An Overview of OR Models for Biomass Supply Chains

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Abstract: The biorefineries of the future will critically depend on efficient supply chains to guarantee continuous flows of biomass while minimizing logistic costs and environmental impacts. OR techniques can be very useful to help decision makers to model, evaluate and optimize such complex and large-scale supply chains at the design stage. This paper provides an overview of the OR models for this recent research domain and proposes a core-model (mathematical program) for the tactical decision level.

1 INTRODUCTION

The actual biorefineries designed for first-generation biofuels (like bioethanol from wheat, maize or sugar cane, or biodiesel from rapeseed or sunflower) raise criticisms concerning possible pressures on other crop usages like human food or animal feed production. This is why the biorefineries of the future will try to combine various types of biomass, by valorizing discarded fractions of current crops, like cotton straw, and using the enormous potential of plants, like switchgrass and short rotation woods, to produce non-food crops. Moreover, beyond biofuels, all these agricultural and forestry resources will provide renewable raw materials for a broad range of other products, such as chemicals, fibers, lubricants, construction materials, etc.

The European Commission has put forward a proposal for a Directive to achieve by 2020 a 20% share of renewable energy and a biofuels' usage with a target of 10% in transport (European Commission, 2008).

While research on interesting vegetal species and biorefinery processes is well developed, the actors concerned realized only recently that the Achilles' heel of the planned systems could be the logistic part. For instance, each type of biomass is produced during a short period in the year while biorefineries have a more regular activity. Hence, an efficient supply chain must be implemented to play the role of a buffer in between and supply the biorefineries without shortage. Moreover, as the biomass itself is relatively cheap, the economic equilibrium of the whole system critically relies on logistic costs. OR is an adequate tool to derive quantitative models for these biomass supply chains, evaluate their performance and optimize criteria like the total cost of the chain, the energy consumption and the GHG (greenhouse gas) emissions.

The goal of this contribution is to depict the OR models proposed for biomass supply chains, for readers having a general OR culture but not specialists in biomass issues. This work is extracted from a preliminary study conducted by the same authors in the GENESYS French national project on the lipids biorefinery of the future. This study has surveyed more than 150 research articles on biomass logistics but, due to limited space, only some representative papers will be cited here, to provide the interested readers with good entry points. The papers are selected among recent research papers considering different decision time frames (i.e., strategic, tactical, operational, and integrated) and proposing some general approaches to model biomass supply chains.

2 BIOMASS SUPPLY CHAINS

A complete biomass supply chain includes various activities like cultivation, harvesting, pre-processing (e.g., drying, baling, granulation), transportation, handling, storage, conversion processes in the biorefineries, and distribution to end-users. Figure 1 from Zhang et al., (2013) shows a nice example for a single biorefinery producing ethanol from a plant called switchgrass. Although a few authors have tried to model the whole chain (for instance Feng et

