Biomass and Bioenergy 142 (2020) 105777

Contents lists available at ScienceDirect

Biomass and Bioenergy

journal homepage: http://www.elsevier.com/locate/biombioe

Review

Biomass supply chain environmental and socio-economic analysis: 40-Years comprehensive review of methods, decision issues, sustainability challenges, and the way forward

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A R T I C L E I N F O

Keywords:
Biomass supply chain
Biofuel
Sustainability
Optimization methods
Uncertainty

A B S T R A C T

Biomass is a valuable renewable source of energy as an alternative to fossil fuels. The main barriers in biomass and biofuel development are feedstock high cost, lack of reliable supply, and uncertainties. A systematic review of comprehensive solution tools to overcome the biomass supply chain (BSC) planning challenges is critical for both academic research and industry. Therefore, the aim of this study is to conduct a systematic review of BSC modeling and optimization and identify future research directions. We reviewed 300 papers that have been published in the past 40 years on this topic to assess the various models of BSCs, their objective functions, solution approaches, and decision levels employed. Results show that researchers are motivated to use mixed integer programming models for BSC problems because of the complexities of nonlinear models, as well as the simplicity of the linear approaches. There is a lack of multi-objective optimization approaches to address the economic, social, and environmental issues simultaneously in BSC. Although factors such as the political regulation, governmental subsidy, impact of biomass and oil price and cost of raw material are uncertain, most studies formally treat only the supply and demand of biomass as uncertain parameters. It is highly recommended that an integrated and holistic model that consider all facilities in the whole BSC be developed and tested with real data. In addition, incorporating strategic, tactical, and operational decision levels in the model is suggested to address the challenges of incorporating day-to-day inventory control and fleet management issues.

1. Introduction

Nowadays, global warming (GW) is known as one of the most critical issues across the world. Many efforts have been made by many international communities to diminish greenhouse gas (GHG) emissions to slow down the GW process. As a result, developing the energy sources sustainably can have a great effect on success of global policies adopted worldwide for the reduction of GHG emissions; the basic idea in this sense is to replace the fossil fuels [1]. The increase of alarms regarding the GHG-induced climate changes and energy security has given scholars strong encouragements to conduct research into exploring potential sources for generating renewable energies. Something that can have a great effect in this context is biomass that refers to any biological material that is derived from living or recently living organisms [2]. Biomass has been recognized widely as a multipurpose and renewable source of energy, which can be utilized in producing combined heat and power (CHP) and also it can be employed in transportation system [2]. Recently, the number of countries that make use of this substance for the purpose of generating required energy has rapidly increased. It has caused biomass to be a valued alternative in comparison with other renewable energy sources. Biomass can produce energy in various areas, e.g., large-scale power production, small-scale thermal heating stores, or CHP at public, or different institutions [1].

A number of countries like Malaysia, United States (US), and many European ones have made recent efforts to enhance the commercialization activities of the biomass industry [3]. Indeed, many attempts have been made to enhance the potential of biomass in a way to use it for lessening the human dependency upon currently used fossil fuels. Biomass can be derived all plants and plant-derived material like sugar, oil crops, and animal manure used to produce energy and food [4]. The key types of biomass sources across the globe are presented in Fig. 1 [5].

A critical challenge in this sense is to utilize biomass in an efficient way considering the lower cost of supply chain and activities required for converting biomass into a valuable energy source. The use of biomass

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https://doi.org/10.1016/j.biombioe.2020.105777
Received 27 January 2020; Received in revised form 24 June 2020; Accepted 14 September 2020
Available online 24 September 2020
0961-9534/

for power production has numerous benefits; on the other hand, a number of barriers affect its effectiveness, including accessibility of feedstock, cost and quality, transportation costs, handling and stock, and logistic system [6–8]. The above-mentioned factors significantly affect the efficacy of the BSC. For the purpose of improving the performance of the environmental, economic, and social parameters and the BSC efficiency, there is a need to provide an optimized design. For designing an optimized BSC, practitioners and researchers can make use of mathematical and optimization models or techniques [7,9].

1.1. Objective and scope of study

Numerous scholars in recent years have contributed to design highly efficient BSC. As a result, several review papers have focused on BSC and/or logistics optimization. A group of studies have been published only on forest-based biomass [9] and agricultural-based biomass [10]. Ko et al. [11] reviewed the biomass transportation and logistics literature focused on current research gaps, ideas, and challenges. They highlighted that there is a knowledge gap to evaluate the sustainable transportation cost considering economic, environmental, and social parameters. Another review study, assessed the important factors of biomass logistic operations incorporated in the mathematical optimization models [12]. Results showed that most of the biomass logistic models focused on economic objectives. Moreover, there is a lack of investigation focused on aspects related to the economic and environmental objectives of biomass logistics operations. Social aspects related to biomass transportation have received limited investigations [12]. Nunes et al. [13] evaluated the models developed by recent studies that consider the selection of suppliers, biomass type, optimum location for storage and refineries, and the type of warehouses that should be used to collect the raw materials and biomass products. Few recent review studies focused on just modeling approaches such as mathematical modeling, transportation, and storage aspect of BSC [9]. In summary, despite the substantial works in the BSC modeling and optimization for nearly four decades, there is a lack of systematic review on this topic, especially the classification of the optimization approaches, geographic coverage of the study, objectives of the study, decision issues, sustainability issues, political regulations, limitations of the study and identification of new or emerging research directions. This paper contributes to address those gaps in the literature by conducting a systematic review of 300 papers specifically addressing BSC modeling and optimization that were published from 1980 to June 2020. Further, based on the synthesis of the literature, emerging challenges, and possible approaches to address those challenges are also presented.

This paper is categorized into six sections. Section 2 describes a summary of the role of biomass renewable energy, while Section 3 is the BSC component, sustainability concept, and decision levels in BSC. Section 4 reviews, analyzes, and classifies the literature in detail based on the methods, objectives, limitations, and decision levels. A critical discussion, conclusion, and future direction is shown in Sections 5 and 6.

2. Role of biomass supply chain

Through a BSC process, various activities are involved: cultivating, harvesting, preprocessing, transporting, handling, and storing. Some particular activities involved in this process need a variety of resources [14]:

- Harvesting is typically done during a limited time at places that are committed to biomass production by means of some machines (e.g., combine harvesters). Generally, 10–20% of biomass loss is expected in this procedure.
- Storage appropriately brings into line the generation plans of the conversion facilities with the certain calendar of biomass generation. The storing procedure can be performed simply in the forest or field, within some particular centered stores, on the farm, or within the conversion plants, prior to activities.
- Preprocessing refers to useful activities done to handle (baling, pelletization) and enhance preservation (drying) [15]. The simplest procedures of baling can be performed on the field. After that, compressions and other transformation operations can be performed by means of some heavier tools and/or devoted sites.

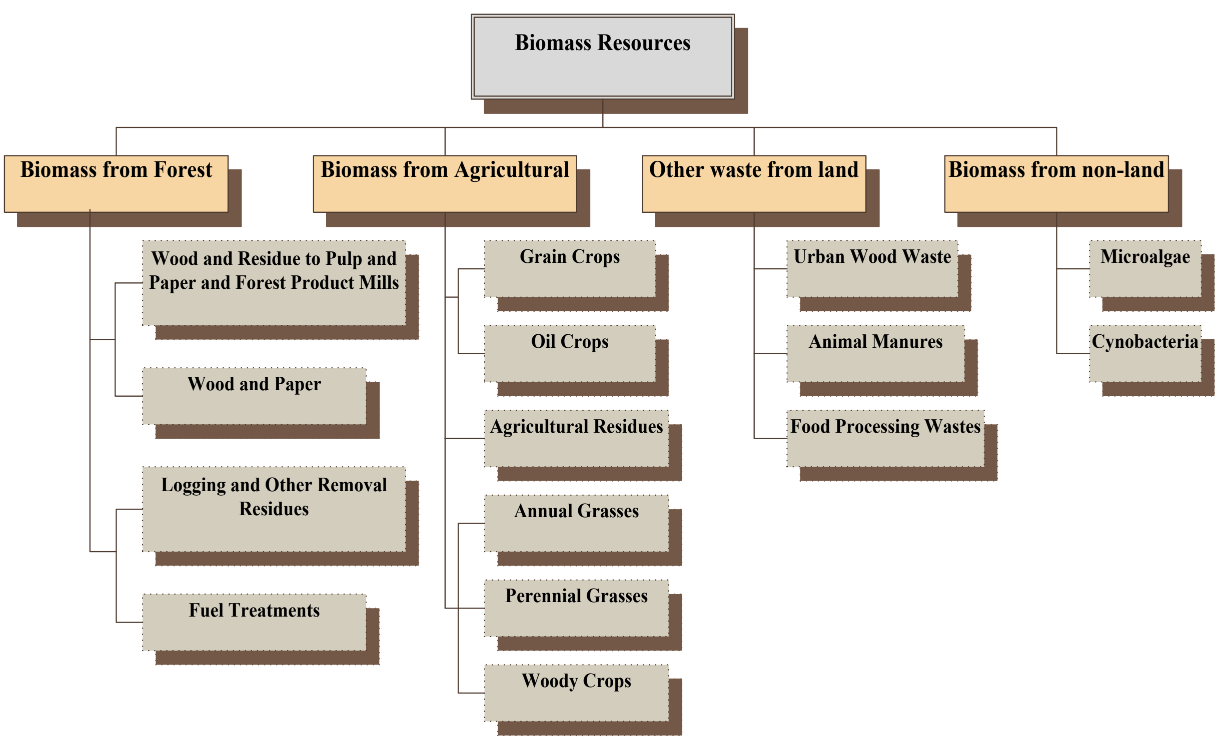

Fig. 1. Biomass resources categories [5].

- Transportation operations like industrial logistics and a variety of other transportation methods are selectable. Normally, there is a limitation on the fleet of vehicles as well as the number of travels possible per period considering the range of the vehicle and the general regulations regarding the driving time. This is worth noting that transportation through the roads is typically the single way the production sites with limited accessibility have, and trucks are popular for these procedures because they can load and handle in a large amount. A typical BSC network is depicted in Fig. 2.

These chains need to be designed in a way to diminish the complexities, and to this end, it is required proper modeling tools. By considering the total costs into consideration, practitioners need to determine the chain dynamics and decision variables regarding the issues like the amount harvested (to exactly determine which crop, when, where, and how much), the network flow (the transported values), the safety level of storage, and the vital resources (equipment, works, means of transportation, and energy).

2.1. Sustainable biomass supply chain

Sustainability satisfies energy requirements of the current world in terms of environmental, economic, and life-quality applications without thinking about the capability of the future generations in meeting such requirements of energy for themselves [16]. Alonso-Ayuso et al. [17] and Levis and Papageorgiou [18] maintain that the assessment of the factual potentials of sustainability requires trading, producing, and the finally converting the biofuel. Sustainability needs to be evaluated exactly considering the concepts of environmental and socio-economic policies and regulations [19].

2.1.1. Environmental

Environmental concern have become an important issue for environmentalists and industrial sectors as well as have a considerable impact on the all parts of the society [20]. Environmental considerations generally outline the regulations established in order to decrease the volume of GHG emissions and protect the agricultural forests from getting degraded [21]. When the environmental sustainability is the topic, the most important issues are discussed include the GHG emissions, degradation of soil, loss of biodiversity, and water resources quality.

The GHG, as atmospheric gases, take in radiation. Biofuels have less emission rate and burn cleaner in comparison with gasoline. Compared to other fuel additives, biofuel can be entirely biodegraded. Cellulosic ethanol is capable of minimizing the emission of greenhouse gases by roughly 86% [22]. The achievement of low or zero GHG emissions, an optimized water-energy nexus, and a well-protected environment are issues that have become increasingly significant for the biomass industry [23]. Efficient use of resources and mitigation of emissions have been emphasized in adaptation policy of global supply chain management but has rarely been considered in BSC policy mechanisms [24]. For example,

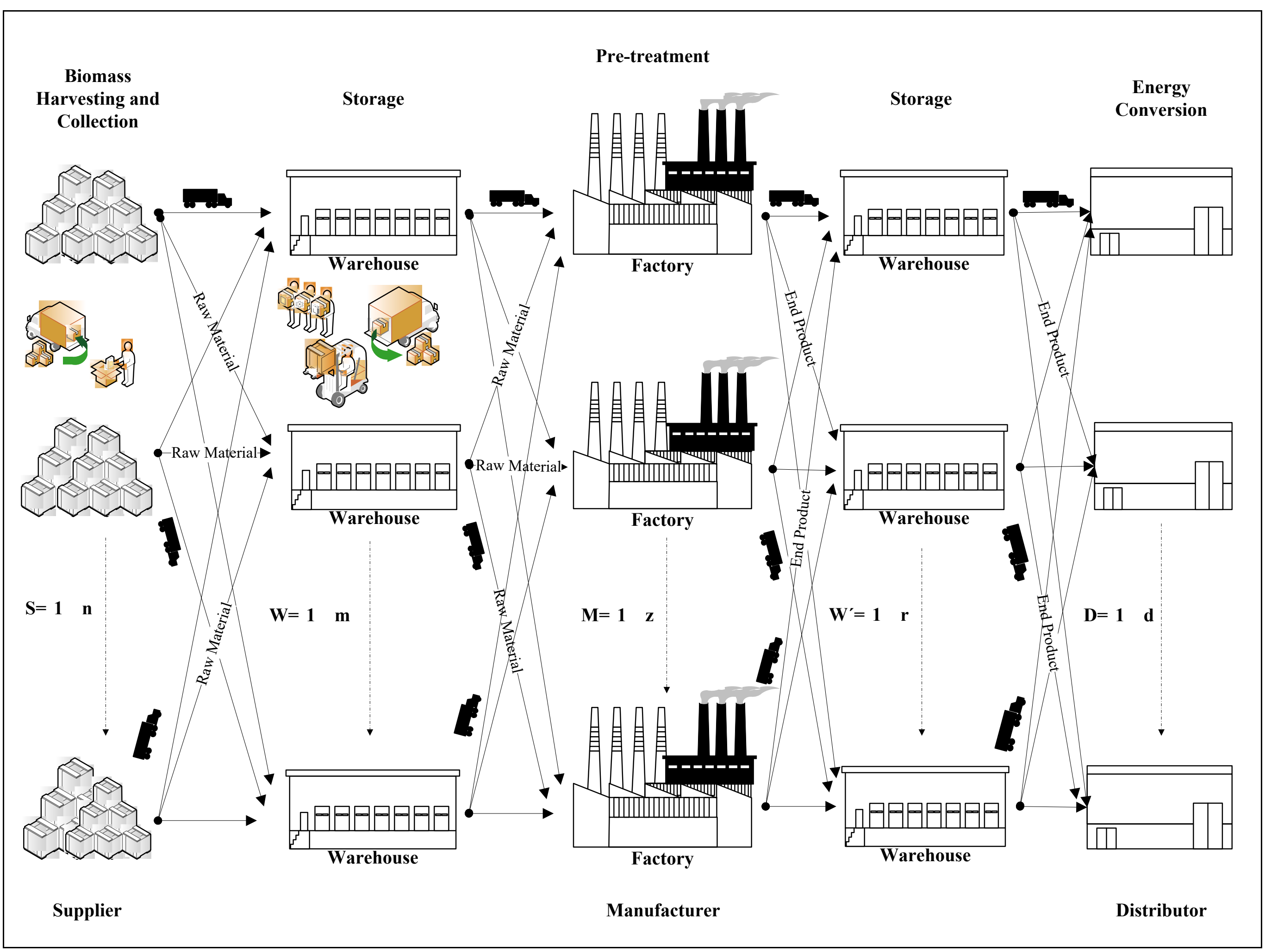

Fig. 2. Biomass supply chain network [5].

as demands are rising for energy crops, it increases the price of crops. This encourages farmers to increase their crop yields, which in turn have impacts on the lands set for protection of habitat and control of erosions [22]. A number of natural phenomena and artificial actions through washing over the land surface cause the degradation of soil and its erosion. Without proper regulation and policy, this problem can lead to negative environmental impact.

2.1.2. Economic

Economically, the biofuel concept outlines the following issues (but not necessarily limited to them): (1) the debate over food versus fuel, (2) efficiency and balance of energy, and (3) growth of financial budget for biofuel programs [19]. The first item is connected to lots of biofuel raw materials, e.g., sugarcane, soybeans, and corn, which are the key source of food that is converted for energy. The production of crops for bioenergy applications might replace the crops produced for food. It decreases the accessibility of foodstuffs, including plant-based and animal-based foods and, at the same time, augments the costs [25]. This well justifies the examination of cellulosic grass, switch grass, miscanthus, and algae as the second, third, and fourth generation biofuel raw materials in this research. Such feedstocks cannot make a competition with food; however, they may enhance higher conversion levels and cheap cultivating costs.

