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Models for optimization and performance evaluation of biomass supply chains: An Operations Research perspective

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ABSTRACT

The production of biofuels, bioenergy and chemical intermediates from biomass is a promising solution to reduce the consumption of fossil fuels and greenhouse gas emissions. While a significant research effort has been devoted to biomass production and conversion processes, the importance of logistics was detected more recently. Indeed, efficient supply chains are essential to provide conversion facilities with sufficient quantities of quality biomass at reasonable prices. As large territories and hundreds of biomass producers are involved, quantitative models are very useful to evaluate and optimize the resources required, the associated costs, the energy consumptions and the environmental impacts. This article surveys the recent research on models for biomass supply chains, from an Operations Research perspective. 124 references, including 72 published since 2010, have been analyzed to present the structures and the activities of these chains, a typology of decisions in three levels (strategic, tactical and operational), and a review of models based either on performance evaluation techniques (e.g., simulation) or mathematical optimization. A conclusion underlines the contributions and shortcomings of current research and suggests possible directions.

1. Introduction

Simply speaking [114], *biomass* is any material of biological origin, *biofuels* are fuels produced directly or indirectly from biomass, and *bioenergy* refers to the energy produced from biofuels. For instance, forest wood can be chipped and incinerated to produce heat and power, while sugar cane can be fermented to produce bioethanol. The last two decades have seen a growing interest in biomass as a means of reducing dependence on fossil fuels and developing a clean and renewable energy. For instance, the Ref. [40] issued a directive to achieve, by 2020, 20% of renewable energy, including from biofuels, with a target of 10% in transport.

While research on crop production and conversion processes is well developed, the actors concerned realized only recently that the Achilles' heel of the planned bioenergy production systems could be logistics. For instance, each crop is harvested during a short period in the year while conversion plants have to work continuously. Hence, an efficient supply chain must be implemented, to act as intermediate buffer and supply conversion units without shortage. Moreover, as the biomass itself is relatively cheap, the economic equilibrium of the whole system critically depends on logistic costs. Operations Research (OR) is an adequate approach to bring quantitative models for these biomass supply chains, evaluate their performance and optimize criteria such as their total cost, their energy consumption and their GHG (greenhouse gas) emissions.

The goal of this contribution is to depict the OR models proposed for biomass supply chains and to provide good entry points for readers having a general OR culture without being specialists in biomass. We have read more than 170 research articles, published from 1989 to 2014, to select 124 significant references in terms of modeling. This review demarcates from the few existing surveys by adopting an OR perspective, insisting on the types of models and solution methods employed, and gathering very recent references, with 72 papers published from 2010 onwards. It also highlights the gaps in the existing research and proposes a few possible directions for improvement.

The paper is organized in four sections. Section 2 is a general presentation of biomass supply chains (structures, activities, decision levels) and comments the few existing surveys. Section 3 describes performance evaluation models based on spreadsheets, geographical information systems, or simulation. Section 4

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considers optimization models based on mathematical programs, before a critical conclusion in Section 5.

2. Biomass supply chains

2.1. Structure and activities

A biomass supply chain includes various activities, such as cultivation, harvesting, pre-processing, transportation, handling, and storage. It stops usually at the gates of a *conversion unit*, in general a *biorefinery*, producing biofuels and chemical intermediates, or a *bioenergy conversion plant*, generating electricity, heat and/or cooling. A few papers add the distribution stage, from conversion facilities to end-users. Compared to industrial supply chains, several differences must be underlined:

- Biomass supply chains cover a vast collection territory, with many scattered cultivation areas;
- Long planning horizons are considered, because most crops have a one-year cultivation cycle;
- Inputs (biomass productions) and outputs (conversion activities) are desynchronized;
- Because of degradations, the crops cannot wait and must be harvested quickly when ready.

Both industrial and biomass supply chains can be modeled as *networks* (graphs) where the nodes correspond to the locations of interest while the arcs represent product flows. However, biomass supply chains involve specific activities that require various resources:

- *Harvesting activities* are possible in a limited time window at the input nodes devoted to biomass production, when the crop is ready, and they compete for a limited fleet of machines, like combine harvesters. The yield is not perfect, with a typical 10–20% loss.
- *Storage* is required in practice to synchronize the biomass production calendar with the production plan of conversion plants. It can take place in the fields or forests as simple stacks, in the farms, in centralized storage sites, or before the processes in conversion facilities.
- *Pre-processing* is useful to improve preservation (drying) and handling (baling, pelletization) and to reduce transportation costs by increasing density. For instance, switchgrass density is 60–80 kg/m^3 when harvested, 140–180 after baling and 700–800 for pellets [102]. The simplest treatments like baling can be done on the field. Stronger compressions and other transformations like roasting are possible, but using heavier equipment and/or dedicated sites.
- *Transport.* Like in industrial logistics, several transport modes can be used, the fleet of vehicles is often limited and the number of travels per period is restricted by vehicle range and driving time regulations. However, road transport is often the only solution for production sites with limited accessibility (forests), and truckload operations are systematic due to the large amounts handled.

The designers of such chains need modeling tools to cope with this complexity. Before coming to a total cost, they must understand the dynamics of the chain and determine many variables, like the amounts harvested (which crop, where, when, in which amount), the network flows (quantities transported), the advisable stock levels, and the resources consumed (harvesting equipment, vehicles, energy, manpower). Subtle tradeoffs must be found. For instance, densification can be done on the field, using balers, or in a more efficient densification plant. The second option adds a transport step to the plant, but then transport costs are cheaper thanks to the higher density.

2.2. Sustainability concepts

Sustainable development consists in meeting the current needs of humanity by combining the rational use of natural resources, environmental protection, economic prosperity and quality of life, without compromising the ability of future generations to meet their own needs. Sustainability must be analyzed taking into account the environmental, economic and societal aspects [7,32].

Environmental sustainability aims to prevent environmental degradation. The environmental impact of human activity is characterized by three main ecological footprints, affecting atmosphere (greenhouse gas emissions, GHG), water, and soils [104]. However, the implementation of good practices, like the ones recommended by the International Energy Agency [59], can limit the degradations induced by biomass industries.

Biofuel production may promote economic development, for example by attracting investors, favoring biomass sources which are currently unused, increasing and diversifying farmers' incomes, and boosting associated industries such as agricultural machinery [28].

However, it raises many societal issues, such as social acceptability, impact on rural populations, land use, and territorial development, potential for job creation, and poverty reduction. Hence, according to [108], relevant energy indicators for a developing economy should not be limited to environmental and economic issues: they must integrate social criteria such as poverty.

A few authors have presented analyses of supply chains which take into account these sustainability concepts, see for instance [42,23].

