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Analysis of cost-environmental trade-offs in biodiesel production incorporating waste feedstocks: A multi-objective programming approach

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A B S T R A C T

Decision-makers in government and industry must develop policy and strategy for highly complex systems, trading off competing objectives such as environmental and economic impact. These trade-offs can be difficult to analyze, which may lead to misinformed choices. There is lack of decision support tools that both include multiple objectives and facilitate communication to decision-makers in a comprehensive and simple way. To address this gap, a mathematical model that facilitates the decision process by allowing an agent to decide based on an explicit overall economic and environmental performance but simultaneously visualize graphically the trade-offs among the different objectives was developed. This model was used to assess the trade-offs of using waste-based feedstocks in blends with conventional feedstocks for biodiesel production, and explore opportunities to improve biodiesel cost effectiveness whilst managing environmental impacts, particularly in the feedstock selection process. The compositional uncertainty of the feedstocks is considered in the model ensuring that the final quality of the biodiesel is not compromised by the high uncertainty associated with the composition of waste materials. Reductions on production costs (3%) and on environmental impacts (from 2% to 32%) were obtained using this model to select the blend composition. The model was shown to be useful to inform decision-making by allowing comprehensive, simplified visualization of the trade-offs among cost and environmental impacts. The model can be used to support biodiesel production planning with lower environmental impacts.

1. Introduction

The combination of Life-Cycle Assessment (LCA), a tool used to assess environmental impacts, with multi-objective optimization (MOO), a mathematical modeling tool that supports decision-making considering multiple objectives, has led to the development of life-cycle multi-objective (LCMO) frameworks to analyze trade-offs between environmental and economic aspects in several applications (Jacquemin et al., 2012; Pieragostini et al., 2012; Yue et al., 2016). Case studies can be found in the literature in several areas such as processing (Capón-Garcia et al., 2011), recycling (Ponce-Ortega et al., 2011), energy systems (Bamufleh et al., 2012; Cristóbal et al., 2012; Gerber and Gassner, 2011; Gutiérrez-Arriaga et al., 2012; López-Maldonado et al., 2011), or buildings (Carreras et al., 2015; Safaei et al., 2015). Nevertheless, they are often focused on a single economic and a single environmental objective, typically greenhouse gas (GHG) emissions. A few studies include a higher number of objectives, like is the case of the recent work presented by Vadenbo et al. (2017) that developed an environmental multi-objective optimization model to determine the environmentally optimal use of biomass for energy using the

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Danish energy system as case study. In this work, six environmental impact categories are considered to be minimized. However, a pitfall of these studies is the lack of a simple and intuitive visual communication of the trade-offs among the different objectives in order to facilitate the decision process.

The challenge of including more environmental impact categories as objective functions in a LCMO model is related to the complexity of trade-off analysis when considering many competing objectives. For example, one may be concerned on minimizing GHG emissions and costs but in fact, the solution that minimizes these two objectives may bring burdens to other relevant environmental issues such as water scarcity. For this reason, the development of tools that facilitate the trade-off analysis and the decision process is very important within the LCMO framework (Tsang et al., 2014). This paper presents an alternative LCMO decision-aiding approach that facilitates the decision process by allowing the decision-maker to decide based on an explicit overall environmental performance and, at the same time, visualize the trade-offs among the different objectives to support decisions in a more comprehensive manner.

The model developed is illustrated by assessing the use of Waste Cooking Oils (WCO) in blends for biodiesel production. WCO have been gaining prominence as an alternative feedstock for biodiesel production due to their potential to improve the economic and environmental performance of biodiesel compared with crop-based oils (e.g. soya, rapeseed or palm, also designated as virgin oils in this paper) (Caldeira et al., 2015; Carla Caldeira et al., 2016; Dufour and Iribarren, 2012). However, the high uncertainty and variability in WCO chemical composition due to a high diversity of sources hinder guaranteeing biodiesel quality (Knothe and Steidley, 2009). A potential strategy to deal with this issue is to blend WCO with virgin oils, such as soybean, rapeseed, and palm oil as presented by Caldeira et al. (2017b). The authors showed that, using chance constrained programming (CCP) to address compositional uncertainty, blends containing WCO can have the same technical performance as blends composed only of virgin oils while reducing costs. However, besides costs, it is also important to assess the potential environmental benefits. Although the main environmental concern of biodiesel is related to GHG emissions, another relevant aspect to consider when evaluating the environmental impacts of biodiesel is water use. Water use impacts have been insufficiently addressed in the literature, but if the location where the crops are cultivated is water scarce, the water consumption impacts can be significant (Pfister and Bayer, 2014). Moreover, the water quality may be compromised due to the use of fertilizers and pesticides in the crops cultivation (Emmenegger et al., 2011).

Few studies can be found in the literature that combine LCA and MO under uncertainty. Some of these studies are focused on the uncertainty of the LCA impact either by using CCP (Guille and Grossmann, 2009; Guillén-Gosálbez and Grossmann, 2010) or by describing the LCA uncertain parameters through scenarios with given probability of occurrence (Sabio et al., 2014). Other studies address uncertainty related to prices and demand uncertainty, using scenarios with given probability of occurrence in the design of sustainable chemical supply chains (Ruiz-Femenia et al., 2013) and chemical processes network (Alothman and Grossmann, 2014) or, uncertainty in several parameters expressed as fuzzy possibility distributions and probability distributions to help design better waste management strategies (Zhang and Huang, 2013). No study that optimizes blends for biodiesel production minimizing costs and multiple environmental impacts considering the feedstocks compositional uncertainty was found in the literature.

