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Methods to Manage and Optimize Forest Biomass Supply Chains: a Review

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Abstract

Purpose of Review This paper aims to provide a comprehensive but concise review of the various quantitative methods, in particular, optimization techniques, for the efficient management and control of complex forest biomass supply chains. The review is structured around a top-down hierarchical planning approach that includes strategic, tactical, and operational decisions. At each planning level, the review presents and analyses the problem to be solved, the solution (optimization) methods, and the various aspects to take into consideration for the successful implementation and use of these methods by biomass supply chain planners.

Recent Findings Forest biomass constitutes one of the various sources of renewable energy with the potential to reduce the consumption of fossil fuels and greenhouse gas emissions. Fo rest biomass supply chains are systems with complex network designs consisting of many supply, demand, and intermediate points where the biomass is collected, stored, processed, and transported. The complexity of these supply chains as well as various factors impact the effective supply of forest-based biomass. For example, the biomass characteristics (e.g., energy content or quality), the variability in the market and economic conditions, and processing of the biomass are the main factors. The complexity requires a good understanding of the methods that exist to manage and optimize forest biomass supply chains.

Summary Although substantial research has been done around forest biomass supply chain management and optimization, future research should focus on developing integrated frameworks that allow the optimization of biomass supply chains at the strategic, tactical, and operational level. These studies should also explore and propose approaches for the successful implementation of the proposed optimization methods.

Keywords Biomass · Supply chain · Logistics · Modeling · Optimization · Decision support systems

Introduction

Biomass is any material of biological origin, and in that broad sense, forest biomass comprises the total mass of roots, stems, branches, leaves, etc. of all the species found in the forest [1]. For the bioenergy industry, only part of the total biomass (residues) is available due to the production of other more valuable products (logs, poles, pulp, etc.). These residues remain on the forest site after the completion of the harvesting operations. This also includes special wood assortments, dedicated energy crops, and wood industry by-products [2].

A forest biomass supply chain is a system of organizations, people, activities, information, and resources involved in delivering residues (bulk residues, chips, bundles, etc.) from suppliers to customers. A forest biomass supply chain involves the transformation of trees or tree components (e.g., branches, bark, tops, etc.) into a finished product (e.g., chips

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for power generation, liquid fuels, etc.) that is delivered to the end customer. These activities include the harvesting, collection, preprocessing (e.g., chipping, grinding), storage, and transportation from supply to demand points [3] (Fig. 1).

Harvesting and collection with mechanized equipment (e.g., harvester/processors, forwarders, multi-stem feller bunchers) are expensive, and hence critical activities in the biomass supply chain. Storage and drying at the supply points, terminals, or mill yards are critical to reduce the moisture content (MC) and to increase the net energy value of the forest biomass before it is delivered to energy consumers. Biomass products (stems, residues, bundles, etc.) are usually stacked at the roadside and eventually covered to avoid their re-wetting. Storage at different points in the supply chain also acts as an inventory buffer which is required to secure the supply of the biomass and satisfy the demand of the energy plants throughout the year. Preprocessing is essential to increase the density of biomass products; this reduces transport costs by maximizing the volumetric capacity of the transport vehicles.

Supply chain management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. Optimal design of the supply chain is critical to provide the best service to customers at the lowest cost. Also biomass supply chain planners need to understand the complexities involved in 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) [4].

Management and optimization of biomass supply chains often involve decisions at strategic, tactical, and operational levels using a top-down hierarchical approach [4–6]. Table 1 presents a summary of the major decisions involved in each planning level. Strategic decisions are

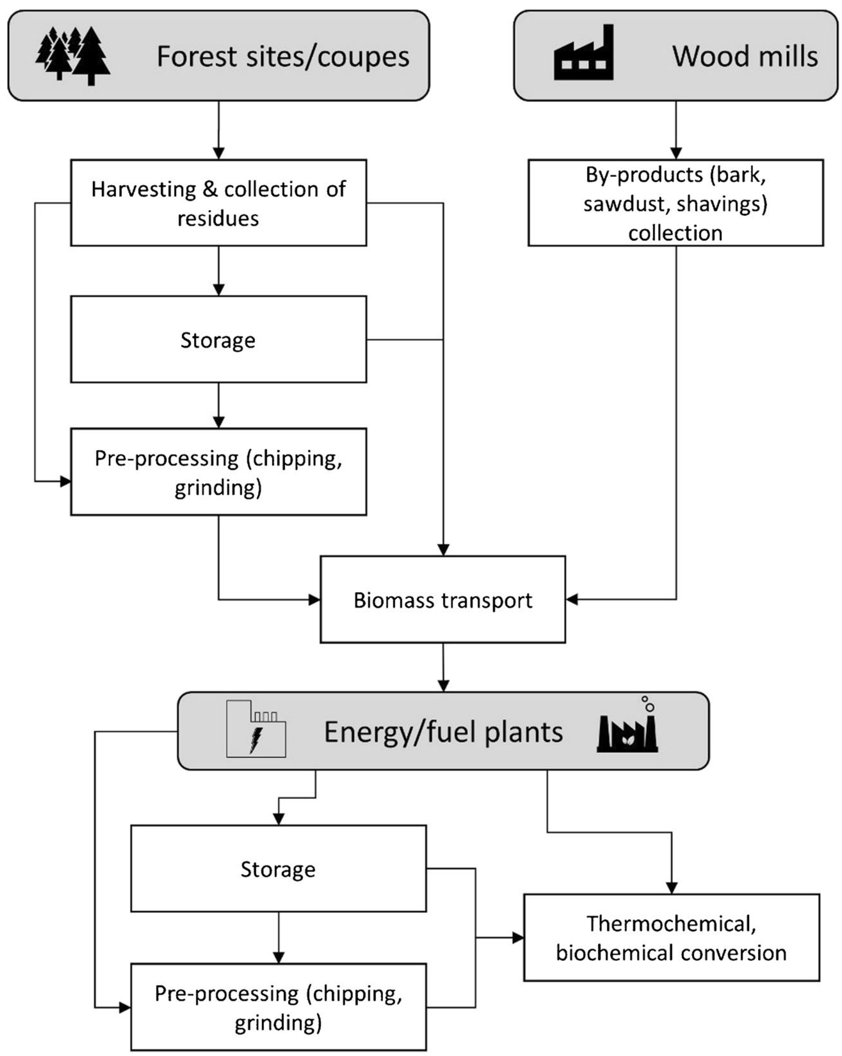


Fig. 1 Biomass supply chain including the major activities

Table 1 Biomass supply chain decisions at strategic, tactical, and operational levels

Decision level		
Strategic (> 5 years)	Tactical (1–5 years)	Operational (< 1 year)
- Supply chain network design, including location, type, and size of facilities (storage, preprocessing, and energy plants) - Biomass procurement strategy - Harvesting, collection, and transportation technology - Equipment and infrastructure investment (e.g., roads, trucks, chip vans, ships) - Investments in information technology and planning systems - Contracts, price, and service strategy	- Forests/coupes to be harvested per year - Volume of stems and residues to harvest, store, and transport to intermediate facilities and energy plants per year - Allocation of harvesting, collection, and transport equipment to forests/coupes - Road planning and route definition - Customers' energy demand per year - Seasonal inventory at intermediate facilities and energy plants	- Forests/coupes to be harvested per month - Volume of stems and residues to harvest, store, and transport to intermediate facilities and energy plants per month - Transport scheduling and dispatching from forests to intermediate facilities and energy plants - Customers' energy demand per month and week - Monthly and weekly inventory at intermediate facilities and energy plants

concerned with long-term goals (> 5 years), and the focus is on biomass supply chain network design, which consists of processes and information that, when linked together, connect the raw materials to the end user [5]. Other decisions at this level include biomass procurement strategies and investment decisions around infrastructure. Supply chain networks are depicted as a series of nodes connected by arcs that reflect pathways or flows of the necessary material or information. These types of systems provide opportunities to find ways to improve the performance of the processes at a single node, arc, combination of both, or across the entire network [6].

