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REVIEW ARTICLE

A Review on Optimization Methods for Biomass Supply Chain: Models and Algorithms, Sustainable Issues, and Challenges and Opportunities

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Abstract

The urgent desire to relieve the pressure of dependence on petroleum in energy industry and the growing demand for protection of our environment stimulate the researches and practices in biomass supply chain management. Due to special characteristics of biomass, this particular kind of supply chain is different from the classic supply chains in different ways. The optimization methods, including mathematical programming and heuristic algorithms are widely used in the domain of biomass supply chain management in both tactical and practical manners. In this review, literatures are classified by different components throughout the entire supply chain: harvesting and collection, storage, transportation, pretreatment, and conversion. In order to achieve a robust biomass supply chain and also to enable wide applications of classic and well-studied optimization models, the connections between them are analyzed and reviewed. The classic optimization models include network design problem, scheduling problem, facility location problem, vehicle routing problem, and technology selection problem. Additionally, environmental and sustainable issues, uncertainties, and challenges and opportunities in biomass supply chain are discussed. A bibliometric analysis is also performed in this review to obtain comprehensive understanding of this area.

Keywords Biomass supply chain · Optimization models and algorithms · Sustainability · Uncertainty

Introduction

Biomass Supply Chain

As a good replacement of fossil fuels, biofuels have been attracting people's interest recently in order to reduce greenhouse gas emissions and mitigate the climate change problem. Biofuels are produced through a lot of conversion technologies, such as biochemical and thermochemical conversion processes. They are playing an important role in the energy consumption market, together with fossil fuels, nuclear energy, and other renewable energy. The USA is the largest producer of biofuels, followed by Brazil and China. World biofuels production has increased by 3.5% in 2017, where the USA provided the largest increment (Biofuel Production 2018). Biomass, resource for biofuels, encompasses plant and animal materials such as wood from forests; crops; seaweed; materials left over from agricultural and forestry processes; and organic industrial, human, and animal wastes (Saidur et al. 2011). Biomass is a competitive source of energy as a result of its abundant and flexible storage and supply, worldwide availability, and conversion efficiency (De Meyer et al. 2015; Iakovou et al. 2010).

Biomass has some typical characteristics, such as spacial fragmentation, high moisture content, low bulk density, and seasonal availability. There are also uncertain issues related to weather variability, policy, and market (De Meyer et al. 2015; Iakovou et al. 2010; Shabani et al. 2013; Shabani and Sowlati 2016). These factors together make biomass supply chain highly cost and complicatedly handled, which is different from traditional supply chains. A biomass supply chain usually consists of the following operational components (see Fig. 1): biomass harvesting and collection, pretreatment, transportation, storage and conversion, and end uses (De Meyer et al. 2013; Mafakheri and Nasiri 2014; Iakovou et al. 2010). Some works focus on the generic biomass supply chain configuration (Yu et al. 2014; De Meyer et al. 2015; Huang et al. 2010; Zhang et al. 2013;

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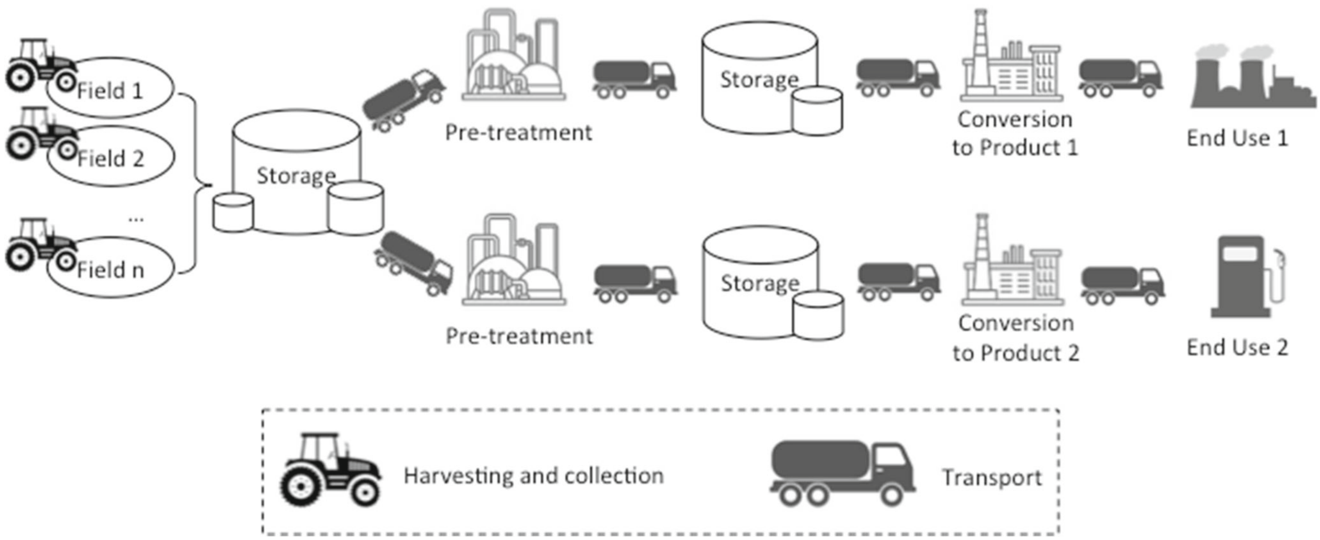

Fig. 1 A biomass supply chain

Kim et al. 2011b; An et al. 2011) in order to achieve the minimum cost of the entire supply chain, while more works concentrate on only one operational component of the supply chain. The supply chain is an inseparable whole, and one component of it may have some overlaps with another. Some studies may emphasize on one component or a part of the supply chain, which will be reviewed in details in the rest of this paper.

Motivation and Contributions

The overall objective of the supply chain management is to develop cost-efficient and sustainable ways to help the materials flow smoothly and efficiently in the network. In order to reach the goal, models and approaches studied in optimization community can be linked and applied to different design or operational components of biomass supply chain. These classic and well-studied optimization problems, including network design problem (embedded in transportation and conversion), scheduling problem (embedded in harvesting and collection, storage, and transportation), facility location problem (embedded in pretreatment, storage, and conversion), vehicle routing problem (embedded in harvesting and collection, and transportation), and technology selection problem (embedded in pretreatment and conversion), are highly related to biomass supply chain management. Figure 2 shows more details on their connections. In this paper, different optimization methods including mathematical modeling and approximate approaches are reviewed and presented, in the order of each operational component (harvesting and collection, storage, transportation, pretreatment, and conversion).

In the literature, some comprehensive reviews on optimization methods and biomass supply chain have been studied in the past decade (Shabani et al. 2013; Mafakheri and Nasiri 2014; Sharma et al. 2013; Castillo-Villar 2014; Ba et al. 2016; Melis et al. 2018; Atashbar et al. 2016; Zandi Atashbar et al. 2018). In Shabani et al. (2013), the authors classify the optimization models in two categories: deterministic optimization models and stochastic models. They review some common problems studied in a biomass supply chain without detailed discussion about the relationships between these problems and different supply chain operations. In Mafakheri and Nasiri (2014), mathematical optimization models are reviewed along the biomass supply chain, in order of operational components. In Sharma et al. (2013), the authors classify the reviewed papers on the following aspects: decision level, supply chain structure, modeling approaches, quantitative performance measure, shared information, novelty and practical application, assumptions, restrictions, and future work. However, both Mafakheri and Nasiri (2014) and Sharma et al. (2013) focus on the mathematical modeling side and ignore the heuristic algorithms, which are an important component of optimization methods. In Castillo-Villar (2014), the classification of the problems in a bioenergy supply chain and the corresponding metaheuristic solution approaches are presented. The classified problems include integrated supply chain planning, production process optimization, network design problem, scheduling problem, and facility location problem. In Ba et al. (2016), the authors present the structures and activities of a biomass supply chain. The models are classified into two categories: the first is the performance evaluation models and the second is the optimization models. The optimization models are further classified into deterministic optimization, stochastic optimization, and multi-objective optimization models. In Melis et al. (2018), the authors