The famers' economic activities can be enhanced through giving higher budget to programs related to biofuels. Such objectives can be achieved through cultivating raw materials, altering lands for different commodity harvesting, acquiring new lands, and enhancing income from investors [26].

2.1.3. Social

In the social sustainability area of study, the key issues involve: (1) the increase of the poverty potential, (2) indirect influence of crop and land, and (3) impacts upon social sources like the water systems. Biofuel can be further developed within rural areas in which there is higher opportunity for agricultural activities. In general, small-scale, subsistence, and underprivileged farmers occupy such areas. Biofuels can have a great effect on decreasing the poverty rate through augmenting the income and enhancing the economic situations by provision of energy [27]. Through the distribution of such wealth, the development of biofuel is capable of helping to effectively enhance the life quality of individuals living there and establish a reasonable equity among people.

2.2. Decision levels in biomass supply chain

The decision in BSC is the same as production management and industrial logistics, which can be categorized into three levels that are based on the time horizon discussed in the following sections:

2.2.1. Strategic decisions

Strategic level of decisions involves those decisions made for long-term period regarding a key financial investment. Firms used strategic decisions for over a year at the very least, like constructing a new factory or designing of a novel airplane [28]. When bioenergy is to be developed, these decisions encompass the selection of biomass type, the size and position of preprocessing plants and conversion equipment, the means for transporting, and making a long-term contract for supply. Since there may not be enough historical data available or accessible, the strategic decisions are usually made according to the aggregated information. In majority of the studies, researchers take into consideration a single-time period [28]; though, it may be sometimes helpful to take into account multi-period horizons to model the demand fluctuations in long-term, e.g., five periods of three years [29].

2.2.2. Tactical decisions

The tactical level of decisions that account for medium-term ones encompass a multi-period planning horizon over a range of a few months. In the industrial contexts, the decisions in relation to the plan of production (for example, finding the quantity of the products generated in each period of time) are made under aggregate resource restrictions. In a BSC setting, the tactical decisions are made about the number of means of transportation that are needed to be bought (fleet size), the harvesting rate in each period of time on each piece of land, and the safety stock level. It is worth mentioning that the time period applied might be varying from one day [30] to one month [31].

2.2.3. Operational decisions

Operational level of decisions is made generally for a short-term period. These decisions involve the detailed operations obtained through decomposing the tactical decisions mentioned earlier. For instance, the planning of industry production determines the arrangement and starting points of the production operations. Two important decision components in the BSC are: details about the route of vehicles and the right time for doing the harvesting activity. To determine whether a decision is tactical or operational, one needs to check if the starting time and/or the exact arrangement of activities have been specified. If it is specified, then it is considered as an operational decision. Most of the scholars in this field of study have focused on the strategic and tactical decision levels. Nevertheless, few researches carried out on BSCs have focused on the operational levels, for example, planning the activities of a truck [32] or a detailed plan of harvesting [33]. Indeed, the most important goal is to specify appropriate tools to be used by decision makers in assessing and modeling a BSC for their performance. Fig. 3 shows schematic view of decisions in each level for a BSC.

3. Methodology

To reach the objectives of this paper, a literature review of relevant investigations in the area of BSC was undertaken. A general internet search as well as the following key databases were used to source investigations for the review. Boolean searches of databases (ISI Web of Science, Scopus, Google Scholar) were conducted to obtain literatures from those electronic databases. The key words used for search were "biomass supply chain", "biomass", "biomass optimization", "biomass supply chain and optimization" in the available titles, abstracts, or keywords. There was not restriction on the geographical places or year of relevant literature was selected. Only publications in English are considered in this review as they are widely accessible to the researchers. The search resulted in a total of 300 papers, which are taken into consideration in the present research. The selection of a paper for review was based on whether the paper developed or examined quantitative assessments/methods by considering the performance indicators and optimization criterion that are relevant to BSC. The quantitative assessments/methods included, for example; the presence of static, simulation and mathematical models.

4. Literature review

It was found that numerous studies apply optimization techniques to manage BSC from different viewpoints such as operational, tactical, and strategic. Majority of the studies have been carried out based on mathematical programming, and relatively few studies have made use of simulation and heuristics approaches. In this section, major researches in the past that considered static approaches, mathematical programming, simulation, and multi-criteria decision analysis of BSC are systematically examined. Particularly, we will focus our discussions on the novelty in BSC optimization, consideration of different supply chains designs and promising modeling approaches.

4.1. Static analysis and modeling in the biomass supply chain

The main goal of the strategic decision of BSC is to design a logistic

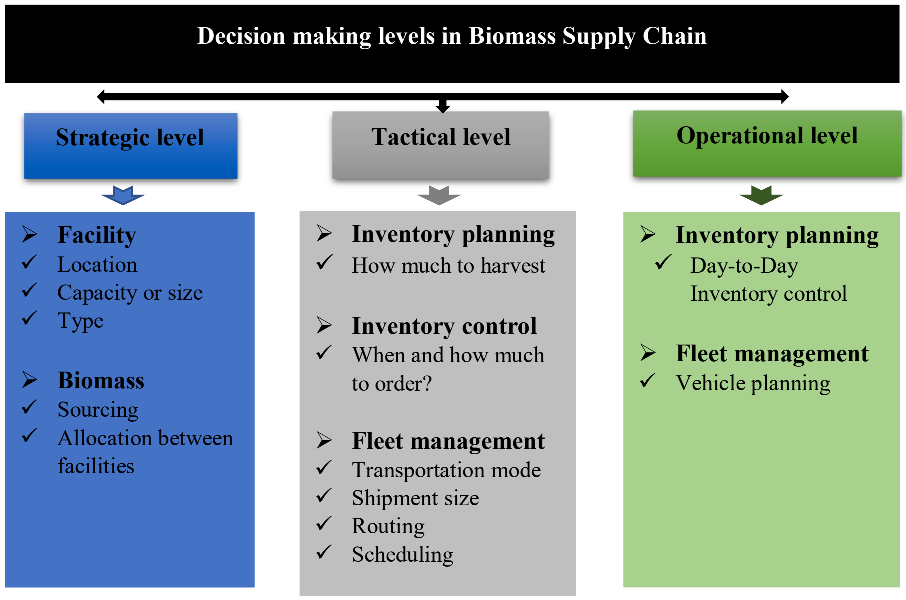

Fig. 3. Decision-making levels in BSC (Source: adapted and modified from Refs. [34]).

network to minimize the total cost related to facilities, transportation, harvesting, and collection. Some methods have been used to decrease the total cost of BSC, including the spreadsheet, which is one of the easiest and foremost method applied to evaluate logistic costs and biomass delivery. The cost of using biomass for bioenergy production has been estimated by Clegg and Noble [8], Brundin [35], Floden [36], Mitchell [37], Allen et al. [38], and Sokhansanj and Turhollow [39]. They developed the statistical spreadsheet models as Decision Support System (DSS) with different ingredients such as database, user interface, as well as a component that assesses the information and results screen. In this model, the harvesting, storage, and transportation as logistic activities are explained as equations and connected with the programming codes. Following that, the different logistic alternatives are evaluated by considering the "what if" type equation.

A Geographic Information System (GIS)-based model called 'Biomass Resource Assessment Version One (BRAVO)' was created as a DSS by Noon and Daly [40]. It evaluates the availability of woody biomass involving short rotation woody crops, mill residues, and logging residues, as well as calculates the biomass delivery cost to coal-fired plants in the Valley Authority area. The digital map of the states and countries' boundaries, plant locations, and road networks are considered as the information input in the BRAVO system. Moreover, GIS has been frequently used for the assessment of BSC, the collection site selection, and related costs like transportation cost. According to researches, the GIS-based modeling is a useful and independent analytical method for DSS on storing, showing geospatial data, managing, and supplying important spatial patterns [40]. This approach is applied to evaluate resource allocation and calculate logistic costs.

Graham et al. [41] used the BRAVO to identify bioenergy plant locations. They calculated the transport cost and farm-gate cost for selected locations and the location with the lowest total biomass cost is chosen as the optimum location. The BRAVO model was applied by Graham et al. [42] to 21 locations in the state of Tennessee to study biomass demand and farmer participation rate effect on delivery costs. In 2001, the GIS-based decision supporting method was suggested by Voivontas et al. [43] to determine the geographic region of exploited waste biomass that were useful for power production. To optimize the installation of biomass energy system based on the production of an optimal energy at minimum cost, a methodology was proposed by Dornburg and Faaij [44] that analyzed different biomass energy systems. It considered energetic and economic performances as a function of scale relevant to initial fossil energy-saving. Based on the main results, biomass costs, income (rent and lifetime), transport costs, investment costs, electricity prices, and heat distribution costs posed a significant effect on the cost of energy saved. Decision support system was developed by Ramachandra et al. [45] to evaluate regional biomass, as well as to conduct land analysis using GIS. They developed the DSS system for the evaluation of biomass energy potential that considered the available resources and demand. Their system was comprised of the graphic user interface that applied the Visual Basic and Access database. This system helped develop operational information and reporting tools to record data of resources and deliver the information of daily activities. Therefore, it not only saved time, but also evaluated the effect of different alternatives and assesses the benefits and cost of decisions to be made.

Zhan et al. [46] used the GIS-based DSS to study the economic feasibility of locating a switch grass-to-ethanol conversion facility in Alabama. They evaluated two methods: the fixed and the discriminatory of pricing procurement based on the delivered cost surfaces to make the location decision under several facility size alternatives. The result showed that the discriminatory method of pricing procurement had more cost advantage compared to the fixing method. Papadopoulos and Katsigiannis [47] proposed a general computer program as a flexible computational approach for biomass energy. In this research, they studied a wide geographical area to determine the proper site location for electric power and heat generation using a combined system in the northeastern parts of the Eastern Macedonia-Thrace Region of Greece. They claimed that it was suitable to install the profitably CHP units by using solid biomass as fuel, as it helped decrease GHG. In addition, it caused positive development in both the local and national economies.

The potential of manure for clean energy generation and related resource mapping was investigated by Batzias et al. [48], Dagnall et al. [49], and Ma et al. [50]. A methodology was suggested by Panichelli and Gnansounou [51] using the GIS-based method along with the biomass allocation algorithm to choose the appropriate location of energy facilities. In 2007, an investigation was conducted by interviewing supervisors of related local authorities and data about the available agricultural residues and animal waste in Greece was collected [52]. Another study was done by Singh et al. [53] to estimate especial potential through agricultural biomass and develop a mathematical model for collection of biomass using GIS in an Indian state. For multi-biomass energy conversion applications, DDS was developed by Rentizelas et al.

[2] to optimize the net present value of investment at the municipality of Thessaly. This approach attempted to identify the best location to set up biomass facilities and determine the optimum base load of generated heat and power. It was also used to find the location of biomass-type parameters in a particular place. Kinoshita et al. [54] conducted an investigation on forest biomass using the GIS for city of Yusuhara in Japan. They used the wide application of woody biomass energy by developing a cost model to determine a cost-effective harvesting approach. Harvesting costs are mainly estimated by geographical parameters and are higher for more distant stands. Based on the result, they were able to determine that the stands with the lower operational cost by considering the total demand in a selected region.

A heuristic method was introduced by Brownell and Liu [55] to calculate the number and size of satellite storage locations. The supply area, location, and bioenergy plant size were used as the input data. The model then attempted to identify a more optimal scenario that has the lowest field, satellite, and transportation costs by changing the size and number of locations of satellite storage. In their model, three different plant sizes were considered: small (2000 tons/day), medium (5000 tons/day), and large (10,000 tons/day). Based on their results, they required 25, 64, and 105 satellite storage sites respectively. The focus of this study was on satellite storage. Therefore, the at-plant storage was not considered and only the handling system was modeled. Another raster-based model was created to estimate the potential production of switch grass and determine the satellite storage location near Gretna and Keysville, Virginia [56]. It was found that the switch grasses in both areas could be raised in a mass scale to feed commercial-scale bioenergy plants [56]. Several criteria were assessed to determine satellite storage location. The first criterion was that the switch grass bales can be gathered from the chosen surrounding lands within a 3.2 km radius around the storage. Apart from evaluating the direct road access for the ease of transporting the switch grass from the satellite storage locations to the conversion facilities, they also considered the minimum 40 ha of switch grass production available within a 3.2 km radius, as well as the level land areas with average slopes of less than 10% [56]. Shi et al. [57] suggested constructing a new biomass power plants in supply area located in Guangdong, China using the GIS modeling techniques to find their optimum design in a supply chain. A recursive Data Envelopment Analysis (DEA) model was proposed by Grigoroudis et al. [58] to determine a facility location based on the maximum efficiency and minimum cost. In the last recent work, GIS tools were used to determine potential bioenergy areas as well as to optimize biomass transportation, and help to find power plant sizing when available bioenergy plant candidates have not been determined in advance [59]. Table 1 shows a summary of the studies done on BSC design using static methods.

The static methods play a fundamental role in comprehending the BSC easily by considering the total delivery cost and quantity of produced biomass. However, based on the continuous changes in the supply chain design, and the dynamic behavior of supply chain, this method has deficiencies when it comes to evaluating the behavior of BSC comprehensively. Therefore, results obtained from the static approach may not be reliable, and therefore it is necessary to develop new approaches to consider this constraint and time dependencies in the BSC network.

Table 1
A summary of investigations on biomass supply chain design using static methods.

Author	Solution method	Objective of study	Limitations of study	Decision levels Strategic/ Tactical/ Operational
Mitchell [37]	Spreadsheet	to estimate cost of logistic, delivery and collection	• Feedstock options • Conversion processes and outputs	
Noon and Daly [40]	GIS	to Investigate availability of woody biomass, biomass delivery cost	• Modes of transport for wood • Logging residue volumes by costs at all the nine plants	
Voivontas et al. [43]	GIS-based decision supporting method	to determine the geographic distribution of exploited waste biomass	• Biomass residue is uniformly spread over the entire area of the geographic object	
Ramachandra et al. [45]	DSS	to evaluate regional biomass as well as to conduct land analysis using GIS	• Local constraints	
Zhan et al. [46]	GIS	to investigate the economic factors for evaluating the feasibility and sustainability of locating conversion facilities of switchgrass	• Speed limit	
Panichelli and Gnansounou [51]	GIS-based method combined with biomass allocation algorithm	to choose appropriate location of energy facilities	• Administrative limits	
Kinoshita et al. [54]	GIS	to develop a cost model to determine cost-effective harvesting approach	• Thinning timber from the second cycle onward is all used for energy	
Perpiñá et al. [60]	GIS	to define a procedure for determining an optimal use of agricultural and forest residue biomass	• Environment and social constraints – generating influence areas (buffer)	
Brownell and Liu [55]	Satellite Storage Locations model	to find the optimal scenario which has the lowest filed, satellite and transportation cost	• Legal loading limits	
Resop et al. [56]	Raster-based model	to determine the satellite storage location	• Bioenergy plant limits	
Delivand et al. [61]	GIS along with Multi-Criteria Analysis (GIS-MCA)	to assess the logistics of biomass-to-electricity in the Southern Italy	• Number of geophysical environmental and cultural heritage	
Shen How and Lam [62]	Principal Component Analysis (PCA)/Analytical Hierarchy Process (AHP)	to solve the multi-echelon biomass supply chain problem with the consideration of economic, environmental, and social dimensions	• Hub determination • Delivery time and safety • Vehicle capacity	
How et al. [63]	Debottlenecking Approach/ Analytical Hierarchy Process (AHP)	to identify and subsequently remove the underlying bottlenecks	• Some other Important sustainability indicators should be considered in future extension of the proposed method	
Furubayashi and Nakata [64]	GIS	to estimate the costs and CO_2 emissions of wood biomass co-firing	• Resource generation point • Potential and availability of each resource	
Laasasenaho et al. [59]	GIS	to develop a model to investigate optimal locations for two different types of bioenergy plants, for farm and centralized biogas plants, and for wood terminals	• Existence and availability of required data	

4.2. Simulation modeling in the biomass supply chain

Simulation, as confirmed in literature, is an effective and compressive method that is highly capable and flexible in evaluation of complex dynamic systems concerning the uncertainties and variabilities that exist in systems [65]. Simulation tools have been offered in four different types: discrete-event simulation, system dynamics, business games, and spreadsheet simulation [66]. Simulation modeling is one of the most suitable methods because of its flexibility and capability in simulating and assessing dynamic and static systems in terms of variability and uncertainty between systems—like manufacturing lines [67,68], ports and maritime industry [69,70], healthcare systems [71], supply chains [72], construction sector [73] and building industry [74]. The discrete-event simulation is the best tool for simulating the intricate stochastic systems [65,75]. This type of simulation has been extensively employed by different researchers for the aim of modeling and assessing BSC; such popularity in this context is due to its time-dependency and stochasticity of BSC [75]. In the BSC context, a key approach is simulation. It helps in modeling the BSC logistics and in calculating how much biomass is needed to deliver to a bioenergy plant and how costly it will be in the end. At first, simulation modeling was used for the aim of scheduling the activities done in farm, including the selection of forage machinery on dairy farms [76], evaluating the management practices or technologies in forage systems on a dairy farm [77], planning the labors and providing required equipment in harvesting wheat [78], and scheduling the equipment of hay-harvesting [79]. Benock et al. [80] created the General Activity Simulation Program (GASP) IV-based simulation model for the purpose of the assessment of corn drying, harvesting, and transportation.

