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A mixed 0-1 MOLP approach for the planning of biofuel production

George Mavrotas*, Stelios Rozakis**

* Lab. of Industrial and Energy Economics, National Technical University of Athens, Dpt. of Chemical Engineering, Div.II, Greece ** UMR Economie Publique, Institut National de Recherche Agronomique, France

Abstract: Multiple Objective Linear Programming (MOLP) models have been widely used in planning problems that involve several conflicting objectives. However, continuous variables are not sufficient to accurately represent the discrete phenomena encountered in many practical decision situations. This paper presents a new approach based on a mixed 0-1 MOLP model applied to the planning of biofuel production from energy crops. A partial equilibrium micro-economic approach is opted to represent the biofuel system that consists in different chains. This resulted in a problem of considerable size that required the use of continuous but also discrete variables in order to satisfactorily simulate the real-world policy problem. The core of the model is a branch and bound algorithm, which has been modified suitably for the multi-objective case, including mixed integer problems. It is capable of generating the entire set of efficient (non-dominated) solutions which is a prerequisite of successful decision making processes in order to select among alternative policy scenarios.

Keywords: Multiple Objective Linear Programming, Integer programming, Energy crops, Biofuels.

Introduction

Growing awareness about the environmental impacts of energy has significantly broadened the policy goals set in the energy sector. Therefore, Multiple Objective Linear Programming (MOLP) methods began to be increasingly used in energy planning in order to effectively incorporate environmental and social considerations in energy decisions (Cohon, 1978; Zionts and Deshpande, 1981; Siskos and Humbert, 1983; Kavrakoglu and Kiziltan, 1983; Climaco *et al.*, 1995). However, MOLP models are not able to accurately represent the discrete phenomena that are often encountered in energy planning. Power dispatching, facilities siting and power expansion are typical examples of such types of problems for which some of the decision variables are represented by integer and/or binary (0-1) variables.

When all the variables of the problem under consideration are integer, the problem can be formulated with a Multiple Objective Integer Linear Programming (MOILP) model. In the case where integer values are restricted to zero or one, a 0-1 MOLP model is used. Finally, if some of the decision variables are continuous and some are integer or binary, the problem is modeled by a mixed-integer MOLP or a mixed 0-1 MOLP model, respectively.

Up to now, research has mainly focused on pure 0-1 or pure integer MOLP problems (see for example Bitran, 1977 and 1979; Klein and Hannan, 1982; Kiziltan and Yocaoglu, 1983; Chalmet et al., 1986; Deckro and Winkofski, 1986; Rasmussen, 1986). However, the inadequacy of the above algorithms to handle relatively big or mixed-integer problems considerably restricts their implementation area. In order to overcome these difficulties, several interactive algorithms for integer MOLP have been developed (Gabbani and Magazine, 1986; Marcotte and Soland, 1986; Steuer 1989; Karaivanova et al., 1993). Although some of the proposed interactive procedures can be used to solve mixed-integer MOLP problems, they do not allow for determining the entire set of efficient solutions, even in small problems. Besides, interactive methods based on the optimization of a weighted sum of the objective functions cannot generate unsupported efficient solutions (Steuer, 1989). Thus, interesting solutions may be ignored by the analysis (for an

overview of integer MOLP approaches, see also Climaco et al., 1997; Ulungu and Teghem, 1999).

This paper presents a mixed 0-1 MOLP model which is capable of generating the complete set of efficient solutions (generating approach) through the implicit enumeration of all potentially efficient solutions and their pairwise comparison for elimination of the non-efficient ones (Mavrotas and Diakoulaki, 1998). More specifically, the model used is based on the branch and bound algorithm which is extensively used in the single objective case. If the size of the MOLP problem is manageable, generating approaches are usually more advantageous than interactive ones. The latter provide the Decision Maker (DM) with a sample of efficient solutions for directing the searching process. Instead, generating approaches illustrate the whole context of the decision situation and, thus, reinforce the DM's confidence to the final decision. Furthermore, in real problems, the frequent interaction with the DM, which is assumed by interactive approaches, is not always easy to achieve.