This paper presents a model to facilitate trade-off analysis in LCMO problems illustrating its use in the assessment of the incorporation of secondary material (WCO) in blends for biodiesel production. The model objectives (to minimize) include feedstock costs, life-cycle GHG emissions, water scarcity, toxicity, acidification and eutrophication impacts. The oils compositional uncertainty is incorporated in the model, minimizing the risk of noncompliance with biodiesel technical requirements. The efficient solutions obtained allow the production planner to analyze the trade-offs between economic and environmental performance, and select blends that will lead to a product with lower environmental impacts.

2. Material and methods

2.1. Life-cycle multi-objective (LCMO) chance constrained model

The model framework is presented in Fig. 1. The model determines blends that minimize costs and environmental impacts by calculating the quantity of each feedstock (palm, rapeseed, soya and WCO) to use in the blend, addressing the feedstock compositional uncertainty. The input information is the profile of the different feedstocks: chemical composition and its associated uncertainty, costs and environmental impacts. The outputs are optimal blends that are in compliance with the required biodiesel properties with minimum cost and environmental impact. Typically, there is no feasible solution that minimizes costs and all the environmental impacts simultaneously thus, the model is a decision support tool that helps decision-makers find Pareto-optimal solutions, i.e. solutions such that it is not possible to improve one of the objectives without worsening some other objective. Decision-makers may thus observe the trade-offs between their objectives and select their most preferred solution.

Since the biodiesel production cost is mainly attributed to feedstock costs (about 85%) (Haas et al., 2006), the costs considered in the model concern the purchase of feedstock. Price information from 2011 to May 2014 for palm, canola and soya oils was taken from IndexMundi (2014) and prices for WCO were obtained from a European broker (Grennea, 2014). The month July 2013 was selected because it is the month when the price of WCO was closer to the virgin oils price, which represents a conservative situation to evaluate the benefits of WCO. The prices were 559 €, 767 €, 765 € and 400 € per ton of palm, rapeseed, soya and WCO. The environmental impacts categories include: Climate Change (CC), Water Stress Index (WSI), Freshwater Eutrophication (FE), Aquatic Acidification (AC), Human Toxicity (HT) and Ecotoxicity (ET). The model is illustrated using the Portuguese context as a case study because the authors had access to primary data and detailed information about the biodiesel production in Portugal to determine the environmental impacts of the feedstocks used in the model. Nevertheless, this case is used to illustrate the model and the assessment herein presented can be replicated for biodiesel production in other countries.

2.1.1. Life-Cycle Assessment model

LCA was used to assess the environmental profile of four feedstocks: three crop-based oils (palm, soya and rapeseed) and WCO. The data used to build the LCA model was retrieved from another work done by some of the authors (Caldeira et al., 2018). As the goal of this paper is to illustrate the LCMO model, the LCA model is

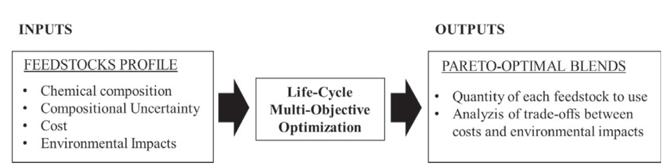

Fig. 1. Life-cycle multi-objective chance constrained model framework.

briefly described and the impacts values used in the optimization model are presented in Table 1. The life-cycle (LC) model was built to assess the GHG emissions impacts (CC), water consumption impacts (measured by the impact category WSI) and water degradability impacts (measured by the impact categories FE, AC, HT and ET). The functional unit chosen was 1 kg of vegetable oil. It is assumed that after the refining step, the virgin oils and the WCO have the required characteristics for the transesterification reaction (biodiesel production). Technically, the production of biodiesel from WCO is similar to conventional transesterification processes of the virgin oils (Knothe et al., 1997). The variation on the energy content (low heating value) of biodiesel produced from palm, soya, rapeseed and WCO is below 1% (Hoekman et al., 2012).

The system boundaries of the crop-based oils systems, schematically represented in Fig. 2, include cultivation, oil extraction, feedstock transportation and oil refining, considering that the oils are refined in Portugal. Different cultivation locations were considered: Colombia and Malaysia for palm fruit; Argentina, Brazil and US for soybean; and, Germany, France, Spain, Canada and US for rapeseed. The palm oil extraction was made in the cultivation site while the soya and rapeseed oils were extracted in Portugal. The transportation of the palm oil, soybeans and rapeseeds to Portugal was considered in the model.

Virgin oil production is a multifunctional system because from the oils extraction phase other co-products are obtained: from palm oil extraction is also obtained palm kernel meal and kernel oil; from soybean oil extraction, soybean meal; and, from rapeseed oil, rapeseed meal. The distribution of the impacts between the oils and the co-products was made using energy allocation (method suggested in the European Directive 2009/28/EC (European Comission, 2009) on the promotion of the use of energy from renewable sources).

For the WCO, the stages considered within the system boundaries (Fig. 2) are the WCO collection and refining in Portugal. Depending on the quality of the WCO (mainly related to the percentage of free fatty acids, FFA) the refining process is different. For low quality WCO, the refining consists in an acid-catalyzed process to reduce the percentage of FFA (Jungbluth et al., 2007) while for high quality WCO, the refining consists in filtering to remove impurities and heating to remove water (above 100 °C during approximately 2 h) (Caldeira et al., 2015). The two alternative WCO refining processes are considered in the study.

The inventory was built with data collected from several references: palm cultivation and palm oil extraction in Colombia

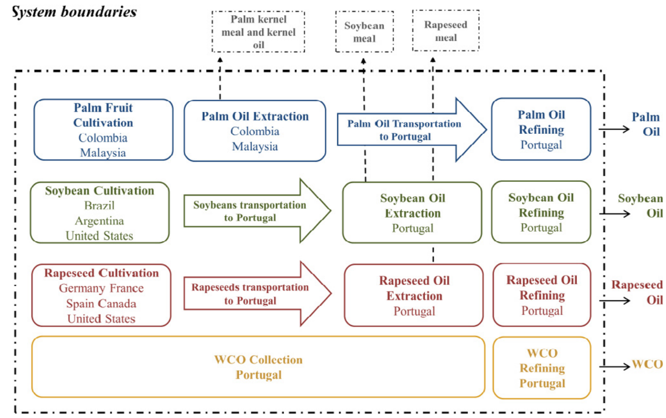

Fig. 2. System boundaries of the oils systems.