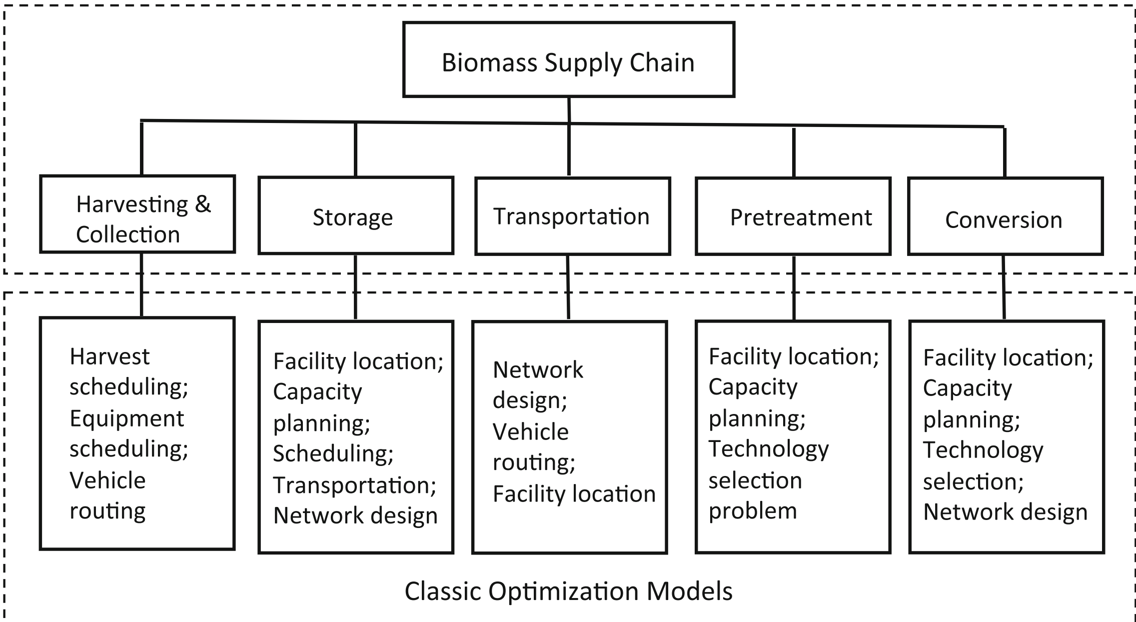

Fig. 2 Classic optimization problems in a biomass supply chain

review the most recent works of models and approaches in a biomass supply chain design and management. They also compare the recent works with previous literatures in three dimensions: decision level, mathematical methodology, and objective types. In Atashbar et al. (2016) and Zandi Atashbar et al. (2018), the authors introduce both the mathematical programming models and heuristic algorithms. But more attentions are paid to comparison between industrial supply chain and biomass supply chain instead of detailed optimization methods.

Our contributions of this optimization-oriented review are stated as follows: (1) We conduct a bibliometric analysis to learn the development of this area; (2) we present a comprehensive review on both mathematical modeling and heuristic algorithms utilized in the biomass supply chain design and management in line with each operational component; (3) we discuss the relationships between problems embedded in a biomass supply chain and some classic and well-studied optimization models; (4) we review the uncertainties and challenges in a biomass supply chain and optimization methods corresponding to different characteristics of uncertain problem parameters; and (5) we consider the environmental and social issues in a sustainable biomass supply chain and review the life cycle assessment (LCA) usage integrated with optimization methods.

With this review, the reader in the domain of biomass can apply the most advanced model and techniques to solve problems in biomass supply chain. In the meanwhile, besides enabling wide applications of classic and well-studied optimization models and algorithms, the optimization research community has the opportunities to understand new requirements and needs from practical areas.

The remainder of this paper is organized as follows. Section "Bibliometric Analysis" presents a bibliometric analysis on optimization methods used in biomass supply chain. In Section "Models and Algorithms Development for Biomass Supply Chain," we carefully review the existing optimization methods, include mathematical programming models and heuristic approximate algorithms. We review the works along the operational components in a biomass supply chain, in the order as harvesting and collection, storage, transportation, pretreatment, and conversion. In each component, we discuss common and widely researched problems and models. Additionally, we discuss the relationships between these models and some classic optimization models. In Section "Sustainable Biomass Supply Chain," we first give a brief introduction of the classic four-phase LCA, followed by the usage of multi-objective optimization methods by integration of optimization tools with LCA processes. Some uncertainty sources and types and their corresponding optimization solution approaches are presented in Section "Challenges and Opportunities." Some challenges and potential future directions are also presented in Section "Challenges and Opportunities." Section "Conclusions" concludes the paper.

Bibliometric Analysis

A bibliometric analysis is conducted to reveal the trends in optimization and biomass supply chain domain. In the analysis, the leading journals, scholars, and organizations are identified, and the highly cited articles and keywords distribution are revealed. Web of Science (Web of Science n.d.) Core Collection database is used in this study. The records are generated by using the following keywords: "(biomass OR bioenergy OR biofuel) AND (supply chain) AND (mathematical programming OR MIP OR MILP OR heuristics)." Here MIP refers to Mixed Integer Programming, and MILP refers to Mixed Integer Linear Programming. A time span of 2009–2019 is chosen because there are only 2 related articles before 2009.

The Annual Publication Trends

There are total 258 results found by using the searching keywords. The number of publications in each year and the trend can be found in Fig. 3. The general trend of related research is upward in the past decade with a peak in year 2014. More and more attentions are paid to relieve global warming is one possible reason. The acceleration around 2013 may due to strong federal support for biofuel production in that time period (Schnepf 2010).

Publication Distributions

Each column in Table 1 reports top 10 journals, countries/regions, institutions, and scholars respectively. The number in the parenthesis is the number of articles found in the results. From the table, we can observe that most of the works are published in chemical engineering and energy fields. Optimization methods are used as a tool to deal with an engineering problem. As a leading country in renewable energy as well as a big consumer, the USA contributes most works in the area.

Keywords density analysis is generated by VOSviewer software (Van Eck and Waltman 2010) and shown in Fig. 4. In the figure, more frequent keywords are represented by warmer colors. From the software, we can also know the occurrences of each keyword. The most frequently used keywords are biomass, design, and supply chain with 99 occurrences, 72 occurrences, and 63 occurrences respectively.

Within all of the 258 results, 238 are using mathematical programming optimization methods, and only 26 of them are using heuristics. This may due to relatively small size of the biomass supply chains. Most of biomass supply chains are local or regional. Thus, the problems need less computational resource and could easily obtain global optimization results.

Models and Algorithms Development for Biomass Supply Chain

A typical biomass supply chain contains the following components, harvesting and collection, storage, transportation, pretreatment, and conversion. In this section, we are going to present optimization methods applied in each component accordingly.

Harvesting and Collection

Harvesting and collection consist of scheduling, cutting, routing, and resource allocation (machines, labors) problems. Sometimes, harvesting and collection is considered as part of integration of preprocessing or inventory control problem (Grisso et al. 2013).

In this section, we introduce three classes of problems related to the process of harvesting and collection in

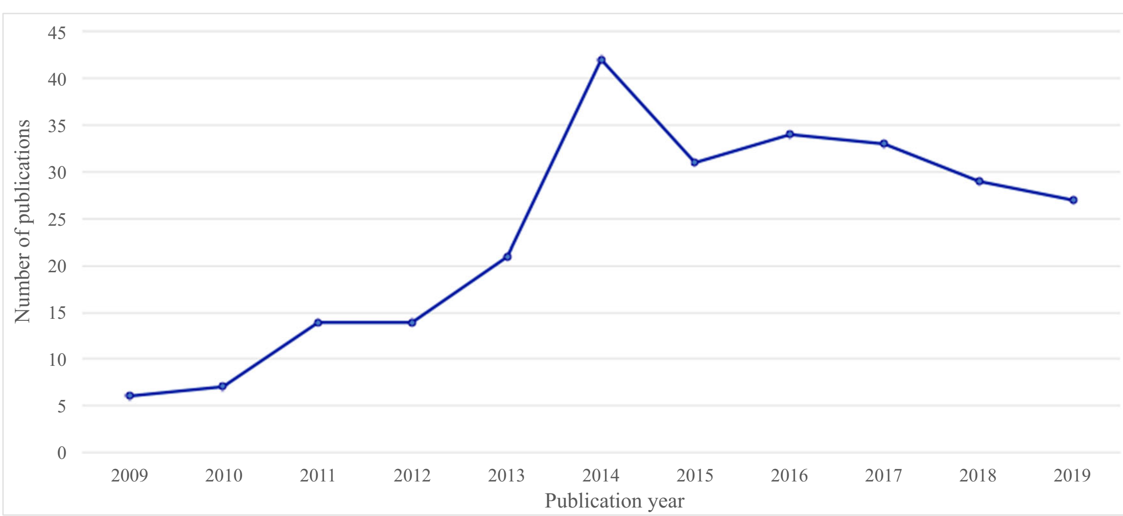

Fig. 3 The annual publication trend (Web of Science n.d.)

Table 1 Top 10 journals, countries/regions, institutions, and scholars (Web of Science n.d.)

No.	Journals	Countries/regions	Institutions	Scholars
1	Computer Aided Chemical Engineering (31)	USA (101)	Imperial College London (22)	Shah N (19)
2	Applied Energy (16)	England (31)	Northwestern University (16)	You F(17)
3	Computers Chemical Engineering (16)	Italy (24)	University Of Padua (16)	Bezzo F (15)
4	Biomass Bioenergy (15)	Spain (17)	Texas A M University College Station (11)	Giarola S (15)
5	Energy (13)	Mexico (14)	Texas A M University System (11)	Santibanez-Aguilar Je (11)
6	Journal Of Cleaner Production (12)	Canada (12)	Universidad Michoacana De San Nicolas De Hidalgo (10)	Ponce-Ortega Jm (10)
7	Renewable Energy (10)	South Korea (11)	Mississippi State University (9)	Kravanja Z (9)
8	Industrial Engineering Chemistry Research (9)	Iran (10)	University Of Maribor (9)	Marufuzzaman M (8)
9	Chemical Engineering Transactions (6)	Peoples R China (10)	Polytechnic University Of Catalonia (7)	Yue D (8)
10	European Journal Of Operational Research (6)	Malaysia (9)	University Of British Columbia (7)	El-Halwagi Mm (7)

a biomass supply chain. The first one is forest harvest scheduling problem, which aims to achieve the sustainable planning of a forest by decisions made on which area to harvest each time. The second problem is the crop harvesting problem, which is a complex system, considering the limited time window and resource constraints, such as equipment and labor. It is also uncertain in terms of quantity and timing due to weather condition and unpredictable issues. The third scheduling problem is to schedule the equipments (e.g., balers) for harvesting to minimize the total operational costs during the process. Some mathematical formulations and heuristic algorithms are developed to solve these harvest-related problems.

