Current Sustainable/Renewable Energy Reports (2018) 5:138–149
https://doi.org/10.1007/s40518-018-0108-6

BIOMASS AND BIOFUELS (P FOKAIDES, SECTION EDITOR)

An Overview of Current Models and Approaches to Biomass Supply Chain Design and Management

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Published online: 4 June 2018
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Abstract

Purpose of Review The paper focuses on the progress related to models and approaches for an optimal design and management of biomass supply chains. A literature review has been conducted, and previous review papers have been used as bases. Do most of the current models adopt the same decision level, mathematical methodology and type of objective of those identified by previous reviews? Are there any innovative approaches to revitalise the considered research topic?

Recent Findings Most of the works published in 2017 and in early 2018 reflect the past literature reviews; regrettably, few relevant advances have been achieved in the recent period to face up the major gaps. Innovative works apply Life Cycle Assessment, Multi-Criteria Analysis, CyberGIS or Agent-Based approaches to biomass supply chain optimisation.

Summary Future research should address, for instance, sustainability of biomass supply chains through a more comprehensive approach including economic, environmental, social and policy-related issues, integration of the decision levels to meet the needs of different stakeholders.

Keywords Biomass · Supply chain · Design · Management · Optimisation · Simulation

Introduction

The development of biomass supply chains is increasing over time, to meet the requirements of the climate policy targets and the national policies to resource-efficient and post fossil-carbon societies. Thus, new and more performing models and approaches have been developed to an optimised design and management of biomass supply chains, which most important objective is to maximise the related economic profits and the sustainability of investments. A valid point of view to deal with an idea of sustainable biomass supply chain made of a set of dependent variables, which concern not only economic and financial issues (as it is usually considered), can be found in [1••]. The authors have suggested the use of the MCDM (Multi-Criteria Decision-Making) approach and a mathematical model to calculate the optimisation criteria (environmental, energetic and economic objectives), to better address the complexity of biomass supply chains.

With regard to biomass types and the purpose of the supply chain, the largest number of papers has focused on lignocellulosic biomass for biofuels production, followed by the same kind of biomass for hydrocarbon biofuels production [2], but due to the large variety of biomass, its different availability, yield and seasonality, a generic model applicable to the generality of cases, cannot be produced. Furthermore, different types (e.g. forest biomass for energy, biomass for bio-based materials and chemicals), sizes and spatial dimension of biomass supply chains drive the optimisation approach. With specific reference to the type of supply chain, in [3], it has been provided a review of scientific publications from 2012 to 2015, focused on forest biomass supply chain optimisation for a biorefinery. The authors have found that a huge number of the considered papers in this specific sub-topic of biomass supply chains have a final product referred to biomass for bioenergy, instead of biomass to materials and chemicals or both, which are considered by a few works. Thus, the authors have gathered that interest in diversified biorefinery portfolios is recent, and future research should address the forest biomass optimisation for high value bio-based products.

This article is part of the Topical Collection on *Biomass and Biofuels*

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Moreover, the modelling of supply chains should take into account, through a preliminary assessment of the biomass market, the potential circular economy including supply chains of biomass residues or biomass wastes. A clear and synthesised framework of the scope and decisions for biomass supply chain management has been provided by [4•]. In this paper, the integrated biomass supply chain problem is defined by four main parts: biomass harvesting and management, the integrated biorefinery, the product distribution and biomass logistics. Each of them contains a number of decision problems (e.g. transportation mode, transportation scheduling, routing problem...) to be addressed via various approaches.

This paper provides an analysis of the scientific literature of the last 5 years, to assess the degree of evolution of the developed models with respect to the antecedent state-of-the-art, as well as to identify the most innovative approaches and possible directions for future research.

Approach

Fifty-two papers published between 2013 and 2017 and two works published at the beginning of 2018 have been analysed (the highest number of papers has been found in 2016). In addition to this, ten extensive review papers have been considered from 2014 to 2017, which have been used to make some comparisons and evaluations.

Basically, papers have been classified in accordance with [5], in which a number of works, published between 1997 and 2012, have been reviewed. Three levels have been recognised:

1. Mathematical methodology
2. Decision level
3. Objective/s to be optimised

With respect to the mathematical methodology applied, three categories have been considered:

(1) Mathematical programming
(2) Heuristic approach
(3) Multi-Criteria Decision Analysis

Three main decision levels have been used:

i. Operational
ii. Strategic
iii. Tactical

Also, the combinations of the above-mentioned decision levels have been included.