(Castanheira et al., 2014); palm cultivation and palm oil extraction in Malaysia, Ecoinvent 3.1 database (Jungbluth et al., 2007) soybeans cultivation in Argentina (considering the reduced tillage cultivation system) (Castanheira and Freire, 2013); soybeans cultivation in Brazil (considering cultivation in Mato Grosso) (Castanheira et al., 2015); soybeans cultivation in the US, Ecoinvent 3.1 database (Jungbluth et al., 2007); rapeseed cultivation in Spain, Germany, France, Canada (Malça et al., 2014); rapeseed cultivation in the US, Ecoinvent 3.1 database; soybean oil extraction in Portugal (Castanheira et al., 2015); rapeseed oil extraction (Castanheira and Freire, 2016); palm, soybean and rapeseed oils refining, (Castanheira and Freire, 2016); low quality WCO refining (Jungbluth et al., 2007); high quality WCO refining (Caldeira et al., 2016) and WCO collection (Caldeira et al., 2015, 2016).

Climate Change (CC) and Freshwater Eutrophication (FE) were assessed using the impact assessment method ReCiPE (Goedkoop et al., 2009); water consumption impacts (WSI) using the method presented by Pfister et al. (2009) and Ridoutt and Pfister (2013); Aquatic Acidification (AC) using Impact 2002+ (Jolliet et al., 2003); and Human toxicity (HT) and Ecotoxicity (ET) using Usetox recommended version (Rosenbaum et al., 2008).

2.1.2. *Addressing feedstock compositional uncertainty using chance constrained optimization*

Compositional uncertainty has been addressed by several authors using chance constrained programming (CCP) optimization

Table 1
Environmental impacts - Climate Change (CC), Water Stress Index (WSI), Freshwater Eutrophication (FE), Aquatic Acidification (AC), Human Toxicity (HT) and Ecoxicity (ET) - for the different oils analyzed, palm, soya, rapeseed and WCO (Caldeira et al., 2018).

Feedstock_origin	CC	WSI	FE	AC	HT	ET
	kg CO_2 eq kg^{-1} oil	m^3 eq kg^{-1} oil	kg P eq kg^{-1}oil ($\times 10^{-4}$)	kg SO_2 eq kg^{-1}oil ($\times 10^{-2}$)	CTUh kg^{-1} oil ($\times 10^{-11}$)	CTUhe kg^{-1} oil
Palm_CO	0.90	0.076	3.98	1.24	0.44	0.004
Palm_MY	0.72	0.078	1.83	1.09	0.69	2.47
Soya_AR	0.90	0.264	7.15	0.80	0.74	5.54
Soya_BR	1.29	0.109	7.81	1.08	1.08	8.32
Soya_US	1.23	0.088	1.97	1.02	40.1	0.39
Rapeseed_DE	1.69	0.111	2.62	2.23	1.1	0.45
Rapeseed_FR	1.68	0.182	2.6	2.56	60.2	6.57
Rapeseed_SP	1.85	2.113	2.87	2.88	213.0	23.38
Rapeseed_CN	1.75	0.095	4.42	2.84	79.2	18.06
Rapeseed_US	3.32	0.172	1.88	3.30	52.2	3.09
WCO_PT _Hi[a]	0.23	0.0020	0.71	0.15	1.37	0.03
WCO_PT_Lo[b]	0.12	0.0015	0.56	0.01	1.33	0.03

CO:Colombia, MY:Malaysia AR:Argentina, BR:Brazil, US:United States, DE:Germany, FR:France, SP:Spain, CA:Canada, PT:Portugal.
[a] High Quality Waste Cooking Oil.
[b] Low Quality Waste Cooking Oil.

(Gaustad et al., 2007; Gülşen et al., 2014; Li et al., 2012; Sakallı et al., 2011). The application of CCP in blend optimization of conventional feedstocks (palm, canola, sunflower and soya) used in biodiesel production showed that feedstock diversification (blending) can: i) help control costs while ensuring fuel quality by spreading the risk of price volatility across multiple feedstocks (Gülşen et al., 2014); and, ii) manage GHG emissions uncertainty characteristics of biodiesel (Olivetti et al., 2014).

Using CCP formulation, Caldeira et al. (2017b) analyzed the use of a secondary material (WCO) in blends with conventional feedstocks. The same set of constraints was used in this paper to address compliance with technical constraints in face of composition uncertainty. The constraints were defined based on existing prediction models that relate the composition, specifically the vegetable oils fatty acids (FA) content of the feedstocks and biodiesel properties: density (Den), cetane number (CN), cold filter plugging point (CFPP), iodine value (IV) and oxidative stability (OS) (Caldeira et al., 2017a). The explanation of these prediction models and derivation of these constraints can be found in previous work of the authors (Caldeira et al., 2017b, 2014).