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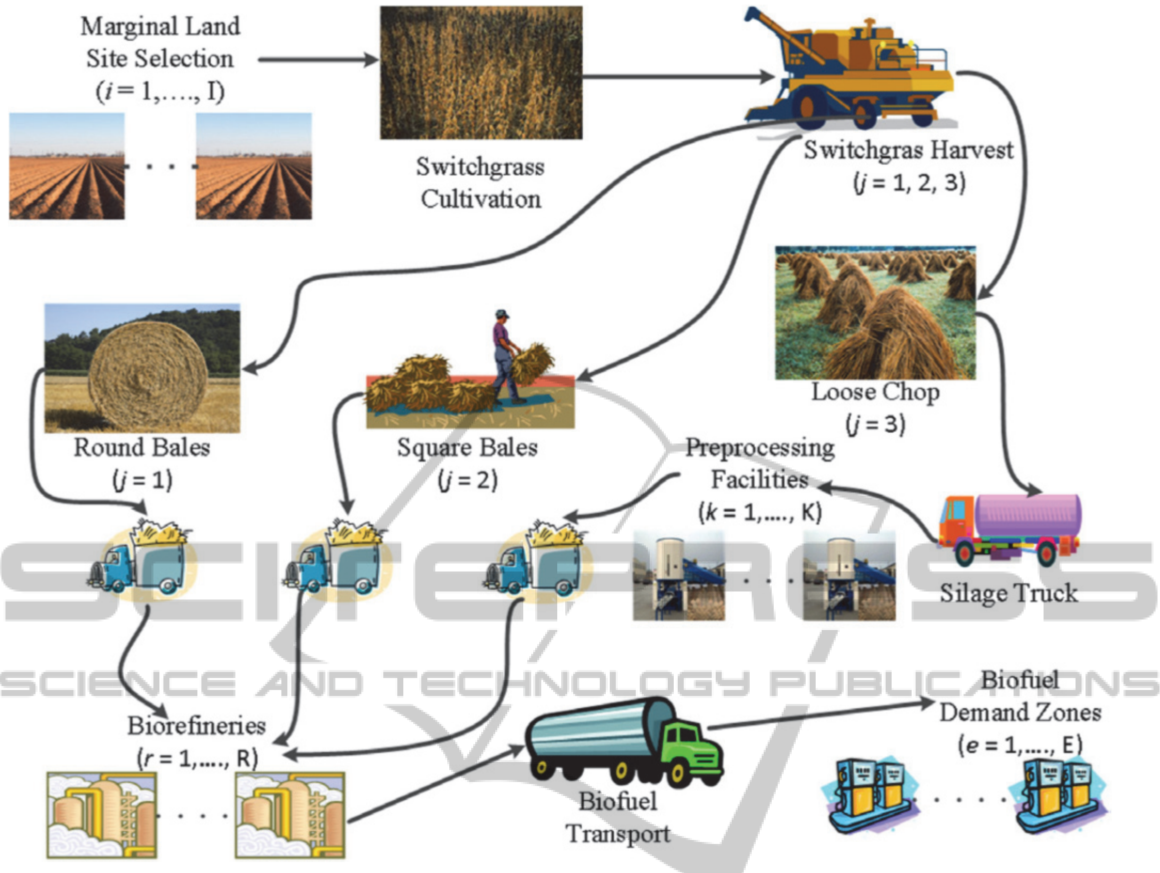

Figure 1: Example of supply chain to produce bioethanol from switchgrass (Zhang et al., 2013).

al., (2010) for forest products), a global optimization is still extremely difficult because very different actors intervene in the two main parts of the chain, before and after the biorefineries. Therefore, like in the vast majority of studies, we consider in the sequel a supply chain that goes from the fields to the doors of biorefineries. It is assumed that this chain is driven by demands issued by refineries for several types of biomass and that these needs must be satisfied, if possible.

The structure of the chain in Figure 1 suggests a network model with the following node types (recall that from now on we stop at the biorefineries):

- *Input nodes* or *production nodes*, where biomass is produced and harvested;
- *Output nodes* or *consumption nodes*, where biomass is consumed (biorefineries);
- *Intermediate nodes*, the main ones being storage sites, pre-processing facilities, transshipment nodes (railway stations for instance) and simple transit nodes (villages traversed).

Compared to an industrial supply chain, several differences must be underlined:

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

Pre-processing activities lead to a longer preservation (dry forms, granulates, pellets) and/or easier and cheaper transportation (increase in density). For instance, harvested switchgrass has a density of 60-80 kg/m^3, which becomes 140-180 for a bale and 700-800 for granulates (Sokhansanj et al., 2009). Simple preprocessing like baling is often done directly on the field by harvesters, like in Figure 1.

Biomass supply chains can also be described in terms of activities that involve various resources:

- *Harvesting Activities*. They are possible in a limited period at input nodes, when the crop is ready, and they compete for a limited fleet of machines like harvesters or balers. The yield is not perfect, with a typical 10 to 20% loss.