In another study, Mantovani and Gibson [81] developed a simulation model of biomass logistic written in the simulation language of GASP IV. Its objective was the evaluation of the impacts of nonconformity of weather and late harvest upon biomass obtainability and equipment costs. They also examined the historical weather information and the changes occurring to the farmers' attitudes regarding harvesting biomass. In addition, a comparison was made among the harvesting and managing systems for hay, corn stover, and wood residues used to produce ethanol. The obtained results were developed for a plant in the area of central Indiana generating a total of twenty million liters of liquid fuel per year.

Gallis [82] made use of a computational stochastic for the aim of obtaining an optimized use of forest biomass. The Straw HAndling Model (SHAM) has been recognized in fact as an efficient simulation model that is able to design a biomass delivery system [83]. SHAM can be used as a dynamic simulation approach for the analysis of different transportation scenarios only for straw. Interestingly, in Sweden, straw has been acknowledged as a key source of renewable energy. As a result, in this country, SHAM is employed aiming for the analysis of agricultural fields. It is worth noting that the delivering biomass costs depend on factors like heating plants, transportation between the storage points, size of the field, and straw yield; as a result, the SHAM model can be employed for the purpose of evaluating the effects of biological, climatic, and geographical parameters upon the costs of biomass delivery [84,85]. The obtained results revealed that harvesting is extremely dependent upon geographical and climatic conditions. Furthermore, managing strategies like the selection of storage site, the harvest season extension, and the use of optimized number of balers and transportation are greatly effective on reducing the costs.

Later, Nilsson and Hansson et al. [86] made use of SHAM for the purpose of combining a novel type of crop recognized as the Red Canary Grass (RCG). They examined the use of RCG as raw material in the area of heating facilities, and its oil and straw. Findings indicated roughly 15–20% reduction in the total cost of delivery process in cases where a combination of RCG and straw was used in suitable proportions rather than the use of straw only. RCG is a costly feedstock (exceeding three times the cost of straw); although, its consumption has been proved more cost effective. Such cost effectiveness is because of the better utilization of required machines and storage space in addition to less use of oil as the first fuel. In the Hansen et al.'s [87] study, another simulation model was suggested to investigate mill delivery systems and the sugar harvest in South Africa. In addition, Huisman [88] proposed a simulation model capable of determining the minimum cost of BSC through the selection of the well optimized harvesting and storage systems in case of each energy crop. Though, the present paper is not going to explain a detailed information regarding the simulation models helping in identification process of the best supply chain. Rather, it discusses only the simulation model framework.

Arinze et al. [89] and Sokhansanj et al. [90] carried out simulation studies into other agricultural productions like corn grain. In their research, the simulation modeling was used aiming at investigating the changes that occur to quality of potash fertilizer and alfalfa cubes in the course of storing and transporting these crops. On the other hand, a simulation model termed Integrated Biomass Supply Analysis and Logistics (IBSAL) was created by Sokhansanj et al. [91]. It was developed to show different steps towards collecting, storing, processing, and transporting the biomass. Their proposed model was used for the analysis of the supply logistic system in case of various crop residues like cereal straw, corn Stover, and some types of grass, e.g., the switch grass. The SHAM model was applied to this case for the purpose of analyzing the logistics systems of cereal straw. It was also used to estimate the variety of outputs that were involved in cost of logistic operations, the quantity of biomass that was transported to conversion locations, the volume of carbon emission, and the period of time needed to finish each activity. In recent study, simulation-based Multi-Objective Optimization (IBSAL-SimMOpt) was proposed to assess the BSC costs associated with harvesting, transportation, and storage by considering the stochastic behavior of whole BSC. The model was tested on 1916 farms in Ontario, Canada. Results showed that this approach is efficient to determine a feasible non-dominated solutions [92]. According to a number of researchers, e.g., Sokhansanj and Fenton [93], Sokhansanj et al. [94], Sokhansanj et al. [95], Sokhansanj and Hess [96], Sokhansanj et al. [15], Stephen [97], and Stephen et al. [98], IBSAL has the required capacity to be used in case of various types of biomass and logistic options. In another project, the discrete-event simulation model was created and applied by Ravula et al. [99] to delivery system of cotton gin aiming for scheduling trucks working in the logistic system of biomass.

A simulation model was provided by Hess et al. [100], the Idaho National Laboratory (INL), and US Department of Energy (DOE) for the purpose of predicting the cost of herbaceous lignocellulosic BSC in case of the biofuel generation. The model proposed by them involved 800, 000 tons of plant size per year in addition to raw material supply radius of 80 km for Stover and 105 km for switch grass. The model considered three accessible types of lignocellulosic biomass, namely switch grass, corncob, and corn Stover. Furthermore, their supply systems comprised three feedstocks: old bale, pioneer, and advanced uniform. Initially, the systems were different in terms of the site of pre-treatment activities within the supply chain. As shown by their findings, the target cost of \$34.7 dt-1 for DOE was not obtained by supply system of pioneer uniform and old bale. It was due to that fact that the average cost of transportation and logistics (\$/dt-1) for corncob, switch grass, and stover was \$68.9, \$49.6, and \$55.4, respectively. After that, a sensitivity analysis was carried out to demonstrate the fact that enhancement in biomass properties and effectiveness of equipment can lead to a cost-effective supply chain system of bale stover [100].

Remember that the models mentioned above, including SHAM and IBSAL, have provided no plan satisfying daily demands in this context. In addition, a constant value is assumed as the distance between the distribution of farms. The simulation modeling discussed above has been also used in determining the place of satellite storage facilities in BSC. Simulation modeling was used by Cundiff et al. [101] for the purpose of finding the delivery distance between the production sites and the satellite storage. It was also used to determine the number of satellite warehouse places within the supply chain. Zhang et al. [102] developed a simulation model using Arena software for the aim of examining the woody residue supply chain. Their model comprised of the basic BSC activities like harvesting/processing, storage, and transporting the crops. For the assessment of the model, some performance measurements were taken into account, including the GHG emission volume, delivery feedstock cost, and the amount of energy consumed throughout the process. In another study discrete-event simulations were used in order to predict the work time cost for two forest BSC in Finland and Germany [103]. Through the use of SIMEVENTS [104],

Table 2
A summary of investigations on biomass supply chain design using simulation modeling.

Author	Solution method	Objective of study	Limitations of study	Decision levels Strategic/ Tactical/ Operational
Benock et al. [80]	GASP IV-based simulation model	to evaluate drying, harvesting and transportation of corn	• No allowance for stochastic occurrences, and field geometry is not a major consideration	
Humphrey and Chu [109]	Discrete-event simulation combined with search algorithm	to analyze the facility performance of corn-processing facility	• Assumptions were discussed with personnel in knowledgeable positions	
Mantovani and Gibson [81]	GASP IV-based simulation model	to assess the impact of late harvest and weather digression on feedstock availability and equipment cost	• Just three harvest systems were analyzed • Limited field working days	
Nilsson [83]	SHAM	to develop an efficient biomass transportation system	• The intensity of rainfall affects was not possible to consider in this project	
Nilsson [84] Nilsson [85]	SHAM	to evaluate the effect of climatic, geographical, and biological factors on the biomass transportation cost	• Useful for old harvesting systems considering the high-density bales	
Hansen et al. [87]	Simulation model	to analyze the sugar harvest and mill transportation system in South Africa	• 40 h was regarded as a reasonable delay estimate • Effects of mill breakdowns	
Huisman [88]	Simulation model	to find the minimum cost of BSC by selecting the best harvesting method and storage system for each energy crop	• Only useful for local conditions • Variation of the weather changes between years for a long period	
Sokhansanj et al. [91]	(IBSAL)	to design different activities of biomass collection, storage, processing, and delivery mode	• Volume remains unchanged at different moisture contents	
Ravula et al. [99]	Discrete-event simulation model	to analyze trucks scheduling in biomass logistic system	• Maximum number of modules truck operating time	
Hess et al. [100]	Uniform-Format Solid System	to estimate the cost of herbaceous lignocellulosic BSC for biofuel production	• Existing harvesting and collection equipment and incorporation of biomass depots	
Cundiff et al. [101]	Satellite Storage Locations (SSL)	to determine the location of satellite storage sites in the BSC	• Typical method used for in-field hauling	
Zhang et al. [102]	Discrete-event simulation method: Arena software	to analyze the study the delivery raw material cost, GHG emissions, and energy consumptions of woody residues supply chain	• Road restrictions: limited use of truck transportation on certain roads	
Windisch et al. [103]	Discrete event simulation	to calculate worktime expenditure for organizational and managerial tasks of BSC	• The results cannot be directly generalized	
Pinho et al. [104]	Dynamic simulation (SIMEVENTS)	to assess the biomass supply chain behavior in a case study located in Finland	• Problem with a dimension of six clients and four wood piles	
Prinz et al. [105]	Discrete-event simulation method: Witness software	to investigate the effect of chipper and transportation types on the cost and energy efficiency of BSC	• Material delivered by the trucks was limited to forest chips from logging residues and small-diameter trees as bulk	
Kim et al. [110]	Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC)/ agent-based simulation (ABS): AnyLogic	To determine the optimal locations of biomass storage facilities	• Potential yield	
Munasinghe et al. [106]	Life Cycle Analysis (LCA)	To analyze the socio-economic of small holder farmers in BSC	• Omits carbon emissions and energy consumption associated with land use change, land preparation or carbon sequestration from palm trees, due to data and time limitations.	
Lozano-Moreno and Maréchal [111]	Dynamic modeling/Biomass Logistics and Environmental impact Model (BLEM)	to investigate the supply of sugarcane to mills and the supply of green harvesting residues to second-generation ethanol plants under three different strategies	• Weather conditions	
Akhtari et al. [112]	AnyLogic simulation modeling	to compare demand fulfilment, cost, and emission of a forest BSC for two inventory systems	• Duration and cost of transporting harvesters and grinders between cut blocks were ignored	
Zahraee et al. [5]	AnyLogic simulation modeling	to evaluate the impact of changing the efficiency of transportation and production technology on the environmental sustainability of the palm oil BSC in Malaysia	• Number of suppliers	
Zahraee et al. [107]	Discrete-event simulation method: Arena software	to analyze the transportation mode, labors, and cost of EFB BSC in Perak sate of Malaysia	• Transportation mode	
Zahraee et al. [23]	AnyLogic simulation modeling/ Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model	to develop a combined life cycle and dynamic simulation model to investigate water-energy nexus under uncertainties, as well as estimation of GHG and particulate matter emissions of the BSC in Malaysia	• Number of suppliers	

which is a computing platform, this work offered modeling of an ordinary biomass production chain. In the latest work, the researchers developed a discrete-event simulation model for the purpose of assessing the way the transportation types and the novel chipper with increased delivery capacity exert impact on energy efficiency level and cost of the forest chip supply chain [105]. An evidenced-based analysis was carried out by Munasinghe et al. [106] on sustainability of the crude palm oil supply chain in Brazil. Zahraee et al. [107] developed a computer simulation model using Arena software from current situation of empty fruit bunches (EFB) BSC in Perak state of Malaysia. Sixteen potential palm oil suppliers had been assessed in terms of oil capacity, oil production, and distance between the suppliers and nearest power plants. This case study was analyzed by defining two scenarios focused on increasing the number of trucks (economic factor) and decreasing the number of labours (social factor). Results showed that output was decreased from 4.59 to 4.336 ton/ha by decreasing the labours (First scenario). Meanwhile, cycle time, value added (VA) time, and other time were increased near 15%, 25%, and 15% respectively. Second scenario claimed that output of the process was enhanced by 23% (from 4.59 to 6.02 ton/ha) by adding two trucks. Additionally, time cycle of all activities was increased from 7.2 to 8.95 h due to an increase in VA and Other time by 34% and 23% respectively. Zahraee et al. [5] constructed a dynamic simulation model to evaluate the impact of the change to the efficiency level of the transportation and production technology upon the environmental sustainability of the BSC in the case of palm oil during a period of 50 years (from 2000 to 2050). The study focused on three palm biomass suppliers in three different states of Malaysia. Findings confirmed that the highest level of total GHG emissions was from the supplier in Perak. The largest components emissions were from Johor and Perak suppliers' EFB transport processes, which emitted 180–240 megatonnes (Mt) CO_2 eq and 375–400 Mt CO_2 eq, respectively. Regarding production, the Perak supplier showed the highest (and near-constant) GHG emissions of up to 160 mt CO_2 eq, while the Pahang supplier was found to emit the lowest volume of GHG.

Review of the related literature indicates that the simulation modeling can be implemented as an efficient method to the assessment of supply chain through testing various potential conditions. On the other hand, simulation modeling is not applicable to optimization purposes. In addition, such models cannot be effectively applied to complicated systems that involve objective functions with no data uncertainties, many interacting processes, acknowledged analytical expressions, and stochastic phenomena. Consequently, mathematical methods can be used as efficient tools to mark optimum alternatives out of multiple possible scenarios in regard to criteria concerning the biomass inventory, size of amenities, location, and delivered biomass [108]. A number of key studies carried out on the evaluation of the BSC design by means of simulation modeling are presented in Table 2 briefly.

4.3. Mathematical programming in the biomass supply chain

In a mathematical programming techniques three factors of objective function, decision variables, and constraints are involved, which are taken into consideration for the purpose of achieving an optimized value for the decision variables and objective function and, at the same time, meeting all existing limitations [113]. Considering the above-mentioned factors, the mathematical programming models offered by the investigations chosen to involve linear programming (LP), nonlinear programming (NLP), mixed integer linear programming (MILP), and mixed integer nonlinear programming (MILNP) models. In the following, each section discusses some promising studies conducted in 2010-present. Please note that in Table 3, there is a summary of studies carried out in a period of 40 years, between 1980 and June 2020 considering the key issues of uncertainties, sustainability, approaches, limitations, decision levels, objective functions, and geographic regions.

4.3.1. Linear programming

LP is one of the mathematical programming approaches in which both objective function as well as limitations are in a linear condition. A model was developed by Ren et al. [114] to design sustainable BSC, in which numerous biomass feedstocks, patterns and modes of transportation, technologies of production, and disposal methods are conceivable. However, this model suffers from a limitation that has negative impacts on the objective function that is mainly aimed to reduce as far as possible the overall ecological footprint. In the process of developing a BSC, a key challenge is uncertainty [22]. In regard to the biomass production level, uncertainty takes place because of the variance that may happen in the climatic conditions during various times of growth and harvest. A multi-period scenario-based linear model of programming was designed by Sharma et al. [115] for the optimization of the design of a BSC when the climatic condition is uncertain.

4.3.2. Nonlinear programming

NLP models, on the other hand, have nonlinear limitations and/or objective functions. Due to either using or not using of integer parameters, the model gets one of either the MINLP kind or nonlinear programming type. Because of the complexity of the real problems, we cannot apply the linear modeling to lots of cases. Accordingly, the nonlinear model's complexity and the linear model's simplicity have motivated scholars to make some developments on the linear ones when addressing various problems. As can be observed in Table 3, the majority of nonlinear models, e.g., Bai et al. [116], Singh et al. [117], Marufuzzaman et al. [118], considered only economic objective function. In contrast, few researchers, e.g., Wang et al. [119], Yue et al. [120], Akgul et al. [121], Gong and You [122], have simultaneously taken into account economic and environmental optimizations. Only the nonlinear model proposed by Čuček et al. [123] has considered all three sustainability pillars, i.e., environmental, economic, and social objectives, at the same time. Investigating the MINLP and NLP models, we can see that two studies that have taken into consideration multiple-time periods [124,125]. A multi-objective possibilistic model was developed by Babazadeh et al. [125] for the purpose of handling uncertainty data for design a second-generation biodiesel SC in terms of risky conditions.