2.3. Decision levels

Like in production management and industrial logistics, the decisions in biomass supply chains can be conveniently classified in three levels, according to the time horizon concerned.

2.3.1. Strategic decisions

Strategic decisions are long-term decisions which involve important financial investments and engage companies over 1 year at least, such as the construction of a new factory or the design of a new aircraft. In bioenergy context, such decisions include for instance the selection of accepted biomass types, the location and size of pre-processing plants and conversion facilities, the transportation modes used, and the long-term supply contracts. Due to the lack of precise information several years in advance, strategic decisions are often based on aggregated data. Most authors consider a single time period [37], but multi-period horizons are sometimes useful to model long-term demand fluctuations, e.g., 5 periods of 3 years in Ref. [15].

2.3.2. Tactical decisions

Tactical decisions are medium-term decisions applied to a multi-period horizon, over a few months. In industry, production planning is based on such decisions, e.g., determining the number of products manufactured in each period, under aggregate resource constraints. Examples in biomass supply chains include the amount to harvest in each farm and each period, the number of vehicles to be purchased (fleet size), and the definition of safety stock levels. The time period considered may vary between one day [99] and one month [24].

2.3.3. Operational decisions

Finally, operational decisions are short-term decisions, typically over a few days. They result from a decomposition of tactical decisions into detailed operations. For instance, production scheduling determines the sequence and start times of manufacturing operations, while assigning ad hoc resources. In biomass supply chains, the timing of harvesting operations in a given day and the determination of detailed vehicle routes are typical examples. A good test to distinguish between tactical and operational decisions is to see if the precise order of tasks and/or their start times must be defined: If this is the case, the decision pertains to the operational level.

Even if a few studies on biomass supply chains address the operational level, for instance a truck scheduling problem in Ref. [54] or a detailed schedule of harvesting operations in Ref. [89]; most works focus on the strategic and tactical decision levels. Indeed, the goal is to provide decision makers with tools to model and evaluate a chain before its implementation, and not to develop software for day-to-day operations. Anyway, the data for detailed operations are never known precisely at the design stage.

2.4. Surveys on biomass logistics

Many review articles on logistics can be found in the literature but a vast majority concerns industrial supply chains (e.g., Ref. [76]. Ahumada and Villalobos [1] include agricultural production, but in the frame of the agri-food industry. Gold and Seuring [47] published a very general survey on biomass and bioenergy, listing the articles published and ranking them according to different criteria. However, surveys including modeling issues are still scarce. We will not discuss the modeling of biomass resources and harvesting systems, to focus on the state of the art on systems for bioenergy and biofuel production and, in particular, their supply chains.

Jebaraj and Iniyan [60] examine planning and forecasting models for energy production in general, with one section on renewable energy (including bioenergy) and one on optimization models. Awudu and Zhang [10] review the uncertainties and sustainability concepts to design robust biomass supply chains. Here again, only one section is consecrated to analytical and simulation models.

Baños et al. [14] identify publications on optimization methods applied to renewable energy. They identify exact and heuristic solution approaches but devote a single page to bioenergy models. Multi-objective decision methods for sustainable energies and bioenergy systems are examined by Refs. [113,94].

Three syntheses consider the special case of forest biomass. Optimal location methods for biofuel facilities are discussed in Ref. [61]. Wolfsmayr and Rauch [114] survey the different logistic steps for primary forest fuel, i.e., the fuel produced from forest wood by a mechanical process like chipping. Cambero and Sowlati [19] present a review of studies that assess or optimize the economic, social and environmental aspects of forest biomass supply chains.

The main objective of all these surveys is to provide a general description of biomass supply chains, including soft modeling techniques like process diagrams. Quantitative models based on mathematic programming or simulation techniques, when mentioned, are reduced to a single section. To our knowledge, only the following six papers are a little more in the spirit of our state of the art.

Iakovou [58] review the management of biomass supply chains, distinguishing between strategic, tactical and operational decisions. Contrary to our article, the authors do not adopt an OR perspective. Besides articles on modeling, they cite more general references and papers on conversion technologies. Moreover, their separation of tactical and operational decisions does not comply with our definitions, which come from industrial logistics.

A short paper by Ref. [71]; easy to read and little technical, gives lists of publications on the modeling of the various stages of a biomass supply chain, while mentioning the social, environmental and financial aspects.

Sharma et al. [97] present the main optimization models developed for biomass supply chains and identify challenges and research directions. Their article is rather a taxonomy of models, based on the chain structure, the constraints taken into account to determine decisions, and the optimization criteria. It does not cover approaches such as simulation, stochastic optimization, and computational methods used to solve the models. In addition, the bibliography stopping in 2011 does not include the numerous recent developments.

Shabani et al. [95] comment the studies that have used mathematical models for deterministic and stochastic optimization of forest biomass supply chains, to produce electricity, heat or biofuels. They emphasize the fact that future studies should take into account environmental and social goals, as well as economic aspects. The article cites publications dealing with uncertainties in demand, yields of conversion technologies, biomass supply, and prices.

A general assessment by Ref. [117] brings an overview of logistic modeling for biomass, including the optimization of cultural systems, harvesting methods, conversion processes, and distribution of biofuels. It ends with challenges, such as integration with the logistics of oil refineries, competition with other agricultural productions, and international trade of biomass and biofuels.

De Meyer et al. [29] wrote the most recent and interesting review for OR scientists, dealing with deterministic optimization models and methods for biomass supply chains. A general description of biomass-for-bioenergy supply chains is provided, with the decisions related to their design and management. A classification of articles is also presented, according to the decision level, the objective to optimize, and the kind of mathematical model used.

Compared to the six previous syntheses, our goal is to provide an updated review of quantitative models and computational methods in a rapidly evolving domain, in the double light of Operations Research and industrial logistics. Unlike [29], the chains surveyed can go beyond conversion facilities (i.e., down to final markets) and, in addition to deterministic optimization, we cover stochastic optimization models and performance evaluation techniques, including simulation and simpler approaches based on spreadsheets or GIS-based systems.

3. Performance evaluation models

Two main approaches are used in numerical modeling, *performance evaluation* and *optimization*. In the first class, covered in this section, the user defines the structure of his system and its parameters to compute performance indicators. The simplest models focus on cost calculations. Geographical information systems (GIS) bring spatial indicators like land use and distances. The most powerful approaches rely on simulation, which reproduces in a few minutes of CPU time the events occurring in a real system over a long period. Performance evaluation tools can cope with complex systems, e.g., with uncertain data, but they are not designed for optimization. If for instance several locations are envisaged for a refinery, the user has to run one simulation per location and analyze the results to determine the best site. Optimization models, like the ones reviewed in Section 4, can find the optimal location in a single run, using binary variables to know which site should be selected.

