT literature, e.g. the pricing out method (Keeney and Raiffa 1976). In practice, the tradeoff method is difficult and time consuming compared with the other methods (Borcherding et al. 1991). However, its advantage is that it compels decision makers to take attribute ranges into account in the elicitation (Keeney and Raiffa 1976, Weber and Borcherding 1993).

The elicitation process of attribute weights is subject to many biases. They may originate from the behaviour of the decision makers or the procedures and techniques used in the elicitation (see e.g. Weber and Borcherding 1993, Pöyhönen and Hämäläinen 1998, Pöyhönen et al. 2001). Because subjective attribute weights are determined on the basis of the same theory as impact category weights, the biases phenomenon is discussed in Section 6.2.

Suppose that there are s interventions under an impact category z. The final weights can be computed when s-1 pairs of attributes have been compared because the sum of attribute weights is 1 due to normalization into the [0,1] range (i.e. $v_z(x_1^*,...,x_s^*) = \sum_{j=1}^{s} k_{z,j} \cdot v_{z,j}(x_j^*) = \sum_{j=1}^{s} k_{z,j} = 1$).

In principle, the value measurement techniques offer a possibility to handle attributes (interventions) that do not have natural value scales. For example, in the crudest version of direct rating technique, attribute values are directly assigned to alternatives. An attribute is defined in qualitative terms. Next, the alternatives that seem best and worst with respect to that attribute are identified. All other alternatives are ranked between the two extremes. The above rating step can be useful in some streamlined LCA applications. However, it introduces subjective judgment and leads to subjective characterisation which is against ISO recommendations. According to ISO (2000a), characterisation should be performed with scientifically based characterisation factors and technically based amounts of interventions. However, in the absence of such technically based factors and data, subjective judgements are the only alternative to derive category indicator results in order to obtain a complete picture of the environmental impacts of a product system under investigation. This idea can also be found in the conclusions of the SETAC-North American LCA impact assessment workgroup (Barnthouse et al. 1997). In articles I and III, it is shown how to conduct such subjective characterisation with weighting factors and attribute values obtained from expert judgments.

5 Normalisation

5.1 Normalisation as a separate stage

Normalisation is commonly used as a separate stage for the interpretation of category indicator results. In this case the purpose of normalisation is to provide better understanding of the relative proportion or magnitude for each impact category of a product system under investigation (ISO 2000a). In normalisation, the following equation is typically used:

$$\frac{I_i(a)}{N_i} = \frac{\sum_{j=1}^{m} C_{i,j} \cdot x_j(a)}{\sum_{j=1}^{m} C_{i,j} \cdot x_j(R)} \quad , i=1,\ldots,n \qquad (11)$$

where $I_i(a)$ = indicator result of impact category i caused by product system a
N_i = normalisation value of impact category i
$C_{i,j}$ = characterisation factor for intervention j within impact category i
$x_j(a)$ = amount of intervention j caused by product system a
$x_j(R)$ = amount of intervention j caused by reference system R

Thus, in this basic equation denominator, the normalisation value (N_i), is an indicator result of impact category i caused by the reference system R, i.e. N_i=$I_i(R)$.

Behind the use of Eq. 11 there are strong assumptions. Firstly, the calculations of category indicator results I_i and normalisation values N_i are carried out by the additive model, which requires that difference independence between different interventions under impact categories i holds. If this assumption fails, the multiplicative or multilinear model may still be appropriate. To apply these models, weaker independence assumptions must be fulfilled (see e.g. von Winterfeldt and Edwards 1986). Multiplicative or multilinear models lead to different presentations in the calculation of indicator results.

Secondly, the same characterisation factors are used both for calculations of impact category indicator results and of normalisation values. In practice, this means that, for example, a 10% reduction of intervention j causes the same unit decrease of effect within impact category i as a 100% reduction. This linearity assumption is not obvious for regional categories such as acidification, tropospheric ozone formation and terrestrial eutrophication or local impact categories such as odour. In this work, local scale in the context of impact categories refers to distances from about one kilometre to some tens of kilometres, and regional scale encompasses distances from tens of kilometres to some hundreds of kilometres.

Suppose that country-specific characterisation factors for intervention j within impact category i ($C'_{i,j,co}$ where co is country) are derived from 30% reductions in each country separately. To be exact, these characterisation factors $C'_{i,j,co}$ can only be used in the $[0.7x_j(co), x_j(co)]$ range. Furthermore, 100% reductions lead to characterisation factors $C''_{i,j,co}$ and $C''_{i,j,co} \neq C'_{i,j,co}$. Thus, if the additive model holds the correct normalisation is carried out by

$$\frac{I_i(a)}{N_i} = \frac{\sum_{co=1}^{r}\sum_{j=1}^{m} C'_{i,j,co} \cdot x_{j,co}(a)}{\sum_{co=1}^{r}\sum_{j=1}^{m} C''_{i,j,co} \cdot x_j(co)} \quad , i=1,\ldots,n \qquad (12)$$

if the purpose is to show the contribution of product system a to the total impact of category i caused by the interventions of reference system R. Note that $x_{j,co}(a)$ is the amount of intervention j caused by product system a in country co and $x_j(a) = \sum_{co=1}^{r} x_{j,co}(a)$.

It is important to note that in the determination of country-specific characterisation factors carried out, for example, by Potting et al. (1998) and Krewitt et al. (2001), the linearity of damage functions was not studied. The characterisation factors were based on 10 % reductions or increases of interventions. Thus, it is not sure whether their characterisation factors can be used in the calculation of normalisation values. In addition, the independence assumptions were not tested.

The finding that characterisation factors may be different in calculations of category indicator results of product system *a* and of reference systems (N_i) is new in the LCIA methodology. For example, in the newest guide of LCA adapted by CML there is a recommendation that the same characterisation factors should be used in both calculations (Guinée et al. 2002).

5.2 Normalisation as part of weighting

In order to calculate the total impact value caused by product system *a* the typical aggregation rule applied in LCIA is

$$I(a) = \sum_{i=1}^{n} w_i \frac{I_i(a)}{N_i} \tag{13}$$

which consists of impact category weights, w_i, and normalisation results of impact categories *i*. In this context it is often stated that the purpose of normalisation is to increase the comparability of the data from the different impact categories in order to provide a basis for a valuation step (e.g. Consoli et al. 1993, Lindeijer 1994).

According to MAVT the additive model can be written as

$$I(a) = \sum_{i=1}^{n} w_i \sum_{j=1}^{m} k_{i,j} \cdot v_{i,j}(x_j(a)) \tag{14}$$

In article I it is shown that Eqs. 13 and 14 are the same if and only if single-attribute value functions are linear and go through the origin. In addition, it is assumed that additive models can be used for the calculations of indicator results. The result is important because the traditional aggregation rule used in LCIA (Eq. 13) has been shown to be a special case of the multiattribute value function.

According to MAVT, the form of normalisation value depends on the shape of single-attribute value functions and the feasible range of attributes. In practice, the issue is not elaborated in the field of LCIA. If single-attribute value functions are linear, then (see Eq. 7)

$$v_{i,j}(x_j(a)) = \alpha_{i,j} \cdot x_j(a) = \frac{1}{x_j^* - x_j^o} \cdot x_j(a) \quad \text{for all } i \text{ and } j \tag{15}$$

where the values of value functions were normalized into the [0,1] range. Assume that $x_j^* = x_j(R)$ and $x_j^o = 0$. On the basis of Eqs. 7 and 10 it can be seen that weighting factors $k_{i,j}$ are $C_{i,j} \cdot x_j(R)$. Furthermore, we get $k_{i,j} = C_{i,j} \cdot x_j(R) / \sum_{i=1}^{n} C_{i,j} \cdot x_{i,j}$ (for all *i* and *j*) because weights are summed to 1 due to the normalization into the [0,1] range. If the above-mentioned conditions and difference independence assumption hold, we derive Eq. 13 from Eq. 14. Thus, in this case the normalisation value N_i is $I_i(R)$.

Suppose that the single-attribute value function $v_{i,j}(.)$ is linear, crossing the X_j axes at value points $x_j^{\otimes}(R)$. If $x_j^{\otimes}(R)$ > 0 then there exists a threshold. This means that there is zero damage below the emission $x_j^{\otimes}(R)$ that is greater than zero. Let $x_j^o = x_j^o(R) = x_j^{\otimes}(R)$. In the case of site-generic characterisation factors, this leads to the form of normalisation

$$\sum_{j=1}^{m} k_{i,j} \cdot v_{i,j}(x_j(a)) = \frac{\sum_{j=1}^{m} C_{i,j} \cdot x_j(a)}{\sum_{j=1}^{m} C_{i,j} \cdot (x_j(R) - x_j^o(R))} = \frac{I_i(a)}{I_i(R) - I_i^o(R)} \quad , i=1,\ldots,n \tag{16}$$

where $I_i^o(R)$ is the best achievement level of indicator results of impact category *i* caused by reference system *R*. In this case, the normalisation value N_i can be considered as $I_i(R) - I_i^o(R)$.

In the case of country-specific characterisation factors, where linearity exists in the single-attribute functions and characterisation factors only hold in the $[x_j^o(co), x_j(co)]$ range, the following "normalisation" rule is obtained

$$\frac{I_i(a)}{I_i(R) - I_i^o(R)} = \frac{\sum_{co=1}^{r}\sum_{j=1}^{m} C_{i,j,co} \cdot x_{j,co}(a)}{\sum_{co=1}^{r}\sum_{j=1}^{m} C_{i,j,co} \cdot (x_j(co) - x_j^o(co))} \quad , i=1,\ldots,n \tag{17}$$

where $0 \le x_{j,co}(a) \le (x_j(co) - x_j^o(co))$ for all *j* and *co*. In this case, country-specific characterisation factors are the same in the calculations of normalisation values and of impact category indicator results of product system *a*.

The findings related to normalisation values in the cases of Eqs. 16 and 17 have not been elaborated in any LCIA models although there is a need to use them from the point of view of environmental pollution research (e.g. Posch et al. 1999). Therefore, the findings may be particularly valuable for the development of a more site-dependent impact assessment framework in the future.

Note that in the DAIA model applied in both case studies, the use of Eq. 16 is avoided by using ratings $x_{i,j}$ instead of amounts of interventions x_j. In these cases damage/value functions go through the origin because ratings only include the "effective" parts of amounts of interventions which cause adverse effects on the environment (see Appendix 1). Hogan et al. (1996) also used a similar "only above thresholds" approach to interpret the inventory data but they did not connect the transformed amounts of interventions to the characterisation phase as has been done in DAIA.

Sometimes it is presented that the aggregation of different impact category indicator results into a single impact value can be calculated without normalisation, i.e. in the case of an additive model with site-generic characterisation factors the calculation rule is

$$I(a) = \sum_{i=1}^{n} w_i \cdot I_i(a) = \sum_{i=1}^{n}\sum_{j=1}^{m} w_i \cdot C_{i,j} \cdot x_j(a) \tag{18}$$

For example, Finnveden (1994) wrote that normalisation may in some cases provide a better basis for valuation and it is necessary for some valuation methods. However, among LCIA practitioners it is unclear in which situations normalisation is allowed or not allowed (see Finnveden et al. 2002).

According to MAVT, Eq. 18 can be used only if linearity and indifference assumptions hold, and impact category weights should fulfill the property expressed in the next section (Eq. 21).

6 Weighting

6.1 General aspects of the determination of impact category weights

According to MAVT, the aggregation of different impact category indicator results into a single value, i.e. Eq. 13 can also be expressed by (article II)

$$I(a) = \sum_{i=1}^{n} w_i \cdot v_i(I_i(a)) \tag{19}$$

where v_i is a normalized value function for impact category i and I_i(a) is a vector consisting of weights $k_{i,j}$ and values $v_{i,j}(x_j(a))$. The value function $v_i(.)$ expresses the strength of preference related to relationships between effects within impact category i and impact category result $I_i(.)$. More precisely, v_i is a single-attribute value function for impact category i and $v_{i,j}$ is a single-attribute value function for intervention j within impact category i.

Impact category weights, w_i, express trade-offs between environmental effects of different impact categories from the point of view of their severity. Environmental effects of different impact categories are calculated as impact category results, which are not commensurable, and there are no such models as in the case of characterisation where the model $f_{i,j}(.)$ can be used for generating weights (characterisation factors) within impact category i (see Section 4.1). Different impact category results can only be aggregated into a single value with the help of subjective weighting factors.

According to MAVT, the impact category weights in Eq. 19 and in the case where normalisation corresponds to Eq. 16 can be interpreted as

$$w_i = v'_i(I_i(R)) - v'_i(I_i^o(R)) \tag{20}$$

where $v'_i(.)$ is an un-normalized value function, $v'_i(I_i(R)) = v'_i(x_1(R),...,x_m(R))$ and $v'_i(I_i^o(R)) = v'_i(x_1^o(R),...,x_m^o(R))$.

Note that in Eq. 19 value functions are normalized into the [0,1] range as in the additive characterisation model (Section 4.2). This means that $v_i(I_i(R)) = 1$ and $v_i(I_i^o(R)) = 0$ (and $w_1 + w_2 + ... + w_n = 1$). Thus, the value of Eq. 19 is always 1 for all w_i. For this reason, the weights cannot be calculated. They can only be produced by valuation; the decision maker's task is to estimate the strength of effects (damages) related to indicator results of impact category i caused by the intervention intervals of reference system R. These subjective assessments of different impact categories are weighted against each other. To assist this process, various elicitation techniques developed in decision analysis can be used.

In the case of Eq. 18, in which impact category weights are directly multiplied by category indicator results, impact category weights should be (see Eq. 7)

$$w_i = \frac{v'_i(I_i(R)) - v'_i(I_i^o(R))}{I_i(R) - I_i^o(R)} \tag{21}$$

if linearity at the $[I_i^o(R), I_i(R)]$ interval and the indifference dependency assumption hold.

In the basic additive aggregation model, Eq. 13, it is assumed that $x_j^o(R) = 0$ for all j and that the linearity in the $[0, I_i(R)]$ range holds. On the basis of these assumptions, Eqs. 18 and 21 produce Eq. 13 and the same characterisation factors can be used in the calculations of impact category results of product *a* and reference system *R*. Assume the other situation, Eq. 12, in which different characterisation factors are used for the calculations of impact indicator results and normalisation values. In both cases, impact category weights can be interpreted according to Eq. 20. If $I_i^o(R) = 0$ for all i the impact category weights can be interpreted as

$$w_i = v'_i(I_i(R)) \tag{22}$$

Thus, in the elicitation of weights the task is to assess relative severity of current effects of impact categories caused by the interventions of the reference system *R*. Unfortunately, this is easier to say than to carry out. In the case of the Finnish forest industry, interventions caused by Finland were used for the calculation of $I_i(R)$, i.e. the reference area was Finland. In global and regional impact categories, interventions caused by activities outside Finland have their own effects on the Finnish environment. For this reason, the task is also to separate those effects caused by sources outside

Finland. In addition, Finnish emissions cause harmful effects outside Finland, which must also be taken into account in valuation. To compare global and regional impacts against each other in weighting, the question format should be changed so that respondents know that emissions caused by Finland are valuated against each other (see article II).

Furthermore, MAVT can explain precisely how attribute weights are obtained in the two-level hierarchy model in which there are also sub-categories. In the case of Fig. 3 in the determinations of weights of ecotoxicity sub-category *SC* (ka_{sc}) and weights of attribute $X_{7,sc,j}$ within the ecotoxicity sub-category *SC* ($kb_{sc,j}$), the panelists are asked to adjust their weights to $x^{*}_{7,sc,,j}$,which represents the total ratings caused by all the emissions of the chosen reference system.