The second level in the planning hierarchy corresponds to tactical decisions. These decisions involve medium-term goals and span between 1 and 5 years. They are primarily concerned with logistical aspects including the optimization of biomass flows between supply and demand points, inventory management, and allocation of harvesting and transport equipment to forest sites, among others.

Operational decisions are at the bottom of the top-down hierarchical approach. These include monthly, weekly, or daily decisions that focus primarily on operational logistics including the allocation and scheduling of harvesting and transport equipment, short-term inventory control, among others so that customers' demand is met at the lowest cost possibly [4, 7].

Using the above hierarchal planning approach, this paper is a comprehensive but rather concise review of methods for biomass supply chain management and optimization. It begins with a review of biomass supply chain management and optimization at the strategic and tactical level. Specifically, this section includes aspects of supply chain network design including facility location and flow optimization, biomass supply chain modeling, and implementation of decision support systems (DSSs) for biomass supply chain optimization at the tactical level. The second major section is devoted to biomass supply chain management and optimization at the operational level. It covers decision support for residue collection in gentle terrain, residue processing and transport including optimization, machine interactions, moisture management, truck scheduling, management of solid wood content, and implementation of DSSs at the operational level.

Biomass Supply Chain Management and Optimization at the Strategical and Tactical Level

The effective management and implementation of optimization techniques at the tactical and strategic level are critical for the efficient functioning of biomass supply chains. Optimized decisions at these levels will also be essential for the efficient supply of biomass at the operational level. Strategic and tactical decisions are made for goals that range from months to several years. Some DSSs for biomass supply chains have focused at the strategic and tactical level, which are supported primarily by mathematical programming techniques such as linear programming (LP), mixed-integer programming (MIP), heuristics, multi-criteria decision analysis (MCDA), as well as geographical information systems (GIS) and simulation techniques.

The discussion of DSSs at the strategic level is organized with examples of biomass supply chain network design including facility location and supply decisions. In addition, some examples of DSSs developed for harvesting, collection, storage, and transport of residues at the tactical level are presented.

Biomass Supply Chain Network Design Including Facility Location and Supply Decisions

Supply chain network design is a strategic, long-term decision that impacts the economic, environmental, and social performance of biomass supply chains. It is concerned primarily with the location, type, and size of facilities (storage, preprocessing, and energy plants), equipment and infrastructure investment, and biomass procurement strategies including supply, collection, preprocessing, processing, intermediate processing, blending, and distribution sites. The design of the supply chain network is a critical decision at the strategic level, as it gives form, structure, and shape to the entire supply chain and logistic system [8].

A few comprehensive reviews (e.g., [9•, 10••, 11]) have been conducted on biomass supply chain network design. Sharma et al. [9•] analyzed 30 papers on biomass supply chain network design. Their review includes energy trends, renewable energy targets, biomass feedstock required for biofuel production, and conversion processes in the biomass supply chain. The authors also present and analyze the various mathematical modeling used to optimize biomass supply chains (mainly mixed integer linear and multi-objective programming models) and provide an overview of issues and challenges, describing potential future work. De Meyer et al. [10••] reviewed 68 papers on biomass supply chain network design. Their review presents an overview of the optimization methods and models focusing on the design and management of biomass supply chains. They also introduce the structure of a typical upstream biomass supply chain highlighting the biomass handling operations and present the typical decisions and time spans considered in the supply chain design and management. The classification of the selected papers is performed based on the mathematical optimization approaches, as well as decision level, decision variables, and objective functions included in the optimization models. Ghaderi et al. [11] provides a comprehensive and systematic analysis of 146 papers published on biomass supply chain design from 1997 to 2016. Their review considered the uncertainty of parameters, dynamism, and solution methods, elements that were neglected in the reviews conducted by [9•] and [10••]. The literature review conducted by [11] included decision levels in biomass supply chain network design, the mathematical modeling approaches, solution methodologies, model characteristics, uncertainty, sustainability aspects, among others.

Strategic decisions regarding the location of biomass facilities (storage, preprocessing, and energy plants) are keys for the economic, environmental, and social performance of biomass supply chains [3], as well as for the success of a biomass-based energy industry [12]. Decisions about the location of bioenergy facilities are affected by a wide variety of factors and criteria, such as the location of the biomass feedstock, and the transportation costs and GHG emissions associated with the transport of residues between feedstocks and intermediate storage facilities or energy plants [12•, 13•, 14]. Since transportation is the single major cost component in the supply chain, site selection for new biomass facilities in the proximity of available biomass resources is the preferred option when designing biomass supply chain networks [14]. Ghaderi et al. [11] indicates that the location of processing facilities has drawn more attention than other facilities. The location of processing facilities directly affect the allocation of the biomass feedstock, and the proximity of supply points and processing facilities is a factor that results in competition among the biomass supply regions [15].

In addition, biomass plant design should factor in environmental and social factors to determine the number, location, and size of biomass facilities within the network of feedstock collection points, plants, and storage units [3, 12].

Strategic decisions are also concerned with the type, sourcing, and allocation of biomass products from supply to demand points [11]. Due to the interaction between biomass logistics (i.e., allocation of biomass types from different sources) and the design of the supply network (i.e., facility location), stakeholders and supply chain planners frequently want to identify the optimal facility locations simultaneously with the determination of the optimal flow of biomass between supply and demand supply chain points [10••].

At the tactical level, most solution techniques and DSSs have focused primarily on optimizing the flow of biomass from supply (storage) sites to demand points. The biomass flow problem balances demand at consumption centers against supply from the forests, whereas backhauling extends the network flow problem where routes are included to consider efficient routing explicitly [8].

Acuna [16••] presents the network structure of the wood and biomass flow problem (Fig. 2), assuming two generic products, roundwood, and biomass. A forest site can supply just roundwood or both products, whereas a destination point can demand one or both products. In the latter case, the mill (e.g., a pulp mill) and the energy plant are part of the same industrial complex and have the same geographic location. This problem can be formulated as an LP model that extends the classic transportation optimization models. The goal of the model is to determine the optimal flow of products (roundwood and biomass) from supply to demand points. The formulation comprises an objective function that minimizes total biomass flow costs as well as constraints to ensure that the flow of products does not exceed the capacity of the supply points and that demand at the consumption centers (e.g., mill and energy plant) is met.

In the timber and biomass problem, it is assumed that a truck runs loaded from a wood pickup point to a customer (demand) point and empty in the other direction (left side of Fig. 3) [16••]. Thus, the running loaded percentage (distance traveled loaded is just half of the total distance traveled) in this example is equal to 50%. This value will increase if routes involving several loaded trips (that is, backhauling) are performed (right side of Fig. 3). As indicated by [8], the possibilities for backhauling are dependent on the type of transportation and the geographical distribution of mills and harvest areas and requires wood flows going in opposite directions.