2.1.3. Model formulation

The mathematical formulation of the problem is presented below and the nomenclature used is described in Table 2. The goal is to determine the Pareto optimal blend that minimizes production costs and environmental impacts that are calculated according to equation (1), multiplying the quantity of each feedstock used in the blend (the decision variable in the model, QU_i) by the coefficient for each objective k of each feedstock i ($C_{k,i}$). This coefficient indicates the cost or impact on objective k per unit of feedstock i used in the blend. Table 1 presents the coefficients of the environmental impact for each feedstock and, as explained in section 2.1 (2nd paragraph), the coefficient for the feedstock prices were 559 €, 767 €, 765 € and 400 € per ton of palm, rapeseed, soya and WCO. The model is subject to demand and supply constraints (equations (2) and (3)). Since the goal is to analyze the proportion of each feedstock in the blend, the demand was set equal to 1 and no supply limitations were considered. For each property (Den, CN, CFPP, IV and OS) the final blend must comply with the technical specifications (equations (4) and (5) for lower and upper limits). β represents a risk tolerance parameter that determines the maximum accepted non-compliance rate level chosen by the user. Assuming a normal distribution of the uncertain parameter ($q_{i,j}$), β is the normal distribution test coefficient (z-value), one-tailed. The constraints thresholds were defined according to the European Standard EN 14214 (CEN, 2008).

Objective functions

$$\min z_k = \sum_{i \in I} (C_{k,i}\, QU_i) \quad \forall\ k \tag{1}$$

Demand and Supply constraints

$$\sum_{i \in I} QU_i = D \tag{2}$$

$$QU_i \le S_i\ \forall\ i \tag{3}$$

Technical Constraints

$$\sum_{j \in J}\left(PropCoef_{l,j} \sum_{i \in I} QU_i\, \overline{q}_{ij}\right) + PropConst_l - \beta \sqrt{\sum_{j \in J} PropCoef_{l,j}^2 \sum_{i \in I} QU_i^2 \sigma_{ij}^2} \ge PropGT_l \quad \forall\ l \tag{4}$$

$$\sum_{j \in J}\left(PropCoef_{m,j} \sum_{i \in I} QU_i \overline{q}_{ij}\right) + PropConst_m + \beta \sqrt{\sum_{j \in J} PropCoef_{m,j}^2 \sum_{i \in I} QU_i^2 \sigma_{ij}^2} \le PropLT_m \quad \forall\ m \tag{5}$$

$$QU_i \ge 0 \quad \forall\ i \tag{6}$$

2.2. An approach to facilitate the trade-off analysis between cost and environmental impacts

As typically occurs in multi-objective problems, the competing nature of the objectives makes it difficult for decision-makers to identify the "best" solution. Methods exist that use "à priori" decision-maker preferences to aggregate the multiple objectives into a single objective (by attributing weights to each objective). However, the decision-maker may find it hard to define such weights in an explicit way in the absence of a thorough

Table 2
Biodiesel blending optimization problem nomenclature.

Indices and sets	$i \in I$	I = {soya, canola, palm, WCO}, feedstock oils
	$k \in K$	K = {Cost, CC, WSI, FE, AC, HT, ET}, objective functions
	$j \in J$	J = {1, 2, …, 18}, Fatty Acids (FA) 1 to 18 types of FA
	$l \in L$	L = {DenLB, CN, OS}, set of properties with lower limit
	$m \in M$	M = {DenUB, IV, CFPP}, set of properties with upper limit
Parameters	$C_{k,i}$	Coefficient of objective k concerning feedstock i
	D	Demand
	S_i	Supply of feedstock i
	$\overline{q}_{i,j}$	Average quantity (%) of FA-j in feedstock i
	$\sigma_{i,j}$	Standard deviation for $q_{i,j}$
	$PropCoef_{l,j}$	Coefficient of FA-j in the prediction model for property l
	$PropCoef_{m,j}$	Coefficient of FA-j in the prediction model for property m
	$PropConst_l$	Constant in the prediction model for property l
	$PropConst_m$	Constant in the prediction model for property m
	$PropGT_l$	Threshold for property l
	$PropLT_m$	Threshold for property m
	β	Test coefficient for normal distribution, one tailed
Decision Variables	QU_i	Quantity of feedstock i to use in the blend

understanding of the problem.

Alternatively, an approach to visualize the trade-off among cost and environmental impacts without attributing weights to objectives is the ε-constraint method, in which one objective is minimized while the other are considered as constraints. In particular, if cost is the objective being minimized, the following (mono-objective) mathematical program could be solved:

Objective function

$$\min z_{Cost} = \sum_{i \in I} (C_{Cost,i}\, QU_i) \tag{7}$$

Subject to:

$$z_k = \sum_{i \in I} (C_{k,i}\, QU_i) \le \varepsilon_k \quad \forall\ k \ne Cost \tag{8}$$

Demand and Supply constraints, i.e. equations (2) and (3)

Technical Constraints, i.e. equations (4)–(6).

The above mathematical program yields a Pareto-optimal solution for each combination of impact limits defined by the ε_k right-hand side values, if feasible (some limits might be impossible to attain). Hence, different solutions can be obtained by varying these limits. However, it might be difficult for a decision-maker to deal with all the ε_k parameters simultaneously. For this reason, in this work a single parameter Θ is used to define Pareto-optimal solutions corresponding to cost versus environmental impact trade-offs. This approach consists in replacing all the ε_k-constraints in equation (8) by the constraints in equation (9):

$$\sum_{i \in I} (c_{k,i} \cdot QU_i) \le Ideal + \Theta(Anti\ ideal - Ideal) \quad \forall k \setminus \{Cost\},\ \theta\ \varepsilon [0,1] \tag{9}$$

In this equation, Θ is a parameter that reflects the constraint level of the environmental impacts and ranges from 0 to 1. The so-called "ideal" and "anti-ideal" values are obtained by optimizing each environmental objective at a time. The "ideal" value for each objective corresponds to minimum impacts on this objective among all the solutions. The "anti-ideal" value for each objective is the maximum impact found when examining the solutions that optimize the other objectives. The "ideal" and "anti-ideal" values provide an indication of the range of impacts obtained by Pareto optimal solutions. When $\Theta = 1$, the environmental impacts are allowed to be as high as the "anti-ideal" value and the solution with the minimum cost can be obtained. As Θ decreases, the upper limit for all environmental impacts also decreases, departing from the "anti-ideal" values and getting closer to the "ideal" values (e.g., $\Theta = 0.5$ means that the upper limit on each environmental indicator will be halfway between the ideal and anti-ideal values). Thus, the feasible region decreases leading to more expensive solutions, up to a minimum value (Θ_{Lim}) such that for $\Theta < \Theta_{Lim}$ the problem becomes unfeasible. The parameter Θ determines if the decision-maker wants to be closer to the environmental impacts "ideal" value and therefore, having the best environmental performance (within the constraints of the problem), or to be closer to minimum costs achievable. The decision-maker can vary Θ to learn what the involved trade-offs are, and results can be conveniently depicted graphically presenting costs as a function of Θ.