In the developed multi-objective branch and bound algorithm, the notion of optimality characterizing single objective problems is replaced with that of efficiency (non-dominance) used in the multi-objective optimization. This implies that a mixed 0-1 MOLP problem is more difficult to solve than its single objective counterpart. Especially for big problems, with hundreds or thousands of constraints and variables, the generation of the complete set of efficient solutions becomes practically impossible. In these cases, techniques such as the filtering of efficient solutions and/or the bounding of the objective functions (Mavrotas and Diakoulaki, 1998; Mavrotas et al., 1998) can be incorporated into the algorithm and help the DM to obtain an adequate approximation of the set of the efficient solutions according to his own preferences.

The problem examined in this paper is the planning of biofuel production in France (mainly bio-ethanol and bio-diesel) from wheat and rapeseed (energy crops) respectively. Production is government controlled as bio-fuel production is deficitary being viable only due to public support in the form of tax credits. The two policy criteria are the economic surplus of producers and the resulting CO₂ abatement due to the use of bio-fuels instead of conventional fuels. Efficient tax credits, exonerating biofuel prices to the consumer from fossil fuel taxes in order to support their market penetration have to be determined. Budgetary, environmental and social concerns will affect policy decisions, and multi-criteria optimisation modules that project the decision-maker aims at the closest feasible compromise solutions to the preferred (that depends on decision-maker's preferences) have been applied to this case (Rozakis *et al.*, 2001) using interactive procedures to facilitate the decision process. A caveat of the above study is that interactive procedures have been applied to a non-exhaustive set of efficient solutions, as they used approximative methods (such as the e-constraint method) to generate them that, especially in case of discrete variables may omit some efficient solutions. This paper overcomes precisely this problem.

The rest of the paper is organized as follows: The methodological issues of the proposed method are described in the next section. The application study, with the model formulation, are described in the third section while the obtained results are presented in the fourth section. Some concluding remarks are given in the last section.

Methodological approach

The developed method relies on a branch and bound algorithm that is formulated so as to generate the efficient set in mixed 0-1 MOLP problems. The branch and bound algorithm is widely used to solve mixed integer and mixed 0-1 linear programming problems. In single objective problems, the optimal solution is found by examining all possible combinations of the discrete variables. In the presence of multiple objectives, the conventional branch and bound algorithm is properly modified in order to provide the whole set of efficient solutions resulting from all possible combinations of the binary variables.

General formulation

The general mixed 0-1 MOLP problem is defined by the following formulation:

 $\label{eq:max} \begin{array}{ll} \mbox{max} \left\{ \mbox{Cx=z,} \mid \ x \in S \right\} \\ S = \left\{ \mbox{x} \in Rn \quad \mid \mbox{Ax=b,} \ x \geq 0, \ \mbox{if} \ j \in I_B \ \mbox{then} \ x_j = 0 \ \mbox{or} \ 1, \ \ \mbox{b} \in R^m \end{array} \right\}$

where:

n is the number of variables, m is the number of constraints. For p objectives, **C** is the p 'n criterion matrix (matrix of objective function coefficients) and **z** is the criterion vector, **A** is the matrix $m \times n$ of technological coefficients, **b** the right hand side vector, **x** is the decision variable vector, I_B is the set of the indices of the 0-1 variables with n_B elements.

A solution \mathbf{x}' is efficient (non-dominated, Pareto optimal) if and only if $\mathbf{x}' \in S$ and there is no other $\mathbf{x} \in S$ such that $\mathbf{c}_k \mathbf{x} \ge \mathbf{c}_k \mathbf{x}'$, k=1, 2, ..., p, with at least one strict inequality.

In the presence of integer variables with an upper bound UB these are transformed to a sum of 0-1 variables by using the following equation:

 $\mathbf{y} = \delta_0 + 2\delta_1 + 4\delta_2 + 8\delta_3 + \ldots + 2^k \delta_k$

where the δ_i are 0-1 variables and $\ 2^k \leq UB \leq 2^{k+1}$.

