Multiple Criteria Decision Making

Julio Berbel · Thomas Bournaris
Basil Manos · Nikolaos Matsatsinis
Davide Viaggi *Editors*

Multicriteria Analysis in Agriculture

Current Trends and Recent Applications

Springer

Multiple Criteria Decision Making

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Nikolaos Matsatsinis • Davide Viaggi
Editors

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Allocating Shadow Prices in a Multi-objective Chance Constrained Problem of Biodiesel Blending

Carla Caldeira, Luis Dias, Fausto Freire, Dimitris Kremmydas, and Stelios Rozakis

Abstract Biodiesel can be produced from different vegetable oils and the choice of the blend (mix of oils) to be used for biodiesel production has an important impact on its cost and environmental performance. This chapter presents a model that determines the optimal blend that minimizes production costs and GHG emissions and assesses the influence of technical constraints on the decision objectives. For this purpose, an algorithm for the allocation of shadow prices to the constituent parts of the composite objective function was implemented. The technical constraints in the model control biodiesel properties based on the feedstock's chemical composition, taking into account inherent compositional uncertainty. The information obtained from the shadow prices allowed the identification of which technical constraint limits GHG reduction and cost effectiveness. Thus, the model can be used for evaluating the effects of technical progress or policy mandatory measures relatively to the cost and GHG emissions of the biodiesel production process.

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1 Introduction

Biodiesel is typically produced from vegetable oils as feedstocks that represent between 80% and 85% of the total production costs (Gülşen et al. 2014). Many types of vegetable oils can be used in biodiesel production and diversification in feedstock blending may reduce costs while maintaining biodiesel quality. Gülşen et al. (2014) provided evidence that a skillful selection of a diversified portfolio of feedstocks at the conversion phase can provide a significant financial advantage and stabilize overall costs, reducing financial risk.

The implementation of policies such as the European Directive on Renewable Energy (RED) (European Comission 2009) led to a significant increase of biofuels production so that the share of renewable energy to be used in transportation imposed by the Directive could be achieved. However, the controversy raised about GHG emissions of biofuels, mainly due to direct and indirect land use change (Soimakallio and Koponen 2011), has forced the biodiesel industry to take into account not just the costs but also GHG emissions (Buratti et al. 2012; Tomaschek et al. 2012). Models that accommodate GHG constraints and cost of biofuel chains have been used to analyze trade-offs between costs and GHG emissions (You et al. 2012; Akgul et al. 2012; Thomas et al. 2013; Bairamzadeh et al. 2016). Focusing on policy analysis, Palak et al. (2014) used a model to assess the impacts of carbon regulatory mechanisms on emission and cost performance of biofuel supply chains. Caldeira et al. (2014) developed a bi-objective mathematical programming model to determine the blend of virgin oils for biodiesel production minimizing costs and life-cycle GHG emissions to analyze the trade-offs between these two dimensions.

However, none of these studies considered the uncertainty of the feedstock's chemical composition, which influences the biodiesel quality. Indeed, biodiesel properties are highly influenced by the compositional uncertainty of the feedstock (Caldeira et al. 2017) and, for this reason, the cost and GHG dimensions should be examined taking into account the feedstock composition uncertainty. The latter was considered in the work developed by Gülşen et al. (2014) and Olivetti et al. (2014) using Chance Constrained Programming (CCP) to assess, respectively, cost effectiveness and GHG emissions uncertainty. However, this was not done considering a multi-objective approach.

To ensure that the biodiesel has the requisite quality to be used as automotive diesel fuel, standard specifications for biodiesel have been established worldwide (Hoekman et al. 2012). However, some specifications vary from country to country or can change with the technical evolution of engines. Therefore, it is important that policy makers are aware of the opportunity costs associated with technical specifications imposed. In mathematical programming blending models this piece of information is embedded in the dual or shadow prices associated to the constraints.

The goal of this chapter is to present an approach to determine optimal blends (minimizing biodiesel production costs and GHG emissions) considering technical uncertainties and to provide detailed shadow price information useful for policy analysis. To determine optimal blends we have used a multi-objective programming model. To inform decision makers about the opportunity costs of biodiesel technical specifications, we have implemented a special approach for assigning the sensitivity on marginal changes of each different objective caused by the right hand side value of the imposed technological constraints.