At the tactical level, several authors have proposed and implemented optimization solutions for the biomass flow problem [16••, 17–19, 20••]. Eriksson et al. [17] developed an LP model to determine the quantity of biomass to transport directly to the energy plant or after storage at the roadside for a few months. Decisions about where to do the chipping (at the

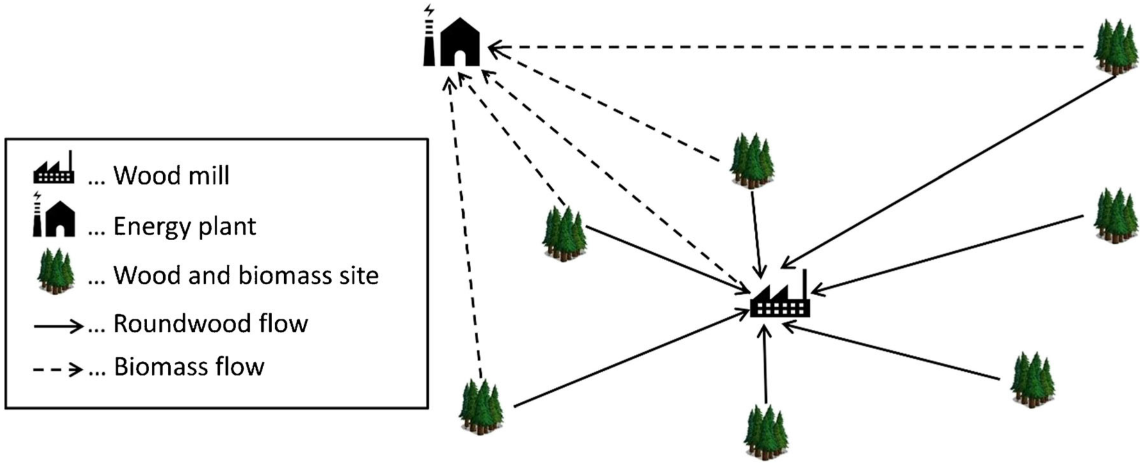


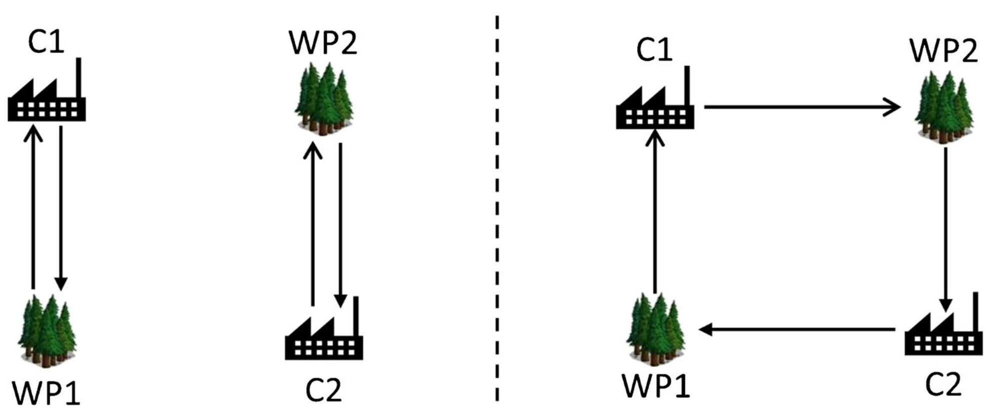
Fig. 2 Network structure for the timber and biomass flow problem. Source: [16••]

roadside in the forest or energy plant) were also included in the model. The optimal solutions obtained prescribed in-field chipping and direct transport of the chips to the energy plant. Additional transport costs were incurred when the terminal that was used was not offset by the lower MC of the biomass after storage at the roadside. Gunnarsson et al. [18] developed a MIP supply chain model to optimally decide when and where forest residues are to be converted into forest fuel, and how the residues are to be transported and stored to satisfy demand at heating plants. Decisions also included whether or not to contract additional harvest areas and sawmills. In addition, the optimal flow of products from sawmills and import harbors was determined, including decisions about which terminals to use. The planning horizon spanned 1 year including monthly periods.

Kanzian et al. [19] also developed two versions of an optimization model (LP and MIP) to model a regional biomass supply chain in Austria. The problem included four different supply scenarios, one for 9 plants and one for 16 plants. The results indicated that direct transport of solid fuel wood as round wood and chipping at the plant was the cheapest supply system; using terminals led to higher logistical costs, which confirmed the results obtained by [17]. Akhari et al. [21] developed a linear programming model to minimize the delivery cost of forest biomass to the gate of heating plants and determine the optimal monthly flow of biomass to the plants. The model has a 1-year planning horizon with monthly periods. It determines (1) the volume of woodchips that should be transported to the plants from supply sources directly and through the terminal storages, (2) the volume of biomass that should be stored at supply sources and at terminal storages, and (3) the volume of biomass that should be chipped at supply sources and at terminal storages. The model was applied to a potential district heating system in British Columbia, Canada. The results of the optimization model indicated that it would not be economical to carry out the chipping process at the terminal storage. Biomass should be chipped at supply sources, and woodchips should be sent to the terminal storage and/or directly to the plant.

Sosa et al. [22], Sosa et al. [23•], and Ghaffariyan et al. [24] implemented different versions of an LP model developed by [25]. The model minimizes total supply chains costs (harvesting, collection, storage, chipping, and transports) and provides spatial and temporal solutions, which include volumes to be harvested per period and supply point, drying times for roundwood and biomass, and flows from supply to demand points. It uses MC curves as the driving factor for the optimization of supply chain costs, and the optimization tool is typically used

Fig. 3 Flow in two directions (left) and a backhauling tour (right). WP wood pickup point, C customer. Source: [16••]



to investigate the effect of MC on storage, chipping, and transportation costs of roundwood and biomass delivered to mills and energy plants under different MC, operational, and drying scenarios. A basic formulation of the optimization model can consider two or more generic products (e.g., roundwood and biomass), multiple supply points and demand destinations for the biomass products. Decisions on how much volume of roundwood and residues to be harvested and collected are made on a monthly basis (24 periods), and the optimal drying period is provided by the optimal solution of the linear programming model and does not exceed the maximum nominal drying period established in the model's formulation. Constraints include volume capacity in a supply area, demand for wood products, and energy demand for biomass products, among others.

Using the model developed by [26••], [24] investigated the impact of five operational factors: energy demand, MC, interest rate, transport distance, and truck payload on total forest residues supply chain cost in Western Australia. The supply chain consisted of four phases: extraction of residues from the clear-felled area to roadside by forwarders, storage at the roadside, chipping of materials by mobile chippers, and transport of chips to an energy plant. Sosa et al. [22] used a spatial version of the model the LP model developed by [16••] to analyze the impact of MC and truck configurations (five-axle and six-axle trucks) on supply chain costs and spatial distribution of the supply materials in Ireland. The inclusion of wood chips from whole trees reduced the costs of wood energy supply in comparison with only producing wood chips from short wood to satisfy the demand, with 9.8% and 10.2% cost reduction when transported with five-axle and six-axle trucks, respectively. Constraining the MC of the wood chips delivered to the power plant increases both transport and overall supply chain costs, due firstly to an increase in the haulage distance and secondly to the number of counties providing the biomass material. Sosa et al. [23•] also used the model developed by [26••] to analyze the supply of wood biomass (short wood) to the three peat power plants in Ireland and the impacts on the competing wood-based panel industries. Results show that the planned maximum 30% co-firing rate at the three peat power station could be met with the forecasted short wood availability from both the private and the public sectors. The costs of supply increased not only with higher demands but also with tighter constraints on the MC demanded by power plants. Spatial distribution and operational factors such as efficiency in transportation and truck loading were shown to be sensitive to changes in MC.

Most supply chain models have been unimodal, emphasizing truck transport [27]. Rail transport is regionally important in several countries (e.g., Sweden, Germany, Austria), and barge transport is important in Finland. But, in general, rail and barge transport make up less than 10% of raw wood transport of internal transport, often much less (for statistics, see [28]). Average transport distance for raw wood transport is less than 100 km. Several studies have shown that the break-even costs for multi-modal truck/rail is much longer (e.g., 200 km in Michigan USA [29], 180–250 km in Sweden [30], 200–300 km in Finland [31, 32], 380 km in France [28]). Russia, Finland, and the Baltic countries use a different gauge track than the rest of Europe. Similarly, Russia and China use different gauge tracks that challenge continental rail transport. Multi-modal barge transport on inland waterways is more competitive (e.g., breakeven at 120–230 km [29], 100–150 km [33]). Discrete event simulation and GIS have been useful for evaluating the competitive feasibility for multi-modal transport [27, 33], but development of DSSs has been challenged by the point-to-point, case-by-case, costing models for estimating multi-modal operations, particularly rail [29]. Kogler et al. [27] used Discrete Event Simulation (DES) in perhaps the most detailed railroad terminal study to date for the wood supply chain. Currently, the trend worldwide is to increase truck load capacity on public roads. However, rail and barge offer a smaller CO_2 footprint, and their importance may grow. Multi-modal transport may have its greatest advantage where forest biomass can provide the backhaul on rail or barge, or if fossil fuel prices escalate.