This transformation is widely used in the literature (Brooke *et al.*, 1988; Williams, 1985, 1993) and it greatly expands the implementation area of the proposed algorithm. Its main drawback is that the number of the resulting 0-1 variables is much greater than the number of the initial integer variables.

Traversing the combinatorial tree

Figure 2 displays the steps followed in the developed multi-criteria branch and bound algorithm in order to achieve a comprehensive first search for the combinatorial tree. The process moves from the root node downward (steps 5-12 in Figure 1) until the final level is reached, and the partially efficient solutions of the corresponding node are generated (step15). The term "partially" is used to denote that their efficiency concerns the particular combination and not the general MOLP problem. The partially efficient solutions are candidates for being efficient solutions of the general MOLP problem (*incumbent solutions*) and they are stored in a database (D_{ex}). The final set of the efficient solutions is formed once the combinatorial tree has been fully traversed.

In the intermediate nodes of the combinatorial tree, the ideal vector of the current MOLP partition is calculated (step 8) by separately optimizing each objective function. If the ideal vector of an intermediate node is dominated by any of the partially efficient solutions stored in D_{ex}, then the specific node is fathomed (steps 10, 11, 13) and the corresponding branch is terminated. An intermediate node is also fathomed if it results in an infeasible solution (step 9). If a node is found to be fathomed, a backtracking procedure is then initiated to evaluate other combinations (steps 14, 17-19). This process is repeated until every possible combination of the binary variables has been examined.

Generation of the partially efficient solutions

An MOLP generation approach (Mavrotas, 2000), using the Evans-Steuer test for nondominance (Steuer, 1989), is developed for the extraction of the partially efficient solutions in the final nodes (step 15). The partially efficient solutions, which are generated from every final node, along with the code of the corresponding combination of binary variables, are added to the database D_{ex} . Before this addition, a comparison takes place between points generated by the last final node and the old ones already stored in D_{ex} . This pairwise comparison is aimed to discard from D_{ex} those points that are dominated by the partially efficient solutions of the new combination. At the same time, the partially efficient solutions of the new combination, which are dominated by some efficient solutions in D_{ex} , are excluded from addition. The updating of D_{ex} takes place after every visit to a feasible final node in the combinatorial tree (step 16). This iterative procedure is essential to keep the size of D_{ex} at manageable limits. It should also be noted that only the partially efficient solutions with different values in the objective functions

are considered during the above process in order to avoid the storing of redundant information. The combinations of 0-1 variables that lead to efficient solutions are called *efficient combinations*. A full description of the above described algorithm and its main differences with the single objective case can be found in Mavrotas and Diakoulaki (1998).

The case study

France is the leading European producer in terms of volumes of liquid fuels from agricultural biomass. Two types of bio-fuels are actually produced, namely methyl esters from vegetable oil of rape seed which is used by diesel vehicles and ETBE (ethyl-tertio-butyl-ether) from ethanol of wheat and sugar-beet used by gasoline consuming vehicles. The total annual quantity of bio-fuels reaches approximately 560 thousand tons or 1.5% of the national liquid fuel consumption. The conversion of biomass to liquid fuels process is concentrated in a dozen of plants while the raw material (agricultural biomass) is produced by thousands of farms located in different regions of the country at various unitary costs. The bio-fuel program was launched in France in 1993 as a result of fuel supply uncertainty and environmental concerns, and also it purported to support rural incomes affected by the revised Common Agricultural Policy of 1992. Set aside land obligations that aimed to control cereal overproduction created a favourable environment for the cultivation of non-food crops. However, today, more than five years after the take-off of the program, bio-fuels are still more costly than fossil liquid fuels and agro-energy chains largely depend on government subsidies in the form of tax exemptions for their viability. Earmarked funds for financing tax exemption policy are set by the government at the level of 1.2 million FF and permits that are allocated to industry to produce in the from of agreements have set maximum quantities at 387 and 375 thousand tons for RME and ETBE, respectively, for the horizon of 2002, which correspond to 17700 ha of sugarbeet, 24000 ha of wheat and 250000 ha of rape-seed.