The categories of objectives to be maximised or minimised, suggested by [5], are: economic, energetic, social and environmental. In this review, also time and distance have been considered.

Operational Level

At the operational decision level, Bochtis et al. [6] have developed a problem of scheduling sequential biomass handling operations, by minimising the total completion time of all tasks in all fields. In the same year, this new mathematical problem has been improved by Orfanou et al. [3], to provide a more complete approach of scheduling sequential tasks in biomass harvesting and handling operations, by including an estimation of the machinery variable cost. This study is based on the "greedy" heuristic algorithm and the "Tabu search" meta-heuristic algorithm. It appears that, although the authors have continued the work of [6], their major effort has focused not on bridging the previously identified gaps, but on expanding the complexity in terms of available number of machines per task type and on incorporating an economic objective.

Another heuristic approach has been developed by Caffrey et al. [7] that have proposed a logistic model to minimise the overall costs of system operations in a multi-crop and multi-harvest system; a heuristic approach has been used to identify the potential location of biorefinery facilities. A hybrid approach, based on both genetic and local search methods (heuristic and meta-heuristic algorithms), has been developed to optimise minimum cost routes for a fleet of agricultural vehicles from different production locations to a common storage location [8]. In this work, the minimisation of the travelled distance has been addressed through the application of the VRP (Vehicle Routing Problem). Indeed, this variable affects the total cost of biomass harvesting and collection, but the model needs some improvement, such as corrections to sub-optimal patterns, in order to obtain more realistic savings. To be applied in a real case, it can be useful to adopt a programmable navigation-aided system.

The mathematical programming has been applied to deal with logistic operations and biomass transportation, by focusing on biomass feedstock supply systems, including long-distance intermodal transport modes [9], assess task times and costs of activities and operations performed by different machinery configurations [10], or solving scheduling problems by using a MIP (mixed integer programming) model minimising the fleet dimension and the idle time [11]. Some authors have implemented their models in a GIS environment and applied a spatial approach to support efficient operational work plans ([9, 12]). For large-scale instances, which occur in real-world cases, also, heuristic algorithms should be implemented to improve the proposed models and to support an extension to more complex operational configurations.

A statistically based approach has been developed by Igathinathane et al. [13] to simulate bale collection logistics and to assess the effects of different parameters (such as the number of stacks) on distances, to increase the infield logistics performance of the biomass supply chain at an operational level. The coding for simulation, data analysis and visualisation of results has been realised by using the "R" software.

At the operational level, a review paper has been provided in 2017 [14]. Future research related to this specific decision level should take into account (but not limited to) the suggestions provided by the authors (e.g. the inclusion of environmental impacts in the objective functions or the incorporation of uncertainties in truck routing and scheduling models; the integration of chipping operation decisions in transportation models).

Strategic Level

As reported in Table 2, the most part of the considered scientific publications focuses on proposing new models and approaches to support strategic decision-making in the biomass sector (55.8%).

The discrete-event approach has been used to model interactions and relationships between the parts of a supply chain (wood pellet production [15]), or to identify the business processes and the stakeholders involved [16], allowing the managerial and organisational people to make appropriate decisions (e.g. by considering work load and time consumption per activity); the discrete-rate approach has been applied to wood pellet distribution. In Sahoo and Mani [17], a discrete-event simulation platform developed in a GIS environment has been proposed, aiming at a sustainable biomass supply chain, to minimise costs. Possible improvements could include other types of objectives (environmental, energetic, etc.). As an evolution of the traditional discrete-event, object-oriented and dynamic micro-simulation approaches, the agent-based simulation approach shows a variety of advantages, and it can be a powerful tool to face up to complex interactions in a biomass supply chain. An example of application to this field is provided by the work of Holmgren and Ramstedt [18•], which have extended two already existing models (TAPAS, TAPAS-Z), with the aim of enabling stochastic variation of the locations of senders and receivers of freight in a timber supply chain. This new model is an agent-based freight transport analysis tool of simulation for decision-making related to transport chains of timber wood. The main aim is to assess the potential consequences of a change from a time-based to a distance-based Swedish directive for heavy freight trucks, with respect to an increase of costs.