Biomass Supply Chain Modeling at the Strategical and Tactical Levels

Several optimization techniques (mathematical programming, multi-objective optimization MOO, heuristics) and non-optimization techniques (multi-attribute decision making (MADM), GIS, simulation) have been used separately or in combination to model biomass supply chains at the tactical and strategic level [7]. A comprehensive review of these techniques to optimize biomass supply chains has been conducted by [4], [10••], and [34••].

Among the mathematical programming techniques, LP and MIP are the most popular techniques used to model biomass supply chains [34••]. All these modeling techniques involve linear equations, and they comprise one or more objective functions to be minimized (e.g., costs, GHG emissions) or maximized (e.g., maximize revenues, local jobs), constraints (e.g., customer demand, budget), and decision variables (e.g., location of facilities, flows of residues to deliver from supply to demand points). LP and MIP models comprise just continuous and integer/binary decision variables, respectively, while MIP models use integer or binary decision variables in combination with continuous decision variables.

At the strategic and tactical levels, MIP has been used to optimally determine (1) the number, location, and size of terminals and biomass plants; the biomass storage duration; the selection of conversion technologies; use of terminals; and the design of biomass processing network (e.g., [18, 19, 20••, 35–39]) and (2) the flow of biomass within the supply network, the quantity of biomass chipped and stored at the roadside, terminal or energy plant, the quantity of biomass harvested at each harvesting location and to be used at each plant location, and volume of wood chips transported from each terminal to each plant (e.g., [18, 19, 20••, 38]). LP has been used at the strategic and tactical levels to optimally determine the annual quantity of biomass harvested from each supply area, the volume of biomass harvested and transported to energy plants, the flow or biomass (direct or via storage), and the volume to be collected, stored and transported from harvesting locations to energy plants (e.g., [17, 22, 23•, 26••, 40]). For large multi-period, multi-commodity, multi-modal preprocessing location problems, a two-phase procedure combining dynamic programming, or LP in the first phase with MIP or heuristics in the second phase, can significantly reduce problem complexity [41, 42] (Fig. 4).

Most of the problems solved with LP and MIP techniques involve a single-objective function to be minimized or maximized. When several conflicting objective functions need to be optimized simultaneously (e.g., maximize return and minimize GHG emissions), models are solved using the MOO techniques. MOO is part of multi-criteria decision-making (MCDM) methods that include problems consisting of a set of objective functions which are optimized subject to a set of constraints [43]. MOO for biomass supply chains uses Pareto optimality to offer several compromises (non-dominated solutions) to the decision maker. A solution is called Pareto optimal if none of the objective functions can be improved in value without degrading some of the other objective values [44]. At the strategic and tactical levels, MOO has been used to minimize the total cost and GHG, taking into account environmental and societal issues [45], to maximize profit and reduce GH emissions and water consumption in biorefinery supply chains [46], and to optimize large-scale forest biomass supply networks [25].

Heuristics are an alternative to mathematical programming techniques when solving combinatorial, large-scale spatial harvest planning and biomass supply chain problems. These problems involve multiple discrete decision variables that involve long solution times [47, 48]. Heuristics comprise algorithms that cannot guarantee optimality when solving complex optimization problems, but they can find good solutions in a relatively short time. Some of the heuristics commonly used to solve forest biomass supply chain problems include simulated annealing (SA), particle swarm optimization (PSO), genetic algorithms (GA), and Tabu search (TS). Ghaffariyan et al. [24] used SA to analyze the effect of operational factors on forest residue supply chain costs; [49] used PSO to locate biomass

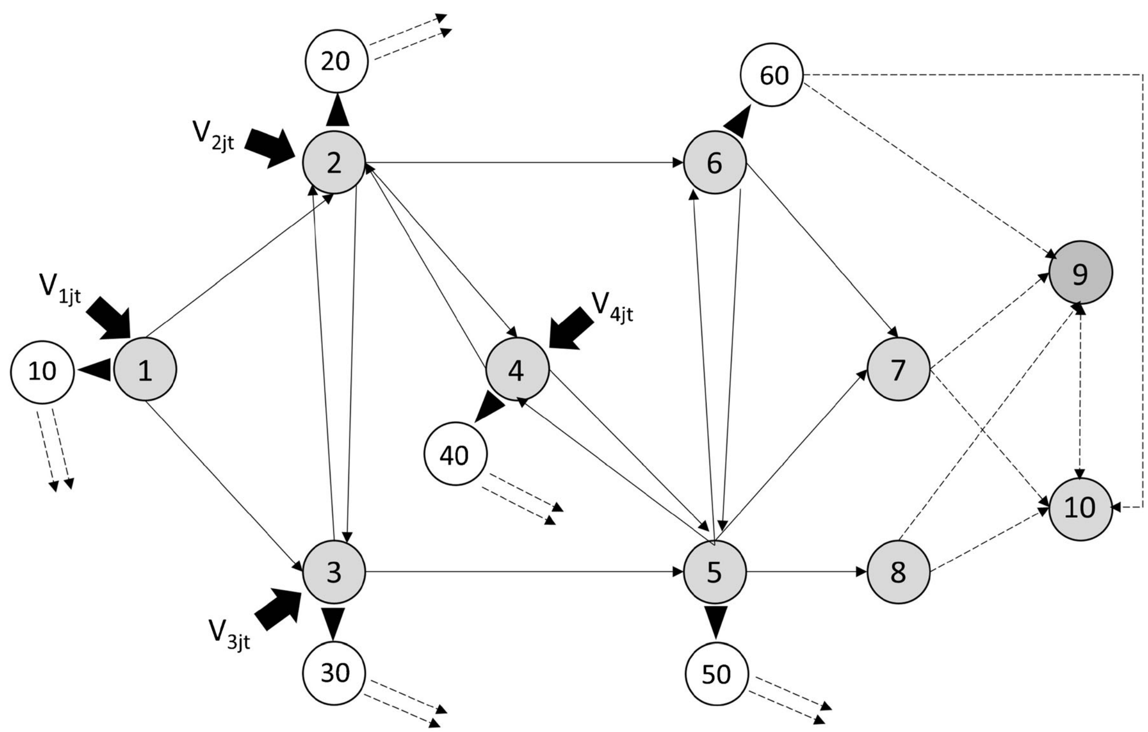


Fig. 4 Expanded network showing possible preprocessing locations using the two-phase procedure. Source: adapted from [41]. Volumes (V_{ijt}) are biomass volume entering node *i* of quality proportion *j* in period *t*, and the added dotted arcs represent the weighted value of quality proportion *j* going to its final destination upon leaving a preprocessing location at node *i* if a preprocessing center was built at node *i*. Volume over arc from node *i* to node *i*0 triggers the construction of the preprocessing center.

power plants and compared it with simulated SA and TS. Venema et al. [50] applied a GA approach to solve a p-median problem describing the bioenergy spatial design to optimize supply locations, conversion facility locations, domestic and commercial energy demands, and energy flows.

Mathematical programming problems can be deterministic or stochastic. Whereas the above deterministic optimization problems are formulated with known parameters, real-world problems almost invariably include some unknown parameters. In stochastic biomass supply chain optimization problems, uncertainties are incorporated in the decision making, which may include raw material supply uncertainties, transportation and logistics uncertainties such as arrival times of trucks, production and operation uncertainties, demand and price uncertainties, and other uncertainties (e.g., regulatory policies). Analytical methods are one of the methodologies that are used to solve problems with uncertainty; these include stochastic mixed integer linear programs (SMILP), integer stochastic programming (ISP), stochastic mixed integer non-linear programs (SMINLP), and Markov decision process (MDP), among others. Several examples that show the application of these techniques in biomass supply chain problems can be found in [51].