The multi-objective formulation of the blending problem is presented in Sect. 2.1 and the shadow price decomposition method for multi-objective problems in Sect. 2.2. To incorporate the feedstock compositional uncertainty within the required technical specifications we used CPP. The methodological issues concerning the joint application of multi-objective programming and CCP to the blending problem are presented in Sect. 2.3. The model is illustrated with a case study for a two-objective (costs and GHG emissions) biodiesel blending problem in Portugal (Sect. 3). Results are presented in Sect. 4 along with discussion, analyzing the constraints on fuel specifications currently enacted in the EU and the US. Conclusive comments in Sect. 5 complete the chapter.

2 Material and Methods

2.1 The Deterministic Multi-objective Blending Problem

Blending problems consist in determining the combination of raw materials that leads to the optimal value of the objective function. The general mathematical formulation for a multi-objective blending problem can be written as:

$$
\begin{aligned}
&\min\left\{\sum_{i\in I}\left(c_{ki}\,x_i\right) : k \in K\right\} \\
&\text{st.} \sum_{j\in J}\sum_{i\in I}\left(q_{ji}\,x_i\right) \le b_p \quad \forall\ p \in P \\
&\sum_{i\in I} x_i = D \\
&x_i \ge 0\ \ \forall\ i \in I
\end{aligned}
\tag{1}
$$

where K is the set of objectives, I is the set of raw materials, J is the set of ingredients, P is the set of regulated properties of the final blend which are functions of its ingredient composition, c_{ki} are the individual objective coefficients, x_i is the raw material quantity (decision variable), q_{ji} is the concentration of j-ingredient in i-raw material, b_p is the limit of p-property, and D is the demand.

The main characteristic of multi-objective problems is that the concept of optimal solution gives place to the one of non-dominated (Pareto efficient) solutions, i.e., those solutions that cannot be improved in one objective without worsening at least one of the other objectives. Multi-objective methods can be classified into three categories: the *a priori* methods, the interactive methods and the generation or *a posteriori* methods (Hwang and Masud 1979). In *a priori* methods the decision maker expresses his or her preferences before the solution process (e.g. setting goals or weights for the objective functions) so that a most preferred solution is identified without no further involvement of the decision maker. In interactive methods, phases of dialogue with the decision maker alternate with computation phases, iteratively computing new solutions until the most preferred solution is identified. In generation methods the efficient solutions of the problem (all of them or a sufficient representation) are generated and then the decision maker may compare them in order to select the most preferred one, or may simply explore the trade-offs involved thus supporting the decision process.

In this work we opted for an *a posteriori* approach implementing the "weighting method" to generate the Pareto efficient solutions, minimizing a weighted sum of the K objectives for several weight vectors. Although the weighting method's caveats are known and more sophisticated algorithms are proposed in the literature (Mavrotas 2009), it is appropriate for this case study since a large number of alternative solutions is provided so that the stylized blending problem adequately illustrates the shadow price decomposition. For the blending problem presented in (1), the mathematical formulation of the weighting method corresponds to a single-objective optimization model as follows:

$$
\begin{aligned}
&\min \sum_{k \in K} \left(w_k \sum_{i \in I} (c_{ki}\, x_i) \right) \\
&\text{st.} \sum_{j \in J} \sum_{i \in I} \left(q_{ji}\, x_i \right) \geq b_p \quad \forall\ p \in P \\
&\sum_{i \in I} x_i = D \\
&x_i \geq 0 \quad \forall\ i \in I
\end{aligned}
\tag{2}
$$

The w_k represents the weight of the individual objectives and problem (2) is solved for various weight combinations (such that $w_k > 0$ and $\sum_{k \in K} w_k = 1$) assigned to the objectives in order to obtain the Pareto efficient set of solutions.

2.2 *Decomposing Shadow Price for the Various Objective Function Components*

The shadow prices generated by linear programming models represent the objective value change for a unit change on the Right Hand Side (RHS) value of a certain constraint (Cohon 1978). In resource allocation problems, the shadow price of a resource constraint can be interpreted as the maximum value the decision maker is willing to pay for obtaining an additional unit of that resource. In blending problems, the shadow price represents the improvement in the objective function for relaxing a requirement of the final blend.

The allocation of the shadow price information has been applied in joint production: Nejad M. (2007) proposed a two-stage methodology based on the marginal contribution of oil products and the production elasticity of unit processes to provide an additive CO_2 allocation scheme in joint product industries; Moghaddam and Michelot (2009) presented a methodology to use the shadow price information for joint cost allocation; and revenue loss from decreasing nitrogen pollution was estimated by Shaik et al. (2002).