The model was implemented in GAMS 24.4. (GAMS, 2011). The problem was solved using the non-linear solver CONOPT (Drud, 2014) which is well suited for models with nonlinear constraints with a fast method for finding a first feasible solution for very constrained models. The solver makes use of the Generalized Reduced Gradient (GRG) method with some extensions added. It has been widely used for solving stochastic and multi-objective optimization models (Cristóbal et al., 2012; Guillén-Gosálbez and Grossmann, 2010; López-Maldonado et al., 2011; Sabio et al., 2014). Each run of the model took approximately 40 s on an intel (R) Core ™ i5-3337U CPU@ 1.8 GHz machine.

3. Results and discussion

It was first analyzed the results of the model minimizing three objectives because this is the limit of objectives that can be visualized: costs, climate change (CC) and water consumption impacts (WSI) (section 3.1). Then, the assessment was extended by adding the other environmental impact categories FE, AC, HT, ET. In this situation, since it is impossible to visualize the trade-offs the approach described in 2.2 was used. Results are presented in section 3.2. The analysis was performed for two cases: a) WCO is available to blend with the virgin oils; and, b) only virgin oils are available (the reference scenario for biodiesel production in Portugal for the price period considered). The latter is used as benchmark to evaluate the use of WCO in the blends.

3.1. Cost, climate change and water consumption

This section presents and discusses the results obtained by minimizing costs, CC and WSI. Table 3 presents the pay-off tables obtained for both scenarios considering three objectives: Cost, Climate Change (CC) and Water Stress index (WSI). Each row corresponds to minimizing a different objective. The diagonal of each table (bold values) presents the "ideal" value of each objective (column) and the shaded area indicates the "anti-ideal" value of each objective.

When WCO is available to blend with the virgin oils, the blends incorporate 34% of WCO when the cost objective is minimized, 10% when CC is minimized and 32% when WSI is minimized. The incorporation of WCO allows a reduction of the minimum value obtained for each objective ("ideal" values) comparatively to the

Table 3
Pay-off tables obtained by minimizing cost, CC and WSI in two scenarios: a) WCO is available to blend with the virgin oils and, b) only virgin feedstocks are available.

	a) With WCO			b) Without WCO		
Objective minimized	Cost (€/ton)	CC (kg CO_2 eq kg^{-1} oil)	WSI (m^3 eq kg^{-1} oil)	Cost (€/ton)	CC (kg CO_2 eq kg^{-1} oil)	WSI (m^3 eq kg^{-1} oil)
Cost	**642.7**	1.48	0.354	**662.4**	1.43	0.304
CC	677.9	**1.07**	0.149	692.1	**1.09**	0.159
WSI	650.1	1.31	**0.065**	689.6	1.26	**0.086**

The diagonal contains "ideal" values of the objective (column).
The shaded values are "anti-ideal" values of the objective (column).

"ideal" values obtained with blends composed only of virgin oils (Table 3). The "ideal" value for cost, CC and WSI obtained with WCO available are 3%, 2% and 32% lower than the "ideal" values obtained when only virgin feedstocks are available. Also the "anti-ideal" value for cost is lower (2%) when WCO are included in the blend. Nevertheless, for the "anti-ideal" values for CC and WSI there is an increase of 3% and 14%.

A set of Pareto optimal solutions were obtained using the ε-constraint method miminizing costs and using CC and WSI as constraints, incorporating them in the constraint part of the model. The contraint level ranges, interactively, from the "anti-ideal" to the "ideal" values presented in Table 3**.** The iteration step for each objective is one tenth of the difference between the "anti-ideal" and "ideal" value. Fig. 3 shows the Pareto surface obtained minimizing cost, CC and WSI for the two scenarios considered: (a) having WCO available in the model (right-hand side) and, (b) without WCO available (left-hand side). The Pareto surface is displaced to lower costs when WCO is included in the blends. The quantity of WCO incorporated in the blends ranges from 10% to 34%. Lower CC and WSI solutions can be obtained at a lower cost if WCO is included in the blends.

3.2. Extended environmental assessment

In this section, the analysis was extended to include the other environmental impacts: eutrophication (FE), acidification (AA), human toxicity (HT) and ecotoxicity (ET). The pay-off tables obtained for the two scenarios, with and without WCO available, are presented in Table 4 and Table 5. Similarly to what was observed for the "ideal" values obtained for cost, CC and WSI, the use of WCO also reduces the ideal values in 9% for FE, 3% for AA and 4% for ET relatively to the situation when only virgin oils are available to blend. For HT, the ideal value is the same in both situations. The quantity of WCO incorporated in the blend when minimizing FE is 33% and 11% when minimizing AA or ET. The blend obtained when minimizing HT has no WCO in its composition.

This analysis shows the potential competing nature of objectives. For example, minimizing cost leads to solutions (blends) that correspond to the anti-ideal solution for CC and WSI. On the other hand, minimizing WSI leads to the anti-ideal solution for AC, HT and ET (Table 4).

As the number of objectives increased to seven, it would be impossible to visualize the Pareto solutions as it was shown for Cost, CC and WSI in Fig. 3. In this case, the approach described in section 2.2 (equation (9)) was applied. Results for the cost obtained for different Θ for the two scenarios, with and without WCO available, are depicted in Fig. 4.