- *Storage*. Storage is required in practice to synchronize the biomass production calendar with the production planning of the biorefineries. It can take place in the fields or forests as simple stacks, in intermediate storage sites or at the entry of biorefineries.
- *Pre-processing*. Baling is a simple form of pre-processing, which can be done directly on the field by a quader-baler. Stronger compressions and other transformations are possible, but using heavier equipments and/or dedicated sites.
- *Transport*. Road transport is often preferred, due to limited accessibility of some production sites like forests. However, other modes like trains can be used. In many cases, the fleet of vehicles is limited and the number of travels per period is restricted by various constraints like vehicle range or driving time regulations.

A real biomass supply chain can be much more complex than the simple example of Figure 1 : other activities can be distinguished (e.g., material handling); several types of biomass and a multi-period horizon can be added; the locations of some facilities can be left as decision variables, etc.

Hence, biomass supply chain designers need modeling tools to cope with this complexity. Before coming to a total cost, they must understand the dynamics of the chain and fix many variables, like the amounts harvested (which type of biomass, where, when, in which amount), the flows in the network (amounts transported), the advisable stock levels, the resources consumed (machines, vehicles, energy, manpower). Subtle tradeoffs must be found: for instance, deciding either to densify on the field, using light equipment, or to get a higher density at a remote dedicated facility, at the expense of an additional transportation step.

Like in production management and industrial logistics, the decisions can be classified into three levels, according to the time horizon concerned:

- *Strategic decisions* include for instance the selection of accepted biomass types, the location and size of biorefineries, storage sites and pre-processing plants, the transportation modes, the long-term supply contracts. In general, a single-period horizon of one year or a multi-period horizon of a few years is considered.
- *Tactical decisions* correspond to production planning in industry. A multiperiod horizon of a few months is involved, with a time period varying from one day to one month. Examples: amount of each type of biomass harvested in each period at each production node, vehicle fleet size, definition of safety stock levels, etc.
- *Operational decisions* correspond to scheduling in industry. Contrary to the tactical level, the order and starting times of tasks are specified. Examples: vehicle routing and scheduling, detailed harvesting operations, idle times.

Even if some studies address the operational level (e.g., truck scheduling in Han and Murphy, 2012), research on biomass supply chains focuses on the strategic and tactical decision levels. Indeed, the goal is to provide decision makers with tools to model a chain before its implementation, and not to develop software for day-to-day operations. Anyway, the data for detailed operations are never known at the design stage.

Three main approaches presented in the sequel are used to model biomass supply chains: simple decision support systems, performance evaluation tools, and optimization techniques.

3 SIMPLE SYSTEMS

The simplest decision support systems rely on spreadsheets and geographical information systems (GIS). Their apparent simplicity must not hide the underlying need for many accurate data, e.g., biomass production statistics, cost estimates for all steps and (for the GIS) geographical maps.

A good example of spreadsheet-based system is described by Delivand et al., (2011) to assess the supply of rice straw in Thailand. A detailed cost analysis of a typical rice straw logistic process for two baling options (small or large rectangular bales) in three regions shows that the difference in logistic costs is finally marginal, due to the higher ownership and operating costs of the equipment for using large rectangular bales. However, the fuel consumption is substantially lower for large bales, which induces a significant reduction of transport costs.

GIS are more powerful and perform non-trivial calculations for the user. The centroid of a polygon describing a cultivation area can be easily computed, e.g., to estimate the Euclidean distance between this area and a plant. In case of accessibility problem in a forest, the GIS can find the closest road.

Brechbill et al., (2011) determine up-to-date biomass production costs using recent prices for all important cost components including seed, fertilizer, herbicide, mowing/shredding, raking, baling, storage, handling, and transportation, from the fields to the plant gate. The role of the GIS used (ArcMap) is to map production and supply data over selected geographical locations.

GIS are also used as nice visualization tools on top of simulation or optimization software. For instance, Frombo et al., (2009) present a GIS-based Environmental Decision Support System (EDSS) to define planning and management strategies for the optimal logistics for energy production from woody biomass. The EDSS is organized in three modules (GIS, data management system, optimization). In particular, through a GIS-based graphic interface, a decision maker can visualize the forest parcels of the territory under concern, select those parcels that can be used, calculate the distance from each parcel to the first available road and to the conversion plant location, and set the parameters related to costs and technical issues. Then, the optimization module can be run and the results stored in the database and displayed on a map.