Forest harvest scheduling problem is an essential ingredient in harvest scheduling problem. The main idea of this problem is to maximize the profit from harvesting while prohibiting the harvesting of contiguous areas larger than a specified value (varies in different regions: e.g., 20 hectares in Sweden and 48 ha in Oregon in the USA, Carvajal et al. 2013) for the sake of sustainability of the silviculture and environment. There are two classic integer programming (IP) or MIP models for forest harvest scheduling problem: one is called unit restriction model (URM) (O'hara et al. 1989; Murray and Church 1995) and the other is area restriction model (ARM) (McDill et al. 2002; Gunn and Richards 2005; Martins et al. 2005; Constantino et al. 2008; Carvajal et al. 2013). They are distinguished by the spatial scale of one unit. In URM, each spacial unit is less than the area restriction, such that harvesting any two adjacent units would violate the spatial restriction. However, in ARM, each unit is significantly less than the area restriction so that the selection of adjacent units is feasible (Murray 1999). Some metaheuristic approaches have also been developed to solve this problem, such as simulated annealing (SA) (Murray and Church 1995; Lockwood and Moore 1993), Tabu search (TS) (Murray and Church 1995, 1996; Caro et al. 2003) and evolutionary algorithm (EA) (Liu et al. 2006; Liu and Lin 2015). Some other considerations are also included in this problem to manage the forest harvesting in a sustainable manner, such as the conservation of old-growth forests and natural reserve site protection (Carvajal et al. 2013; Caro et al. 2003; Rebain and McDill 2003).

Crop harvesting is a complex activity constrained by the maturity period of crop, weather conditions, yield perishability, quality loss, and resource availability (Kusumastuti et al. 2016). The main purpose of crop harvest scheduling is to achieve the maximum revenue or profit by deciding on the harvest period, detailed harvest plan, and resource allocation. Due to different characteristics of different crops, the main focus for each crop may be different. The key issue in harvesting sugarcane is how to cut it at the peak of its sugar content. Jena and Poggi

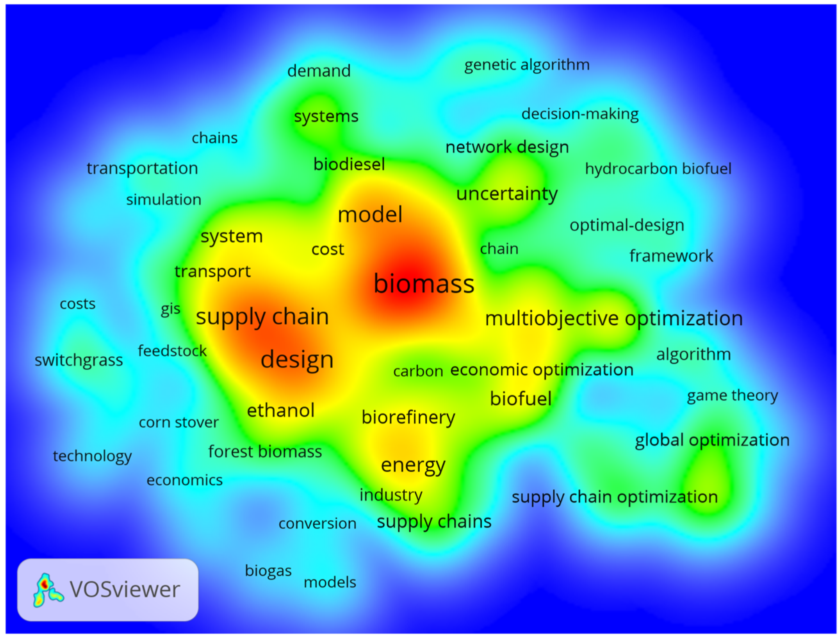

Fig. 4 Keywords density (Van Eck and Waltman 2010)

(2013) study the harvest planning for sugarcanes in Brazil in both long-term and short-term horizon. On one side, they make tactical plans for the entire harvest season of about 7 months; on the other side, the authors propose detailed plans for several days within a planning horizon. They focus on finding the best time at which the sugarcrane has most sugar content to do the harvesting in order to maximize the overall profit. Two MIP models are proposed to do the allocation of harvesting and transportation of crews to fields. Same as sugarcane, wine grapes need to be harvested inside the optimal harvesting period in order to avoid quality and revenue loss. In Bohle et al. (2010), a robust optimization model is formulated under uncertainties including productivity uncertainty and available grape volume. A MILP model with an objective to maximize the profit is used to determine the number of workers needed, allocate workers, and generate harvesting schedules in vineyards. In Ahumada and Villalobos (2011), a MILP is proposed to maximize the total revenue of growers of perishable agricultural products by making harvesting, packing, and distribution decisions during harvest season. A trade-off between time/quality of products and cost is provided by the approach. For crop-related harvest scheduling problem, we refer to a sophisticated review paper (Kusumastuti et al. 2016). The common restrictions the researchers have are the time window constraint due to the perishability or quality loss issues, resource limitations such as land capacity/productivity and available machines or labors, and uncertainty from unpredictability of weather.

A lot of harvest scheduling problems are formulated to fall into the class of vehicle routing problem (Laporte 1992; Ghiani et al. 2003). A routing plan for the machinery (harvesters or balers) is designed for such problem (Blanco et al. 2010; Orfanou et al. 2013; Carpente et al. 2010; Cerdeira-Pena et al. 2017; Aguayo et al. 2017). In Carpente et al. (2010), a binary linear programming model is formulated to design an efficient routing plan in order to minimize the working time of the forage harvesters, which implies the minimal cost. The formulation is a special case of the traveling salesman problem (TSP) considering clusters, time windows (the tolerance level of harvesting dates for each field), and processing time. Furthermore, two heuristic algorithms, including a local search and Tabu Search, are designed and applied to a real problem in northern Spain to enhance the computational performance. The heuristic algorithms are modified by an improved TS algorithm and a SA algorithm in Cerdeira-Pena et al. (2017) applied for complex instances. In Aguayo et al. (2017), the authors address the corn stover harvesting scheduling problem. After the corn grain is harvested, the corn stover will start to be harvested and moved to a plant for further cellulosic ethanol production. In this problem, the authors intend to find the best routing for the balers in order to minimize the total cost, including the routing cost of the balers and the late penalties for not harvesting in time. The ready time for each field to be harvested may or may not be known before the harvesting actions are taken. A MILP model is formulated to address the problem if the ready time was noticed before actions. If the ready time was not noticed before, then a dynamic algorithm is designed which can resolve the problem based on previous made schedule whenever there is a new field called in.

Some selected references in the area of harvesting and collection are shown in Table 2.

Table 2 Selected references of harvesting and collection

Ref.	Main objective/goal of the model	Math model	Heuristic Algorithm	Other techniques used	Biomass type/location in case study	Relevant optimization models
O'hara et al. (1989)	Make a harvest schedule with the spatial constraints that each spatial unit is less than the area restriction to maximize the harvested volume.	ILP			Forest/Western Montana, the USA	Harvest scheduling
Murray and Church (1995)	Make a harvest schedule with the spatial constraints that each spatial unit is less than the area restriction in order to maximize the discounted net value.	ILP	SA, TS		Forest/British Columbia, Canada	Harvest scheduling
Martins et al. (2005)	Make a harvest schedule with the spatial constraints that each spatial unit is significantly less than the area restriction.	ILP		Column generation and a heuristic	Forest/Portugal	Harvest scheduling
Lockwood and Moore (1993)	Make a harvest schedule to minimize the total cost.		SA		Northeastern Ontario, Canada	Harvest scheduling
Liu et al. (2006)	Generate a long-term harvest schedule to maximize the harvested volume and compare different methods.		EA, SA, Random Hill Climbing		Forest	Harvest scheduling
Jena and Poggi (2013)	Determine the number of workers needed, allocate workers, and generate harvesting schedules in vineyards to maximize the profit.	MILP			Sugarcane/Brazil	Harvest scheduling
Bohle et al. (2010)	Find the best time at which the sugarcrane has most sugar content to do the harvesting in order to maximize the overall profit.	MILP			Wine grape/Chile	Harvest scheduling
Ahumada and Villalobos (2011)	Make harvesting, packing and distribution decisions during harvest season to maximize the total revenue of growers of perishable agricultural products.	MILP			Tomato and bell pepper	Harvest scheduling
Carpente et al. (2010)	Design an efficient routing planning in order to minimize the working time of the forage harvesters.	IP	a local search algorithm, TS		Corn/Northern Spain	Vehicle routing
Cerdeira-Pena et al. (2017)	Design optimal routes for harvesters to minimize the total traveling time.		TS, SA		Corn/Northern Spain	Vehicle routing
Aguayo et al. (2017)	Find the best routing for the balers in order to minimize the total cost, including the routing cost of the balers and the late penalties for not harvesting in time.	MILP		a dynamic algorithm	Corn stover/Iowa, the USA	Vehicle routing, equipment scheduling

"ILP" refers to integer linear programming; "Relevant optimization models" means classic optimization models/problems used in the corresponding reference

Storage

After harvesting, biomass feedstocks are potentially stored at harvesting sites. After pretreatment, the pretreated/densified biomass can be stored at a depot before it is sent to the biorefinery. Some researchers consider on-field biomass storage to save delivery and transportation cost. However, many types of biomass are characterized by seasonal availability, which means they are harvested at a specific time of the year but are required to satisfy the demands on a year-round basis. Thus, it is necessary to store them. The storage site can be located in the farm, at the power station, or at an intermediate site (Rentizelas et al. 2009).