The second SETAC-Europe working group on life cycle assessment concerning normalisation, grouping and weighting in LCIA (Finnveden et al. 2002) pointed out that case-specific (internal) normalisation requires case-specific weighting. According to the working group, in case-specific (internal) normalisation, data from two different options within the same LCA study are referenced relative to each other in Eq. 16. In the report the claim was not proved. It is easy understand on the basis of the above mentioned relationships between weights and value functions that if alternative product system *b* is chosen as reference system *R* (e.g. $N_i=I_i(b)$), impact category weights are interpreted according to Eq. 20 in which *R* is replaced by *b*. Furthermore, MAVT offers the clarification for external normalisation referring to a situation in which the reference system is larger than the product system of the application (e.g. if $N_i=I_i(Western\_Europe)$ then weights reflect $v'_i\,(I_i\,(Western\_Europe))$ – $v'_i\,(I_i^o\,(Western\_Europe))$.

Norris (2001) first pointed out that the above-mentioned requirement for congruence in normalisation is violated in many LCIA applications in North America. In the cases of site-specific normalisation, generic weighting factors have been used. In addition, in Eco-Indicator 99 normalisation values *a* are calculated by using Dutch-specific damage factors (characterisation factors), but safeguard subject (impact category) weights in Eco-Indicator 99 are derived from the weighting survey in which the relative importance of weights reflects damages in Europe (Hofstetter et al. 2000b).

In general, it can be stated that knowledge about relationships between weights and other elements of weighting is poorly elaborated in the field of LCA although in the early LCA literature there can be found some studies attempting to clarify the issue. Both Heijungs (1994) and Tukker (1994a, 1994b) used Eq. 19 as a starting point for their representations. Tukker (1994b) proposed that weighting factors could be determined by using iso-utility functions (=indifference curves in the context of MAVT/MAUT (Keeney and Raiffa (1976)) for two or more impact categories. In practice, this approach leads to the difficult elicitation of weights. Despite this, his observations on relationships between normalisation and the determination of weights are consistent with this work. The same concerns the study of Heijungs (1994). In his study, he demonstrated the relationship between weighting and normalisation on the basis of trade-off procedure (see Keeney and Raiffa 1976). He concluded that normalisation is required in the context of weighting. However, in both presentations the role of value/utility functions was, in practice, omitted due to the use of linear functions. Furthermore, the effects of the attribute ranges and links to characterisation factors were missing.

Lundie (1999) conducted a weighting application of TV-housings concepts by a simple additive weighting (SAW) method (Hwang and Yoon 1981). This simple MAVT method uses directly an equation that corresponds to Eq. 13. In the study, category indicator results of the product system were normalised in proportion to global contribution per year per impact category. However, Lundie did not indicate whether the global scale was taken into account in the determination of impact category weights according to the MAVT requirements (see also Lundie and Huppes 1999).

Miettinen and Hämäläinen (1997) pointed out that weighting should be carried out on a case-by-case, i.e. problem specific, basis in which the attribute ranges of alternatives should be taken into account. However, this does not mean that weighting should always be made case-by-case. As can be seen in this thesis, generic weighting factors for a chosen large reference system offer a solution in which it is not necessary to evaluate impact category weights in every LCA case.

6.2 Methods for weight elicitation

In the context of MAVT, it is assumed that the weights are directly derived from an individual or a group of people by elicitation. Elicitation is a process of gathering judgements concerning the problem through specially designed methods of verbal or written communication (Meyer and Booker 1990). In the context of these so-called panel methods, a well-known problem is that the panelists are sensitive to biases in the judgements. Bias is a systematic error, i.e. a deviation from the “true value” in one direction (Armstrong 1985).

In the case studies of the Finnish forest industry and the Finnish metals industry, impact category weights were obtained from the experts working with environmental issues by using decision analysis elicitation techniques. The results showed that weights derived from individual respondents differ widely partly due to different opinions, and partly due to biases originating from the behaviour of the experts and the procedures and techniques used in the elicitation. It was not possible to quantify the biases. In article I the main aspects of weighting raised during the case study of the Finnish forest sector were discussed. The aspects were:

1) Appropriate panel composition
2) Question format
3) Available information
4) Applied criteria
5) Weight elicitation situations
6) Weight techniques
7) Combining individual answers

In principle, decision analysis cannot give an answer to the question of which type of panelists should be chosen (environmental experts, experts from other sciences, shareholders, or a representative mix). The issue of to whom the questionnaires should be directed depends on the application and the nature of impacts.

The question format is an important element in the weight elicitation process from the point of view of MAVT. The questions should be formulated so that the issues queried are clear to the respondents. In articles I and II it is pointed out that the question format should be consistent with the chosen $[x_j^o, x_j^*]$ range and reference system *R*. However, the differences of results derived from different elicitation techniques (e.g. ratio estimation, SWING) of value trees may partly originate from the way the elicitation questions introduce the meaning of an attribute weight to decision makers (Pöyhönen and Hämäläinen 2001). For this reason, the role of question format related to the elicitation techniques should be studied in the context of LCIA problems.

In practice the panelists have different information concerning effects within each impact category. For this reason, in the case studies of the Finnish forest industry and metals industry the background information about impact categories was gathered, discussed and delivered to respondents before they gave their answers in the elicitation. However, Hofstetter (1996) warned that it may be dangerous to brief panelists even with such apparently neutral information because of the potential bias inherent in the condensing of the information. However, in the light of experience obtained from the case studies it appears very important to provide panelists with appropriate information about environmental themes.

Research has shown that people have difficulty in correctly translating their judgements into quantities if the judgement concerns a complex task (e.g. Meyer and Booker 1990). The rule of decision analysis - breaking a problem into its component parts - has been shown to yield more accurate answers in the context of expert judgements. Therefore the multicriteria analysis approach may be useful for determination of impact category weights. Information related to impact categories (e.g. scarcity, reversibility, substitutability, geographical extension and uncertainty of effects) should be arranged according to the weighting criteria (see e.g. Volkwein et al.1996). Further work is needed to develop a formal and structured manner for combining criteria and related information.

An elicitation situation is the setting in which the expert's judgement is elicited (Meyer and Booker 1990). There are many different elicitation situations (an individual interview with or without a face-to-face situation and feedback loops; advanced interactive group methods in which the experts are in a face-to-face situation both with one another and with a session moderator when they give their data; or the Delphi method in which the experts, in isolation from one another, give their judgements to a moderator (Dalkey 1969)). Although there is some experience with different elicitation situations in the field of LCA, further research is needed to provide an answer to the question of which elicitation situation is the most favourable in LCA.

Decision analysis can offer weighting techniques for the elicitation. The techniques, knowledge and experience in multiattribute utility/value measurement presented in the determination of attribute weights (Section 4.3) also concern the determination of impact category weights. In addition, techniques such as pairwise comparison of AHP with the qualitative response mode (Saaty 1980) can be carried out so that the results are in accordance with MAVT (Salo and Hämäläinen 1997). Note that Pöyhönen and Hämäläinen (2001) studied the convergence of five multiattribute weighting methods (ratio estimation, DIRECT weighting, SWING, Tradeoff weighting, AHP) and they concluded that there is no superior multiattribute weighting technique.

One further possibility is that weights can be calculated on the basis of so-called ranking methods such as a rank order centroid (ROC) (Edwards and Barron 1994). These methods can be used if the panelists are able only to rank the criteria (impact categories) in order of importance. From the point of view of MAVT, it is important to ensure that these approximate methods attempt to take into account the range of attributes/impact categories.

The elicitation technique for impact category weights developed and used in the case study of the Finnish forest industry corresponded to the PAIRS technique introduced by Salo and Hämäläinen (1992). Both techniques generate the interval-valued ratio judgements into hierarchical weighting models. In comparison to the usual point estimates, such judgements are better suited for modelling the decision maker's subjective uncertainty. However, the ratio estimation with range input and Monte Carlo simulation give probability distribution of weights rather than intervals for weights in the case of PAIRS. It is clear that in the uncertainty analysis the methods produce outcomes with different shapes of probability distributions.

One possible way of eliciting weights is to use the ratio estimation with different probability distribution inputs and Monte Carlo simulation. In this case a respondent is also asked to provide the probability distribution for his or her judgements.

To ensure that the weights given will correctly reflect the opinions of the respondents, an interactive decision analysis approach is recommended. The computer-supported weighting allows the respondent to analyse the results, which can help to avoid errors (e.g. Marttunen and Hämäläinen 1995).

Although the roots of monetarization methods (see Section 1.2) are in environmental economic science, these methods can be applied for the determination of impact category weights from the point of view of MAVT. In order to apply such weights in Eqs. 13, 14 or 19 the one important requirement is that a monetary measure including direct and indirect effects related to impact category *i* must cover the effects caused by the $[x_j^0, x_j^*]$ ranges of reference system *R*.

Distance-to-target weighting methods are widely used in life cycle impact assessment. These methods rank impacts as being more important the further away society's activities are from achieving the desired targets for the pollutants. Finnveden and Lindfors (1997) first pointed out that these methods are suitable if the targets of impact categories have the same significance. In article II this was demonstrated more precisely. Applying distance-to-target weighting is consistent with the impact assessment framework derived from MAVT if non-zero targets with equal importance are used and linear damage functions passing through the origin hold in the basic aggregation equation (Eq. 13).

The fact is that different methods for weight elicitation produce different results (e.g. Weber and Borcherding 1993, Pöyhönen and Hämäläinen 2001). This raises questions about what methods are effective for improving the consistency and validity of weighting judgements in LCA situations. There is no simple answer, because different methods consist of different elements. The key issue is that these methods are consistently applied according to their principles. Pöyhönen and Hämäläinen (2000) emphasised that good interaction between an analyst and a decision maker is needed in order to eliminate biases in attribute weighting. In addition, the analyst must be skilful and aware of the biases related to different techniques. Furthermore, a good practice is that the elicitation is carried out by using two or more different methods at the same time.

Experimental work carried out in the field of decision analysis has shown that different elicitation techniques with behavioural and procedural biases are not the only factors causing different weights. The structure of a value tree can also affect the results (Weber et al. 1988, Borcherding and von Winterfeldt 1988, Pöyhönen and Hämäläinen 1998, Pöyhönen et al. 2001). The so-called splitting bias refers to the phenomenon that a decision maker increases (or decreases) the weight of an attribute when it is divided into sub-attributes and weighted non-hierarchically. In the context of LCIA, non-hierarchical weighting means that interventions are directly weighted against each other without characterisation as, for example, by Ong et al. (2001). However, hierarchical weighting, in which characterisation factors and impact category weights are determined and multiplied through the value tree, is a more appropriate procedure in the context of LCA due to the complex intervention-effect relationships in the environment.

Aggregation of questionnaire answers is required if multiple respondents are used and a single representation of their answers is needed. This introduces the problem of how to aggregate respondent estimates. Methods of combining responses can be classified into either behavioural or mathematical aggregation procedures. Behavioural methods rely on the experts reaching a consensus, e.g. the Delphi method uses successive iterations to reach one estimate, whereas mathematical aggregation is the use of mathematical means to combine multiple questionnaire data into a single estimate or a single distribution of estimates (Meyer and Booker 1990).

Several studies have indicated that assuming equal expertise for all respondents and the calculation of weighted mean from respondents' answers is a feasible idea in this weight determination problem (Seaver 1978, Genest and Zidek 1986). However, this easily leads to the well-known problem that mathematically combined estimates from individual interviews outperform individual estimates (Seaver 1976). This also applies in the field of LCA. Averaging of individual weights generates a meaningless number (Hofstetter 1996). As can be seen in the results of the case study presented in the Finnish forest industry (article I), the ecological impact category weights vary on a large scale, but the difference between the average weights is only a factor of five. For example, Kortman et al. (1994) recognized this distortion and proposed not to average over the whole group but over a number of separate groups that exhibit a high covariance in their answers. The starting points of different DAIA applications have been that the results are calculated by using different weight groups.

6.3 Aggregation

In Section 2 it was pointed out that the use of additive models for the calculation of total impact value (Eqs. 13 or 18) requires that the assumption concerning difference independence between impact category results must hold. This is not a clear issue for all impact categories. For example, acidification and terrestrial eutrophication may have dependences in some geographical areas due to nitrogen load. Dependences may be more obvious in local scale impact categories. For example, it is a well-known mechanism that metals deposited to soil can easily be leached under acidifying conditions.

If difference independence does not hold, multiplicative or multilinear models may be applied. These models have their own independence tests for impact category indicator results (see von Winterfeldt and Edwards 1986). The issue is poorly elaborated in the field of LCIA. In practice, the work has not yet started.

In article II it was shown that the aggregation rule of the Eco-scarcity method (Ahbe et al. 1990, BUWAL 1998) does not correspond to the rules of MAVT.

From the perspective of MAVT, the key issue is that aggregation is carried out consistently according to the assumptions and variables. This is illustrated in the next section.

6.4 Weighting applications

Suppose that country-specific characterisation factors based on 30% of emission reductions differ from those derived from 100% of emission reductions due to the non-linearity in regional impact categories. In the characterisation of interventions caused by product system *a*, characterisation factors ($C^{'}_{i,j,co}$) based on the 30% reductions of each country *co* are used, whereas in the calculations of reference scores characterisation factors ($C^{''}_{i,j,co}$) derived from the 100% reductions of each country *co* are used. Suppose that the reference area is Europe and difference independence holds between interventions and impact category indicator results. Now the total environmental impact value is calculated by

$$I(a) = \sum_{i=1}^{n} w_i^{Europe} \cdot \frac{I_i(a)}{I_i(Europe)} = \sum_{i=1}^{n} w_i^{Europe} \cdot \frac{\sum_{co=1}^{r}\sum_{j=1}^{m} C^{'}_{i,j,co} \cdot x_{j,co}(a)}{\sum_{co=1}^{r}\sum_{j=1}^{m} C^{''}_{i,j,co} \cdot x_j(co)} \tag{23}$$

where w_i^{Europe} indicates that impact category weights describe the severity of effects within impact category *i* caused by interventions released from Europe. If linearity holds, Eq. 23 can be written as

$$I(a) = \sum_{i=1}^{n}\sum_{co=1}^{r} w_i^{co} \cdot \frac{\sum_{j=1}^{m} C^{'}_{i,j,co} \cdot x_{j,co}(a)}{\sum_{j=1}^{m} C^{''}_{i,j,co} \cdot x_j(co)} \tag{24}$$

where w_i^{co} is a country-specific impact category weight indicating the severity of effects within impact category *i* caused by interventions released from country *co*. Because the linearity holds it can be calculated by

$$w_i^{co} = w_i^{Europe} \cdot \frac{\sum_{j=1}^{m} C^{'}_{i,j,co} \cdot x_{j,co}(a)}{\sum_{co=1}^{r}\sum_{j=1}^{m} C^{''}_{i,j,co} \cdot x_j(co)} \quad , i=1,\ldots,n \tag{25}$$

Article III illustrates how global, regional and local environmental impacts caused by the production stages of metals can be assessed with the help of decision analysis, beginning from the determination of impact categories and ending with weighting. In the case study of the Finnish metals industry, a detailed LCIA model was constructed for the production stage of each metal product in the following way. (An area of the activities of a mill is here called a production stage). First total impact values of production stages were calculated by Eq. 13, in which Finland-specific characterisation factors and impact category weights, w_i^F, were used. From these calculations, production stage-specific category indicator results of interventions within each impact category (climate change=1, acidification=2, tropospheric ozone formation=3 and aquatic eutrophication=4) were obtained. Under each impact category these indicator results were normalised to 1, i.e. the reference system was the production stage. Assuming that linearity holds, production stage-specific weights for the impact categories were calculated as:

$$w_i^{ps} = w_i^F \cdot \frac{I_i(ps)}{I_i(F)}, \qquad i = 1,2,3,4 \tag{26}$$

where $w^{ps}{}_i$ is a site-specific impact category weight for the production stage of metal *M* within impact category *I*, $w^F{}_i$ is an original weight of impact category *i* in the national scale impact assessment model, $I_i(ps)$ is an indicator result of impact category *i* caused by the production stage of metal *M* and $I_i(F)$ is a reference value of impact category *i* related to Finland.