4 PERFORMANCE VALUATION

The aim of performance evaluation techniques is to compute performance indicators for real systems characterized by a complex structure, dynamic aspects, random variables and/or objective functions whose each computation is time-consuming (for instance when these functions have no analytical formula). The main performance evaluations tools are simulation methods, stochastic processes like Markov chains and queuing systems, and Petri nets.

The ones used for biomass logistics are mainly simulation models. In general, a network-like model composed of graphical objects (workstations, queues, random event generators) is defined using the modelling language of a commercial simulation software like Arena, then the software simulates in a few minutes a long period of activity of the real system.

Sokhansanj et al., (2006) developed a dynamic Integrated Biomass Supply Analysis and Logistics model (IBSAL) to simulate the collection, transport and storage operations and the flow of biomass (corn stover) from fields to a biorefinery daily throughout the year. The model includes weather conditions such as rain and snow which influence the moisture content and the dry matter loss of biomass through the supply chain. IBSAL predicts the number and size of equipment to meet the rate of harvest and biorefinery demand schedule for feedstock, and also calculates the costs, energy input and emissions.

IBSAL is very popular as one of the most sophisticated simulation models, reproducing a multi-period supply chain with hundreds of production areas, but with one type of biomass only. Kumar et al., (2007) applied it to study the logistics of switchgrass and compare several options for the collection and transport. IBSAL was also used to analyze the logistics of different cultures in different regions (Mani et al., 2006) and (Stephen et al., 2010). An extended simulation model, called IBSALMC (IBSAL Multi Crop) was derived from IBSAL by Ebadian et al., (2011). This model was developed to evaluate a chain supplying multi-agricultural raw materials for a proposed cellulosic ethanol production in Canada.

Ravula et al., (2008) designed a simulation model to study transport in the logistic network of cotton, as a possible model for more general biomass transportation systems. In general, cotton is collected and compressed into large blocks, known as modules of cotton transport. Then the cotton modules built by several farmers are transported to a gin for processing. Considering a continuous supply of cotton modules, the originality of this study is to solve a zero-one knapsack sub-problem which is solved to optimality to estimate the number of trucks required in each period. In fact, this work belongs to the rare publications combining simulation and optimization.

Zhang et al., (2012) also selected a simulation approach to take into account the main activities of the supply chain of biomass, including harvesting, processing, transportation and storage. Their model considers the cost of raw materials delivered, energy consumption and GHG emissions as criteria for measuring system performance. Compared to the authors previously cited, this work includes the distribution sub-network, i.e., beyond the refinery.

Compared to mathematical programming models, the main advantages of simulation approaches are the following:

- A fine-grain modelling is possible, tackling for instance resource conflicts, queues of vehicles waiting for loading in the fields, biomass production variations or delays due to unexpected climatic conditions, etc.
- System dynamics can be appraised.
- Stochastic events are possible.
- The operational level can be handled.
- Large and complex chains can be modelled.
- Practitioners like this kind of models, that they can easily understand and even modify.

However, simulation models have also some limits:

- The running time can be huge for large supply chains or long time horizons.
- No optimization is possible: the user defines the input parameters and obtains the corresponding

performance indicators.

- In practice, it is possible to evaluate only a few scenarios to select the best one. For instance, if a biorefinery is not yet located, a simulation model can be used to compare a few possible locations, while ad-hoc variables in a mathematical program can lead to an optimal location.

5 OPTIMIZATION MODELS

5.1 Principles and Main Works

The formalism used in optimization models is quite different. The decisions must be described in terms of variables while the constraints to satisfy are expressed as equations which link these variables. Most works consider mixed integer linear programs (MILP) with a single objective function.