There are two main optimization problems related to the storage process. One is the storage location problem, which is significant to the entire biomass supply chain since the storage location connects the supplies and processing facilities/customers together, and it has great influences on the transportation costs. In the storage location problem, the locations and corresponding capacities are decided. The other one is shipping scheduling problem; it helps make decisions on the delivery system, including storage capacities and shipping batches. Most of the storage-related problems can be solved directly by mathematic formulations.

Due to the low bulk density of biomass, the quantity and volume of incoming raw materials at a biorefinery are larger than the quantity and volume of outgoing final products in a supply chain. One optional approach to alleviate this problem is to pretreat the biomass prior to transporting to the biorefineries. Another approach is to reduce the transportation burden by selecting appropriate storage locations. Thus, the storage location is important in a biomass supply chain to reduce the transportation and operational costs. In EkşioğLu et al. (2010), a MIP model aiming to minimize the total delivery cost is created to investigate the impact of an intermodal facility on location and transportation decisions for the biomass supply chain. An intermodal facility in the paper refers to bulk transload terminals for loading and unloading bulk commodities. The intermodal facility plays a role as a storage location. The result indicates that locating a biorefinery close to an intermodal facility can help to reduce the delivery cost of biofuel, as well as the number of truck shipments. In Marufuzzaman et al. (2014) and Poudel et al. (2016a), a reliable transportation network is designed by MILP to help decide on the locations of intermodal hubs and biorefineries, taking the uncertainty from disruption of intermodal hubs (Marufuzzaman et al. 2014) or failures from links between the facilities (Poudel et al. 2016a) into consideration. In Zhu et al. (2011), the locations and capacities of intermediate warehouses, together with locations and capacities of biorefineries and transportation-related decisions are made to design a biomass supply chain. The MILP with objective of maximizing the annual profit is formulated. The candidate warehouse locations include intermediate locations as well as farms and biorefineries since the storage in field is allowed and may be necessary. In Judd et al. (2010), Judd et al. (2012), and Ebadian et al. (2013), the IP/MIP models are formulated to find the optimal number and locations of storage aiming to achieve the minimal costs incurred during the process of hauling and storing. In the studies, each farm is considered as a potential storage candidate, and the assignments of farms to storage locations need to be determined. Thus, the problem is assumed to be a location–allocation problem. In Ayoub et al. (2007), a two-level general bioenergy decision system for bioenergy production planning and implementation is developed. The decision support system integrated with GIS obtains the decisions through optimization and simulation. A genetic algorithm (GA) is used in the simulation part to help decide on the optimal locations of both storage and the bioenergy conversion plant. The storage type in the case study is selected as indoor storage because of the wet Japanese climate.

Making optimal shipping schedules and determining on storage capacities are significant in coordinating a biomass supply chain. In Cundiff et al. (1997), a biomass delivery system including storage, scheduling, and transportation is studied. In this problem, a linear programming is modeled to determine an appropriate monthly shipment schedule and capacity expansion schedule to accommodate the shipments under four possible weather conditions. Two types of storage locations are considered in this problem, which are ambient storage and covered storage. The lead time of capacity expansion, the storage capacity, and allowed capacity violation amount of the two different storage types are different. The objective of the problem is to minimize the costs of transportation and capacity expansions at storage sites. In Ebadian et al. (2013), except for the number and locations of the storage, the authors also determine the inventory level of each storage location in each contract period (5 years in this problem) and the amount of biomass transported from each storage location to the ethanol plant.

Some selected references in the area of storage are shown in Table 3.

Transportation

Due to the low bulk density of the biomass and the dispersed distribution of biomass suppliers geographically, transportation plays an important role in designing a cost-efficient supply chain (Mirkouei et al. 2017). After harvesting, the biomass would either be shipped to a biorefinery or a pretreatment depot. After pretreatment,

Table 3 Selected references of storage

Ref.	Main objective/goal of the model	Math model	Heuristic algorithm	Other techniques used	Biomass type/location in case study	Relevant optimization models
EkşioğLu et al. (2010)	Minimize the total delivery cost and investigate the impact of an intermodal facility on location and transportation decisions for the biomass supply chain.	MILP			Corn/Mississippi, USA	Facility lcoation, capacity planning
Zhu et al. (2011)	Decide on the locations and capacities of intermediate warehouses, together with locations and capacities of biorefineries and transportation-related decisions to maximize the annual profit.	MILP			Switchgrass	Facility location, capacity planning
Judd et al. (2010)	Find the optimal number and locations of storage aiming to achieve the minimal costs incurred during the process of hauling and storing. Each farm is considered as a potential storage candidate, and the assignments of farms to storage locations need to be determined.	ILP			Switchgrass/South Central Virginia, USA	Facility location, capacity planning
Ayoub et al. (2007)	Develop a two-level general bioenergy decision system integrated with GIS through optimization and simulation for bioenergy production planning and implementation.		GA	GIS	Forestry residues/Japan	
Cundiff et al. (1997)	Design a biomass delivery system including storage, scheduling, and transportation with minimal costs. Determine a shipment schedule and capacity expansion schedule under four possible weather conditions.	LP			Switchgrass/Virginia, USA	Transportation problem, scheduling problem, network design
Ebadian et al. (2013)	Find the optimal number and locations of farms and storages. Determine the inventory level of each storage location in each contract period. Evaluate the impact of the storage systems on the incurred costs.	MILP			Wheat straw/ Saskatchewan, Canada	Facility location, capacity planning

Here “LP” refers to linear programming

the intermediate biomass need to be transported to the biorefinery.

There are two main branches of transportation problems from the perspective of optimization. One is the network design problem and the other is the vehicle routing problem. They both focus on the road network, and they both aim to minimize total costs of the transportation system either by designing the network and deciding on the material flows on the network, or by scheduling the optimal vehicle routes.

Transportation Network–Related Problems

A renewable biomass-to-hydrogen network system is studied in Woo et al. (2016). A MILP model is formulated to minimize the total annual cost. In this work, the feedstock comes from various types of biomass, including energy crops, forest residues, industrial residues, and agricultural residues. The optimal facility locations, the transportation flows, the quantities of biomass to hydrogen, and the quantities of hydrogen to be imported are determined in the design of the network. Transportation network of both biomass feedstock and product distribution is considered (Kang et al. 2010; Bai et al. 2011). In Kang et al. (2010), a MILP model is built to determine the optimal biorefinery location in the transportation network. The goal of the model is to minimize the system cost, at the same time, to decide on the flow of materials in the network, and location and capacity of the biorefinery. The traffic congestion impact is introduced into the problem in Bai et al. (2011). A MIP model with a nonlinear objective function to minimize the total cost is proposed to address the biorefinery location and the transportation network flows. A Lagrangian relaxation–based heuristic algorithm is proposed to solve the model to obtain a near optimal solution, and also two branch-and-bound algorithms are introduced to further improve the solution to optimality.

Geographical information system (GIS) has been widely applied to road network problems (Kanzian et al. 2009; Alam et al. 2012). In Kanzian et al. (2009), two LP models aimed to minimize the transportation costs are formulated to construct the networks of the transport from storage to plant, and the transport from forest to plant. The models integrated with GIS could show the optimal material flows and whether to use storage locations or not. Sensitivity analysis is also conducted on the demand, supply, transport costs, and the utilization of storages. The results show that direct transport of solid fuel wood and chipping at the plant is the cheapest supply system in the study case. In Alam et al. (2012), GIS was combined with a road network minimization algorithm to decide on the choice of route in response to given demand for transporting material from each source to each destination. The algorithm works iteratively to find the least time and cost (shortest distance) route in the road network. A tool called Alternative Fuel Transportation Optimization Tool (AFTOT) (Lewis et al. 2015) is developed by the US Department of Transportation (DOT) Volpe National Transportation Systems Center in order to find the optimal routes in the biomass supply chain. Optimal routing and flows are evaluated through an optimization module including an MIP formulation and a GIS module. The tool generates the potential biorefinery locations and identifies the lowest cost transport patterns. It is a flexible scenario testing tool, where different data resources are tested, from regional to national scale.

