Integrating Life-Cycle Assessment and Multi-Criteria Decision Analysis to compare alternative biodiesel chains

Luis C. Dias[1,2], Carolina Passeira[2], João Malça[3,4], Fausto Freire[3]

[1] CeBER and Faculty of Economics, University of Coimbra, Av Dias da Silva 165, 3004-512 Coimbra, Portugal. Email: lmcdias@fe.uc.pt.

[2] INESC Coimbra, Coimbra, Portugal.

[3] ADAI-LAETA, Dept. of Mechanical Engineering, University of Coimbra, Coimbra, Portugal.

[4] Dept. of Mechanical Engineering, ISEC, Polytechnic Institute of Coimbra, Coimbra, Portugal.

Abstract

The transport sector is highly dependent on fossil fuels with significant environmental impacts. This motivates the environmental assessment of alternative fuel options, including biodiesel based on agricultural crops. The assessment of biofuel alternatives for transportation can be facilitated by the integration of Life-Cycle Assessment (LCA) and Multi-Criteria Decision Analysis (MCDA).

In this article, we compare four Rapeseed Methyl Ester biodiesel production chains, corresponding to four different feedstock origins. The environmental impact of each chain is assessed in the context of a LCA encompassing cultivation, transportation to Portugal, extraction and transesterification. We apply two different MCDA additive aggregation methodologies to aggregate various impact categories resulting from the Life Cycle Impact Assessment (LCIA) phase of the LCA.

The chosen MCDA methodologies, Stochastic Multicriteria Analysis and Variable Interdependent Parameter Analysis, are two complementary approaches to address one of the main difficulties of MCDA: setting the relative weights of the evaluation criteria. Indeed, weighting the various impacts in the LCIA phase is a controversial issue in LCA research and studies. The LCIA-MCDA approach proposed in this work does not require choosing a specific weighting vector, seeking to assess which conclusions are robust given some freedom allowed in the choice of weights. To study further the robustness of the conclusions concerning the choice of the criteria, the effects of removing one criterion are analyzed, one at a time.

Keywords: Multi-Criteria Decision Analysis (MCDA), Stochastic Multicriteria Acceptability Analysis (SMAA), Robust conclusions, VIP Analysis, Life-Cycle Assessment (LCA), weighting, rapeseed, biodiesel, biofuel.

Acknowledgements: This research was partially supported by FCT grants PEst-OE/EEI/UI0308/2014, PTDC/SEN-TRA/117251/2010-FCOMP-01-0124-FEDER-021495 and PTDC/AAG-MAA/6234/2014.

1. Introduction

The transport sector is highly dependent on fossil fuels, with significant impacts on climate change, among other environmental impacts (EEA 2009). As a result, in recent years environmental assessment studies of alternative fuel options have been conducted to assess opportunities for decreasing impacts. According to the European Union (EU) goals, by 2020, 10% of the total energy used in transportation should come from renewable energy sources (EPC 2009). Biofuels based on agricultural crops, and in particular biodiesel in Europe, are currently the main alternatives; however, controversies exist concerning the sustainability of agro-based biodiesel due to competition with the food sector, reduced availability of agricultural land, environmental impacts due to land use and land use change (LUC), and reduced soil fertility due to intensive farming and depletion of soil (Dinh et al. 2009; Malça et al. 2014).

Usually, when assessing biofuels, some or all of the evaluation criteria represent potential environmental impacts obtained by Life-Cycle Assessment (LCA), a methodology that assesses the environmental impacts of products (or processes or activities) throughout the successive stages of their life cycle (Cherubini and Strømman 2011). But weighting the various impacts in the Life Cycle Impact Assessment (LCIA) phase of an LCA in order to support decision making is a controversial issue in LCA research and studies (Finnveden 1999; Myllyviita et al. 2014).

Multi-Criteria Decision Aiding, also known as Multi-Criteria Decision Analysis (MCDA) (for an overview see e.g. Belton and Stewart (2001) and Ishizaka and Nemery (2013)) has been proposed as a solution to aggregate different LCIA indicators in a theoretically sound manner. MCDA methods are able to aggregate evaluations performed on multiple criteria, taking into account a model of decision maker preferences, synthetizing the results in the form of a recommended alternative, a ranking of the alternatives, or a classification. Research on combining LCA and MCDA includes using MAVT/MAUT (Seppälä et al. 2002), ELECTRE methods (Domingues et al. 2015), PROMETHEE methods (Geldermann and Rentz 2005), and other approaches (e.g., Zhou et al. 2007).

There are several studies combining LCA and MCDA to assess biofuels. Some studies selected for their relevance for this work are reviewed in Table 1. These include assessments of biofuel production chains (Dinh et al. 2009; Finco et al. 2012; Kralisch et al. 2013; Myllyviita et al. 2012; Narayanan et al. 2007; Perimenis et al. 2011; Ren et al. 2015; Rivière and Marlair 2009; Suwelack and Wüst 2015) and assessments of alternative fuels for transportation, comparing biodiesel or bioethanol with fossil fuels, and also electric propulsion (Daystar et al. 2015; Hayashi et al. 2014; Maimoun et al. 2016; Mohamadabadi et al. 2009; Rogers and Seager 2009; Streimikiene et al. 2013; Turcksin et al. 2011; Zhou et al. 2007). Most of the indicators used in the literature reviewed consider a life cycle perspective in the assessment of environmental impacts, as is the case in our study. Concerning the MCDA method, the most used approach is an additive aggregation (five of the studies), which is also used in this article.

In general, studies reviewed in Table 1 acknowledge that weighting the criteria is a critical issue in MCDA. Typically this requires that a decision making entity provides subjective judgments about the importance of each criterion. The literature in MCDA assessment of biofuels follows different strategies. Most studies present results for the case of equal weights, often complementing this case with a few other possibilities proposed by the authors that place more weight on some of the criteria (e.g. an environmental perspective and a customer perspective (Streimikiene et al. 2013)). Other authors, such as Myllyviita et al. (2012), used a survey to experts and/or stakeholders to set the weight values. Rogers and Seager (2009) proposed the use of stochastic weights.