Tembo et al., (2003) are worth citing as one of the first complete models. They developed a multi-region, multi-period MILP handling alternative feedstock, feedstock production, field losses, harvests, storage, storage losses, transport, bio-refinery size, and biorefinery location. To take into account the fluctuations in biomass availability, one-month time slots are considered. The solution minimizing logistic costs indicates the best locations and sizes of warehouses, the storage policies, the flow of biomass in the logistic network, the planning of annual crops, the required vehicle fleet, and the optimal location of the biorefinery.

More recently, Ekşioğlu et al., (2009) proposed another MILP model that uses agricultural and woody biomass to produce ethanol. Their multi-period model prescribes strategic decisions such as the location, number and size of refineries and collection sites, and tactical decisions like material flows. The objective is to minimize over one year a sum of costs concerning biomass (harvest, storage, transport, conversion) and the distribution of ethanol. Ekşioğlu et al., (2010) extended this study to different modes of transport. The objective was to identify locations for refineries, transportation modes to use, transport planning and biofuel production scheduling to minimize the total cost for delivering the fuels to end-customers.

Zhu et al., (2011) designed also a MILP for a single product (switchgrass) supply chain, involving strategic decisions about the design of the supply chain and tactical decisions over an annual schedule. The planning horizon is discretized into one-month time slots. The MILP takes into account biomass seasonality, harvesting and transport operations, energy consumption, and residue handling. The model determines the best location and capacity for new warehouses, an effective policy for storage, the flows of switchgrass transported in the logistic network, the timing of annual harvest and the best configuration from a set of candidates bio-refineries. Zhu and Yao (2011) extended the previous work to a biorefinery accepting three types of biomass (switchgrass, corn stover and wheat straw). An original aspect of their study is that additional biomass can be purchased from external sources.

The previous papers consider as objective function a linear combination of various costs, which is not considered as a true multi-objective optimization. Multi-objective approaches in Pareto's sense are all very recent. For instance, Santibañez-Aguilar et al., (2011) investigated a multi-objective optimization model for the optimal planning of a biorefinery, considering various types of production technologies, raw materials and products. The model was applied to a case study of a refinery in Mexico. It simultaneously maximizes the profit and minimizes the environmental impact.

A few authors have studied non-linear programming formulations, although they can be quite hard, computationally speaking. A good example can be found in Shabani and Sowlati (2013), who designed a nonlinear mixed integer program (MINLP) to optimize the supply chain of a biomass power plant in Canada. Biomass procurement, storage, energy production and ash management are considered at the tactical level to maximize the profit. The model provides estimates of the amount of biomass to be purchased, stored and consumed in each month, over a one-year planning horizon.

The mathematical models solved by commercial solvers are still limited to small networks in terms of nodes, contrary to simulation models for instance. However, still very few authors have proposed metaheuristics to tackle larger problems. For instance, Vera et al., (2010) compared a Binary Particle Swarm Optimization (BPSO) metaheuristic and a genetic algorithm (GA) to efficiently determine the optimal location of a biomass power plant, avoiding a greedy exhaustive search which would be too time-consuming. The proposed approach allows to get the location, plant size and supply area that offer the best profitability from the investor's perspective.

Optimization models offer the following advantages compared to simulation:

- Optimal decisions can be taken;
- Tactical and strategic levels are easily tackled;

- Commercial solvers with a high-level modelling language are available.

But they have still some drawbacks:

- The model is difficult to modify for end-users.
- The running time may be excessive when integer variables or non-linearity are involved.
- Commercial solvers fail on large instances and dedicated algorithms must be designed, e.g. metaheuristics or decomposition approaches.
- Handling stochasticity and multiple objectives is not obvious, although ad hoc extensions exist.

5.2 A Detailed Example

To fix ideas, we propose a tactical model of biomass supply chain, inspired by the different models from the literature but more general and flexible. We allow both a multi-period planning horizon H, a set of biomass types B (e.g., corn straw, switchgrass), a set of biomass forms or "products" P (e.g., straw bales, straw pellets, switchgrass briquettes), a set of production zones Z, a set of storage sites S, a set of transformation (pre-processing) sites T and a set of biorefineries R.