4.3.3. Mixed integer linear programming

The MILP models, parallel to the LP ones, possess linear objective functions and limitations; however, they are different in an issue: in the MILP models, all or at least one number of decision variables are integers. The MILP models are properly applicable to solving problems; in this sense, the presence of integer variables is of a high importance because of the existence of discrete phenomena. According the literature reviewed in this study, MILP is extensively applied to the BSC problems as a modeling technique. A significant reason for the use of the MILP models is making the facility-location decisions since the corresponding binary decision variables are capable of properly modeling the facilities establishment in a variety of capacities. BSC has some effects on the biomass logistics; as a result, decision makers need to identify simultaneously the optimal state of BSC and material flow between the energy plants [126]. Vlachos et al. [126], Bowling et al. [127], and De Meyer et al. [128] have employed the continuous parameters of MILP to display the material flows among the locations. In the above-mentioned models, the optimization is performed on either environmental, economic, or social objectives [128], or in a number of cases, this is performed at the same time, on all environmental, economic, and social aspects [129,130].

The MILP models possessing the cost minimization objective function have been used to different problems, e.g., evaluating the production of electrical energy and heat from biomass at a regional level [131], designing and planning the process of supply chain for the purpose of producing heat out of biomass [132], designing and assessing the waste biomass sustainable supply chains [126], strategically planning the supply chain systems of bioethanol [133], optimally designing the

Table 3
Summary of investigations on biomass supply chain design using Mathematical Programming.

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
Eriksson and Björheden [165]			LP	• Potential of the model for operational planning	✓ Strategic	to find the optimization design of storage and heating plant location.	Sweden
Cundiff et al. [31]	✓ Production level of biomass		LP	• Average travel speed for loaded trucks • Coverage storage sites	✓ Strategic	to design the delivery system of biomass for switchgrass producers	US
Mol et al. [166]			MILP	• Selection of energy plants	✓ Strategic ✓ Tactical	to develop two models to analyze the costs and energy usage of the logistics	Netherland
Nagel [167]			MILP	• Limitation of capacity	✓ Strategic	to find the most economical and ecological supply structure	Germany
Kaylen et al. [168]			NLP	• Annual feedstock availability	✓ Strategic	to evaluate the economic ability of creating ethanol from different lignocellulosic biomass materials	US
Rozakis et al. [169]			MODM	• Local surveys and biological growth	✓ Strategic	to use spatial decision support system particularly designed for the assessment of bio-electricity projects	Greece
Tembo et al. [170]			MILP	• Gasification-fermentation technology • Institutional constraints • Maintenance of the yield of protentional feedstocks	✓ Strategic	to optimize the industry's net present value by finding the most saving source of biomass, inventory management, harvest, and storage scheduling and biorefinery size and location	US
Tatsiopoulos and Tolis [171]			LP	• Biomass price	✓ Strategic	to organize an integrated logistics network and optimize its transportation economy	Greece
Venema and Calamai [172]			Meta-heuristic (GA)	• Biomass supply	✓ Strategic	to shows an optimized design of bioenergy landscape	Numerical example
Gunnarsson et al. [173]			MILP	• Specified total storage capacity	✓ Strategic ✓ Tactical	to deal with the six problems pertinent to raw material of forest fuel supply chain by considering multiple time steps in the model	Sweden
Freppaz et al. [131]			MILP	• Operation time of Plants	✓ Strategic	to evaluate the feasibility of biomass exploitation for both electric energy generation and thermal	Italy
Morrow et al. [174]			LP	• Data limitations of transportation costs	✓ Strategic	to evaluate the economic costs of delivering different ethanol fuel blends to all urban regions in the US	US
Bruglieri and Liberti [175]			MINLP	• Material conservation	✓ Strategic ✓ Tactical	to find of the biomass to produce and/or buy, transportation decisions to deliver the materials to the related plants, and plant design	Numerical example
Mapemba et al. [176]			MILP	• Quantity of biomass harvested per month • Potential feedstock • A specific conversion process was not modeled	✓ Strategic	to estimate the cost to buy, harvest, store, and transport to an energy conversion	US
Dunnett et al. [132]			MILP	• Lack of utility requirement parameters • Assessing biomass processing on a seasonal rather than monthly basis	✓ Strategic ✓ Tactical ✓ Operational	to show a general view of harvesting, densification, drying, storage, and transportation processes	Numerical Example
Dunnett et al. [177]			MILP	• Storage-related issues have been neglected • Constant operational profiles • Dynamic factors applicable to the operational, planning,	✓ Strategic	to study optimal cost of system formation for the technological, biomass supply, system scale, and scenarios of ethanol demand distribution	Europe

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
				and strategic timeframes			
Ayoub et al. [160]			MODM/Meta-heuristic (GA)	• Limited access distances and low-density forests	✓ Strategic	to consider each stakeholder in BSC such as supplier of biomass resources, transportation, conversion, and electricity suppliers	Japan
Mapemba et al. [178]			MILP	• Quantity of feedstock harvested	✓ Strategic	to find how the method of modeling harvest cost affected the estimate of the number of deliver lignocellulosic biomass harvest machines	US
Vlachos et al. [126]			MILP	• Fixed costs of setting up a node at any level • There is no set up cost for the final node	✓ Strategic	to show an optimization model of a generalized BSC for the strategic determination of related flows and its nodes	Greece
Leduc et al. [179]			MILP	• Biomass costing calculator	✓ Strategic	to identify the optimal geographic places and sizes of methanol plants and gas station based on cost minimization	Austria
Tursun et al. [180]			MILP	• Actual sizes of the existing plants • Maximum capacity limit	✓ Strategic	to minimize the cost of total system for processing and transportation of biomass, shipping of ethanol from refineries to the blending location and demand terminals	US
Celli et al. [181]			Meta-heuristic (GA)	• Geographically limited market	✓ Strategic	to analyze availability of biomass, shipping, and power facilities as well as all the territory related limitations	Italy
Izquierdo et al. [182]			Meta-heuristic (PSO)	• Whole forest territory	✓ Strategic	to determine the optimal flows of biomass from sources to energy production location	Italy
López et al. [183]			Meta-heuristic (PSO)	• Electric power generated by the plant	✓ Strategic	to find the best location for biomass-based power plants	Numerical example
Leduc et al. [184]			MILP	• Only the emissions from the transport were considered	✓ Strategic	to estimate the optimum number and geographic locations of biodiesel plants based on cost minimization of supply chain	India
Frombo et al. [185]			LP	• Italian regulations over forest exploitation • Restrictions over the forest biomass collection	✓ Strategic ✓ Tactical	to find optimal logistics for energy production from woody biomass by making plane and management strategies	Italy
Frombo et al. [186]			MILP	• Harvesting forest biomass in each parcel	✓ Strategic	to evaluate the optimal planning of forest biomass for energy production	Italy
Zamboni et al. [141]			MILP (Multi-objective)	• Biomass demand • Biomass production • Local transportation	✓ Strategic	to minimize the operation cost of BSC and environmental effects based on GHG emissions	Italy
Rentizelas et al. [187]			Meta-heuristic (GA)	• Certain technological legislative • Social constraints	✓ Strategic	to assess an investment for supporting an investor in locally existing multi-biomass utilization for tri-generation applications in a given region	Greece
Ekşioğlu et al. [188]			MILP	• Amount of biomass	✓ Strategic ✓ Tactical	to made long, short, and medium decisions related to supply chain and logistic design in terms of biofuel delivery cost minimization	US
Kanzian et al. [189]			LP/GIS	• Fuel wood potential	✓ Strategic	to test and design four various supply scenarios: one for 9 plants and one for 16 plants in Australia	Numerical example
Zamboni et al. [140]			MILP (Multi-objective)/MODM	• GHG emissions	✓ Strategic ✓ Tactical	to assess the process of biofuel supply systems considering the economic effectiveness of the supply	Italy
			MILP	• Selecting optimal	✓ Strategic		Italy

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
Chinese and Meneghetti [190]				Harvesting technologies		to investigate the trade-offs between decentralized early treatment and centralized final treatment of biofuel based on transportation costs	
Wang et al. [155]			MINLP (Multi-objective)/MODM	Production capacity limit	✓ Strategic Tactical	to address the selection of technology, operation situations, flow rate of each stream, energy usage of each part, economic performance, environmental effects, and sizes of equipment	Numerical example
Vera et al. [191]			Meta-heuristic (PSO)	• Technical constraints	✓ Strategic	to find the optimal location, supply area of biomass, and size of power plant	Spain
Leduc et al. [192]			MILP	• No distinction was made between road types or port size	✓ Strategic	to assess the optimal locations for such plants in Sweden by considering energy supply and demand chain from biomass outtake to gas stations filling	Sweden
Huang et al. [133]			MILP	• Refinery will not be shut down once it opens • All transportations are performed by truck	✓ Strategic	to investigate the economic potential and infrastructure needs to produce bioethanol from eight waste biomass areas in California as a case study	US
Van Dyken et al. [193]			MILP	• Moisture reduction • Biomass supply	✓ Strategic	to assess the BSC operational plan regarding transportation, storage, and processing during the 12 weeks	Numerical Example
Akgul et al. [134]			MILP	• Biofuel production rate • Local biomass cultivation rate • Local roads	✓ Strategic ✓ Tactical	to optimize the locations and scales of the bioethanol production plants, flows between areas, as well as the number of transport units needed	Northern Italy
Kim et al. [194]			MILP	• Minimum demand level • Maximum supply level	✓ Strategic ✓ Tactical	to evaluate 1) which factors have main impacts on the total economics, and 2) advantages of going to more distributed kinds of processing networks	US
Mas at el [158].	✓ Biofuel price		MILP	• Delivery rates	✓ Strategic	to determine the optimum design and planning of biomass-based fuel supply networks	Italy
Judd et al. [195]			MILP	• Boundary of farms • Center points of a set of farms • Distance between farms	✓ Strategic	to find the best number of satellite warehouse locations and the allocation of production plants to the selected warehouses	Numerical Example
Čuček et al. [196]			MILP	• Equipment cost • Available quantity of corn and forest for each area • Maximum loading capacity	✓ Strategic ✓ Tactical	to optimize the economically potential application of resources, accounting for the competition between energy and food production	Central of Europe
Parker et al. [197]			MILP	• Location of biorefineries • Price of corn supply	✓ Strategic	to evaluate the potential biofuel supply from forest, agricultural, urban, and energy crop biomass.	US
Tittmann et al. [198]			MILP	• Potential biorefinery locations • Conversion technologies	✓ Strategic ✓ Tactical	to optimize the system applying spatially explicit raw material supply curves, double viable conversion technologies and geographically identified bioenergy demand	US
Ekşioğlu et al. [28]			MILP	• Amount of biomass available • Transportation mode	✓ Strategic ✓ Tactical	to minimize the biofuel delivery cost as well as to determine each plant, the transportation mode selected, transportation time, size of	US

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
						shipment and inventory, and production schedule	
Rentizelas and Tatsiopoulos [199]			Meta-heuristic (GA)	• Energy demand • Warehousing • Legislation • Social variable • Logical variable	✓ Strategic	to investigate the optimal location of a bioenergy production facility for district energy applications	Greece
Mele et al. [200]			MILP	• Capital investment • Production capacity	✓ Strategic	to use a decision-making tool to determine the optimal design of supply chain for the combined production of sugar and ethanol	Argentina
Leão et al. [201]			MILP	• No limitation in case study/model	✓ Strategic	to develop an optimal biodiesel plant of supply chain sourced from family farms	Brazil
Dal-Mas et al. [144]	✓ Biomass price		MILP	• Biomass production	✓ Strategic	to find the optimum design and planning of biomass-based fuel supply networks	Italy
Giarola et al. [202]			MILP	• Production rate	✓ Strategic	to address the strategic plan and designing of corn grain and stover-based bioethanol supply chains	Italy
Kim et al. [203]	✓ Biomass availability ✓ Biofuel demand and price		MILP	• Data limitation for model	✓ Strategic	to investigate: 1) which variables have main impacts on the total economics, and 2) the advantages of going to more distributed kinds of processing networks	US
Zhu et al. [204]			MILP	• Storage space • Limited handling machines • Production capacities of biorefineries	✓ Strategic	to determine the optimal place of warehouse, scheduling and size of harvesting, and transportation flow of switchgrass in the logistic configuration	Numerical Example
Corsano et al. [205]			MINLP	• Warehouse capacity	✓ Strategic	to propose an optimization model for sustainable design and behavior analysis of sugar/ethanol supply chain	Numerical example
Marvin et al. [206]			MILP	• Amount of biomass harvested and processed • System of collection and densification of biomass	✓ Strategic	to find the optimum biorefineries locations and capacities by considering biomass harvest and distribution	US
An et al. [207]			MILP	• Capacity limit for each open facility	✓ Strategic	to find the highest profit of a lignocellulosic biofuel supply chain changing from feedstock suppliers to biofuel customers	US
Bai et al. [116]			MINLP	• Not considering the roadway capacity expansion or background traffic driver diversions	✓ Strategic	to minimize total cost of system for refinery investment, feedstock and product shipment and public delivery	US
You and Wang [138]			MILP (Multi-objective)/MODM	• Transportation mode • Moisture content of the biomass feedstock • Specific demand in each county	✓ Strategic ✓ Tactical	to determine optimum design and planning of biomass-to-liquids supply chains under economic and environmental criteria	US
Lam et al. [208]			MILP	• The road congestion • Weather condition	✓ Strategic	to address (i) decreasing the connectivity in a BSC network, (ii) reducing unessential parameters and constraints, (iii) combining the collection sites	Center of Europe
Zhu and Yao [209]			MILP	• Biorefinery production capacity • Limited handling machines	✓ Strategic	to decide the areas of distribution centers, the extent of harvesting group, the sorts and measures of biomass harvested/obtained, stored, and prepared in every month	Numerical example
Kim et al. [210]	✓ Supply amount		MILP		✓ Strategic		US

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
	✓ Market price and demand ✓ Processing technology			• Availabilities of five biomass type • Available inventory • Demand for each scenario		To find the optimum network design of BSC in terms of variables that result in the most change in the revenue	
Bowling et al. [127]			MILP	• Feedstock Supply • Product Demand	✓ Strategic	to recognize the optimum supply chain, operational strategies, size, and places of the biorefinery and preprocessing hub facilities	US
Aksoy et al. [211]			MILP	• Available biomass	✓ Strategic	to investigate the raw material allocation, the best facility location, and economic assessment	US
Singh et al. [117]			MINLP	• Number of collections centers • Amount of residue collected in dry form • Biomass Demand	✓ Strategic	to assess the possibility of constructing biomass-based power plants and optimum location.	India
Giarola et al. [212]			MILP (Multi-objective)/MODM	• Biomass cultivation delivery • Fuel production	✓ Strategic	to design bioethanol supply chains by considering environmental and financial performance design drivers and alternative process design	Italy
Akgul et al. [213]			MILP	• No limitation in case study/model	✓ Strategic	to show an optimization model for a hybrid first/ second generation bioethanol supply chain network	UK
Giarola et al. [142]	✓ Feedstock and carbon cost		MILP	• Logical constraints	✓ Strategic	to evaluate the planning and designing of a multiperiod and multi-echelon bioethanol upstream supply chain	Italy
Avami [214]			MILP	• Regional limitations	✓ Strategic	to develop a regional framework based on techno-economic factors to deeply comprehend the technical, agricultural, and economic features of biodiesel supply chain	Iran
You et al. [129]			MILP (Multi-objective)/MODM	• Feedstocks Capacity	✓ Strategic ✓ Tactical ✓ Operational	to assess the main characteristics of cellulosic ethanol supply chains, such as supply seasonality and geographical diversity	US
Andersen et al. [215]			MILP	• Land availability • Railway transportation	✓ Strategic	to determine the optimum design and planning of the biodiesel supply chain	Argentina
Judd et al. [216]			MILP	• Limited road speed • Volume limitations	✓ Strategic ✓ Tactical	to determine the optimum number and location of satellite warehouses	Numerical Example
Akgul et al. [217]			MILP	• Production • Demand • Sustainability • Transportation	✓ Strategic	to model the bioethanol supply chain based on the environmental and economic criteria simultaneously	UK
Han and Murphy [32]			Meta-heuristic (SA)	• Routes • Working time • Order requirement	✓ Strategic ✓ Tactical	to solve a truck scheduling problem for transporting four types of woody biomass	US
Chen and Fan [135]	✓ Feedstock supply ✓ Biofuel demand		MILP	• Feedstock sites • Ethanol refineries • Demand centers	✓ Strategic	to support bioenergy supply chain systems strategic planning and optimal feedstock resource allocation	US
Walther et al. [218]	✓ Biomass production ✓ Biofuel demand ✓ Investment cost		MILP	• Capacity limits • Planning horizon	✓ Strategic	to integrate location, technology planning, and capacity for the design of production networks of synthetic bio-diesel	Germany
Kostin et al. [219]	✓ Biofuel demand		MILP	• Capacity limitations • Demand • Prices of final products, raw materials, and the investment	✓ Strategic	to determine the optimum expected performance of the supply chain in terms of some financial risk mitigation alternatives	Argentina
Natarajan et al. [220]			MILP	• Technical risk and high investment cost	✓ Strategic	to find the minimum costs of the entire biomass supply,	Numerical example