Lower cost blends are obtained if WCO is available (yellow crosses). Blend 1 was obtained setting $\Theta = 1$ and corresponds to the lowest cost solution (642.7 € ton^{-1}). Decreasing the value of Θ increases the cost and for Θ values lower than 0.15 the problem becomes unfeasible. For $\Theta_{Lim} = 0.15$ the solution corresponds to blend 7 which has a cost of 665.1 € ton^{-1}. In the scenario were WCO is not available (green squares), the cost of blend obtained with $\Theta = 1$ (Blend 1′) is 670 € ton^{-1}, 4% higher than blend 1. The Θ_{Lim} for this scenario is 0.27 and corresponds to blend 6′ that has a cost of 686.6 € ton^{-1}, 2.3% higher than Blend 7. The cost and environmental impacts obtained with $\Theta = 1$ (Blends 1, 1′) and $\Theta = \Theta_{Lim}$ (Blends 7, 6') in both scenarios (with and without WCO) are presented in Table 6.

Using 34% of WCO in Blend 1 needs to be compensated with the use of rapeseed feedstocks to comply with the technical constraints, whereas in Blend 1′ there is a high quantity of palm feedstocks (20% Palm_CO + 26% Palm_MY). Since the rapeseed feedstocks have higher impacts than the palm ones, the environmental impacts of Blend 1 are higher than those of Blend 1'. Nevertheless, with decreasing Θ, the environmental impacts decrease and for $\Theta = 0.15$ (Blend 7) the environmental impacts are

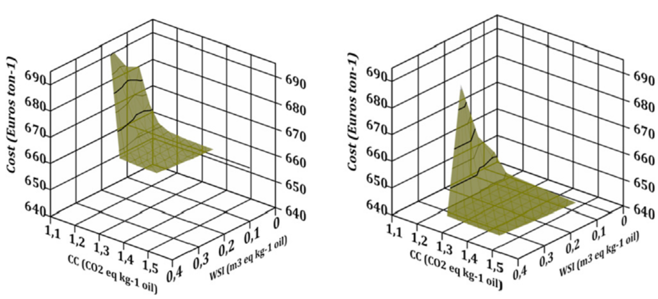

Fig. 3. Pareto surface obtained minimizing cost, climate change (CC) and water stress index (WSI) having WCO available in the model (right-hand side) and without WCO available (left-hand side).

Table 4
Pay-off table for Cost, Climate Change (CC), Water Stress Index (WSI), Freshwater Eutrophication (FE), Aquatic Acidification (AC), Human Toxicity (HT) and Ecoxicity (ET) when WCO is available.

Objective minimized	Cost €/ton	CC kg CO_2 eq kg^{-1} oil	WSI m^3 eq kg^{-1} oil	FE kg P eq kg^{-1} oil ($*10^{-4}$)	AC kg SO_2 eq kg^{-1} oil ($*10^{-2}$)	HT CTUh kg^{-1} oil ($*10^{-11}$)	ET CTUhe kg^{-1} oil
Cost	**642.7**	1.48	0.354	4.36	1.87	54.03	6.82
CC	677.9	**1.07**	0.149	3.62	1.39	13.10	4.09
WSI	650.1	1.31	**0.065**	3.22	1.98	54.32	12.30
FE	647	1.24	0.101	**1.95**	1.64	23.62	2.55
AC	676.9	1.11	0.127	3.60	**1.34**	2.79	2.36
HT	693.7	1.17	0.146	4.49	1.44	**0.74**	1.86
ET	668	1.32	0.091	3.07	1.74	0.83	**0.25**

The diagonal contains ideal values of the objective (column).
The shaded values are anti-ideal values of the objective (column).

Table 5
Pay-off table for Cost, Climate Change (CC), Water Stress Index (WSI), Freshwater Eutrophication (FE), Aquatic Acidification (AC), Human Toxicity (HT) and Ecoxicity (ET) when WCO is not available.

Objective minimized	Cost €/ton	CC kg CO_2 eq kg^{-1} oil	WSI m^3 eq kg^{-1} oil	FE kg P eq kg^{-1} oil ($*10^{-4}$)	AC kg SO_2 eq kg^{-1} oil ($*10^{-2}$)	HT CTUh kg^{-1} oil ($*10^{-11}$)	ET CTUhe Kg^{-1} oil
Cost	**662.4**	1.43	0.304	4.57	1.96	40.60	5.74
CC	692.1	**1.09**	0.159	3.87	1.43	12.37	4.24
WSI	689.6	1.26	**0.086**	3.27	1.70	38.73	6.54
FE	693.4	1.20	0.105	**2.13**	1.50	24.36	2.28
AC	689.7	1.13	0.132	3.85	**1.38**	3.35	2.57
HT	693.7	1.17	0.146	4.49	1.44	**0.74**	1.86
ET	676.9	1.35	0.096	3.21	1.80	0.79	**0.26**

The diagonal contains ideal values of the objective (column).
The shaded values are anti-ideal values of the objective (column).

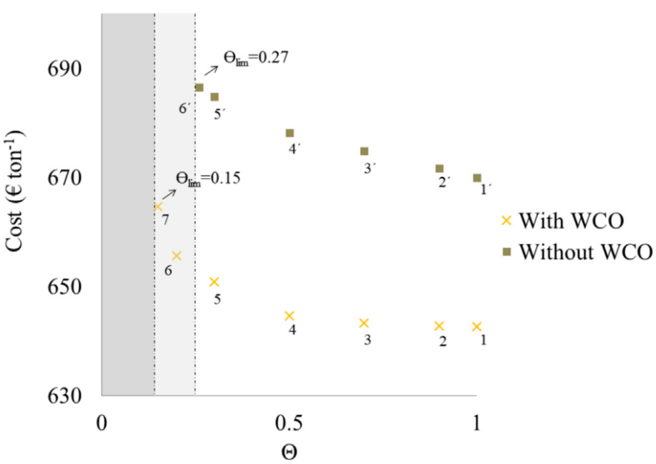

Fig. 4. Blends cost obtained for different Θ. For Θ lower than 0.15 and 0.27 the problem is unfeasible (shaded area) for the situation with and without WCO.

lower than the ones of Blend 6’ (blend with the lowest environmental impacts in the no WCO available scenario). This means that lower environmental impacts at a lower cost are obtained when WCO is available.