In this article, we compare four Rapeseed Methyl Ester biodiesel production chains, corresponding to four different feedstock origins. The environmental LCIA of each alternative chain encompasses cultivation, transportation to Portugal, extraction and transesterification. LCIA indicators are aggregated using MCDA, in particular the additive aggregation model. To cope with the issue of weights, we propose the combined use of robustness and stochastic analyses, as suggested by Kadziński and Tervonen (2013), rather than basing the results on equal weights or on the specific preferences of a decision maker. This approach does not elicit value judgments about which criteria are more important. All the criteria are treated in an equitable way, but without considering they must have the same weight. To study further the robustness of the conclusions concerning the choice of the criteria, the effects of removing one LCIA criterion are analyzed, one at a time.

Table 1 - Studies combining LCA and MCDA to assess biofuels (* denotes multiple indicators)

	Alternatives	Criteria	MCDA method	Weights
(Zhou et al. 2007)	Fossil fuels, fossil-biofuel mix	Global Warming Potential Net energy Nonrenewable resource depletion Life-Cycle Cost	Additive aggregation	Five cases (by the authors): 1) equal weights 2)-5) Priority given to one indicator (at a time)
(Narayanan et al. 2007)	Biofuels	Environmental performance(*) Economic performance(*) Safety(*) Fuel performance(*)	AHP and additive aggregation	Provided by the authors, directly or through AHP judgments
(Dinh et al. 2009)	Biofuels	Environment(*) Economic Safety(*) Fuel performance(*) Raw material performance	AHP	Provided by the authors, through AHP judgments
(Rivière and Marlair 2009)	Biofuels (fictitious example)	Health risk Environmental risk Explosion / fire risk	Additive aggregation	Equal weights
(Rogers and Seager 2009)	Fossil fuels, biofuels, electric fuels	6 TRACI impact categories	PROMETHEE / SMAA	Stochastic weights
(Mohamadabadi et al. 2009)	Vehicles: fossil fuels, fossil-biofuel mix, biofuel	Vehicle cost Fuel cost Charging stations distance Number of options GHG emissions	PROMETHEE	Two cases (by the authors): 1) Cost Scenario 2) Environmental Scenario
(Perimenis et al. 2011)	Biofuels (from rapeseed)	Economic(*) Environmental(*) Social(*) Technical(*)	Additive aggregation	Authors (as an example of user weights)
(Turcksin et al. 2011)	Fossil fuels, biofuels	33 criteria, grouped by stakeholder	AHP	Stakeholders panel (survey) through AHP judgments
(Finco et al. 2012)	Biofuels	Energy balance GHG emissions Direct and Indirect land use change Commodity price	REGIME	Three cases: 1) equal weights without price 2) policymakers survey without price 3) 50% weight for price
(Myllyviita et al. 2012)	Biomass for the biodiesel and pulp industry	14 ReCiPe impact categories	Additive aggregation	Survey to a panel of 39 experts (the mean values were used)

Table 1 (cont) - Studies combining LCA and MCDA to assess biofuels (* denotes multiple indicators)

	Alternatives	Criteria	MCDA method	Weights
(Streimikiene et al. 2013)	Fossil fuels, biofuels, electricity (from different sources)	Emissions (GHG, PM10, NOx, CO, HCs), Cost/km	Interval TOPSIS	Three cases (by the authors): 1) equal weights 2) environmental perspective 3) customer perspective
(Kralisch et al. 2013)	Biofuel	Environmental dimension (CML)(*) Risk dimension (EHS)(*) Life Cycle Costs	PROMETHEE (separately for each dimension)	Equal weights (for indicators within each dimension)
(Hayashi et al. 2014)	Biofuel, fossil fuel (Diesel)	14 indicators (environmental, social, and economic)	Additive aggregation	Average weights from 10 stakeholders
(Daystar et al. 2015)	Ethanol (pine, eucalyptus, unmanaged hardwood, forest residues, switchgrass), gasoline	9 TRACI impact categories	Additive aggregation	Literature reference (referring to a survey)
(Ren et al. 2015)	Three scenarios for bioethanol production	1) Climate change, terrestrial acidification, human toxicity, particulate matter; 2) Life Cycle Costs; 3) Three social criteria	VIKOR	Provided by the authors, through AHP judgments; Equal weights; One dominant weight (8 scenarios)
(Suwelack and Wüst 2015)	Biofuels (fictive example)	1) Natural land use, global warming potential, fossil resource depletion; 2) Jobs created, rural development; 3) Production costs, specific investment	MCBB (a type of additive aggregation) and radar plots	Equal weights for 3 main dimensions; author weights inside each dimension
(Maimoun et al. 2016)	Natural gas (2 sources of CNG and two sources of LNG), biodiesel (BD100, BD20, 2 scenarios each), diesel	Economic(*) Environmental(*)	Additive aggregation and TOPSIS	Entropy weights

Stochastic Multicriteria (or Multiobjective) Acceptability Analysis (SMAA) (Lahdelma et al. 1998) is a way to address lack of knowledge about weights by Monte-Carlo simulation: weight vectors are drawn randomly following an input distribution (typically uniform), results are computed and summary statistics are provided. Its use in conjunction with LCA has been advocated in recent years (Prado-Lopez et al. 2014; Rogers and Seager 2009). In the present work, we depart from the original focus of SMAA on ranking positions and consider instead a pair-wise comparison perspective (Kadziński and Tervonen 2013; Leskinen et al. 2006).