Because of physical characteristics of biomass and typically scattered, small- or medium-sized biomass suppliers, using trucks to offer short distance biomass transportation is a popular option. However, according to the research in Hess et al. (2009), it is necessary to invest on large capacity plants to gain from economies of scale in production and make second-generation biofuels cost-competitive. Large capacity plants rely on large number of farms, most of which would be located far away. Thus, using rail and barge, and multimodal facilities could be an option to reduce the transportation cost. The multimodal facilities are introduced into the biomass supply chain in EkşioğLu et al. (2010), Marufuzzaman et al. (2014), Marufuzzaman and Ekşioğlu (2017), Poudel et al. (2016b), and Roni et al. (2014, 2017). A two-stage stochastic MILP model is designed in Poudel et al. (2016b) to determine the optimal use of multimodal facilities, biomass storage and processing plants, and the shipment routes to deliver biomass to the plants under feedstock supply uncertainty. A hybrid decomposition algorithm is used to solve this problem. From the result, we can see that the high feedstock supply variability increases the unit delivery cost of biomass, while the increase of mean feedstock supply decreases the unit delivery cost of biomass. A hub-and-spoke network design model is studied in Roni et al. (2014) and Roni et al. (2017), and it is modeled as a MILP. The hub-and-spoke network structure is appropriate for the delivery of bulk products, such as biomass and cellulosic ethanol. In the network, the depots serve as shipment consolidation points where small shipments of biomass from pretreatment facilities are consolidated into high volume shipments. In their works, the authors need to identify the locations of depots, the location of plant, and also the flows in the network. In Roni et al. (2014), the objective is to minimize the total necessary transportation costs, hub location costs, and penalty costs to meet demand. A Bender's decomposition algorithm is then applied to solve the model efficiently. In Roni et al. (2017), they incorporate environmental and social objectives to the model and formulate it as a multi-objective MILP. The environmental impact is captured by CO_2 emissions due to transportation-related activities, while the social impact is captured by the total created jobs.

Some heuristic algorithms are also used in this problem. In Utama et al. (2012), an ant colony optimization (ACO) algorithm is developed to search for the routes for both transportation on raw biomass and the final products. A demand-driven biomass network is considered in Ayoub and Yuji (2012). Demand-driven network means that the network is designed based on the demands of local society. The problem is solved by GAs. Since the nonnegative feasible flows can be decomposed into the sum of flows in paths directed from supply nodes to demand nodes, and the sum of flows around directed cycles, the first phase of the algorithm is to decompose the flows in the network into several production paths. Phase two of the algorithms is to calculate the material flows through the network with the goal of minimal total cost and emission.

Route Choice Problems

The industry faces the challenges from scheduling which aims to minimize the logistic costs, travel time, and waiting time while satisfying other constraints.

As part of the biomass supply chain, a cotton module transportation system is studied in Ravula et al. (2008). A cotton module is a compressed block made of seeds, parts of the bole, and pieces of stalk and leaves. After they are collected and stored in the fields, they need to be hauled by the module haulers owned by the gin. Usually, the modules are picked up on a first-in first-out basis which leads to a relatively low utilization factor for the transportation system. A knapsack IP model with objective of minimizing the total number of days that trucks are scheduled to move modules from the fields to the gin is constructed and solved to obtain the lower bound for the transportation system. Then, two greedy algorithms with different transportation policies are implemented and simulated to greatly help optimize the schedules of the module haulers and improve the utilization factor of the system. Two MIP truck route scheduling models are formulated and applied to two companies in New Zealand in Murphy (2003). The substantial cost savings and fleet size reductions are reported from the two companies. The models aim to minimize the transport costs while considering the sharing of transport services, driving time, and requirement from supplies and demands. Some transport scheduling problems can be converted to vehicle routing problems (Rey et al. 2009; Flisberg et al. 2009). In Rey et al. (2009), an IP model is formulated to schedule the daily assignment of available trucks for delivery of forest products satisfying the demand of each destination. The objective is to minimize the costs associated with the transportation. The IP is then solved by column generation algorithm where each column represents the daily trips made by a truck between origins and destinations. In Flisberg et al. (2009), a two-phase hybrid method combining LP and Tabu search (TS) is used to find the minimum cost schedule, one route for each truck, to match demand with supply. In the first phase, a LP model is solved to construct transport nodes, where LP is a relaxed and simplified version of an IP formulation of the full problem. In the second phase, the unified Tabu search algorithm (UTSA) is used to find the optimal scheduling.

The truck scheduling problem is solved by many other heuristic algorithms. In Acuna et al. (2012) and Han and Murphy (2012), the SA algorithm is applied in the truck scheduling problem and tested for the cases in western Oregon. In Acuna et al. (2012), the objective is to minimize the transport costs, travel times, and waiting times, while meeting a minimum level of utilization by the chippers specified by the user. By applying the optimal scheduling, the payload and chipper utilization account for 52% and 29% of the total savings obtained. In Han and Murphy (2012), the algorithm is used to solve the scheduling problem for transporting four types of woody biomass. The objective consists of minimizing total truck costs and total working hours. After applying the algorithm, the average reductions in transportation cost and total travel time are 18% and 15% respectively. The ant colony optimization (ACO) algorithm is used in Beck and Sessions (2013) to schedule multiple biomass operations over a road network. The objective is to minimize the total transportation cost, which includes the modification costs and the costs on road. A MIP is first formulated, and then ACO is used to solve the problem to identify the optimal vehicle choices and road modifications. The result shows that it can help to reduce 27% total transportation costs.

Some selected references in the area of transportation are shown in Table 4.

Pretreatment

After harvesting, the biomass can be transported directly to a biorefinery (and be pretreated on site) or to a regional depot for pretreatment. After pretreatment, it can be transported over long distances economically. Thus, the major primary concerns of the pretreatment process are to reduce material loss and to convert the low density biomass into a more stable, more densified product so that it can be transported over a much longer distance in a cost-efficient way (Quddus et al. 2017). Sometimes, the pretreatment process is seen as just physical treatment. In this case, some mechanical or thermal processing technologies are applied during pretreatment, such as drying, grinding, chopping, shredding, and pelleting. In a typical process of lignocellulosic to ethanol, there are four major operations: pretreatment, hydrolysis, fermentation, and product separation/purification (Mosier et al. 2005). For lignocellulosic biomass, pretreatment is required to

Table 4 Selected references of transportation

Ref.	Main objective/goal of the model	Math model	Heuristic algorithm	Other techniques used	Biomass type/location in case study	Relevant optimization models
Woo et al. (2016)	Design a renewable biomass-to-hydrogen network to minimize the total annual cost. The optimal facility locations, the transportation flows, the quantities of biomass-to-hydrogen, and the quantities of hydrogen to be imported are determined in the design of the network.	MILP			Four types of biomass (energy crops, forest residues, industrial residues, and agricultural residues)/Jeju Island, South Korea	Network design
Kang et al. (2010)	Determine the optimal biorefinery location in the transportation network. Decide on the flow of material in the network, and location and capacity of the biorefinery to minimize the system cost.	MILP			Corn stover and miscanthus/Illinois, USA	Network design
Bai et al. (2011)	Address the biorefinery location and the transportation network flows in order to minimize the total cost. Traffic congestion impact is considered.	MIP with nonlinear obj.		one heuristic and two B&B	Corn and cellulosic biomass/Illinois, USA	Network design
Kanzian et al. (2009)	Construct the networks of the transport from storage to plant, and the transport from forest to plant aiming to minimize the total transportation costs. Determine the optimal material flows and the whether to use storage locations or not.	LP		GIS		Network design
Alam et al. (2012)	Decide on the choice of route in response to given demand for transporting material from each source to each destination			Road network min algorithm, GIS		Network design, vehicle routing
Poudel et al. (2016b)	Determine the optimal use of multimodal facilities, biomass storage and processing plans, and the shipment routes to deliver biomass to the plant under feedstock supply uncertainty.	MILP		A hybrid decomposition algorithm	Corn stover and forest residues/Mississippi and Alabama	Network design, vehicle routing
Roni et al. (2014)	Design a hub-and-spoke network with minimal costs. Identify the location of depots, the location of the plant, and also the flows in the network.	MILP		A Bender's decomposition algorithm		Network design, facility location
Utama et al. (2012)	Search for the routes for both transportation on raw biomass and the final products.		ACO			Network design, vehicle routing

Table 4 (continued)