3.1. Models based on cost calculations

In the simplest models, the performance indicator is a total cost or profit, obtained by summing partial costs over the different stages of the chain. Their apparent simplicity should not hide the need for many accurate and reliable data, such as yield statistics and equipment costs.

Such models have been developed for instance for miscanthus, a kind of reed. Huisman et al. [57] compare eight options for growing this cane on peat soils in the Netherlands. Besides harvesting, storage in the farms, and transport, a strong point of this study is to consider the cultivation system, including soil preparation, fertilization, planting (using plantlets or rhizomes), gradual replacement of dead plants, and weed control. Thorsell et al. [107] prefer to concentrate on the harvesting phase of miscanthus, to quantify the different groups of equipment used in synergy (tractors, mowers, loaders, balers …), including the necessary human resources.

Spreadsheets are ideal for entering data, logically organizing and automating calculations. Hamelinck et al. [53] propose a spreadsheet-based system to assess biomass chains comprising international transportation steps and to rate their costs, energy consumptions and CO_2 emissions. Another spreadsheet model is described by Ref. [27] to evaluate the supply of rice straw in Thailand. A detailed cost analysis is conducted for three regions, by considering two bale sizes. Big bales require more expensive balers but need finally less fuel per ton transported.

3.2. GIS-based models

GIS (Geographic Information Systems) are highly valued to store, represent and analyze cartographic data. Such systems can superimpose several layers of geographic objects. Thus, it is possible to merge a topographic map, a road network, and an infrared satellite picture, to appraise the maturity of a crop, detect illicit plantations, or diagnose diseases. Sophisticated built-in functions are available. For instance, the length of a road with many segments, the centroid of a biomass production polygon, and the closest road to access a forest can be computed quickly, without programming.

Calvert [18] reviews the ways in which GIS have been used in bioenergy projects. As the author notes, geographical aspects are important factors that affect the feasibility of such projects. GIS are invaluable to analyze geographic situations, evaluate biomass resources, visualize land use and natural obstacles, and estimate transport costs. This flexibility comes from the possibility to combine geographic data with any other information: for instance, a crop name, a sowing date and an expected yield can be associated with the geographic object (a polygon) describing a field.

Using a GIS, [49] estimate the costs and environmental implications of supplying specified amounts of energy crop feedstock across a state. Voivontas et al. [112] locate and dimension power plants in Crete, a Greek island, using a GIS to determine whether a plant can collect enough biomass in a given radius. A GIS is also employed by Ref. [105] to divide a region into rectangular sectors and evaluate different chain structures for cotton stalks. Gronalt and Rauch [50] analyze the spatial distribution of forests in Austria to compute the regional forest fuel potential and estimate whether power plants can be served within the region or not.

A geographic analysis is performed by Ref. [52] to identify potential sources of corn stover in Iowa. Brechbill et al. [17] derive accurate biomass production costs from the most recent prices concerning seed, fertilizer, herbicide, harvesting equipment, storage, and transport. In their case, the role of the GIS software is to geographically locate biomass supply data from a national study, for the specific needs of three power plants in Indiana.

GIS are mainly used in a strategic context because they lack the short and medium-term temporal dimension that is required for tactical and operational decisions. Moreover, they cannot directly optimize an objective function but most of them can embed computation programs, written in a classical programming language or in the GIS script language. For instance, the GIS ArcView allows algorithmic developments in Visual Basic. This possibility has been exploited by Ref. [77], who developed a simulated annealing metaheuristic to select waste disposal sites in Indiana.

GIS are also nice visualization tools on top of simulation or optimization software. Frombo et al. [44] designed a GIS-based Environmental Decision Support System (EDSS) to provide bioenergy conversion plants with woody biomass. This system is organized in three modules: GIS, data management system, and optimization. Via a GIS-based graphic interface, the user can display the forest parcels, select the ones to harvest, locate the plant and enter parameters related to costs, demands and conversion efficiency. Then the optimization module determines the plant capacity and the amount of biomass collected each year in each parcel, to minimize a sum of plant, biomass transportation, and collection costs, minus the profits from energy sales.

3.3. Simulation models

The two previous families of models are not suitable for systems characterized by complex structures, dynamic aspects, random events and/or performance indicators whose computation is time-consuming (e.g., when they have no analytical formula). In such situations, more adequate tools are simulation methods, stochastic processes like Markov chains and queuing systems, and Petri nets. Among these tools, only simulation has been applied to biomass logistics up to now.

In general, the user defines a network-like model, using the graphical components (workstations, queues, random event generators) which are now widespread in most general-purpose simulation software like Arena. Then the software simulates in a few minutes the activities of the real system over a long period and calculates statistics and other performance indicators. The fact that users can easily design and modify a model explains the popularity of simulation.

Simulation models of biomass supply chains are based on process analysis and economic calculations to evaluate costs, energy consumption and GHG emissions. They can reproduce all the activities of the chain: harvesting, transport, storage etc. They are mainly used for tactical and operational decisions and consider discrete events. Continuous-time simulation is rarely applied, for instance [101] model biomass degradations via differential equations.

An early work by Ref. [45] develops a model in the SLAM simulation language to estimate the costs of supplying forest biomass, according to several scenarios. A model designed by Ref. [30] evaluates the economic feasibility of a conversion unit. It analyzes all the operations of the supply chain and calculates costs, energy consumptions, biomass flows, dry matter losses, and moisture content. The model created with the simulation software PROSIM is encapsulated in a decision support system called BIOLOGICS (Biomass Logistics Computer Simulation). Like many marketable models, the description given in the article lacks transparency: for instance, the formulas used for each module of the simulator are not given and numerical examples would have been welcome.

Three articles by Refs. [79–81] describe the design and the applications of a simulation model called SHAM (Straw Handling Model), to supply straw to boilers. In particular, it allows to assess the impact of different pretreatments of straw.

More recently, Ref. [101] elaborated a famous and powerful model called IBSAL (Integrated Biomass Supply Analysis and Logistics), using the EXTEND software. Unlike SHAM which was developed only for straw, IBSAL is designed for various agricultural biomasses, including crop residues and dedicated energy crops. IBSAL looks like the model from Ref. [30] but it is well described, including all mathematical formulas used.

IBSAL can tackle horizons of up to one year, divided in days. It takes into account biomass availability, moisture content, meteorological conditions that affect the effectiveness of field operations, equipment performance, loss of dry matter, and various costs. The software can determine the total cost of each step in the chain, the quantities finally delivered and the associated carbon emissions.