The SMAA analysis is complemented in this work by robustness analysis, namely VIP Analysis (Dias and Clímaco 2000), to provide an exact bound for how much better each alternative is compared to another one, in a pair-wise comparison perspective. This is an important information to complement pair-wise SMAA results: given a pair (a_1,a_2) of alternatives, it may happen that a_1 is better for most SMAA weight vectors, although winning by a small difference, whereas there are weight vectors that might lead to a_2 to win by a much larger difference. Besides this contribution to MCDA methodology, this article is also, to the best of the authors' knowledge, the first to apply a combined use of robustness and stochastic analyses for LCA.

2. Multi-criteria analysis methods

2.1. Additive model with partial information

In this article, two MCDA methods were used: Stochastic Multicriteria Acceptability Analysis (SMAA) (Lahdelma et al. 1998) and Variable Interdependent Parameters Analysis (VIP Analysis) (Dias and Clímaco 2000). Both methods are based on additive aggregation, whereby $v(a_i,w)$, the overall value of an alternative a_i, is a weighted sum of its values $v_j(a_i)$ on n evaluation criteria considering a weighting vector w:

$$v(a_i, w) = \sum_{j=1}^{n} w_j v_j(a_i) = w_1 v_1(a_i) + w_2 v_2(a_i) + ... + w_n v_n(a_i) \qquad (1)$$

The value functions $v_1(a_i), \ldots, v_n(a_i)$ may or not be linear functions of the alternatives performances. The criteria weights $w_1, \ldots, w_n$ reflect the tradeoffs a decision maker is willing to make between criteria. One unit of value on the j^{th} criterion is worth w_j/w_k units of value on the k^{th} criterion. All weights are non-negative and the sum of all weights is equal to 1 (a typical convention):

$$w_1, \ldots, w_n \geq 0 \text{ and } \sum_j^n w_j = 1 \qquad (2)$$

In order to obtain robust results as independent as possible from preference information, we used MCDA methods that consider sets of accepted weight vectors rather than a single weights vector. Such methods are often called partial (or incomplete, or imprecise) information methods (Dias and Clímaco 2000). In this article, the sets of accepted weight vectors were defined by imposing a maximum ratio *r* between any two weights, thus bounding the substitution among impacts in the final score:

$$1/r \leq w_j/w_k \leq r,\ \forall j,k \quad (3)$$

According to Eq. 3, a unit of value on the scale of a criterion cannot be worth more than *r* units of value on the scale of any other criterion. This type of bounds takes into account the nature of trade-off weights and they also reflect the criteria scale ranges when the value of the best performance in the scale is set to 1 and the value of the worst performance in the scale is set to 0. Hence, these bounds are different from the bounds suggested elsewhere for an ELECTRE method application (Domingues et al. 2015).

There is not a natural choice for the limit *r*. For this reason, in this work the maximum ratio *r* between the minimum and the maximum weight is considered to be 2, 5, 10, 20, 50 and 100 in different analyses (labels R2, R5, R10, R20, R50, and R100, respectively in section 4).

Let W denote the set of accepted weight vectors, i.e., all vectors ($w_1, \ldots, w_n$) that respect (2) and (3). Considering such a set has the advantage of considering all criteria have the same role without committing to consider the weights are equal, and the conclusions will be robust rather than contingent on a specific weight vector. On the other hand, different vectors of weights in W will lead to different overall values for each alternative according to (1), meaning that the result is unlikely to be a clear-cut ranking of the alternatives.

2.2. Stochastic Multicriteria Analysis

SMAA is an approach that allows obtaining results for the additive model without specifying a single weights vector (also applicable to other parameters and models, see (Tervonen 2014). It explores the feasible parameter space by generating parameter values from stochastic distributions (usually, uniform distributions) and gathering statistics about the results of interest. SMAA focusses on results such as rank acceptability indices and central weight supporting a potential winning alternative (Lahdelma et al. 1998; Lahdelma and Salminen 2001), but in this article we use the same type of stochastic weights analysis focusing on the concept of pair-wise winning probabilities (Leskinen et al. 2006) or pair-wise outranking indices (Kadziński and Tervonen 2013). Let us note that Rogers and Seager's (2009) approach is also a type of SMAA, but it is based on the PROMETHEE method (Brans et al. 1986), instead of the additive aggregation.

Given a pair of alternatives ($a_x, \ldots, a_y$), we use a stochastic analysis to determine what is the probability of a_x being better than a_y. Computations were performed using Monte Carlo simulation software (Oracle Crystal Ball), drawing weight vectors from a uniform distribution, following Butler et al. (1997), and applying the Hit and Run method of Tervonen and Lahdelma (2007) to comply with condition (3). To expedite the process, given a ratio limit r, a lower bound for the weights was computed using equation (4):

$$w_j^{min} = \frac{1}{(n-1)\times r+1} \tag{4}$$

where n is the number of criteria and r is the ratio between the maximum and minimum weights. The number of trials in each simulation was 200 000. Results were obtained for all pairs of alternatives.

2.3. VIP Analysis

VIP Analysis is also based on additive aggregation and sets of weight vectors; this approach uses linear programming to find the most extreme results that correspond to extreme weight vectors, including (for further details, see Dias and Clímaco (2000)):

a) $v^{\max}(a_i) = \max\{v(a_i, w) : w \in W\}$ indicates the maximum value that an alternative a_i can attain given the constraints on the weights;

b) $D(a_x, a_y) = \max\{v(a_x, w) - v(a_y, w) : w \in W\}$ indicates the maximum advantage (value difference) that an alternative a_x can have over another alternative a_y, given the constraints on the weights.

Let us note that if $D(a_x, a_y)$ is negative, this means that a_x cannot have a better score than a_y, and thus it is additively dominated. In other words, there is a necessary preference relation (Kadziński and Tervonen 2013) between these two alternatives.