Ref.	Main objective/goal of the model	Math model	Heuristic algorithm	Other techniques used	Biomass type/location in case study	Relevant optimization models
Ayoub and Yuji (2012)	Design a biomass network based on the demands of local society.		GA		Various types of biomass/Aomori Prefecture, Japan	Network design
Marufuzzaman et al. (2014)	Decide on the locations of inter-modal hubs, the locations of biorefineries, and the routes in the reliable transportation system to minimize the total costs. Consider the disruptions of intermediate transportation hubs.	MILP		An enhanced Bender's decomposition algorithm	Various biomass/nine states in the USA	Facility lcoation, Network design, vehicle routing
Poudel et al. (2016a)	Make a pre-disaster planning to reduce or eliminate risks of the link failures. Identify the facility locations with minimal total expected system cost.	MILP		A generalized Bender's decomposition algorithm	Corn stover and forest residues/Mississippi and Alabama.	Facility location
Ravula et al. (2008)	Construct a schedule to move cotton modules from the fields to the gin to minimize the total number of days of working by IP. The schedules are optimized and improved by implementation and simulation by two algorithms.	ILP	Two greedy algorithms		Cotton/Virginia, USA	Vehicle routing
Murphy (2003)	Schedule the truck routes to minimize the transport costs while considering the sharing of transport services, driving time, and requirement from supplies and demands.	MIP			Forest/New Zealand	Vehicle routing
Rey et al. (2009)	Schedule the daily assignment of available trucks for delivery of forest products satisfying the demand of each destination to achieve the minimal costs associated with the transportation.	IP		Column generation algorithm		Vehicle routing
Flisberg et al. (2009)	Find the minimum cost schedule, one route for each truck, to match demand with supply.	LP	TS		Forest/Chile	Vehicle routing
Acuna et al. (2012)	Make a truck schedule to minimize the transport costs, travel times and waiting times, while meeting a minimum level of utilization by the chippers specified by the user.		SA		Forest/Sweden	Vehicle routing
Beck and Sessions (2013)	Schedule multiple biomass operations over a road network to minimize the total transportation cost.	MILP	ACO		Various biomass/Western Oregon, USA	Vehicle routing

increase the enzyme accessibility improving digestibility of cellulose (Alvira et al. 2010). Then, pretreatment can be classified into four categories including physical (such as milling, extrusion, microwave, freeze pretreatment), chemical (such as acid pretreatment, alkaline pretreatment, ionic liquid pretreatment, organosolv pretreatment, and ozonolysis), physico-chemical (such as stream explosion pretreatment, ammonia fiber explosion pretreatment, CO_2 explosion pretreatment, liquid hot water pretreatment, and wet oxidation), and biological (converting lignocellulosic biomass by microorganisms especially fungi into more accessible compounds for hydrolysis) (Mood et al. 2013; Zheng et al. 2009).

Two main optimization problems are closely related to pretreatment process, which are facility location problem and technology selection problem. The facility location problem helps to find the optimal location and the capacity for pretreatment facility in order to achieve the minimal total costs of investment cost and following operational cost. The technology selection problem helps to select the most appropriate technology from the perspective of both economy and environment.

Some scholars work on finding an optimal pretreatment location. In Ng and Maravelias (2017) and Ng and Maravelias (2016), a multi-period MIP is formulated to find the optimal locations of pretreatment depots and biorefineries in order to minimize the total annual cost. In their assumption, the biomass from a harvesting site is sent to only one pretreatment depot or directly a biorefinery, and the intermediates from a pretreatment depot are shipped to only one biorefinery. In Ng and Maravelias (2016), the problem is formulated as a multi-period MINP, whereas in Ng and Maravelias (2017) some approximation and reformulation techniques for calculating the transportation costs are applied to replace the nonlinear terms by linear ones. In Quddus et al. (2017), the authors focus on multi-purpose pellet processing depots. A two-stage stochastic MIP is formulated to design a sustainable biomass supply chain to minimize the total system costs and carbon emission as an environmental concern. In the first stage, the optimal location and capacity of a biomass processing and densification depot are decided; in the second stage, other decisions, such as transporting and storing are made under the uncertainty of biomass supply. In order to enhance the computational performance, a hybrid decomposition algorithm is designed to solve the model. From simulation of test example, it is revealed that the depots can help to handle supply variation and the biorefineries and coal industries will be greatly benefited by the depots.

Some researches are studying on pretreatment technology selection problem. In Laínez-Aguirre et al. (2015), two pretreatment technologies: chipping and drying are considered to be selection options. The biomass considered in this paper needs to achieve adequate shape and properties (energy content and humidity) through chipping and drying processes to support later processes. A MILP is formulated to minimize the total cost and the environmental impacts at the same time through LCA. A Lagrangian relaxation–based approach is applied to solve this model. The result shows the most appropriate pretreatment technologies at specific pretreatment facility locations, and also suggests to ship raw material instead of pretreated material in short distance. Similarly, in Pérez-Fortes et al. (2014), a multi-objective MILP considering economic and environmental criteria is modeled. They consider more technology selections, including drying, chipping, torrefaction, and pelletization. In order to feed already existing coal combustion plants and help modify the supply chain, they decide on the optimal location, selection, and capacity of pretreatment technologies.

Some selected references in the area of pretreatment are shown in Table 5.

Conversion

A biorefinery is used to describe the industrial process that converts biomass feedstocks into value-added products such as fuels and chemicals (Ng et al. 2009). Almost all of the articles in the domain of energy conversion in a biomass supply chain discuss the conversion from biomass to biofuels. The optimization models used in energy conversion can be mainly found in capacity planning problem, facility location problem, and conversion technology selection problem. Along with these optimization models, some other techniques are used, including GIS and multi-objective models.

The conversion process, together with the upstream suppliers and downstream customers configure a network system. In Duarte et al. (2014), the authors consider the material flow from suppliers to consumers in the problem and model it as a network flow problem by MIP. The location of the facility and the flow rates on different arcs in the network require to be determined in order to obtain the maximal benefits of the process. In the problem, the labor force, capacity, and technology types are all considered as input data. In Marvin et al. (2013), the capacity for each facility and the selection of technology are also need to be determined in the MIP model. Sensitivity analysis is done based on the uncertainties of the market demand in both of the articles. The selection of different technologies has a great impact on the capital cost of technology installation, the conversion rate, and unit production cost. Seven options are considered in the conversion from various types of biomass in Marvin et al. (2013), whereas authors in Ng and Maravelias (2017) consider one pretreatment technology and two conversion

Table 5 Selected references of pretreatment

Ref.	Main objective/goal of the model	Math model	Heuristic algorithm	Other techniques used	Biomass type/location in case study	Relevant optimization models
Ng and Maravelias (2016)	Find the optimal locations of pretreatment depots and biorefineries in order to minimize the total annual cost.	MINP			Corn Stover/Wisconsin, USA	Facility location
Quddus et al. (2017)	Design a sustainable biomass supply chain to minimize the total system costs and carbon emission as an environmental concern. Decide on the optimal location and capacity of a biomass processing and densification depot.	MILP	Rolling Horizon (RH) heuristic	A hybrid decomposition algorithm, GIS	Various biomass/Mississippi and Alabama, USA	Facility location, capacity planning
Laínez-Aguirre et al. (2015)	Find the most appropriate pretreatment technologies at specific pretreatment facility locations to minimize the total cost and the environmental impacts at the same time through life cycle assessment.	MILP		A Lagrangian relaxation–based approach	Woody residues/Spain	Facility location
Pérez-Fortes et al. (2014)	Decide on the optimal location, selection and capacity of pretreatment technologies to feed existing coal combustion plants and help modify the supply chain considering both economic and environmental criteria.	MILP			Woody residues/Spain	Facility location, capacity planning, technology selection

technologies in the conversion processes for corn stover and switchgrass.

Biorefinery facility location decisions require large investment and are vital to the supply chain management due to the long-term influence on accessibility to biomass and other materials. GIS is widely used to help decide on the facility locations. It can be utilized to consider and decide on different related factors, including road network for transportation, water flows, power grid for infrastructure, and population census for labor sources. In Zhang et al. (2016), Serrano et al. (2015), Xie et al. (2010), and Zhang et al. (2017), the MIP formulations are integrated with GIS system to optimize the facility locations and do the simulation to achieve the minimal overall cost. In Zhang et al. (2016), multi-biorefinery locations need to be decided, and the optimal number, locations, and facility capacities are obtained by solving the problem. Most of the GIS-based facility location problems assume all available lands satisfying pre-specified requirements as potential locations for biorefineries (Noon et al. 2002; Panichelli and Gnansounou 2008; Yu et al. 2014). The potential locations are then divided into small cells and each cell is treated as a biorefinery candidate. The authors in Xie et al. (2010), however, developed a tool in GIS to help users select the candidates themselves on the map. In Zhang et al. (2017), nine biorefinery facility location candidates are pre-selected by utilizing GIS considering the factors including country boundaries, road networks, city and village distribution, water and co-fired power plant distribution, biomass accessibility, and census. Then, these nine candidates are implemented into a MILP as input data to achieve minimal supply chain system cost.

Most of the biorefinery-related problems aim to find one or multiple locations with optimal capacities which lead to minimal overall cost. In addition to the economic considerations, some other issues are taken into account in order to formulate a multi-objective optimization problem, among which, environmental and social issues have been put on most emphasis. Reducing the environmental impacts in the biomass supply chain, especially in the phase of biorefinery, is a ubiquitous element. Green house gas (GHG) emissions are one of concerns in using fossil fuels, while using combustion of biomass can be considered GHG neutral. Thus, the GHG emission amount is a popular criteria when it comes to environmental issues. The scholars usually formulate the environmental optimization objectives either by minimizing the GHG emissions (Giarola et al. 2011; Liu et al. 2014) or by maximizing GHG emission savings (Cambero et al. 2016; Cambero and Sowlati 2016). In Cambero et al. (2016), a multi-period, multi-objective MIP is formulated to decide on types and sources of biomass, conversion technology selection, and products and markets. In order to enhance the economic performance, an objective of maximizing net present value is presented. At the same time, an objective of maximizing the life cycle GHG savings is also formulated for the environmental benefits. To deal with the multi-objective, an augmented ϵ-constraint method is provided which can help to reformulate the problem as a single objective problem and provide a set of Pareto-optimal solutions, which can be later selected by the decision maker. Job creation is a widely used indicator to measure the social benefits of the biorefineries could bring to the communities.