In multi-objective problems the interpretation of shadow prices can be useful for decisions in policy and industry. For this type of problems, the shadow prices resulting from solving Model (2) give the marginal change in the weighted objective function for a unit change on the RHS value of a constraint. This type of information, an aggregate measure difficult to interpret, is not particularly useful for decision makers since they are rather more interested in the distinct effect on the individual objectives that compose the multi-objective function. To overcome this issue, McCarl et al. (1996) presented a technique to decompose the dual values of binding constraints in multi-objective problems that allows the allocation of the shadow price information to each specific objective. We applied this technique to the blending problem. A description of the technique is presented in the following paragraphs.

The weighting form of the problem given in Model (2) in matrix notation is transcribed in vector form in (3) to illustrate the decomposition process:

$$\begin{gathered} \min \left(w_1 \overrightarrow{C_1} + w_2 \overrightarrow{C_2} + \ldots + w_k \overrightarrow{C_k}\right) \cdot \vec{x} \\ I_{PxJ} Q \vec{x} \geq \vec{b} \\ \vec{x} \geq 0 \end{gathered} \tag{3}$$

where $\overrightarrow{C_k}$ is a $1 \times I$ vector containing the objective coefficients for the k-objective, $\vec{x}$ is the $I \times 1$ vector of the decision variables, I_{PxJ} is an $P \times J$ unity matrix, Q is a $J \times I$ matrix containing the q_{ji} elements, $\vec{b}$ is a $P \times 1$ vector containing the property limits.

The decomposed form of the objective function of the problem that is given in Eq. (3) is equal to:

$$\min \overrightarrow{C_f} \cdot \vec{x}, \tag{4}$$

where $\overrightarrow{C_f} = w_1 \cdot \overrightarrow{C_1} + w_2 \cdot \overrightarrow{C_2} + \ldots + w_k \cdot \overrightarrow{C_k}$.

We know that the shadow prices are given by

$$\overrightarrow{U_k} = \overrightarrow{C_{fB}} \cdot B^{-1} \tag{5}$$

where $\overrightarrow{\mathrm{C}_{\mathrm{fB}}}$ is a vector that contains the objective functions coefficients for the basic variables of the optimal solution and B^{-1} is the basis inverse. From Eq. (4) we obtain:

$$\overrightarrow{\mathrm{C}_{\mathrm{fB}}} = \mathrm{w}_1 \overrightarrow{\mathrm{C}_{1\mathrm{B}}} + \mathrm{w}_2 \overrightarrow{\mathrm{C}_{2\mathrm{B}}} + \ldots + \mathrm{w}_\mathrm{k} \overrightarrow{\mathrm{C}_{\mathrm{kB}}} \tag{6}$$

where $\overrightarrow{C_{1B}}, \overrightarrow{C_{2B}}, \ldots, \overrightarrow{C_{kB}}$ are the coefficients of the basic variables in the individual objectives context.

Thus, the shadow prices are equivalent to

$$\overrightarrow{\mathrm{U}_\mathrm{k}} = \overrightarrow{\mathrm{C}_{\mathrm{fB}}} \cdot \mathrm{B}^{-1} = \mathrm{w}_1 \cdot \overrightarrow{\mathrm{C}_{1\mathrm{B}}} \cdot \mathrm{B}^{-1} + \mathrm{w}_2 \cdot \overrightarrow{\mathrm{C}_{2\mathrm{B}}} \cdot \mathrm{B}^{-1} + \ldots + \mathrm{w}_\mathrm{k} \cdot \overrightarrow{\mathrm{C}_{\mathrm{kB}}} \cdot \mathrm{B}^{-1} \tag{7}$$

The $\overrightarrow{C_{kB}} \cdot B^{-1}$ component indicates the decomposed shadow prices corresponding to the k-th objective. It is a $1 \times$ P dimension vector, expressing the extent at which one unit of increasing the p-th constraint will affect the k-objective's value, considering that we are already at the optimal solution.

So we need to contrive a way to compute each $\overrightarrow{C_{kB}} \cdot B^{-1}$ in order to complete the decomposition of the shadow prices. However, as McCarl et al. (1996) states: "linear programming solvers do not generally yield the basis inverse". Furthermore, computing the basis inverse from scratch would be computationally equivalent to solving again the LP problem. The algorithm proposed consists of the following steps: Solve the composite problem and save the basis. For each k-th objective set $w_k = 1$ and all other weights equal to zero. Load the saved basis of the composite problem and startup the problem (but make no iterations). The reported shadow prices are given by the $\overrightarrow{C_{kB}} \cdot B^{-1}$ product.

