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A B S T R A C T

This contribution addresses the optimal design of the biomass supply chain as it is crucial to ensure long term viability of such a project. This work is focused on the multi objective optimization by considering all the dimension of the sustainable development, namely economic, environmental, and social. The environmental dimension is quantified through life cycle assessment, and more particularly the Ecocosts method. The social aspect is measured through two indicators: the competition between energy and food, and the total number of local accrued jobs. For the latter a new method based on financial accounting analysis is proposed to estimate the direct, indirect and induced jobs created.

Once the superstructure described, the optimization problem is formulated as a mixed integer linear program (MILP) that accounts for biomass seasonality, geographical availability, biomass degradation, process conversion technologies and final product demand. The output results of the model propose the optimal network design, facilities location, process selection and inventory policy. Since multiple conflicting objectives are involved when optimizing the sustainability of the biomass supply chain and the binary variables have an important influence on the resolution, the MILP problem is solved with the goal programming method to reach the trade-off. The approach is illustrated through a bioethanol supply chain case study in France, for the comparison between agricultural and forest residues biomass.

## 1. Introduction

In recent decades, concerns about energy reliance on exporting countries, climate change, fossil reserve dependency and depletion, greenhouse gas emission, petroleum prices fluctuation are increasing the use of renewable resources for energy and chemicals substitution or complement. In the same time, several countries, *e.g.* European Union (European Commission, 2009), have set mandatory minimal targets to reduce the threshold of their greenhouse gas emission with the following milestones: 35% from 2012, 50% from 2017 and 60% after 2018. Furthermore, another directive has established that in the transport sector, 10% of the energy should be produced from renewable resources by 2020. This commitment is enrolled in a context of a growing worldwide demand of energy (International Energy Agency, 2012), thus viable energy alternatives are urgently needed to anticipate the future energy requirement.

Amongst the various possibilities, biomass as renewable energy will definitely be on the rise in deciding countries energy mix. Biomass has not only the potential to contribute to fill the energy needs for many countries and to ensure their energy independence, but also to combat global warming and climate changes. The main advantage of biomass is its worldwide availability due to its diversity of sources: vegetation, energy crops, animal fats, wood and agricultural residues, municipal and industrial wastes. Amongst the various conversion possibilities from biomass to intermediate or final biochemical, this paper is more focused on bioethanol production as it can be used as gasoline alternatives thanks to its compatibility with automobile engine. The first generation of biorefinery for bioethanol production used corn as raw material. But, this first generation raises many questions such as its interferences with the food sector, its water consumption (especially

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for corn cultivation), and the economical sustainability. Thus, the second generation of biorefineries, which transformed lignocellulosic raw materials into bioethanol, was developed in order to reduce water consumption, utilities consumption in the transformation process and the competition with food (Cucek et al., 2011). But within the wide spectrum of feedstock sources that can be used to synthesize biofuel, plant and microalgae start to be studied extensively. Microalgae is a promising feedstock for production of biofuels since it grows fast, has high oil contents, is a non-food feedstock and its potential culture on non-arable land (Singh et al., 2014; Rizwan et al., 2013). Biofuel production from algae gives rise to the third generation of biorefinery. In the remainder of this paper the attention is more focused on the first and second generation of biorefineries with the purpose to compare them.

While there are many process alternatives to transform biomass into bioethanol, an important part of the cost of the final biochemical comes from the whole supply chain. To improve economic profitability, it is essential to have a biomass infrastructure where raw materials collection, storage, transportation and pre-processing are simultaneously considered. Therefore, the establishment sites of the biorefineries, the amount of the different kind of raw materials and where they are collected, or the construction of facilities are as important as choosing the most suitable conversion process (Giarola et al., 2014). Of course there is a need to improve the technological inputs, the pre-treatment approaches and the production process as underlined by Liu et al. (2012). But among the challenges to use biomass as a sustainable source of energy, the most important bottleneck to leverage is the cost and complexity of its logistics operations. As a consequence, biomass supply chain management has to raise several challenges that differentiate it from conventional supply chain networks. The key challenges and opportunities for the modeling and optimization of biomass to bioenergy supply chain have recently been discussed in Yue et al. (2014). The first one concerns the biomass chemical and physical properties like deterioration with time during storage, moisture, harvesting seasonality, geographical availability, and storage requirements. You et al. (2012) have explained that it is specifically true for cellulosic biomass feedstock. In some cases, the quality of the biomass (moisture content, lower heating value, bulk density and energy density) is the key parameter as these physical properties can vary significantly and influence the process. As a result, optimization of the operating conditions and the control of the process would be required. But as Yue et al. (2014) have underlined, to handle these issues the model must encompass advanced control algorithm and dynamic models to integrate physical and thermodynamic properties. This additional modeling complexity is not included yet in the proposed model, it remains one perspective.

Another challenge results from the multiscale and multisite nature of the problem requiring spatial discretization and multiperiod approach to integrate short, medium and long term considerations. Indeed, the supply chain management involves a complex decision making process gathering the three traditional hierarchical levels, *i.e.* strategic decision with for instance the decision of production technologies and the network configuration, the tactical and operational decisions with for example production planning, selection of collection storage and pre-treatment. A detailed discussion on the hierarchy of decision making process for biomass supply chain is given by Iakovou et al. (2010).

The last challenge deals with the way to quantitatively measure the sustainability of the supply chain and to integrate it in an optimization framework. Indeed, biomass offers several possibilities for developing region because of its potential for providing economic, environmental and social benefits. In addition to the economic and environmental dimension, the integration of the social one leads to complex decision making problem with antagonist criteria.

This work deals with the design of the biomass supply chain by considering all the hierarchical levels of the decision process with their specific issues. Besides, the integration of the three pillars of the sustainable development is mandatory to reach a balance between its conflicting objectives. But as explained in Iakovou et al. (2010), Perez-Fortes et al. (2014a,b) and Kudakasseril Kurian et al. (2013), there is a vast open literature on the biomass supply chain issue which can be addressed using a wide range of decision support system. Among the method to handle biomass supply chain issues, multi objective optimization has attracted an increasing interest within sustainability applications as underlined by Kravanja and Cucek (2013) and Giarola et al. (2011) as it is a suitable approach to support decision. A superstructure of the biomass supply chain network and a multiperiod formulation are regularly considered. As a result, large scale mixed integer (non) linear program (MI(N)LP) are often formulated by modeling all the relevant information for each processing unit, transportation, raw material, geographical area, storage, conversion process. . . Indeed the formulation of MILP (or MINLP) allows to reach relevant data for facility and for flows in the network. Initially based on single objective optimization, often an economic one (Giarola et al., 2014; Haque et al., 2014; Eksioglu et al., 2009; Sheu et al., 2005), this approach was extended to account for other important aspects such as the environmental impact (Wang et al., 2011) (Concept of Green supply chain) and/or social considerations. This leads to multi objective optimization that offers a powerful approach to find trade-off between conflicting objectives as in the case of the multi performance measures of the sustainable development. You et al. (2012) and Perez-Fortes et al. (2014a,b) have presented a detailed state of the art on the combination between multi objective optimization and mathematical programming.

As mentioned before, new industrial activity in general and biomass supply chain in particular will influence positively economic, environmental and social performances of a region. But underlined by You et al. (2012), Yue et al. (2014), few researches cover the social dimension but sustainable biomass supply chain in the long term must rely on collective development of the three pillars of sustainability. Yuan (2012) had given three major reasons to explain the scarce research on social performance: (i) the social influence is of lower priority while implementing new activities, for instance economic or time objectives are dominant, (ii) many social indicators are qualitative and thus difficult to evaluate, and (iii) different groups of participants are affected in different ways. On this point, the author had established two groups:

- The first group encompasses authorities, general public. . . which aims to decrease the environmental impact and improve the social one.
- The second group gathers clients, main subcontractors who are more focused on the economic benefits.

The balance between the two groups is unequal as it is more favorable for the second one which is more powerful in developing industrial activities. Nevertheless, biomass activities have also an important social role to play and more specifically it has the potential to promote rural development. One of the most important key indicators for social assessment is the employment generated as the majority of the other indicators remain constant whatever the option retained. Furthermore this key indicator can be quantitatively measured, *i.e.* the total number of local jobs created in a regional economy. The higher the job creation is, the more the social benefit is favorable for the biomass supply chain. With general recognized agreement to include simultaneously the three aspects of sustainability for both evaluating and elevating the effectiveness of the biomass supply chain, this paper tries to address this issue by

proposing a new method, based on the economic value added of firms, to estimate the total number of accrued jobs.

The second major contribution concerns the development of an efficient solving method because of the problem size, the tremendous computational time and the difficulty to establish the trade-off between the criteria. To solve this kind of multi objective optimization problems with conflicting targets, the $\varepsilon$ constraint method for generating the Pareto front is the more used (Kravanja and Cucek, 2013; You et al., 2012; Pieragostini et al., 2012; Santibañez-Aguilar et al., 2014). This method gives good results for a multi criteria optimization as in the previous works but needs a large computational time in our case. As a consequence the goal programming method is used to solve our mathematical model and to reveal the trade offs.

The remainder of the paper is organized as follows. In the next section, a review of the biomass supply chain literature by focusing on the more recent propositions is presented. The third part deals with the problem statement with the superstructure description, the key assumptions and the MILP mathematical model depiction, objective function with the social performance model formulation. The resolution method with the goal programming approach, used to solve the multi criteria issue, is described in the multi objective optimization methodology section. Before to draw conclusions and to give some perspectives, the computational results are detailed for a case study of the bioethanol supply chain based on the comparison between first and second generation of bio refineries for the French southwest region. The results relying on the different scenarios are discussed.

## 2. Literature review

Due to the large amount of researches on multi objective optimization of the biomass supply chain, the modeling of the most relevant characteristics have to be discussed before to elaborate a model.

The first characteristic deals with the distributed, centralized or two stages (combination of both previous ones) structure of the biomass supply chain. Taking into account the biomass usages, some studies have proposed models to discern between previous modes with respect to different criteria: economic for Bowling et al. (2011) and environmental for Iglesias et al. (2012).

Among the outputs of the MILP or MINLP, the results often discuss location and allocation decisions together with the selection of capacity and the type of technologies. For the former, different possibilities emerge to treat the spatial data for the supply chain network. Indeed, as the geographical distribution of the supply chain components strongly influences the processes profitability and the biomass sources, the regional geographical features must be taken into account. Most of the research papers use a spatial discretization of the regional area under study in order to optimize the conversion operation and transportation flows. This leads to define a fix set of possible locations for the harvesting sites, storage sites, processing sites and end users location. As a result, the location of the different components of the network is determined among this set of possibilities. All the geographical information can be encompassed in one layer as in the approach of Eksioglu et al. (2009), but for a more detailed description of all the relevant information, the multi-layer approach introduced by Cucek et al. (2010) is well suited. In this approach, the supply chain network is divided into four layers, each one containing information on the different generic stages: harvesting and supply area, collection and preprocessing centers, biorefineries, and end users. Links between the layers represent transportation steps. Recently, to improve the geographical description and in particular for transportation (Perez-Fortes et al., 2014a,b) have used the Universal Transverse Mercator coordinate system to calculate the distances between sites. This method calculates the linear distance between two points and then corrects it by a tortuosity factor. To go further in spatial data considerations and to be more precise within the location analysis, some studies combine optimization with geographical information systems to extract information on the region under study (Tavares et al., 2011; Zhang et al., 2011; Gasol et al., 2011).

As mentioned before, the production technology can also be introduced in the set of decision variables. In their model (Giarola et al., 2011) have optimized the economic and environmental performances, providing information in terms of conversion technologies, process size and location for bioethanol production. More recently, the work of Perez-Fortes et al. (2014a,b) proposes a MILP formulation to deal with the different possibilities for biomass pretreatment technologies to feed existing coal combustion plants, because they influence not only the pre-treated biomass properties but also the different echelons of the supply chain.

The static or dynamic behavior of the supply chain is another important feature to consider. Most of the research papers in the literature are focused on steady state but only some scarce papers deal with the dynamic nature of the supply chain in general and in biomass supply chain in particular. In their study on biomass conversion technologies, Fazlollahi and Marechal (2013) have combined multi objective and multi period optimization. To go further, Cucek et al. (2014) present a multi period synthesis of a regional biomass supply chain which combines first, second and third generations of biofuel on the one hand, and introduces recycling and heat integration on the other hand. In the recent years more and more models integrate the multi period aspect (You et al., 2012; Perez-Fortes et al., 2014a,b).

Nowadays, the design and operation of the biomass supply chain must consider multiple performance measures to integrate all the sustainability criteria for decision making. Indeed, a trade-off among the different contradictory metrics is often needed. First, the environmental assessment was progressively extended to consider all the negative impacts based on LCA (Life Cycle Assessment). In a recent study (Cucek et al., 2012c) have detailed the footprints commonly considered to evaluate the environmental impact, and have studied their influence on the multi objective optimization results for biomass energy supply chains. However, a detailed literature review permits to conclude that the majority of current researches have been focused both on the economic and environmental impacts associated with the biomass supply chain but studies remain to be done for the social one. As a result, it still remains a challenge to consider simultaneously the three dimensions in multi objective optimization. A first study on the exploration of measures of social sustainability and how to incorporate them into supply chain decisions was proposed by Hutchins and Sutherland (2008). In their review of footprint analysis tools for monitoring impacts on sustainability, Cucek et al. (2012b) have listed eight social footprints: human rights, corruption, poverty, online social (online information available about a person), job, work environmental (number of lost day per unit of product or number of accidents per person), food to energy, and health. According to Houdin (2012), the indicators that are the most used are: human rights, health and security, governance, working conditions, cultural heritage, economic and social repercussions. But as Standford and Azapagic (2011) have demonstrated, some of these indicators are difficult to assess, *e.g.* human rights, corruption. Moreover, for the design of a new system in a specific region some criteria would have no influence on the choice between some alternatives as they would not undergo large variations. In conclusion, as Yue et al. (2014) have noticed the evaluation methodology for the social dimension is still immature as the choice and formulation of indicators are still under debate in the social LCA community. But

there is a general consensus on the fact that the employment effect is one of the most important perspectives in the social dimension.