Also MIP/MILP (Mixed Integer Programming/Mixed Integer Linear Programming) models have been developed to support strategic decisions. A model has been proposed to provide an optimal spatial arrangement of terminals of plants, by including spatial (via GIS), technological (chipping machines) and physical issues (woody biomass volume) [19]. Another work [20] has included location, technology and capacity planning of different pathways related to biomass used for energy production, by focusing on the trade-off assumption of economies of scale and technological capacity ranges.

MILP and RDEA (Recursive Data Envelopment Analysis) algorithms have been developed [21] to provide a multi-objective programming model which maximises efficiency and minimises overall costs, to the optimal design of a biomass supply chain network, by integrating the assessment and the maximisation of the efficiency of facilities, during the supply chain planning. A MILP approach has been taken into account also to design hub-and-spoke supply chain networks (for biomass co-firing) by minimising demand-related costs [22]; minimise logistic costs and the environmental impacts of wood logistics [23]; and provide the optimised supply chain configurations ([24, 25]) (in [25], it has been realised by developing a multi-objective model and a two-tier approach). In other cases, a linear programming approach has been used to generate a dynamic multiple objective model to support collaborative decisions to manage railway traffic for wood supply [26].

In Paulo et al. [27] and in d'Amore and Bezzo [28], two models based on MILP for strategic design and planning of bioenergy supply chains have been developed: The main objective is economic, but in [28] a multi-objective problem is considered (economic and environmental). As an evolution of these approaches, multiple products and technologies should be taken into account, and uncertainties should be assessed, with respect to biomass feedstock, technological level, costs and demand.

Another multi-objective model has been developed by Lim and Lam [29•], with the aim of including both economic and environmental objectives for an efficient use of biomass. In this model, biomass characteristics (elemental composition—e.g. carbon content, nitrogen content…) are considered in a life cycle perspective, to identify potential underutilised biomass and its efficient use in a biomass supply chain. Further improvements may consist in introducing other constraints and factors, enhancing the process performance by considering its relationship with biomass characterisation with respect to specific technologies.

Already proposed MILP models can be a valid starting point to create more efficient and complete models aimed at the optimisation of biomass supply chain: as an example, Hu et al. [30] have used a MILP model focused on the minimisation of the ethanol production costs, to propose a CyberGIS approach for the optimisation under uncertainties (assessed through a Monte Carlo analysis). About the use of a CyberGIS to support strategic decisions, another example is found in Lin et al. [31•] that have provided a MILP aimed at quantifying and optimising a biomass supply chain system under different crop types, geospatial areas and transportation modes. This kind of platform can be very useful when a high computational performance of complex problems is required, like in real-world cases.

A stochastic quantile-based scenario analysis model has been proposed by Zamar et al. [32] to optimise biomass supply chains competing for the same biomass feedstock under stochastic demand and supply: This model has provided the most performing results compared to those generated by the Scenario Analysis and the Chance Constraint approaches.

In addition, hybrid optimisation methods have been proposed to be applied to biomass supply chain design and management. Rentizelas et al. [33] used the hybrid optimisation model developed in [34], to assess two energy supply chain options: pellet and CHP (combined heat and power). The hybrid model is made of the stochastic "genetic" algorithm (used at the first step of the study) and of an exact quasi-Newton method (applied at the second step), the "Sequential Quadratic Programming", to obtain a very fast convergence of the optimum solution. The main issue is related to the fact that this method does not guarantee the identification of the global optimum solution.

Empirical formulas and simulations for strategic decision-making of optimal biorefinery size and location have been developed by Golecha and Gan [35]. More specifically, the authors have considered that the transport radius influences the variations of biomass yield density and road network. Then, they have proposed an economic index (the Weighted Average Transport Cost per Unit Biomass), which can be used to scaling up biorefineries.

An environmental approach has been applied by [36••], to the optimal location of olive husk management centres. The Life Cycle Assessment methodology ([37, 38]) has been used to assess different scenarios and identify the best solutions. A mathematical parametric model and non-linear programming have been considered for the transportation problem, with the aim of minimising the energy needs for transportation of this type of biomass waste from the production points and for the distribution of the pellet.