This method cannot be directly applied to problems that exhibit degeneracy. Degenerate problems are a special case as far as sensitivity analysis is regarded (Koltai and Terlaky 2000). Although McCarl et al. (1996) gives a technical solution for computing a consistent decomposition of the shadow prices, degenerate problems are expected to have different positive and negative shadow prices (Gal 1986) representing a diverse effect on the optimal price of an increase versus a decrease on the right hand side of a constraint. In this case different approaches would be more appropriate as discussed in Ho (2000).

2.3 *Introducing Uncertainty in the Constraints: Chance Constraint Programming (CPP)*

A critical aspect in blending problems is the stochastic nature of the composition of the raw materials. The consideration of chemical composition uncertainty in blending processes using CCP has been considered by several authors (Kumral 2003; Rong et al. 2008; Sakallı and Baykoç 2013). CCP is a stochastic programming technique that was first presented by Charnes and Cooper (1959) to address system feasibility in an uncertain environment, which is expressed as a requirement on the minimum probability of satisfying constraints (Sahinidis 2004). By controlling the probability that a constraint may be violated, it adds flexibility to the model reflecting the reality under consideration (Kampempe 2012). The advantages of the CCP approach in the development of blending models in relation to deterministic ones are presented by Olivetti et al. (2011). According to the authors, the CCP model formulation always performs better or equal than Linear Risk formulation (LR). The CCP formulation allows increasing the variation while still meeting technical specifications because it identifies portfolios of raw materials whose uncertainty characteristics are better than that of any individual raw material. The creation of these portfolios of raw materials allows to manage risk and cost simultaneously (Olivetti et al. 2011). In this approach, the deterministic constraints are replaced by non-deterministic ones. First, the decision maker specifies a minimum probability of $1 - \alpha$ that each constraint should satisfy:

$$P\left(\sum_{i=1}^{N} a_i x_i \leq b\right) \geq 1 - \alpha, \qquad x_i \geq 0 \text{ and } 0 < \alpha < 1 \tag{8}$$

If a_i is normally distributed parameter, $a_i \sim N\left(\mu_i, \sigma_i^2\right)$ and all a_i are independent, the constraint is converted as follows:

$$P\left(\frac{\sum_{i=1}^{N} a_i x_i - \sum_{i=1}^{N} \mu_i x_i}{\sqrt{\sum_{i=1}^{N} \sigma_i^2 x_i^2}} \leq \frac{b - \sum_{i=1}^{N} \mu_i x_i}{\sqrt{\sum_{i=1}^{N} \sigma_i^2 x_i^2}}\right) \geq 1 - \alpha, \tag{9}$$

Where $\frac{\sum_{i=1}^{N} a_i x_i - \sum_{i=1}^{N} \mu_i x_i}{\sqrt{\sum_{i=1}^{N} \sigma_i^2 x_i^2}}$ represents a standard normal variate with a mean of zero and a variance of one. Then, the stochastic chance-constraint is transformed into the following inequality:

$$\varphi\left(\frac{b - \sum_{i=1}^{N} \mu_i x_i}{\sqrt{\sum_{i=1}^{N} \sigma_i^2 x_i^2}}\right) \geq \varphi\left(K_{1-\alpha}\right) \tag{10}$$

Where $K_{1-\alpha} = 1 - \alpha$ and $\varphi\ (\cdot)$ represents the standard normal cumulative distribution function (Sakallı et al. 2011) This yields the following nonlinear deterministic constraint:

$$\sum_{i=1}^{N} \mu_i x_i + K_{1-\alpha} \sqrt{\sum_{i=1}^{N} \sigma_i^2 x_i^2} \leq b \tag{11}$$

Segarra et al. (1985) demonstrate a linearized, more conservative, substitute for Eq. (11) given by:

$$\sum_{i=1}^{N} \mu_i x_i + K_{1-\alpha} \sum_{i=1}^{N} \sigma_i x_i \quad \leq b \tag{12}$$

3 Application to Biodiesel Produced in Portugal

The proposed approach was implemented for biodiesel produced in Portugal. The feedstocks considered for the application of the model were the main feedstocks used in Portugal for biodiesel production: palm, canola and soya. According to information provided by the Portuguese Energy Agency (DGEG), in 2012, 49% of the feedstocks used for biodiesel production in Portugal were soya, 34% canola and 14% palm.