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
				• Import and export of biomass and biofuel		biomass and biofuel shipment, biomass conversion, energy distribution, and emissions	
Srisuwan and Dumrongsiri [221]			MILP	• Land capacity • Life cycle of crops	✓ Strategic ✓ Tactical	to determine the optimal decisions on crop production by minimizing the transportation routes and decreasing the emission of CO_2	Thailand
Wang et al. [222]			MILP	• Bioenergy conversion plant	✓ Strategic	to find the optimum capacity size and locations of biomass-based facilities	UK
You and Wang [139]			MILP (Multi-objective)/MODM	• Capacity limit • Governmental incentives	✓ Strategic	to investigate the optimum design and planning of biomass-to-liquids supply chains in terms of economic and environmental issues	US
Čuček et al. [123]			MINLP (Multi-objective)/MODM	• Transport of direct products	✓ Strategic ✓ Tactical	to maximize the economic performance and minimize the environmental and social footprints	Europe
Marvin et al. [223]			MILP	• Material Flow • Cash Flow and Facility Capacity	✓ Strategic	to find economical facility location and capacities of biomass processing	US
Bai et al. [224]			MINLP	• Strategic and operational decisions • Fuel market	✓ Strategic	to find the optimum locations and number of biorefineries, the needed prices for these refineries to compete for feedstock resources	US
Gebreslassie et al. [156]	✓ Supply ✓ Demand		MILP (Multi-objective)/MODM	• Production capacities of biorefineries • Harvested biomass	✓ Strategic ✓ Tactical	to minimize the expected annualized cost and the financial risk	US
Zhang and Hu [225]			MILP	• Budget limit	✓ Strategic ✓ Operational	to find the optimal comprehensive logistics decisions to minimize the total BSC cost	US
Giarola et al. [145]	✓ Raw material ✓ Carbon allowances trading cost volatility		MILP (Multi-objective)/MODM	• Analysis has been limited to the upstream supply chain • Sustainability limit	✓ Strategic ✓ Tactical	to optimize the economic and environmental performances by considering the decision makers' risk mitigation preferences.	US
Tong et al. [226]	✓ Biomass availability ✓ Fuel demand ✓ Biomass price ✓ Technology advancement		MILP	• Raw material purchases • Production amounts • Transportation flows	✓ Strategic	to assess the optimum design and strategic planning of the combined biofuel and petroleum supply chain system	US
Ren et al. [114]			LP	• Resources and energy • Storage capacity • Demand of market • Technological limitations	✓ Strategic ✓ Tactical	to design the most sustainable bioethanol supply chain by minimizing the total ecological footprint	China
Sharma et al. [115]	✓ Number of harvesting workdays		LP	• Road transportation units • Harvest and supply	✓ Strategic ✓ Tactical ✓ Operational	to diminish the cost of biomass supply to biorefineries over a one-year planning	US
Yue et al. [120]			MINLP (Multi-objective)/MODM	• Availability of feedstock • Demands of final products • Inventory capacity	✓ Strategic	to suggest a life cycle optimization model for the design of sustainable product and supply system	US
Zhang et al. [227]			MILP	• Capacity • Material flow	✓ Strategic	to find the optimum comprehensive logistics decisions to minimize the total BSC cost	US
Elia et al. [228]			MILP	• Flow rates of feedstock source	✓ Strategic	to share data for the strategic locations of biomass-to-liquid refineries, the allocations of raw material and products in the supply chain	US
Foo et al. [137]	✓ Biomass supply		MILP	• The total amount of EFB	✓ Strategic	to design a synthesis of EFB allocation networks	Malaysia
Ebadian et al. [229]			MILP	• Demand • Inventory balance	✓ Strategic ✓ Tactical	to determine the optimum number and location of farms	Canada

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
				• Farm selection		and storages as well as to find the radius of supply, the farms number needed to assure the annual biomass supply	
McLean and Li [230]	✓ Amount of raw material ✓ Yield of crops ✓ Demand		MILP	• Topology relationships among the units • Capacity limits of plants and warehouses	✓ Strategic	to suggest a new synergy of the scenario and robust techniques for strategic supply chain optimization	Central European
Mansoornejad et al. [231]			MILP	• Inventory limit • Transportation capacity	✓ Strategic	to present a scenario based strategic supply chain design approach based on market and supply chain network scenarios	Canada
Osmani and Zhang [232]	✓ Biomass yield ✓ Biomass price ✓ Rainfall value ✓ Bioethanol price		MILP	• Capacity • Material flow	✓ Strategic ✓ Tactical	to maximize the expected profit while minimizing environmental impact of a lignocellulosic bioethanol supply chain	US
Yue and You [233]			MINLP	• Capacity limit of biorefinery	✓ Strategic	to address the optimal design and planning of non-cooperative supply chain from the manufacturer's view	US
Singh et al. [124]			MINLP/Meta-heuristic (GA)	• Capacities of the biorefineries	✓ Strategic	to increase the net present value of a network of ten biorefineries by 10.7% in comparison with that of the first supply chain network	US
Yue et al. [130]			MILFP (Multi-objective)/MODM	• Seasonal feature in biomass availability	✓ Strategic ✓ Tactical	to address the cradle-to-gate life cycle of bioelectricity involving biomass cultivation and harvesting, raw material pretreatment, energy conversion, and biopower production, as well as transportation and storage	Numerical example
Roni et al. [234]			MILP	• Amount of biomass shipped • Storage capacity	✓ Strategic	to design the supply chain network for biomass co-firing in coal-fired power plants	US
Li and Hu [235]	✓ Biomass availability ✓ Biofuel price		MILP	• Facility capacity limit	✓ Strategic	to optimize biofuel producers' annual profit	US
Balaman and Selim [7]			MILP	• Biomass processing capacity limit • Storage capacity	✓ Strategic ✓ Tactical	to find the most suitable locations for the biomass storages and biogas plants	Turkey
Tong et al. [157]	✓ Supply ✓ Demand		MILP (Multi-objective)/MODM	• Raw material purchases • Production amounts • Transportation flows	✓ Strategic ✓ Tactical	to optimize the supply chain design, insertion point selection, and production planning	US
Tong et al. [146]	✓ Biomass availability ✓ Final demand		MILP	• Balance • Production • Capacity • Logical	✓ Strategic ✓ Tactical	to integrate the supply chain design, strategy selection, and production planning	US
Azadeh et al. [143]	✓ Supply ✓ Demand		MILP	• Balance • Capacity • Logical	✓ Strategic ✓ Tactical	to handle the time-staged, multi-commodity, system of production/distribution, locations and capacities of facilities, flow of material and technologies	Numerical example
Xie et al. [236]			MILP	• Biomass delivery distance by truck	✓ Strategic ✓ Tactical	to reduce the total cost for infrastructure, raw material harvesting, production of biofuel and transportation	US
Palak et al. [237]			MILP	• Limited rail and barge infrastructure	✓ Strategic	to analyze the effect of carbon regulatory mechanisms on resupplying decisions in a biofuel supply chain	Numerical example
Gong and You [122]			MINLP (Multi-objective)/MODM	• Linear relationship between mass flow rate and energy consumption • Production distributions • Algae growth	✓ Strategic	to minimize the unit cost and the unit global warming potential	Numerical example
					✓ Strategic		

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
Grigoroudis et al. [58]			MILP (Multi-objective)/MODM	• Production and biomass limitations		to select the feasible installed facilities in terms of minimum cost and maximum efficiency	Numerical example
Marufuzzaman et al. [118]			MILP (Multi-objective)/MODM	• Plant capacity • Amount of sludge transported • Carbon emission limitations	✓ Strategic	to determine locations and production capacities for biocrude production plants	US
Natarajan et al. [238]			MILP	• Maximum plant size	✓ Strategic	to identify the optimal plant locations with least cost to minimize the total costs of the supply chain	Finland
Shabani et al. [239]	✓ Monthly available biomass		LP	• Storage limitation	✓ Strategic	to optimize the profit of a forest biomass power plant value chain	Canada
Akgul et al. [121]			MINLP (Multi-objective)/MODM	• Demand • Production • Transportation	✓ Strategic	to examine the economic and technical compromises in transforming from a dedicated fossil fuel only to a carbon negative electricity generation network.	UK
Cambero et al. [240]			MILP	• Product demand and price	✓ Strategic	to maximize the net present value of the supply chain over a 20-year planning horizon	Canada
Bairamzadeh et al. [147]	✓ Raw material and bioethanol selling price ✓ Biofuel production and transportation ✓ Environmental effect of biomass production		MILP (Multi-objective)/MODM	• Land area • Harvested biomass quantity • Produced bioethanol	✓ Strategic	to determine the optimal design and planning of a lignocellulosic bioethanol supply chain with respect to optimize sustainability criteria	Iran
Bai et al. [241]	✓ Corn production		MINLP (Multi-objective)	• Future biomass supply (and demand) is deterministic • Capacities of all functioning refineries • Facility disruptions	✓ Strategic	to design of reliable bio-ethanol supply chain to hedge the system against potential operational problems	US
Ren et al. [242]	✓ Demand of market ✓ Quantity of seed ✓ Used human labor ✓ Consumed transportation fuels ✓ Velocity of vehicle		LP	• Resource availability • Transport capacity • Demand	✓ Strategic	to optimize the life cycle cost of biofuel supply chain considering uncertainties	Numerical example
Gonela et al. [243]	✓ bioethanol price and demand ✓ biomass yield		MILP	• GHG emissions • Water usage • Energy efficiency	✓ Strategic	to design a hybrid generation bioethanol supply chain	US
Sharifzadeh et al. [244]	✓ Feedstock availability ✓ Biofuel demand		MILP	• Plants are built in 2 years • Production duration	✓ Strategic	to find the optimum supply chain design and operation, under uncertainty	UK
Murillo-Alvarado et al. [245]			MILP (Multi-objective)/MODM	• Maximum available agave • Demand limit	✓ Strategic	to design supply chain that includes the simultaneous optimization of the net present value and network environmental performance	Mexico
Gonela et al. [246]	✓ Demand and selling price of bioethanol ✓ Yield rate of produced biomass		MILP	• GHG emission limits	✓ Strategic	to evaluate various kinds of bioethanol plant configurations involving industrial symbiosis strategy for meeting high sustainability standards	US
Ahn et al. [247]			MILP	• Limited number of refineries • Demand	✓ Strategic	to estimate where and how much raw material to be shipped, and where and how many refineries to be established to minimize the final total cost	South Korea
Paulo et al. [248]			MILP	• Limited biomass resources • Number of substations	✓ Strategic	to optimize the design and planning of the bioenergy supply chain	Portugal

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
Paolucci et al. [249]			MILP (Multi-objective)/MODM	• No information is given on the optimal location of plants and farms, and the spatially • Averaged values used may ignore local specifications	✓ Strategic	to identify the optimum supply chain framework for biomass production on a given area	Italy
Roni et al. [161]			MILP/MODM	• Availability of biomass • Customer demand • Storage and biorefinery capacity	✓ Strategic	to optimizes the CO_2–CO_2 emissions because of transportation-related activities in the supply chain as well as to optimize the social effects of biofuels by the creating the number of jobs	US
Mohseni et al. [250]	✓ Resource supply ✓ Cost factor ✓ Biodiesel demand		MILP	• Resource availability • Material flow • Pipeline capacity • Demand	✓ Strategic	to design and planning of a microalgae-based biodiesel supply chain	Iran
Babazadeh et al. [125]	✓ Cost and environmental factors		MINLP (Multi-objective)/MODM	• Demand and supply satisfaction • Capacity expansion • Production and inventory	✓ Strategic	to minimize the final costs of biodiesel supply chain from raw material supply hubs to customer centers as well as to minimize the environmental effect	Iran
Duarte et al. [251]			MILP	• Bioethanol or biodiesel can be the final product	✓ Strategic	to design a supply chain Network for second-generation biofuel production	Colombia
Hombach et al. [252]			MILP	• Biomass supply • Production of intermediate and final product • Plant throughput	✓ Strategic	to optimize the net present value of second-generation biofuel supply chain with respect to time-dependent quotas for shares of biofuel market and greenhouse gas emission savings	Germany
Ng and Maravelias [253]			MILP	• Biomass transportation • Biomass feedstock storage	✓ Strategic	to determine the biomass selection and allocation, selection of technology as well as capacity planning at regional depots and biorefineries	US
Woo et al. [254]	✓ Biomass availability ✓ Demand uncertainty of hydrogen		MILP	• Types of biomass • The collection costs of the residues • Overall collection costs of the energy crops • Energy crops harvested • Harvesting times of the energy crops • Transportation modes • Hydrogen demand	✓ Strategic ✓ Tactical	to find the optimum logistics decision-making to minimize the total annual cost for a biomass-to-hydrogen supply chain with import and inventory policies	South Korea
Balaman and Selim [159]	✓ Thermal energy cost of storage ✓ Capacity limit of thermal energy storage ✓ Demand of thermal energy		MILP (Multi-objective)/MODM	• Capacity limit for thermal storage • Plant number and heat production capacity • Energy crop field	✓ Strategic	to address the optimum framework of the supply chain to satisfy the heat demand of a special locality	Turkey
d'Amore and Bezzo [255]			MILP/MODM	• Carbon dioxide emissions • Geographical distribution of ethanol demand centers • Biomass geographical availability • Biomass production costs	✓ Strategic	to carry out a multi-objective environmental and economic model for a spatially explicit bioenergy supply chain network	Italy
Santibañez-Aguilar et al. [256]	✓ Raw material price		MILP (Multi-objective)/MODM	• Demand • Transportation limits and transportation costs	✓ Strategic	to show a novel method for the optimum planning based on uncertainty for a biomass conversion system considering simultaneously economic and environmental objectives	Mexico
			MILP		✓ Strategic		