Regarding non-optimization methods, MADM is a multi-criteria decision making (MCDM) method that is suitable for addressing complex problems featuring high uncertainty, conflicting objectives, different forms of data and information, multi-interests and perspectives, and the accounting for complex and evolving biophysical and socio-economic systems. In MADM, a small number of alternatives are to be evaluated against a set of attributes which are often hard to quantify. Most popular MADM methods are AHP, PROMETHEE, and ELECTRE [43]. Ma et al. [52] used the AHP method to perform land suitability including economic, environmental, and social values. How and Lam [53] incorporated principal component analysis (PCA) and AHP to determine the optimal transportation design and processing hub location in an integrated biomass supply chain.

GIS is another non-optimization method used to model biomass supply chains. A GIS system can collect, store, manage, retrieve, analyze, and display spatial or geographical information. GIS applications are used to analyze spatial information, edit data in maps, and calculate the shortest distance between supply and demand points [7]. GIS systems with or without the combination of other optimization methods have been used to determine the optimal location of wood-fired power plants [14], to optimize biomass supply chain costs including harvesting residues and non-merchantable trees [54], and for the optimal use of wood biomass and the optimal selection of plant size, location, and technology [38]. GIS has been used in combination with other optimization and non-optimization methods to solve biomass supply chain problems. For example, [12] integrated an AHP and a GIS model, to identify and analyze optimal candidate locations that balanced economic, environmental, and social criteria within the biomass supply. Frombo et al. [38] designed a GIS and optimization-based environmental DSS to provide bioenergy conversion plants with woody biomass.

Simulation models are suitable for systems characterized by complex and non-complex structures, dynamic aspects, deterministic and non-deterministic events, and/or performance indicators whose computation is time-consuming (e.g., when they have no analytical formula). Most commercial simulation packages (e.g., ARENA, AnyLogic, EXTEND) include graphical components (workstations, queues, random event generators) that are used to define the model. The simulated model of the real system is run for a few minutes, and at the end of the process, statistics and other performance indicators are computed. 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 [4, 55]. Simulations are useful to model machine interactions/interference in systems that require coupling different machine such as chipper loading directly on trucks. Asikainen [56] found that using static approaches rather than a dynamic approach, such as discrete event simulation, overestimated system performance and underestimated waiting times.

Implementation of DSS for Biomass Supply Chain Optimization at the Tactical Level

A few operational DSSs based on linear programming models (e.g., BIOPLAN and MCPLAN [3, 36]) have been developed for biomass supply chain optimization at the tactical level. They are primarily used to investigate the effect of MC on storage, chipping, and transportation costs of the biomass delivered to energy plants under different MC, operational, and drying scenarios. At the tactical level, DSSs provide spatial and temporal solutions, including volumes of residues to be collected per period and supply point, drying times of residues at the roadside, and flows from supply to demand points. The final objective of these DSSs is to minimize supply chain costs or maximize supply chain revenues [16••].

These DSSs are key tools for the tactical planning of complex biomass supply chains, in particular, those comprising many supply areas, feedstocks, demand points, as well as collection, processing, and transport technology. In some cases (e.g., in plantations), the production of residues for energy might be linked to the amount of roundwood being harvested, which requires that the design and architecture of these DSSs must be flexible and adaptable enough to include and integrate multiple supply chains (e.g., roundwood and residues such as in the MCPLAN tool).

DSSs for supply chain optimization at the tactical level are quite demanding in input data, which requires that labor and computational resources are in place in the organization so that the data are collected and provided in a timely and accurate way so that the DSS can generate reliable outputs. For example, in DSSs that include spatial data, it is essential to have accurate estimates of the amount of forest biomass by regions or harvesting coupe. For this purpose, some methods have been developed to estimate biomass at the individual level, stand level, and large scale [57]. Spatial inputs are obtained and derived with GIS; these include the availability of roundwood and biomass per supply area, the geographical location of supply and demand points, and the average transportation distances from supply areas to demand points [12, 23•]. Other critical inputs include basic density, solid content factors, truck configuration (including net payload, gross and solid volume, etc.), and costs associated with the collection, storage, processing, and transport of residues [18, 22, 26••]. In addition, some DSSs assume a fixed MC or energy value in the optimization problem (e.g., [37]). In the case of MCPLAN [16•], MC curves are inputs that drive the optimization of supply chain costs. These drying models are developed from data collected in drying trials conducted during several seasons to account for the weather impact on drying rates. In [17], the energy content of the fuel chips is used to calculate the total energy produced that satisfies the demand of the energy plants.

Most of the DSSs for biomass supply chain optimization at the tactical level are implemented in GIS or using some friendly graphical user interface (GUI) connected to optimization solvers. For instance, in MCPLAN, the GUI and the optimization model are developed and implemented in Visual Basic for Applications (Excel-VBA) and using the optimization solver "What's Best" developed by LINDO Systems Inc. These models can also be implemented in a variety of other programming languages (e.g., C++, Python), programming frameworks (e.g., QT, Visual Studio), modeling platforms (e.g., AIMMS, IBM CPLEX Optimization Studio), and optimization solvers (e.g., CPLEX, Gurobi, MOSEK). The selection of these tools will depend on the experience of the modelers and potential users of the tools, as well as the license cost of the software, in particular, the modeling platform and optimization solver adopted.

Optimization-based DSSs offer the promise of a powerful technology for processing information as it arrives, but they often struggle in actual field implementation [58]. Thus, the effective implementation of DSSs as tools that facilitate a course of action require that biomass supply chain planners fully understand the capabilities and limitations of the models implemented, as well as the impact that inaccurate, incomplete, and untimely inputs have on the outputs generated by the DSS. Another issue that arises is that computer models use a completely different strategy and mode of reasoning for solving problems compared with humans. As this can impact the trust of supply chain planners on the optimal course of action prescribed by the DSS, the optimization models must be validated, and the planners should know which information needs to be verified to be sure that the decision they make is the right one. In addition, DSSs must have a user-friendly interface that provides report and presentation flexibility to suit planners needs. It is essential that they support an easy import of input data and export of output data, performance of what-if analyses, and visualization of the output results, among other features [58].

Biomass Supply Chain Management and Optimization at the Operational Level

The main source of biomass is different in various parts of the world which may influence the type of applied technologies, type of working method, and working efficiency and costs. European countries seem to be utilizing the wood from thinning operations as well as harvesting residues [59•], while in Oceania or Southern USA, the main source for bioenergy is harvesting residues although in southern parts of the USA logs and stems are also used for bioenergy purposes [60, 61]. The low price of biomass in some countries (e.g., Australia and Canada) has led to the application of integrated biomass and conventional wood recovery to reduce the cost, while in European countries, separate biomass recovery is still an economically viable option [62•].

Delivered forest harvest residue costs have been identified as the highest variable cost in the wood to energy supply chain. Operational decisions are made for short time goals, e.g., weekly, daily, or hourly. As shown in the previous section, most decision support systems (DSSs) for biomass supply chains have focused on the strategic and tactical levels, rather than on the operational level [4, 7]. However, a number of DSS techniques have been found useful for operational planning and scheduling including mathematical programming (e.g., [26••, 63••, 64, 65]), heuristics (e.g., [63••]), MCDA [66], GIS (e.g., [67]), and simulation (e.g., [68••, 69]).

The discussion of DSS at the operational level is organized with examples of residue collection in gentle terrain, residue processing and transport in steep terrain, truck-machine interactions, optimization of processing and transport, moisture and solid wood management, truck scheduling and concludes with considerations for implementing DSS in operational settings.

Decision Support for Residue Collection in Gentle Terrain

An example of decision support for residue collection in gentle terrain is described by [70••]. Residues can be in small piles following cut-to-length processing at the stump or scattered as a result of shovel logging. Residue collection on gentle terrain is often done by forwarder with standard bunks or special larger bunks, or if very close roadside (usually less than 50 m), by excavator loaders. The operational decisions for residue collection and transport typically are (1) reducing the extraction distance to accessible comminution locations, (2) maximizing biomass per trip, and (3) reducing loading and unloading times for the forwarder.