Sokhansanj et al. [101] applied their model to the collection and transport of corn stover. Examples of simulations can be found on the Internet (http://www.biomass.ubc.ca/IBSAL.html). They unveil some classical constraints of simulation models: the structure of the chain must be fixed and the activities completely specified day by day (parcels to harvest, equipment to use …). Even the weather conditions must be provided. In contrast to optimization models, the software cannot choose the fields to harvest and the equipment to use.

Since its initial design, IBSAL has been tested in several projects. Kumar and Sokhansanj [67] and later Sokhansanj et al. [102] employed it to study the logistics of switchgrass. It also served in Ref. [103] to compare four possible sites for a biorefinery in Alberta (Canada). An and Searcy extended the software in 2012 to handle a wider range of equipment.

The popularity of IBSAL should not hide some limitations. IBSAL is a push model, i.e., it seeks to harvest and deliver biomass as fast as possible to the conversion unit. This rule can mobilize more harvesting and transport equipment than a smoothing policy. Moreover, IBSAL is deterministic, a single kind of biomass is collected, only one aggregated production zone is considered (farms are not distinguished), storage capacities are assumed unlimited, and machines are perfect (no breakdowns).

These limitations have led to the development of IBSAL-MC (Multi-Crop IBSAL) by Ref. [35]. IBSAL-MC can manage a mix of crops, several farms, limited storage capacities, and uncertainties modeled by probability laws (weather conditions, machine breakdowns, repair times …). Field operations are still pushed, but then the flows to the biorefinery are pulled to satisfy the demands, using the storage facilities as buffers. IBSAL-MC has been applied to a project of cellulosic ethanol production in Saskatchewan (Canada). The objectives were to determine whether biomass demands could be met throughout the year by regional productions, identify storage capacities in farms and in the conversion plant, deduce the number of machines required in each period for each logistic operation, and finally calculate the overall system cost.

Zhang et al. [122] prefer the graphic modeling language IDEF (Integrated DEFinition), well known in industry and independent from the simulation software used, to obtain a higher-level depiction of activities in biomass supply chains. IDEF decomposes the system studied into activities to identify their inputs, outputs, interconnections (flows of materials and information) and controls (e.g., triggering events). The model is then processed by the ARENA simulation software to determine costs, energy consumption and GHG emissions. It has been applied to the design of a biomass supply chain for a biofuel plant in Michigan. Among simulation models, the approach of Zhang et al. seems a credible alternative to tactical planning models based on multi-period mathematical programming models, but without the optimization capabilities of the latter.

Simulation is sometimes applied to specific stages in a supply chain. Ravula et al. [87] study the transport of cotton bales from the fields to a cotton gin. When their bales are ready, farmers call the gin which sends trucks to fetch the bales, according to a FIFO rule. The study shows that other management policies can reduce both the number of vehicles required and the transportation costs.

To conclude with, the main advantages of simulation approaches can be summarized as follows:

- They offer a high modeling flexibility (flows, events, priorities, waiting times, resource conflicts …).
- Stochastic events can be handled fairly easily using built-in random generators.
- Large and complex supply chains can be modeled and their dynamics appraised.
- They are well suited to the operational level and, to a lesser extent, to the tactical level.
- Models are relatively easy to understand and can be modified by competent users.
- A broad choice of simulation software is available on the market.

However, simulation models have also some drawbacks:

- A detailed description of the chain must be provided (processes, flows, events …).
- The running time can be huge for large supply chains or long time horizons.
- They have a limited interest for strategic decisions.
- No optimization is possible in a simple way.
- They cannot take decisions about chain structure (e.g., facility location).
- Model errors are hard to find (the user always gets indicators at the end, even if they are fancy).

4. Optimization models

Most optimization models are based on *mathematical programs*, in which all unknowns are represented by *decision variables*, the relations linking these variables are expressed by equations called *constraints*, and an *objective function* is maximized or minimized. Such models have been marginal for a long time, due to the limited power of computers and mathematical programming solvers, but a growing number of applications to biomass supply chains can be observed over the last decade. We distinguish in this section between deterministic, stochastic, and multi-objective models.

4.1. Deterministic optimization

4.1.1. Overview of solution methods

Deterministic optimization models represent a vast majority of applications. The easiest ones are *linear programs* (LP), in which the objective function and all constraints are linear combinations of continuous variables. They can be solved via the simplex algorithm or interior-point methods. In biomass supply chains, variables often represent amounts harvested, transported, stored, pre-treated or converted ([24,4]). The aim is generally to minimize the total cost of the chain or to maximize the total profit. However, as pointed by Ref. [33], the most common models nowadays are *mixed integer linear programs* (MILP), which mix continuous variables and integer variables (e.g., number of trucks required). The latter may include binary variables, very useful to model assignment and location decisions. The MILPs are computationally harder than pure LPs. *Nonlinear programs* (NLP) are even harder but rarely necessary, because many nonlinear constraints and objectives can be linearized, at the expense of additional variables.

Almost all authors resort to commercial tools to solve their models. These tools can be delivered as libraries of functions, called *solvers*: The user must write a calling program, for instance in C++. The surveyed papers often cite CPLEX, XPRESS, MATLAB, and OMP. A more recent trend, to avoid programming, is to use a *modeler*. Using a dedicated editor, the user writes the equations in an algebraic language and defines associated data files. Then, the modeler replaces the mathematical symbols by their numerical values and solves the resulting numerical program by calling one solver. Examples of modelers cited in biomass logistics to solve MILP are AIMMS, AMPL, GAMS, LINGO (able to solve NLP too), OPL STUDIO (which calls CPLEX) and XPRESS-IVE. In the sequel, the combination of a modeler with a solver is indicates by a "+", e.g, "GAMS + CPLEX".

In general, the running time grows very rapidly with problem size and the percentage of integer variables. Hence, MILP instances solved have been quite small for a long time, e.g., Ref. [65] report results for a complete chain with 5 biomasses, 30 harvesting areas, 2 conversion units and 10 demand areas. However, larger instances are progressively handled in the literature.

Besides commercial solvers, only a few researchers prefer to develop their own optimization algorithms. Shastri et al. [100] describe an iterative approach alternating between two MILP: One determines the biomass production by farmers while the other one optimizes the downstream part (logistics and biorefinery). The two models consider one product over a multi-period planning horizon. Bai et al. [12] prefer Lagrangean relaxation procedure to solve their model, a difficult NLP.

Metaheuristics are even rarer but three typical articles can be cited. Reche-López et al. [88] consider the optimal location and supply area of a conversion facility, over a single period of one year. They get a nonlinear model which is solved via a binary variant of particle swarm optimization (PSO). The ratio between the net present value and the initial investment is used as fitness function in the PSO algorithm. In a comparison with a genetic algorithm, PSO gives better solutions.