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
Azadeh and Arani [257]	✓ Biomass availability ✓ Demand			• Biodiesel market: water and technology • Biofuel market • Land limitation		to plan and design a biodiesel supply chain from biomass fields to consumption markets	Numerical example
Miret et al. [258]			MILP (Multi-objective)/MODM	• Quantity harvested at a site • No inventory possible at the harvested site	✓ Strategic	to concentrate on multi-objective optimization involving all the aspects of the sustainable issue, called economic, environmental, and social	France
Poudel et al. [259]			MINLP	• Limited budget availability • Biomass availability	✓ Strategic	to design a bio-fuel supply chain system's multi-modal facility links while accounting for restricted budget availability	US
Cambero et al. [260]			MILP (Multi-objective)/MODM	• Amount of bioenergy or biofuel that can be generated/produced	✓ Strategic	to maximize the GHG emission savings and net present value of the biorefinery system	Canada
Bai et al. [261]			MINLP	• Total farmland farmers allocate by the total existing land plus the total reclaimed marginal land	✓ Strategic	to evaluate the impacts of farmland use policies to balance biofuel production and food	US
Yue et al. [262]			MILP/MODM	• Limited number of case studies • Data collection and data processing	✓ Strategic	to assess the environmental effects for a given product to compare various alternatives as well as determine both economically and ecologically better decisions	UK
Zhang et al. [263]			MILP	• No inventory of biomass • Moisture content • Cost information • Storage cost	✓ Strategic ✓ Tactical	to minimize the total cost for framework, raw material procurement harvest, shipment, storage, and process based on strategic and tactical decisions	US
Cambero and Sowlati [162]			MILP/MODM	• Load transportation capacity	✓ Strategic	to optimize the social benefit, greenhouse gas emission saving and net present value potential of a forest-based biorefinery supply chain	Canada
Lim and Lam [264]			LP/Biomass Element Life Cycle Analysis (BELCA)	• Biomass demand	✓ Strategic	to optimize the supply chain network for optimum biomass utilization and application	Malaysia
De Meyer et al. [265]			MILP	• Amount of biomass allowed in the conversion process	✓ Strategic	to optimize strategic and tactical decisions in all types of BSC	Belgium
Shabani and Sowlati [266]	✓ Moisture content and higher heating value ✓ Monthly available biomass		LP	• Additional costs related to hiring an extra person and an extra piece of equipment for material handling	✓ Strategic ✓ Tactical	to incorporate uncertainty in the forest-based BSC by considering the tactical supply chain planning of a power plant	Canada
Kostin et al. [267]			MILP	• Capacities of each technology • Capacity of production in each sub-region • Storage capacity. • Capital investment	✓ Strategic	to propose the optimal configuration of a bioethanol network	Brazil
Akhtari et al. [268]	✓ Medium-term supply ✓ Demand variations		Integrated model	• Conversion technologies • Storage capacity • Biomass loss	✓ Strategic ✓ Tactical	To optimize forest-based biomass supply chains	Canada
Malladi et al. [269]			MILP	• Truck size and space available at each location • Drivers working hours	✓ Tactical	to develop an optimization models for the short-term planning of biomass logistics using the case of a large biomass logistics company	Canada
Nguyen and Chen [270]	✓ Harvest of biomass		Two-stage stochastic model	• Biomass production • Storage capacity	✓ Strategic ✓ Tactical ✓ Operational	to select the supplier and to make decision for planning transportation, inventory, and production operations	Numerical example
Zulkafli and Kopanos [271]			MIP		✓ Strategic	to study the trade-off between costs and emissions levels and	Numerical example

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
				• Establishment and capacity expansion for technologies • Raw materials states availability • States connection and balance		different emissions regulation policies	
Ascenso et al. [272]			MILP	• Total number of circulating vehicles • Time-dependent demands	✓ Strategic ✓ Tactical	to optimize a multi-echelon supply chain simultaneously in terms of economic and environmental performance	Italy
Bairamzadeh et al. [273]	✓ Imprecise conversion rates		MILP	• Quantity limitation of harvested biomass • Mass balances • Fixed cost of biorefineries • Capacities of biorefineries • Demand satisfaction	✓ Strategic ✓ Tactical	to determine the strategic and tactical level decisions of lignocellulosic bioethanol	Iran
Üster and Memişoğlu [150]	✓ Biomass price ✓ Yield of biomass		Multi-stage stochastic model	• Number of scenarios	✓ Strategic	to combined design of a network and biomass pricing decisions under yield uncertainty	Texas
Cobuloglu and Büyüktahtakın [151]	✓ Biomass Price ✓ Yield of biomass		Two-stage stochastic model and L-shaped algorithm	• Energy crop production on cropland	✓ Strategic ✓ Operational	to maximize the economic and environmental aspect of biofuel crops production	Kansas
Castillo-Villar et al. [152]	✓ Moisture and ash contents		Stochastic model	• Amount of biomass available at supplier • Selection of on technology per facility	✓ Strategic	To assess the effect of biomass quality variability on supply chain related decisions and technology selection	Tennessee
Mirhashemi et al. [274]			MILP	• Different aspects of uncertainty use of other parts of Moringa oleifera for commercial purposes	✓ Strategic ✓ Tactical	to optimize the entire supply chain and determine the optimal strategic and tactical supply chain decisions	Iran
Fattahi and Govindan [275]	✓ Facilities' capacity		Multi-stage stochastic model	• Transportation links from a storage facility • Biofuel production and storage capacity	✓ Strategic ✓ Tactical	to design and planning of a biofuel supply chain network from biomass to demand centers where biomass supply is stochastic	Iran
Chávez et al. [276]			MILP (Multi-objective)	• Facilities • Inventory • Capacity • transportation	✓ Strategic	to design of a sustainable supply chain using multiple agricultural coffee crop residues	Colombia
Idris et al. [277]			MILP and GIS	• Only one pre-treatment technology is considered in this study	✓ Strategic	to minimize the supply chain overall cost and its emissions	Malaysia
Galanopoulos et al. [278]			MILP/Advanced Interactive Multidi-mensional Modeling (AIMMS) software	• Demand • Transportation cost • Biomass production	✓ Strategic ✓ Tactical	to study the logistics, network optimization, transportation and inventory management, and the resulting environmental and economic impacts	Germany
Balaman et al. [279]			Bi-level decision support system (DSS)	• Amount of biomass transported to the facilities • Product distribution amount	✓ Strategic ✓ Tactical	to aid modeling and optimization of multi technology, multi product supply chains and co-modal transportation networks for biomass-based production	UK
Sarker et al. [280]			MINLP/Genetic Algorithm	• Seasonal availability of the biomass • limited residues and workforce • Reactors' demand of the residues	✓ Strategic	to optimally locate the hubs (to collect feedstock) and the bio-methane gas plants to minimize the total cost of operating this supply chain system for renewable energy	US
Tsao et al. [281]	✓ Customer demand ✓ Environmental condition		MILP (Multi-objective)	• Assumption in a non-fuzzy decision space	✓ Strategic	to design of a sustainable supply chain network for maximizing social benefits while minimizing economic costs and environmental impacts	Numerical example
Abriyantoro et al. [282]	✓ Biomass delivery volume		Stochastic model	• Dry biomass demand fulfilment	✓ Strategic ✓ Tactical		Numerical example

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Table 3 (*continued*)

Author	Uncertainty factors	Sustainable factors	Solution method	Limitations of study/ model	Decision levels	Objective of study	Case Study
	✓ Time ✓ Moisture content			• Customer order • Inventory level	✓ Operational	to measure the cost-effectiveness of collecting biomass	
Razm et al. [283]	✓ Transfer price ✓ Tax rate		MILP	• Fixed costs for the insurance and salaries of labors • Initial capacity of bio-refineries	✓ Strategic	to propose a global bioenergy supply network management model through logistic decisions, financial problems, and related merits	Iran /Armenia
Albashabsheh and Stamm [284]			MILP	• Biofuel inventory capacity • Number of mobile pelleting machines	✓ Strategic	to minimize the overall cost of producing ethanol from lignocellulosic biomass	US
Jonkman et al. [285]			Multi-actor optimization model	• Total land use per farming region • Supply of sugar beet per farming	✓ Strategic	to explores the design of eco-efficient biomass supply chains and economic gain allocation between the supply chain partners	Netherland
Bambara et al. [286]			MILP	• Regional limitation	✓ Strategic	to determine optimal supply cost and supply network configuration of a cultivated and a wild energy crop	Africa
Fan et al. [287]	✓ Uncertain raw material ✓ Market demand		Two-stage stochastic model	• Corresponding demand for each order • Market demand	✓ Strategic	to find an optimal supply combination that maximizes the farmers' profit	Numerical example
Roni et al. [288]	✓ Feedstock supply		MILP	• Resource availability • Biomass flow • Capacity location • Biorefinery's feedstock demand	✓ Strategic ✓ Tactical	to simultaneously optimize feedstock sourcing decisions, and optimal preprocessing depot locations and size	US
Cooper et al. [289]			MILP	• Biomass yield • Demand center	✓ Strategic	to optimize the biomass supply chain framework by incorporating linear approximation of the biomass yield distribution	Hungary
Saghaei et al. [154]	✓ Material availability ✓ Material quality ✓ Customer demand		Two-stage stochastic model	• Material storage • Capacity of received carbon by pipeline and storage	✓ Strategic ✓ Tactical	to minimize cost and downside risk of the bioelectricity generation supply chain based on the pre- and postdisaster conditions	Mississippi

supply chains of bioethanol and, at the same time, specifying the optimized harvesting and bioethanol production rates [134], and strategically planning BSC and optimally allocating the feedstock with uncertain location decisions [135].

In a BSC model, a variety of objectives are taken into consideration. Table 3 demonstrates that various environmental, economic, and social value of objective functions are provided in the BSC models. They have impact on the BSC decisions; though, the majority of MILP models take into consideration only the economic aspects. In addition, a number of investigations have been done out focusing upon the environmental optimizations with the aim of minimizing the emissions of greenhouse gas [136,137]. In most of the MILP models, the environmental and economic objectives have been modeled through the minimization of the overall cost of the supply chain and emission of the greenhouse gases [138–141]. Furthermore, in these models, maximizing the net present values and minimizing the environmental negative effects [142,143] are determined as environmental and economic objectives. A review of literature showed that only a few scholars have addressed all the three earlier-mentioned aspects of sustainability in the context of BSC problems. MILP models of multi-objective type were developed by taking into account the minimization of costs and greenhouse gas emissions, and maximization of job creations as the objective functions in their models [129,130].

As mentioned earlier, a factor capable of significantly influencing the BSC performance is uncertainty. Some usual examples of uncertainty in the BSC models are uncertainty in biomass and biofuel demand, supply of biomass feedstock, price, production of bioenergy, transportation, and logistics [22]. Nonetheless, some other uncertainty sources exist, which can be taken into account in the BSC models. Literature indicates that in a number of the BSC models, uncertainty is addressed, e.g., Dal-Mas et al. [144], Giarola et al. [145], Azadeh et al. [143], however, the majority of them have made use of stochastic programming in order to address the problem of uncertainty. This is worth noting that in lots of problems that arise in real life, it is not possible to model the uncertainty by the probability distributions. In addition, it is difficult to apply the stochastic programming due to the shortage of knowledge and historical data in regard to uncertain parameters. Several researchers have attempted to solve such problems using fuzzy mathematical programming approaches. A multi-period MILP model was introduced by Tong et al. [146] to design a progressive hydrocarbon BSC in an integration with available petroleum refineries. They suggested a possibilistic programming model with the aim of properly addressing the uncertain parameters. In their approach, the preferences of decision makers were considered in the application of possibility, credibility, and necessity measures. Moreover, a multi-objective MILP model was introduced by Bairamzadeh et al. [147] to make a sustainable bioethanol supply chain in terms of numerous uncertainties. They also designed an innovative multi-objective robust possibilistic model in order to address the problems related to data uncertainty.

4.3.4. Stochastic programming

The physical and chemical production and supply process of biomass have a considerable effect on storage and transportation cost. There are some uncertainties such as the moisture content and demand, increase in storage and transportation cost due to increase in the weight and capacity of the feedstock. The variability in these characteristics need to be taken into account because they affect the total cost of producing and supplying biomass and have an effect on the BSC network design [148]. In recent years, some researchers proposed two-stage stochastic program to model this problem.

Marufuzzaman et al. [149] introduced a two-stage stochastic model to design a biodiesel supply chain in term of cost minimization by focusing on the facility location issues in the state of Mississippi. Another stochastic model along with L-shape algorithm was developed for BSC to find the optimum location of storages and determine the biomass flow between the facilities. Results showed that shipment consolidation lead to decrease the transportation cost because of economies of scale [150]. Cobuloglu and Büyüktahtakın [151] used a two-stage stochastic programming to maximize the biofuels crops production system by considering the environmental and economic aspects. Castillo-Villar et al. [152] developed a two-stage stochastic programming model for bioethanol production considering the uncertain factor related to the moisture content. They determined the optimal locations, feedstock flows among suppliers and biorefineries [152]. Another stochastic programming was developed to optimize the inbound biomass transportation and minimize the production cost in Texas [148]. The proposed model focused on the uncertainty in the moisture and ash content, which affect the cost of biomass production. The first step factors are the available locations of biorefineries and depots, and the unit trains to deliver the feedstock. The second step factor is the biomass flow between the potential locations and the third-party bioethanol supply. Results showed that biomass quality affect the depot/-biorefineries location selection and conversion technology in the optimum supply chain. The cost of biomass poor quality was estimated to be around 8.31% of the investment and operational cost [148].

Another study proposed a two-stage stochastic programming model to assess the effect of biomass quality variables such as moisture content and dry matter loss in different times on supply chain design in a real case study [153]. They used a hybrid decomposition algorithm along with enhanced progressive hedging algorithm with sample average approximation. Results showed that biomass quality variables affected the supply chain design by increasing the capital investment and additional cost. The biomass storage capacity decreased by 88.5% and 97.9% at depots and biorefineries respectively [153]. Saghaei et al. [154] incorporated uncertain variables for disruptive scenarios such as availability and quality of materials in a two-stage stochastic model of bioelectricity generation supply chain based on the strategic and tactical decisions. The performance of the model was tested and validated on the state of Mississippi. Results showed that although carbon tax policy had the greatest downside risk after the occurrence of disaster, this policy had the most investment attractions as compared to carbon capture and storage.

4.3.5. Multi-Criteria Decision-Making

Multi-Criteria Decision-Making (MCDM) models normally address the contradictory attributes or objectives that may arise in decision-making problems. Such models are classified into: Multi-Attribute Decision-Making (MADM) or Multi-Objective Decision-Making (MODM). MADM considers selecting one from amongst the available choices. Generally, these models involve preferential decisions in regard to evaluating, prioritizing, or choosing from amongst the accessible choices considering a number of contradictory criteria [155].

The MODM models, on the other hand, take into consideration multiple objectives, at the same time, in a mathematical programming model. The criterion used to assess a certain objective may completely differ from the criterion used for another objective, and in this procedure, the objectives might be also contradictory. Those objectives in the BSC models can be a combination of two different economic objectives, e.g., Gebreslassie et al. [156], Tong et al. [157], Mas et al. [158], or an environmental objective and an economic one, e.g., Marufuzzaman et al. [118], Wang et al. [119], Yue et al. [120], or it might be a combination of social and economic objectives [159], or a combination of objectives of the three aspects of environmental, economic, and social, e. g, Ayoub et al. [160], Roni et al. [161], Cambero and Sowlati [162]. The obtained results clearly indicate that in case of the MCDM models designed specifically for BSCs, the majority of cases have centered upon the environmental and economic aspects, and just a few studies (only 11 out of 30 papers (33.3%)) have covered all the sustainability aspects. Investigating the MCDM models, we found out that 20 papers (57.14%) have taken into consideration multiple-time periods, whereas only 7 ones (23.3%) have made use of stochastic programming models when addressing the uncertainty issue. The authors in Ref. [163], for instance, proposed an overall framework for the simplification of the Multi-Objective Optimization (MOO) models. This framework makes a combination of MADM methods and the MOO optimization techniques; it is applicable to the sustainability problems in BSCs.

4.3.6. Heuristic and meta-heuristic techniques

Generally, the optimization algorithms perform either exactly or approximately. Exactly-performing algorithms include commercial solvers and they can find exact optimized solutions; however, they cannot be applied to complex optimization problems, namely those problems whose NP-hardness or NP-completeness has been proved. The reason is that in this case, the computational time is exponentially increased. On the other hand, the approximation algorithms make use of heuristic and meta-heuristic methods; they can quickly explore near optimal solutions to complex problems. The most important issue with these approaches is that they might get trapped in local optimums; thus, they are not applicable to a variety of problems. Literature consists of meta-heuristic algorithms introduced for solving complex optimization problems. Such algorithms are indeed a type of approximate optimization methods, which are capable of successfully escaping from local optimums and they are applicable to a broad variety of problems. Reviewing the BSC models, we found out that 14 papers have been published so far on this issue using meta-heuristic approach, which included three Particle Swarm Optimization (PSO) algorithms and seven Genetic Algorithms (GA), one L-shaped decomposition algorithm and one Binary Honey Bee Foraging (BHBF) algorithm. The three algorithms mentioned above are population based, which make them capable of providing a set of solutions at each of the iterations performed in during the operation of the algorithms. Recent investigation combined the metaheuristic approaches such as Tabu Search (TS) and Simulated Annealing (SA) and exact methods [164]. A hybrid meta-heuristic solution procedure was developed to investigate a two-stage stochastic biomass-to-biorefinery supply chain in Texas by considering the uncertainty in its moisture and ash contents. A simulated annealing-simplex approach and tabu search-simplex method was utilized to determine an initial solution as well as to improve the solution. Results indicated that meta-heuristic along with simulated annealing, and tabu search with the simplex method needed 96.57% less time to obtain 2.48% lower costs [164].