In our case, the implantation of biomass supply chain components will provide significant social benefits to rural regions by creating diverse jobs opportunities in cross sector activities such as: agriculture, production, transport, maintenance, services. Perez-Fortes et al. (2014a) have evaluated the creation of jobs by counting the number of sites that have a treatment or pre-treatment system in order to promote working places in the widest range of communities. Even if it is one of the first attempt to introduce the job creation criteria, their social evaluation is not entirely suitable because it does not explicitly estimate the number of jobs created, and it does not account for the specificities of the local region, the capacity of the process as well as the industry type. For the evaluation of the number of jobs that will accrue to a local region, You et al. (2012) have used an input-output multiplier analysis. In their approach a multiplier is a ratio that estimates the total impact resulting from an initial change in economic output. This ratio takes into account some economic and regional considerations. In this previous article, the total impact of a new activity on employment is decomposed into three different levels: direct, indirect and induced job creations. Despite a great progress in the evaluation of this criterion, the precision of the method is to question because of the use of ratio especially since the likelihood interval is not given. Furthermore, the link between the three levels is not obvious and not clearly expressed (and the data for evaluation are only available for United States). Santibañez-Aguilar et al. (2014) have also incorporated simultaneously economic, environmental and social criteria to design and plan biorefinery supply chains with several multiproduct processing plants located at different sites and supply different markets. While their model considers the social impact through the number of jobs generated by all the activities of the supply chain, their evaluation is limited to the direct jobs created.

The aim of this contribution is to propose a multi objective optimization model to fill two gaps in the current state of the art. First the social criterion has very little been introduced in the objective function. To evaluate this criterion a new approach is proposed to estimate the number of accrued jobs created by the activity generated by the implantation of a new biomass supply chain component in a specific area and to optimize it. The integration of all the dimensions of sustainability in a multi objective optimization framework is the cornerstone of the proposed model in order to take relevant decisions. The second novelty is the introduction of another mathematical method to solve the multi objective optimization problem. Indeed in both previous studies dealing with the social criterion, the $\varepsilon$ constraint method was used to provide the Pareto front curves in order to find the trade-off for decision making. But because of the tremendous computing time and the difficulty to find point on the Pareto curve, the goal programming approach is introduced.

## 3. Problem formulation

### 3.1. Modeling and optimization

As noticed by Yue et al. (2014), the multi objective optimization of the biomass supply chain must rely on a multi scale framework to provide a holistic view and to integrate its different components. Based on the work of Yue et al. (2014), Fig. 1 illustrates the three levels of the flowdiagram and how the dataflow is performed in the proposed approach.

The assessment level concerns the impact of the biomass supply chain activities on the system where they occur. In this study, the economic objective is to minimize the total annual costs which concern all the operating costs in the value chain and the annual amortized cost for biorefineries and storage facilities constructions.

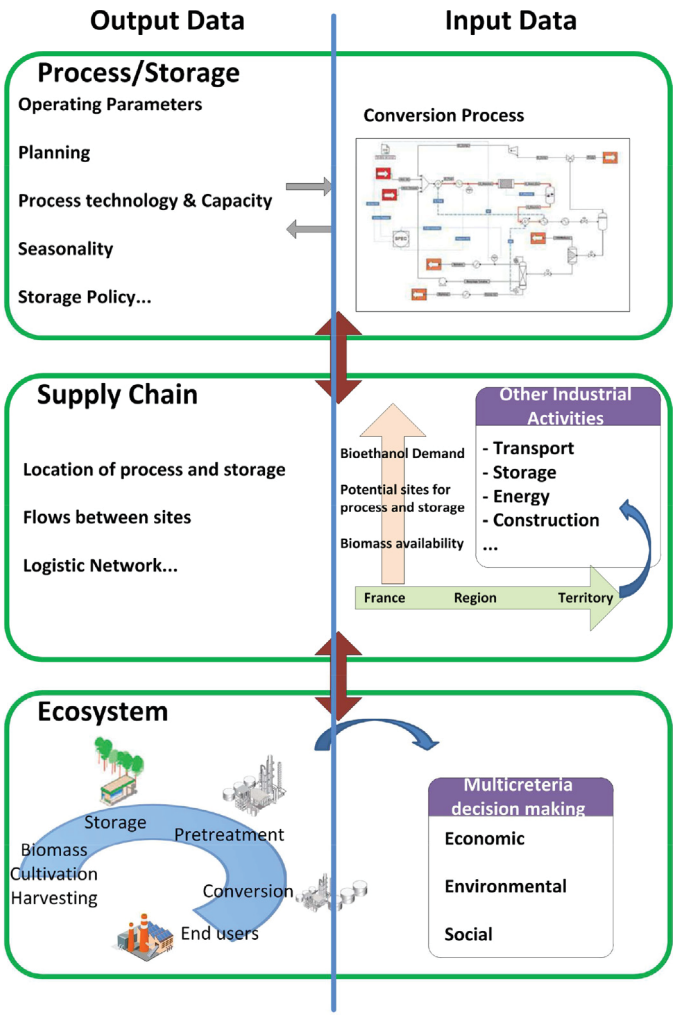


**Fig. 1.** Illustration of the workflow diagram with multi scale modeling (based on Yue et al., 2014).

Concerning the environmental impact, in the same way all the activities that impact the system throughout the whole life cycle of the bio chemical are considered: from biomass cultivation and harvesting until distribution to end users. Finally, in our approach the social benefit is measured through the number of accrued jobs created by the supply chain activities. Here again all the activities in the life cycle are considered, moreover the method not only estimates the direct jobs created but also assesses the total number of both indirect and induced jobs. As explained in the literature review, the simultaneous consideration of the three conflicting dimensions is still a stimulating challenge which leads to complex multi objective optimization problems. While various resolution techniques could be applied to solve these issues, in our study, the goal programming technique is well suited because the binary part of the model is controlling and conditions the problem.

The supply chain level is focused on the optimization of the supply chain network structure which aims to determine the facility locations, transport options, suppliers etc. Indeed as You et al. (2011) have specified biomass supply chain usually consists of multi sites and multi echelons which needs coordination across the whole network. In our approach the various activities involved in the superstructure are described through a mathematical programming approach. However, the design of the superstructure and its modeling require assumptions and choices (as it is still not numerically feasible to address this problem on all its complexity) to that will be detailed in the following subsections.

On the one hand, the process level deals with decisions related to the optimization of the technological choices among candidate conversion processes. On the other hand the operational decisions at the process level also encompass planning, scheduling and control. While they are closely related, only the planning one is addressed with a multi period approach for biomass harvesting, bio ethanol production, and transportation (raw biomass and final bioproduct). The information provided at this level is important to integrate in the other level as it has a strong influence on output variables. More generally, there is a vertical integration and connection between the levels because the assessment level gives objectives that are propagated to the lower level, and inversely, the lower levels provides detailed and relevant data that are introduced and influence the modeling and the optimization of the other levels.

### 3.2. Design of the superstructure

The first step is to define the system boundaries, because the supply chain for biorefineries is different from those of classical refineries. The development of a biomass supply chain for bio chemical production considers specific activities such as biomass harvesting or biomass storage. Once harvested the biomass is shipped to collection centers or directly to biorefineries. In the collection centers the biomass is stored and then sent to processing facilities (biorefineries). The bio chemical produced is then delivered to blending facilities. The goal of the mathematical model is to take decisions related to the supply chain and to optimize the facilities (*i.e.* the biorefineries and collection centers) number, size and location but also to determine all the connections in the network for example: the flows between collection centers and biorefineries or between refineries and blending facilities. As underlined by Eksioglu et al. (2009) the mid-term and short-term decisions in a biomass supply chain relate to determine for each time period: (i) the amount of biomass harvested, (ii) the amount of biomass transported to collection centers or biorefineries (from the harvesting sites or from collection centers for the latter), (iii) the amount of bio chemical transported from biorefineries to blending facilities, (iv) the amount of biomass processed in each biorefinery, (v) the level of inventories of biomass in collection centers and in biorefineries, (vi) the preferred transportation solution for biofuel and the number and capacity of each single element (truck, train. . .), (vii) the economic, environmental and social metrics quantification. . ..

In the proposed model the locations of the harvesting sites and blending facilities (end users) are supposed fixed and the other facilities locations are to be determined.

A superstructure of complete biomass supply chain model and weekly periods for time discretization are considered. In order to support the model formulation, a standardized format for the activity model is used. This multilevel representation provides a comprehensive and detailed analysis of all the components and gives information on the inputs, outputs and metrics. The first level of the representation corresponds to an overview of the model. The second level of the activity model representing all the successive activities for the biomass supply chain is illustrated in Fig. 2. The third level details all the activities of the second level, an example is given in Fig. 4. This framework is well suited for supply chain description as proved by Zhang et al. (2012) for the development of a simulation model for biofuel supply chain. Relying on this visual representation the mathematical model can be established.

### 3.3. Mathematical model

Thanks to the activity model and a deep literature analysis, the model proposed by Eksioglu et al. (2009) gives an interesting base to design the supply chain and manage the logistics of biorefineries. This model relies on three types of discretization:

- Spatial discretization: it consists in decomposing the particular area under study into counties. For each county, the potential location for the harvesting sites, the blending facilities and the conversion processes are listed.
- Size discretization: for each potential technology, the collection facilities and biorefineries capacities are decomposed into a finite number of potential facilities sizes, *i.e.* capacity of production.
- Multi period approach: to take into account the dynamic nature of the decision, the time horizon T is decomposed into a finite number of time periods. In the remainder of the paper the time horizon T is one year and the time period is fixed to one week to be coherent with the data.

During a time period, connections between the different sites (harvesting, collection facilities, biorefineries and blending facilities) represent transportation activities with their specific constraints. Then, the model is subjected to logical and mathematical constraints as well as to mass balances constraints: production capacity, demand fulfilled, flow conservation, capacity constraints on inventories (on raw materials and final products), location constraints (at most one facility or biorefinery of one specific size located in a given area), initial inventory level, non-negative and binary constraints. Moreover, the model also includes various characteristics in the constraints well suited for biomass supply chain:

- during a time period, for each type of biomass the quantity harvested at a site is limited by the amount of biomass available. These constraints enable to model seasonality and land availability.
- in the traditional flow conservation constraints, biomass deterioration with time is considered in facilities and biorefineries inventories.
- the biomass harvested is immediately sent to a storage, *i.e.* no inventory possible at the harvested site whatever the type of biomass.

For inventories capacity constraints between two consecutive time periods have to be established, to ensure that the amount of biomass in facility/biorefinery or of bio product in refinery does not exceed the available capacity. All of these modeling choices lead to a MILP model detailed in annex 1. The model presented in annex 1 also includes some improvements compared to the original one.

As the basic model was described in the paper of Eksioglu et al. (2009), the remainder of this article presents the model evolutions and the new equations relating to the evaluation of environmental and social criteria. Our mathematical model adds four major evolutions:

-1- the first improvement concerns the geographical data. As explained before, the original model is based on a mono layer representation of the geographical features. In the proposed model, this representation is extended with the introduction of the multilayer description previously presented.