Bio-fuel support can be justified in that it represents an alternative to conventional fuels at a time when environmental concerns have become more acute and nations are committed to a reduction in Greenhouse Gas (GHG) emissions. It was agreed at the Kyoto Summit held in December 1997 that E.U. countries should aim to reduce their global emissions by 8% (1990 basis) in the forecast for 2008-2012; obligations for France amounted to stabilising GHG emissions at 1990 levels, which implied the need for prompt additional efforts as CO₂ emissions had increased by 5.9% in the period 1990-1998. The important question as to how to efficiently allocate this amount to the two bio-fuel chains was thus raised by economists and policy makers.

Mathematical modelling is used in this paper to determine economically and environmentally efficient public expenditure policy. Bio-fuel production is modeled through bi-level mathematical programming including from the agricultural production stage to the conversion to liquid fuels. The government can take a leading role as long as bio-fuel chains require subsidies to support their viability. Industry produces bio-fuels in response to unitary tax credits set by the government in order to maximise its profits. Agricultural biomass is sold in the market at prices equal to the opportunity cost of the least efficient producer. It is assumed that government serves diverse interests that presumably optimise public welfare. Decision makers' major concerns would not only be the development of carbon neutral technologies for energy production but also the maximisation of public welfare (industry and farmers' surplus) using fixed government expenditure.

Model formulation

The developed mixed 0-1 MOLP problem describes the process of biomass conversion to biofuels and by-products. Two objective functions are to be maximized, namely, the total economic surplus of the system and the total CO₂ abatement due to the use of bio-fuels instead of conventional fuels. The technological constraints of the model mainly include the corresponding mass balances, capacity constraints, the overall budget constraint and raw material availability constraints. The aim of this multiple objective model is to produce the exhaustive set of the efficient (non dominated) solutions. These efficient solutions form the set of alternatives among which the decision maker(s) will search for the most preferred solution according to his/their judgement (possibly using interactive methods as in Rozakis et al., 2001).

The model uses as input the results of the agricultural model [*]which provides supply curves of energy crops as a series of discrete points. For each pair of prices, the optimal quantity of crops offered by farmers is determined for wheat and rapeseed. As will later be described, this information is embodied in the model through the appropriate 0-1 variables, which form a SOS1 set (see, for example, Williams, 1985).

When optimized, the bio-fuel system model determines bio-fuel mix, plant capacities and optimal biomass quantities to be produced by farmers for given policy scenarios (budget sum earmarked for bio-fuels and unitary tax credits). One of the main aims of this formulation is to determine which tax credit combinations (tax credit for bio-ethanol and bio-diesel) lead to efficient solutions. Consequently, the tax credits for bio-ethanol and bio-diesel are, in essence, decision variables of the model. In order to obtain the total economic surplus, the tax credits have to be multiplied by the corresponding quantities of bio-ethanol and bio-diesel, which are also decision variables of the model. The resulting terms cause the specific objective function to be nonlinear and the problem more difficult to solve.

For this reason, we replaced the originally nonlinear multiple objective model with a number of linear multiple objective models after the parameterization of the decision variables which represent tax credits. In order to achieve this, the following procedure was implemented: First, the range of variation for each one of the two tax credits was decided upon; in this case, set to 240-330 FF/hl for bio-ethanol and 150-240 FF/hl for bio-diesel. These ranges were divided into nine, equal intervals separated by ten characteristic values. Subsequently, we produced all possible combinations of the characteristic values (one hundred combinations). For each combination, we formulated a mixed 0-1 MOLP sub-problem with the tax credits being parameters of the model, and their values were implied by the corresponding tax credit combination. Thus, we were able to replace the non-linear terms with linear ones, but at the cost of solving multiple mixed 0-1 sub-problems, which were identical in everything but the value of the parameters denoting tax credits. The overall public expenditure remained fixed in all sub-problems, so that the results of the latter refer to a common budget in order to be comparable. The efficient solutions obtained from each sub-problem were stored. The final step was to determine which of the collected efficient solutions were non-dominated by other efficient solutions of a different subproblem. The "globally" ("globally" denotes in respect to the one hundred sub-problems) efficient solutions obtained were the efficient solutions of the original non-linear multiple objective problem.