Rentizelas et al. [90] optimize a tri-generation system for a district, taking into account the costs for biomass supply, energy production, and distribution of this energy. The problem is formulated as a hard NLP. A genetic algorithm provides one good initial solution which is then improved using a sequential quadratic programming method (SQP) written in MATLAB. Results are reported for 5 types of biomass and 500 clients. However, biomass production and transport are ignored: each biomass can be ordered (within certain limits) and delivered to the conversion plant with a known price.

Vera et al. [110] compare three metaheuristics to position and size a power plant fueled with olive tree pruning residues: A genetic algorithm, a particle swarm optimization method and a recent approach inspired by bees (honey bee foraging – HBF). HBF outperforms the other algorithms.

The rest of Section 4 is a classification of published models, based on the number of biomass types (one or more) and the kind of planning horizon (single or multi-period), with the methodology used to solve them. The articles cited before for their solution methods are not recalled.

4.1.2. Single-product and single-period

Such models mainly involve strategic decisions and reason on large aggregated quantities. Kanzian et al. [63] evaluate a forest biomass supply chain for a region comprising between 9 and 16 power plants. Decision variables concern treated quantities and the assignment of supply areas to plants. The XPRESS solver handles the resulting MILP.

The other articles employ additional binary variables. Freppaz et al. [43] and Frombo et al. [44] use LINGO to solve mixed integer linear programs modeling forest biomass supply chains. The conversion units are already placed but binary variables serve to determine their capacity and whether they will produce electricity, heat, or both. Numerical evaluations consider 370 to 506 forest parcels, 4 kinds of trees, and 4 conversion units.

Bai et al. [12] consider the location of a biorefinery, taking network congestion into account to derive transport costs. Their model is a MILP, except that the objective function is nonlinear. This hard program requires a dedicated branch and bound algorithm based on a Lagrangean lower bound. Four tests are solved, with up to 38 potential sites in a road network of 418 nodes and 914 arcs.

Finally, Bowling et al. [16] optimize the locations of one refinery and several decentralized pre-processing hubs via a MILP. However, the case solved via GAMS + CPLEX is rather small: 6 production areas, 2 possible locations for the hubs and 2 for the central site.

4.1.3. Multi-product and single-period

Considering several types of biomass is a natural extension of previous models. The price to pay is a multiplication of the number of variables, due to the additional index for the type of biomass.

De Mol et al. [30] introduced a MILP to select the annual amounts of free-of-charge residues, to be pretreated and transported, while selecting pretreatment sites and conversion units among candidate sites. The objective is to minimize the total cost, including transportation, pretreatment and handling costs, as well as the costs of creating facilities. The case resolved with OMP involves 5 types of biomass, 2 possible pretreatments (crushing and drying), 3 transportation modes (road, rail, canals) and 4 sites for one unit. The article gives very few details on the equations and data used.

De Mol et al. model is extended by Ref. [31] to provide a tool for decision support, called BIOLOCO (Biomass Logistics Computer Optimization). In particular, several criteria can be optimized, using goal programming.

An optimization model is proposed by Ref. [85] to place biorefineries fed by agricultural residues, urban waste, forest biomass, conventional crops (corn, soybean) and switchgrass, in the western United States. The model is a MILP whose objective is to determine the locations, sizes and conversion technologies to maximize the total profit. The study considers 12 raw materials and 6 conversion technologies, over 6 states. The calculations are performed by GAMS + CPLEX.

Kim et al. [65] seek to place and size a pyrolysis facility (conversion 1) and a Fischer-Tropsch unit (conversion 2). Conversion 1 accepts five types of biomass to produce bio-oil, gas and charcoal, which are then sent to conversion 2 which produces gasoline and diesel. Conversion 1 has also a local market for gas and charcoal. A centralized option, where the two units share the same location, is compared with a distributed approach where both units are distant. Using again GAMS + CPLEX, the model can manage 30 biomass source locations, 29 possible sites for conversion 1, 10 for conversion 2, and 10 final markets for sale.

A large case is solved by Ref. [75] for placing biorefineries in the Middle West of USA, while determining their capacity and conversion technologies. This strategic study involves 3109 counties producing biomass, 8 types of biomass, 2 transportation modes, 159 existing conversion units, 98 potential new sites, 4 types of biofuels, 7 conversion technologies, and 3 markets. The resulting model, a huge MILP, has 154,765 continuous variables, 5488 binary variables and 39,482 constraints. CPLEX needs 8 h to reach a 0.5% optimality gap. However, this CPU time on a 2.66 GHz PC remains tolerable for a strategic study. The large amount of required data has been made possible thanks to the existence of comprehensive agricultural databases in the USA.

4.1.4. Single-product and multi-period

The introduction of a multi-period horizon allows coping with strategic problems, over a few consecutive years, or most often with tactical planning problems, involving one-month to one-year horizons divided in days or months. At the tactical level, the subdivision into periods enhances model accuracy, e.g., to tackle seasonal variations. Obviously, the size of the models increases because most variables have now a period index. In the two following references, the authors assume that facilities are already placed, which limits the number of variables.

A remarkable early work is presented by Ref. [24] to model a switchgrass supply chain for one biorefinery in Virginia (USA), with a 12-month horizon and a supply radius of 50 km. The model solved via CPLEX is a pure linear program. It is tested on 20 producers, having 3 to 10 fields each, and 4 to 7 storage sites (in the open air or covered), whose capacity can be chosen.

Another example of pure LP is developed by Ref. [105] for harvesting and transportation of cotton stalks in Greece. The one-year planning horizon is divided in days. The region considered is partitioned into rectangular areas, using a GIS which calculates also transport costs. The originality of the study, based on an unspecified solver, is to compare two scenarios: The vehicles and machinery either belong to the farmers or to logistic providers.

A few authors incorporate investment decisions in tactical models to create, locate and dimension conversion facilities and/or storage areas, as shown by the next four papers. Only the last one reports running times.

Haque and Epplin [55] consider one year with a monthly timestep, 6 possible sites for several biorefineries processing switchgrass, and 57 counties in Oklahoma. They develop a MILP in which binary variables specify the locations and capacities of refineries and storage centers, while integer variables are defined to select the number of equipment for harvesting and handling. The model is developed using GAMS + CPLEX.

Zhu et al. [124] rely on OPL STUDIO + CPLEX to address a similar network (switchgrass, 12 months), but with three original features: Both warehouses and refineries must be located, two transport modes are supported (road and rail), and waste from biorefineries can be reused as fertilizer. A case with 10 biomass production areas, 3 warehouse sites and 2 potential refineries is presented.