-2- in the original model, there is only one type of biorefineries with different sizes. Our model offers the possibility to choose between different types of biorefineries with their specific production capacity, operating costs, investment costs. . .. This improvement is important because it allows to compare the first and second (and later the third) generation of biorefineries. This comparison is *a priori* because the choice of the biorefineries technology is included as a decision variable in the model presented in annex 1. Furthermore, with this

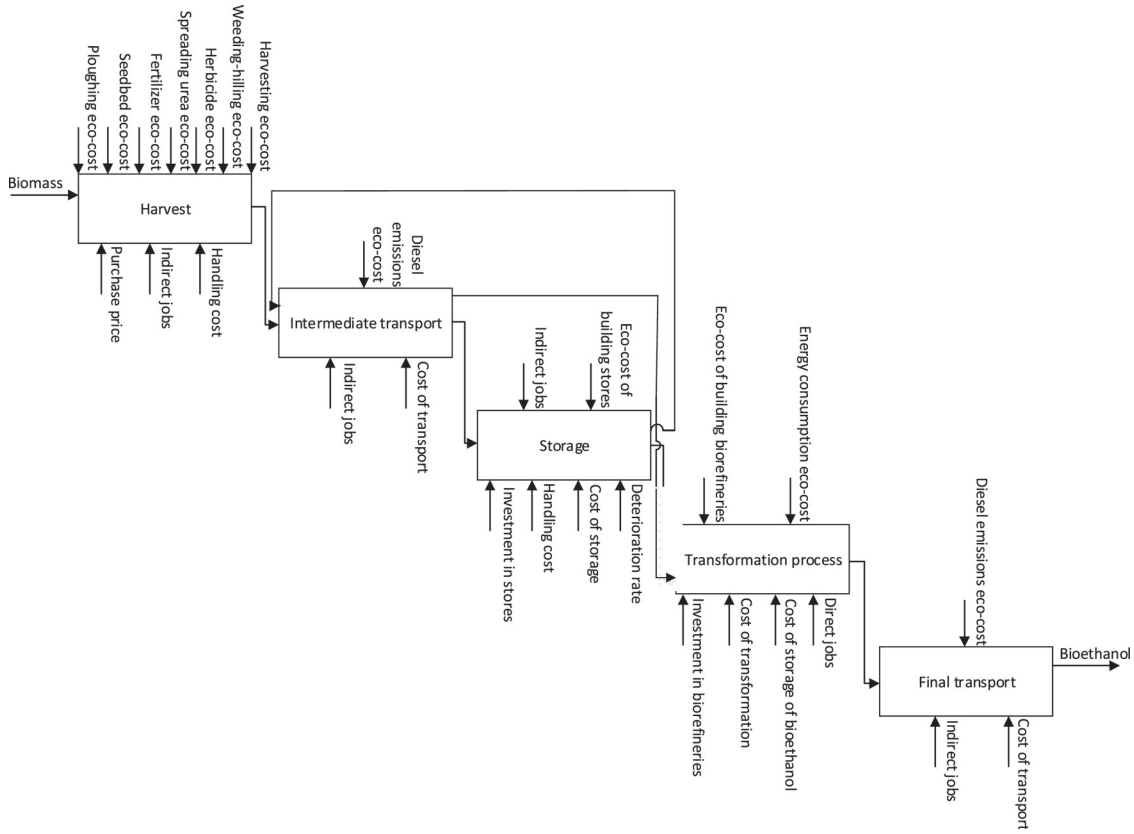


**Fig. 2.** Superstructure of biomass supply chain model.

modification the original MILP model has been transformed into a MINLP one because of new economic terms in the objective function. But a piecewise linearization of the investment costs permits to keep a MILP form to the model.

-3- some additional constraints were added to the original model because of the multi criteria aspect of our model in the one side and because of the numerical method used to solve the new model on the other side, for instance the multicriteria constraints (Eqs. (14) and (15)), detailed in Section 4.

-4- probably the most important evolution is the multi criteria aspect of our objective function since it adds new constraints to the model, it impacts strongly the resolution method (Section 4) and it influences the results (Section 5). Indeed very different results are found according to the criterion the user wants to favor. In addition to the economic and environmental criteria, a social evaluation of a supply chain is included, and more precisely the number of jobs created. The detailed description of the objective function is given in the next part. The biomass supply chain model formulation and resolution leads to a highly computationally demanding model because of the large size and multi objectives problem.

### 3.4. Objective function

As explained in Section 2, there is a vast literature on the research domain of supply chain design and management. There are also numerous papers dealing with location problems. Initially, the optimization of the supply chain was made to achieve cost saving. As a result, all the costs that have an influence on the supply chain performance have to be considered simultaneously. Besides cost considerations, more recently some papers have enlarged the system performance criteria by including energy consumption and GHG emissions across the supply chain as in the Integrated Biomass Supply Analysis and Logistics (IBSAL) model proposed by Sokhansanj et al. (2006) for corn stover to biorefineries, or in the work of Zhang et al. (2012) for biofuel production.

But to evaluate the global performance of a system, it is necessary to describe how human activity can impose different types of impacts on global sustainability, *i.e.* simultaneous progress in economic profitability, environment preservation and social consideration. Thus the use of the multi objective optimization method prior requires translating all the sustainable aspects into suitable criteria that could be optimized simultaneously.

Till now the social assessment is often neglected. But to our knowledge, except the work of You et al. (2012), no study integrates a complete sustainable development view by adding a suitable social criterion to both previous ones in order to optimize the supply chain of industrial products. The main reason is that the evaluation of the social indicators is often a tremendous and difficult task.

#### 3.4.1. Economic criteria

The part of the objective function associated with the minimization of the economic costs includes all the operating costs of the supply chain, from the purchase of biomass feedstock to transportation of the final product, as well as the investment cost of biorefineries and storage facilities. The costs of the supply chain are: the cost of raw material, the transport of raw material to the collection facilities, the cost of handling and storage of biomass, the cost of transport to the biorefineries, the cost of transformation into bioethanol and the cost of final transport to the blending facilities. The economic objective is to minimize the total annual costs. The terms of the cost objective corresponding to the annual operation costs of the supply chain (AOC) are described in the following equation:

$$
\begin{aligned}
\mathrm{AOC} = & \sum_b \sum_h \sum_t CHa_{h,b} \times Ha_{h,b,t} \\
& + \sum_b \sum_t \left( \sum_j \sum_i TCfb_{j,i,b} \times ffb_{j,i,b,t} \right. \\
& \qquad + \sum_i \sum_h TChb_{i,h,b} \times fhb_{i,h,b,t} \\
& \qquad \left. + \sum_j \sum_h TChf_{j,h,b} \times fhf_{j,h,b,t} \right) \\
& + \sum_b \sum_t \left( \sum_i ICb_{i,b} \times bib_{i,b,t} + \sum_j ICf_{j,b} \times bif_{j,b,t} \right) \\
& + \sum_k \sum_i \sum_b \sum_t CC_{k,i,b} \times w_{k,i,b,t} \\
& + \sum_t \sum_i \mathrm{ICE}_i \times eib_{i,t} \\
& + \sum_t \sum_m \sum_i \mathrm{TCE}_{i,m} \times fbb_{i,m,t}
\end{aligned} \tag{1}
$$

In Eq. (1), the summation terms represent, respectively, the annual operating costs for biomass cultivation and harvesting, biomass transport, biomass inventory, biomass conversion, ethanol inventory and ethanol transport.

In order to complete the economic objective, the investment costs of installing biorefineries and collection facilities is added accounting for their specificities (capacity level, technology). To calculate the annual amortized cost for the installation of biorefineries the piecewise linear cost curve approach is used for each production capacity and technology, detailed in You et al. (2012), Dunnet et al. (2008). The same approach is also implemented for collection facilities. As a result the total annual cost to minimize is given by:

$$
\begin{aligned}
\mathrm{EcOF} = \mathrm{AOC} + \frac{ir(1+ir)^{\mathrm{PLT}}}{(1+ir)^{\mathrm{PLT}}-1} & \left( \sum_k \sum_i \sum_l \mathrm{INVb}_{k,i,l} \times y_{k,i,l} \right. \\
& \left. + \sum_{k'} \sum_j \sum_f \mathrm{INVf}_{k',j,f} \times y_{k',j,f} \right)
\end{aligned} \tag{2}
$$

where *ir* is the discount rate and PLT the project lifetime.

All the parameters in the economic objective function are estimated with French data to be in accordance with the case study, for instance: French economic institution for collection facility investment, agricultural journal for wood and corn harvesting, specific journal for transport costs... Concerning the calculation of the investment for the construction of biorefineries, it is estimated by considering the price of a similar biorefinery that is already built, *i.e.* the corn biorefinery in Lacq (France) with a capacity of 200,000 t of bioethanol/year and an investment of 149 million euros in 2008. For wood as raw material, the investment is based on two existing refineries: the plant in Mascoma (2012) that produces 62,000 t of bioethanol per year for an investment of 148 million euros and the plant in Bluefire (2012) that produces 68,000 t of bioethanol per year and its cost was also 148 million euros.

For the other production capacity the Chilton's law is applied to define the investment.

$$
\frac{\text{Investment 1}}{\text{Investment 2}} = \left( \frac{\text{Capacity 1}}{\text{Capacity 2}} \right)^{\text{Coeff}} \tag{3}
$$

The Chilton coefficient is calculated with the data (investment, production capacity) coming from the works (Eksioglu et al., 2009; Wallace et al., 2005), Coeff = 0.678 is used in this work.

*Remark*: The year 2014 is used as reference for all the costs, consequently cost data with reference before 2014, were actualized.

### 3.4.2. Environmental criteria

The environmental impact is quantified with the ecocosts method introduced by Vogtländer and Bijma (2000), Vogtländer et al. (2001), and updated in 2007 and 2012. Ecocosts are a measure that expresses the environmental load of a product on the basis of prevention of that burden during the product life cycle: from the raw materials until its end of life. For a visual display of the system see Fig. 3, and further description is given at www.ecocostvalue.com. This indicator represents the necessary costs that should be made to counteract the negative impact of the activity made on the capacity of earth (Cucek et al., 2012a). It quantifies the impact in terms of pollution and material depletion by allocating a cost penalizing the use of an alternative that would reduce its impact on the environment and would be called sustainable solution. The total Ecocosts are calculated with the sum of the following contributions: (i) Depletion of natural resources, (ii) Effect on ecosystems, (iii) Effect on human health, and (iv) Global warming ($CO_2$ and other greenhouse gases).

- For example the Ecocosts for some emissions are:
- Global warming (0.135 €/kg $CO_2$ equivalent)
- Acidification: acid rain, soil acidification... (8.25 €/kg $SO_x$ equivalent)
- Eutrophication: modification and degradation of aquatic environments (3.90 €/kg Phosphate equivalent)
- Eco-toxicity: pollution of the biosphere, heavy metals, toxins... (55 €/kg Zn equivalent)
- Carcinogenic particles (36 €/kg Benzopyrene equivalent)
- Fine particles (29.65 €/kg PM 2.5)
- Summer smog: atmosphere pollution (9.70 €/kg $C_2H_4$ equivalent)

Ecocosts allow quantifying the environmental impact as a simple indicator easy to understand and compare with other criteria, for example economic. Furthermore, as Cucek et al. (2012a) have underlined, the main advantages of these Ecocosts are: (i) they are expressed as a monetary value, (ii) there is no need to compare with another product (often the case with other life cycle assessment methods), and (iii) calculations are based on European price levels and the costs are updated. In our study, Ecocosts are applied to all the activities of the supply chain. The more penalizing conditions are retained in order to not underestimate this environmental impact. For calculations, the different ecocosts are divided into two groups depending on whether they are fixed or variables:

- Those that do not change whatever the solution such as cultivation of corn, denaturant added.
- Those that can have an influence on the solution and depend on decision variables of the model such as: transportation, energy consumption, creation of collection facilities or biorefineries.

Each activity of Fig. 2 is decomposed into sub-activities (third level of the modeling approach) to evaluate the ecocosts. For example, the harvesting activity for the corn encompasses the cultivation that is decomposed as illustrated on Fig. 4. On this figure, the data required to assess the environmental impact of each sub-activity are mentioned, and it can be noticed that:

- All steps need the use of an agricultural machine that emits mainly $CO_2$, but also carbon monoxide, hydrocarbons and oxides

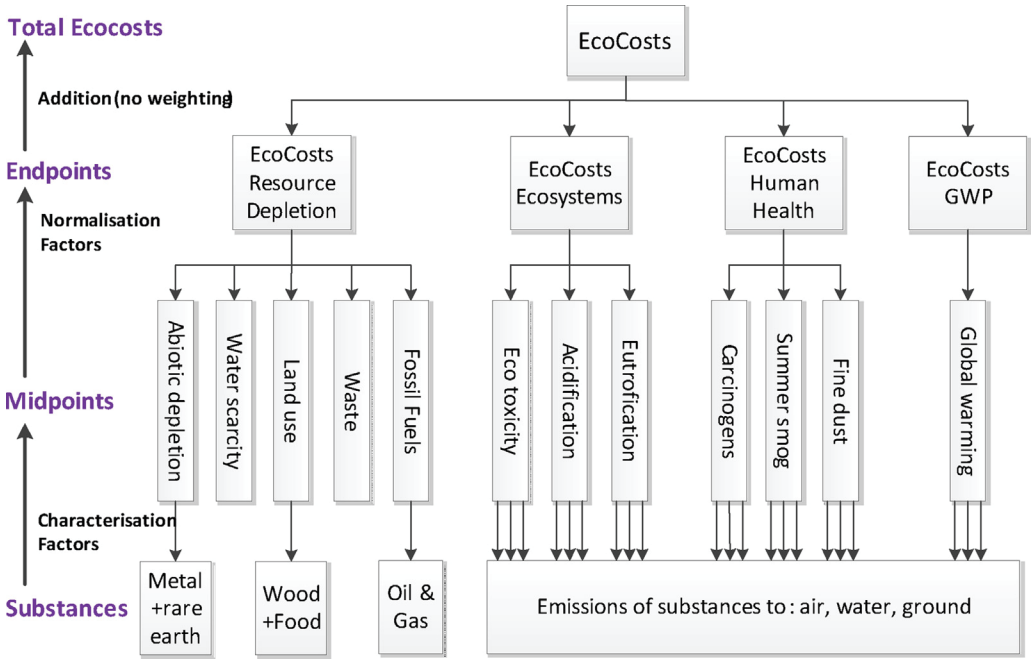


**Fig. 3.** Structure of the system of ecocosts 2012 (www.ecocostvalue.com).

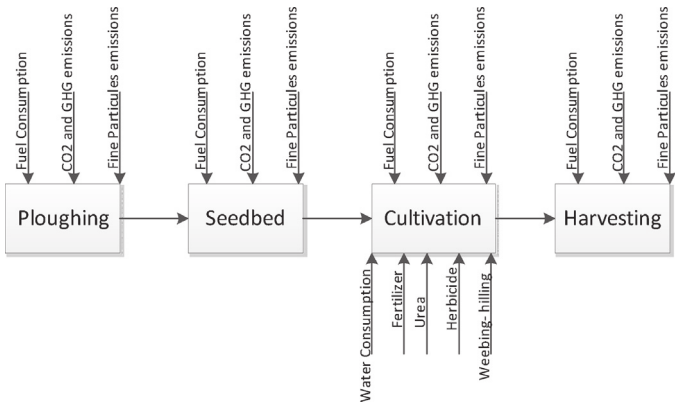


**Fig. 4.** Sub model for the harvesting activity of the superstructure.

**Table 1**
Corn cultivation requirements.

| | |
|---|---|
| Yield (kg/ha) | 10,000 |
| Water requirements ($m^3$/ha and month) | 1000 |
| Time from seedbed to harvest (months) | 6 |
| Consumption of an agricultural machine (L of diesel/ha) | 35 |
| Number of field passages per hectare during one season | 7 |
| Nitrogen requirements (kg/ha) | 220 |
| Selective herbicide (prosulfocarb, L/ha) | 1 |
| PM 2,5 ploughing + harvesting (kg/ha) | 0.1 |
| PM 10 ploughing + harvesting (kg/ha) | 7 |

of nitrogen. These pollutant emissions are based on the European standards Euro 5 and 6 that regulate engine emissions. As they need mechanical device they also emit fine particles to the atmosphere (PM 2.5 and PM 10). The same standards are also used for transport pollutant emissions.