Costs were calculated by multiplying the quantity of each one of the three feedstocks (palm, canola and soybean oil) by its market price. The prices of the feedstock oils used in the model are the average prices between November 2008 and November 2013, provided by IndexMundi (2014). GHG emissions were calculated by multiplying the quantity of each feedstock by its life-cycle emissions per quantity unit. GHG emissions were drawn from Olivetti et al. (2014) for soybean and palm, and were drawn from Malça et al. (2014) for canola. The price and GHG coefficients are presented in Table 1. In order to scale the objectives, the price and GHG coefficients were divided by the largest value in each row resulting in the relative price and GHG emissions that is given in parentheses in Table 1.

Furthermore, the model is subject to technical specification constraints that the biodiesel must comply with. These constraints consider biodiesel properties derived from prediction models based on the chemical composition (fatty acids, FA) of the vegetable oils. Prediction models were used for the following biodiesel properties: density (Den), cetane number (CN), cold filter plugging point (CFPP), iodine value (IV) and oxidative stability (OS) (Bamgboye and Hansen 2008; CEN 2008; Park et al. 2008; Ramos et al. 2009; Refaat 2009; Giakoumis 2013). These prediction models are presented and discussed in Caldeira et al. (2014), who demonstrated that the derived results were in agreement with values found in the literature. The targets (constraint

Table 1 Price and GHG coefficients used in the model (relative value in parenthesis)

	Feedstock Oil		
	Palm	Canola	Soybean
Price (€/t)	629 (0.761)	826 (1.000)	753 (0.911)
GHG emission (g CO_2eq/MJ)	67 (1.000)	48 (0.716)	58 (0.856)

right hand side levels) were established according the European Standard EN 14214 (CEN 2008) that defines the biodiesel (Fatty Acid Methyl Esters—FAME) requirements for diesel engines. For CFPP, EN 14214 climate-dependent requirements are given to allow for seasonal grades to be defined for each country. There are six CFPP grades for temperate climates and five different classes for arctic climates. Level B, with a maximum of 0 °C was selected for this work. To address the compositional uncertainty, the technical constraints were formulated according to the CCP technique described previously. The chemical composition information (average and standard deviation) used in the model was adopted from Hoekman et al. (2012).

To analyze the proportions of each feedstock in the blend the demand (D) is set equal to one. We implicitly consider that the biodiesel produced is fully consumed by the oil refinery industry and that there are no feedstock supply limitations.

The non-linear model is presented in a minimization under constraints form given by Model (13). To apply the shadow price decomposition we proceed with the linearized version of the chance constraint model. The linearized version of the non-linear chance constraints is given by Model (14). Table 2 presents the notation of the biodiesel blend problem

Non-linear Version

$$
\begin{aligned}
&\min\left\{\sum_{i\in I}(C_{Pr,i}\,x_i),\ \sum_{i\in I}(CC_{GHG,i}\,x_i)\right\}\\
&\text{Subject to :}\\
&\mathrm{PropConst}_p+\sum_{j\in J}\Big(\mathrm{PropCoef}_{p,\ j}\sum_{i\in I}x_i\overline{q_{j,i}}\Big)\\
&\qquad -K_{1-\alpha}\sqrt{\sum_{j\in J}\left(\mathrm{PropCoef}_{p,j}{}^2\sum_{i\in I}x_i{}^2\sigma_{j,i}{}^2\right)}\\
&\qquad \geq \mathrm{PropGTgt}_p\quad \forall p\in \mathrm{Plb}\\
&\mathrm{PropConst}_p+\sum_{j\in J}\Big(\mathrm{PropCoef}_{p,\ j}\sum_{i\in I}x_i\overline{q_{j,i}}\Big)\\
&\qquad +K_{1-\alpha}\sqrt{\sum_{j\in J}\left(\mathrm{PropCoef}_{p,j}{}^2\sum_{i\in I}x_i{}^2\sigma_{j,i}{}^2\right)}\\
&\qquad \leq \mathrm{PropLTgt}_p\quad \forall p\in \mathrm{Pub}\\
&\sum_{i\in I}x_i=1\\
&x_i\geq 0\qquad \forall\ i\ \in I
\end{aligned}
\tag{13}
$$