The most comprehensive model is the one proposed by Ref. [99] for one biorefinery producing bioethanol from switchgrass, over one year divided in days. The biorefinery is already placed but several locations are possible for a centralized storage. The strong points of this model reside in a detailed modeling of farm equipment (harvesters, rakes, packing machines) and of transportation vehicles (heterogeneous fleet). Integer variables are used to select and dimension storage areas, harvesting equipment, vehicle fleet size, and the number of vehicles required each day. The model, called BioFeed, comes in two versions: either in pull mode (the capacity of the biorefinery and its demands per period are given, and these needs must be met) or push mode (available biomass is completely collected, then refinery capacity is adjusted accordingly. An online supplement lists the symbols used for data and variables, but the equations for the constraints and the objective function are not provided.

Zhang and Hu [121] consider conversion units producing gasoline from corn stover. The study covers the 99 counties of Iowa and a very long horizon of 30 years, divided into months. It is possible to open a unit with a biomass and gasoline stock, provided it receives at least a certain amount of biomass. The demand for gasoline for a county in a given month can be unsatisfied, but a penalty cost is then incurred. The resulting huge model with 145,000 variables (including 400 binary) and 219,000 constraints is solved in 30 min by CPLEX.

4.1.5. Multi-product and multi-period

Such models are the richest in terms of constraints and decisions handled, but they are also the most complex, given the number of required variables. Like previous models, they can be partitioned into models with or without location decisions.

Most multi-product and multi-period models focus on forest biomass, consider conversion units whose location is already set, but still need integer variables. The products include for example logs, chips, barks, and sawdust from different species of trees.

Gunnarsson et al. [51] model a forest biomass supply chain over 12 months. Binary variables are used to select the parcels cut in each period, the locations of chipping terminals, and the contracts with sawmills. AMPL + CPLEX can solve in 4.5 h a case with 426 harvest areas and 7 heating plants.

Gomes et al. [48] wish to determine, for each type of product, the quantities transported and stored in the form of logs or chipped. The number of mobile chippers and the number of vehicle trips in each period are defined as integer variables, while binary variables are used to select warehouses and decide which ones are equipped with a fixed chipper. Computational tests involve 5 to 150 forest areas, 1–4 products, 1–4 warehouses, 3–7 customers, over 7–150 days. In our hour of CPU time, CPLEX callable library can solve all instances, except the bigger ones (150 forests, 150 periods).

Van Dyken et al. [109] are the only authors who track the changes in density, moisture content and heating power of each product after each operation along the chain. The task is challenging because these changes depends on the drying mode (passive or using a dryer) and vary nonlinearly with drying time. The model developed in AMPL + CPLEX discretizes the nonlinear curves. It is checked on a simple case with 3 products, 1 dryer, 1 chipper, 1 pelletizer, 2 storages and 2 demand points, over 12 weeks. It extends an earlier model "eTransport", which was designed for the planning of energy systems with multiple energy carriers and technologies [13].

Turning now to models which place the conversion units [106], describe a model over twelve periods of one month, to supply bioethanol units with different types of ligno-cellulosic biomass. The originality is to consider variable yields, depending on the level of fertilization, and degradation expressed as functions of storage duration. A problem involving 77 production zones, 9 types of biomass, and 11 possible locations with 3 possible capacities is solved using XPRESS.

Zhu and Yao [125] generalize the model of Ref. [124] (switchgrass only, twelve months) by accepting two biomass types, corn stover and wheat straw. The model programmed with OPL STUDIO + CPLEX allows to place storage sites (on production areas or remotely) and biorefineries, and to choose between road or rail transport.

There are several examples of tactical models, and some even go beyond biorefineries, see for instance Refs. [36,37,41].

To end this section, we cite one of the rare cases of nonlinear program. Usually they can be avoided unless some constraints cannot be linearized by conventional techniques. Shabani and Sowlati [96] consider the supply of a power plant with forest residues (bark, sawdust, pruning products), purchased from different producers. They propose a mixed integer NLP where nonlinearities are induced by two complex constraints that bind the types of biomass consumed, their quantities, their moisture content and the amount of electricity that can be obtained. For 6 suppliers over 12 months, the model has 260 variables and 333 constraints. As this size is reasonable for an NLP, the modeler AIMMS calling the Outer Approximation (OA) algorithm can solve the problem in 1 min.

4.2. Stochastic optimization

Stochastic optimization problems are extremely hard and rather uncommon in biomass logistics, although uncertainties are the rule in practice (e.g., crop yields, weather conditions, demands and prices). The main difficulty is that it is not possible to guarantee constraint feasibility for all realizations of random variables.

Stochastic models for biomass logistics are reviewed by Ref. [10]. The simplest methods use Monte Carlo simulation to estimate the mean and standard deviation of a stochastic objective function. Schmidt et al. [92] for example define a MILP to place plants producing heat and electricity from forest biomass in Austria. Noting that the literature gives highly variable values for some parameters (electricity prices, plant costs, potential harvestable biomass), the authors use a Monte Carlo method to evaluate the impact of Gaussian variations of these parameters around their mean values. The same authors have reused this approach in 2010 to quantify the CO_2 emissions of more diversified systems.

The following models are stochastic mixed integer linear programs with two stages and recourse. We already mentioned [24] for a continuous linear model of switchgrass supply chain over twelve months. They extend this model to handle weather uncertainties in the same article. Two periods (growing season and harvesting seasons) and two weather conditions (good or poor) are considered, which gives four scenarios. The authors weigh the data of the different scenarios with their probabilities of occurrence, to minimize the expected total cost.

Awudu and Zhang[11] want to maximize the expected profit for biorefineries already placed and producing biofuels under uncertainties on selling prices and demands. The demands for finished products follow normal distributions while prices follow a geometric Brownian motion (GBM). The first stage of the stochastic program computes the amounts of biomass purchased, the quantities processed by the refineries, and the amounts of biofuel produced. The second stage considers the actual sales of biofuels, backlogs and inventory levels, which all depend on the realizations of random demands. Using Benders decomposition, the variables of the second stage are approximated by a Monte Carlo method based on a set of scenarios. A case study for two units of bioethanol in North Dakota shows that the stochastic model leads to a higher profit (in terms of expected value), compared with a deterministic model based on average demands.

Osmani and Zhang[82] study a similar problem but with location of conversion units and more uncertainties. To random demands and prices of finished products, they add uncertainties on biomass yields and prices. The solution technique is identical except that the first stage of the stochastic model is extended to locate the conversion units. The tests show that location decisions are very sensitive to uncertainty and that, as in the previous paper, the stochastic approach gives a better profit than a deterministic model.