- The cultivation step spreads various chemicals in nature. The main interest is in $NH_x$ molecules.
- Throughout its growth, corn needs to be irrigated. This irrigation mobilizes significant energy involving Ecocosts, taking also into account the use of specific equipments for irrigation. These data are averages of all existing irrigation techniques.

The sub models for all the activities of the superstructure (Fig. 2) enable to inventory all the input data required to calculate the Ecocosts. For instance, corn crop needs of one hectare are calculated thanks to the data given by the French organization (Semences de France, 2013) and summarized in Table 1. Once collected, these input data are introduced at the lower level, *i.e.* substances level of Fig. 3, of the Ecocosts method. As a result the Ecocosts method gives the impact at the endpoints level (Fig. 3). For corn, the harvesting activity contribution to the environmental objective can be written as follows (at the endpoints level):

$$\text{Corn harvesting EcoCosts} = \sum_{h}\sum_{t} Ha_{h,corn,t} \sum_{a} (ECrd_a + ECes_a + EChh_a + ECgw_a) \quad (4)$$

where $a$ represents the activities in the sub model, for instance: ploughing, seedbed, cultivation and harvesting in the previous case, and the four terms of the sum are the calculated Ecocosts corresponding, respectively, to Resource Depletion ($ECrd_a$), Ecosystems ($ECes_a$), Human and Health ($EChh_a$), and Global Warning ($ECgw_a$). Ecocosts related to the cultivation of woody biomass is zero since it is considered as a waste. Eq. (4) represents only one term of the objective function dedicated to the environmental assessment as explained below.

With the same level of decomposition for all the supply chain activities the whole environmental objective function (EnOF) is defined as (written at the total Ecocosts level for each activity for readability):

$$
\begin{aligned}
\mathrm{EnOF} = & \sum_b \sum_h \sum_t ECh_{h,b} \times Ha_{h,b,t} \\
& + \sum_b \sum_t \left( \sum_j \sum_i ECtfb_{j,i,b} \times ffb_{j,i,b,t} \right. \\
& \qquad + \sum_i \sum_h ECthb_{i,h,b} \times fhb_{i,h,b,t} \\
& \qquad \left. + \sum_j \sum_h ECthf_{j,h,b} \times fhf_{j,h,b,t} \right) \\
& + \sum_b \left( \sum_{k'} \sum_j \sum_f ECsf_{k',j,f,b} \times y_{k',j,f} \right. \\
& \qquad \left. + \sum_k \sum_i \sum_l ECsb_{k,i,l,b} \times y_{k,i,l} \right) \\
& + \sum_b \sum_k \sum_i \sum_l ECb_{k,i,l,b} \times y_{k,i,l} \\
& + \sum_b \sum_k \sum_i \sum_l ECes_{k,i,l,b} \times y_{k,i,l} \\
& + \sum_t \sum_m \sum_i ECet_{i,m} \times fbb_{i,m,t}
\end{aligned}
\tag{5}
$$

In Eq. (5), the first summation term represents the part of the Ecocosts due to Cultivation and Harvesting, the other ones represent, respectively, the Ecocosts generated by Biomass Transport, Biomass Inventory, Biomass Conversion, Ethanol Inventory and Ethanol Transport.

To make the link with the previous section, the first term of the EnOF is calculated with Eq. (4), where the parameter $ECh_{h,bt}$ for $b = Corn$:

$$
ECh_{h,corn,t} = \sum_a (ECrd_a + ECes_a + EChh_a + ECgw_a) \tag{6}
$$

For all the remaining parameters their values are obtained with the same approach and calculated with the Ecocosts 2012 V2 version. The data files are available on the Ecocosts web site and are based on LCIs of Ecoinvent V3 and Idemat 2014, as well as the older versions of eco-costs, Ecoinvent and Idemat. The term $ECb_{k,i,l,b}$ (respectively $ECs_{k',j,f,b}$ and $ECsb_{k,i,l,b}$) for biorefinery (respectively for storage) is the total annual Ecocosts including the annualized Ecocosts for construction and the annual operation Ecocosts. The annualized Ecocosts for biorefinery and collection facility constructions is calculated with the total construction Ecocosts divided by the project lifetime in terms of years.

### 3.4.3. Social criteria

The goal is to quantify the social sustainability of a system. In our approach as the system to implant is completely new, most of the social impacts would remain almost constant for instance human health and security risks, or public acceptability. In our case the two major social indicators are the jobs creation and the food to energy one. The latter assesses the possible competition between food and energy. Cucek et al. (2012b) have explained that it is used as a social indicator as it deals with measuring the quality of life: rise of prices of food, and threat if the safety of food supply. As one aim is to compare first and second generation of biorefineries, this indicator must be taken into account to clearly establish the discrepancies between corn and wood biomass. But this competition is already evaluated through the Ecocosts relative to land-use, Fig. 3.

Concerning jobs estimation, the most important problems are to define the boundary of the evaluation and then to calculate the total number of jobs created. Indeed, this number is not limited to the number of persons who are directly working for the new activity but it must also take into account the jobs created or supported by subcontractors and more generally by all the firms impacted in terms of employments. As a consequence the number of jobs created is classically divided into three categories: (i) Direct jobs (jobs related to plant's operations), (ii) Indirect jobs (new employees in subcontractors) and (iii) Induced jobs (new employees in the local economy). This last number evaluates the employments generated by the two previous categories due to their (and their families) consumption in the local economy.

*3.4.3.1. Direct jobs estimation.* The difficulty is that the estimation of the direct jobs created depends on many parameters like: the size of the firm, the activity sector, the level of automation, the production quantity... In one of the first study on this subject, Dutailly (1983) had used statistical methods to demonstrate that the number of direct jobs depends on the capital invested and the activity sector, *i.e.* the ratio number of direct jobs/capital decreases (not linearly) when the capital cost increases but not in the same way for all the industrial sector. In his approach Dutailly (1983) had used a piecewise linearization of the curve number of jobs created versus the amount of investment. Even if this approach allows to rapidly have an estimation, it has three major drawbacks: it has not been updated since this first study, it gives a very rough estimation, and it has been established and validated only for some industrial sectors (the input data are not available for all the sectors). More recently, Chauvel et al. (2001) have established the following formula that links the number of direct jobs with the production capacity for chemical plant:

$$
\frac{\text{Nber of hour worker/day}}{\text{product production } \left(t/\text{day}\right)} = t \times \frac{\text{Nber steps in the process}}{\left(\text{capacity}\left(t/\text{day}\right)\right)^{0.78}} \tag{7}
$$

where $t = 23$ if discontinuous operation, $t = 17$ if continuous operations with medium instrumentation, $t = 10$ if continuous operations with good instrumentation, $t = 7$ if continuous operations with control line.

This quantification is limited because it only estimates the number of operators, *i.e.* the employees who work directly in the production workshop, it does not account for the employees in the other department of the organization. These two examples allow to put in highlight the two kinds of method that exist for direct jobs estimation: comparatives which use data base to estimate this number by extrapolation as in Eq. (7), and statistics which estimate the indicator by global data coming from statistical studies as in Dutailly (1983).

The proposed approach is based on the annual economic activity of firms in a specific sector which is more representative than the initial investment to estimate the direct jobs created by a new activity. The following equations express some terms of firm financial accounting:

$$
\text{Production} - \text{External Consumption} = \text{VA} \tag{8}
$$

$$
\text{VA} + \text{Grants} - \text{WageBill} = \text{EBI} \tag{9}
$$

*Remark:* The French financial accounting is slightly different from the Anglo-Saxon one, for instance the term EBI has not exactly the same definition. But the approach can be easily adapted to account for each country financial accounting specificities.

In our approach, the added value of the firm is considered rather than the turnover as it is more representative of the real activity (the external consumption are subtracted). The input data (VA and EBI) of our method come from economic results of French companies

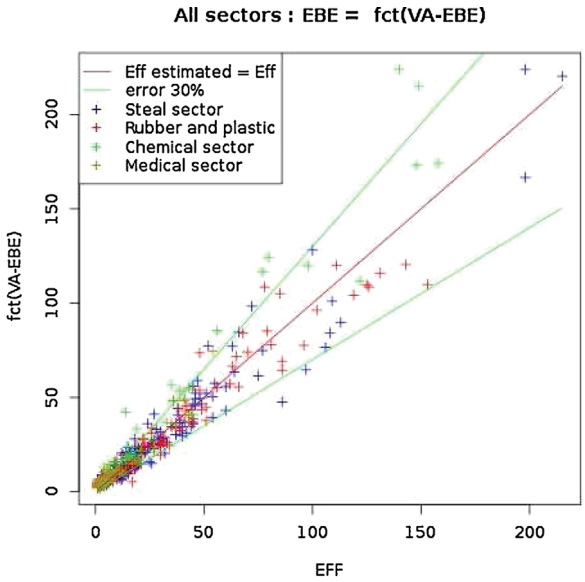


**Fig. 5.** Comparison between Direct Jobs estimation with formula 11 and Real value (EFF).

between 2010 and 2014, and for these companies the number of employees is also accessible.

The approach is validated for four industrial sectors: three with close link with chemical engineering, *i.e.* Rubber and plastic, chemical and steel and another one far from our domain but which represents a new technology sector, *i.e.* medical. In Eq. (9), let's assume that the grants can be neglected with respect to wage bill. Nevertheless, a precise estimation of the accrued jobs in a regional economy is difficult to assess because the jobs created have different categories. For instance, within an organization workers and engineers have varying duties, responsibilities and backgrounds and thus the different categories of employees receive different compensation. As a consequence, their respective family consumption in the local economy is not the same, thus the number of induced jobs is affected. Unfortunately, it is impossible to reach such a detailed information on the number of jobs created per categories and their respective compensation. As a consequence, the average French wage was assumed for all the jobs created:

$$\text{WageBill} = \text{Average Wage of employees in a sector} \times \text{Number of employees} \quad (10)$$

As a result, the number of employees is evaluated thanks to the following formula:

$$\text{DJ} = \alpha \text{VA} - \beta \text{EBI} \quad (11)$$

where the unknown parameter $\alpha$ and $\beta$ are estimated in a multi linear regression model.

The results of our approach are illustrated on Fig. 5 with the comparison between the number of direct jobs calculated with our approach (ordinate) and the real value (Eff) for the four industrial sectors under study and for the 476 firms (data points used to make the regression). On this figure, the upper and lower boundaries corresponding to 30% of error are also presented, to be in the same order of magnitude as the economic and environmental criteria (Cellura et al., 2011). The method gives good results for firms with a number of employees in the range [10; 150] whatever the industrial sector. The method is not extended higher than 150 employees because of a lack of data to validate it. The majority of firms with less than 10 employees are outside the range of 30% of uncertainties, this can be explained by round off errors which can lead to an important error in the final evaluation.

The number of firms considered in the study and the values of the coefficients are given in Table 2 (The total number of points is not the sum of all the sectors because some firms are gathered in more than one sector). The table also contains the results of statistical test (Student test) to verify if the coefficients are statistically consistent. This is the case in this study, excepted for the $\beta$ coefficient for the Rubber and Plastic sector where the Student ratio (ratio between the coefficient estimated and its standard deviation) is near the lower bound (1.98) for a confidence threshold of 5%. As this value is not too far from the lower limit, the error is considered as acceptable. The *p*-value test, not presented here, gives also satisfactory statistical results for the parameter estimated, confirming the confidence that can be placed in the results obtained.

*3.4.3.2. Indirect jobs.* In statistical institute this number for subcontractors is based on the ratio between the sales associated to the company studied over the total sales and multiplies by the manpower part of the turnover coming from the new activity over the global turnover. This ratio is then multiplies by the total number of jobs in the subcontractor. This method is not suitable for two main reasons: the manpower does not vary linearly with the turnover, and the turnover is not representative of the real industrial activity of the firm, the added value is more relevant. In our study, the estimation is based on the difference between the manpower of the company with the additional activity and the same without, in order to take into account the possible non linearity. To estimate the number of indirect jobs, with the additional activity, the same approach as the estimation of the direct job is used. The number of jobs without the new activity is a known input data.