Impact categories which do not have scientifically based characterisation factors, or for which there are no measured data, were also assessed by expert judgements. In the LCIA applications of the Finnish metals industry these impact categories with interventions were: ecotoxicity (metals to the air and water, oil, cyanides), health effects (POPs (e.g. PCB, PAH, dioxins), As, Pb, Cd, Ni, SO_2, NO_x), direct effects on flora (SO_2, NO_x, fluoride, dust), oxygen depletion (biological/chemical oxygen demand, ammonium), solids to water, thermal load, impacts on amenities (dust), wastes (different groups), noise, smell, soil and ground water pollution (different interventions). Under each impact category, indicator results of interventions were assessed on the basis of effects caused by the production stage and the results were normalized to 1. After characterisation, impact category weights were assessed on the basis of effects caused by the production stage. The starting point was that the weights of global and regional impact categories did not need to be weighted against each other. The initial weights of these categories were directly obtained from Eq. 26 and the proportions of these weights remained the same during the weighting task. The panelists` task was to adjust their opinions about the weights of local impact categories to the framework in which the weights of global and regional impact categories were already set (Fig. 4). Finally, the total impact value scores of each intervention were calculated by multiplying through the tree.

7 Interpretation

According to ISO standard 14043 (ISO 2000b), life cycle interpretation is the fourth phase of the life cycle assessment process. It is "a systematic technique to identify, check, and evaluate information from the results of the life cycle inventory (LCI) and/or the life cycle impact assessment (LCIA)." The task of interpretation is to identify significant issues and to evaluate the completeness, sensitivity and consistency of the data. Thus, LCIA does not include the interpretation, whereas sensitivity analysis is always the last phase of the decision analysis process (e.g. Bunn 1984, von Winterfeldt and Edwards 1986, French 1988). In sensitivity analyses, the decision problem is examined by the decision/preference model. The output of a decision model depends critically on data input, and these data should therefore be examined critically. For this reason, interpretation of the results of decision analysis impact assessment is here considered as a part of decision analysis impact assessment.

In practice, the decision analysis impact assessment model is a weighting method in the terminology of LCA. The model based on MAVT is capable of producing a complete ranking of alternatives and it can be written as:

$$v(I_1,\ldots I_n) = f[v_1(I_1),\ldots v_n(I_n), w_1,\ldots,w_n,\ldots w_S] \tag{27}$$

where *v* is an overall value function, I_i is an indicator result of impact category *i* (*i* =1,…,*n*), *f* is an overall function (additive, multiplicative or multilinear), w_i (*i*=1,…,*n*) is an impact category weight, w_i (*i*=*n*+1,…,*S*) is a possible interaction parameter for multiplicative or multilinear function and single-attribute value functions v_i are

$$v_i(I_i) = v_i(x_1,\ldots x_m) = f_i[v_{i,1}(x_1),\ldots,v_{i,m}(x_n), k_{i,1},\ldots,k_{i,m},\ldots,k_{i,F}] \quad , \text{i = 1,…,n} \tag{28}$$

a)

b)

c)

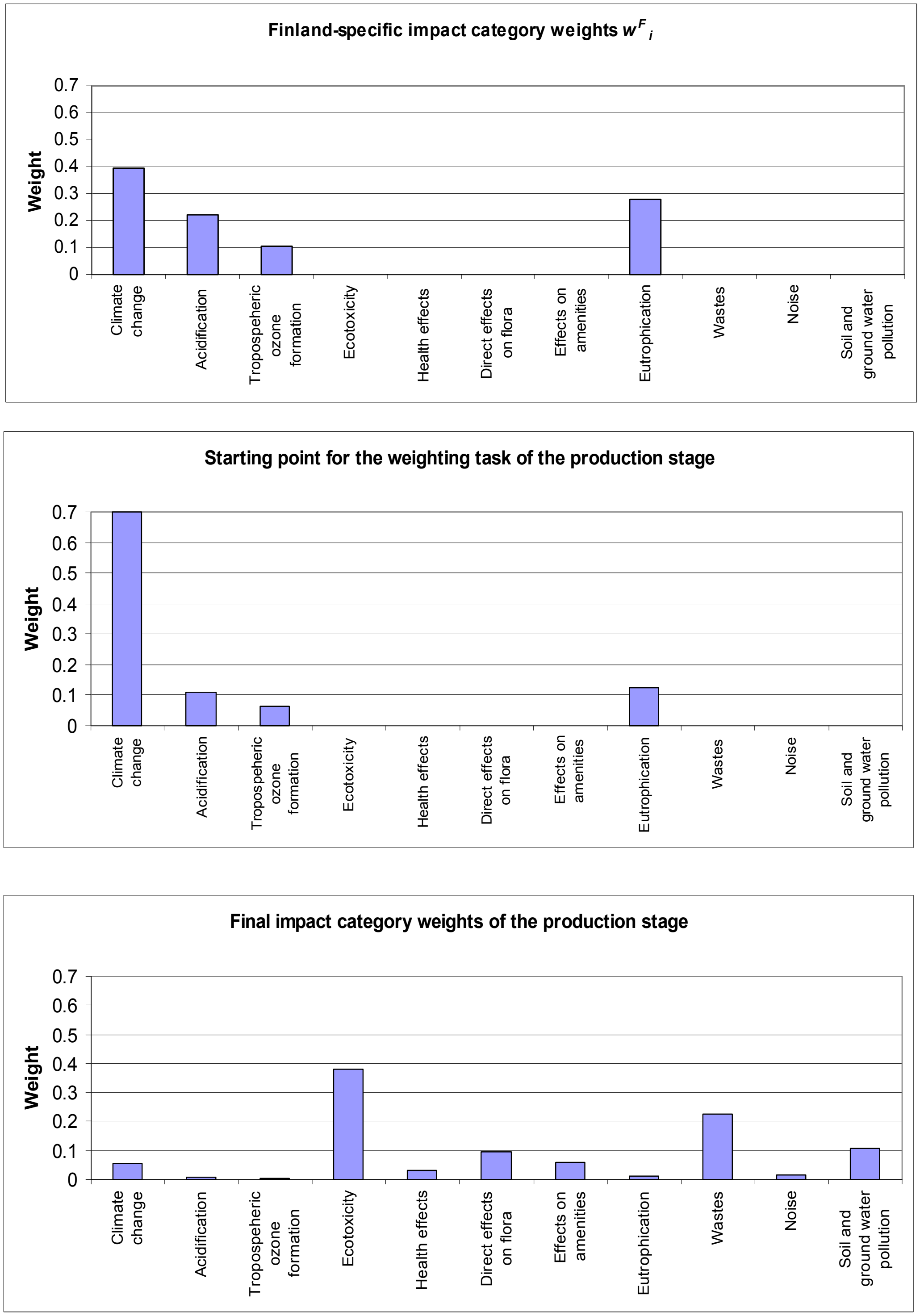


Fig. 4. Impact category weights during the different stages of the weighting task in the case of Finnish metals industry. At first, Finland-specific impact category weights were changed to production stage-specific weights (Fig. 4a->Fig. 4b). Then the task was to draw up or down bars of the other impact category weights, keeping weights of climate change, acidification, tropospheric ozone formation and eutrophication fixed (Fig. 4b and Fig. 4c). The higher the value, the more harmful was the emission caused by the production stage. At the end of the task, attribute weights were normalized to 1 (Fig. 4c).

where f_i is an overall function (additive, multiplicative or multilinear) for impact category i, $v_{i,j}$ is a single-attribute value function for attribute j within impact category i, $k_{i,j}$ (j=1,…,m) is a weight (=scaling constant) of attribute X_j within impact category i and $k_{i,j}$ (j=m+1,…,F) is a possible interaction parameter within impact category i in the cases of multiplicative and multilinear functions.

There are three types of uncertainty that contribute to estimating the credibility of the results of Equation 28. These are trade-off error, input data error and model error. Input data errors include errors related to intervention values, x_j, derived from the inventory analysis or other data sources and characterisation factors if these can be determined without subjective valuation. In the case of subjective characterisation (Section 4.3), both value functions $v_{i,j}$ and attribute weights $k_{i,j}$ are subject to trade-off errors. Trade-off errors include errors associated with the determination of weights. Model errors include choices and assumptions such as inappropriate selection or aggregation of variables, incorrect functional forms for value functions and incorrect boundaries.

Model errors are not subject to analysis using any straightforward statistical or mathematical techniques. In practice, in LCIA the only possibility to study the contribution of the model errors to the results is to use alternative models in which such factors as f, f_i, $v_{i,j}$ and characterisation models (additive, multiplicative or multilinear) vary between different models. It should be noted that careful problem-structuring with a value tree can avoid many model error aspects, such as completeness and redundancy (see Section 3 and article IV). In addition, following MAVT's rules can ensure that data and methodology choices are consistent with theoretical considerations.

Uncertainties related to data input and trade-off errors can be dealt with using the preference model/impact assessment model.. As shown in article I, changing the intervention values x_j has only minor effects on aggregating conclusions, whereas important sensitivities to weights arise at higher levels of the tree. Thus, weights, in particular impact category weights w_i, are the most important factors for sensitivity analysis and must therefore be revised most carefully. This is a well-known feature of hierarchical models. It is often useful to find turnover points where the ranking of alternatives is changed (e.g. Ríos Insua 1990, Ríos Insua and French 1991).

For the reason mentioned above, in multiattribute models "basic" sensitivity analysis is performed by varying a single weight and by observing the effect on the results of the model. A popular manner in the context of 'one-dimensional' sensitivity analysis is that a value of a single weight is varied while the ratios between the other weights are held constant. This was also conducted in the case of the Finnish forest industry (article I, Fig. 5). However, this approach can be misleading as it ignores the potential interaction that can result from simultaneous manipulations of multiple weights (Butler et al. 1997). Note that Geldermann (1999) and Geldermann et al. (2000) used the approach for LCIA conducted with the help of the outranking method PROMETHEE (see Section 8.1).

In order to obtain a more complete view of the results of the assessment problem, some easy-to-use sensitivity analysis techniques are available but their use is restricted to the cases in which there are two or three attributes (see e.g. Butler et al. 1997). In practice, most realistic impact assessment problems in LCIA utilise more than three interventions within impact categories or impact indicator results. Therefore it is desirable to apply high dimensional sensitivity analysis as used in multi-criteria decision analysis.

Uncertainty can be expressed with the help of intervals or probability distributions. This allows performance of a sensitivity analysis in which all input variables and parameters vary over their range of uncertainty. This uncertainty analysis is commonly conducted by Monte Carlo simulation. In article I, Monte Carlo simulation was conducted in the case of an additive model in which attribute values, attribute weights and impact category weights all had their own uncertainty intervals (Fig. 6). For example, impact weights were calculated from the answers in which respondents expressed their uncertainty with regard to trade-offs with the help of the "interval ratio estimation" developed in the LCA study of the Finnish forest industry (article I). The method requires the decision maker first to rank the relevant attributes (or impact categories) according to their importance. The least important attribute is

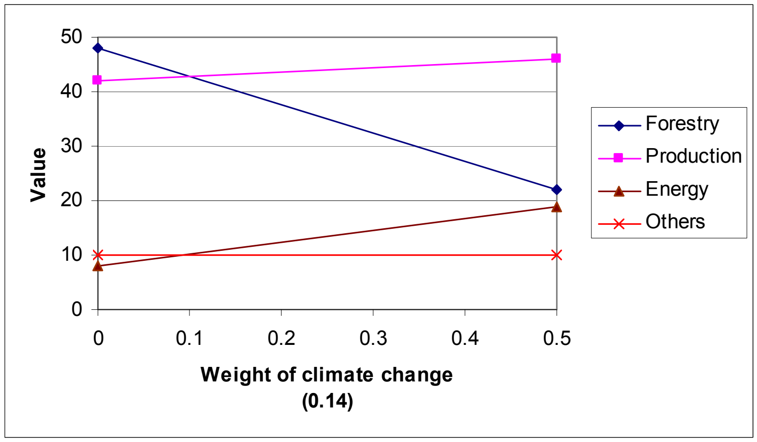


Fig. 5. Sensitivities of the value scores of the life cycle stages to changes in the chosen impact category weight in the case of the Finnish forest industry (article I). The value in parentheses represents a questionnaire average weight. Increasing the original weight to the right (e.g. $w_{climate\ change}$=0.3 instead of 0.14) and keeping the proportions of other impact category weights fixed leads to the result in which the production stage is clearly the most significant life cycle stage causing harmful effects on the environment. The life cycle stage of which the line is highest at a given value of the weight has the most harmful effects.

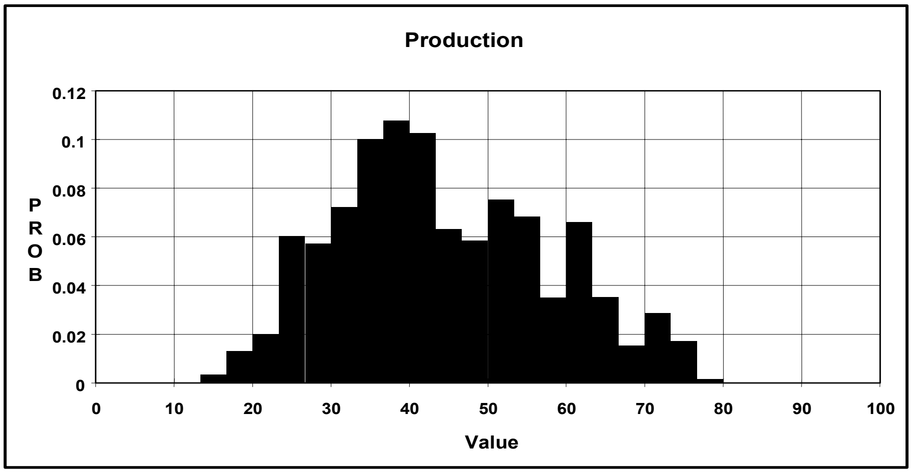
assigned a weight of 10 and all others are judged as multiples of 10. Instead of point estimates the decision maker can also use interval estimates. In the simulation these intervals were interpreted as uniform distributions. However, these uniform distributions could not produce meaningful output distributions, and in practice, the results with intervals could only be used to find dominating or dominated alternatives.

In the MAVT application conducted by Lundie (1999), the intervals for impact category weights were also determined from the results of a questionnaire sent to ten decision makers. Weights were elicited by direct weighting and the intervals were interpreted as uniform distributions. On the basis of these distributions, frequencies of rank order for the alternatives under study were calculated. Lundie and Huppes (1999) also produced a frequency of rank order assuming that the intervals of impact category weights can vary stochastically between 5 and 50 % per impact category.

Because uncertainties of variables/parameters in multiattribute models cannot easily be estimated, easy-to-use methods for examining the effects of the uncertainties under incomplete information are developed in the field of multiattribute problems. These methods can be a better alternative to ensure the decision makers' commitment to the results of impact assessment. Such approaches used in the field of multiattribute problems are, for example, sensitivity analyses by intervals (such as in article I mentioned above, see also Salo and Hämäläinen 2001, Lidstedt et al. 2001), rank order weights and random weights (Butler et al. 1997). The latter method implies no knowledge whatsoever of the relative importance of the weights. Randomly generated weights can be used for finding dominating or dominated alternatives. Rank order weights can be applied for applications in which rank order information related to weights is available.