Forwarders are equipped with a self-loading grapple crane that allows the forwarder to operate independently of a dedicated loading machine. The conventional forwarder was designed for loading logs, not forest residues. Using the self-loading system for forest residues can be challenging due to the limited visibility of the operator while putting the material in the bunk and the limited reach and capacity of the loading boom. In biomass recovery operations in the Pacific Northwest, USA, forwarders are sometimes loaded using excavator-base loaders equipped with fully rotating grapples rather than using the forwarder's grapple in order to load the forwarder more quickly and with greater biomass load. Once the forwarder is fully loaded, it returns to the landing and unloads. Equipment balancing is important to keep all equipment elements producing to optimal capacity. This can be done by simulation [70••].

The farther the collection point is from the landing, the more expensive it is to collect the residue because the forwarder has to spend more time traveling, thus decreasing the forwarder productivity. The use of two forwarders per loader help to minimize the impact of the distance on forwarding productivity however traffic along the trails can cause machine interference. Other equipment such as off-highway dump trucks with skidder tires could be used to move the residues, but the use of this equipment on forest soils could cause more soil compaction compared with the multi-axle forwarders using wheel tracks. Thus, at least five systems can be used alone or in combination:

System 1—Excavator-base loader, working alone
System 2—Forwarder self-loading
System 3—Forwarder loaded by the excavator-base loader
System 4—Two forwarders loaded by one excavator-base loader
System 5—As above, but the loader is manned by the forwarder operators, in turn

An example from [70••] illustrates the zones for the least cost system (Fig. 5).

Using these costs, the optimal forwarder trails are identified beginning with a digital elevation model (DEM) to derive a slope raster image. The slope raster image permits the identification of potential areas that will be difficult for the forwarder to travel on such as steeper slopes or stream. A weighted pixel cost that combines the cost information plus a topographic impedance cost is used to develop a cost distance raster image to estimate the cost of each pixel to each of the potential landings. Then, the least cost path from each harvest residue location to the most cost-effective landing is determined. Once the least cost paths are created, they can be converted into a vector polyline to create the optimal forwarder paths.

In some cases, the forest biomass can be skidded whole tree by grapple skidders prior to comminution at the landing (e.g., [71]). Skidding trails can be located using the GIS procedures previously described. Multi-criteria decision analysis has been applied to minimize operational costs while minimizing different environmental footprints (e.g., [72]).

Decision Support for Residue Processing and Transport in Steep Terrain

Processing and transport operations can be either tightly or loosely coupled. Tightly coupled operations may require elements of equipment scheduling to account for equipment interactions. Among all the feasible options, the supply chain manager has to decide which system is the most cost-effective given road and landing access, material physical properties, pile location, available truck turnaround locations, machine availability, machine performance, and product deliverables.

Comminution options include stationary horizontal grinders (electric or diesel), tub grinders, and forwarder-mounted mobile chippers. The use of bundling and bailing technology, due to relatively high cost, has been quite limited in their application. They tend to be favored in Scandinavia and Northern Spain where there is a need for a longer storage period for moisture management, and as such, their transport tends to be carried out by log transportation technology [73–75]. In the case where excess capacity in the log haul fleet exists, it can be deployed for the biomass bundle transport. Outside of northern Europe, the use of bundlers or bailers have been quite limited and only used in niche applications.

Short distance in-forest transportation options for unprocessed residues comprise small trucks such as hook-lift trucks, bin trucks, and end-dump trucks. Because biomass resources tend to be dispersed across the forest operations, long distance truck transport is favored for its flexibility to easily get to where the material is chipped or ground [66]. Across the southern hemisphere, much of the plantation industry producing pulp fiber has a history of transporting woodchips which is supply chain and transportation knowledge that has directly transferred to biomass transportation. Depending on the road and site access conditions, this transportation is carried out by semi-trailer configurations with a payload usually in the range of 25 to 35 t, on harder to access sites with a shorter transport distance. B-train configurations tend to be favored on longer haul distances with higher payloads of 35 to 45 t. Across

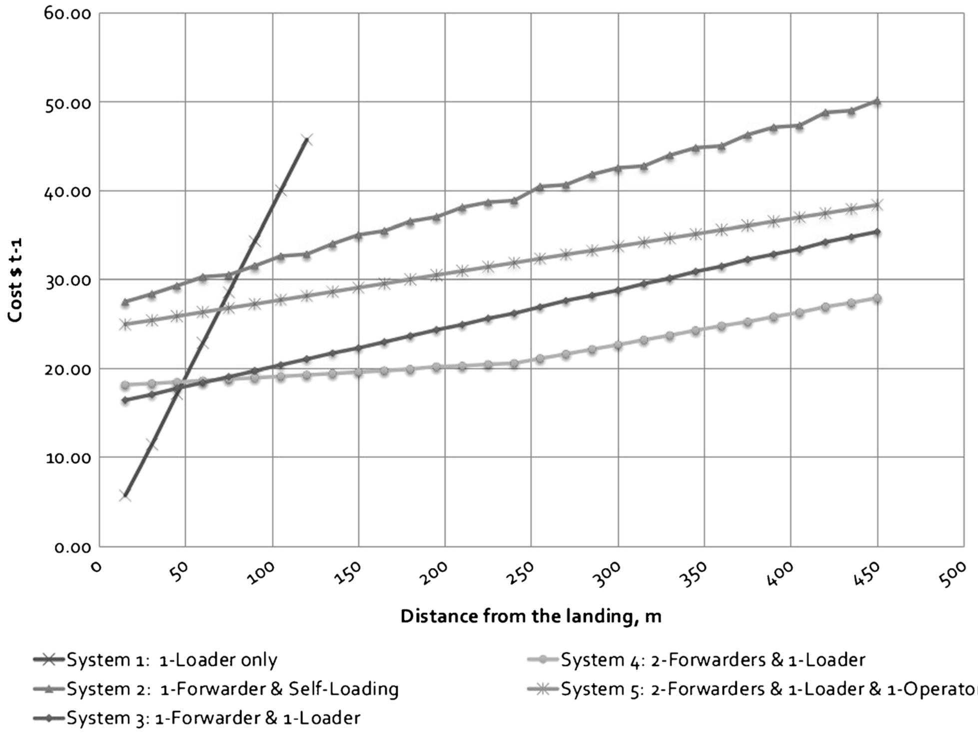


Fig. 5 Collection cost in USD per oven dry ton as a function of the distance from the roadside landing (mobilization costs are not considered). Source: [70••]

Europe, the regional nature of many of the bioenergy facilities is based on local supply. They tend to rely on local supply chain technology and will use smaller trucks common in agriculture businesses with smaller payloads in the 10 to 15 t range. In addition, the larger trucks are used in larger commercial supply chain operations.

In the USA, long distance transportation options include chip vans with different types of tractor-trailer configurations (conventional fifth wheel, sliding axle trailers, self-steering trailers, stinger-steered trailers, and double trailers). Often, trailers vary in length from 9.75 to 16.15 m. They may contain an extension in the bottom center of the trailer (drop center) to increase the trailer capacity. Different processing and transportation systems include (1) stationary grinder at centralized landing with bin, dump, or hook-lift trucks; (2) stationary grinder processing at each pile location; (3) mobile chipper processing at each pile and loading set-out trailers; (4) stationary grinder at centralized processing yard with direct discharge into piles; and (5) bundling in forest and grinding or chipping at the bioenergy plant. Each of the systems has advantages and disadvantages and may be the most cost-effective choice under specific field conditions.