*Remark:* the direct and indirect jobs created depend on the production capacity and the technology used, but do not depend on the location site.

*3.4.3.3. Induced Jobs estimation.* On the local economy, the induced impacts are those related to current expenditures on household consumption that are made by the employment generated (both direct and indirect) by the activity. Each direct or indirect employment is associated with a household (number of people) and an average behavior of consumption. The evaluation of the number of induced jobs for a given region $i$ is thus estimated according to the following formula:

$$\text{Ind}J_i = \text{LF}_i \times LM_i \times \frac{(\text{DJ}_i + \text{IJ}_i) \times \text{MHO}_i}{\text{POP}_i} \quad (12)$$

**Table 2**
Statistical results for the parameters estimation.

| Sector | Rubber and plastic | Chemical | Medical | Steel | All |
|---|---|---|---|---|---|
| Number of points | 139 | 64 | 115 | 255 | 476 |
| $A$ | $2.082 \times 10^{-5}$ | $1.431 \times 10^{-5}$ | $1.816 \times 10^{-5}$ | $1.729 \times 10^{-5}$ | $1.903 \times 10^{-5}$ |
| $B$ | 1.458 | 2.539 | 4.615 | 3.999 | 1.241 |
| $R^2$ | 0.94 | 0.875 | 0.922 | 0.920 | 0.860 |
| Student test $\alpha$ | 47.24 | 18.13 | 36.11 | 94.52 | 63.57 |
| Student test $\beta$ | 1.64 | 2.50 | 2.45 | 7.16 | 6.19 |

The term $LF_i \times LM_i$ represents the whole induced jobs in a specific region, $(DJ_i + IJ_i) \times MHO_i$ is the total household concerned by the direct and indirect jobs creation, and POP is the global population in the region. Thus the ratio $(DJ_i + IJ_i) \times MHO_i/POP_i$ indicates the proportion of the population that is going to create the induced jobs related to the new activity. For each specific region, the values for year 2014 of the parameters $LF_i$, $LM_i$, $MHO_i$ and $POP_i$ are obtained thanks to the French national institute of statistics and economic studies (INSEE, 2012).

As a result the social objective of the model is to maximize the total number of jobs created by the new project.

$$\begin{aligned}
SOF = & \sum_b \sum_h \left(IJ_{b,h}\left(ECH_{b,h}\right) + IndJ_{b,h}\left(ECH_{b,h}\right)\right) \\
& + \sum_b \left( \sum_h \left(IJ_{b,h}\left(ECT_{b,h}\right) + IndJ_{b,h}\left(ECT_{b,h}\right)\right) \right. \\
& \qquad \left. + \left( \sum_{j=1}^{J} IJ_{b,j}\left(ECH_{b,j}\right) + IndJ_{b,j}\left(ECH_{b,j}\right) \right) \right) \\
& + \sum_b \sum_j \sum_f \sum_{k'} \left( \left(DJ_{b,j}\left(ECI_{b,j,f,k'}\right) + IJ_{b,j}\left(ECI_{b,j,f,k'}\right) \right. \right. \\
& \qquad \left. \left. + IndJ_{b,j}\left(ECI_{b,j,f,k'}\right)\right) \times y_{k',j,f} \right) \\
& + \sum_b \sum_i \sum_l \sum_k \left( \left(DJ_{b,i}\left(ECC_{b,i,l,k}\right) + IJ_{b,i}\left(ECC_{b,i,l,k}\right) \right. \right. \\
& \qquad \left. \left. + IndJ_{b,i}\left(ECC_{b,i,l,k}\right)\right) \times y_{k,i,l} \right) \\
& + \sum_i IJ_{e,i}\left(ECET_{e,i}\right) + IndJ_{e,i}\left(ECET_{e,i}\right)
\end{aligned} \tag{13}$$

The first two terms correspond to the jobs created by the harvesting and transportation activities for biomass. They are considered as indirect jobs because the firms supporting these jobs exist and they are going to increase their activity thanks to the supply chain implantation. Concerning storage facilities (Third summation term) and conversion processes (fourth term) as they will be constructed both direct and indirect jobs resulting from operating the biofuel supply chain are considered. Furthermore for the conversion process, biomass storage and ethanol storage are included in the estimation of jobs as they are implemented on the same site. The number of jobs created by the ethanol transportation is estimated through the last term. The same estimation assumption as the biomass transportation is also applied. For all the term the number of induced jobs is quantified through Eq. (12).

As in our approach the employment quantification relies on economic data, each term of the economic objective function is used as a basis to calculate the number of jobs in the social objective, *i.e.* to calculate the terms $ECH_{b,h}$, $ECT_{b,h}$, $ECI_{b,j,f,k'}$, $ECC_{b,l,l,k}$ and $ECET_{e,i}$. However for biomass storage, biomass conversion process and ethanol storage, their respective costs are added to estimate the global number of jobs (as they are located on the same industrial site). As mentioned before all the regional parameters, *i.e.* local household consumption habits, population size, size of an average family and labor force are derived from the French institute INSEE (2012).

## 4. Multiobjective optimization methodology

The main objective of this study is to find a solution that reaches a compromise between the three previous criteria to help the decision maker to select place to establish one or some refineries.

**Table 3**
Payoff table using corn.

| Mono-optimisation case | Economic costs value (M€) | Environmental costs value (M€) | Total number of jobs created |
|---|---|---|---|
| Min EcOF | EcoF = 343.3 | EnoF = 223.5 | SOF = 1110 |
| Min EnOF | EcoF = 414.7 | EnoF = 219.3 | SOF = 2047 |
| Max SOF | EcoF = 620.1 | EnoF = 347.9 | SOF = 2679 |

Before solving the multi objective optimization problem, a series of single optimization problems were considered. Making a payoff table is the first step to obtain a balanced solution. In payoff table (Table 3 is an example), each row represents a mono objective optimization with the objective function that is being minimized or maximized, and at the optimum point the value of the decision variables are used to calculate the value of the other objective functions, the result for each of them is represented in columns. Then by optimizing each objective function on its own, Table 3 is obtained using corn as biomass feedstock (the values on the diagonal are optimum value for each mono objective optimization). The CPLEX 12.5 algorithm implanted in ILOG is used to solve the mono objective optimization problem. The initial problem consists of 91,558 constraints with 9240 binary variables and 222,556 positive continuous variables. Moreover, 1390,132 coefficients are nonzero. The CPLEX presolver reduced the MIP problem has 4620 binary variables with 12,013 constraints and 108,808 continuous variables. The CPU time in a personal computer four cores 3 GHz varied between few seconds to 12 h.

The main conclusion is that the resolution of the multi objective optimization problem must be difficult because the criteria are antagonistic, and the range of each criterion is very large. In this case, it is very important to find a good compromise between these three criteria. Several alternatives can be proposed: build the Pareto Front using an epsilon constraint method and use a Multi Criteria Decision Methodology (like TOPSIS), or use a goal programming methodology.

A post optimal analysis of the series of mono objective optimization problems leads to the fact that the binary variables are the most sensitive variables in the MILP optimization. Generally speaking, in the great majority of works dealing with optimization network design, the formulation of the problem only contains continuous variables what leads to continuous (or discontinuous by jumps) Pareto curves. Indeed, when the problem is of NLP or LP type, the Pareto front associated is continuous or almost continuous so that one solution always exits in the interval. Although not always fast enough, the research of a feasible solution in this case is consequently easy because one solution is known to exist.

Things are totally different when the problem contains binary variables so that the formulation is of MINLP or MILP. In these types of problems, the Pareto curves may contain a very few number of optimal solutions. During the resolution, the binary components are calculated by means of a Branch-and-Bound (or Branch-and-Cut) methodology that generates the space search. It is known that these methodologies provide a good way to deal with the binary part of a MILP/MINLP problem as long as it is not conditioning the whole problem. If the binary part is controlling and conditions the problem, this methodology is very limited. Indeed, when the research of a feasible solution begins, the existence of a feasible solution in the interval of solution is not *a priori* known. Consequently, the size of the space search explodes (the number of the branches is very large) in order to find one feasible solution, and the program returns an infeasible error message before finding a solution.

The great advantage of applying the methodology of goal programming to problems of supply chain network design is to avoid the generation of a complex research tree with no

solutions available and thus large computational times. With the goal programming, the problem containing binary variables is guided within a limited interval what limits the computational time and it necessarily returns a feasible solution. This method has never been applied to the design of supply chain networks although it is performing and particularly adapted to these problems containing binary variables and with very few solutions in the research interval, especially in the case of multi objective optimization.

The aim of the goal programming methodology is to minimize the deviation of the different objective functions. In order to do it, objective functions become constraints and deviation variables are added to them. So the value that restricts the constraint is the sum of the goal and the deviation. In this case, the goal value for each constraint is obtained by minimizing each objective function separately; it represents the level of aspiration for each objective function. Then, the objective function is the sum of all deviation variables (Collette and Siarry, 2012). The process is as follows:

- An initial vector of objective functions $\vec{F} \in |\mathrm{R}$ is chosen;
- Two new variables, called deviations ($d_i^+$ and $d_i^-$), are associated to each objective related to the initial objective functions $f_i\left(\vec{x}\right), i \in \left\{1, \ldots, nf\right\}$ (where $\vec{x}$ represents the vector of continuous and discrete variables), obtaining the following problem:

$$\begin{aligned} &\text{Minimize} && \left(d_1^+ ord_1^-, \ldots, d_k^+ ord_k^-\right) \\ &\text{with} && f_1\left(\vec{x}\right) = goal_1 + d_1^+ - d_1^- \\ & && \vdots \\ & && f_{nf}\left(\vec{x}\right) = goal_k + d_k^+ - d_k^- \\ & && \vec{h}(\rightarrow x) = 0 \\ &\text{and} && \vec{g}\left(\vec{x}\right) \leq 0 \end{aligned} \tag{14}$$

The deviation variables to be minimized must respect some constraints:

$$\begin{aligned} &d_i^+ \text{ and } d_i^- \geq 0, \\ &d_i^+ \cdot d_i^- = 0 \text{ with } i \in \left\{1, \ldots, nf\right\} \end{aligned} \tag{15}$$

- Then, one of these two deviation variables is minimized. The selection of the variable is based on the type of exceeding desired (above or below the objective that is set). Depending on the desired way to achieve the goal $\vec{F}$, different combinations of minimizing $d_i^+$ and $d_i^-$ are possible. These combinations are shown in Table 4.

For example, if all goals are desired to be reached by higher values, the following problem is obtained:

$$\begin{aligned} &\text{Minimize} && \left(d_1^+, \ldots, d_k^+\right) \\ &\text{with} && f_1\left(\vec{x}\right) = goal_1 + d_1^+ \\ & && f_{nf}\left(\vec{x}\right) = goal_{nf} + d_k^+ \\ & && \vec{h}(\rightarrow x) = 0 \\ &\text{and} && \vec{g}\left(\vec{x}\right) \leq 0 \end{aligned} \tag{16}$$

**Table 4**
Deviation variables.

| Type | Deviation value | Variable |
|---|---|---|
| The goal is desired to be reached by higher values | Positive | $d_i^+$ |
| The goal is desired to be reached by lower values | Negative | $d_i^-$ |
| The goal is desired to be reached without exceeding | No deviation | $d_i^+ + d_i^-$ |

This methodology allows a multi-objective optimization problem being reduced to minimize a vector. This vector may minimize the weighted sum of deviations. For example:

$$\min\left(4 \cdot d_1^+ + 2 \cdot d_2^- + \left(d_3^+ + d_3^-\right)\right) \tag{17}$$

The different weights define a user selection in the relevance of objective functions.

In order to obtain a balanced solution as close as possible to desired solutions, the magnitude order of the three criteria have to be matched. For this reason, the objective functions and goals have to be normalized.

As a result the goal programming approach consists in the traditional multi objective optimization problem (Eq. (18)) in a single objective problem (Eq. (19)).

$$\begin{aligned} &\text{Min } \left(f_1\left(\vec{x}\right), f_2\left(\vec{x}\right), \ldots, f_{nf}\left(\vec{x}\right)\right) \\ &\text{Subject to} \\ &\quad \vec{h}(\vec{x}) = 0 \\ &\quad \text{and } \vec{g}(\vec{x}) \leq 0 \\ &\vec{x} \in \mathbb{R}^n, \vec{h} \in \mathbb{R}^p, \vec{g} \in \mathbb{R}^r \end{aligned} \tag{18}$$

$$\begin{aligned} &\text{Min} \sum_{i \in NF} w_i \left(d_i^+ \vee d_i^- \vee d_i^+ + d_i^-\right) \\ &\text{Subject to} \\ &\rightarrow f^{\text{norm}}(\rightarrow x) = \rightarrow goal^{\text{norm}} + \rightarrow d^+ - \rightarrow d^- \\ &\quad \rightarrow d^+ \geq 0, \rightarrow d^- \geq 0, \rightarrow w \geq 0 \\ &\quad \rightarrow d^+ \cdot \rightarrow d^- = 0 \\ &\quad \vec{h}(\rightarrow x) = 0 \\ &\text{and } \vec{g}\left(\vec{x}\right) \leq 0 \\ &\vec{x} \in \mathbb{R}^n, \quad \vec{h} \in \mathbb{R}^p, \quad \vec{g} \in \mathbb{R}^r, \quad \rightarrow d^+, \rightarrow d^- \in \mathbb{R}^{nf} \\ &\text{with } \forall i \quad f_i^{\text{norm}}(x) = \frac{f_i(x) - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \end{aligned}$$

$$goal_i^{\text{norm}} = \frac{goal_i - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \tag{19}$$

$f_i^{\min}$ and $f_i^{\max}$ are respectively the minimum and maximum value of each $i$th objective function reached in individual single-objective optimizations.