An alternative approach for modelling uncertainty or imprecision arises from the fuzzy set theory. The concept of fuzzy sets is a way to deal systematically with un-sharp figures, which better captures the subjectivity of human behaviour (Chen and Hwang 1992). In LCIA the fuzzy applications have been conducted by using the outranking PROMETHEE method (Le Tenó 1999, Geldermann 1999, Geldermann et al. 2000). The application of fuzzy set theory is not restricted to the outranking methods. In principle, it can be applied to a large variety of MADA methods, also to MAVT (Chen and Hwang 1992).

a)



b)

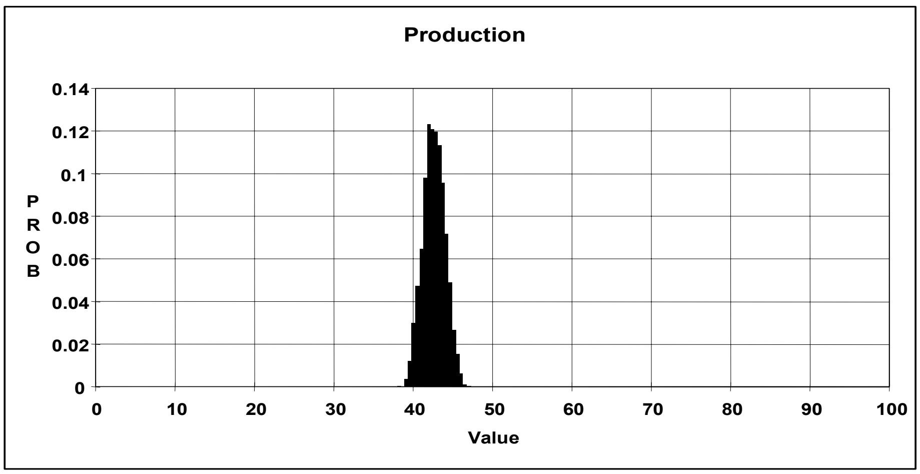


Fig. 6. Uncertainty in the value scores for the production stage due to uncertainty in all model input variables (a) and due to uncertainty in model input variables other than the impact category weights (b) in the case of the Finnish forest industry (article I). The questionnaire average weights were used in the Monte Carlo simulation of Figure 6b.

8 Discussion

8.1 Decision analytic foundations

In this study, MAVT was chosen as a theoretical foundation of life cycle impact assessment. However, there exists some criticism of MAUT/MAVT within the multi-criteria decision analysis (MCDA) community. Firstly, opponents point out that the method requires fulfilling assumptions (axioms) which are too restrictive for decision makers. A starting point for the method is that the decision maker analyses all the alternatives and tries to maximise his welfare. However, experimental studies in psychology and behaviour have revealed that people do not in practice behave in this way in the context of decision making (e.g. Simon 1957, Zeleny 1992). For this reason, for example, Forman and Grass (2001) asked: Must we use a particular axiomatic (normative) model that tells us “what ought to be”? Especially, the MAUT/MAVT axiom of transitivity (see Section 2) is considered as a problem. For example, Fishburn (1991) stated: “Transitivity is obviously a great practical convenience and a nice thing to have for mathematical purposes, but long ago this author ceased to understand why it should be a cornerstone of normative decision theory".

Secondly, the MAUT/MAVT axioms lead to the situation in which enormous input data is required and the decision maker is asked to give information which cannot be quantified. For example, the construction of value functions and quantifying the trade-offs between attributes require too much hard work. In real life, the decision maker is often faced with an elicitation situation under conditions of incomplete information.

The aspects mentioned above and a need for practical methods have led to development in the field of MCDA. The results can be seen as a wide variety of methods with different assumptions and calculation rules. Many of these methods have roots in MAUT/MAVT. SMART (Edwards 1977) is an example of a practical method of MAVT. Using linear value functions leads to a practical solution. It is possible to use attribute values directly, without transformation by value functions. On the other hand, Edwards and Barron (1994) introduced an approximate method for MAVT, SMARTER, in which difficult judgements related to weight elicitation are substituted by calculations based on ranks (only order information is needed). Furthermore, the problems concerning the determination of weights can partly be avoided by conducting sensitivity analysis with different degrees of information (see Section 7). Several methods have been developed to solve decision problems under incomplete information. For example, Salo and Hämäläinen (2001) presented a survey of major imprecise methods in the MAVT context.

Note that Lundie (1999) analysed the decision analysis methods based on cardinal information on attributes taking the requirements of LCAs into account. He selected the simple additive weighting (SAW) method (Hwang and Yoon 1981) as a most appropriate method for weighting in the context of LCIA. The SAW method can be considered as a simple MAVT (see Section 6.1). The arguments for the choice were that SAW is easy to apply, transparent and broadly accepted in decision-making theory. Despite Lundie's opinion and the choice of the author of this thesis it is still necessary to say something about the possibilities of other widely used MADA methods in the context of LCIA.

As was mentioned earlier, the theoretical foundations of MAVT can be found in MAUT (Keeney and Raiffa 1976, Dyer and Sarin 1978). MAUT can be used in special LCA applications in which the consequences of alternatives are not certain and uncertainties can be assessed as probabilities. For example, MAUT may be useful for LCIA applications in which scenarios are used.

In article IV there is a short description of different popular MADA methods and their use in life cycle impact assessment. The simplest methods are so-called elementary methods (e.g. maximin, maximix, conjunctive, disjunctive, lexicographic (Hwang and Yoon 1981, Yoon and Hwang 1995)), which do not require explicit evaluation of quantitative trade-offs between criteria or attributes in order to select or rank alternatives, i.e. no inter-criteria weighting is required and in some cases not even a relative ranking of criteria is required. The use of elementary methods appears to be rather limited in LCIA because of their simplicity.

AHP (Saaty 1980) is one of the most popular MADA methods. Although AHP has a different basis compared to MAVT, Salo and Hämäläinen (1997) demonstrated that the elicitation procedures in AHP could be carried out such that the results are in accordance with MAVT. Thus, pairwise comparisons for weight elicitation can be used in the model in which value functions are constructed or linear value functions are used. In the context of the elicitation it is possible to check the consistency of judgements supplied by the decision maker.

In principle, AHP can also be directly applied for LCIA purposes. On the other hand, the original 1-9 ratio scale in the attribute level is a too restrictive characteristic for LCIA. However, Pöyhönen and Hämäläinen (2001) pointed out that in the elicitation procedure of AHP it is, in principle, permissible to use any numbers. The disadvantage of AHP is the problem of rank reversal, i.e. the ranking of alternatives can be changed by the addition (or deletion) of irrelevant alternatives.

The LCIA applications conducted with the help of the outranking methods (PROMETHEE applied by Geldermann 1998, Le Téno 1999 and Geldermann et al. 2000, and ELECTRE applied by Basson et al. 2000) indicate that these popular MADA methods (especially in French-speaking countries) can offer an alternative approach for LCIA purposes compared with MAVT. PROMETHEE, like SMART, is 'easier' for the decision makers than ELECTRE. On the hand, the family of ELECTRE methods offers more properties to aid the decision process (Salminen et al. 1998).

A starting point for the outranking approach is that it does not aim to develop a theory of decision making, but attempts to provide decision aid for the structuring of decision makers' preferences (Stewart and Losa 2003). The legitimacy of outranking models is not obtained from axiomatic bases. The legitimacy is therefore to be seen as the model's prescriptive validity and as its acceptance by the decision maker. The approach includes different types of relations and criteria in order to structure a context-dependent representation of the problem (Vincke 1992). The outranking approach attempts to take into account the explicit recognition of the fact that individual preferences are neither stable nor completely defined (e.g. Roy 1990). One of the fundamental features of outranking methods is the definition of a partially compensatory decision rule. According to the outranking relation (through the concordance, discordance and veto threshold in ELECTRE) it is possible to apply non-compensatory features in outranking methods. The non-compensatory rule does not allow good performance relative to one attribute to compensate for low performance relative to another attribute. Preference relation concerning incomparability is also one important feature emphasized by the outranking school (Stewart and Losa 2003). The incomparability relation is applied in the situation where the decision maker will be unable to state which of the two alternatives is best because there are not enough arguments to make the choice.

It is often assumed, falsely as Stewart and Losa (2003) argued, that MAVT practice is normative or descriptive. According Stewart and Losa (2003) the axiomatic foundation of MAVT must be seen as part of a decision aid process, providing among other things explicit guidance to analysts and decision makers about what information is needed to construct the model. The axioms are easily discussed due to their simplicity. If the axioms are violated by participants in the process, such deviations from "rationality" can be debated in a fully informed manner. In such contexts it is possible to apply other methods in order to aid decision making. Thus, constructivism is as much a fundamental principle of modern MAVT practice as it is of the outranking approach (Stewart and Losa 2003).

In principle, the MAVT model is based on the notation of full compensation due to the aggregation principle in which the trade-offs between criteria (weights) derived from value functions play a key role. This means that a sufficiently good performance on attribute A (e.g. dirty water) will eventually compensate for a poor performance on attribute B (e.g. clean air). In article IV, this issue was discussed in the context of LCIA. The conclusion was that non-compensatory features can be most useful in environmental impact situations in which the thresholds of performance can be identified. In practice, this aspect in particular arises in the contexts of local impacts. However, it is not clear how LCIA results, which are tied to the functional unit and so are often cited as being scale-independent, could be assessed with respect to thresholds. On the other hand, in the case of regional impacts (e.g. acidification, terrestrial eutrophication) exceedences of critical loads have been taken into account in the determination of site-dependent characterisation factors (see e.g. Potting et al. 1998, Huijbergts et al. 2000). As it is shown in this thesis these site-specific characterisation factors are determined according to the MAVT principle. The same concerns the calculation of the category indicator results. It is important to note that the classical characterisation equation, an additive aggregation rule with linear damage functions, is based on the notation of full compensation.

In principle, the MAVT approach can to some extent be modified to consider, where appropriate, limits to full compensation. Stewart and Losa (2003) suggested that non-compensatory features should be dealt with at the stage of problem structuring, by explicit consideration. In addition, the features can be taken into account in the definition of single-attribute value functions (non-linear value functions with thresholds).

In contrast to the outranking methods, the construction of an MAVT model is based on the completeness axiom (strict and indifference preference, transitivity), which implies that all consequences are in principle comparable. Despite this, the difficulties of the completeness axiom are a well-known feature among MAVT practitioners. According to Stewart and Losa (2003) non-completeness of preference structures is seen to be an implicit result of MAVT application, usually identified during the sensitivity analysis phase (see Section 7).

The experiences on outranking methods in LCIA have hitherto been restricted to the weighting phase, in which impact category indicator results are considered as attributes. It is not clear whether they can be used in characterisation. Furthermore, it seems that selection of impact categories and classification cannot be included in the framework of outranking methods. In addition, it should be noted that applying these methods leads to different aggregation rules compared with Eq. 13, and that weighting factors should derived according to the principles of these methods (Mousseau 1995, Brans and Mareschal 1990, Figueira and Roy 2002).

8.2 Weighting as part of LCIA

Decision analysis can offer the full framework for weighting methods used in LCIA. However, weighting is one of the optional elements in ISO standard 14042 (ISO 2000a). This is due to the fact that weighting is considered as a subjective, value-based process whereas LCIA from selection of impact categories to characterisation is a more objective evaluation process. However, the mandatory phases of LCIA can also include subjectivity, for example in the context of selection of impact categories, as discussed in many forums (e.g. Barnthouse et al. 1997, Owens 1998, Udo de Haes 1999). On the other hand, opponents point out that in the mandatory phases subjectivity is related to choices and assumptions, which can in principle be tested and validated. The situation is different in impact category weights, which are based on the mixing of scientific, ideological, political and ethical points of view.

The most rigorous opponents want to avoid weighting in LCA. Schmidt and Sullivan (2002) gave three reasons for this aim. Firstly, the aggregation of non-commensurable issues is not acceptable. Secondly, causal relationships between category indicators (e.g. disability adjusted life years in the case of human health) and aspects of human health and ecological effects cannot be determined in a reliable way on the basis of current scientific knowledge. For this reason, such things cannot be weighted against each other. Thirdly, the results of elicitation of weights vary too much to obtain the appropriate weighting factors. Weighting surveys showed that even on an expert level, no consensus has been reached on quantitative weighting factors for life cycle impact assessment categories.

The first criticism is intuitively understandable but in many decision making situations it is desirable to achieve or respond to several objectives at once. For example, in evaluating alternatives for proposed streets, the aim is simultaneously to minimise the cost of construction and maintenance, maximise positive social impacts of transportation and land use, minimise environmental impacts, etc. Although these metrics cannot express commensurable units, the solution has to be argued somehow. For this purpose, members of the decision analysis community have developed a number of different methods to help decision makers identify and select preferred alternatives. Weighting is a way to find the basis, from the point of view of environmental impacts, to why one or a group of alternatives is more preferable than others (see also Section 8.3).

The second criticism is more against endpoint-related modelling (see Section 1.2). Midpoint modeling includes less uncertainty than endpoint modelling. In midpoint-related weighting it is not important that indicator results are proxy attributes for respondents (valuators). The key issue is that effects within each impact category are determined and that the respondents are familiar with these effects. From the decision analysis point of view, it is important that all impacts related to interventions caused by the alternatives are taken into account. In midpoint-related elicitation processes respondents (valuators) have to keep in mind the determined effects when impact categories are weighted against each other. Furthermore, it is required that all interventions are taken into account and impact categories or sub-categories are determined according to known cause-effect chains. If some interventions also have different consequences than others under an impact category, there is a need to create a new impact category for those interventions with additional effects. In this way, the requirement of completeness can be fulfilled in midpoint-oriented weighting.

One weakness of endpoint-related modelling is that the approach leads to the situation in which there are too few damages for weighting from the point of view of cause-effect chains. For example, in Eco-Indicator 99 (Goedkoop and Spriensma 1999) there are only three impact categories (i.e. human health, ecosystem quality and resources), expressed as disability adjusted life years (DALY), potentially affected fraction (PAF) of species and MJ surplus energy, respectively. Do these consequences cover all effects related to interventions caused by alternatives? In addition, the uncertainty in endpoint modelling also includes factors associated with choices and weighting. How is it otherwise possible to combine biodiversity effects on water ecosystems and terrestrial ecosystems to a single number? One solution is that endpoint modelling is used in those cause-effect chains where it can be performed according to scientific bases. If this is not possible, the modelling is conducted leaving the indicators on the midpoint level. This principle leads to a mixed model in which there are both endpoint and midpoint indicators.

The third criticism is that weighting produces meaningless numbers because different weighting factors lead to different prioritisation and there is no basis to say that some weights are more reliable than others. The diversity of opinions among respondents (valuators) is a fact, although every respondent has the same data concerning impact categories. However, this does not mean that the results cannot be utilised in the decision making process. Different results calculated by different groups can be used as alternative results. It is the decision maker's task to choose the best weights for his purpose. In addition, sensitivity analysis is always needed before the interpretation of results (Section 7).

On the other hand, variation of values of weights can be due to technical weakness in the elicitation process or to inconsistencies between weights and other elements in weighting methods. An example of the latter issue is when weighting factors representing European situations are used for the model with Finland-specific characterisation factors. Decision analysis offers theoretical aspects to check that weights are consistent with other elements in weighting methods, and helps to avoid technical biases in the weight elicitation process.