It is to be noted that the meta-heuristic algorithm with the highest level of popularity in BSC problems is GA, a particular type of evolution algorithms. This algorithm typically adopts the natural evolution techniques, e.g., mutation and heredity, for the purpose of finding approximate solutions for optimization and search problems [37].

Table 3 summarized and categorized all the literature during the four decades in different regions based on the uncertainty, sustainability, limitation of case studies or developed models, decision-making levels, and objectives.

4.4. Sustainability optimization

Growing demand and focus on energy efficiency, cost reduction, and sustainability have characterized the need for supply chains to improve in areas such as environmental and social sustainability. Currently, some businesses in general and supply chains in particular have become conscious of the need to incorporate sustainability as part of the decision-making process, especially at the strategic level [290]. Supply chains have been addressed to increase more responsibility towards social and environmental aspect in their operations [290]. Today, companies are held accountable for the impact their entire supply chain activities have on the society and environment. Indeed, pressure from consumers, non-governmental organizations, local communities, legislatures, and regulatory bodies has affected how manufacturers or producers currently view sustainability [145]. When considering the biofuel supply chain for either profit maximization or cost minimization, it is important to consider sustainability within the decision-making process [291].

In terms of addressing sustainability factors in BSC, Table 3 shows that only few researchers have integrated the environmental, economic, and social objectives in the optimization process of the BSCs in order to produce bio-energy and bio-products using MOO approaches. Fig. 4 summarizes the number of papers during the last decade related to sustainable criteria of BSC. Number of papers that considered the social, economic, and environmental concepts in their model were relatively stable from 2009 to 2017, but saw a sharp increase in numbers in 2018 and is continuing to rise in 2019 as well. This suggests there have been increased interest on the research on BSC design and optimization, particularly incorporating sustainability factors. However, only a handful of papers considered all these three sustainability parameters simultaneously during the last decade. Fig. 5 also shows the Sankey diagram that put a visual emphasis on the major flows of investigations from sustainability, economic, environmental, and social perspectives in BSC design. The figure shows that sustainability and social factors have received less attention in BSC design in the past, but there is a growing trend in recent years.

4.5. *Financial and political policies in biomass supply and production system*

European Union (EU) has pushed toward a bio-based low carbon economy in terms of political agenda on energy policy and climate change [292]. Resource depletion and climate change have a considerable effect on the design and establishment of future policies toward a sustainable biomass supply and production system. Some interrelated

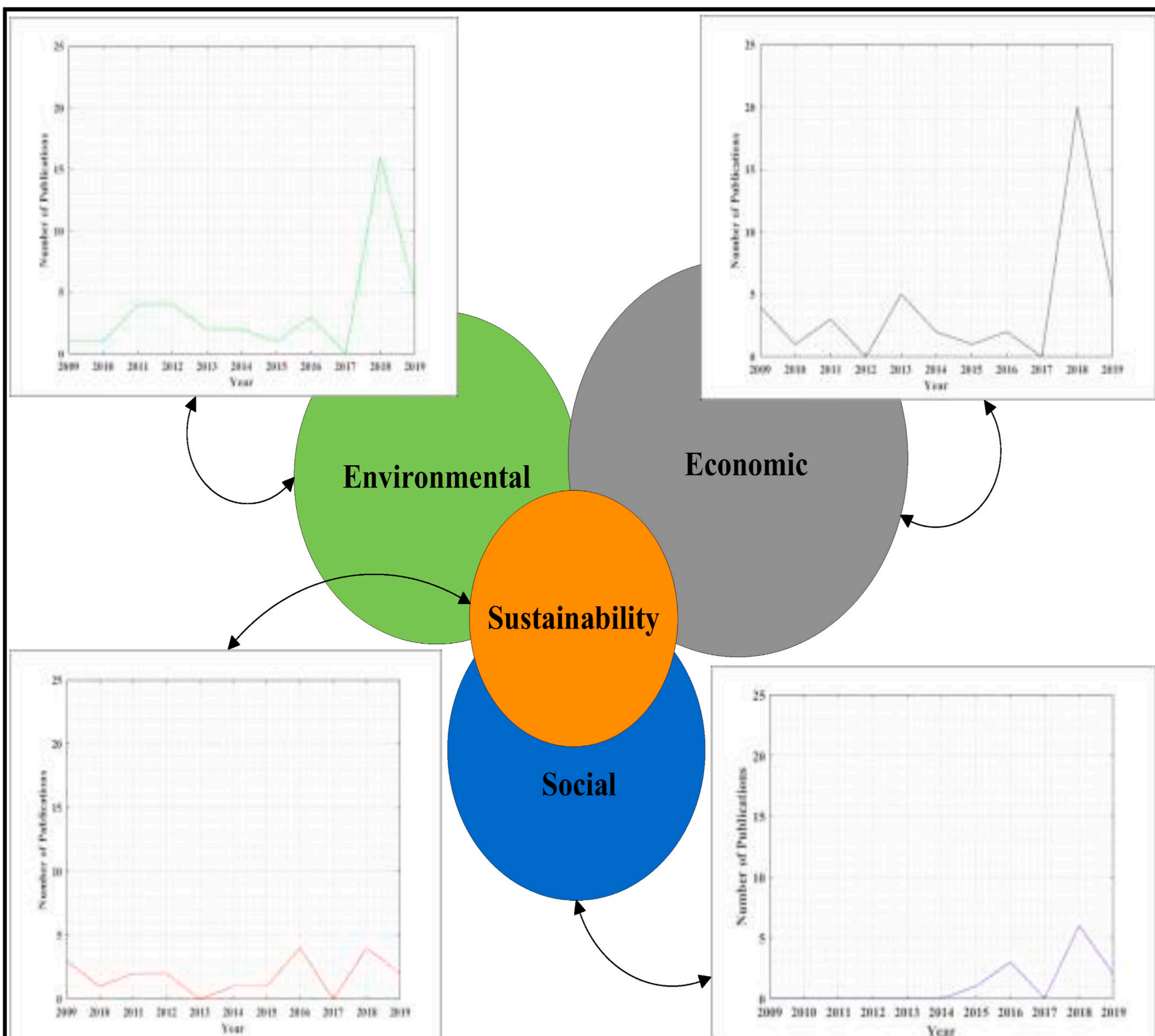

Fig. 4. Sustainability analysis of literature.

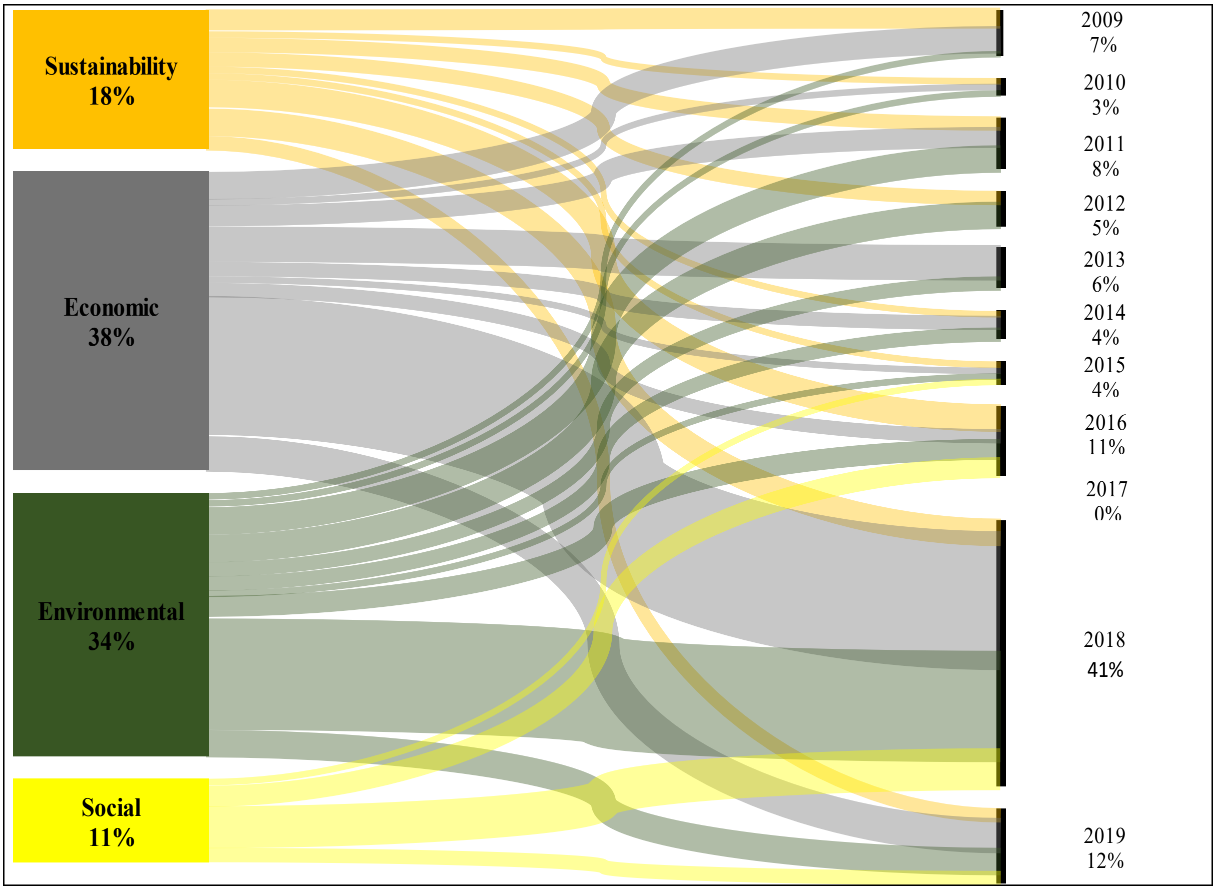

Fig. 5. Visualization flow of sustainability literature.

factors such as uncertainty and carbon cycle also play a vital role in circular bioeconomy model of sustainable biomass prosperity and growth [293]. Biomass industries and stockholders try to diversify and secure the supply of energy, uncertainties related to oil prices, and to decrease the GHG emissions by defining the financial and political regulations and policies [293]. This will need financial support in terms of reliability, storability, environmental, and social benefits, as well as improve efficiency in harvesting, comminution, delivery and production [294].

Biomass environmental issues are of lower less attention in the regional and local scales and much more relative regulations and policies should be taken into consideration. EU 2030 Climate and Energy Framework and the Paris Climate Accord as well as national and sectoral targets for transport, agriculture, and forestry are some examples of intergovernmental initiatives that have been deigned in the world [295]. EU biofuel regulation was developed to manage the social and environmental issues as well as to deal with the multiple crisis related to ideological assumption using by 'neoliberal governance regimes' [295]. There are some studies that have addressed the effect of financial and political regulation through the biomass energy and supply system. Bush et al. [296] studied the interactions between 'sustainability governance' of biofuels and value chain. Geographical concerns of biomass energy production and consumption is another main challenge that is growing among the scientific communities. This means that geographical connections and interactions in a BSC have a considerable effect on the energy-related activities [297]. Land availability and labor are two main parameters that become intertwined, when the biomass energy market expand. In this process, social issues such as job opportunities, negotiating as well as geographic locations are vital to meet the overlapping demand. Therefore, political regulation and governmental subsidy would be helpful support to satisfy the emerging biomass-based market [295].

In addition, there are some uncertainties and variabilities in biomass demand and market, feedstock cost, production cost and price differences that may affect based on the local and global condition. Especially price levels are the main driver in developing international trade that vary with the country and season or scale of industrial consumers [298]. Availability of sustainable feedstock and biomass volatility are important issues for biomass production and supply industry to meet the demand. Increasing the demand cause to increase the biomass price with competition among the different biomass sectors [299].

In one recent study in Denmark and Sweden, governments defined some regulations such as CO_2-taxes to encourage the bioenergy such as straw and forest biomass type in general [300]. Ranta et al. [301] investigated the effect of incentives, taxation and price levels of biofuels and fossil fuels on increasing the usage of renewable sources in Finland. They believed that there is a correlated relation between the future demand and the price of emission allowances and electricity. Results showed that their current low price lead to decrease the CHP plant investment activity. They recommended that policy regulation is necessary to encourage the bioenergy CHP investment to make a secure energy infrastructure in the future in Finland [301].

On the other hand, feed-in tariffs are not the most effective political action in terms of economic vision. The continuous approach of EEG (German: Erneuerbare-Energien-Gesetz) 2017 would be a more effective to save the cost and energy generation for biomass power plants in Germany. It is claimed that this approach is interesting for countries that are in early stages of power generation from biomass [302]. Landis et al.

[303] mentioned that there are trade-offs between stakeholders and policymakers that need to be communicated. They showed that establishment approaches, management practices, fertilization and intensive harvesting regimes can improve the diversity and sustained biomass crop. Bößner et al. [304] recommended the adoption of a specific biomass target in a national or regional level, that would help to make a secure relationship between stakeholders and investors in the long term. The lack of knowledge about the biomass production and supply system and its maintenance necessities should be trained to collaborate the economic, environmental, and social aspects of biomass simultaneously.

In another study, the political regulations of biomass design in Sweden were analyzed [292]. They investigated how the public authorities would help to develop guidelines and rules for the supply and production of slash and stumps. The results showed that these policies had an important impact on the new job opportunities and decrease dependency on energy supplies for abroad. Moreover, energy prices also affected the annual harvest rate positively [292]. Shahbaz et al. [305] examined the effect of comprehensive environmental policy for biomass energy consumption by considering globalization measures, financial development, and capitalization in terms of economic, social, and political criteria. The results revealed that biomass energy consumption and capitalization have a converse effect on CO_2 emissions. Globalization increases CO_2 emissions and financial development deteriorates environmental quality. In addition, institutional quality using the efficient economic and environmental rules improved the environmental quality [305]. Zahraee et al. [306] highlighted several recommendations and policy implications related to cost and strategic planning of BSC in Malaysia. Biomass standards, political regulation and governmental subsidy certification regulation could be addressed at the national or provincial level to further support BSC development. Such regulations could enhance the quality of biomass production and supply system and improve consumer satisfaction that lead to increasing demand for the biomass industry. Policy and business strategies should be defined to save the energy in a cost-effective and timely manner [304].

Therefore, it is important that all stakeholders from different sectors (market chain, policy makers, and businesses) collaborate in an effective way to develop a sustainable BSC network by addressing right supportive policies. Otherwise, it causes to slow down of investment return and increase price.

5. Discussions

The present paper was mainly aimed to investigate various models proposed in literature for BSCs, the objective functions of the models, decision levels, and the adopted solution methods. Assessment of the summary tables and keywords visualization graphs shows that there are some knowledge gaps in the modeling and optimization of BSCs that need to be addressed in future.

Solution methods for BSC problems are challenging due to computational complexity of the supply chain process. Our study indicates that most of the related papers on BSCs apply mathematical programming techniques. MILP methods are highly used to optimize the biomass facility locations. Simple MILP methods cannot solve the sophisticated BSC problems. However, researchers are motivated to use MILP models for BSC problems due to the complexities of nonlinear models, as well as the simplicity of the linear approaches. Nonlinear models are more flexible than simple linear approaches for real-world BSC problems. To solve the sophisticated, sizeable, real-world, and nonlinear problems, heuristic methods, approximation, and exact solution algorithms like hybrid solution or decomposition-based algorithms are very useful and, therefore, need more attention in future. For instance, multi-objective metaheuristic approaches, e.g., the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), are potentially capable of solving the real-world, non-linear problems; however, they have not been used for optimizing BSC. Except for [307], this review found no paper taking into account multi-objective evolutionary algorithms such as NSGA-II and simulation-based optimization algorithms.

Literature shows that variability and uncertainty of data in biomass supply chains have been mostly overlooked by the researchers of the field. Most studies address data uncertainty in BSCs using stochastic methods. Some studies use methods such as chance-constrained, scenario-based, two-stage, and probabilistic, as well as possibilistic programming. Additional opportunities exist to apply such as fuzzy logic, chaos theory, robust optimization, and interval methods. For instance, a two-stage (linear) stochastic programming model was formed for the purpose of minimizing the final cost of technology selection process, location, and transportation through doing a case study in the state of Tennessee, US [152]. Benders decomposition method was used to solve the problems by considering the uncertainty factors include moisture and ash contents [152]. In another paper, Osmani and Zhang [308] used Sample Average Approximation (SAA) approach along with Benders decomposition method to deal with the problems of stochastic sustainable of bioethanol supply chain in terms of bioethanol demand and sale price as the uncertain parameters.