SMAA and VIP Analysis use the same inputs to provide complementary outputs. For a pair of alternatives (a_x, a_y), the stochastic analysis for the weights can indicate the probability that a_x is better than a_y (yielding the proportion of the weight space that yields higher score to a_x than a_y). VIP Analysis, in turn, can indicate how much better can a_x be relatively to a_y, and vice versa. This is important because it may happen that a_x is better for a majority of the weight vectors, although winning by a small difference, whereas there are weight vectors that might lead it to lose by a much larger difference. Figure 1 presents a graphical illustration of this situation.

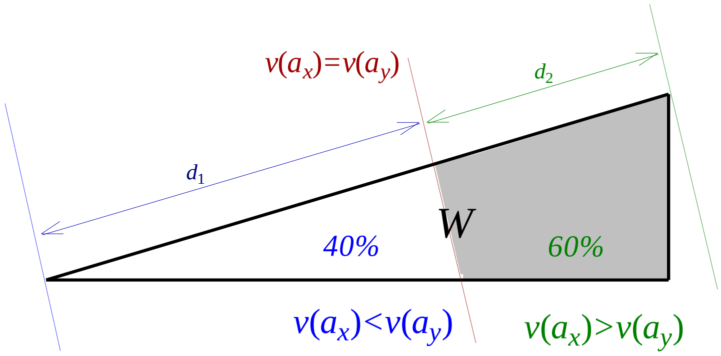

Figure 1. A weights space W is divided in two regions: one where a_x is better than a_y (right region, shaded) and another where the reverse occurs (left region). Although the shaded region represents a larger volume, the maximum difference by which a_x may win over a_y (proportional to d_2) is less than the maximum difference by which a_y may win over a_x (proportional to d_1).

3. Application

3.1. Life cycle impact assessment of biodiesel

The MCDA methodology presented in the previous section was applied to an LCA of biodiesel produced from rapeseed (Malça et al. 2014). This article builds on that prior study, in which an extensive data collection was conducted to perform an LCA of alternative scenarios for rapeseed cultivation and transportation to Portugal (Malça et al. 2014). The scenarios address specific cultivation systems with alternative agricultural management practices in four different geographical locations: three rapeseed producing regions in Europe (alternative scenarios A1, A2 and A3), and one in North America (scenario SQ). The cultivation scenarios differ mainly on the biomass yield, fertilizer application rates and fuel consumption of agricultural machinery. The oilseeds from each region are transported to Portugal where oil extraction, refining and transesterification take place. Mechanical pressing is first used to extract the oil, followed by chemical extraction using hexane to extract the remaining oil from the rapeseed cake. The next steps include oil refining and transesterification. The refining process includes degumming, neutralization and drying. In the transesterification reaction, methanol is mixed with rapeseed oil producing rapeseed methyl ester (RME), with glycerin as a by-product (Malça et al. 2014). The criteria considered in this article for comparing the four biodiesel systems were Well-to-Tank LCIA results (calculated with CML 2001), encompassing rapeseed cultivation, transportation, oil extraction and biodiesel production, considering as a functional unit 1 MJ of biodiesel. Use-phase impacts were not considered since biodiesel properties were assumed similar for the four scenarios.

Six environmental impact categories were considered to be the evaluation criteria: Global Warming (GW), Abiotic Depletion (AD), Acidification (Ac), Eutrophication (Eu), Ozone Layer Depletion (OLD) and Photochemical Oxidation (PO). Life-cycle results per MJ of biodiesel produced are presented in table 2.

Table 2 – Life-cycle impact assessment results for each alternative (per MJ of biodiesel).

	GW ($kg\ CO_{2,eq}$)	AD ($kg\ Sb_{eq}$)	Ac ($kg\ SO_{2,eq}$)	Eu ($kg\ PO_4^{-}{}_{eq}$)	OLD ($kg\ CFC_{11}^{-}{}_{eq}$)	PO ($kg\ C_2H_4\ _{eq}$)
SQ	4,668E-02	2,668E-04	6,164E-04	4,027E-04	6,588E-09	8,038E-06
A1	4,840E-02	2,535E-04	4,520E-04	3,138E-04	4,476E-09	4,752E-06
A2	5,258E-02	2,768E-04	5,856E-04	4,370E-04	6,015E-09	4,872E-06
A3	4,810E-02	2,176E-04	4,907E-04	4,140E-04	4,308E-09	3,635E-06

3.2. Normalization

Since these criteria are related to environmental impacts, the goal is to minimize them. To perform a meaningful weighting operation on these results, the criteria scales were converted to become commensurable. Commensurable scales can be obtained by eliciting value judgments from a decision maker to construct nonlinear value functions (Seppälä and Hämäläinen 2001), or by a normalization operation (Heijungs et al. 2007) that corresponds to a linear value function. Nonlinear functions are sometimes used in cases where a target has been identified, or cases in which there are diminishing (or increasing) returns to scale. In our case, the criteria correspond to environmental impacts per functional unit (1 MJ of biodiesel), thus there are no scale effects and we use a linear value function using a proper normalization operation.

Normalization is an optional step in the LCA framework. According to Heijungs et al. (2007), it is a controversial topic since it can return biased results. A normalization operation can be internal, when it is based on the set of alternatives being evaluated or external when a reference not dependent on the contingent alternatives is used. Using an internal normalization anchoring on the extreme values of the alternatives is not recommended, because adding a new and possibly irrelevant alternative may change the relative position of the original alternatives (e.g., see Dias and Domingues 2014).

Normalization can also represent a means to facilitate the communication with decision makers, if it is based on a well-defined and recognizable reference system. In an assessment of vehicle alternatives, Domingues et al. (2015) suggested to use the status quo as a reference system, which consisted of the impacts of the current vehicle fleet. In this article, we performed a similar choice. Ideally we would use the impacts (per MJ) of rapeseed-based biodiesel currently in use in Portugal. Since these data are not available, we considered as a reference the impacts of the system that represents by far the largest share of rapeseed biodiesel in Portugal (information provided from biodiesel producers), which is scenario SQ (status quo). Hence, scenarios A1, A2 and A3 represent possible alternatives to replace the prevailing scenario.