8.3 Uses of decision analysis impact assessment

Decision analysis impact assessment embodies a philosophy, and an approach to formally and systematically examine an impact assessment problem in LCA. The purpose of "full" DAIA is not to replace judgement concerning total environmental impact caused by different alternatives, but to help organise it and to provide a model of the problem which can develop greater understanding of the assessment.

Decision analysis impact assessment does not need to be complete. Partial assessments, which give cursory qualitative attention to some steps in LCIA, are appropriate for many LCA applications. These partial analyses should focus on the aspects of the overall problem where insight might be most fruitful to the decision makers.

Because of the focus on assessment complexities, there are many useful by-products of DAIA, which can be derived from experiences of decision analysis applications (e.g. Keeney 1982, von Winterfeldt and Edwards 1986). The framework of decision analysis promotes honesty by providing the opportunity for various independent checks, and facilitates communication on crucial problem features (Keeney 1982). Even the structuring of a problem can develop an understanding of the environmental issues among participants.

Many decision analysis applications can be very important in conflict identification and resolution (see e.g. Marttunen and Hämäläinen 1995). This can also be the purpose of LCIA. Different subjective judgements in DAIA can identify conflicts among various individuals concerned with the impacts. The results and the corresponding input data of DAIA can easily be documented and this offers a basis for transparency. Once conflicts are identified, attention can be focused on their causes. During this analysis it may be revealed that there are misunderstandings or lack of information, which can provide opportunities to resolve the assessment. On the other hand, the result of the analysis can also be that there are justifiable differences in values. This may itself be an important preliminary result in order to find the final solution.

DAIA can offer complete rankings if the scalar inputs and judgements are available. However, as mentioned above, uncertainty in input data and difficulties in finding bases to judgements are typical characteristics of impact assessments. For this reason, the aim of DAIA can also be to find dominating or dominated alternatives, or a feasible alternative group. In principle, DAIA based on MAVT can sort alternatives into predefined homogeneous classes with the help of sensitivity analysis techniques (see Section 7). However, a literature review by Zopoundis and Doumpos (2002) revealed that for classification and sorting there are many alternative MADA methods such as outranking methods, which are more attractive due to their user friendliness. There is a need to study the capability of these methods in the grouping phase of LCIA. Note that the methodology of grouping is not elaborated in the LCA literature (see Finnveden et al. 2002).

LCIA can only provide a particular type of information for decision making; a life cycle perspective of environmental impacts associated with each alternative. LCA does not take into account technical performance, cost, or political and social acceptance, which are often inevitable issues to be taken into account in environmental decision making. These multiple objectives including environmental impacts can be arranged hierarchically according to a value tree. Thereafter, it is possible to determine the preference model based on MAVT, which allows the orderly and simultaneous evaluation of multiple objectives. Thus, MAVT can be used for constructing the final priority model in which environmental value scores derived from DAIA can be used as input data.

As mentioned in the introduction, LCA forms only one part of the decision-making support toolbox and is increasingly being integrated with other tools and approaches for environmentally sustainable production and consumption. For example, life cycle management (LCM) offers a broad context to use the results of LCA (see e.g. Solgaard 2002). In the field of environmentally sustainable production and consumption, the role of LCIA is to provide information on environmental impacts in a wide context, whereas other tools produce information on other objectives. Because these many objectives affect the desirability of an alternative, the decision situation needs clear values concerning achievement of the objectives. Thus, it is expected that the use of weighting methods of LCIA will increase due to the integration.

9 Summary and conclusions

Decision analysis is a set of methods of systems analysis and operations research, which are applied in supporting extensive decisions. In the LCA literature, decision analysis methods are known as tools for the weighting phase of LCIA, especially in the context of panel methods in which opinions about impact category weights are asked from an individual person or a group of persons. However, the use of decision analysis tools has not been very common in LCIA applications. This is partly due to the fact that LCA practitioners have been reluctant to use weighting. Weighting is only an optional phase in the ISO standards due to its subjective results, and in the development of LCIA methodology researchers have concentrated on the mandatory phases during the recent years. On the other hand, this author would claim that so far only few LCA researchers have enough information to use decision analysis tools for weighting purposes. Decision analysis has developed over the years within the realms of operations research, management science and psychology. However, the practical decision support tools based on decision analysis methods have only been developed quite recently.

In this thesis, the role of decision analysis in LCIA is shown to be broader than discussed in earlier LCA literature. Other authors have chosen the results of characterisation, impact category indicator results, as attributes for decision analysis exercises, whereas environmental interventions (emissions, resource extractions and land use) were chosen in this thesis. This choice leads to a solution in which the decision analysis framework also includes the mandatory phases of LCIA, i.e. selection of impact categories, classification and characterisation.

In particular, methods developed for the sorting or ranking of a finite set of alternatives in decision making situations with multiple objectives are attractive for life cycle impact assessment purposes. From these methods, so-called multiattribute value theory (MAVT) methods were chosen for the basis of decision analysis framework of impact assessment in LCA because in article I the current life cycle impact assessment methodology was demonstrated to be based on the same mathematical equation derived from MAVT. The similarity between LCIA methodology and MAVT means that the MAV theory also provides a foundation for a logical and rational approach to impact assessment in LCA.

In this thesis, the LCIA model conducted according to the rules of MAVT is called a decision analysis impact assessment (DAIA) model. DAIA was used in two case studies concerning the Finnish forest industry and the Finnish metals industry. In both case studies, it was shown that a value tree, a tool used for structuring multicriteria decision making problems, is useful for the selection of impact categories and classification in LCIA. Value trees can be used to ensure that all relevant impact categories and interventions are taken into account in an appropriate way. The use of a value tree also helps discussion about the assessment problem between analyst, experts and decision makers and enhances the further process of making trade-offs amongst attributes and impact categories. The value tree can be constructed so that there are sub-categories and MAVT can assist in solving the model according to a logical rule.

In the thesis it is shown that a typical characterisation equation corresponds to an additive weighting model of MAVT. Furthermore, it is shown that the "objective" principles for the determination of characterisation factors related to scientific impact assessment models are consistent with those derived from preference models. In MAVT, attribute weights (characterisation factors) are derived with reference to the single-attribute value functions (damage functions). According to MAVT, the additive model should only be used if the so-called difference independence assumption holds, i.e. the preference on the outcome of one attribute does not depend on the outcomes of the other attributes. For this reason, there is a need to check systematically the validity of this assumption in the context of different impact categories. If the assumption of additive aggregation model does not hold, multiplicative or multilinear models may be still be appropriate. This issue is not elaborated in the LCA community and therefore the other models have not yet been used in any LCIA applications. In the future, the use of different models should be studied in order to produce correct category indicator results.

The LCIA framework developed with the help of MAVT clarifies the debate concerning marginal and average approaches in the determination of characterisation factors. The framework is flexible and suitable for different impact assessment approaches developed in LCIA. It is not important whether the method is midpoint- or endpoint-oriented. In the work it was shown that site-dependent characterisation methods can easily be fitted into the framework. In the case study of the Finnish forest industry, a Finland-specific characterisation model utilising the results of other tools, such as air quality and transport models and even expert judgements, was developed and used.

According to ISO, characterisation factors should be based on scientifically derived knowledge. In the absence of scientifically based characterisation factors, MAVT offers rules to determine subjective characterisation factors. Such factors are determined according to the same theory as impact category weights. In both case studies, characterisation factors based on expert judgements were used together with scientifically based characterisation factors in order to produce indicator results of all relevant impact categories related to products under study.

In the guides of LCIA it is recommended that, in normalisation, category indicator results of a product system and a chosen reference system should be calculated by the same characterisation factors. However, in this thesis it is shown that for producing correct category indicator results, characterisation factors can vary in normalisation depending on the shapes of damage (or value) functions and on the used intervals of interventions in the determination of characterisation factors. This finding should be tested in particular in the context of site-dependent characterisation factors for regional impact categories (e.g. acidification, tropospheric ozone formation). In addition, the assumption of an additive aggregation rule should be checked in the calculation of indicator results of reference systems.

MAVT can offer a clarification of whether or not to use normalisation in weighting. In LCIA, different category indicator results are typically aggregated into a single score by multiplying normalized category indicator results with the corresponding impact category weights and summing up the results. From the viewpoint of MAVT, this means that linearity between interventions and effects holds and that there are no thresholds (i.e. below a certain magnitude of intervention zero damage exists). However, this assumption has a weak scientific basis. In the case of thresholds, MAVT leads to the aggregation solution where a normalisation value (denominator in normalisation) differs from the value used in the traditional normalisation. However, this second type of aggregation rule is not elaborated in any LCIA methods. In the DAIA model the use of this equation is avoided by using "only above threshold" values for interventions in country-specific characterisation instead of amounts of interventions.

According to MAVT, in the determination of impact category weights there is a need to take into account the range of category indicator results used in the calculation of normalisation value in the aggregation equation. On the other hand, the feasible range of category indicator results can be directly derived from the feasible range of attributes (interventions) used for the determination of characterisation factor. In addition, there is a need to test the validity of the difference independence assumption in the context of impact categories although the assumption holds in the context of interventions within each impact category. The finding that characterisation, normalisation and weighting are related to each other in the way mentioned above is new in the LCA literature.

In multiattribute decision analysis it is typical that alternative specific ranges in attributes are taken into account in the weighting. However, in the case of LCIA it is better that the ranges are greater than the attribute ranges of alternatives. In this way, it is easier for the decision makers to make judgements concerning trade-offs in the context of impact categories. Furthermore, wide ranges allow that there is no need for a case-by-case impact category weighting task in specific LCA studies. This also means that in the case of linear conditions characterisation factors for the calculation of impact category indicator results of a product system under study are the same as used in normalisation. If linearity does not hold, there is a need to determine the own characterisation factors for the calculation of normalisation value in order to obtain wide ranges for weight elicitation.

In practice, weighting models used in LCIA have been based on linear assumptions. The linearity leads to a convenient solution to calculate the total impact from the various impact categories, as was illustrated in the case of the Finnish metals industry where global, regional and local environmental problems were assessed in the same framework. However, the scientific bases for the linearity are relatively weak. The framework developed can help the methodological development in which it is attempted to take the non-linearity aspects of impact assessment into account.

In both case studies, impact category weights were obtained from the experts working with environmental issues by using decision analysis elicitation techniques. The results showed that weights derived from individual persons differ widely partly due to different opinions, and partly due to biases originating from the behaviour of the experts and the procedures and techniques used in the elicitation. It was not possible to quantify the biases. The decision analysis experiences emphasise that in order to eliminate biases an analyst must be aware of the biases related to different techniques, and a good interaction between the analyst and the decision maker is needed. Although the techniques, knowledge and experiences in decision analysis can be utilized, further LCA-specific research is needed to avoid biases in the determination of weights.

Experiences and techniques for the sensitivity analysis of multi-criteria decision models can be utilised in LCIA. Because impact category weights are difficult to determine or their values are controversial, the sensitivity techniques based on no information, order information or partial information regarding the weights appear to be attractive for LCIA purposes. In the context of the case study of the Finnish forest industry, the so-called ratio estimation method for the elicitation of impact category weights was applied and developed so that interval-valued ratio judgements could be used in the uncertainty analysis of the model.

Although decision analysis offers a full framework for weighting in LCIA, there is no need to conduct a complete quantitative assessment. There are experiences that the qualitative or partial assessment can be definitely appropriate for many multi-objective decision making problems. As by-products the problem structuring can provide a learning process among participants, or the LCIA process can mitigate conflicts between stakeholders. On the other hand, MAVT offers measurement techniques for subjective judgements in situations in which “objective” data is missing. This permits quantitative analysis in which all important impact factors are taken into account. This kind of subjective assessment can be carried out in order to define the contributions of different factors to the final result. The assessment can enhance finding of the most serious data gaps.

MAVT is not the only approach for decision analysis impact assessment. The recent LCIA applications conducted with the help of the outranking methods (especially PROMETHEE and ELECTRE) indicate that they can offer an alternative approach for LCIA purposes compared with MAVT. However, the experiences on outranking methods in LCIA have hitherto been restricted to the weighting phase. It seems that the outranking methods are attractive methods for the grouping phase of LCIA. On the other hand, it is unlikely that they can be used in characterisation and other mandatory phases of LCIA. Furthermore, it is not clear how to utilize the non-compensatory property of outranking methods in the context of LCIA. In the future there is a need for research to study the strengths and weaknesses of the different methods for LCIA purposes.

In this thesis, some methodological weaknesses in the current LCIA practice were identified with the help of MAVT and several possibilities to elaborate more accurate LCIA were proposed. In the future there is a need to demonstrate quantitatively the differences between LCIA conducted according to MAVT and LCIA conducted according to the current practices.

Glossary

This glossary provides definitions of the technical terms used in the thesis.

aggregation

Quantitative compression of information.

attribute

The degree to which an objective is achieved is measured by an attribute.

average approach

A way of determining characterisation factors whereby changes in damage functions are made on the basis of a "wide" intervention interval in order to derive characterisation factors.

category endpoints

Variables which are of direct societal concern, such as human life span or incidence of illnesses, natural resources, valuable ecosystems or species, fossil fuels and mineral ores, monuments and landscapes, man-made materials, etc. (ISO 2000a).

The level of the endpoints is also called the “damage level” (Udo de Haes et al. 1999).

category indicator

A quantifiable representation of an impact category, being the object of characterisation modelling.

Aggregation of environmental interventions within an impact category takes place in the units of the category indicator. The category indicator can be defined at any level of the environmental mechanism.

category indicator result

Characterised result, i.e. value obtained by multiplying the amount of environmental intervention by the corresponding characterisation factor.

category midpoints

Variables in the environmental mechanism of an impact category between the environmental interventions and the category endpoints, such as the concentration of toxic substances, the deposition of acidifying substances, global temperature or the sea level (SETAC-North America term, Udo de Haes et al. 1999).

characterisation

The component of a life cycle impact assessment (LCIA) in which the contributions made by the environmental interventions to each impact category are assessed by quantitative or qualitative methods.

characterisation factors

Factors by which the environmental interventions are to be multiplied for aggregation within an impact category (sometimes called “equivalency factors”).

The links between the environmental interventions and the category indicator are modelled as much as possible in a scientifically valid and quantitative way; the links between the category indicator and the category endpoints must be identified either in a quantitative or a qualitative way (Udo de Haes 1999).

classification

The component of a life cycle impact assessment (LCIA) in which the data from the inventory are classified into impact categories.

criteria

Arguments used for weighting.

damage function

A function describing the shape of relationships between interventions and the indicator results within an impact category.

decision analysis

A set of methods of systems analysis and operations research which are applied in supporting extensive decisions. The objective of decision analysis is to support decision making by applying models and mathematical or formal analysis.

decision analysis impact assessment (DAIA)

A life cycle impact assessment framework based on the rules of decision analysis.

decision maker

A single person or a group of persons who must solve a decision problem.

elicitation

Process of gathering expert judgement in a specially designed manner.

environmental effect

A consequence of an environmental intervention in the environmental system.

environmental mechanism

System of physical, chemical and biological processes for a given impact category, linking the LCI results (environmental interventions) to category indicators and to category endpoints (ISO 2000a).

environmental impact

Any adverse change to the environment including one or more environmental effects.

environmental interventions

Variables such as extractions from or emissions into the environment and other variables at the boundary of the product system and the environment, like different types of land use (SETAC-Europe term, Udo de Haes et al. 1999).