The heuristic approach has been used by some authors to optimise biomass supply chain design, by addressing logistic costs and benefits (minimised fixed costs of harvesting machines and capital investment in fixed inventory facilities) (in [39], a "Tabu search" algorithm has been applied), but some improvements should be realised to extend too simplified conditions (e.g. partial cost accounting), and study possible interactions between crop types affecting crop yield.

At a strategic decision level, also, Multi-Criteria Decision-making models, implemented in a GIS environment, have been proposed. Martinkus et al. [40] have provided a GIS framework to combine social asset indicators into a unique measure and integrate it with biogeophysical assets for biorefinery site selection decision-making at a county level. GIS has been used to develop a Multi-Criteria Analysis to identify a set of appropriate locations for the generation of energy from biomass [41, 42•]. In [42•], a fuzzy logic approach has been considered, taking into account economic, environmental and social complexities, by minimising transport distances and costs. An economic assessment of different wood transport scenarios has been proposed by [43], which combines a network analysis with a raster-based GIS, by taking into account a number of factors, to identify the potential profits related to an upgrade of the forest road network, to an increased efficiency of transport and a reduction of fibre losses. Another Multi-Criteria Decision model based on GIS has been proposed by Guilhermino et al. [44], aimed at selecting the most adequate locations for power plants, by considering economic/financial issues of investment and logistics of forest biomass residues. Criteria of preference are availability of forest biomass, power grid and transport infrastructures and risk of forest fires.

GIS is a powerful system to meet many scopes in biomass supply chain research. One of the most interesting applications is related to the implementation of spatial models for biomass estimation, transport and location-allocation approaches to develop optimised supply chains. Martinkus et al. [45•] have compared two spatial methods of estimation of biomass volume and costs of delivered forest residues to a biorefinery. One is a past-predictive model [46], making use of Thiessen polygons to estimate residue volume assigned to each loading node. The second one is a future-predictive bio-economic model [47], consisting in a computer-based decision support system developed in a GIS environment to estimate costs of supplying wood fuel to power plants. The results show that both methods may be applied at a national level. A site selection analysis including a number of biorefinery operational costs varying geospatially may produce a reduction in financial risk.

Tactical Level

The tactical decision level concerns medium-term decisions (6 months to 1 year), which depend on the defined strategic level. It can be related, for instance, to production planning [48], logistics planning (truck configuration) [49], allocation of biomass products from production sites to terminals/power plants [50] and planning of a power plant under tactical conditions [51], but it is not limited to those cases (e.g. inventory planning or fleet management).

LP models have been developed to manage production planning for biomass supply and storage [48], to explore the influence of moisture content and its optimisation for efficient logistic planning [49–51]. In Marques et al. [50], the authors assert that further studies should be carried out to solve larger instances related to real conditions, and that, as a next step of their research, they will provide a generalised lot sizing and

Table 1 Classification in accordance with the defined criteria

Publication	Decision levels						Mathematical optimisation /simulation methodology	
	Strategic	Tactical	Operational	Strategic+operational	Tactical+operational	Strategic+tactical	Mathematical programming	Heuristic approach
Ackerman et al. [43]	x							
Balaman et al. [60]						x	x	
Bochtis et al. [6]			x				x	
Caffrey et al. [7]			x					x
Correll et al. [39]	x							x
d'Amore and Bezzo [28]	x						x	
de Meyer et al. [62]						x	x	
Delivand et al. [41]	x							
Ekşioğlu and Karimi [56]				x			x	
Ekşioğlu et al. [55]				x			x	
Golecha and Gan [35]	x						x	
Gracia et al. [8]			x					x
Grigoroudis et al. [21]	x						x	
Guilhermino et al. [44]	x							
Hoefnagels et al. [9]			x				x	
Holmgren and Ramstedt [18•]	x						x	
How et al. [58]						x	x	
Hu et al. [30]	x						x	
Igathinathane et al. [13]			x				x	
Kylili et al. [36••]	x						x	
Lim and Lam [29•]	x						x	
Lin et al. [24]	x						x	
Lin et al. [31•]	x						x	
Lin et al. [61]						x	x	
Marques et al. [50]		x					x	
Martinkus et al. [40]	x							
Martinkus et al. [45•]	x						x	
Mobini et al. [15]	x						x	
Montgomery et al. [12]			x					
Orfanou et al. [63]			x					x
Palander [26]	x						x	
Paolucci et al. [25]	x						x	
Paulo et al. [27]	x						x	
Pavlou et al. [10]			x				x	
Pudel et al. [54]					x		x	
Rauch and Gronalt [19]	x						x	
Rentizelas et al. [33]	x						x	
Ribeiro Teixeira et al. [42•]	x							
Roni et al. [22]	x						x	
Rudi et al. [20]	x						x	