Let $x_{ref,j}$ represent the impact category j for the normalization reference (1 MJ of biodiesel in scenario SQ). This reference is absolute since it is independent from the set of alternatives being evaluated, i.e. if new alternatives are added to the analysis, the normalization values of the remaining ones will not change. The normalization applied is:

$$v_j(a_i) = \frac{x_{ref,j} - x_{ij}}{x_{ref,j}} \tag{5}$$

where $v_j(a_i)$ is the normalized value and x_{ij} is the impact for alternative a_i and category j. Preference increases with $v_j(a_i)$. Negative values mean that the alternative a_i is worse than the reference used for a certain impact category, whereas a positive value indicates a better performance when compared to the reference.

Table 3 indicates the values of the normalized criteria: for instance, scenario A1 is 3.7% worse than the SQ reference for category GW, and 5% better than the reference in category AD.

Table 3 - Normalized criteria for the alternative scenarios.

	GW	AD	Ac	Eu	OLD	PO
SQ	0.000	0.000	0.000	0.000	0.000	0.000
A1	-0.037	0.050	0.267	0.221	0.321	0.409
A2	-0.126	-0.037	0.050	-0.085	0.087	0.394
A3	-0.031	0.185	0.204	-0.028	0.346	0.548

Let us note that using the additive aggregation of eq. (1), performing a normalization using eq. (5) leads to results equivalent to those of a ratio normalization $x_{ij}/x_{ref,j}$. When comparing two alternatives, e.g. a_i and a_k, their score difference is the same with sign reversed, since:

$$\sum_j^n w_j \frac{x_{ref,j} - x_{ij}}{x_{ref,j}} - \sum_j^n w_j \frac{x_{ref,j} - x_{kj}}{x_{ref,j}} = -\left(\sum_j^n w_j \frac{x_{ij}}{x_{ref,j}} - \sum_j^n w_j \frac{x_{kj}}{x_{ref,j}}\right)$$

4. Results

Results are presented as a pairwise comparison table for both methods in order to summarize the complementary outputs of the stochastic weights and VIP Analysis. Table 4 presents the results for different ratio limits (*r*=2 up to *r*=100): left values refer to stochastic weights analysis whereas right values refer to VIP Analysis. For *r*=2 (the maximum weight cannot be more than twice the minimum weight), A1 and A3 are better than SQ and A2 in all cases. A2 is always better than SQ, but the maximum difference in favor of A2 is relatively low (0.097). A1 is better than A3 for 52% of the cases. However, VIP Analysis complements the stochastic weights information indicating that these two alternatives have always a similar score at best A1 wins by a margin of 0.04 and at worst loses by a margin of 0.033.

Results for higher values of *r* have a similar interpretation. As *r* increases, more weight vectors are accepted (for *r*=100, it is accepted that one criterion unit weights as much as 100 times another criterion unit). Accepting more weight vectors means that the maximum difference of value will increase, and some of the negative maxima become positive. For instance, SQ cannot be better than A2 if *r*=2 (maximum advantage is -0.004), but it can be better if *r*=5 (or higher).

Results in Table 4 can be gathered in 3 groups: the first group is defined by R2; the second by R5, R10 and R20; and the third by R50 and R100. Within each group, there is a stable partial order for all accepted weights, as summarized in table 5. The shading degree represents a position in the ranking. When an alternative is positioned in more than one square, it means the alternative can be positioned in two or more ranks:

1. For *r*=2 (R2) it is not possible to distinguish between A1 and A3; since both are ranked as first or second. On the other hand, A2 is always ranked third and SQ fourth.

2. For $r \in \{5,10,20\}$ (R5, R10 and R20) there is no robust preference between A1 and A3 or between A2 and SQ. The robust conclusions are that A1 and A3 are ranked first or second, whereas for A2 and SQ the doubt is between the third and fourth places. The previous conclusion that A2 is better than SQ no longer holds.

3. For $r \in \{50,100\}$ (R50 and R100), A2 loses against A1 and A3 and SQ can be positioned in any rank.

Table 4 – SMAA (left) and VIP Analysis (right) results for the 6 environmental impact categories.

		SQ	A1	A2	A3
R2	SQ		0% | -0.155	0% | -0.004	0% | -0.146
	A1	100% | 0.247		100% |0.189	52 % | 0.040
	A2	100% | 0.097	0% | -0.127		0% | -0.137
	A3	100% | 0.265	48% | 0.033	100% | 0.178	
R5		SQ	A1	A2	A3
	SQ		0% | -0.092	7% | 0.040	0% | -0.071
	A1	100% | 0.296		100% | 0.222	49 % | 0.100
	A2	93% | 0.186	0% | -0.095		0% | -0.111
	A3	100% | 0.343	51% | 0.078	100% | 0.205	
R10		SQ	A1	A2	A3
	SQ		0% | -0.056	15% | 0.068	0% | -0.029
	A1	100% | 0.327		100% | 0.247	48% | 0.150
	A2	85% | 0.255	0% | -0.072		0% | -0.097
	A3	100% | 0.410	52% | 0.102	100% | 0.220	
R20		SQ	A1	A2	A3
	SQ		0% | -0.021	20% | 0.085	0% | -0.002
	A1	100% | 0.360		100% | 0.271	48% | 0.190
	A2	80% | 0.311	0% | -0.049		0% | -0.081
	A3	100% | 0.465	52% | 0.118	100% | 0.235	
R50		SQ	A1	A2	A3
	SQ		0% | 0.011	23% | 0.107	0% | 0.016
	A1	100% | 0.387		100% | 0.290	47% | 0.222
	A2	77% | 0.356	0% | -0.031		0% | -0.068
	A3	100% | 0.510	53% | 0.129	100% | 0.248	
R100		SQ	A1	A2	A3
	SQ		**0.0005%** | 0.023	24% | 0.116	**0.0097%** | 0.023
	A1	**99.9995%** |0.397		100% |0.298	47% | 0.235
	A2	76% | 0.374	0% | -0.023		0% | -0.063
	A3	**99.9903%** |0.528	53% | 0.131	100% | 0.253	

Table 5 - Interpretation of the results for the 6-criteria scenario (ratio limits from R2 to R100).