The extractions and emissions are together called “elementary flows” and “environmental inputs and outputs” (ISO 1997).

expert

A person who has background in a subject matter at the desired level of detail and who is recognized by his peers or those conducting the study as being qualified to answer questions.

expert judgment

Judgments of those with expertise or knowledge in the area.

exposure

The concentration of a chemical at the external surface of the target organism.

functional unit

Quantified performance of a product system for use as a reference unit in a life cycle study (ISO 1997).

goal and scope definition

The first component of a life cycle assessment in which the functional unit, the periods as well as system boundaries are specified and a clear delimitation of the scope of a specific LCA is described. It also reveals a specific interest and indicates the target group.

impact category

A class representing environmental issues into which LCI results may be assigned (ISO 2000a).

impact category indicator result

→ category indicator result.

impact value score

Number representing the potential contribution of an alternative to a given environmental impact category or categories.

interpretation

The last phase of a life cycle assessment in which the inventory and impact assessment results are analysed against the aim of the study including an assessment of uncertainties and key assumptions as well as recommendations for actions.

interventions

→ environmental interventions.

inventory analysis

The second component of a life cycle assessment in which an analysis is made of the environmental interventions associated with the processes required for that functional product unit. Such an analysis should be as objective as possible and adequately substantiated.

life cycle

The combination of processes needed by a product or a function. A complete life cycle includes everything from raw material extraction, processing, transportation, manufacturing, distribution, use, re-use, maintenance and recycling to final disposal (Consoli et al. 1993).

life cycle assessment (LCA)

A method for analysing and assessing environmental impacts of a material, product or service during its entire life cycle.

life cycle impact assessment (LCIA)

The third component of a life cycle assessment in which the data gathered in the inventory analysis are interpreted and assessed in terms of their environmental impact potential.

life cycle stage

Life cycle stage consists of unit processes and covers a certain defined part of the product system.

marginal approach

A way of determining characterisation factors; a tangent at the working point of damage function corresponds to a characterisation factor.

Monte Carlo simulation

A computational technique for investigating properties and behaviour of a variable by repeated random sampling from a known or assumed (e.g. normal) distribution representing the variable.

multiattribute utility theory (MAUT)

One of the major decision theories for a multi-objective decision analysis in which multi-attribute utility functions are used and there are uncertainties about the consequences of the alternatives.

multiattribute value theory (MAVT)

One of the major decision theories for a multi-objective decision analysis in which multi-attribute value functions are used and there are no uncertainties about the consequences of the alternatives.

multicriteria decision analysis (MCDA)

A group of methods by which a formal or informal structure can be applied for treating multi-objective/criteria decision making problems.

multiattribute decision analysis (MADA)

A group of methods under MCDA by which a formal or informal structure can be applied to treating finite multi-objective/criteria decision making problems.

normalisation

Part of a life cycle impact assessment in which impact category indicator results caused by a product system are divided by the corresponding impact category indicator results caused by a reference system (e.g. activities in a given area over a certain time period).

normalisation value

The impact category indicator result by which the impact category indicator result of a product system under study is divided in normalisation.

normalisation

A process in which the results are changed to dimensionless units and into a certain range, e.g., [0,1].

objective

A statement of something that is desired to be achieved. Decision objectives are criteria or attributes on which the decision will be made.

preference model

A model for prioritising decision alternatives.

product system

Collection of materially and energetically connected unit processes which performs one or more defined functions (ISO 1997).

rating

A measurement level of an attribute.

ratio method

A weight elicitation method which requires the decision maker to first rank the relevant attributes according to their importance. The least important attribute is assigned a weight of 10 and all others are judged as multiples of 10. The resulting raw weights are normalized to sum to one.

reference system

A region, an economic sector or group of sectors, or a product type or group which is used for normalisation in order to calculate a reference value. The determination of the reference system includes choices about activities, spatial and temporal aspects (e.g. all human activities in a given area over a certain time period).

reference value

Impact category indicator result caused by a reference system.

safeguard subjects

A class of endpoint which has some well recognisable value for society (Udo de Haes et al. 1999).

sensitivity analysis

Analysis to determine the sensitivity of the outcome of a calculation to small changes in the assumptions or to variations in the range within which assumptions are assumed to be valid.

uncertainty analysis

Analysis to determine the variation in an output function based on the collective variability of model inputs.

unit process

The smallest portion of a product system for which data are collected when performing a life cycle assessment (ISO 1997).

valuation

Process of assessing the relative importance of the different environmental impact categories according to their environmental effects.

value function

A real-valued function expressing the preference of the attribute.

value score

Number representing the potential contribution of an alternative to a given issue.

value tree

One of the major tools for structuring objectives. The final value tree includes objectives and attributes in the hierarchy.

weighting

Optional part of the life cycle impact assessment (LCIA). It includes the determination of impact category weights and the aggregation of different environmental impact categories in order to compress multi-dimensional information into a single value score.

Symbols used in the study

a	alternative or product system
$C_{i,j}$	characterisation factor for intervention j within impact category i
$C^{'}_{i,j}$	characterisation factor, suitable for the $[x_j^o, x_j^*]$ range where $x_j^o \geq 0$
$C^{''}_{i,j}$	average characterisation factor, suitable for the $[0, x_j^*]$ range
$C_{i,j,co}$	country-specific characterisation factor for intervention j within impact category i
$C_{i,j}(a)$	alternative-dependent characterisation factor
co	country
$Eqv_{i,j}$	equivalency factor, i.e. site-generic characterisation factor for intervention j within impact category i
f	function
f_i	function identifying an overall impact model for impact category i
$f_{i,j}$	damage function for intervention j within impact category
i	impact category
I	total impact value score due to all I_i
I_i	impact category indicator result of impact category i
I_i^o	best level of impact category indicator result of impact category i
j	environmental intervention
$k_{i,j}$	weight (or scaling constant) of attribute $X_{i,j}$, weight of intervention j within impact category i
m	number of interventions
n	number of impact categories
N_i	normalisation value (denominator in normalisation)
r	number of countries
R	reference system
$v(.)$	overall value function
$v_i(.)$	(normalized) single-attribute value function over attribute $X_{i,}$
$v'_i(.)$	un-normalized single-attribute value function over attribute $X_{i,}$
$v_{i,j}(.)$	(normalized) single-attribute value function over attribute $X_{i,j}$
$v'_{i,j}(.)$	un-normalized single-attribute value function over attribute $X_{i,j}$
w_i	weight of impact category i
$x_{i,j}$	rating, i.e. measurement on attribute $X_{i,j}$

$X_{i,j}$	attribute of intervention j within impact category i
x_j^o	best level of attribute $X_{,j}$
x_j^*	worst level of attribute $X_{,j}$
x_j	measurement on attribute X_j
X_j	attribute of intervention j
u	product unit
$v(.)$	overall value function
$v_i(.)$	single-attribute value function over impact category i
$v_{i,j}(.)$	single-(sub)attribute value function over (sub)attribute $X_{i,j}$
$v_j(.)$	single-attribute value function over attribute X_j
$\alpha_{i,j}$	slope parameter for linear value function $v_{i,j}(.)$
$\beta_{i,j}$	constant parameter for linear value function $v_{i,j}(.)$
$\eta_{i,j}$	exposure/transport factor for intervention j within impact category i
$\mu_{i,j}$	effect factor for intervention j within impact category i
$\in$	is a member of

References

Ahbe, S., Braunschweig, A. & Müller-Wenk, R. 1990. Methodik für Ökobilanzen auf der Basis ökologischer Optimierung (Methodology for ecobalances on the basis of ecological optimisation). Bundesamt für Umwelt, Wald und Landschaft (BUWAL), Bern, Switzerland, *Schriftenreihe Umwelt* Nr.133. (In German.)

Alexander, B., Barton, G., Petrie, J. & Romagnoli, J.A. 2000. Process synthesis and optimisation tools for environmental design: methodology and structure. *Computers and Chemical Engineering* 24(2-7): 1195-1200.

Al-Shemmeri, T., Al-Kloub, B. & Pearman, A. 1997. Model choice in multicriteria decision aid. *European Journal of Operational Research* 97: 550-560.

Armstrong, J.S. 1985. *Long-range forecasting: From Crystal Ball to computer*. John Wiley & Sons, New York.

Azapagic, A. 1996. *Environmental system analysis: the application of linear programming to life cycle assessment*. PhD dissertation. University of Surrey, Surrey.

Azapagic, A. & Clift, R. 1998. Linear programming as a tool for Life Cycle Assessment. *International Journal of Life Cycle Assessment*. 3(6): 305-316.

Bana e Costa, C.A., Stewart, T.J. & Vansnick, J.-C. 1997. Multicriteria decision analysis: Some thoughts based on the tutorial and discussion sessions of the ESIGMA meetings. *European Journal of Operational Research* 99: 28-37.

Bare, J.C., Hofstetter, P., Pennington, D.W. & Udo de Haes, H.A. 2000. Midpoints versus endpoints: The sacrifices and benefits. *International Journal of Life Cycle Assessment* 5: 319-326.

Bare, J.C., Pennington, D.W. & Udo de Haes, H.A. 1999. Life cycle impact assessment sophistication. *International Journal of Life Cycle Assessment* 4: 299-306.

Barnthouse, L., Fava, J., Humphreys, K., Hunt, R., Laibson, L., Noesen, S., Norris, G., Owens, J., Todd, J., Vigon, B., Weitz, K. & Young, J. 1997. *Life-cycle impact assessment: The state-of-the-art*. Society of Environmental Toxicology and Chemistry (SETAC), Pensacola.

Basson, L., Perkins, A.R. & Petrie, J.G. 2000. The evaluation of pollution prevention alternatives using non-compensatory multiple criteria decision analysis methods. Presentation Record 230c. *Annual Meeting of the American Institute of Chemical Engineers (AIChE),* Los Angeles, CA, November 2000. AIChE Manuscript Center, New York.

Baumann, H. & Rydberg, T. 1994. Life cycle assessment – A comparison of three methods for impact analysis and evaluation. *Journal of Cleaner Production* 2(1): 13-20.

Bengtsson, M. 2000. Weighting in practice. *Journal of Industrial Ecology* 4(4): 47-60.

Borcherding, K. & von Winterfeldt, D. 1988. The effects of varying value trees on multiattribute evaluations. *Acta Psycholologia* 68: 153-170.

Borcherding, K., Eppel, T. & von Winterfeldt, D. 1991. Comparison of weighting judgements in multiattribute utility measurement. *Management Science* 37(12): 1603-1619.

Brans, J.P., Mareschal, B. & Vincke, Ph. 1984. PROMETHEE: A new family of outranking methods in multicriteria analysis. In: Brans, J.P. (ed.), *Operational Research'84*. Elsevier, Amsterdam, pp. 477-490.

Brans, J.P. & Vincke, Ph. 1985. A preference ranking organisation method (the PROMETHEE method for multiple criteria decision-making). *Management Science* 31(6): 647-656.

Brans, J.P., Vincke, Ph. & Mareschal 1986. How to select and how to rank projects: The PROMETHEE method. *European Journal of Operational Research* 24: 228-238.

Brans, J.B. & Mareschal, B. 1990. The PROMETHEE methods for MCDM; The PROMCALC, GAIA and BANKADVISER software. In: Bana e Costa, C.A. (ed.), *Readings in Multiple Criteria Decision Aid*. Springler-Verlag Berlin, Heidelberg, pp. 216-273.

Bunn, D.W. 1984. *Applied decision analysis*. McGraw-Hill Publishing Company, New York.

Butler, J., Jia, J. & Dyer, J. 1997. Simulation techniques for the sensitivity analysis of multi-criteria decision models. *European Journal of Operational Research* 103: 531-546.

BUWAL 1998. Bewertung in Ökobilanzen mit der Methode der ökologischen Knappheit: Ökofaktoren 1997 (Evaluation in ecobalances using the Eco-scarcity method: Eco-factors 1997). Bundesamt für Umwelt, Wald und Landschaft, Bern, Switzerland. *Schriftenreihe Umwelt* Nr. 297. (In German.)

Consoli, F., Allen, D., Boustead, I., Fava, J., Franklin, W., Jensen, A.A., de Oude, N., Parrish, R., Perriman, R., Postlethwaite, D., Quay, B., Séguin, J. & Vigon, B. (eds.) 1993. *Guidelines for life-cycle assessment: A 'Code of Practice'*. Society of Environmental Toxicology and Chemistry (SETAC), Brussels.

Chen, S.-J. & Hwang, C.-L. 1992. *Fuzzy multiple attribute decision-making*. Springer-Verlag, Berlin.

Dalkey, N.C. 1969. An experimental study of group opinion: The Delphi method. *Futures* 1: 403-406.

Dyer, J.S. & Sarin, R.K. 1979. Measurable multiattribute value functions. *Operations Research* 27(4): 811-822.

Edwards, W. 1977. How to use multiattribute utility measurement for social decision making. *IEEE Transactions on Systems, Man and Cybernetics, SMC-7*: 326-340.

Edwards, W. & Barron, F.H. 1994. SMARTS and SMARTER: improved simple methods for multiattribute utility measurement. *Organizational Behaviour and Human Decision Processes* 60: 306-325.

Fava J., Consoli, F., Denison, R., Dickson, K., Mohin, T. & Vigon, B. (eds.) 1993. *A conceptual framework for life-cycle impact assessment*. Society of Environmental Toxicology and Chemistry (SETAC), Pensacola.

Figueira, J. & Roy, B. 2002. Determining the weights of criteria in the ELECTRE type methods with a revised Simos' procedure. *European Journal of Operational Research* 139: 317-326.

Finnveden, G. 1994. Some comments on normalisation. In*: First Working Document on Life-Cycle Impact Assessment Methodology*, Workshop held at ETZ Zürich from July 8-9, 1994 organised by the SETAC-Europe Working Group on Life-Cycle Impact Assessment, Swiss Federal Institute of Technology (ETZ), Zürich, pp. 143-145.

Finnveden, G. 1997. Valuation methods within LCA – Where are the values? *International Journal of Life Cycle Assessment* 2: 163-169.

Finnveden, G., Hofstetter, P., Bare, J., Basson, L., Ciroth, A., Mettier, T., Seppälä, J., Johansson, J., Norris, G. & Volkwein, S. 2002. Normalization, Grouping and Weighting in Life Cycle Impact Assessment. In: Udo de Haes, H.A., Jolliet, O., Finnveden, G., Goedkoop, M., Hauschild, M., Hertwich, Hofstetter, P., Klöpffer, W., Krewitt, W., Lindeijer, E. W., Müller-Wenk, R., Olson, S.I., Pennington, D.W., Potting, J. & Steen, B. (eds.), *Towards best practice in life cycle impact assessment – report of the second SETAC-Europe working group on life cycle assessment*. Society of Environmental Toxicology and Chemistry (SETAC), Pensacola, pp. 177-208.

Finnveden, G. & Lindfors, L-G. 1997. Life-cycle impact assessment and interpretation. In: Udo Udo de Haes, H.A. & Wrisberg, N. (eds.), Life cycle assessment: State of the art and research needs. Ecoinforma, Bayreuth, Germany. *LCA Documents* Vol. 1, pp. 89-118.

Fishburn, P.C. 1991. Nontransitive preferences in decision theory. *Journal of Risk and Uncertainty* 4: 113-134.

Forman, E.H. & Gass, S.I. 2001. The analytic hierarchy process – An exposition. *Operations Research* 49(4): 469-486.

French, S. 1988. *Decision theory: An introduction to the mathematics of rationality*. Ellis Horwood Limited, Chichester.

Geldermann, J. 1999. *Entwicklung eines multikriteriellen entscheidungsunterstützungssystems zur integrierten technikbewertung* (Development of multicriteria decision support system for integrated technique assessment). Fortschritt-Berichte VDI, Düsseldorf, Nr. 105. (In German.).