The model in Cambero et al. (2016) is extended by Cambero and Sowlati (2016) to incorporate social benefits integrated with economic and environmental performances. In this model, they measure the social benefits by a weighted sum of the created jobs, where the specified weights are based on the types and locations of the created jobs. Besides environmental and social benefits, some other issues are also considered. In El-Halwagi et al. (2013), safety issues are considered in not only the manufacturing process of biorefinery, but also the related transportation, storage, and processing phases of biorefining. In the case study, a Pareto curve is used to analyze the trade-off between risks and cost, and it turns out that the economic and risk objective may contradict each other in a certain range. In Liu et al. (2014), energy is taken into account, together with economic, environmental performance to be a "3E" criteria formulated by a multi-objective MILP problem. In this work, energy objective is measured by the average input fossil energy per megajoule of biofuel.

Some metaheuristic algorithms are applied to the facility location problem for finding the optimal location of biorefinery facilities. In López et al. (2008), Vera et al. (2010), and Sedighizadeh et al. (2013), some algorithms are used to find the optimal location, the plant capacity, and the supply areas for a biomass-based power plant. The profitability index, which defined as the ratio between net present value (NPV) and initial investment (INV), is selected as the objective function. In Milan et al. (2006), a binary particle swarm optimization (BPSO) is proposed, while GA and BPSO are applied in Sedighizadeh et al. (2013) for a power plant using animal manures as biomass. In Vera et al. (2010), a Binary Honey Bee Foraging (BHBF) approach is applied, where olive tree pruning is used as main biomass resources in the case study. The BHBF is a particle swarm algorithm inspired by the swarm behavior of honey bees proposed in Baig and Rashid (2006). The comparison between the BHBF and other evolutionary algorithms, such as GA and BPSO is also done in Vera et al. (2010). The comparison of some metaheuristic techniques, including SA, TS, GA, PSO, and BPSO, used to determine the optimal location for a biomass-based facility power plant is done in Reche-López et al. (2009). A GA integrated with GIS is proposed in Celli et al. (2008). All the relevant information from cartography is gathered within GIS, and then the algorithm is processed to find the optimal number, position, and power capacity of biorefinery in a whole Italian region.

Some selected references in the area of conversion are shown in Table 6.

Sustainable Biomass Supply Chain

Life Cycle Assessment

Sustainable supply chain management is defined as the management of material, information, and capital flows as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, i.e., economic, environmental, and social, into account which are derived from customer and stakeholder requirements (Seuring and Müller 2008). In order to achieve the sustainable development of biomass supply chain and avoid negative impacts brought by different operational processes on our environment, LCA is used by a lot of scholars as a tool to assess the environmental impacts.

There are four main phases in LCA according to ISO (for Standardization 2006), including goal and scope definition, life cycle inventory analysis, impact assessment, and interpretation. (1) In the phase of goal and scope, project description, the functional unit, the system boundaries, and the impact categories are defined and stated. (2) Life cycle inventory (LCI) analysis deal with inventory flows of inputs (e.g., water, energy, and raw materials) and outputs for a given product throughout its life cycle. (3) In the phase of impact assessment, the assessment of impacts on environment is made based on the LCI flows according to some damage assessment model. (4) In the final phase, the results from analysis of LCI and impact assessment are summarized and reported. The classic four-phase LCA principle is widely integrated into the biomass supply chain.

Multi-Objective Optimization Integrated with LCA

More attentions have been paid to environmental and social issues in the configuration of a biomass supply chain instead of only economical effects. According to this situation, multi-objective optimization models are built considering environmental and social issues simultaneously.

Recently, multi-objective optimization has been utilized and coupled with classic LCA to construct a framework to not only assess and evaluate the environmental impacts, but also identify the optimal solution.

To achieve the green supply-chain management (GrSCM), environmental responsibility is an important aspect in the supply chain design. In Paolucci et al. (2016), a

Table 6 Selected references of conversion

Ref.	Main objective/goal of the model	Math model	Heuristic algorithm	Other techniques used	Biomass type/location in case study	Relevant optimization models
Duarte et al. (2014)	Determine the location of facility and the flow rates on different arcs in the network to obtain maximal benefits of the process.	MILP			Coffee tree residues/Colombia	Facility location, network design
Marvin et al. (2013)	Decide on the capacity for each facility and selection of technology.	MILP			Various biomass/ 12-state region of the midwestern US	Facility location, capacity planning
Zhang et al. (2016)	Decide on optimal number, locations, and facility capacities.	MILP		GIS	Various lignocellulosic biomass/Michigan	Facility location, capacity planning
Xie et al. (2010)	Decide on the optimal facility location by implement the self-developed tool in GIS.	MILP		GIS		Facility location
Zhang et al. (2017)	Select the optimal facility location from nine candidates pre-selected by utilizing GIS to achieve minimal supply chain system cost.	MILP		GIS		Facility location, capacity planning
Cambero et al. (2016)	Decide on types and sources of biomass, conversion technology selection, and products and markets to enhance both environmental and economical performance.	MILP			Forest and wood residues/British Columbia, Canada	Technology selection
Cambero and Sowlati (2016)	Extend the model in Cambero et al. (2016). Incorporate social benefits integrated with economic and environmental issues to enhance the supply chain system performance.	MILP			Forest and wood residues/British Columbia, Canada	Technology selection
Milan et al. (2006)	Locate the optimal location for biomass-based power plantsand offer the supply area for the biomass plant.		Binary particle swarm optimization	GIS	Forest residues	Facility location
Vera et al. (2010)	Determine the optimal location, biomass supply area and power plant size that offer the best profitability for investor		Binary Honey Bee Foraging, GA, binary particle swarm optimization	GIS	Olive tree pruning residues/ Spain	Facility location
Reche-López et al. (2009)	Deal with the power plant location problem and offer the supply area at the same time. Compare different metaheuristic algorithms.		SA, TS, GA, particle swarm optimization, binary particle swarm optimization	GIS	Forest residues	Facility location

two-tier optimization approach is proposed for the design of a pyrolysis-based biomass supply chain. In the first tier, by given rough geographic data, simplified analysis is done and the characteristic size and number of the bio-oil plants can be obtained. In the second tier, a detailed multi-objective MILP model using weighted sum method is presented. Economic performance, including operational and capital costs are measured by net present value (NPV), while environmental issues are measured by the total GHG emissions from LCA of each stage of the supply chain. After that, a weight parameter $\alpha \in [0, 1]$ is introduced to combine the two objective items together. Emphasis of each part can be adjusted by selecting different values of α by the decision maker. In You and Wang (2011), economic and environmental dimensions are integrated in a multi-period MILP model and it is addressed from a life cycle perspective. In Giarola et al. (2012), the economic and environmental impacts are measured simultaneously by NPV and GHG emissions as well using weighted sum multi-objective optimization method. The proposed multi-objective MIP can help to make decisions of technology selections based on their economic and environmental performance over the long term in the corn grain– and corn stover–based bioethanol production system. The assessment of environmental impacts are made along the biofuel life cycle, LCA stages in this problem include biomass production, biomass pretreatment, biomass transport, and biofuel production. In Vadenbo et al. (2017), a fuzzy linear programming extension for matrix-based LCA is developed. The objective is to minimize the aggregated life cycle impact for each category of activity or process with specific activity level over some time period. In this problem, each environmental impact category is one objective. In Budzinski et al. (2019), a multi-objective MILP model is developed in order to decide on the selection of new technology as well as optimal region for feedstock supply. The environmental and economic assessment of new candidate technologies are considered together. To deal with multiple objectives, a weighted goal programming is used as a priori approach followed by ϵ-constraint method as posteriori approach. Social benefit is also an important ingredient during the design of a supply chain. In You et al. (2012), Santibañez-Aguilar et al. (2014), Garcia and You (2018), Gebreslassie et al. (2013a), and Wang et al. (2013), the environmental objective is measured by life cycle GHG emissions and the social objective is measured by the number of created local jobs during construction and operation of the whole supply chain. The multi-objective MILP model can help to determine the associated planning decisions over the supply chain. After obtaining a set of solutions by using ϵ-constraint method, the trade-off between economic, environmental, and social aspects are analyzed by Pareto-optimal curves. In Julio et al. (2017), a new framework was proposed to achieve a sustainable design of biorefinery process. The design assess economic, environmental, and social considerations of the process in an integrated way, from a life cycle perspective. A multi-objective optimization of the process is performed and supported by a decision-making tool to find the most sustainable design, where the optimization can be accomplished by a metaheuristic method.