Table 1 (continued)

Publication	Decision levels						Mathematical optimisation /simulation methodology	
	Strategic	Tactical	Operational	Strategic+operational	Tactical+operational	Strategic+tactical	Mathematical programming	Heuristic approach
Sahoo and Mani [17]	x						x	
Shabani and Sowlati [51]		x					x	
Shabani et al. [48]		x					x	
Sosa et al. [49]		x					x	
Taskhiri et al. [23]	x						x	
Torjai and Kruzslicz [11]			x				x	
Vasković et al. [1]	x							
Windisch et al. [16]	x						x	
Xie et al. [57]						x	x	
Zamar et al. [32]	x						x	
Zhang and Hu [53]				x			x	
Zhang et al. [59]						x	x	

Publication	Mathematical optimisation /simulation methodology	Types of objective					
	Multi-Criteria Decision Analysis	Economic/financial objective	Distance	Time	Efficiency/volume /energetic objective	Social objective	Environmental objective
Ackerman et al. [43]	x	x			x		
Balaman et al. [60]		x			x		x
Bochtis et al. [6]				x			
Caffrey et al. [7]		x					
Correll et al. [39]		x					
d'Amore and Bezzo [28]		x					x
de Meyer et al. [62]					x		
Delivand et al. [41]	x	x					x
Ekşioğlu and Karimi [56]		x					
Ekşioğlu et al. [55]		x					
Golecha and Gan [35]		x					x
Gracia et al. [8]		x	x				
Grigoroudis et al. [21]		x			x		
Guilhermino et al. [44]	x	x					
Hoefnagels et al. [9]		x			x		x
Holmgren and Ramstedt [18•]		x					
How et al. [58]		x					
Hu et al. [30]		x					
Igathinathane et al. [13]			x				
Kylili et al. [36••]					x		x
Lim and Lam [29•]		x					x

Table 1 (continued)

Publication	Mathematical optimisation /simulation methodology	Types of objective					
	Multi-Criteria Decision Analysis	Economic/financial objective	Distance	Time	Efficiency/volume /energetic objective	Social objective	Environmental objective
Lin et al. [24]		x					
Lin et al. [31•]		x					
Lin et al. [61]		x					
Marques et al. [50]		x					
Martinkus et al. [40]	x					x	
Martinkus et al. [45•]		x					
Mobini et al. [15]		x		x	x		x
Montgomery et al. [12]	x				x		
Orfanou et al. [63]		x		x			
Palander [26]		x		x			
Paolucci et al. [25]		x					x
Paulo et al. [27]		x					
Pavlou et al. [10]		x		x			
Pudel et al. [54]		x					
Rauch and Gronalt [19]		x					
Rentizelas et al. [33]		x					
Ribeiro Teixeira et al. [42•]	x	x	x				
Roni et al. [22]		x					
Rudi et al. [20]		x					
Sahoo and Mani [17]		x					
Shabani and Sowlati [51]		x					
Shabani et al. [48]		x					
Sosa et al. [49]		x					
Taskhiri et al. [23]		x					x
Torjai and Kruzslicz [11]				x	x		
Vasković et al. [1]	x	x			x		x
Windisch et al. [16]				x			
Xie et al. [57]		x					
Zamar et al. [32]		x					
Zhang and Hu [53]		x					
Zhang et al. [59]		x					

scheduling problem [52]. However, they suggest also the use of other heuristic methods to solve this kind of problems.