Model specification

Decision variables

- P_1 and P_2 are the decision variables which express the profit (economic surplus) from the respective biofuel processes: P_1 for the wheat to ethanol process, P_2 for the rapeseed to ester process (in million FF).
- *Xeth, Xest, Xddgs, Xcake, Xglyc* express the produced quantity of ethanol, ester, DDGS, cakes and glycerine respectively (kt).

 X_{wh} express the quantity of wheat transformed to ethanol and by-products by chain 1 (kq).

- X_{rp} express the quantity of rapeseed transformed to ester and by-products by chain 2 (kq).
- N_1 , N_2 are integer decision variables which express the number of units required for chain 1 and chain 2 respectively.
- *Di* are the 0-1 decision variables which declare if the ith pair of prices for wheat and rapeseed are selected by the model.
- B_{11} , B_{12} , B_{13} , B_{21} , B_{22} , B_{23} are the auxiliary 0-1 variables in order to transform the integer variables N_1 and N_2 into a sum of 0-1 variables.

Parameters

- *df*_{eth}, *df*_{est} are the tax credits for ethanol and ester respectively. They are considered as parameters in each mixed 0-1 MOLP sub-problem (1000 FF/hl). These are the only parameters that vary in the one hundred sub-problems. Their values are 240, 250, 260, 270, 280, 290, 300, 310, 320, 330 for *df*_{eth} and 150, 160, 170, 180, 190, 200, 210, 220, 230, 240 for *df*_{est}.
- *cfeth, cfest* are the coefficients of transformation from volume to mass for ethanol and ester respectively in hl/t (*cfeth*=5.8785, *cfest*=11.360).
- *peth, pest, pddgs, pcake, pglyc* are the market prices for ethanol, ester, DDGS, cakes and glycerine respectively in 1000 FF/t. (*peth=*0.6, *pest=*1.5, *pddgs=*0.7, *pcake=*0.75, *pglyc=*2)
- *cvwh, cvrp* are the variable conversion cost for chain 1 (wheat to ethanol) and chain 2 (rapeseed to ester) respectively in1000 FF/t (*cvwh*=0.0171, *cvrp*=0.0506)
- f_1 , f_2 are the fixed costs for processing units of chain 1 and chain 2 respectively in million FF (f_1 =94.86, f_2 =144.72)
- p_{whi} , p_{rpi} are the prices of wheat and rapeseed according to the i-th price scenario (1000 FF/kq). Their values are decided in the agricultural model and are $p_{whi}=27$, 29, 31,...,63, 65 and $p_{rpi}=40$, 45,50,...,130,135. There are 20 values for p_{whi} and 20 values of p_{rpi} which make the number of examined combinations m=400 [*]
- q_{whi} , q_{rpi} are the optimal quantities of wheat and rapeseed according to the i-th price scenario (kq). Their values are determined by the agricultural model (see appendix).
- *m* is the number of different price scenarios for wheat and rapeseed and it is decided in the agricultural model (*m*=400).
- *sveth, svest* are the unitary amounts of CO₂ emissions, saved by the use of ethanol and ester respectively in kt CO_{2eq saved} / kt biofuel (*sveth* =1.4, *svest*=2.2)

budg is the total budget that can be spent for biofuels' tax credits in million FF (*budg*=1260.155)

- *cap*₁, *cap*₂ are the capacities of each one unit for chain 1 and chain 2 respectively in1000 hl (*cap*₁=990, *cap*₂=1400)
- *awh_eth, awh_ddgs* are the conversion factors from wheat to ethanol and the by-product DDGS respectively in kt / kq biomass (*awh_eth* =0.029, *awh_ddgs*=0.0417)
- *a*_{*rp_est}, <i>a*_{*rp_cake*}, *a*_{*rp_glyc*} are the conversion factors from rapeseed to ester and the by-products cakes and glycerine in kt / kt biomass (*a*_{*rp_est*} =0.040, *a*_{*rp_cake*} = 0.0559, *a*_{*rp_glyc*}=0.004)</sub>

Each one of the mixed 0-1 MOLP sub-problems has the following structure:

Objective functions

The two objective functions of the described model express both economic and environmental criteria.