Additionally to Fig. 4, that so far was used to analyze the cost savings from using WCO in the blends, this approach allows to depict Fig. 5 that shows the value for each environmental impact and the position relatively to the “ideal” and “anti-ideal” value for the blends. This figure helps the decision-maker to understand in a more comprehensive manner the trade-offs associated with different Θ values. Fig. 5 shows the relative position of the solution obtained with $\Theta = 0.5$ (Blend 4) to the “ideal” and “anti-ideal” values (extreme values of the line in the graphs) and also to the solution obtained with $\Theta = 1$ (Blend 1, red dots) and with $\Theta = 0.15$ (Blend 7, green squares). The combination of Figs. 4 and 5 allows the decision-maker to visualize graphically what happens to cost (Fig. 4) and to each impact environmental objective (Fig. 5) for different values of Θ. For example, if the decision-maker wants to be sure that the blend is closer to the “ideal” value than to the “anti-ideal” in all the environmental performance objectives, Θ can be set as equal to 0.5 and the optimal solution is Blend 4 (yellow crosses in Fig. 5). The choice of Blend 4 represents an increase in the cost of 0.3% relatively to Blend 1 (lower cost blend) but a reduction of 11% in AC, 13% in CC, 40% in WSI, 45% in FE, 50% in HT and 72% in ET.

Another interesting aspect of this approach is that, if there is a limit value for a specific environmental impact category, this information can be included in the model by limiting the specific constraint and performing the analysis having that impact category limited to its threshold. This is the case, for example, for biofuels production in the EU, where the Renewable Energy Directive establishes a reduction target of 50% relatively to fossil fuel for biofuels produced after 2016 (European Comission, 2009) meaning that the oil blend must have at the most a value for CC of 1.395 g CO_2 eq kg^{-1} oil blend.

The composition of Blends 1, 4 and 7 are presented in Fig. 6.

Table 6
Results for Cost, Climate Change (CC), Water Stress Index (WSI), Eutrophication (FE), Acidification (AC), Human Toxicity (HT) and Ecotoxicity (ET) obtained for $\Theta = 1$ and $\Theta = \Theta_{lim}$ when WCO is available (a) and when it is not (b).

Objective	$\Theta = 1$ (a) (Blend 1)	$\Theta = 1$ (b) (Blend 1′)	$\Theta = 0.15$ (a) (Blend 7)	$\Theta = 0.27$ (b) (Blend 6′)
Cost (€ ton^{-1})	642.7	670.0	665.1	686.6
CC (kg CO_2 eq kg^{-1} oil)	1.48	1.22	1.17	1.18
WSI (m^3 eq kg^{-1} oil)	0.354	0.304	0.120	0.145
FE (kg P eq kg^{-1} oil $\times 10^{-4}$)	4.35	3.13	2.41	2.79
AC (kg SO_2 eq kg^{-1} oil $\times 10^{-2}$)	1.87	1.7	1.44	1.47
HT (CTUh kg^{-1} oil $\times 10^{-11}$)	54.08	27.83	8.07	11.5
ET (CTUhe kg^{-1} oil)	6.82	4.25	1.52	1.94
Quantity of WCO (%)	34	–	18	–

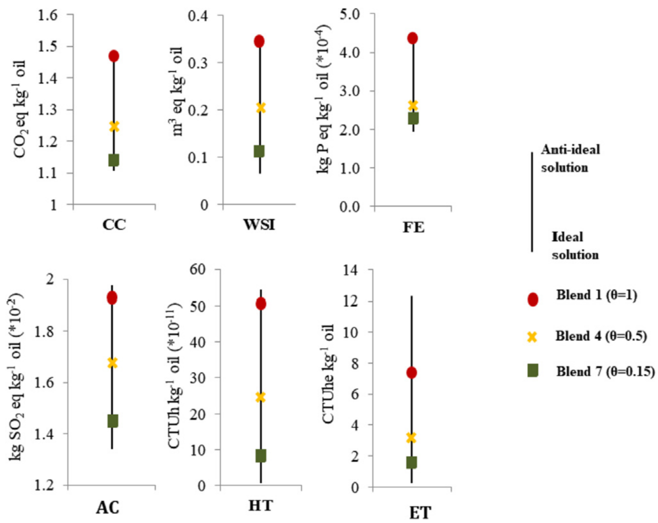

Fig. 5. Relative position to the ideal and anti-ideal values of blend 1 (obtained with $\Theta = 1$), blend 4 (obtained with $\Theta = 0.5$) and blend 7 (obtained with $\Theta = 0.15$).

Blend 1, the lowest cost blend (obtained with $\Theta = 1$), is composed of WCO and rapeseed. Since the goal is to minimize cost and this blend is obtained for the less stringent constraint level for the environmental impacts, the model distributes the quantity of WCO and rapeseed equitably for the different "types" of those feedstocks that only differ in the environmental impacts value. Blend 1 is the blend that incorporates the highest quantity of WCO, 34% (adding the low and high quality WCO).