Table 2 Notation used along the manuscript

Variables	
x_i	Quantity of each raw material i to be used in the blend
$\vec{x}$	I × 1 vector of the decision variables
Sets/Indices	
K	Set of objectives
I	Set of raw materials
J	Set of ingredients
P	Set of properties
k ϵ K	K = {cost, GHG}, objectives
i ϵ I	I = {soya, canola, palm}, feedstock oils
j ϵ J	J = {1, 2,. . ., 18}, Fatty Acids index
p ϵ P	P = {DenLB, DenUB, IV, CN, OS, CFPP}, set of properties
Subsets	Plb = {DenLB, CN, OS}, set of properties with lower bound
	Pub = {DenUB, IV, CFPP}, set of properties with upper bound
Parameters	
$c_{k,i}$	Coefficient of objective k for raw material i
$\vec{C_k}$	$\vec{C_k}$ is a 1 × I vector containing the objective coefficients for the k-objective
w_k	Weight of the individual objectives
$q_{j,i}$	Concentration of ingredient j in raw material i
b_p	Limit value for property p
$\vec{b}$	P × 1 vector containing the property limits
I_{PxJ}	P × J unity matrix
Q	Q is a J × I matrix containing the q_{ji} elements
$\overrightarrow{C_{fB}}$	Objective functions coefficients vector for the basic variables of the optimal solution
$\overrightarrow{C_{kB}}$	Coefficients of the basic variables in the individual objective
B^{-1}	The basis inverse
U_k	Shadow prices of objective k
$\vec{C_f}$	Composed form of the objective function
a_i	Uncertain parameter in the CCP formulation
μ_i	Average value of parameter a_i
σ_i	Standard deviation of parameter a_i
$\overline{q_{j,i}}$	Average value of ingredient j in raw material i
$\sigma_{j,\ i}$	Standard deviation of the concentration of ingredient j in raw material i
α	Confidence level
$K_{1\ -\ \alpha}$	Test coefficient for normal distribution, one tailed: z-value corresponding to the chosen confidence value level
$C_{Pr,\ i}$	Ratio of the price of feedstock i to the most expensive feedstock
$CC_{GHG,\ i}$	Ratio of the GHG emission of feedstock i to the feedstock with the highest GHG emissions
$PropCoef_{p,\ j}$	Coefficient of FA-j in the prediction model for property p
$PropConst_p$	Constant in the prediction model for property p
$PropGTgt_p$	Target for properties with lower bound
$PropLTgt_p$	Target for properties with upper bound

Linearized Version of the Constraints

$$\begin{aligned}
&\mathrm{PropConst_p} + \sum_{j\epsilon J}\left(\mathrm{PropCoef_{p,\ j}}\sum_{i\epsilon I}\left(\mathrm{x_i}\overline{\mathrm{q_{j,i}}}\right)\right)\\
&\qquad - \mathrm{K_{1-\alpha}}\sum_{j\epsilon J}\left(\mathrm{PropCoef_{p,j}}\sum_{i\epsilon I}\left(\mathrm{x_i}\sigma_{j,i}\right)\right)\\
&\qquad \geq \mathrm{PropGTgt_p}\ \ \forall p \in \mathrm{Plb}\\
&\mathrm{PropConst_p} + \sum_{j\epsilon J}\left(\mathrm{PropCoef_{p,\ j}}\sum_{i\epsilon I}\left(\mathrm{x_i}\overline{\mathrm{q_{j,i}}}\right)\right)\\
&\qquad + \mathrm{K_{1-\alpha}}\sum_{j\epsilon J}\left(\mathrm{PropCoef_{p,j}}\sum_{i\epsilon I}\left(\mathrm{x_i}\sigma_{j,i}\right)\right)\\
&\qquad \leq \mathrm{PropLTgt_p}\ \ \forall p \in \mathrm{Pub}
\end{aligned} \tag{14}$$

Both approaches, non-linear and linear, were implemented in GAMS version 23.7.3 (GAMS 2011). The non-linear problem was solved using the CONOPT solver and the linearized version using CPLEX. The Pareto frontier was obtained using the weighted method. The weight combination of the two objectives was calculated in 0.01 steps, in a total of 101 points. For a 95% confidence level (z-value = 1.96) the model was infeasible. This can be attributed to the fact that the linearized model is a much more restricting transformation of the probabilistic constraint, since $\sqrt{\sum_{i=1}^{N}\sigma_i^2 x_i^2} < \sum_{i=1}^{N}\sigma_i x_i$. For this reason we reduced the confidence interval to 90% (z-value = 1.645).

4 Results and Discussion

Figure 1 depicts the Pareto frontier obtained for the non-linear chance constraint problem (blue points, triangles) along with those of the linearized version (red points, crosses).