Geldermann, J., Spengler, T. & Rentz, O. 2000. Fuzzy outranking for environmental assessment. Case study: iron and steel making industry. *Fuzzy Sets and Systems* 115: 45-65.

Genest, C. & Zidek, J.V. 1986. Combining probability distributions: A critique and an annotated bibliography. *Statistical Science* 1(1): 114-148.

Goedkoop, M. 1995. The Eco-Indicator 95. Amersfoort: Pré Consultants, Amersfoort, The Netherlands, *NAOH report* 9523.

Goedkoop, M. & Spriensma, R. 1999. The Eco-Indicator 99. *A damage oriented method for life cycle impact assessment*. Pré Product Ecology Consultants, Amersfoort, The Netherlands.

Guineé, J.B. (ed.), Gorrée, M., Heeijungs, R., Huppes, G., Kleijn, R., de Koning, A., van Oers, L., Sleeswijk, A.W., Suh, S., Udo de Haes, H.A., de Bruijn, H., van Duin, R., Huijbregts, M., Lindeijer, E., Roorda, A.A.H., van der Ven, B.L. & Weidema, B.P. 2002. *Handbook on life cycle assessment – Operational guide to the ISO standards*. Kluwer Academic Publishers, Dordrecht.

Guitouni, A. & Martel, J.M. 1998. Tentative guidelines to help choosing an appropriate MCDA method. *European Journal of Operational Research* 109: 501-521.

Hansen, O.J. 1999. Status of Life Cycle Assessment (LCA) activities in the Nordic region. *International Journal of Life Cycle Assessment* 4: 315-320.

Hauschild, M. & Wenzel, H. 1998. *Environmental assessment of products – Volume 2*. Chapman & Hall, London.

Heijungs, R. 1994. Valuation: A societal approach. In: Udo de Haes, H.A., Jensen, A.A., Klöpffer, W. & Lindfors, L.-G. (eds.), *Integrating impact assessment into LCA*, Proceedings of the LCA symposium held at the Fourth SETAC-Europe Congress 11-14 April 1994. The Free University, Brussels, pp. 107-113.

Heijungs, R., Guinée, J.B., Huppens, G., Lankreijer, R.M., Udo de Haes, H.A., Wegener Sleeswijk, A., Ansems, A.M.M., Eggels, P.G., van Duin, R. & de Goede, H.P. 1992. Environmental life-cycle assessments of products. Center of Environmental Science, Leiden, The Netherlands, *NOH report* 9266.

Heijungs, R. & Hofstetter, P. 1996. Definitions of terms and symbols. In: Udo de Haes, H.A. (ed.), *Towards a methodology for life cycle assessment*, Society of Environmental Toxicology and Chemistry (SETAC) - Europe, Brussels, pp.31-37.

Hertwich, E.G., Hammitt, J.K. & Pease, W.S. 2000. A theoretical foundation for life-cycle assessment. *Journal of Industrial Ecology* 4(1): 13-28.

Hertwich, E.G. & Hammitt, J.K. 2001a. Decision-analytic framework for impact assessment. Part I: LCA and decision analysis. *International Journal of Life Cycle Assessment* 6(1): 5-12.

Hertwich, E.G. & Hammitt, J.K. 2001b. Decision-analytic framework for impact assessment. Part II: Midpoints, endpoints and criteria for method development. *International Journal of Life Cycle Assessment* 6(5): 265-272.

Hertwitch, E.G., Jolliet, O., Pennington, D., Hauschild, M., Schultze, C., Krewitt, W. & Huijbregts, M. 2002. Fate and exposure assessment in the life cycle impact assessment of toxic chemicals. In: Udo de Haes, H.A., Jolliet, O., Finnveden, G., Goedkoop, M., Hauschild, M., Hertwich, Hofstetter, P., Klöpffer, W., Krewitt, W., Lindeijer, E. W., Müller-Wenk, R., Olson, S.I., Pennington, D.W., Potting, J. & Steen, B. (eds.), *Towards best practice in life cycle impact assessment – report of the second SETAC-Europe working group on life cycle assessment*. Society of Environmental Toxicology and Chemistry (SETAC), Pensacola, pp. 101-122.

Hofstetter, P. 1996. Towards a structured aggregation procedure. In: Braunschweig A., Förster R., Hofstetter, P. & Müller-Wenk, R. (eds.), *Developments in LCA valuation*. Universität St.Gallen, Institut für Wirtschaft and Ökologie, Switzerland, *Diskussionsbeitrag* Nr. 32, pp. 123-211.

Hofstetter, P., Baumgartner, T. & Scholtz, R.W. 2000a. Modelling the valuesphere and the ecosphere: Integrating the decision makers' perspective into LCA. *International Journal of Life Cycle Assessment* 5(3): 161-175.

Hofstetter, P., Braunschweig, A., Mettier, T., Müller-Wenk, R. & Tietje, O. 2000b. The mixing triangle: correlation and graphical decision support for LCA-based comparisons. *Journal of Industrial Ecology* 3(4): 97-115.

Hogan, L.M., Beal, R.T. & Hunt, R.G. 1996. Threshold inventory interpretation methodology – a case study of three juice container systems. *International Journal of Life Cycle Assessment* 1(3): 159-167.

Huang, J.P., Poh, K.L. & Ang, B.W. 1995. Decision analysis in energy and environmental modeling. *Energy* 20(9): 843-855.

Huijbregts, M.A., Schöpp, W., Verkuijlen, E., Heijungs, R. & Reijnders, L. 2000. Spatially explicit characterization of acidifying and eutrophing air pollution in life-cycle assessment. *Journal of Industrial Ecology* 4(3): 75-92.

Hwang, C-L. & Yoon, K. 1981. Multiple attribute decision making, Methods and applications, A state-of-the-art survey. In: Beckmann, M. & Künzi, H.P. (eds.), *Lecture Notes in Economics and Mathematical Systems* 186. Springer-Verlag, Berlin.

ISO (International Organization for Standardization) 1997. *ISO 14040: Environmental management - Life cycle assessment - Principles and framework*. International Organization for Standardization, Geneva.

ISO (International Organization for Standardization) 2000a. *ISO 14042: Environmental management - Life cycle assessment - Life cycle impact assessment*. International Organization for Standardization, Geneva.

ISO (International Organization for Standardization) 2000b. *ISO 14043: Environmental management - Life cycle assessment - Life cycle impact interpretation*. International Organization for Standardization, Geneva.

Janssen, R. 1992. *Multiobjective decision support for environmental management*. Kluwer Academic Publishers, Dordrecht.

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*. Harvard University Press, Cambridge, MA.

Keeney, R.L. & Raiffa, H. 1976. *Decisions with multiple objectives*. John Wiley & Sons, New York.

Khan, F.I., Sadiq, R. & Husain, T. 2002. GreenPro-I: a risk-based life cycle assessment and decission making methodology for process plant design. *Environmental Modelling & Software* 17: 669-692.

Kortman, J.G.M., Lindeijer, E.W., Sas, H. & Sprengers, M. 1994. *Towards a single indicator for emissions - an exercice in aggregating environmental effects*. Ministerie van Volkshuisvesting, Ruimtelijke Ordening en Milieubeheer, Haag, The Netherlands, nr. 1994/12.

Krantz, D.H., Luce, R.C., Suppes, P. & Tversky, A. 1971. *Foundations of measurement*. Academic Press, San Diego.

Krewitt, W., Trukenmüller, A., Bachmann, T.M. & Heck, T. 2001. Country-specific damage factors for air pollutants: A step towards site dependent life cycle impact assessment. *International Journal of Life Cycle Assessment* 6(4): 199-210.

Le Téno, J.F. 1999. Visual data analysis and decision support methods for non-deterministic LCA. *International Journal of Life Cycle Assessment* 4(1): 41-47.

Le Téno, J.F. & Mareschal, B. 1998. An interval version of PROMETEE for the comparison of building products' design with ill-defined data on environmental quality. *European Journal of Operational Research* 109: 522-529.

Lindeijer, E. 1994. The valuation within LCA: aim, criteria and procedure. In*: First Working Document on Life-Cycle Impact Assessment Methodology*, workshop held at ETZ Zürich from July 8-9, 1994 organised by the SETAC-Europe Working Group on Life-Cycle Impact Assessment, Swiss Federal Institute of Technology (ETZ), Zürich, pp. 163-172.

Lindeijer, E. 1996. Normalisation and valuation. In: Udo de Haes, H.A. (ed.), *Towards a methodology for life cycle assessment*, 75-93. Society of Environmental Toxicology and Chemistry (SETAC) - Europe, Brussels.

Lindstedt, M.R.K., Hämäläinen, R.P. & Mustajoki, J. 2001. Using intervals for global sensitivity analysis in multiattribute value trees. In: Köksalan, M. & Zionts, S. (eds.), *Lecture Notes in Economics and Mathematical Systems* 507, Proceedings of the Fifteenth International Conference on Multiple Criteria Decision Making (MCDM), Ankara, Turkey, July 10-14, 2000, pp. 177-186.

Lundie, S. 1999. *Ökobilanziering und Entscheidungstheorie. Praxisorientierte Produktbewertung auf der Basis gesellschaftlicher Werthaltungen* (Life cycle assessment and decision theory. Practice-oriented product assessment based on social valuation). Springer-Verlag, Berlin. (In German.)

Lundie, S. & Huppes, G. 1999. Environmental assessment of products – The ranges of the societal preference method. *International Journal of Life Cycle Assessment* 4(1): 7-1.

Marttunen, M. & Hämäläinen, R.P. 1995. Decision analysis interviews in environmental impact assessment. *European Journal of Operational Research* 87: 551-563.

Meyer, M.A. & Booker, J.M. 1990. *Eliciting and analyzing expert judgement*. Los Alamos National Laboratory, Los Alamos. U.S. Nuclear Regulatory Commission Washington, DC 20555. NUREG/CR-5424, LA-11667-MS.

Miettinen, P. & Hämäläinen, R.P. 1997. How to benefit from decision analysis in environmental life cycle assessment (LCA). *European Journal of Operational Research* 102: 279-294.

Mousseau, V. 1995. Eliciting information concerning the relative importance of criteria. In: Pardalos, P., Siskos, Y. & Zopounidis, C. (eds.), *Advances in Multicriteria Analysis*. Kluwer Academic Publishers, Dordrecht, pp. 17-43.

National Institute of Standards and Technology 2000. BEES 2.0: Building for environmental and economic sustainability – technical manual and user guide. National Institute of Standards and Technology (NIST), Caithersburg, MD, USA, *NISTIR 6520*.

Norris, G. A. 2001. The requirement for congruence in normalization. *International Journal of Life Cycle Assessment* 6(2): 85-88.

Ong, S.K., Koh, T.H. & Nee, A.Y.C. Assessing the environmental impact of materials processing techniques using an analytical hierarchy process method. *Journal of Materials Processing technology* 113: 424-431.

Owens, J.W. 1998. Life cycle impact assessment: The use of subjective judgements in classification and characterisation. *International Journal of Life Cycle Assessment* 3(1): 43-46.

Posch, M., De Smet, P.A.M., Hettenlingh, J.-P. & Downing, R.J. (eds.) 1999. *Calculation and mapping of critical thresholds in Europe. Status report 1999*. Coordination Centre for Effects, National Institute of Public Health and the Environment, Bilthoven, The Netherlands.

Potting, J., Schöpp, W., Blok, K. & Hauschild, M. 1998. Site-dependent life cycle impact assessment of acidification. *Journal of Industrial Ecology* 2(2): 63-87.

Potting, J., Klöpffer, W., Seppälä, J., Norris, G. & Goedkoop, M. 2002. Best available practice in life cycle impact assessment of climate change, stratospheric ozone depletion, photo-oxidant formation, acidification, and eutrophication. In: Udo de Haes, H.A., Jolliet, O., Finnveden, G., Goedkoop, M., Hauschild, M., Hertwich, Hofstetter, P., Klöpffer, W., Krewitt, W., Lindeijer, E. W., Müller-Wenk, R., Olson, S.I., Pennington, D.W., Potting, J. & Steen, B. (eds.), *Towards best practice in life cycle impact assessment – report of the second SETAC-Europe working group on life cycle assessment*. Society of Environmental Toxicology and Chemistry (SETAC), Pensacola, pp. 65-100.

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

Pöyhönen, M. & Hämäläinen, R.P. 2000. There is hope in attribute weighting. *INFOR* 38(3): 272-282.

Pöyhönen, M. & Hämäläinen, R.P. 2001. On the convergence of multiattribute weighting methods. *European Journal of Operational Research* 129(3): 569-585.

Pöyhönen, M., Vrolijk, H.C.J. & Hämäläinen, R.P. 2001. Behavioral and procedural consequences of structural variation in value trees. *European Journal of Operational Research* 134(1): 218-227.

Ríos Insua, D. 1990. *Sensitivity analysis in multiobjective decision making*. Springer-Verlag, Berlin.

Ríos Insua, D. & French, S. 1991. A framework for sensitivity analysis in discrete multi-objective desision-making. *European Journal of Operational Research* 54: 176-190.

Rogers, M., Bruen, M., Maystre, L.-Y. 1999. *Electre and decision support methods and applications in engineering and infrastructure investment*. Kluwer Academic Publishers, Dordrecht.

Roy, B. 1973. How outranking relation helps multiple criteria decision making. In: Cochrane, J.L. and Zeleny, M. (eds.), *Multiple Criteria Decision Making*. University of South Caroline Press, Columbia, pp. 179-201.

Roy, B. 1990. The outranking approach and the foundations of ELECTRE methods. In: Bana e Costa, C.A. (ed.), *Readings in Multiple Criteria Decision Aid*. Springler-Verlag Berlin, Heidelberg, pp. 155-183.

Roy, B. & Hugonnard, J.C. 1982. Ranking of suburban line extension projects on the Paris metro system by multicriteria method. *Transportation Research* 4: 301-312.

Saaty, T.L. 1980. *The analytical hierarchy process*. McGraw Hill, New York.

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

Salo, A.A. & Hämäläinen, R.P. 1992. Preference assessment by imprecise ratio statements. *Operations Research* 40(6): 1053-1061.

Salo, A.A. & Hämäläinen, R.P. 1997. On the measurement of preferences in the analytic hierarchy process. *Journal of Multi-Criteria Decision Analysis* 6: 309-319.

Salo, A.A. & Hämäläinen, R.P. 2001. Preference ratios in multiattribute evaluation (PRIME) -elicitation and decision procedures under incomplete information. *IEEE Transactions on Systems, Man and Cybernetics-Part A: Systems and Humans* 31(6): 533-545.

Saur, K., Gediga, J., Hesselbach, J., Schuckert, M. & Eyerer, P. 1996. Life cycle assessment as an engineering tool in the automotive industry. *International Journal of Life Cycle Assessment* 1(1): 15-21.

Schmidt, W.-P. & Sullivan, J. 2002. Weighting in life cycle assessment in a global context. *International Journal of Life Cycle Assessment* 7(1): 5-10.

Seaver, D.A. 1976. *Assessments of group preferences and group uncertainty for decision making*. Social Science Research Institute, University of Southern California, Los Angeles, CA.

Seaver, D.A. 1978. Assessing probability with multiple individuals: Group interaction versus mathematical aggregation. University of Southern California, Social Science Research Institute, Los Angeles, *SSRI Research Report* 78-3.

Simon, H.A. 1957. *Administrative behavior*. Free Press, New York.

Solgaard, A. 2002. Promoting a life-cycle approach – Background paper. *UNEP's 7th International High-level Seminar on Cleaner Production,* Praque, Czech Republic, April 29-30, 2002.