In economic and environmental cases, the goals for each criterion are the minimum value of Table 3 multiplied by 1.01, in order to not getting zero but being close to the minimum; and in the case of social aspects the maximum is multiplied by 0.99 in order to keep the same policy of being around 1% of the goal. More details on the goal programming method are given in (Ramos et al., 2014).

## 5. Results and discussions

### 5.1. Corn as raw material

Firstly, the ethanol supply chain is optimized using the corn as raw materials. In this case, the results show the difficulty in finding a balance between the three criteria. On the one hand, if balanced weights are applied to the model, acceptable Ecocosts and employment are obtained but economic costs are high. On the other hand, if a greater weight is applied to the economic cost, its result is acceptable but Ecocosts increase to the double and employment is reduced to a half. These results are due to the sensitivity of the binary variables. Moreover to justify the used methodology, it will

**Table 5**
Results for corn as raw material.

| Category: Weights | Economic: 1<br>Eco-cost: 1<br>Social: 1 | Economic: 0.6<br>Eco-cost: 0.3<br>Social: 0.1 | Economic: 0.9<br>Eco-cost: 0.09<br>Social: 0.01 | Goal |
|---|---|---|---|---|
| Economic cost (M€) | 402.1 (+17%) | 396.1 (+15%) | 358.5 (+4%) | 343.3 |
| Eco-cost (M€) | 221.3 (+0.9%) | 226.1 (+3.1%) | 251.3 (+14%) | 219.3 |
| Total jobs created | 2508 (−6.4%) | 1831(−31.6%) | 1262(−53%) | 2679 |
| City: Capacity of refineries(ton/year) | Pau: 400,000<br>Niort: 400,000 | Pau: 400,000<br>Tarbes: 150,000 | Bordeaux: 400,000 | – |
| City: Capacity of storages (t) | Tulle: 5000<br>Niort: 5000<br>Poitiers: 70,000 | La Rochelle: 70,000<br>Agen: 100,000<br>Tarbes: 250,000 | Montauban: 40,000<br>Périgueux: 70,000<br>Agen: 70,000<br>Pau: 100,000<br>Angoulême: 100,000<br>Poitiers: 100,000<br>Limoges: 100,000<br>Mont-de-Marsan: 250,000<br>Tulle: 250,000<br>La Rochelle: 250,000<br>Niort: 250,000 | – |

be very difficult to obtain a complete Pareto Front. Different weight coefficients were tested to explore the workspace in the goal to describe the Pareto Front. In Table 5, we represent the three only points calculated with many coefficients. Indeed, the same points with different coefficients were found many times. The first row of the table gives the weights for each criterion for the three different results (columns#2, #3 and #4). In the following rows, the three criteria are reported with the most important decision variables in particular the number, the location (city where they would be implemented) and the capacity for both the refineries and the storages. For each criteria value, the relative difference with respect to the best solution reached during individual single-objective optimization is given in parenthesis. The values of these best solutions in individual single-objective optimization are also reported in the last column, namely "Goal". This goal represents a utopic point which would be the optimal solution if it can be reached. For the remainder tables, results are presented in a similar way.

Table 5 shows that working at full capacity with one biorefinery is economically more interesting than building two or more biorefineries (economy of scale). However, the fact of building a single biorefinery increases the Ecocosts of transportation and storage, as well as reduces the creation of jobs. In the case of the first generation of biorefinery, biomass is cultivated only during one small time period of the year (*i.e.* 13 weeks from September to November for corn in France), costs and Ecocosts of transportation and storage become very relevant. When the weight of the social criteria is important, the number and the capacity of the biorefineries is higher, as a consequence the number of direct and indirect jobs is increased. Furthermore, it is important to notice that the biorefineries are located in more rural city leading also to an increase of the induced jobs. Both increases for jobs creation explain the value of the social criteria. Another comment concerns the location of storages and refineries, which are mainly in the west part of the studied area because corn density is higher in part of the region due to water availability (cultivation of corn requires a lot of water).

The last result, i.e. column#4, needs deeper explanation. First, it is important to remember that in this type of multi objective problem there is a small number of different solutions (here only three). As a consequence, while this solution satisfies the mathematical constraints of the problem it is not relevant as the number and capacity of storage increase sharply compared to the two previous solutions. First the number of storage is increased in order to satisfy the social criteria. Moreover, these storages are located in the more rural cities for the same reason as before, i.e. to increase the induced jobs. The high capacity can be easily explained, because the change of capacity on storage have a very small influence on the economic cost but have a greater influence on jobs creation (direct and indirect jobs and as consequence induced jobs) and especially in rural area.

Considering the value of the three criteria, the suggested solution (column #2 in Table 5) is the grey disk in Fig. 6. In this figure, the three criteria values are represented: Economic cost in abscise, Environmental impact on ordinate, and each disk diameter is proportional to the numbers of total created jobs. Fig. 6 gathers the values of the payoff table (Table 3) and the results obtained using goal programming (Table 5).

### 5.2. *Wood as raw material*

As no storages are required for wood (because it can be collected during all year), it can be observed that some solutions are very similar and all of them could be simplified in two main solutions, Table 6. Moreover, it is assumed that the wood production can be adapted to the demand for each period and the pretreatment was a continuous process like the biorefinery. So the supply chains do not need to contain specific storage facilities. As wood is processed to produce bioethanol, the wood pretreatment is constituted of these three successive operations: grinding, acid explosion and enzymatic hydrolysis.

In order to compare the results with the previous ones, the retained solution of the previous section is remembered in the last column of Table 6. In the first solution, two refineries are built (Bordeaux and Toulouse), both with a capacity of 400,000 t. This solution is reachable because of the absence of the total production capacity constraint in refineries used when maximizing employment. This constraint has not been considered because the minimization of costs does not allow the building of many refineries. Moreover, as that constraint is not considered, more jobs than the goal (maximum obtained during the single objective optimization with the constraint) are created. Referring to economic costs and Ecocosts, the proposed refineries are oversized twice time in comparison with the production. In the second solution only one refinery is built (Bordeaux) and its economic costs and eco-costs are quite similar to the goal. However, the number of created jobs decreases considerably.

If oversizing capacity of refineries is not a problem, it is not easy to choose a solution which balances the three criteria. Otherwise, if oversized refineries are not convenient, the best solution is the one that uses wood and establishes only one refinery in Toulouse (column#3). It has the minimum cost and Ecocosts but employment creation is far from the "non-oversized capacity solutions" maximum, due to the economy of scale.

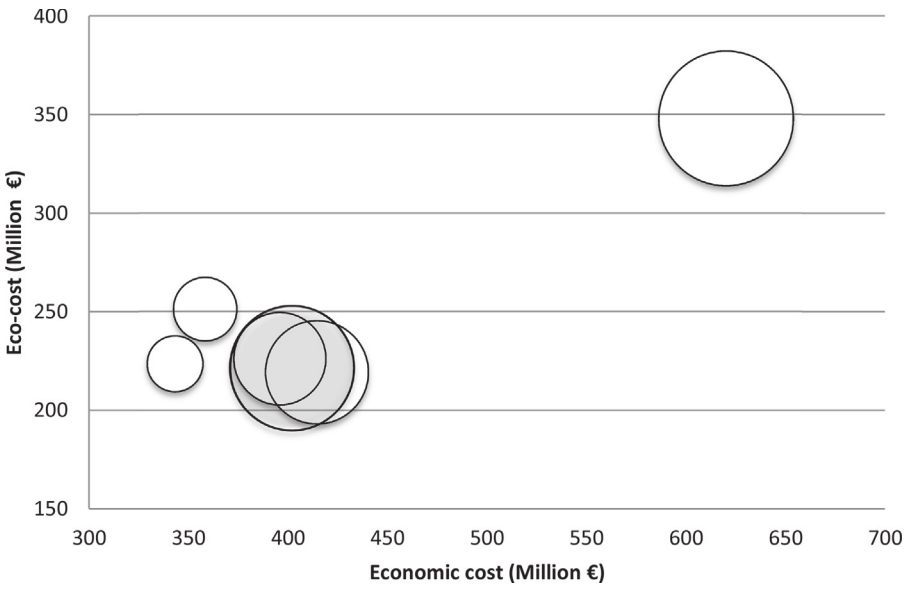


**Fig. 6.** Comparison between economic cost, Ecocosts and jobs creation for corn biorefineries.

**Table 6**
Results for wood as raw material.

| Category: Weights | Economic: 1<br>Eco-cost: 1<br>Social: 1 | Economic: 0.6<br>Eco-cost: 0.3<br>Social: 0.1 | Goal | Suggested solution<br>Corn case |
|---|---|---|---|---|
| Economic cost (M€) | 435.5 (+34%) | 330.3 (+1%) | 325.7 | 402.1 (+23%) |
| Eco-cost variable (M€) | 219.4 (+4.3%) | 210.55(+0.1%) | 210.3 | 221.3 (+5%) |
| Total jobs created | 3418* (+10%) | 1725 (−45%) | 3113 | 2508 (−19%) |
| City: Capacity of refineries (ton/year) | Bordeaux: 400,000<br>Toulouse: 400,000 | Toulouse: 400,000 | – | Pau: 400,000<br>Niort: 400,000 |
| City: Capacity of storages (ton) | 0 | 0 | – | Tulle: 5,000<br>Niort: 5,000<br>Poitiers: 70,000 |

* Higher than maximum due to the absence of a constraint.

In this case of second generation of biorefinery, the fact that wood can be collected all along the year makes the cost and Ecocosts of storage decrease a lot compared to corn. In fact, unlike corn, wood as raw material has low influence on Ecocosts due to its cultivation and harvesting which require less water, chemical compound, fuel consumption and limit GHG emissions. Then in this situation, the only disadvantage found is the creation of jobs.

Second generation of biorefinery has a lower purchasing price than first generation, but transformation cost is higher. What will make a difference are the amount processed or the plant yield and the cost of storage. Taking these terms into account, the use of second generation seems to be more advisable if a single biorefinery is established and works at full capacity since economic costs and Ecocosts are lower than any possibility concerning corn. Fig. 7 contains the values of the payoff table and the results obtained using goal programming (Table 6). For example, the right hand upper corner circle corresponds to the maximum total created jobs.

In Fig. 7, the suggested point (column #2 in Table 6) was the dark disk. The comparison between the two suggested points using corn and wood alone leads to the fact that raw materials have an influence on the design of the supply chain and on the values of the different criteria.

### 5.3. Corn and wood as raw materials

Looking to the previous results, it can be concluded that wood as raw material gives the best economic and ecological results, and corn is more interesting for both employment and rural development. Thus, it could be interesting to combine both of them in order to improve the results obtained using only one of them.

However, it does not lead to find a really good compromise between the three criteria. None of the solutions found establish storages outside the biorefinery (indeed in the model when a biorefinery is located at a city automatically there is also a corn storage created) because they are economically and environmentally expensive, and not necessary when using wood due to the possibility to collect wood during all the year. Furthermore, storage is not the major contribution for job creation.

The environmental impact is lower when using more wood than corn due to the storage and cultivation reasons explained before. Also, the best economical solution is the one that establishes a single biorefinery and uses 75% of wood. The solution that provides more employment processes more wood (around 2900) than corn (around 2500).

In Fig. 8, the corn feed coupled with wood leads to decrease the Ecocosts and the economics costs, while keeping the same number of created jobs. But, in this suggested solution (dark disk) (obtained with the weight for economic equal to 0.5, Eco-cost equal to 0.25 and Social equal to 0.25, column #4 in Table 7), the capacity is twice time greater than the production. So it is necessary to add a constraint to limit the total capacity of biorefinery.