1. Total economic (producer) surplus: The first objective function concerns the maximization of the system's economic surplus (in million FF) and is expressed by the following relation:

$$\max Z_1 = P_1 + P_2$$

(O1)

2. Total CO₂ emissions abatement: The second objective function concerns the maximization of the total amount of CO₂ emissions (in kt) that will be avoided due to the use of biofuels. The biofuels under consideration are bio-ethanol and bio-diesel (ester).

$$\max Z_2 = sv_{eth} \cdot X_{eth} + sv_{est} \cdot X_{est}$$
(O2)

Constraints

The constraints of the mixed 0-1 MOLP are the following:

1. *Definition of profits P*₁ *and P*₂: The profits P1 and P2 from the two chains (wheat-ethanol and rapeseed-ester respectively) are given by the following equations:

$$P_{1} = [(df_{eth} \cdot cf_{eth}) + p_{eth}] \cdot X_{eth} + p_{ddgs} \cdot X_{ddgs} - cv_{wh} \cdot X_{wh} - fc_{1} \cdot N_{1} - \sum_{i=1}^{m} p_{wh}^{i} \cdot q_{wh}^{i} \cdot D_{i}$$
(C1)

$$P_2 = [(df_{est} \cdot cf_{est}) + p_{est}] \cdot X_{est} + \sum_{j=cake,glyc} p_j \cdot X_j - cv_{rp} \cdot X_{rp} - fc_2 \cdot N_2 - \sum_{i=1}^m p_{rp}^i \cdot q_{rp}^i \cdot D_i$$
(C2)

2. *Budget constraint*: The total amount of public expenditure that can finance the tax credits for biofuels is limited:

$$(df_{eth} \cdot cf_{eth}) \cdot X_{eth} + (df_{est} \cdot cf_{est}) \cdot X_{est} \le budg$$
(C3)

3. *Capacity constraints*: The quantities of biofuels produced cannot exceed the total capacity of the corresponding units times the number of the units:

$$cf_{eth} \cdot X_{eth} - cap_1 \cdot N_1 \le 0 \tag{C4}$$

$$cf_{est} \cdot X_{est} - cap_2 \cdot N_2 \le 0 \tag{C5}$$

4. *Mass balances*: The following five equations are the mass balances that describe the conversion of energy crops to biofuels and by-products

$$X_{eth} - a_{wh_eth} X_{wh} = 0 \tag{C6}$$

$$X_{est} - a_{rp_est} X_{rp} = 0 \tag{C7}$$

$$X_{ddgs} - a_{wh_ddgs} X_{wh} = 0 \tag{C8}$$

$$X_{cake} - a_{rp_cake} X_{rp} = 0$$
(C9)

$$X_{glyc} - a_{rp\ glyc} X_{rp} = 0 \tag{C10}$$

5. *Raw material availability*: The required quantity of energy crops (wheat, rapeseed) must not exceed the production of the corresponding energy crop:

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$$X_{wh} - \sum_{i=1}^{m} q_{wh}^{i} \cdot D_{i} \le 0$$
(C11)

$$X_{rp} - \sum_{i=1}^{m} q_{rp}^{i} \cdot D_{i} \le 0$$
(C12)