The supply chain structure is described by a digraph G with a node-set $N = Z \cup S \cup T \cup R$ and an arc-set A. G models the real road network but simple transit nodes are removed and each arc (i,j) stands for a path from node i to node j in the actual network, with a length d_{ij} pre-computed by a shortest path algorithm. The chain considered covers a biomass basin corresponding to one French department, so any implicated arc is traversed in a single period. It is assumed that each production node, storage node and preprocessing node is dedicated to a single product (several products are easily handled by placing several nodes at the same location). Our model involves the following data.

For each type of biomass $k \in B$:

- $spb(k)$ set of products for this biomass, e.g., bales and pellets from wheat straw.

For each product $p \in P$:

- tbo_p type of biomass of origin, e.g. wheat straw for straw bales and straw pellets;
- $dens_p$ density in tons/m^3;
- dry_p dry fraction, e.g. 0.8 for 20% humidity.

For each production zone $i \in Z$:

- $dprod(i)$ delivered product;
- W_i harvest window (set of consecutive periods);
- $avail_i$ amount available in tons;
- $hcap_i$ harvesting capacity in tons/period;
- $hcost_i$ harvesting cost in €/ton.

For each storage site $i \in S$:

- $sprod_i$ stored product;
- $scap_i$ storage capacity in tons;
- $scost_i$ storage cost in € per ton and per period.

For each preprocessing site $i \in T$:

- $iprod_i$ input product;
- $oprod_i$ output product (same biomass of origin);
- $wconv_i$ weight conversion factor (e.g., 0.9 if 10 tons on input yield 9 tons on output);
- $tcap_i$ transformation capacity in tons/period;
- $tcost_i$ transformation cost per ton.

For each refinery $i \in R$:

- abt_i set of accepted biomass types in B;
- dem_{ikt} demand for biomass type k in period t, in dry tons.

For each arc $(i,j) \in A$:

- d_{ij} arc length in km;
- c_{ijp} transportation cost in € per ton of product p.

Variables (amounts in tons)

- $h_{it} \geq 0, \forall i \in Z, \forall t \in W_i$: amount harvested per zone and period;
- $s_{it} \geq 0, \forall i \in S, \forall t \in H$: stock level for each storage node and period;
- $q_{it} \geq 0, \forall i \in T, \forall t \in H$: amount of input product treated for each transformation node and period;
- $x_{ijpt} \geq 0, \forall (i,j) \in A, \forall p \in P, \forall t \in H$: flow for each arc, product and period.

The minimization of the different costs of the chain can be modeled by the linear program given on next page, in fact a kind of multi-commodity, minimum cost flow problem (declarations of variables are not recalled).

The objective function (1), to be minimized, is the total cost of operations, composed of four terms: harvesting costs, storage costs, preprocessing costs and transportation costs. Constraints (2) to (4) concern production zones: equations (2) mean that the sum of product flows leaving the zone is equal to the amount harvested, equations (3) ensure that this amount does not exceed harvesting capacity, while equations (4) state that the total amount harvested while the crop is ready cannot exceed crop availability. Constraints (5) guarantee the inventory balance at each storage site while constraints (6) prevent storage capacity overflows. Constraints (7) mean that the amount processed at each preprocessing plant corresponds to the sum of incoming flows. Constraints (8) say that this amount is equal to the sum of outgoing flows after preprocessing. The capacity of preprocessing plants is respected via constraints (9). Finally, biorefineries are handled by constraints (10), which state that the demands expressed in dry weight for each accepted biomass type and each period are satisfied.

This model is very flexible because the user may interleave freely storage nodes and transformation nodes between the input layer (production zones) and the output layer (refineries).