Spengler, T., Geldermann, J., Hähre, S., Sieverdingbeck, A. & Rentz, O. 1998. Development of a multiple criteria based decision support systems for environmental assessment of recycling measures in the iron and steel making industry. *Journal of Cleaner Production* 6: 37-52.

Steen, B. 1999. A systematic approach to environmental priority strategies in product development (EPS): version 2000. Chalmers University of Technology, Göteborg. *CPM Report* 1999: 4 & 5.

Steen, B. & Ryding, S.-O. 1992. The EPS Environ-Accounting Method. An application of environmental accounting principles for evaluation and valuation of environmental impact in product design. IVL, Stockholm. *Rapport B 1080*.

Stewart, M. 1999. *Environmental life cycle assessment for design related decision making in minerals processing,* PhD dissertation. University of Cape Town, Cape Town.

Stewart, T.J. 1992. A critical survey on the status of multiple criteria decsision making theory and practice. *Omega International Journal of Management Science* 20(5/6): 569-582.

Stewart, T.J. & Losa, F.B. 2003. Towards reconciling outranking and value measurement practice. *European Journal of Operational Research* 145: 645-659.

Tellus Institute 1992. *The Tellus packaging study*. Tellus Institute, Boston, MA, USA.

Tolle, D., Vigon, B. and Evers, D. 1998. Life-cycle impact assessment demonstration for the GBU-24.National Risk Management Research Laboratory, U.S. Environmental Protection Agency, Cincinnati, Ohio, *EPA/600/R-98/070*.

Tukker, A. 1994a. Review of quantitative valuation methods. In: Udo de Haes, H.A., Jensen, A.A., Klöpffer, W. & Lindfors, L.-G. (eds.), *Integrating impact assessment into LCA*, Proceedings of the LCA symposium held at the Fourth SETAC-Europe Congress 11-14 April 1994. The Free University, Brussels, pp. 127-132.

Tukker, A. 1994b. Iso-utility functions as a tool for valuation in LCA. In*: First Working Document on Life-Cycle Impact Assessment Methodology*, Workshop held at ETZ Zürich from July 8-9, 1994 organised by the SETAC-Europe Working Group on Life-Cycle Impact Assessment. Swiss Federal Institute of Technology (ETZ), Zürich, pp.182-194.

Udo de Haes, H.A. (ed.) 1996. *Towards a methodology for life cycle impact assessment*. SETAC-Europe, Brussels.

Udo de Haes, H.A. 1999. Weighting in life-cycle assessment. Is there a coherent perspective? *Journal of Industrial Ecology* 3(4): 3-7.

Udo de Haes, H.A. & Wrisberg, N. (eds.) 1997. Life cycle assessment: State of the art and research needs. Ecoinforma, Bayreuth, Germany. *LCA Documents* Vol. 1.

Udo de Haes, H.A., Jolliet, O., Finnveden, G. Hauschild, M., Krewitt, W. & Müller-Wenk, R. 1999. Best available practise regarding impact categories and category indicators in life cycle impact assessment. *International Journal of Life Cycle Assessment* 4: 66-74 and 167-174.

Vincke, P. 1992. *Multicriteria decision-aid*. John Wiley and Sons, Chichester.

Volkwein, St., Gihr, R. & Klöpffer, W. 1996. The valuation step within LCA. Part II: A formalized method of prioritization by expert panels. *International Journal of Life Cycle Assessment* 1(4): 182-192.

von Neumann, J. & Morgenstern, O. 1947. *Theory of games and economic behaviour*. Princeton University Press, New Jersey.

von Winterfeldt, D. & Edwards, W. 1986. *Decision analysis and behavioral research.* Gambridge University Press, New York.

Weber, M., Eisenführ, F. & von Winterfeldt, D. 1988. The effects of splitting attributes on weights in multiattribute utility measurement. *Management Science* 34: 431-445.

Weber, M. & Borcherding, K. 1993. Behavioral influences on weight judgments in multiattribute decision making. *European Journal of Operational Research* 67(1): 1-12.

Wenzel, H., Hauschild, M. & Alting, L. 1997. *Environmental assessment of products* - *Volume 1*. Chapman & Hall, London

Werner, F. & Scholz, R.W. 2002. Ambiguities in decision-oriented life cycle inventories. *International Journal of Life Cycle Assessment* 7(6): 330-338.

White, P., De Smet, B., Udo de Haes, H. & Heijungs, R. 1995. LCA back on track - but is it on track or two ? *LCA News* 5(3): 1,3.

Yoon, K. P. & Hwang, C.-L. 1995. *Multiple attribute decision-making - An introduction*. Sage University, Thousands Oaks, Sage, Sage University Paper series on Quantitative Applications in the Social Sciences 07-104.

Zeleny, M. 1992. An essay into a philosophy of MCDM: A way of thinking or another algorithm?. *Computers and Operations Research* 19: 563-566.

Zopounidis, C. & Doumpos, M. 2002. Multicriteria classification and sorting methods: A literature review. *European Journal of Operational Research* 138: 229-246.

Appendix 1

Site-dependent characterisation

In article I a starting point for characterisation is the following equation

$$I_i = \sum_{j=1}^{m} k_{i,j} \cdot v_{i,j}(x_{i,j}(a)) \qquad (1)$$

where I_i = indicator result of impact category I
$k_{i,j}$ = weight (=scaling constant) of attribute $X_{i,j}$
$v_{i,j}$ = normalized single-attribute value function for attribute j within impact category i
$x_{j,j}$ = rating on attribute $X_{i,j}$ caused by product system a
$X_{i,j}$ = attribute describing intervention j within impact category i

In the cases of regional impact categories (acidification, tropospheric ozone formation and aquatic eutrophication), attribute values are calculated by:

$$x_{i,j}(a) = \eta_{i,j}(a) \cdot \mu_{i,j}(a) \cdot x_j(a) \qquad (2)$$

where $x_{i,j}(a)$ = measurement on attribute $X_{i,j}$ (rating) due to product system a
$\eta_{i,j}(a)$ = exposure/transport factor of attribute $X_{i,j}$ $(0 \le \eta_{i,j}(a) \le 1)$
$\mu_{i,j}(a)$ = effect factor of attribute $X_{i,j}$ $(0 \le \mu_{i,j}(a) \le 1)$
$x_j(a)$ = amount of intervention (emission) j due to product system a

The exposure factor $\eta_{i,j}$ indicates what quantity of a given receptor may be exposed as a result of the emission j within impact category i. In the context of non-toxic pollution the factor $\eta_{i,j}$ could be called a transport factor, because in this case it represents the proportion of an emission reaching a receptor area. The effect factor $\mu_{i,j}$ identifies the quantity of exposed/emitted substance j which causes the effects in a receptor which a given exposure may lead to.

Eqs. 1 and 2 lead to the site-specific characterisation solution in which only those emissions which cause adverse effects related to impact categories are taken into account. The transformation is made because in this way the impact assessment produces more realistic impact value scores. The fact is that the same amount of intervention j can cause different magnitudes of adverse effects on the environment depending among other things on given locations and types of intervention sources. This differentiation can be taken into account by using Eq. 2. In the value of attribute $X_{i,j}$, denoted $x_{i,j}$, only the effective part of intervention j related to impact category i is included. The value of $x_{i,j}$ relates the quantity of an intervention that affects a receptor (e.g. population) to the physical effect (=response) on this receptor (e.g. an incremental number of deaths). Thus, in the determination of attribute value $x_{i,j}$ the task is to assess the quantity of intervention j, which causes adverse effects under impact category i.

In article I, Eq. 2 was applied for interventions caused by domestic product systems. Exposure and effect factors were adjusted to take into account the conditions of geographical areas in which Finnish emissions have an effect. Assuming simple linear conditions Eq. 1 can be written as (article I)

$$\begin{aligned} I_i(a) &= \sum_{j=1}^{m} k_{i,j} \cdot \frac{x_{i,j}(a)}{x_{i,j}(F)} = \sum_{j=1}^{m} Eqv_{i,j} \cdot x_{i,j}(F) \cdot \frac{x_{i,j}(a)}{x_{i,j}(F)} = \sum_{j=1}^{m} Eqv_{i,j} \cdot x_{i,j}(a) \\ &= \sum_{j=1}^{m} Eqv_{i,j} \cdot \eta_{i,j,F}(a) \cdot \mu_{i,j,F}(a) \cdot x_j(a) \qquad (3) \end{aligned}$$

where $Eqv_{i,j}$ = equivalency factor
$x_{i,j}(F)$ = worst level of attribute $X_{i,j}$, i.e. rating caused by human activities in Finland.

$\eta_{i,j,F}(a)$ = alternative-dependent exposure/transport factor related to Finnish emission *j* within impact category *i*

$\mu_{i,j,F}(a)$ = alternative-dependent effect factor related to Finnish emission *j* within impact category *i*

Equivalency factor is assumed to be based on scientific knowledge of environmental processes in the conditions where all magnitudes of intervention cause adverse effects on impact categories. It expresses the contribution of a single intervention to a specific impact category as a ratio to the contribution of a standard intervention. In the case of acidification these worst-case equivalency factors correspond to the acidification potential of each substance *j* which is typically used as site-generic characterisation factor in LCIA (see e.g. Heijungs 1992). In aquatic eutrophication, equivalency factors are based on the so-called Redfied ratio which is also typically used for the basis of site-generic characterisation factors in LCIA (see e.g. Heijungs 1992).

In the case of acidification for transport factors it is assumed that $\eta_{acidification,j,F}(a) = \eta_{acidification,j,F}$, i.e. all domestic acidifying emissions are treated by the same factors. Finland-specific exposure factors were determined by using the results of the RAINS model (Barret et al. 1995). Effect factors of acidification were not determined. In the case of aquatic eutrophication both transport and effect factors are alternative-dependent. In fact, different product units of product system *a* cause nutrient emissions into various water bodies with different limiting nutrient conditions. This feature was taken into account in transport factors. The fates of nutrient emissions were determined according to mathematical models and expert factors. In the effect factors the so-called biological availability of nutrients is taken into account. Biological availability of a nutrient is here considered to be the sum of nutrient forms that can be transformed into a form available to algae. It varies on the basis of sources. An average phosphorus emission from agriculture, for example, may cause less eutrophication than the same amount of phosphorus from a pulp mill in the same watercourse because of the different chemical forms of nutrients in the emissions (Ekholm 1998).

From Eq. 3 can be derived a generic solution for the situation in which product system *a* consists of different product units u_d (d = 1,…,D). Assume that product units u_1 and u_2 occur in Germany, whereas the rest of product units ($u_{3\ldots}$ u_D) locate in Finland. In this case, values of interventions caused by product units u_1 and u_2 should be multiplied by German-specific exposure and effect factors. By contrast, the other values are multiplied by Finland-specific exposure and effect factors.

An alternative approach for site-dependent characterisation is that characterisation factors are directly derived from environmental modelling, i.e. there exists $f_i(x_1, x_2, ..., x_m)$. This approach of type 2 was applied in the case of tropospheric ozone formation, in which Finland-specific characterisation factors were obtained from a version of the Harwell trajectory model for ozone formation (Lindfors et al. 1995). The approach appears to be more attractive because fate and exposure processes and the effect mechanism as well as the $[x_j^o, x_j^*]$ ranges can be taken into account in the determination of characterisation factors in an appropriate way. In practice, the approach is currently commonly used in the determination of site-specific characterisation factors (see Potting et al. 2002). In this case there exist environmental impact assessment models from which it is possible to derive country-specific characterisation factors $C_{i,j,co}$ for interventions *j* within impact categories *i*. For country A, this can be carried out by keeping other countries' emissions fixed at the current level and reducing the emissions of country A by a certain percentage in the case of each impact category.

In the case of country-specific characterisation, approaches 1 and 2 lead to the same results if

$$C_{i,j,co}(a) = Eqv_{i,j} \cdot \eta_{i,j,co}(a) \cdot \mu_{i,j,co}(a) \qquad i = 1,\ldots,n \text{ and } j = 1,\ldots,m \qquad (4)$$

In practice, the parameters in approach 1 can be determined with the help of $f_i(x_1, x_2, ..., x_m)$.

References

Barret, K., Seland, Ø., Foss, A., Mylona, S., Sandnes, H., Styve, H. & Tarrasón, L. 1995. *European transboundary acidifying air pollution: Ten years calculated fields and budgets to the end of first Sulphur Protocol.* Falch Hurtigtrykk, Oslo.

Ekholm, P. 1998. Algal-available phosphorus originating from agriculture and municipalities. Finnish Environment Institute, Helsinki, *Monographs of the Boreal Environment Research 11*.

Heijungs, R., Guinée, J.B., Huppens, G., Lankreijer, R.M., Udo de Haes, H.A., Wegener Sleeswijk, A., Ansems, A.M.M., Eggels, P.G., van Duin, R. & de Goede, H.P. 1992. Environmental life-cycle assessments of products. Center of Environmental Science, Leiden, The Netherlands, *NOH report* 9266 .

Lindfors, V., Lurila, T. & Hakola, H. 1995. A model study of photochemical oxidant formation in the Finnish environmental conditions. In: Anttila, P., Kämäri, J. & Tolvanen, M. (eds.), *Athmosphric Pollution*, Vol. 2. Proceedings of 10th World Clean Air Congress, held at Espoo, Finland, May 28 – June 2, 1995.

Potting, J., Klöpffer, W., Seppälä, J., Norris, G. & Goedkoop, M. 2002. Best available practice in life cycle impact assessment of climate change, stratospheric ozone depletion, photo-oxidant formation, acidification and eutrophication. In: Udo de Haes, H.A., Jolliet, O., Finnveden, G., Goedkoop, M., Hauschild, M., Hertwich, Hofstetter, P., Klöpffer, W., Krewitt, W., Lindeijer, E. W., Müller-Wenk, R., Olson, S.I., Pennington, D.W., Potting, J. & Steen, B. (eds.), *Towards best practice in life cycle impact assessment – report of the second SETAC-Europe working group on life cycle assessment*. Society of Environmental Toxicology and Chemistry (SETAC), Pensacola, pp. 65-100.

Appendix 2

Errata in article I due to technical reasons.

p. 10, line 11: DM=s should be DM's

p. 15, in Equation (1): $a > b$ should be $a \succ b$

p. 15, in Equation (3): $a \geq b$ should be $a \succsim b$

p. 16, line 3: $a > b$ and $b > c$, then $a > c$ should be $a \succ b$ and $b \succ c$, then $a \succ c$

p. 16, in Equation (4): $a > b$ should be $a \succ b$

p. 16, in Equation (6): $(b \Leftarrow a) > (d \Leftarrow c)$ should be $(b \Leftarrow a) \succ (d \Leftarrow c)$

p. 17, in Equation (8): $(x_1,\ldots,x_m) > (x_1',\ldots,x_m')$ should be $(x_1,\ldots,x_m) \succ (x_1',\ldots,x_m')$

p. 19, line 7: Aswing@ should be "swing"

p. 20, line 2: x=, i.e., $<(p_1,x_1,\ldots, p_n,x_n)> \sim x$= should be x', i.e., $<(p_1,x_1,\ldots, p_n,x_n)> \sim x'$

p. 20, line 13: Amonetary@ should be "monetary"

p. 21, line 29: w_j=s and $w_j(a_i)$=s should be w_j's and $w_j(a_i)$'s

p. 43, line 3: Aswing@ should be "swing"

p. 44, line 28: Aswing@ should be "swing"

p. 72, in note (3 of Table 5: Aeffective@ should be "effective"

pp. 104-106, Figs. 29-32: the decimal symbol on the vertical axis should be a dot (.) instead of a comma (,)

p. 172, Figs of Appendix 5: the decimal symbol should be a dot (.) instead of a comma (,)