Strategic and Operational Levels/Tactical and Operational Levels

Few papers have focused on more than one decision level. Only two of the considered publications have proposed models to support both strategic and operational decisions, by using a MILP approach. In Zhang and Hu [53], an annual model for long-term strategic planning has been developed for the feasibility of biofuel production (operational level), and a second model has been developed at a strategic level for a detailed operational planning on feedstock and biofuel allocation. These models can be enhanced by extending the types of biomass, of pre-treatment technologies and of final products, to be more flexible with respect to a variety of cases.

Another MILP model has been proposed to optimise a multi-commodity and multi-time period biomass co-firing supply chain network design [54]. This is the uniqueness of the analysed papers which addresses both tactical and operational levels. The authors have used the outcomes of previous studies (e.g. [22, 55, 56]), to include seasonality. This is a two-stage model, based on stochastic programming, which solution is obtained by using a hybrid decomposition algorithm combining the sample average approximation with an enhanced progressive hedging algorithm, to minimise planning and operational costs at the same time.

Strategic and Tactical Levels

As regards to strategic and tactical decision levels, all the scientific works addressing these types of decisions have applied the mathematical programming approach (MIP and MILP models). Transportation modes ([57–60]) and multi-modal transport modelling or inventory monitoring are often combined with biomass allocation [58], biomass feedstock seasonality [57], number, capacity and location of facilities [59, 61]. In another study, a facility location planning problem is developed to take into consideration the changes occurred in the characteristics of a biomass product due to handling operations [62].

Results and Discussion

The papers have been classified in accordance with the defined criteria, as reported in Table 1. Percentage distributions of publications per type of criterion are reported in Table 2.

As reported in Fig. 1, most of the scientific papers address strategic decision issues related to biomass supply chains, mainly using mathematical programming (MILP and MIP are the most commonly used approaches) and fixing a single objective.

With respect to the objectives of the considered studies, the highest number of them covers economic/financial issues. Only one paper has fixed social objectives [40]. It has to be considered that, after 2014, the analysed publications do not take into account social objectives into their models, but the authors assert that this is a possible improvement and expansion of some of their works. Thus, it appears that the scientific community is less involved in such aspects than in minimising costs/maximising profits of biomass-related supply chains, maybe to meet the requests of new and more efficient tools to maximise profits of the investors.

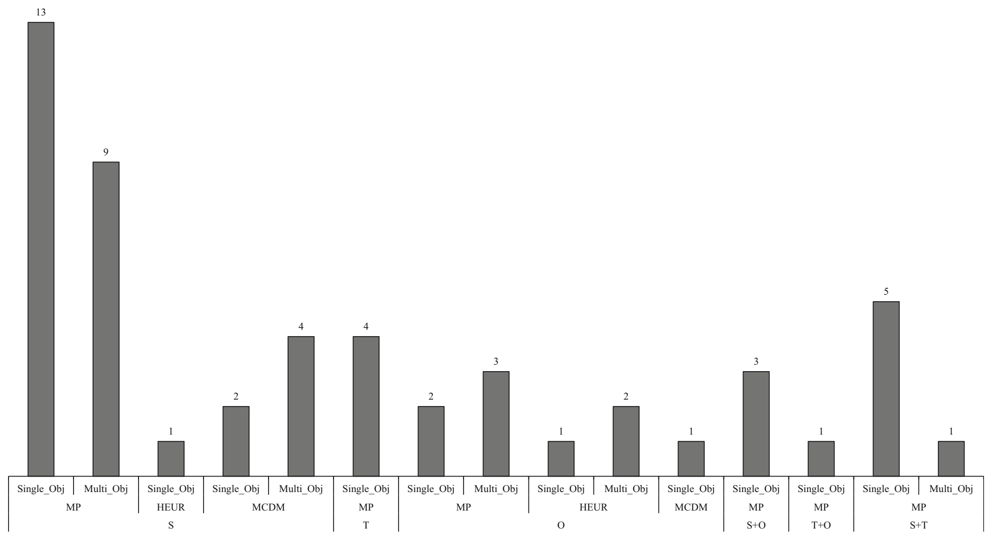
Two categories of objectives which are getting an increasing attention cover the environmental and the efficiency/energy subjects. With respect to the former, it is often related to the CO_2/greenhouse gas emissions, instead of the overall environmental impacts. Few studies include the Life Cycle Assessment approach; other tools have not been considered (e.g. Ecological Footprint and Water Footprint).