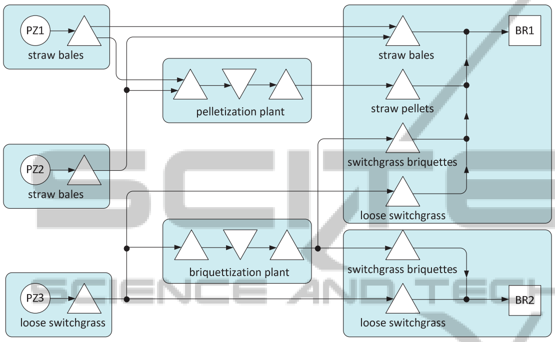

Figure 2: Example of supply chain tackled by our model.

Figure 2 shows an example of possible network with seven sites: three production zones, two preprocessing plants and two biorefineries (BR), respectively symbolized by circles, inverted triangles and squares. All these sites have local stocks depicted by triangles.

Production zones PZ1 and PZ2 supply straw already packed into bales while PZ3 yields loose switchgrass. Refinery BR1 accepts straw and switchgrass, but refinery BR2 switchgrass only. Straw bales can be sent directly to BR1, or to the first preprocessing plant for pelletization. Switchgrass can be shipped to BR1 and BR2, or to the other preprocessing plant to give briquettes. Both plants have local stocks on input and output.

The core-model has been tested on such examples, using the OPL-STUDIO modeling environment from IBM (based on CPLEX) and providing some preliminary results.

6 CONCLUSIONS

This short review indicates that interesting optimization problems are raised by the design of biomass supply chains. Compared to industrial logistics, many input nodes scattered over vast territories have to continuously supply output nodes with biomass produced by slow-growing crops, which leads to large-scale models.

$$\min \sum_{i\in Z}\sum_{t\in W_i} hcost_i \cdot h_{it} + \sum_{i\in S}\sum_{t\in H} scost_i \cdot s_{it} + \sum_{i\in T}\sum_{t\in H} tcost_i \cdot q_{it} + \sum_{(i,j)\in A}\sum_{p\in P} c_{ijp}\cdot d_{ij}\cdot x_{ijpt} \tag{1}$$

$$\forall i \in Z, \forall t \in W_i\colon \sum_{j\in A_i} x_{i,j,dprod(i),t} = h_{it} \tag{2}$$

$$\forall i \in Z, \forall t \in W_i\colon\ h_{it} \le hcap_i \tag{3}$$

$$\forall i \in Z\colon \sum_{t\in W_i} h_{it} \le avail_i \tag{4}$$

$$\forall i \in S, \forall t \in H\colon s_{i-1,t} + \sum_{j\in B_i} x_{j,i,sprod(i),t} - \sum_{j\in A_i} x_{i,j,sprod(i),t} = s_{it} \tag{5}$$

$$\forall i \in S, \forall t \in H\colon\ s_{it} \le scap_i \tag{6}$$

$$\forall i \in T, \forall t \in H\colon\ q_{it} = \sum_{j\in B_i} x_{j,i,iprod(i),t} \tag{7}$$

$$\forall i \in T, \forall t \in H\colon wconv_i \cdot q_{it} = \sum_{j\in B_i} x_{j,i,oprod(i),t} \tag{8}$$

$$\forall i \in T, \forall t \in H\colon\ q_{it} \le tcap_i \tag{9}$$

$$\forall i \in R, \forall k \in abt(i), \forall t \in H\colon \sum_{j\in B_i}\sum_{p\in spb(k)} x_{jipt}\cdot dry_p \ge dem_{it} \tag{10}$$

Our analysis of literature has shown that the genericity of proposed models is still insufficient. Very few can cope simultaneously with several types of biomass, a multi-period horizon, strategic and tactical decisions. We are also surprised by a majority of articles that neglect storage nodes, contrary to our model.

Moreover, most authors belong to laboratories of agriculture, chemistry or energy. Their models are often solved on small instances, using commercial software. OR scientists can contribute to the field by designing dedicated methods based on relaxation or metaheuristics to solve larger instances in acceptable running times, and by designing more advanced models which could incorporate further criteria such as economic, environmental and social measures, and further features as uncertainty and sustainability issues. The next step of our work is to enrich our model to make it more generic and scalable, and to study decomposition techniques, relaxation methods, and a metaheuristic for large problems.

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