Challenges and Opportunities

Uncertainty Issues and Corresponding Optimization Solutions

Uncertainties are ubiquitous, of various types and varying degrees, and emerging from all stages and activities in the biomass supply chain (Awudu and Zhang 2012). Uncertainty mainly comes from biomass availability/supply (Shabani and Sowlati 2016; Tong et al. 2014a; Azadeh et al. 2014; Gebreslassie et al. 2012) (due to seasonality of biomass, geographical disperse, unpredictable climates), product demand (Chen and Fan 2012) (due to unstable economic situations and product prices), prices and costs (Dal Mas et al. 2010; Tong et al. 2014c) (due to markets and related policies), technologies (Marvin et al. 2012) (due to improvements and evolutions of technologies), and policies and regulations (Marufuzzaman et al. 2014; Zakeri et al. 2015) (due to efforts in obtaining a green and reliable biomass supply chain).

Among all the uncertainties, biomass supply uncertainty has been studied most frequently. The biomass supply fluctuates highly from one time period to another depending on climatic conditions such as rain, temperature, and humidity along with other extreme events such as, natural disasters and human intervention (Persson et al. 2009). In Serrano et al. (2015), the authors take two sources of uncertainty from supplies into account, which are climate zone in which the biomass planted, and the type of crops. They approximate the biomass availability with a triangular distribution related to climate zone and a uniform distribution related to the crop type. By using the distribution of biomass instead of a fixed available amount, the authors are able to identify the location of one biorefinery location as well as the size of biorefinery depending on the assumed outstock risk. Sensitivity analysis is made in Zhang et al. (2017) due to the uncertainties of demand and supply amount. The authors find that the cost increases significantly as the demand grows or the supply decreases. At the same time, they find that the optimal facility locations and sizes vary with uncertainties from demand and supply.

Except for the uncertainties coming from feedstock supply (Poudel et al. 2016b), there are impacts on supply infrastructures coming from various adversary incidents, including water scarcity, flooding, routine maintenance, and adverse weather condition. Uncertainties from the components of transportation system are considered in Marufuzzaman et al. (2014), Marufuzzaman and Ekşioğlu (2017), and Poudel et al. (2016a). A reliable transportation network is designed in Marufuzzaman et al. (2014) and Marufuzzaman and Ekşioğlu (2017) under the disruptions of intermodal hubs. The work in Marufuzzaman et al. (2014) takes the disruptions of intermediate transportation hubs into account, and estimate the probability of disruption by a probabilistic model. A MILP model is formulated to decide on the locations of intermodal hubs, the locations of biorefineries, and the routes in the transportation system. The objective of this problem is to minimize the total costs, including the set up cost and long-run transportation costs. An enhanced Bender's decomposition algorithm is applied to solve this problem. The reliability of the model can be reflected to selection of locations in areas with low disruption probabilities. Also, the model tends to select less locations and satisfy the remaining demand in other ways when the disruption probability becomes high. In Marufuzzaman and Ekşioğlu (2017), a dynamic multimodal transportation network is designed to mitigate risk from disruptions of hubs by deciding at the planning stage in what hub to use or discontinue using during different time periods of the year. The problem is formulated by a MILP with the objective of minimizing the total costs, and then solved by an accelerated Bender's decomposition algorithm and a hybrid rolling horizon algorithm. By considering uncertainties coming from natural disruptions and biomass seasonality, the reliable model is able to adjust short-term and mid-term supply chain decisions dynamically under different scenarios. In Poudel et al. (2016a), a transportation network is designed under the link failures between different facilities. The goal of this work is to make a pre-disaster planning to reduce or eliminate risks of the link failures. The authors build a MILP model to identify the facility locations aiming to minimize the total expected system cost. The link failure is characterized by a spatial statistic model in this work. A generalized Bender's decomposition algorithm is used to solve this problem. After improvement of vulnerable links recommended from model, the resulting network is capable to prevent possible losses due to transportation link disruption by natural disaster.

Some optimization methods are implemented to capture and integrate the uncertainties into optimization models. Stochastic programming is useful when the uncertain parameter is known and it is possible to define potential scenarios. The mixed integer two-stage stochastic programming models are built in Chen and Fan (2012), Kim et al. (2011a), Tong et al. (2014b), and Zakeri et al. (2015) considering uncertainties of supply, demand, prices and technologies, and policies and regulations. In the first stage, the planning decisions can be made before the actual realization of system uncertainties. In the second stage, the operational decisions are made after a random event occurs or based on the outcome of the first-stage decision. One alternative, robust optimization method is effective to provide satisfactory performance of the system and computationally intractability when the uncertainty set is selected. The uncertainty parameter is usually known within a certain bound without exact distribution. A robust optimization is formulated as a MILP to capture uncertainties from different sources and types of uncertainties in Bairamzadeh et al. (2018). In Ghaderi et al. (2018), a multi-objective robust optimization model is developed to maximize the mean value of supply chain performance and to control the optimality as well as feasibility robustness under uncertainties from different parameters. To achieve this, three distinct objective functions, including the basic objective, one related to optimality robustness and one related to feasibility robustness are formulated. In Shabani and Sowlati (2016), uncertainties from biomass quality and biomass availability are considered. First, a robust optimization formulation incorporated biomass quality, including moisture content and higher heating value is constructed. Then, a hybrid multi-stage stochastic programming–robust optimization model is built by taking biomass quality and monthly available biomass into account simultaneously. When there is a requirement of high probability to meet some restriction, chance constraints are used. In the chance-constrained approach, uncertainties are represented through random variables with known probability distribution and are included in the constraints. In Quddus et al. (2018), a two-stage chance-constrained stochastic programming is modeled. The chance constraint ensures that, with high probability, a significant portion of the overall biomass demand at each season will be satisfied by the municipal solid waste. Moreover, some statistic approximation (Serrano et al. 2015; Poudel et al. 2016a) methods are also employed to capture the uncertainties in the biomass supply chain management.

Future Research Trends and Directions

Depend on the type of biomass, the biofuel production can be classified as first generation, second generation and third generation, referring to biomass used to be animal and human food; lignocellulosic biomass, woody crops, agricultural residues or waste; and algae. According to all the reviewed paper, there is a trend of research from the first-generation biomass to second and third generation (Avami 2012; Gebreslassie et al. 2013b), which helps to relieve the pressure and competition of food supplies. Lignocellulosic biomass includes virgin biomass (e.g., trees, bushes, and grass), waste biomass (e.g., corn stover, sugarcane bagasse, and straw), and energy crops (e.g., saw mill and paper mill discards). There are increasingly researches on lignocellulosic biomass due to its abundance and accessibility.

There is a long history of converting the sugar or starch from the crops like corn and sugarcane to useful biofuels. The conversion technologies are relatively mature and cost-efficient due to continuous improvement in the past decades. However, these supply feedstocks are expensive since they are good source of food. There are some inexpensive supply feedstocks, such as lignocellulosic biomass. In addition, the current conversion processes for them are complex and conversion technologies are uneconomical (Sharma et al. 2013). Thus, there is a trade-off between the cost of supply feedstocks and conversion or operational costs (Mirkouei et al. 2017). To overcome these challenges, there are two potential research directions: one is to centrally manage the biomass feedstocks and avoid the small-scale and scatter-distributed supplies to obtain the economies of scales; another is to research on the improvement of conversion technologies to achieve the primary products efficiently and utilize the co-products effectively at the same time.

Except for research directions following the current trends, there are more directions that scholars could focus on due to lack of emphasis right now. Currently, more researches are focused on one isolated component in a biomass supply chain instead of developing a sustainable biomass supply chain to integrate the isolated components together. In order to construct the biomass network structure, the P-graph method and its corresponding software is used in order to allocate available resources as well as identify and relieve bottlenecks in the network. More algorithms should be designed from optimization perspective to construct and manage biomass supply chain network (Benjamin et al. 2016; Benjamin 2017; Lam et al. 2017). Moreover, more efforts should be put on implementation of optimized supply chain into industry practice in order to bridge the gap between advanced biomass supply chain research and industry production.

Policies and regulations play an important role in and stimulate development of a biomass supply chain. However, there is a lack of design of models taking this uncertainty into considerations. The possible reasons include difficulty of quantifying policies and regulations as well as region-wise characteristics of policies and regulations. Generalized models considering policies and regulations will be valuable.

Conclusions

The biomass and biofuel industry is in the period of rapid growth due to the environment restriction and sustainable and renewable energy requirements. The optimization methods, including mathematical programming and heuristic algorithms play a vital role in decision-making in every step of the supply chain. A bibliometric analysis is done to reveal the publication trends and publication distributions. A detailed review for each key component throughout the supply chain is studied in this work. The main research directions in each component and the representative references are presented, some common techniques and considerations, and the research trends are discussed and summarized in the review. Uncertainty issues and challenges and sustainable concerns are also discussed from the perspective of optimization.

There are still some challenges and research gaps need to be filled in the future. Second- and third-generation biomasses need more focus to relieve the pressure on competing with food supplies by using the first-generation biomass. Even though each component in a biomass supply chain is carefully studied by scholars, a generic framework should be put more efforts on to integrate different inseparable components together. Throughout current publications, most optimization methods are focused on a single objective function. Multiple objectives including environmental and social considerations should be paid more attention to in order to design a sustainable biomass supply chain. Policies and regulations should not be ignored while we consider uncertainty issues.

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