In future, robust optimization and multi-stage stochastic methods are suggested to resolve uncertainties in BSCs. Prices of biomass and biofuel, costs of raw material, and types of production technologies are uncertain, but in most of the BSC papers, the supply and demand of biomass and biofuels are the most significant variables addressed using uncertainty methods. Dynamic Problems are even less studied. Dynamic simulation approaches (e.g., using AnyLogic software) are very helpful for analyzing the dynamic nature of BSCs and environmental impacts, such as carbon footprint, that are not possible to be considered independently for each stage of BSCs. With the use of system dynamic modeling, scholars and practitioners are able to design the models with one or more values that change over time. Moreover, this makes available a graphical interface to effectively model the complicated environments, it allows us to examine and explore different possible scenarios, and it helps to observe the behavior of the system during a specific time at any level of detail. Furthermore, it is important to know the way complicated relationships within BSC process with different 'what-if' scenarios with the presence of uncertainties in the system. Zahraee et al. [5] showed the way to construct a dynamic simulation model for the purpose of evaluating the impacts of changing the effectiveness of the transportation and production technology upon the environmental sustainability of the BSC during a period of 50 years (from 2000 to 2050) in case of three main suppliers of biomass in Malaysia.

The sustainability of BSCs is another important issue. It requires the simultaneous consideration of economic, environmental, and social aspects. Based on Table 3 and Fig. 4, it is noted that only a small number of studies used the multi-objective approaches, in which the three sustainability criteria are assessed simultaneously. Therefore, designing a model that combines economic, environmental, and social aspects presents another research opportunity for investigators who are willing to dive into sustainable BSCs. Tackling sustainability issues in BSC models cause to make robust decisions that is less risky. Therefore, a decision support tool that can simultaneously quantify and optimize the economic, environmental, and social performance criteria of the BSC would be a very valuable resource to the managers. For example, Lim and Lam [264] used Biomass Element Life Cycle Analysis (BELCA) for BSC optimization in Malaysia. Tools such as multi-objective optimization approaches can also be useful to quantify sustainability impacts.

The focus of most studies was on analyzing facility-related strategic decisions for processing facilities. There were only few studies have filled the gap in the analysis of hubs allocated to preprocessing or preconversion, and storage between harvesting areas and biorefineries based on the interdependence and interrelationships between the locations of all facilities and their capacities. Li et al. [309] suggested a multi-modal MILP to optimize the feedstock supply chain design with and without distributed pretreatment using GIS analysis based on the total cost of procurement, pretreatment and transportation. Therefore, it is highly recommended that, in future, an integrated and holistic BSC model that consider all facilities in the whole BSC be developed and tested with real data.

Additionally, most of the studies considered strategic and tactical decisions in their models while only a few recent studies also focused on the operational short-term decisions [270,282]. Akhtari et al. [268] developed an integrated model involves strategic and tactical decisions simultaneously to optimize forest-based BSC. So, incorporating these three decision levels in the model is suggested for the future to address the challenges of incorporating day-to-day inventory control and fleet management issues. Another important research gap is related to limited studies on multi-objective and multi-period methods to solve complex BSC optimization. More studies are essential to consider the dynamics and changes in variables and parameters and their impacts on the strategic decisions of BSCs. As seen in Table 3, little research used the multi-objective models in BSC models [256,258,276]. Therefore, in

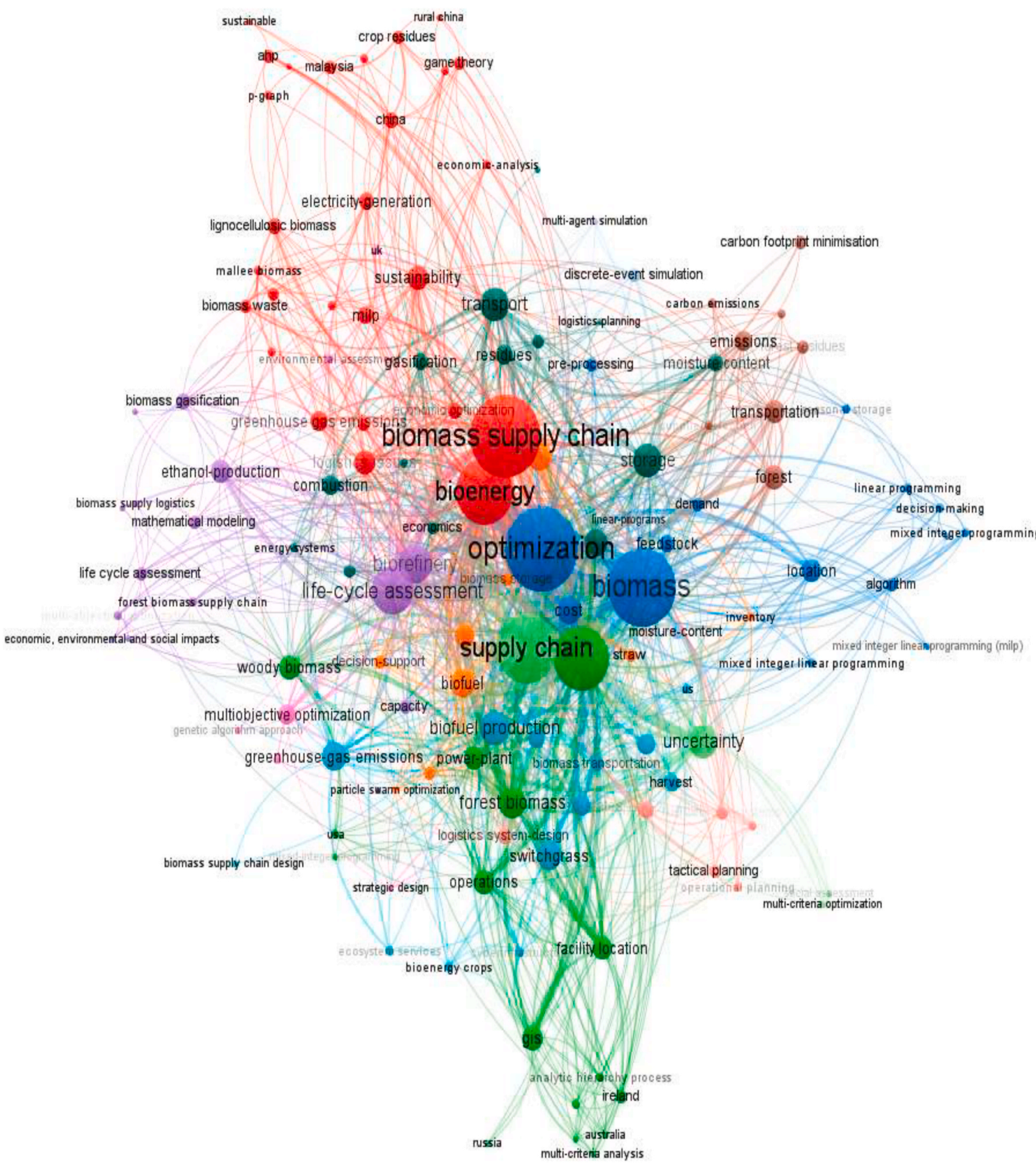

Fig. 6. Network visualization of key theme occurrences.

future, more studies are suggested to focus on the application of multi-objective models.

A potential direction for future research is to use extended multi-objective optimization model by combining strategic-tactical-operational decision levels to address the environmental and social gains of bioenergy and biofuel production. This synthesis needs:

(1) conducting life cycle assessment for identifying the environmental impacts related to all the stages of bioenergy and biofuel production,
(2) determining appropriate indicators for quantifying the social gains on a case-by-case basis, and (3) developing environmental and social objective functions.

Future studies could account for uncertainties in other variables of the model, such as biomass quality, product demand, equipment failure and repair times, and prices. To obtain this, the probability distribution functions for uncertain factors could be predicted and incorporated into the model.

Although models are useful to investigate and analyze problems related to BSC, it needs to be acknowledged that they do have limitations as well. There is a chance for some degree of bias when analyzing the biomass production and supply system due to stochastic and non-stochastic nature of model parameters and assumptions related to feedstock, suppliers, investment, and market. These factors pose some limitations to design a sustainable BSC. Biomass price levels, feedstock availability, impact of oil price, land use, policy regulations, sustainability criteria, and current international biomass market and demand are main issues that directly or indirectly have challenged the accuracy and reliability of the BSC optimization methods and models.

Studies of biofuel production and processing have been limited to particular countries that have particular types of biomass raw materials, climates, and economic and political contexts. It is suggested to conduct case studies of BSCs in countries with climates different to average any geographical bias. Additionally, it is observed that most of the BSC studies are done at chemical or agriculture engineering departments at universities, which usually have expertise in biomass conversion processes and cultivation systems. Operation researchers and industrial engineers are other specialists who could contribute valuable knowledge about biomass logistics to BSC models. In our opinion, a collaboration of multi-disciplinary teams involving all these different disciplines could lead to more-robust and more-practical results.

To identify the aggregate level of the density of keyword occurrences in published works, the VOSviewer software tool was used [310]. This software assists in the visualization, through infographics, of the clusters of key topics or themes, inter-relations between the topics, and densities of particular areas of study [310]. Through this tool, density of interests, identification of areas that need attention and trends in the BSC over time from 2005 to 2019 could be observed (Fig. 6 and Fig. 7). Fig. 6 indicates that there are 15 distinct clusters. It is observed that the most dominant cluster is the red cluster (Fig. 6), in which investigators have given attention to MILP, logistic, bioenergy, and economic analysis. As

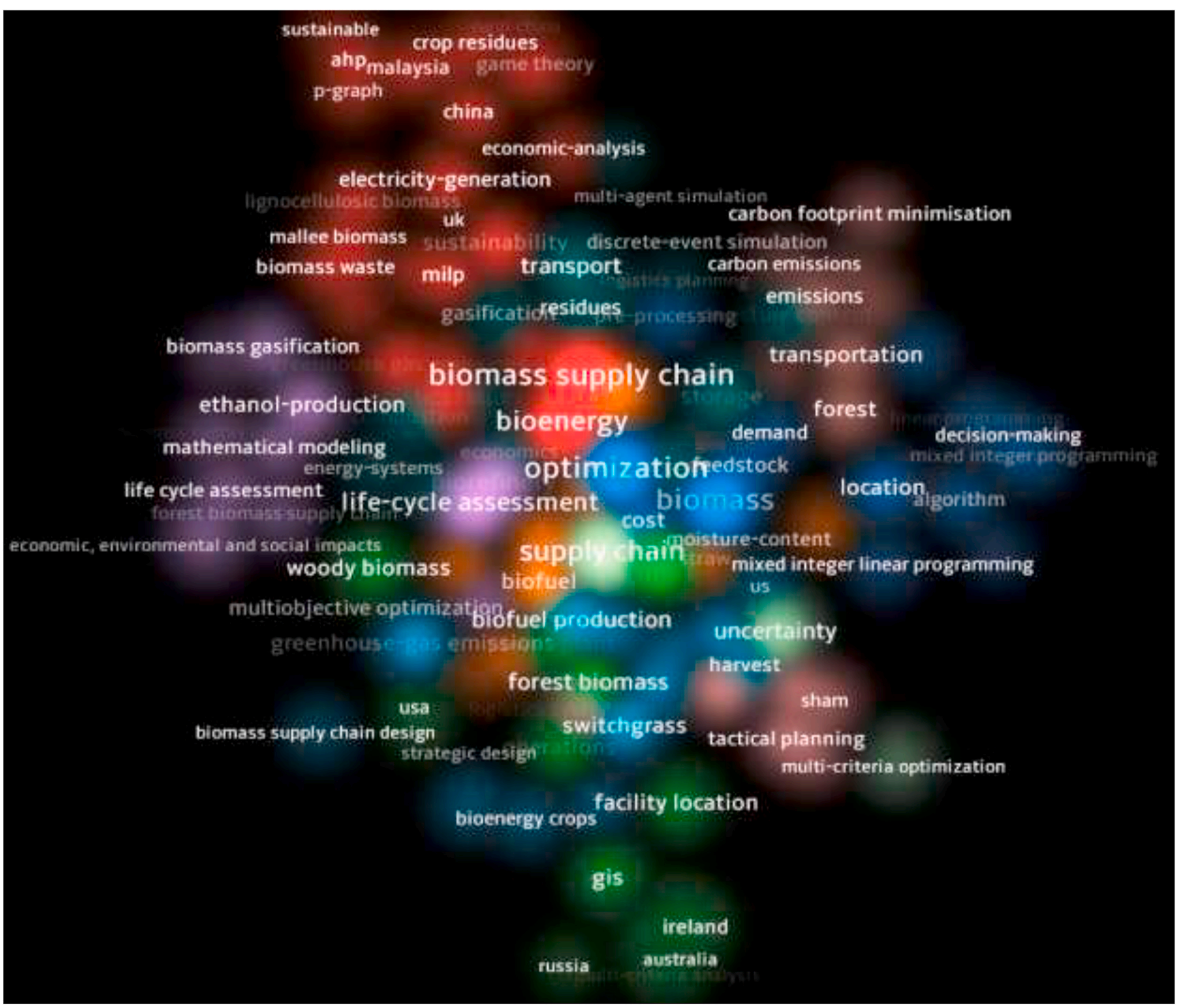

Fig. 7. Density visualization of key theme occurrences.

discussed earlier, sustainability (economic, environmental, and social impacts), uncertainty, and decision levels are not adequately covered (blue and purple clusters). Also, BSC optimization and logistics attract attention from a large number of scholars (red and green clusters). Moreover, Fig. 7 demonstrates the cluster density of co-occurrences that shows words used along with gaps in BSC literature. The results confirmed that carbon emissions measurements, sustainability, uncertainty, operation and tactical planning, and algorithm approaches receive less attention from scholars than the other categories.

6. Conclusion

The role bioenergy can play as 'energy supply' in the future is dependent upon the degree to which the pertinent barriers are removed. The BSC network design is a key issue in developing a sustainable, competitive bioenergy market capable of addressing the existing uncertainties and hurdles. In the present study, a total of 300 papers that have specifically addressed the issues of BSC modeling and optimization (those published in scientific conference proceedings and journals between 1980 and June 2020) were comprehensively reviewed. The papers chosen for the purpose of this study were analyzed and classified on the basis of their solution approaches, sustainability, modeling techniques, uncertainties, model features, and area of the case studies to precisely identify the research gaps, and discuss opportunities and future directions.

Various methods and approaches have been used to optimize and improve BSC stages such as facilities, transportation, and storage. Although biomass energy comprises many research fields, much of the focus has been on details of biomass production facilities such as production technology, sizes, and locations. The main issues concluded from this comprehensive review paper are the lack of appropriate tools to handle tactical decisions with different constraints for BSCs and ensuring sustainability of the BSC. Most of the optimization techniques are implemented using commercial solvers that are very general and are unable to completely exploit their mathematical framework to handle tactical decisions. Further, those commercial solvers are computationally inefficient, causing model running times to increase very fast with respect to the size and number of variables in the BSC, especially for models handling tactical decisions and multiple constraints. Therefore, developing algorithms such as decomposition approaches, relaxation methods, and metaheuristics to solve these issues could be rewarding future research directions. Although there have been some studies that have shown the potential of these algorithms in tactical decision making in industrial logistics, the algorithms have not yet been used in BSC network models that apply simulation-based optimization and multi-objective genetic algorithms (e.g., NSGA-II). Further, it is suggested to use decision support approaches that can simultaneously quantify and optimize the economic, environmental, and social criteria of the BSC. It is to be noted that there are some external factors that might influence the BSC such as the political regulation, governmental subsidy, geographic location, and the impact of oil price.

Finally, although BSC is closely related to industrial engineering (in terms of logistics and transportation issues), it is also a topic that is of significant relevance to chemical and agricultural communities. We hope that this comprehensive review will provide impetus for scholars from the logistics or production research areas to solve some of the challenges outlined in this review for the optimal design and sustainability of BSC. It is suggested that collaborative efforts between industrial engineering, chemical engineering, agricultural engineering, and operations research scholars be carried out to model and optimize BSC networks to develop more-realistic and more-accurate models.

Acknowledgments

The authors would like to acknowledge the postgraduate research stipend scholarship provided by the RMIT University. The authors would like to sincerely thank the editor and two anonymous reviewers whose constructive feedback has helped us to improve the paper.

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