The linearized version provides just two possible solutions: one when more relevance is given to the environmental objective (Cost weight ∈ [0.00, 0.54]), and the other when the economic objective is more relevant for the decision maker (Cost weight ∈ [0.55, 1.00]). The solutions are presented in Table 3.

Figure 2 shows the blend composition for the mentioned weight combinations for the linearized version. The X-axis gives the weight combination and the Y-axis indicates the proportion of each input feedstock in the final blend. The solutions are associated with blends composed only by palm and canola. When we shift from an environmental to an economic “preference” we can observe an increase of the quantity of palm and a reduction of the quantity of canola in the blend. As palm is the feedstock with the lowest cost (Table 1), this change in the blend leads to a 2.4%

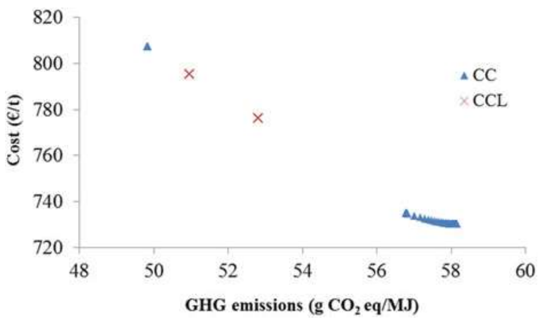

Fig. 1 Pareto frontier of non-linear (CC) and linear (CCL) chance constraint models obtained for a 90% confidence level

Table 3 Pareto frontier solutions of the linearized chance constraint model

Weights range	Cost (€/t)	GHG (g CO_2 eq/MJ)
Cost weight ∈ [0.00, 0.54]	795.44	50.94
Cost weight ∈ [0.55, 1.00]	776.24	52.79

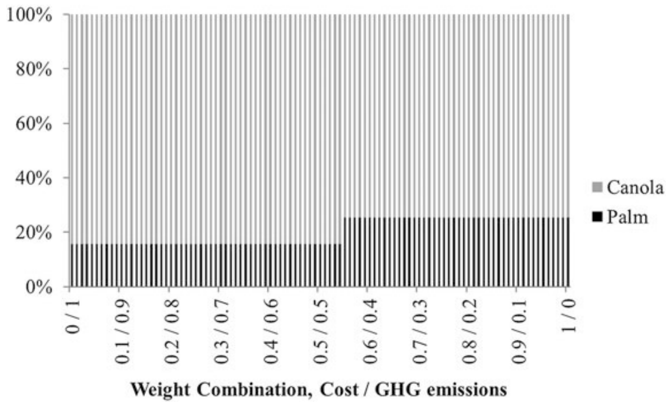

Fig. 2 Blend composition for all weight combinations of the linearized chance constraint model

cost reduction. However, since palm presents higher GHG emissions (Table 1), the improvement in the cost objective due to the increase of palm in the blend, worsens the environmental performance by 5%.

The non-linear version presents more solutions than the linearized one due to the fact that the technical constraints are not as conservative as in the linear version. For this reason, when more weight is given to the environmental objective (Cost weight ∈ [0.00, 0.54]), the algorithm suggests a blend with less palm and

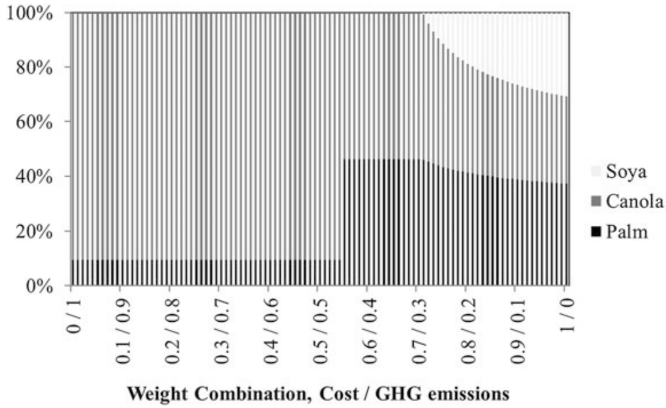

Fig. 3 Blend composition for all weight combinations of the non-linear chance constraint model

Table 4 Shadow price decomposition results for the linearized version

Weight combination	Binding constraint	Cost (€/t)	GHG (g CO_2 eq/MJ)
Cost weight ∈[0.00, 0.54]	Upper bound of iodine value ($IV \leq IV_0$)	+0.0034	−0.041
Cost weight ∈[0.55, 1.00]	Upper bound of cold filter plugging point ($CFPP \leq CFPP_0$)	−0.0179	+0.021

more canola. The proposed solution corresponds to lower GHG emissions than the one obtained for the same preference weights in the linearized approach. When the cost objective becomes more important, the blend increases the use of soya at the same time reducing canola quantity (which is the feedstock with higher cost) leading to solutions with lower cost than the ones obtained for the linearized version. The blend composition for the mentioned weight combinations in the non-linear version is shown in Fig. 3.