<table>
<tr><th colspan="4">R2</th></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td></tr>
<tr><td colspan="2">A1</td><td rowspan="2">A2</td><td rowspan="2">SQ</td></tr>
<tr><td colspan="2">A3</td></tr>
</table>

<table>
<tr><th colspan="4">R5 – R10 – R20</th></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td></tr>
<tr><td colspan="2">A1</td><td colspan="2">A2</td></tr>
<tr><td colspan="2">A3</td><td colspan="2">SQ</td></tr>
</table>

<table>
<tr><th colspan="4">R50 – R100</th></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td></tr>
<tr><td colspan="2">A1</td><td colspan="2" rowspan="2">A2</td></tr>
<tr><td colspan="2">A3</td></tr>
<tr><td colspan="4">SQ</td></tr>
</table>

Rank 1	Rank 2	Rank 3	Rank 4

The previous analysis is based on VIP Analysis, which uses an exact optimization approach to validate if one alternative is (or not) always better than another. If we consider only the stochastic weights analysis provided by Crystal Ball (table 4), the results for R50 suggest that SQ cannot be better than A1 or A3. Although the stochastic weights analysis provides rich information, it is based on random numbers and it can have difficulties to cover all the weights space.

VIP analysis also provides the weights vectors leading to each maximum difference. As an example of these outputs, considering the ratio limit R10, Table 6 indicates the optimal vectors that each alternative in the first column would choose when confronted with the alternative in the second column. For instance, the maximum advantage of A1 when confronted with SQ (0.327, according to Table 4) is obtained when all the impacts have a weight of $2/30 \approx 0.067$, except the weight of PO which would be 10 times higher.

Table 6 – Optimal weights vector for a ratio limit of 10.

		GW	AD	Ac	Eu	OLD	PO
SQ	A1	0.417	0.417	0.042	0.042	0.042	0.042
	A2	0.417	0.042	0.042	0.417	0.042	0.042
	A3	0.417	0.042	0.042	0.417	0.042	0.042
A1	SQ	0.067	0.067	0.067	0.067	0.067	0.667
	A2	0.067	0.067	0.067	0.667	0.067	0.067
	A3	0.067	0.067	0.067	0.667	0.067	0.067
A2	SQ	0.067	0.067	0.067	0.067	0.067	0.667
	A1	0.067	0.067	0.067	0.067	0.067	0.667
	A3	0.417	0.042	0.042	0.417	0.042	0.042
A3	SQ	0.067	0.067	0.067	0.067	0.067	0.667
	A1	0.042	0.417	0.042	0.042	0.042	0.417
	A2	0.042	0.417	0.042	0.042	0.417	0.042

It is possible to observe that to maximize the score of one alternative, VIP Analysis gives less weight to the categories in which it has worse impact and selects higher weights for the categories with better impacts. The broader the range of accepted weights, the easier it is to decrease bad and increase good criteria, respectively. This feature allows SQ to be ranked at any position for R50 and R100.

The robustness of the previous results was also assessed concerning the selection of impact categories: one impact category at a time was removed from the results (number of criteria reduced to 5). When GW is removed, the main conclusions about the ranking of the alternatives do not change between R2 and R20. However, for R50 and R100, and without the GW category, SQ is always worse than A1, whereas for the initial set of 6 criteria there is a small probability that SQ wins against A1. If AD is removed from the analysis, the superiority of A3 over SQ, at R20, is lost. However, the probability given by SMAA is still very favorable to A3 (around 99%). It is also important to emphasize that, although the superiority of A1 over SQ, and vice-versa, is not clear, by VIP Analysis results, the probability of A1 winning against A3 increases by 23% to 48% for all ratios. If the removed category is Ac, OLD or PO, in R2 no preference is defined between SQ and A2, and at R20, the superiority of A3 over SQ is lost, as when AD is removed from the analysis. However, SMAA gives different information for each case. The probability that A3 is better that A1 increases between 10 and 28%, when Ac is eliminated from the results. On the other hand, by excluding PO, the probability that A1 is better that A3 increases between 23 and 48% (as removing AD). Besides, the chance of SQ to win against A2 increases over 51-100%. Finally, if the removed category is Eu then A3 becomes always better than A1 in R2, which allows a linear order of the alternatives (A3>A1>A2>SQ) and the probability that A3 is better than A1 increases between 41 and 52%, for the remaining ratios.

5. Conclusions

This article shows how a novel MCDA approach can be integrated in LCIA to support robust decisions in the interpretation phase of LCA, without the need to define specific weights for incommensurable environmental impacts (usually defined based on subjective preference information), which is a controversial and difficult topic in both MCDA and LCA literature. This approach allows considering that the criteria have similar roles, but not necessarily the same weights. This is an important aspect in interpreting LCIA studies, since the use of any specific set of weights (including a vector of equal weights) is prone to controversy.

From an MCDA point of view, the methodology presented shows a virtuous combination of the SMAA and VIP Analysis approaches. Kadziński and Tervonen (2013) suggested to use SMAA to complement mathematical programming approaches in a robust regression setting, to add information about possible but not necessary preferences. In this article, we suggest to use the mathematical programming approach of computing extreme value differences to complement pair-wise SMAA results. For a pair of alternatives such that either alternative can win depending on the weights, the stochastic weights analysis indicates what is the probability of each alternative being better considering randomly drawn weights. Complementarily, the VIP Analysis method indicates how much better an alternative can be compared to the other.