Kim et al.[66] also model a network with location of biorefineries but in their case two types of conversion facilities are considered: pyrolysis units, producing bio-oil, and Fischer-Tropsch units, which convert bio-oil into bio-diesel through a synthesis gas. In their article which generalizes their earlier deterministic model [65], uncertainties about transport and conversion costs are added to the ones treated by Ref. [82]. The first stage determines the location and capacity of conversion plants, but apart from this detail, the same solution approach as in the previous articles (Monte Carlo) is used to evaluate recourses.

4.3. Multi-objective models

Most works on multi-objective optimization for biomass supply chains use Pareto-optimality to offer several compromises (non-dominated solutions) to the decision maker. Some authors have focused on multi-product, single-period models with several optimization criteria. Two representative examples can be given, which do not deal with location decisions.

Santibañez-Aguilar et al.[91] seek to maximize the total profit of the chain while minimizing the value of the Eco-indicator 99 which measures the environmental impacts. Their model is a mixed linear program which is solved by the ε-constraint method, using GAMS + CPLEX.

Cucek et al.[23] model a complete chain by considering the total cost and several environmental impacts, including the social impact inherent to decreased food production when food crops are replaced by energy crops. The proposed model is a nonlinear program. As in the previous article, it is solved via the ε-constraint approach and GAMS + CPLEX.

Other authors have published multi-product, multi-period and multi-criteria models, which are obviously more complex.

You and Wang[116] propose a model minimizing the total cost and GHG, taking into account environmental and societal issues. They integrate a life cycle analysis (LCA) and a regional economic input–output analysis. The aim is to include an environmental objective, measured by life-cycle greenhouse gas emissions, and a social objective, measured by the number of local jobs resulting from the construction and exploitation of the cellulosic biomass supply chain. The article deals with a case study for the 99 counties in Iowa, with a 12-month horizon, 3 types of biomass and 3 types of biofuels. The originality is to consider several potential sites for both pre-conversion and conversion units (pyrolysis, gasification) and several technologies. Each county is considered both as a harvest area, a potential site for a conversion unit, and a demand zone. The model is the largest one ever treated in biomass logistics: 4,294,326 continuous variables, 1782 binary variables, and 772,506 constraints. The resolution with GAMS and CPLEX employs the ε-constraint technique, testing 20 values for the GHG emissions used as ε, and requires a huge total computation time of 1060 h. You et al.[115] slightly modify this model for two case studies involving the 102 counties of Illinois.

It is worth noting that, in contrast with the other multi-objective models [23,116,115] are the only ones to handle simultaneously the economic, environmental and social issues in their models.

Bernardi et al. [15] propose a tri-objective model for northern Italy, over 15 years divided into three-year periods, which shows that multi-period horizons can also be used at the strategic level. The model covers biofuel consumption areas and distinguishes 3 transportation modes (trucks, trains and barges) and 10 conversion technologies. The three objectives minimized are the total profit, the GHG emissions and water consumption. In fact, this work generalizes an earlier paper by Ref. [46], which considers the two first objectives. Like Ref. [116], an ε-constraint method calling GAMS + CPLEX determines Pareto-optimal solutions. The large case solved requires 307,000 continuous variables and 9300 integer variables but CPU time is not indicated.

A few multi-objective models do not rely on Pareto-optimality. Instead of minimizing greenhouse gas emissions, [38] maximize the subsidies received for these reductions. As the other criterion is to maximize the profit from the sale of biofuels, the model can combine the two objectives in a weighted sum. Alam et al. [5] employ the goal programming method, another multi-objective approach, to handle three criteria in a forest biomass supply chain: Supply cost, average distance to biomass resources (weighted by the amounts) and biomass quality (moisture).

4.4. Summary of optimization models

Compared with simulation approaches, models based on mathematical programs have the following strong points:

- They provide a high-level, abstract and compact specification of the problem at hand.
- Their resolution indicates the best possible decisions for one or several criteria.
- They are well suited to strategic and tactical problems.
- Powerful commercial and public-domain solvers are available.

However, a few drawbacks and limitations must be underlined:

- Designing and modifying efficient formulations requires strong modeling skills.
- On large instances, the running time of nonlinear and integer programs can be prohibitive.
- Stochastic and multi-objective extensions do exist, but they are very technical.

Tables 1 and 2 use a tree structure to list representative publications which contain mathematical models to optimize biomass supply chains [2–9,11,15,16,20,21–25,30,31,34,36–39,41,43,44,46,48,51,54–56,62–65,66,68,70,73–75,78,82–86,88,90–93,96,98–100,104–106,109–111,115,116,118–121,123–125]. They distinguish between single or multi-period models, and then between models with or without facility location decisions. The tables include all papers cited in the text, plus some other articles of interest. Table 1 gathers articles dealing with non-forest supply chains, based on energy crops and various agricultural residues. Table 2 displays references dedicated to forest supply chains and their specific features, e.g., location of road terminals, chipping operations, traceability of wood moisture and calorific value. It includes also a few references focusing on the design of heating systems.

To save space, several other articles are included in the list of references without being commented in the text. However, an online supplement (see last pages of submission) is proposed to summarize the main features of each published optimization model: Its context (kind of supply chain, types of biomass, kind of conversion unit, end-products), some additional attributes (single or multi-product, single or multi-period, horizon length, special constraints), the main decision variables, the optimization criteria, and, finally, the kind of model (LP, MIP, or NLP) with the solver or dedicated algorithm used to solve it.

5. Conclusion

This review shows that original and interesting optimization problems are raised by the design of biomass supply chains. Compared with industrial logistics, many input nodes scattered over vast territories have to continuously supply output nodes with biomass produced by slow-growing crops. These characteristics may lead to large-scale models, especially when detailed operations and/or multi-period are considered. Thanks to the rapid advances in computers and optimization software, a growing number of publications propose nowadays more and more realistic supply chain models.

However, several trends, current limitations and possible research directions can be detected from our analysis of literature. They can be listed in three categories, related to the characteristics of supply chains studied, the modeling issues, and the algorithms used to solve the models.

5.1. Supply chains studied

- The kind of supply chain studied and the constraints handled are strongly influenced by the national and local policies concerning bioenergy, agricultural practices, and land management. These differences explain that there is no ubiquitous model of biomass supply chain, in the current state of research.
- After a wealth of strategic models with highly aggregated data, more and more models address the tactical decision level and a multi-period horizon. However, the way they handle harvesting and transport equipment is still limited, even if some recent progress can be observed [55,69,99].
- When several types of biomass are taken into account, they come from different sources (crops, urban waste, or forest biomass), from different plants, or from different forms of the same biomass (e.g., switchgrass in bales or pellets). No author discusses the possibility to value, at varying degrees, different parts of the same plant, such as seeds, straw and chaff for colza.
- Most models handling biomass degradations use a very simple method, a loss coefficient per period spent in stock. Only a few works have gone further and show that an accurate modeling of degradations is not trivial [24,99,109].
- Still few authors consider nodes dedicated to storage, preprocessing, or pre-conversion between harvesting areas and biorefineries. When such nodes are dealt with, they most often represent on-farm storages and simple pretreatments like baling. Such facilities should be modeled more precisely. For instance, preprocessing facilities have input and output storages, and the silos of a centralized storage can be used by different products over time.