Truck-Machine Interactions

Truck-machine interactions occur when operational circumstances and/or road access limit productivity. Simulation is useful to evaluate the system performance. For example, [68••] identified two general cases of truck-machine interactions that primarily affect forest harvest residue recovery operations in steep terrain. These interactions mainly occur with stationary equipment. With mobile equipment, these interactions are minimized with the use of setout trailers that partially decouple the chipping from the transport. Case 1 occurs when access to the pile is restricted to single lane roads, and the comminution site is limited in space allowing only in-road loading and the turnaround is located farther from the processing location. If an incoming truck needs to reach the comminution site, but another truck is being loaded, the in-coming truck must wait at a turnout (e.g., wide spot in the road, an intersection or a turnaround) until the loaded truck passes the point where the in-coming truck is waiting. In case 2, the turnaround for the comminution site is located before the processing location and the in-coming truck can reach the turnaround and wait for the other truck to be loaded. After the loading process is finished, the incoming truck has to wait for the loaded truck to pass the turnaround and then the waiting truck can back up to the grinding site. This causes an obstruction depending on the back-up distance, but its impact in grinder productivity is not as high as in case 1. Results from the simulation can be combined with optimization models. Kogler et al. [27] identify [59•] as the only paper out of more than 80 papers on multimodal and unimodal wood transport that combines optimization, discrete event simulation, and GIS methods at the operational level.

Optimizing Processing and Transport

The optimization of processing and transport can be viewed in a network framework and classified as a special case of the multi-commodity, multiple-facility problem and solved using mixed integer programming and heuristics. Zamora-Cristales et al. [63••] provide an example where forest residues exist at some predefined locations (nodes). At each predefined location, a defined quantity of forest residues could be transformed into chippable or non-chippable (grindable) material, and either processed at the roadside, bundled, or carried to some predefined transshipment points (either a centralized landing or centralized yard). At a transshipment point, residues can be upgraded (comminuted) and loaded for longer distance transport to plant facilities. Transshipment points can usually be accessed by larger capacity highway trucks. Residues are assumed to be located at the roadside, as is typical of most operations in steep terrain.

To optimize processing and transport, the decisions are what volume of residue at each forest location, *z*, will be processed in location, *w*, into product type, *p*, by equipment type, *m*, and transported by truck type, *t*, with destination to a plant, *k*, to minimize total cost subject to road accessibility, centralized yard availability, and truck turnaround and turnout availability and location. The optimization model can be considered as a capacitated network problem $B = (V,L)$, where V are the nodes (piles, processing locations, turnarounds, centralized landings, centralized yards, bioenergy plants) and L represents the directed links. A mathematical formulation of the optimization problem can be found in [63••]. MIP solution time can be reduced by bounding the solution with a heuristic. An example of a road network and comminution options is shown in Fig. 6.

Comparisons of optimized selection of processing and transport options to ongoing field operations indicate that an average saving of 10% or more is possible [68••]. Han et al. [64] solve a similar problem using MIP and found similar savings were possible. Montgomery et al. [67] used a set of heuristic rules based on breakeven analysis and implemented using GIS to determine the optimal set of centralized landing locations. To introduce social, ecological, and social impacts into the supply chain choice at the individual stand level, [66] propose a multi-criteria decision tool that considers costs, energy efficiency, nutrient balance, resilience of the remaining stand, employment, working safety, transportation distance, and MC. The overall utility of various treatment alternatives is calculated with an additive utility model.

Moisture Management

Truck transportation can make up 50% of the processing and transport costs, and moisture can account for 50% or more of the net truckload. The single most important quality attribute is the MC of chips or raw material delivered to energy plants [26••]. When a cogeneration plant pays for delivered biomass depending on its MC, potential price premiums can be as high as 14% per dry ton for MC reduction from 50 to 30% wet basis [76•]. Recently cut forest residues during the spring can have MCs above 60% (wet basis), while the MC of field-dried forest residues can be less than 30%. The MC of fresh needles, branches, and tops is higher than wood from the tree bole, but these smaller materials dry more rapidly.

Increasing the dry fraction is done by letting biomass dry in the field, on the landing, or in a satellite yard before delivery to the plant. The MC of forest residues depends upon a number of factors including species, diameter, season of year harvested, length of time the material has been on the ground or in piles, pile construction [77], and level of residue protection before comminution such as covering of residues to prevent rewetting during periods of precipitation [78]. Unpiled forest residues dry more rapidly than piled forest residues [79]. A reduction in MC over ranges where the truck is weight limited can reduce transport costs in proportion to the water weight reduction.

Two decision support approaches have been used for modeling natural moisture loss in the field, heuristic models (e.g., [80–82]), and finite element modeling (e.g., [83]). Biomass moisture prediction can then be used in developing biomass collection and truck delivery schedules to optimize biomass value (e.g., [22, 26••, 65]).

Managing Solid Wood Content

The ratio of solid wood content to occupied trailer volume is about 0.20 to 0.25 for tops and branches without comminution to 0.30 to 0.45 after comminution. Although there are significant comminution cost savings for processing residues at the plant (e.g., higher grinder/chipper utilization, availability of electricity, and lower machine maintenance), transportation of loose residues is usually restricted to shorter distances. Ranta and Rinne [84] reported that for biomass of approximately the same MC (46–47%), the average truck in Finland carried about 1.63 times as much equivalent energy per load of forest chips as compared with loose residues.

Even after comminution, depending upon trailer characteristics, material-specific gravity, and particle size, trailers are volume-limited when the MC is below 35–40% MC (wet basis). Increasing the solid wood content per truckload is important to reduce transportation costs. Vibration is one option. Load consolidation during transport over forest roads has been measured at 6–7% reduction in load volume [85]. Vibration of rail cars has been shown to increase solid content by 20–25% [85]. Zamora-Cristales et al. [86] increased load density over 25% by blowing comminuted residues vertically into a trailer. The advantage of barge over truck in Finland at

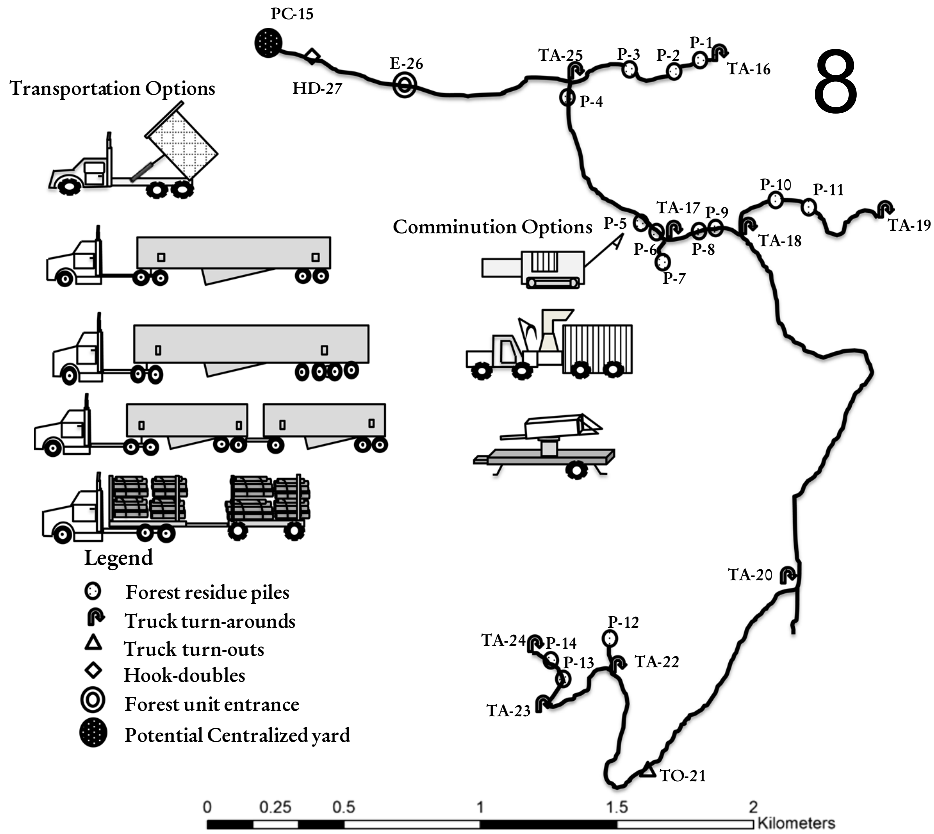


Fig. 6 Available processing and transportation options and spatial locations of forest residue piles and potential centralized landings (P), truck turnarounds (TA), truck turnouts (TO), potential centralized yards (PC), harvest unit entrance (E), and double trailers setup location (HD). Source: [63••]

greater than 100 km was due significantly to the ability to compact the chips on barge using a tracked machine [33].