The new LCIA-MCDA approach proposed was applied to a comparative LCA of RME biodiesel to provide insights on the relative ranking of four rapeseed cultivation systems. These systems represent the status quo and three possible substitutes from different geographical origins. Six environmental impact categories from the CML 2001 LCIA method were used as evaluation criteria, using a status-quo based normalization, and considering a feasible weights set that respects the trade-off nature of weights in the additive model.

Without the need of subjective preference information for weighting the criteria, the results still allow to draw robust conclusions. The results show that for the 6-criteria scenario, A1 and A3 were consistently ranked first or second, whereas A2 and SQ obtained the third and fourth ranking position most of the times. By removing each criterion at a time, it was observed that the lost information sometimes leads to less decisive results (if either one of AD, Ac, OLD or PO is removed from the analysis), whereby some of the necessary preferences disappear, and some other times leads to a more decisive output with added necessary preferences (if the removed category is Eu). The latter case, which leads to the linear order A3>A1>A2>SQ, occurs because category Eu brings an important advantage for A1 when compared with A3, whereas the majority of the categories favor A3. Without Eu, this counter-balance effect disappears making A1 a winner. Finally, the influence of GW is not very significant for the ranking of the scenarios.

In this application, robust conclusions were obtained even when weights differ by an order of magnitude (maximum ratio of r=10); some of the conclusions still hold when weights differ by two orders of magnitude (maximum ratio of r=100). Although it would be easy to fabricate an artificial example where such robust conclusions do not emerge, we conjecture that in many real-world decisions the LCIA-MCDA approach proposed in this article will be able to identify a single or very few scenarios as being the most preferable ones without committing to a specific vector of weights. Corroborating this type of “flat maxima” effect (von Winterfeldt and Edwards 1986) for LCIA-MCDA studies based on additive aggregation is an interesting topic for future research.

References

Belton, V., & Stewart, T. (2001). *Multiple Criteria Decision Analysis*. Kluwer Academic Publishers.

Brans, J. P., Vincke, P., & Mareschal, B. (1986). How to select and how to rank projects: The Promethee method. *European Journal of Operational Research*. doi:10.1016/0377-2217(86)90044-5

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. doi:103(3):531–546

Cherubini, F., & Strømman, A. H. (2011). Life cycle assessment of bioenergy systems: state of the art and future challenges. *Bioresource Technology*, *102*(2), 437–51. doi:10.1016/j.biortech.2010.08.010

Council, E., & Parliament, E. Directive 2009/28/EC (2009). Official Journal of the European Union.

Daystar, J., Reeb, C., Gonzalez, R., Venditti, R., & Kelley, S. S. (2015). Environmental life cycle impacts of cellulosic ethanol in the Southern U.S. produced from loblolly pine, eucalyptus, unmanaged hardwoods, forest residues, and switchgrass using a thermochemical conversion pathway. *Fuel Processing Technology*, *138*, 164–174. doi:10.1016/j.fuproc.2015.04.019

Dias, L. C., & Clímaco, J. N. (2000). Additive aggregation with variable interdependent parameters: The VIP analysis software. *Journal of the Operational Research Society*, *51*(9), 1070–1082. Retrieved from http://www.jstor.org/stable/10.2307/254228

Dias, L. C., & Domingues, A. R. (2014). On multi-criteria sustainability assessment: Spider-gram surface and dependence biases. *Applied Energy*, *113*, 159–163. doi:10.1016/j.apenergy.2013.07.024

Dinh, L. T. T., Guo, Y., & Mannan, M. S. (2009). Sustainability Evaluation of Biodiesel Production Using multicriteria decision making. *Environmental Progress Sustainable Energy*, *28*(1), 38–46. doi:10.1002/ep

Domingues, A. R., Marques, P., Garcia, R., Freire, F., & Dias, L. C. (2015). Applying multi-criteria decision analysis to the life-cycle assessment of vehicles. *Journal of Cleaner Production*, *107*, 749–759. doi:10.1016/j.jclepro.2015.05.086

EEA, E. E. A. (2009). *Greenhouse gas emissions trends and projections in Europe 2009 – Taking progress towards Kyoto targets*.

Finco, A., Bentivoglio, D., & Nijkamp, P. (2012). Integrated evaluation of biofuel production options in agriculture : An exploration of sustainable policy scenarios. *International Journal of Foresight and Innovation Policy*, *8*(2-3), 173–188.

Finnveden, G. (1999). *A critical review of operational valuation/weighting methods for life cycle assessment (AFR-REPORT 253 AFN)*. Swedish Environmental Protection Agency, Stockholm.

Geldermann, J., & Rentz, O. (2005). Multi-criteria Analysis for Technique Assessment: Case Study from Industrial Coating. *Journal of Industrial EcologyTechnology*, *9*(3), 127–142.

Hayashi, T., van Ierland, E. C., & Zhu, X. (2014). A holistic sustainability assessment tool for bioenergy using the Global Bioenergy Partnership (GBEP) sustainability indicators. *Biomass and Bioenergy*, *66*, 70–80. doi:10.1016/j.biombioe.2014.01.040

Heijungs, R., Guinée, J., Kleijn, R., & Rovers, V. (2007). Bias in normalization: Causes, consequences, detection and remedies. *The International Journal of Life Cycle Assessment*, *12*(4), 211–216.

doi:10.1007/s11367-006-0260-x

Ishizaka, A., & Nemery, P. (2013). *Multi-criteria Decision Analysis: Methods and Software*. Chichester: Wiley.

Kadziński, M., & Tervonen, T. (2013). Robust multi-criteria ranking with additive value models and holistic pair-wise preference statements. *European Journal of Operational Research*, *228*(1), 169–180. doi:10.1016/j.ejor.2013.01.022

Kralisch, D., Staffel, C., Ott, D., Bensaid, S., Saracco, G., Bellantoni, P., & Loeb, P. (2013). Process design accompanying life cycle management and risk analysis as a decision support tool for sustainable biodiesel production. *Green Chemistry*, *15*(2), 463–477. doi:10.1039/c2gc36410g

Lahdelma, R., Hokkanen, J., & Salminen, P. (1998). SMAA - Stochastic multiobjective acceptability analysis. *European Journal of Operational Research*, *106*, 137–143.