5.2. Modeling issues

- Models lack genericity and scalability. They impose a temporal granularity (e.g., a one-year horizon subdivided in months), a spatial granularity (e.g., a geographic area divided into elementary squares using a GIS), and a fixed network structure.
- The integration into real application programs is rarely discussed, for instance, the way of gathering, structuring and storing the large amount of required data (in a database for example).
- The model with its equations can only be defined by the designer of the model. Most users cannot change it easily, given the special skills required. However, it seems possible and more interesting to let the user describe his network in a flexible way, for example in graphical form, and then to generate automatically the mathematical model from this description.
- The proposed models are either strategic or tactical, with or without facility location decisions. We believe it is possible to offer the user a choice of complementary models, for instance one with facilities already placed and one when the sites are not yet determined.

5.3. Solution methods

- Optimization models are almost all solved with commercial solvers, which are too general to fully exploit their mathematical structure and display running times growing very quickly with the size of the chain and the number of integer variables. This explains that models are still relatively small or need large CPU

Table 1
Optimization models for non-forest biomass supply chains. “NS” means “not specified”.

Non-forest supply chains	Single period	Without location decisions	Awudu & Zhang 2013	1 period NS
			Santibañez-Aguilar et al. 2011	1 x 1 year
			Tan et al. 2012	1 x 1 year
		With location decisions	Akgul et al. 2011, 2012	1 x 1 year
			Alfonso et al. 2009	1 x 1 year
			Bai et al. 2011	1 x 1 year
			Bowling et al. 2011	1 x 1 year
			Chen & Fan 2012	1 x 1 year
			Cucek et al. 2012	1 x 1 year
			De Mol et al. 1997	1 x 1 year
			Ekşioğlu et al. 2010	1 x 1 year
			Judd et al. 2012	1 x 1 month
			Kim et al. 2011a, 2011b	1 period NS
			Lam et al. 2011	1 x 1 year
			Marvin et al. 2012, 2013	1 x 1 year
			Osmani & Zhang 2013	1 x 1 year
			Parker et al. 2010	1 x 1 year
			Reche-López et al. 2008	1 x 1 year
			Rentizelas et al. 2009	1 x 1 year
			Tatsiopoulos & Tolis 2003	1 x 1 year
			Vera et al. 2010	1 x 1 year
			Vlachos et al. 2008	1 x 1 year
			Zamboni et al. 2009a, 2009b	1 x 1 year
	Multi period	Without location decisions	Cundiff et al. 1997	12 x 1 month
			Dunnett et al. 2007	12 x 1 month
			Elms & El-Halwagi 2010	Periods NS
			Machani et al. 2013	20 x 1 year
			Papapostolou et al. 2011	12 x 1 month
			Sharma et al. 2013b	12 x 1 month
			Zamboni et al. 2011	10 x 1 year
		With location decisions	An et al. 2011, 2012	12 x 1 month
			Bernardi et al. 2013	5 x 3 years
			Dal-Mas et al. 2011	10 x 1 year
			Diekema et al. 2005	12 x 1 month
			Ekşioğlu et al. 2009	52 x 1 week
			Feng et al. 2010	N x 1 year
			Giarola et al. 2011	15 x 1 year
			Haque & Epplin 2012	12 x 1 month
			Huang et al. 2010	10 x 1 year
			Mapemba et al. 2008	12 x 1 month
			Shastri et al. 2011a, 2011b	365 x 1 day
			Papadopoulos & Katsigiannis 2002	12 x 1 month
			Tembo et al. 2003	12 x 1 month
			You et al. 2012	12 x 1 month
			You & Wang 2011	12 x 1 month
			Zhang et al. 2013	12 x 1 month
			Zhang & Hu 2013	12 x 1 month
			Zhu et al. 2011	12 x 1 month
			Zhu & Yao 2011	12 x 1 month

Table 2
Optimization models for forest supply chains.

Category	Periods	Location	Reference	Horizon
Forest supply chains	Single-period	Without location decisions	Alam et al. 2009	1 x 1 week
			Chinese & Meneghetti 2009	1 x 1 year
			Han & Murphy 2012	1 x 1 day
			Kanzian et al. 2009	1 x 1 year
		With location decisions	Freppaz et al. 2004	1 x 1 year
			Frombo et al. 2009	1 x 1 year
			Keirstead et al. 2012	1 x 1 year
			Rauch & Gronalt 2011	1 x 1 year
	Multi-period	Without location decisions	Akhtari et al. 2013	12 x 1 month
			Eriksson & Björheden 1989	6 x 2 months
			Gunnarsson et al. 2004	12 x 1 month
			Shabani & Sowlati 2013	12 x 1 month
			Van Dyken et al. 2010	52 x 1 week
		With location decisions	Chinese & Meneghetti 2005	52 x 1 week
			Gomes et al. 2012	7-150 x 1 day
			Nagel 2000	4 periods
			Schmidt et al. 2009, 2010	4 seasons

times, especially those dealing with tactical decisions and various constraints.

- Treating larger instances and/or more detailed models requires developing dedicated algorithms, such as decomposition methods, relaxation techniques, and metaheuristics. This need is critical for models which spends too much time in multiple calls to a solver, as it is common in stochastic programming (scenarios evaluation) or multi-objective optimization (ε-constraint method).
- Some approaches which have already demonstrated their efficiency in industrial logistics have not yet been applied to biomass, e.g., multi-objective genetic algorithms like NSGA-II [26] and simulation-based optimization [72].
- Simulation and stochastic optimization are the main tools to determine robust solutions, i.e., little affected by uncertainties. Robust optimization, a recent discipline which does not rely on probability distributions, could be useful.

Finally, we are struck by the predominance of authors working in university departments or laboratories devoted to agricultural engineering [99], wood science [95], chemistry [112], or energy [109]. Although many ideas from industrial logistics could be transposed to biomass supply chains, very few authors are affiliated to industrial engineering departments [29,36]. Computer scientists and OR specialists, who could optimize the formulations or design algorithms for large cases, are even rarer [48]. In our opinion, composing multi-disciplinary research teams is a key success factor to design accurate and realistic models for biomass supply chains.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.renene.2015.07.045.

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