6. *Mutually exclusive price scenarios*: Among the m price scenarios for the energy crops one and only one can occur:

$$\sum_{i=1}^{m} D_i = 1 \tag{C13}$$

7. *Transformation of integer variables to binary*: The upper bound for the integer variables N1 and N2 which express the required units for chain 1 and chain 2 is computed to be 6. Therefore, in order to transform the integer variables into a sum of 0-1 variables we use the following equations:

$$N_1 - B_{11} - 2 B_{12} - 4 B_{13} = 0 \tag{C14}$$

$$N_2 - B_{21} - 2 B_{22} - 4 B_{23} = 0 \tag{C15}$$

The formulated model, which expresses a typical sub-problem comprises, in total, two objective functions, 15 constraints and 417 variables, 400 of which are binary and 2 are integer. Integer variables are transformed into 6 binary variables. One hundred of these mixed 0-1 MOLP problems are solved in order to cover all the possible combinations of the tax credits.

Results and discussion

The generation of the efficient points for each one mixed 0-1 MOLP sub-problem was performed using the Multicriteria Branch & Bound method (MCB&B, Mavrotas and Diakoulaki, 1998). The solution time in a Pentium II, in 333 Mhz, varied between one and seven minutes, with an average of three minutes for the one hundred sub-problems. The output of each run was the set of the efficient points (the objective functions' values, along with the decision variables' values). From the one hundred mixed 0-1 MOLP problems, 378 efficient solutions were generated. In order to separate the "globally" efficient solutions, a screening procedure was performed through a pairwise comparison of the objective functions' values of the 378 efficient solutions. From these 378 efficient solutions, only 14 were eventually found to be "globally" efficient solutions. Therefore, the decision-maker is only interested in this reduced set of 14 "globally" efficient solutions. The efficient frontier, which is formed by the 14 "globally" efficient solutions, is depicted in Figure 1 (in the Annex).

For these 14 variables, the values of the objective functions along with the corresponding tax credits and the values of the discrete variables are shown in Table 1, while in Table 2 the corresponding values of the continuous variables are shown.

	<i>df_{eth}</i> (FF/hl)	df _{est} (FF/hl)	Z ₁ (millionFF)	$Z_2 \ (kt \ CO_{2eq})$	N ₁	N_2	D_i	P _{wh} ⁱ (FF/q)	P _{rp} ⁱ (FF/q)
1	240	240	44.09	1130	3	2	D ₂₇₄	53	105
2	250	230	48.3	1129.6	3	2	D ₂₇₄	53	105
3	260	240	63.3	1125.3	4	1	D ₂₉₃	55	100
4	250	240	99.03	1090	3	2	D ₂₅₄	51	105
5	280	220	113.9	1089.7	3	2	D ₂₅₄	51	105
6	290	230	145	1047.4	1	3	D ₂₁₅	47	110
7	250	240	147.26	1047	1	3	D ₂₁₅	47	110
8	300	230	153.6	1046.8	1	3	D ₂₁₅	47	110
9	290	240	160.6	1027.8	3	2	D ₂₅₃	51	100
10	300	150	200.7	992.9	5	0	D ₂₆₁	53	40
11	330	190	244.5	985.3	4	1	D ₂₅₂	51	95
12	330	200	323.1	971.1	3	1	D ₂₅₂	51	95
13	320	230	328.9	968.5	3	1	D ₂₅₂	51	95
14	330	150	388.5	898.2	4	0	D ₂₄₁	51	40

Table 1: The tax credits, criteria values, number of processing units and the selected pair of prices for wheat and rapeseed crops for the 14 "globally efficient solutions.

Worthwhile remarks about these results can be summarized as follows:

- There are cases where no bio-diesel is produced (solutions 10 and 14).
- Bio-ethanol production varies from 168.4 to 709.2 kt, while bio-diesel production varies from 0 to 368.9 kt.
- The preferred price for wheat is about 50 FF/q (from 47 to 55), while for rapeseed is about 100 FF/q (most of them between 95 and 110).
- In the environment supporting solutions (higher values for CO_{2eq}), a mixture of the two chains is present, as bio-ethanol and bio-diesel co-exist. In these cases, the tax credits are relatively low for bio-ethanol and high for bio-diesel. In the profit oriented solutions, chain 1 (wheat to bio-ethanol) dominates the biofuel system.