Solid wood content can be increased by reducing particle size, although comminution energy increases. DSSs to assist in evaluating economic tradeoffs for increasing solid wood content would be valuable.

Truck Scheduling

Depending upon transport time, almost one half of the forest biomass, collection, comminution, and transport cost is road transport. Truck scheduling is an important consideration in system balancing for coupled operations and for efficient truck utilization in both coupled and uncoupled operations. For several decades, DSSs for truck scheduling and dispatch strategies have been used for log transport to reduce waiting times at the landing and plant and to reduce backhaul (e.g., [87–90, 91•]). Similarly, these DSSs would be useful for the transport of forest residues (e.g., [92]), but are in more limited use. Solution methods often employ heuristics for larger problems.

With GPS, cell phones, on-vehicle computers, and increasing contact with their home base, trucks are more flexible and are not so tied to their home areas. The driver can quickly and easily find the way between the landing and the facilities, especially if they are in an unknown area. Transport capacity can, therefore, be switched between different areas and deployed where there is a most need for capacity [93]. Truck scheduling of chip vans is potentially even more flexible than log haul, as chip vans move mill residues between sawmills and manufacturing plants and power generation facilities using many of the same trailers as used for woods residues transport. Collaboration, in various forms, including trading of logs to shorten transport distances has been identified by several authors as important to reduce transport costs (e.g., [94, 95]). Forest residues may be even more "tradeable" than logs due to fewer differences in quality.

A partial list of DSSs in current or recent use in log transportation include Trimble Forest Logistics and Optimization (FLO) System (USA), Asset Forestry WSX Logistics (New Zealand acquired by Trimble Sept 2013), ASICAM/ForesTruck (Chile), FastTRUCK (Australia), DESCARTES Route Planner (Canada), SEON Compass Logistics (formerly ESRI ArcLogistics), ArcGIS Network Analyst (USA), TRUCK SCHEDULER (Canada), and RuttOpt (Sweden).

The worldwide surge in interest in electric vehicles to mitigate climate change may call for development of new DSSs for forest transportation that could consider strategies for optimal location of recharge or battery exchange stations and harvesting elevation potential from mountain forests [96].

Implementation of DDS at the Operational Level

Cost-effective logistics requires careful planning of logistic operations to match the field conditions to the processing and transport equipment. A comparison of improved planning of processing and transport in case studies indicated that cost reductions of 10–20% were possible. Moisture management coupled with increasing load density suggests that transportation costs can be reduced significantly through operational planning. A combination of moisture management and bulk density management show potential for reducing transportation costs by one third. Implementation requires knowledge of machine costs, machine productivity, and terrain. In both gentle and steep terrain, large truck access, equipment balancing, and moisture management are the most important variables. Often, the greatest challenge to implementing a DSS is people. Change can be frustrating, and inertia has a powerful effect. Everyone must be committed. Windisch et al. [97] investigated the introduction of supply chain management applications for forest fuel procurement. In their analyses, they assumed a learning curve of 3 years for personnel to become familiar with the system.

Elements to consider for the successful adoption and implementation of DDS at the operational level are

The need for DSS to improve operations

As we discussed, DSS can help reduce cost by maximizing resources available and assigning the best combination of methods for collecting, processing, and transporting biomass. The need of a DSS will depend on the complexity of the operation and the options available. In places where few transportation and comminution options are available, the potential use of DSS at the operational level can be limited. Fewer options lead to less complexity. Given that forest biomass has lower value compared with other products along the supply chain, DSS can provide invaluable information to reduce costs and increase productivity when used at the operational level. The quality of the inputs is also a key factor when planning to use a DSS. New technologies to monitor machine and trucks can be used to track and identify partners in operations. GPS technology linked with GIS systems can provide invaluable information to improve the accuracy of inputs.

Main inputs and outputs of the model

It is important to understand the critical inputs and outputs of the model and if the current operation can provide them. Important inputs in forest biomass operations are the amount of forest biomass available, but given their heterogeneous nature can be difficult to estimate although some methods are available [98, 99••]. Information on cost and productivity for processing and transportation are important given that the final objective of many DSSs is to maximize revenues.

Validation of the DSS

Decision support systems are an abstraction of the reality. It is important to assess if the conditions under which these models were validated apply to your current situation. A model focused on flat terrain conditions will not be effective to support steep terrain biomass operations. Similarly, the number of technologies available for processing and transportation can be a significant limiting factor for adoption and use of DSS to local conditions. One important factor to consider is the experience of operator and drivers. It is important to understand the degree of experience of the operators at the time of the model validation.

The main user of the information

When using DSS for operations, it is important to design a system that allows efficient use of the model outputs to take an adequate course of action. The DSS is a tool that can facilitate adaptive management, so the user can take important decisions timely to maximize the benefits of the biomass operation. Many models could have a robust optimization mechanism, but how the model reports the information is also important. Friendly user interfaces can offer the user easy access to the report, so it can be included to support management decisions.

Conclusions

Biomass supply chains for forest biomass share similarities to other biomass supply chains, particularly, that they are less valuable than the primary product. But the field conditions are often more challenging and variable, road conditions more limiting, the forest areas are large, and the transportation distances to processing centers are often longer. These considerations increase the need for decision support systems to make transport efficient for these businesses to remain profitable. Most decision support systems for biomass supply chains have focused on the strategic and tactical levels, rather than on the operational level. Many of these decision support systems have been modifications of decision support systems that have been shown to be useful for transport of logs and mill residues.

The value of a decision support system will be often determined by the cost and ease of data inputs, the understandability of model output, the level of model abstraction from reality, and the ability to update the model. Due to changing conditions, the ability to update the decision support model becomes more important as the planning horizon shortens. Future work in the use of modern information systems that show the location of the supply, grinders, and trucks for operational management can be developed to improve the efficiency of operations.

Mathematical programming has been shown to be most useful for strategic and tactical planning, where simulation, sometimes combined with optimization techniques has been useful for operational planning. This is due to its ability to incorporate the uncertainty in the supply and production data. For large problem instances, in tactical and operational planning, decision support systems often use heuristics to solve the underlying mathematical formulation. A combination of simulation, LP/MIP, and heuristics could provide useful decision support for forest manager and landowners interested in optimizing their operations.

At the operational level, new technologies such as the use of aerial unmanned vehicles, LIDAR, and improved geospatial tracking can help to improve the data used in the optimization models developed. The increased use of LIDAR in forest inventories can provide an accurate estimation of biomass volume, a key input to accurately estimate cost effective ways to process and transport biomass. Many major forest harvesting manufacturers provide telematic packages that could provide data inputs for biomass collection systems.

Future research on optimized biomass supply chain is needed. Increasing environmental concerns have the potential to increase operational limitations for harvesting biomass. For planning purposes, increasing constraints will require more robust models to account for the amount of data available in the inputs. Currently, most decision support systems are single objective, accompanied by constraints. Multi-objective decision support systems, similar to those used in industrial settings, may be useful in helping decision makers evaluate courses of action. New decision support systems may follow technological change. The emergence of the electric vehicle for freight transport may spur the need for new tactical and operational planning decision support systems to include strategies for energy management, fleet management, and transshipment points.

Compliance with Ethical Standards

Conflict of Interest The authors declare they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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