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Review

Tools for Optimization of Biomass-to-Energy Conversion Processes

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Abstract: Biomasses are renewable sources used in energy conversion processes to obtain diverse products through different technologies. The production chain, which involves delivery, logistics, pre-treatment, storage and conversion as general components, can be costly and uncertain due to inherent variability. Optimization methods are widely applied for modeling the biomass supply chain (BSC) for energy processes. In this qualitative review, the main aspects and global trends of using geographic information systems (GISs), linear programming (LP) and neural networks to optimize the BSC are presented. Modeling objectives and factors considered in studies published in the last 25 years are reviewed, enabling a broad overview of the BSC to support decisions at strategic, tactical and operational levels. Combined techniques have been used for different purposes: GISs for spatial analyses of biomass; neural networks for higher heating value (HHV) correlations; and linear programming and its variations for achieving objectives in general, such as costs and emissions reduction. This study reinforces the progress evidenced in the literature and envisions the increasing inclusion of socio-environmental criteria as a challenge in future modeling efforts.

Keywords: biomass supply chain; optimization models; mathematical programming; energy processes

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1. Introduction

The search for energy solutions to replace fossil fuels includes a set of technologies aimed at sustainable development [1]. Dependence on the oil industry is huge, but the finite nature of petroleum and its inherent environmental impacts underscore the need for ecologically friendly processes that can compete economically. Therefore, it is necessary to pay attention to the optimization of alternative processes and systems [2].

Different thermochemical technologies are used for the conversion of biomass, such as pyrolysis, gasification and direct combustion (Figure 1) [3]. Pyrolysis can occur in three forms. Torrefaction produces enhanced biomass with greater calorific power and lesser density and hygroscopicity [4], slow pyrolysis produces charcoal, and fast pyrolysis produces bio-oil. Direct combustion for the generation of thermal energy is the oldest and most consolidated technology [5,6]. The use of biomass is justified by its carbon-neutral status, i.e., the emissions of carbon dioxide are compensated by its fixation during the process of photosynthesis. As a result, an overall increase has recently been observed in the use of biofuels for electricity generation [7]. From a practical standpoint, however, this balance is not completely neutral due to the emissions involved in biomass transport and the disproportion between the replanting of native species and consumption that leads to deforestation [8]. For this reason, residual biomass (i.e., second-generation biomass) is preferable in most cases. To reduce emissions and costs, all aspects of the supply chain—planting, transporting, pre-treatment and final use—can be improved with different types of optimizations [4].

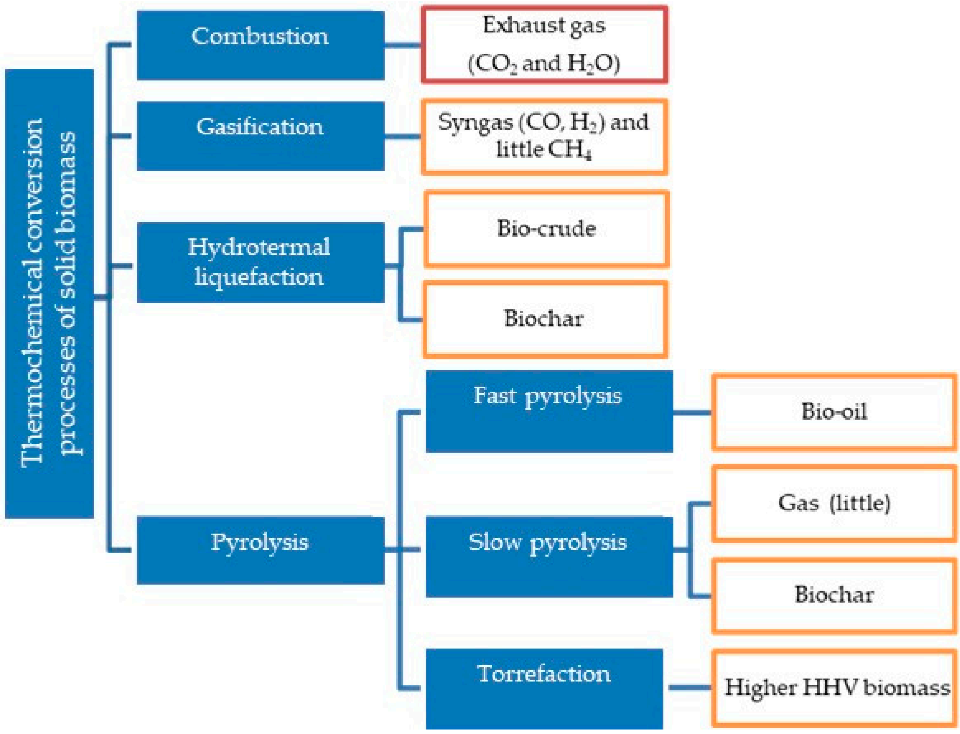

Figure 1. Thermochemical processes for production of fuels or chemical products (orange rectangles) and thermal energy (red rectangles) from solid biomass.

Optimization may involve the thermochemical processes indicated in Figure 1 or the supply chain and management processes. One of the lines of thermochemical process optimization is that concerning the combustion process itself. Improvements in combustion efficiency generally take into consideration aspects intrinsic to the reaction, such as composition, stoichiometric proportion of reagents (fuel and air), interaction of phases (liquid–gas, solid–gas) and geometry of the combustion chamber and accessories (grills, heat exchangers, etc.). Other thermodynamic processes concerning the conversion system (boiler, steam generator, etc.) can also be optimized [9]. Such measures enable the entire lower calorific power of biomass to be converted into heat for use in different processes.