The efficiency or energy issues have been taken into account in some papers, because of their relevant impact on performance levels associated with the machinery and equipment used in different parts of the supply chain, as well as because of the maximisation of the energy production, which have a great influence on costs. Distance and time minimisation have their major importance in those papers that develop scheduling models and focus on tactical or operational decisions.

Table 2 Scientific publications focus on proposing new models and approaches to support strategic decision-making in the biomass sector (55.8%)

Decision level	%
Strategic	55.8
Tactical	7.7
Operational	17.3
Strategic+operational	5.8
Tactical+operational	1.9
Strategic+tactical	11.5
Mathematical optimisation/simulation methodology	%
Mathematical programming	78.8
Heuristic approach	7.7
Multi-Criteria Decision Analysis	13.5
Types of objective	%
Economic/financial objective	57.9
Distance	3.9
Time	9.2
Efficiency/volume/energetic objective	13,2
Social objective	1,3
Environmental objective	14,5

Fig. 1 Graphical representation of publication distribution in accordance with the three main classification criteria (S strategic; O operational; T tactical; S+O strategic+operational; S+T strategic+tactical; T+O tactical+operational; MP mathematical programming; HEUR heuristic approach; MCDM Multi-Criteria Decision-Making Analysis; Single_obj single objective; Multi_obj multi-objective)



By comparing the results of this literature review and those of previous extensive review papers, it can be stated that (i) the strategic decision level is still the most frequently considered, as well as the mathematical programming to deal with design and management of biomass supply chains [5] and (ii) economic objectives (also if associated with other types of objectives) continue to cover the most part of the reviewed papers, if they are compared to the results of [64].

Conclusions

With regard to the results of the review carried out by [65], the most of the future challenges and gaps in the scientific literature identified in 2014 are still to be filled or tackled.

From the analysis of the most recent literature, some efforts have been made by the scientific community to fill the gaps identified by [66], but few relevant improvements have been achieved after that. Indeed, the highest number of publications covers the strategic decision level, applies a mathematical programming approach and mainly focuses on a single objective. The economic objective is still the most considered.

Technological issues are not very well defined and implemented into the considered decision models, by including also dynamic multi-criteria and constraints. Moreover, a huge part of the analysed papers are case-based. Even if a unique and comprehensive model cannot cover the whole of biomass supply chains and cannot meet all purposes, a more generic/general framework should be developed, to provide more widely applicable tools for a variety of cases.

Social issues are yet to be considered as an important objective and, in some cases, only a point of view is taken into account (e.g. [16]), but a potential conflict should be considered as a type of constraint to the development of sustainable biomass supply chains.

From the environmental point of view, a very limited number of current models and approaches take into account all the environmental matrices and related impacts or damages on people and ecosystems, or apply standardised methodologies like the Life Cycle Assessment [36••]. None of the papers has applied the Water Footprint concept [67] or fixed the main objective of designing sustainable supply chains. This has been identified as a suggestion for future research, and it is supported also by the review carried out by [68]. In that paper, the authors have stated that a common framework and a set of environmental, economic and social sustainability metrics and indicators are needed in order to make comparisons and analyses across all the dimensions.

A holistic approach to technological, social, environmental and economic aspects of the biomass supply chain design and management will be the greatest challenge for the future research, because of its high complexity level and cost, and it is time-consuming.

This paper embraces the position of [4•] about the sustainable supply chain implementation: The strengths, weaknesses, opportunities and threats (SWOT) of the successful cases should be assessed, to provide points of reference to guide the effective and sustainable supply chain design, implementation and management. Furthermore, newly proposed theoretical models should be tested by using real-world cases, to define their performances by putting them into practice.

Moreover, about policy and regulations, there is still a lack of scientific literature and some efforts should be made to fill this gap. As asserted by [69], it is true that the kind of supply chain and the considered constraints strongly depend on national and local policies; it can be a reason of the absence of ubiquitous models of biomass supply chains in the current literature, and it is a limit to the development of such models and approaches.

Compliance with Ethical Standards

Conflict of Interest Emanuela Melis, Andrea Vincis and Pier F. Orrù each declare no potential conflicts of interest.

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

References

Papers of particular interest, published recently, have been highlighted as:
• Of importance
•• Of major importance

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