	P ₁ (million FF)	P ₂ (million FF)	X _{eth} (kt)	X _{est} (kt)	X _{wh} (kq)	X_{rp} (kq)	X _{ddgs} (kt)	X _{cake} (kt)	X _{glyc} (kt)
1	1.31	42.79	477.4	209.7	16460.5	5242.4	685.6	293.0	21.0
2	29.37	18.97	477.4	209.7	16460.5	5242.4	685.6	293.0	21.0
3	41.66	21.66	650.3	97.7	22424.2	2441.3	934.0	136.4	9.8
4	3.79	95.24	396.8	242.8	13684.3	6069.9	570.0	339.2	24.3
5	73.80	40.07	396.8	242.8	13684.3	6069.9	570.0	339.2	24.3
6	82.64	62.32	168.4	368.9	5807.3	9223.1	241.9	515.5	36.9
7	43.03	104.23	168.4	368.9	5807.3	9223.1	241.9	515.5	36.9
8	92.54	61.10	168.4	368.6	5807.3	9215.7	241.9	515.1	36.9
9	148.65	11.92	450.4	180.6	15531.6	4514.1	646.9	252.3	18.1
10	200.69	0.00	709.2	0.0	24456.7	0.0	1018.6	0.0	0.0
11	237.42	7.10	515.4	119.9	17770.9	2997.3	740.2	167.5	12.0
12	302.36	20.72	505.2	119.9	17421.8	2997.3	725.6	167.5	12.0
13	267.27	61.58	503.4	119.9	17357.7	2997.3	722.9	167.5	12.0
14	388.47	0.00	641.5	0.0	22122.3	0.0	921.4	0.0	0.0

Table 2: The profit from each biofuel chain and the values of continuous decision variables for the14 "globally efficient solutions.

For Tables 1 and 2, it can furthermore be observed that efficient solutions 1 and 2 are essentially identical (same values for the decision variables). What differentiates them is the tax credit parameter. The CO₂ abatement (second objective function) is only slightly different, probably due to round-off errors. The same case is also observed for the efficient solutions 4,5 and 6,7,8. Different tax credit parameters imply that similar efficient solutions correspond to different values of total subsidy budget allocated to bio-fuels. If an additional criterion, such as that of budget minimisation, is introduced, it would facilitate decision on the above efficient solution. At the same time, the introduction of a third criterion would result in an increasing number of global efficient solution and an increased time lapse in the MOLP algorithm process. If the budget became a decision variable that had to been minimized, then the problem would become more complicated, with more efficient solutions per sub-problem and higher solution times. This hypothesis would be worth investigating in.

Concluding remarks

the aim of this work was to develop a method to solve the problem of biofuel production, taking into account multiple objectives. the problem is complicated because it combines multiple objectives, along with discrete variables and non-linear terms in one of the objective functions. the initial mixed 0-1 monlp problem is decomposed into several mixed 0-1 MOLP subproblems, which are solved using the multicriteria branch & bound method. the solution time is not prohibitive, as it requires about 3 minutes to generate the set of the efficient points for each sub-problem. with the mixed 0-1 MOLP formulation, we can incorporate discrete phenomena into the multiple objective model. in the present case, we can use integer variables for the number of biofuels' plants and 0-1 variables for the mutually exclusive events predetermined in a previous decision stage (agricultural model).

the specific multiple objective formulation of the problem offers a useful tool to the decisionmaker. he can obtain all the information (for example, which tax credits lead to efficient solutions, what are the values of decision variables etc.) for the whole set of the efficient solutions. subsequently, using this wealth of information and according to his judgement, he can choose where on the efficient frontier his most preferred solution lies. the use of multiple criteria analysis procedures facilitates the real time decision process in order to enhance interaction, especially when more agents are involved. the more information is available to the decision maker about the decision situation, the more confident he is of his final choice.

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Annex



Figure 1. The efficient frontier of the problem



Figure 2. Flowchart of the multicriteria branch and bound algorithm