The shadow price decomposition discussed in the methodology section was applied to the linearized version and the results are presented in Table 4.

For both solutions the binding constraint was identified and shadow prices were allocated to both objectives. In the case where GHG emissions are evaluated as more important (Cost weight ∈[0.00, 0.54]) the binding constraint is iodine value (IV). If the upper bound of IV (IV_0) is increased by one unit, then the cost component of the objective value would increase by 0.0034 (2.74 €/t) while the GHG emissions would decrease by 0.041 (2.09 g CO_2 eq/MJ).

When the cost is more important than GHG emissions (Cost weight ∈[0.55, 1.00]), CFPP replaces IV as the binding technical constraint. In this case, an increase of one unit (1 °C) in the upper bound of CFPP ($CFPP_0$) would result in a decrease (−0.0179, i.e. 13.89 €/t) in the cost component (which has a positive context since the target is to minimize cost) and an increase in the GHG emissions (+0.021, i.e., 1.12 g CO_2 eq/MJ).

The results obtained refer to the European market, using the EN 14214 standard limit values. Nevertheless, some of the specifications vary from region to region, favoring the use of domestic feedstocks within the regions. This is the case for IV that has no requirement in the US standard—ASTM D6751 (ASTM 2008) while in the European standard—EN 14214 (CEN 2008) it is limited to a maximum of 120. In one hand, this favors the use of soya in the US (US is the world leading soya producer) and, on the other hand, it limits the use of soya and favors canola in the EU as it is observed by the blends composition obtained with our model (Fig. 2). As IV is the limiting property for GHG emission reduction and the US market has no limit for IV, it favors, according to our results, the reduction of GHG emissions.

5 Conclusions

Worldwide biofuel policies have been implemented leading the biodiesel industry to take into account not just costs but also GHG emissions, together with biodiesel technical performance. Some biodiesel technical specifications are "soft"and vary (e.g. between regions, climate conditions). It is therefore important that policy makers learn what the opportunity costs of technical specifications are. This article presents an approach to provide this information using an algorithm for the allocation of shadow prices to the constituent parts of the composite objective function articulated in a multi-objective chance constrained formulation. The information obtained from the shadow prices allowed the identification of the limiting technical properties for GHG reduction and cost effectiveness in the Portuguese policy context with three feedstocks entering the blend: CFPP (cold filter plugging point) is the limiting factor for cost effectiveness and IV (Iodine Value) is the limiting factor for reducing GHG emissions.

The biodiesel cost effectiveness can be increased when the biodiesel is commercialized in warmer countries. CFPP, the binding constraint for cost effectiveness, was limited to a maximum of 0 °C in this article. This property is determined regionally based on climate conditions. In warmer countries, this constraint could be limited to a maximum of 5 °C (Grade A in EN 14214) favoring biodiesel cost reduction. As both IV and CFPP have different limits in regional standards, biodiesel producers can adapt their production (choice of feedstocks blends) according to specific environmental and economic goals and to the destination market.

To illustrate the method we focused on technical specifications that are directly related to the chemical composition of the three feedstocks considered in the case study. However, this model can be further used with alternative feedstocks in order to analyze "regional blends" that would favor cost or GHG reduction targets. The shadow prices obtained provide information to the decision maker about the changes in each objective function that result from relaxing a requirement of the final blend. Thus it can be used as a guideline for evaluating the effectiveness of technical specifications relatively to the cost and GHG emissions and other objectives related to the biodiesel production process. That could be the case when new technologies with the potential to alter technological specifications of the input biodiesel oil are under consideration.

Further research should focus on the decomposition of shadow prices in non-linear multi-objective chance constrained formulations of the blending problem. As it is shown in the aforementioned example, the nonlinear version outperforms the linearized one in numbers of efficient blends. Although efficient blends obtained with the nonlinear formulation lie in the same frontier as those by the linear formulation, they represent more detailed information that could result in smoother dual values enriching policy options regarding the technical standard levels.

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