Lahdelma, R., & Salminen, P. (2001). SMAA-2 : Stochastic multicriteria acceptability analysis for group decision making. *Operations Research*, *49*(3), 444–454.

Leskinen, P., Viitanen, J., Kangas, A., & Kangas, J. (2006). Alternatives to Incorporate Uncertainty and Risk Attitude in Multicriteria Evaluation of Forest Plans. *Forest Science*, *52*(3), 304–312.

Maimoun, M., Madani, K., & Reinhart, D. (2016). Multi-level multi-criteria analysis of alternative fuels for waste collection vehicles in the United States. *The Science of the Total Environment*, *550*, 349–361. doi:10.1016/j.scitotenv.2015.12.154

Malça, J., Coelho, A., & Freire, F. (2014). Environmental life-cycle assessment of rapeseed-based biodiesel: Alternative cultivation systems and locations. *Applied Energy*, *114*, 837–844. doi:10.1016/j.apenergy.2013.06.048

Mohamadabadi, H. S., Tichkowsky, G., & Kumar, A. Ã. (2009). Development of a multi-criteria assessment model for ranking of renewable and non-renewable transportation fuel vehicles. *Fuel*, *34*, 112–125. doi:10.1016/j.energy.2008.09.004

Myllyviita, T., Holma, A., Antikainen, R., Lähtinen, K., & Leskinen, P. (2012). Assessing environmental impacts of biomass production chains – application of life cycle assessment (LCA) and multi-criteria decision analysis (MCDA). *Journal of Cleaner Production*, *29-30*, 238–245. doi:10.1016/j.jclepro.2012.01.019

Myllyviita, T., Leskinen, P., & Seppälä, J. (2014). Impact of normalisation, elicitation technique and background information on panel weighting results in life cycle assessment. *International Journal of Life Cycle Assessment*, *19*, 377–386. doi:10.1007/s11367-013-0645-6

Narayanan, D., Zhang, Y., & Mannan, M. S. (2007). Engineering for sustainable development (ESD) in bio-diesel production. *Process Safety and Environmental Protection*, *85*, 349–359. doi:10.1205/psep07016

Perimenis, A., Walimwipi, H., Zinoviev, S., & Miertus, S. (2011). Development of a decision support tool for the assessment of biofuels. *Energy Policy*, *39*, 1782–1793. doi:10.1016/j.enpol.2011.01.011

Prado-Lopez, V., Seager, T. P., Chester, M., Laurin, L., Bernardo, M., & Tylock, S. (2014). Stochastic multi-attribute analysis (SMAA) as an interpretation method for comparative life-cycle assessment (LCA). *International Journal of Life Cycle Assessment*, *19*, 405–416. doi:10.1007/s11367-013-0641-x

Ren, J., Manzardo, A., Mazzi, A., Zuliani, F., & Scipioni, A. (2015). Prioritization of bioethanol production pathways in China based on life cycle sustainability assessment and multicriteria decision-making. *International Journal of Life Cycle Assessment*, *20*(6), 842–853. doi:10.1007/s11367-015-0877-8

Rivière, C., & Marlair, G. (2009). BIOSAFUEL®, a pre-diagnosis tool of risks pertaining to biofuels chains. *Journal of Loss Prevention in the Process Industries*, *22*(2), 228–236. doi:10.1016/j.jlp.2008.09.014

Rogers, K., & Seager, T. P. (2009). Environmental Decision-Making Using Life Cycle Impact Assessment and Stochastic Multiattribute Decision Analysis : A Case Study on Alternative Transportation Fuels. *Environmental Science & Technology*, *43*(6), 1718–1723.

Seppälä, J., Basson, L., Norris, G. A., Seppala, J., Basson, L., & Norris, G. A. (2002). Decision Analysis frameworks for Life-Cycle Impact Assessment. *Journal of Industrial Ecology*, *5*(4), 45–68.

Seppälä, J., & Hämäläinen, R. P. (2001). On the meaning of the distance-to-target weighting method and normalisation in Life Cycle Impact assessment. *The International Journal of Life Cycle Assessment*, *6*(4), 211–218. doi:10.1007/BF02979376

Streimikiene, D., Balezentis, T., & Balezentiene, L. (2013). Comparative assessment of road transport technologies. *Renewable and Sustainable Energy Reviews*, *20*, 611–618.

Suwelack, K., & Wüst, D. (2015). An approach to unify the appraisal framework for biomass conversion systems. *Biomass and Bioenergy*, *83*, 354–365. doi:10.1016/j.biombioe.2015.10.012

Tervonen, T. (2014). JSMAA: open source software for SMAA computations. *International Journal of Systems Science*, *45*(1), 69–81. doi:10.1080/00207721.2012.659706

Tervonen, T., & Lahdelma, R. (2007). Implementing stochastic multicriteria acceptability analysis. *European Journal of Operational Research*, *178*(2), 500–513. doi:10.1016/j.ejor.2005.12.037

Turcksin, L., Macharis, C., Lebeau, K., Boureima, F., Van Mierlo, J., Bram, S., … Pelkmans, L. (2011). A multi-actor multi-criteria framework to assess the stakeholder support for different biofuel options: The case of Belgium. *Energy Policy*, *39*(1), 200–214. doi:10.1016/j.enpol.2010.09.033

von Winterfeldt, D., & Edwards, W. (1986). *Decision analysis and behavioral research*. New York: Cambridge University Press.

Zhou, Z., Joang, H., & Qin, L. (2007). Life cycle sustainability assessment of fuels. *Fuel*, *86*, 256–263. doi:10.1016/j.fuel.2006.06.004