### 5.4. Corn and wood as raw materials with a total capacity of biorefinery constraint

Economic costs and eco-costs rise as the number of refineries and the capacity does while the number of jobs decreases because

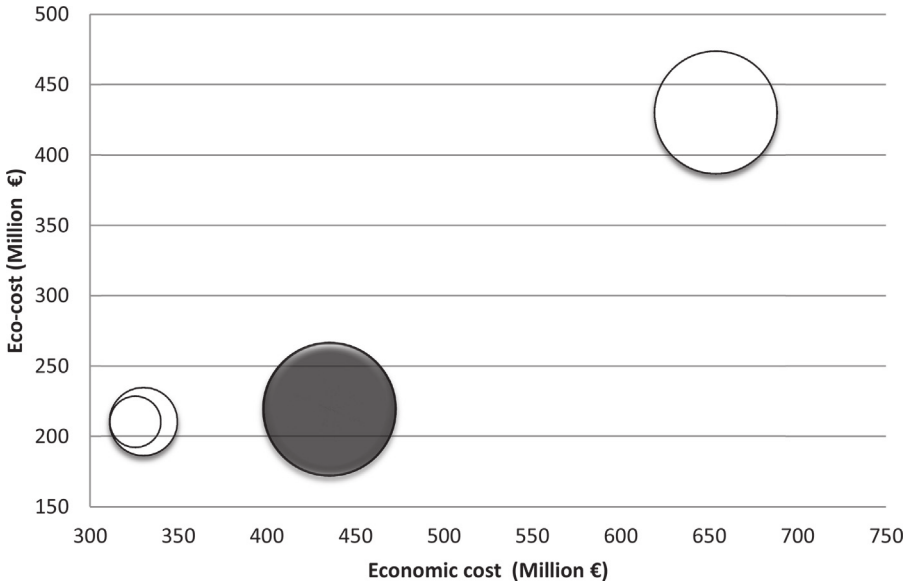


**Fig. 7.** Comparison between economic cost, Ecocosts and jobs creation for wood biorefineries.

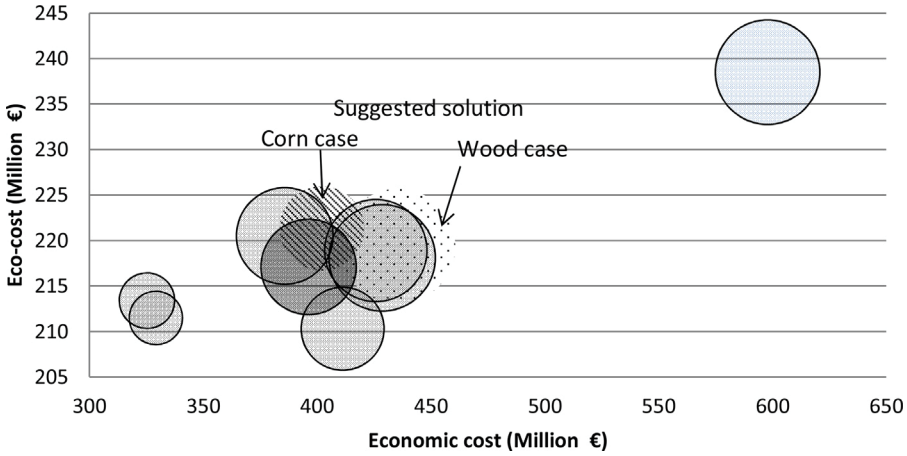


**Fig. 8.** Comparison between economic cost Ecocosts and jobs creation for wood and corn biorefineries.

**Table 7**
Results using corn and wood as raw materials.

| Category: Weights | Economic: 1<br>Eco-cost: 1<br>Social: 1 | Economic: 0.6<br>Eco-cost: 0.3<br>Social: 0.1 | Economic: 0.5<br>Eco-cost: 0.25<br>Social: 0.25 | Economic: 0.55<br>Eco-cost: 0.3<br>Social: 0.15 | Economic: 0.6<br>Eco-cost: 0.2<br>Social: 0.2 | Goal |
|---|---|---|---|---|---|---|
| Economic cost (M€) | 425.8 (+31%) | 329.3 (+1%) | 396.3 (+22%) | 428.6 (+32%) | 385.8 (+19%) | 325.3 |
| Eco-cost variable (M€) | 218.9 (+8%) | 211.5 (+0.5%) | 217.1 (+3%) | 218.1 (+4%) | 220.5 (+5%) | 210.3 |
| Total jobs created | 3043 (−2%) | 1584 (−49%) | 2829 (−9%) | 3158 (−1%) | 2871 (−8%) | 3113 |
| City: Capacity of refineries (ton/year): Repartition (%corn/%wood) | Bordeaux: 400,000: 0%/100%<br>Toulouse: 400,000: 85%/15% | Bordeaux: 400,000: 25%/75% | Bordeaux: 400,000: 65%/35%<br>Toulouse: 400,000: 70%/30% | Bordeaux: 400,000: 55%/45%<br>Toulouse: 400,000: 5%/95% | Bordeaux: 400,000: 45%/55%<br>Toulouse: 400,000: 80%/20% | |

it is assumed that the technology used and the degree of automation remain the same. It is interesting to analyze the economic and environmental costs as well as the number of jobs with different number of refineries established but always on a global constraint on ethanol production (400,000 T/year). Some simulations imposing the number of refineries to study the tendency of each criterion have to be done. So, eight simulations are done with one refinery to eight refineries using goal programing methodology. The results in Table 8 showed what is expected, economic cost and eco-cost increase as the number of refineries increases. For the economic cost it can be explained by the fact that the more the number of refineries, the less the economy of scale. The environmental cost is enhanced because when the number of biorefineries is increased, the transports of raw material and final product produce more emissions. Moreover, when the number of refineries increases, the number of new jobs increases too. As with this criterion we try to have the optimum number of accrued jobs, the refineries are located in the more rural region (excepted Toulouse and Bordeaux which are crowded cities) because for instance for a new industrial activity, the impact on the local economy is different in rural area

**Table 8**
Results using corn and wood as raw materials and imposing the number of biorefineries.

| Number of refineries | Economic cost (M€) | Eco-cost (M€) | Total jobs | City/Refineries (capacity in tons) {composition %Corn/%wood)} | | | |
|---|---|---|---|---|---|---|---|
| 1 | 330.5 | 211.6 | 1614 | Toulouse (400,000) {25%/75%} | | | |
| 2 | 367.8 | 212.5 | 1752 | Bordeaux (200,000) {40%/60%} | Toulouse (200,000) {35%/65%} | | |
| 3 | 402.2 | 214.0 | 1981 | Bordeaux (150,000) {30%/70%} | Toulouse (200,000) {40%/60%} | Niort (50,000) {35%/65%} | |
| 4 | 435.4 | 215.1 | 2192 | Bordeaux, Pau (50,000) {5%/95%} | Toulouse (200,000) {40%/60%} | Niort (100,000) {35%/65%} | |
| 5 | 469.9 | 218.1 | 2482 | Bordeaux (50,000) {10%/90%} | Pau (50,000) {5%/95%} | Toulouse (200,000) {15%/85%} | Niort, Poitiers (50,000) {0%/100%} |
| 6 | 505.4 | 218.3 | 2656 | Bordeaux, Rodez (50,000) {5%/95%} | Toulouse (150,000) {35%/65%} | Tulle, Niort, Poitiers (50,000) {0%/100%} | |
| 7 | 537.9 | 220.0 | 2891 | Bordeaux, Pau, Rodez, Tulle, Niort, Poitiers (50,000) {5%/95%} | | | Toulouse (100,000) {10%/90%} |
| 8 | 569.2 | 220.5 | 3088 | Bordeaux, Mont-de-Marsan, Pau, Rodez, Toulouse, Tulle, Niort, Poitiers (50,000) {5%/95%} | | | |

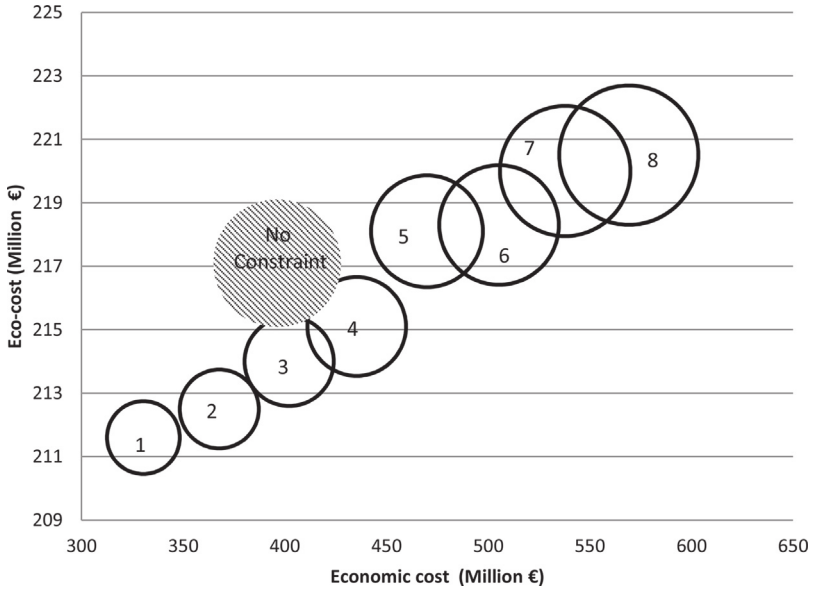


**Fig. 9.** Comparison between economic cost, Ecocosts and jobs creation for wood and corn biorefineries with total capacity constraints.

rather from crowded cities. For the latter all the infrastructures to absorb the new population already exist, whereas for the former the new industrial activity has the effect of promoting stronger rural development.

However, there are always one refinery in Toulouse and Bordeaux when there are two or more refineries. This can be explained by the fact that in these two towns we have the two mains (in capacity) blending facilities (end user of ethanol). Due to the strong influence of the transport costs both economic and environmental, biorefineries are located in these two towns to reduce final product transportation impacts.

Another comment concerns the production which is mainly based on wood because it is economically better although job creation is less than with corn. Moreover, the more refineries are imposed, higher is the amount of wood used. This is because the lack of jobs is supplemented with a greater number of refineries. Furthermore there is no storage because whatever the number of refineries the percentage of corn is low, consequently the storage in the refineries is sufficient.

Applying the same weights to economic, environmental and social criteria and imposing the number of refineries, the processed amount of wood is always higher than the amount of corn. In fact, if more than four biorefineries are established, the amount of wood processed is at least 90% of the total amount.

These results clearly represent the different solutions obtained during the study. The difficulty is to find a compromise between economic and environmental aspects and social aspects. On the one hand, if only one refinery was chosen, it would have low economic costs and Ecocosts but only a half of all possible jobs would be created. On the other hand, if the maximum refineries were established (8), the objective of the number of jobs would be achieved but economic costs and Ecocosts would be too high. The point is

to find some way to create the maximum number of jobs possible and at the same time try not to get that high costs. In Fig. 9, in comparison with the previous suggested point, the three values of the criteria are lower.

## 6. Conclusions

This article deals with a multi objective optimization approach for the design and operation of the biomass supply chain under economic, environmental and social criteria. The MILP model is based on a multi period approach to take into account the features of the biomass supply chain: biomass seasonality, biomass degradation, geographic availability, diversity of conversion technologies. . ..The main purpose of the model is to propose the optimal network design, collection facility and conversion process locations, storage level and policy, and logistics management decisions. As numerous current studies the MILP model optimizes the techno-economic and environmental performances of the network. To go further, our first major contribution is to include the social dimension to the biomass supply chain sustainability. Among the different social criteria, a new approach is proposed to predict the most important perspective, *i.e.* the employment effect, which is estimated by the total number of jobs created by the supply chain activities. To evaluate this number of jobs accrued, the employment effect is decomposed into three categories: direct, indirect, and induced jobs in the local economy. The direct jobs refer to the immediate employment generated by the new activities. In our approach economic data, *i.e.* the annual firm financial accounting in a specific sector, is used to estimate the direct jobs created by a new activity. The main assumption in the method is that an average wage was assumed for all the jobs created because it is impossible to reach the detailed information on the number of jobs created per categories (depending on employees duties, responsibilities and backgrounds) and their respective compensation. The approach was validated for four industrial sectors: Rubber and plastic, chemical, steel and medical which represents a new technology sector. The method gives results with uncertainties lesser than 30% which is the same order of magnitude as the economic and environmental assessments. Indirect jobs refer to new employees created by subcontractors. It is calculated by the difference between the manpower of the company with the additional activity and the same without, in order to take into account of possible non linearity. To estimate the number of indirect jobs, with the additional activity, the same approach as the estimation of the direct jobs is used. The number of induced jobs refers to the new employees in the local economy generated by the changes induced by consumption and expenditure in the local economy of the both previous categories. As the induced effect is more important in rural region than in urban on, this number is calculated by accounting for the local specificities such as: average behavior of consumption, the local population. The method demonstrates the positive benefits of this kind of industrial activities to promote rural development.

The second major contribution concerns the multi objective optimization solving method. In the current literature, the MILP optimization model for economic and environmental criteria is solved with the epsilon constraint approach. While it is interesting for our MILP problem, with our objective function with very antagonist criteria, the Pareto curves contain a very few number of optimal solutions. A post optimal analysis in the mono objective optimization concludes that the binary variables are the most sensitive variables in the MILP optimization. As a result when the research of a feasible solution begins, the existence of a feasible solution in the interval of solution is not *a priori* known. Consequently, the size of the space search explodes in order to find one feasible solution, and leading to an infeasible error message. For the resolution, the goal programming method is applied to avoid the generation of a complex research tree with no solutions available and thus large computational time. With the goal programming, the problem containing binary variables is guided within a limited interval what limits the computational time and it necessarily returns a feasible solution. This method is performing and particularly well suited for the design of supply chain networks which contains binary variables and very few solutions in the research interval, especially in the case of multi objective optimization.

A first possible perspective to this work is to include the third generation of biorefinery in the decision process but also the possibility to choose between a final product portfolio. A second future extension is to decentralize the biomass pretreatment in the collection facilities. The main advantage is that it will improve the whole performance of the supply chain. Indeed it will reduce transportation costs and environmental impact because it is more convenient to store and transport biomass with more added value (*i.e.* after pretreatment). Furthermore the decentralized pretreatment process will also have social benefits for instance by improving the local employment. Another future work can be to extend the study to the nation level that allows more possibility for biomass feedstock. But as a consequence, the model size will increase sharply and thus some improvements of the solving method will be required to have an efficient multi objective optimization resolution in a reasonable computational time.

## Appendix A.

The interested reader can obtain the ILOG and data files from the corresponding author.