When the feasible region contracts by decreasing Θ, the quantity of WCO diminishes and palm is added to the blend. The quantity of WCO incorporated in Blend 4 is 32%. For $\Theta_{Lim} = 0.15$, Blend 7 is the optimal blend obtained and the four types of feedstock compose it: palm, soya, rapeseed and WCO. The quantity of WCO in this blend is 18%. The quantity of WCO in the blend diminishes with decreasing Θ because WCO have higher impacts for HT and to reduce this category, this feedstock is replaced by others that have lower impacts such as Palm_MY, Soya_US or Rapeseed_DE.

An interesting aspect to analyze is the fact that the blend with lower environmental impacts (obtained with $\Theta = 0.15$) presents a higher diversity of feedstocks and an uneven distribution in opposition to what is observed for $\Theta = 1$. When the value of Θ is decreased up to the limit of the model feasibility ($\Theta = 0.15$) the constraints for the environmental impacts are quite demanding (impacts cannot surpass the ideal value plus 15% of the difference between the anti-ideal and ideal values) and the model selects feedstocks that, although being more expensive, have lower environmental impacts in some categories relatively to rapeseed and even WCO. Nevertheless, since each of the feedstocks have different environmental profiles, the model will blend different proportions of each. For example, it selects Palm_MY, Soya_AR and Soya_Br because these feedstocks have lower environmental impacts for HT (Table 1). Also the proportion of Rapeseed_DE is higher in the blend because among the rapeseeds is the one with lower impacts for HT. Additionally, the amount of WCO is reduced because these have higher impacts for HT than, for example, palm. The share of rapeseed has to be kept to comply with the technical constraints. The proportion of the two WCO feedstocks is the same because both WCO feedstocks have similar environmental impacts profile (Table 1) and the differences between them is not sufficient to change their proportion in the blend, considering the other feedstocks environmental impact profile. This is why the lower environmental impacts solution (obtained with $\Theta = 0.15$) presents more diversity of feedstocks and proportions (the other environmental impact categories are also taken into account but their influence is not so evident because the values for the alternative feedstocks are not so different).

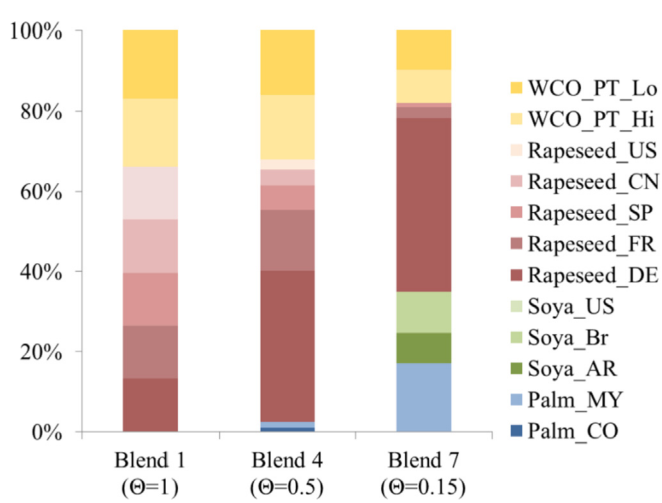

Fig. 6. Blends composition obtained for $\Theta = 1$, $\Theta = 0.5$ and $\Theta = 0.15$ (Θ_{Lim}).

One should note that the results obtained correspond to a single period price – July 2013. As mentioned in section 2.1, this period was selected to illustrate the model because it is the month when the price of WCO is closer to the virgin oils price, representing a more conservative situation to evaluate the cost benefits of WCO. Nevertheless, although in the other periods the use of WCO is expected to be beneficial, the type and quantity of each feedstock used in the blend may change and consequently, the environmental impacts of the blends may also be different.

4. Conclusions

The decision-aiding model herein presented was developed combining environmental LCA with blending algorithms using multi-objective optimization towards novel engineering systems methodologies to analyze and better communicate potential trade-offs among multiple objectives. It was used to assess economic and environmental trade-offs of decisions at the operational level in biodiesel production, addressing feedstock compositional uncertainty. Although the model was designed with particularities of the biodiesel systems, it can be adapted to other industries, particularly recycling industries and be used to support production planning at the operational level to enhance the technical, economic and environmental performance of these industries.

The application of this tool to assess the use of secondary material (WCO) in blends for biodiesel production showed that the use of WCO leads to reduction of biodiesel production costs and environmental impacts relatively to blends composed only with crop-based oils. Blending WCO with crop-based oils is an attractive approach to reduce costs and environmental impacts of biodiesel while new technologies and alternative feedstocks for biodiesel production are still evolving and are not yet cost competitive. Moreover, the collection and use of this residue for biodiesel production avoids its disposal through sewage systems, reducing economic and environmental burdens by avoiding sewage treatment at wastewater treatment plants.

The technical constraints thresholds used in the model are based on European regulation but they can be adapted to other standards (for example in the US regulation there is no threshold for Iodine Value and there is a lower limit for Oxidative Stability (OS)) and the Cold Filter Plugging Point (CFPP) limit values vary according to the type of climate. Also, OS and CFPP, that are the biding properties in the model, can be enhanced using additives and so, the model developed in this work together with these techniques, increases the spectrum of possible Fatty Acid (FA) based feedstocks to be used in biodiesel production. Moreover, this model can also be used to assess the use of secondary material like for example animal fats or the viability of emerging feedstocks such as algae.

This study presents some limitations that can be addressed in future research: (i) the biodiesel production costs considered in the model are the feedstock cost and, although different cultivation locations were analyzed, the feedstock cost does not take this issue in consideration; (ii) the technical constraints were defined for properties that are related directly related to the chemical composition of the oils and other parameters need to be considered to address other technical difficulties that may be related to the use of WCO; and (iii) the uncertainty associated with the availability and price of the feedstock (and its inter-relation based on supply and demand curves), and the uncertainty related to the environmental impacts are also relevant aspects to be addressed and included in a more comprehensive uncertainty model.

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