**Acronyms:**
AOC: annual operating costs
EBI: earnings before interest
EcOF: economic objective function
EnOF: environmental objective function
GHG: greenhouse gas
MILP: mixed integer linear program
MINLP: mixed integer non linear program
SOF: social objective function
VA: value added

**Parameters:**
$Av_{h,b,t}$ (kg): Total amount of biomass $b$ available at site $h$ during the time period $t$
$CHa_{h,b}$ (€/kg): Unit cost for cultivation and harvesting biomass $b$ in harvesting site $h$
$CC_{k,i,b}$ (€/kg): Unit cost for conversion of biomass $b$ at biorefinery $i$ with conversion technology $k$
$DJ_i$ (Number of jobs): number of direct jobs created in the region $i$
$d_{m,t}$ (kg): Ethanol demand of end user m during a time period $t$
$ECb_{k,l,i,b}$ (€/kg): Total ecocosts for the construction and operation of a biorefinery at location $i$ with size $l$ and technology $k$ for biomass $b$
$ECC_{b,i,l,k}$ (€/year): Annual economic cost to store and to convert biomass $b$ at biorefinery $i$ with size $l$ and technology $k$ (it also includes ethanol storage)
$ECes_a$ (€/kg): Ecosystems ecocosts for activity $a$
$ECes_{k,i,l,b}$ (€/kg): Total ecocosts to store ethanol at location $i$ with biorefinery of size $l$ and technology $k$ for biomass $b$
$ECET_{e,i}$ (€/year): Annual economic cost to ship ethanol from biorefinery $i$
$ECet_{i,m}$ (€/kg): Total ecocosts to ship ethanol from biorefinery $i$ to end user $m$
$ECgw_a$ (€/kg): Global Warming ecocosts for activity $a$
$ECH_{b,h}$ (€/year): Annual economic cost for harvesting biomass $b$ at harvesting site $h$
$EChh_a$ (€/kg): Human Health ecocosts for activity $a$
$ECh_{h,b}$ (€/kg): Total ecocosts for cultivating and harvesting biomass $b$ at site $h$
$ECl_{b,j,f,k'}$ (€/year): Annual economic cost to store biomass $b$ at collection facility $j$ with size $f$ and technology $k'$
$ECrd_a$ (€/kg): Resource depletion ecocosts for activity $a$
$ECsf_{k',j,f,b}$ (€/kg): Total ecocosts to store biomass $b$ at collection facility $j$ with size $f$ and technology $k'$
$ECsb_{k,i,l,b}$ (€/kg): Total ecocosts to store biomass $b$ at biorefinery $i$ with size $l$ and technology $k$

$ECT_{b,h}$ (€/year): Annual economic cost to ship biomass $b$ from harvesting site $h$
$ECtfb_{j,i,b}$ (€/kg): Total ecocosts to ship biomass $b$ from collection facility $j$ to biorefinery $i$
$ECthb_{i,h,b}$ (€/kg): Total ecocosts to ship biomass $b$ from harvesting site $h$ to biorefinery $i$
$ECthf_{j,h,b}$ (€/kg): Total ecocosts to ship biomass $b$ from harvesting site $h$ to collection facility $j$
$ICb_{i,b}$ (€/kg): Unit cost for the storage of biomass $b$ at biorefinery $i$
$ICE_i$ (€/kg): Unit cost for the storage of ethanol at biorefinery $i$
$ICf_{j,b}$(€/kg): Unit cost for the storage of biomass $b$ at collection facility $j$
$IJ_i$ (Number of jobs): number of indirect jobs created in the region $i$
$IndJ_i$ (Number of jobs): number of induced jobs created in the region $i$
$INVb_{k,i,l}$ (€): Investment to set up a biorefinery of size $l$ in the location $i$ with technology $k$
$INVf_{k',j,f}$ (€): Investment to set up a collection facility of size $f$ in the location $j$ with technology $k'$
$ir$: discount rate
$LF_i$ (Number of jobs): Labour force in the region $i$
$LM_i$: percentage of the labour force related to the household consumption in the region $i$
$MHO_i$ (Number of persons): size of an average French household having at least one person in the labour force
$PC_{k,l}$ (kg): Vector of possible maximum weight production capacity for biorefinery with respect of the conversion technology
$POP_i$ (Number of persons): Global population in the region $i$
$SCmax_{k',f}$ (kg): Vector of possible maximum weight capacity for biomass storage at collection facility with respect of the storage technology
$SCmax_{k,l}$ (kg): Vector of possible maximum weight capacity for biomass storage at biorefinery with respect of the conversion technology
$TCE_{i,m}$(€/kg): Unit cost for the transport of ethanol from biorefinery $i$ to end user $m$
$TCfb_{j,i,b}$ (€/kg): Unit cost for the transport of biomass $b$ from collection facility $j$ to biorefinery $i$
$TChb_{i,h,b}$ (€/kg): Unit cost for the transport of biomass $b$ from harvesting site $h$ to biorefinery $i$
$TChf_{j,h,b}$ (€/kg): Unit cost for the transport of biomass $b$ from harvesting site $h$ to collection facility $j$
*Greek parameter:*
$\alpha_b$: Biomass $b$ deterioration rate
$\beta_{b,k}$: Conversion rate of biomass $b$ with conversion technology $k$

**Variables**

*Binary:*
$y_{k,i,l}$: 1 if production capacity of biorefinery of size $l$ with conversion technology $k$ is installed at location $i$, 0 otherwise
$y_{k',j,f}$: 1 if storage capacity of collection facility of size $f$ with storage technology $k'$ is installed at location $j$, 0 otherwise
*Continuous:*
$bib_{i,b,t}$ (kg): Amount of biomass $b$ stored at the biorefinery $i$ during the time period $t$
$bif_{j,b,t}$ (kg): Amount of biomass $b$ stored at the collection facility $j$ during the time period $t$
$eib_{i,t}$ (kg): Amount of bioethanol stored at the biorefinery $i$ during the time period $t$
$ep_{i,t}$ (kg): Amount of ethanol produced at biorefinery $i$ during the time period $t$
$fbb_{i,m,t}$ (kg): Amount of bioethanol shipped from the biorefinery $i$ to the end user $m$ (blending facility) during the time period $t$
$ffb_{j,i,b,t}$ (kg): Amount of biomass $b$ shipped from the collection facility $j$ to the biorefinery $i$ during the time period $t$
$fnb_{i,h,b,t}$ (kg): Amount of biomass $b$ shipped from the harvesting site $h$ to the biorefinery $i$ during the time period $t$
$fnf_{j,h,b,t}$ (kg): Amount of biomass $b$ shipped from the harvesting site $h$ to the collection facility $j$ during the time period $t$
$Ha_{h,b,t}$ (kg): Amount of biomass $b$ harvested at site $h$ during the time period $t$
$w_{k,i,b,t}$ (kg): Amount of biomass $b$ processed at biorefinery $i$ with conversion technology $k$ during the time period $t$

**Indices**

*a:* Sub activity in sub model
$b$: Biomass type
$f$: Size for storage capacity at collection facility
$h$: Harvesting site location
$i$: Biorefinery possible location
$j$: Collection facility possible location
$k$: Conversion technology
$k'$: Storage technology
$l$: Size for biorefinery capacity
$m$: End user (blending facility) site location
$t$: Time period

**Sets**

$A_h$: Set of sub-activity for the harvesting activity
$B$: Set of type of biomass
$F$: Set of storage capacity for collection facility
$H$: Set of harvesting site location
$I$: Set of possible locations for biorefinery implementation
$J$: Set of possible locations for collection facility implementation
$K$: Set of possible conversion technology
$K'$: Set of possible storage technology
$L$: Set of production capacity for biorefinery
$M$: Set of end user (blending facility) site location
$T$: Set of time period

$$Ha_{h,b,t} \le Av_{h,b,t} \qquad \forall h \in H, \quad \forall b \in B, \quad \forall t \in T \tag{A.1}$$

This constraint expresses that the total amount of a biomass $b$ harvested in a site $h$ in a time period $t$ cannot exceed the amount of biomass available. The seasonality and the geographical availability of the different kind of biomass can be easily taken into account thanks to the value of the parameter $Av_{h,b,t}$.

$$Ha_{h,b,t} \le \sum_j fhf_{j,h,b,t} + \sum_i fhb_{i,h,b,t} \qquad \forall h \in H, \quad \forall b \in B, \quad \forall t \in T \tag{A.2}$$

During a time period, the previous equation shows that the amount of biomass $b$ shipped from the harvesting site to the collection facilities $j$ and to the biorefineries $i$ is limited by the amount of biomass harvested.

$$\sum_h fhf_{j,h,b,t} + (1-\alpha_b)\, bif_{j,b,t-1} = \sum_i ffb_{j,i,b,t} + bif_{j,b,t} \qquad \forall j \in J, \quad \forall b \in B, \quad \forall t \in T \tag{A.3}$$

Eq. (A.3) represents the mass balance on a collection facility $j$ for biomass $b$ during the period $t$. This mass balance takes into account biomass deterioration during the storage but also the inventory levels at the beginning (equal to the inventory level at the end of the previous time period $t-1$) and the end of the time period.

$$\sum_h fhb_{i,h,b,t} + \sum_j ffb_{j,i,b,t} + (1-\alpha_b)\, bib_{i,b,t-1} = \sum_k w_{i,b,k,t} + bib_{i,b,t} \qquad \forall i \in I, \quad \forall b \in B, \quad \forall t \in T \tag{A.4}$$

Eq. (A.4) is the same mass balance as Eq. (A.3) but on a biorefinery $i$, thus the term that determines the amount of biomass $b$ processed at the biorefinery $i$ with technology $k$ during the time period is added.

$$ep_{i,t} \le \sum_k \sum_b \beta_{b,k} w_{i,b,k,t} \qquad \forall i \in I, \quad \forall t \in T \tag{A.5}$$

The amount of bioethanol produced using the type of biomass is calculated with Eq. (A.5) where $\beta_{b,k}$ is the conversion rate of biomass $b$ in biorefinery with technology $k$.

$$ep_{i,t} + eib_{i,t-1} = \sum_m fbb_{i,m,t} + eib_{i,t} \qquad \forall i \in I, \quad \forall t \in T \tag{A.6}$$

The previous constraint expresses the mass balance on bioethanol at biorefinery. Here again the inventory level at the beginning and at the end of the period is specified $eib_{i,t}$. We have also introduced the quantity of ethanol which is shipped from the

biorefinery $i$ to the blending facility (end user in our network) $m$ during the time period $t$, $fbb_{i,m,t}$.

$$\sum_i fbb_{i,m,t} = d_{m,t} \qquad \forall m \in M, \quad \forall t \in T \tag{A.7}$$

With Eq. (A.7) we ensure that the demand is fulfilled for each time period and for each end user.

$$\sum_b bif_{j,b,t} \leq \sum_{k'} \sum_f \mathrm{SCmax}_{k',f} \times y_{k',j,f} \qquad \forall j \in J, \quad \forall t \in T \tag{A.8}$$

Constraints Eq. (A.8) are capacity constraints: the amount of stored biomass during a time period $t$ should not exceed the available weight capacity in a storage facility $j$ with storage technology $k'$. $SCmax_{k',f}$ is the storage capacity of a collection facility of size $f$ with storage technology $k'$. This maximum capacity is decomposed into a set of a finite number of possibilities. $y_{k',j,f}$ is a binary variable to establish a collection facility location with a particular storage technology.

$$\sum_b bib_{i,b,t} \leq \sum_k \sum_l \mathrm{SCmax}_{k,l} \times y_{k,i,l} \qquad \forall i \in I, \quad \forall t \in T \tag{A.9}$$

Constraints Eq. (A.9) are the same storage capacity constraints as Eq. (A.8) but at biorefineries. Here $\mathrm{SCmax}_{k,l}$ represents the maximum storage capacity for a biorefinery of size $l$ with technology $k$, and $y_{k,l,l}$ a binary variable for biorefinery location with a particular conversion technology.

$$ep_{i,t} \leq \sum_k \sum_l \mathrm{PC}_{k,l} \times y_{k,i,l} \qquad \forall i \in I, \quad \forall t \in T \tag{A.10}$$

The preceding constraints define the production capacity constraints where $\mathrm{PC}_{k,l}$ is the production capacity for a biorefinery of size $l$ with conversion technology $k$. Combined with the previous constraints, these constraints express that when a biorefinery of size $l$ is located at place $i$, automatically storage at the biorefinery is also implanted.

$$\sum_k \sum_l y_{k,i,l} \leq 1 \qquad \forall i \in I \tag{A.11}$$

When a biorefinery is installed in one location, at most one type of capacity production and one conversion technology can be chosen. Eq. (A.11) represent these constraints.

$$\sum_{k'} \sum_f y_{k',j,f} \leq 1 \qquad \forall j \in J \tag{A.12}$$

The same as Eq. (A.11) but for collection facility, *i.e.* at most one storage of particular size and one storage technology can be opened in a location.

$$bib_{i,b,0} = 0, \quad bif_{j,b,0} = 0, \quad eib_{i,0} = 0 \qquad \forall i \in I, \quad \forall j \in J, \quad \forall b \in B \tag{A.13}$$

These constraints define the initial inventory level for biomass and bioethanol.

$$\begin{aligned} &bib_{j,b,t} \geq 0; \quad bif_{j,b,t} \geq 0; \quad eib_{i,t} \geq 0; \quad ep_{i,t} \geq 0; \\ &ffb_{j,i,b,t} \geq 0; \quad fhb_{i,h,b,t} \geq 0; \quad fhf_{j,h,b,t} \geq 0 \\ &Ha_{h,b,t} \geq 0; \quad w_{k,i,b,t} \geq 0 \end{aligned} \tag{A.14}$$

We have also to establish the classical positivity constraints.

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