From the global standpoint, the optimization of the supply chain as a whole involves supply (quality and variability of biomass), logistics, pretreatment, storage and burning. Complex logistics relating to the transport of biomass and its economic, energy use and environmental implications may be a barrier to the development of the sector due to the variations in the calorific power and density of biomass as well as its high moisture content [10–13].

The steps of the biomass supply chain (BSC) involve the harvesting of planted biomass or the provision of residual biomass, bagging, storage in warehouses, pretreatment (fragmentation, lixiviation, drying, mixing and densification), loading, conversion in the boiler and energy distribution. Changes can occur in the order in which the steps occur, such as treatment prior to harvesting (genetic improvement, fertilization, pest control, etc.). The number of warehouses, boilers and plants depends on the process in question and logistics relating to the region, while the availability and variability of biomass depend on the endemic and adaptable species as well as the inherent seasonality. Figure 2 summarizes the basic steps.

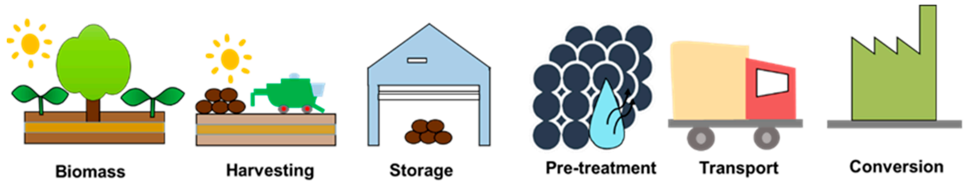

Figure 2. General steps of biomass supply chain.

The optimization approach varies according to the objectives of the model (e.g., minimizing costs, maximizing calorific power or maximizing electricity generation), the characteristics of plant location, and the parameters to create the model. The choice of the mathematical modeling method depends on how the restrictions are presented to the problem and the volume of data available a priori. Historical data enable the use of stochastic programming, whereas data resulting from experiments with multiple variables enable the use of heuristic or meta-heuristic models, such as artificial neural networks, due to their high complexity and sometimes nonlinear nature.

The present article offers an overview of how optimization models are intrinsically related to the supply chain, addressing the basic premises of modeling the BSC to generate energy and highlighting the economic, environmental and operational particularities of each process/model. So, the research objective of the article is to distinguish the applicability of optimization modeling in the BSC. The key question is: what is analyzed when optimizing BSC? What optimization methods have been used globally? What sets them apart? This article also aims to contribute to the field of biomass research and emerged from the need to understand academic modeling methods for industrial applications in the energy field without embarking on an exhaustive systematic review, rather serving as an overview for the reader on the topic.

This article is structured as follows: Section 1.1 discusses the important characteristics to consider regarding biomass as the raw material in a BSC. Section 2 offers a succinct description of the methodology adopted for the study. Section 3 provides an overview of possible BSC modeling with a discussion on the main recent applications and criteria. Section 4 presents conclusions on the findings. In this way, it is hoped that the reader understands the application of mathematical modeling for optimization of the BSC and the factors involved.

1.1. Biomass Characteristics Influencing the Supply Chain

Biomass is defined as organic material derived from plants and organic (agricultural, forest, industrial, human, animal and municipal) waste [14]. The main constituents of plant biomass are cellulose, hemicellulose and lignin, along with lipids, proteins, simple sugars, starch, inorganic compounds and moisture [15]. Biomass, such as wood, grass, agricultural waste, animal and human waste, algae, etc., is a natural, renewable source produced sustainably in large quantities in many parts of the world [16].

Plant-based biomass is classified as herbaceous (grass, agricultural waste, wheat straw, rice straw, bamboo, etc.) or arboreal (leaves, branches, sawdust and wood scraps) biomass [17]. Biomass can be converted into fuels, chemical products or heat and electricity. Biomass as a renewable energy source should have high yield (dry matter per unit of land area) and energy content [18] as well as attributes such as ease of acquisition, low cost and neutrality in terms of greenhouse gas emissions without affecting the availability of land and food [19]. Wiranarongkorn et al. [20] suggested a flowchart for the selection of plants to compose mixes of biomass. For this purpose, they grouped them by cultivated region and harvest time, creating a calendar that initially supplies 50% wood chips, and made analyses of the mixes to determine the chlorine content and predictive indices of slagging and fouling to prevent corrosion and encrustations, thereby obtaining an adequate multi-biomass composition.

The composition of biomass influences the process yield and determines the need for pretreatment for cofiring. Such characteristics vary with the species and seasonal crop conditions and should be considered along with the boiler properties. A high moisture content (mass of water in the biomass per unit of dry mass or mass of water in relation to total mass) requires biomass drying, while a high concentration of inorganics, such as chlorine and potassium, suggests a lixiviation step. Steps such as pelleting and briquetting should also be evaluated. However, the greater the need for preliminary biomass treatment, the higher the costs. Moisture confers variability to the calorific power, increases transport costs due to the indirect purchasing of water, can cause obstruction of biomass in lines, and reduces the efficiency of the firing process due to the increase in time for moisture vaporization. The cause of reduced combustion efficiency due to solid biomass moisture is mainly related to a longer time required before biomass begins its combustion process (evaporation of water, volatilization, pyrolysis and combustion—Figure 3) and poorly established residence time in the boiler or furnace. Biomass moisture also varies with the part of the plant used or the climatic season, as biomass tends to equalize its moisture content with that of the surrounding air. Bartzanas et al. [21] used simulations involving computational fluid dynamics (CFD) to describe the biomass drying process given the climatic conditions as part of the boundary conditions necessary for drying calculations using weather data from Denmark. CFD can simulate accurately, helping to design and optimize virtually with less experimental runs, and can estimate the moisture content, among other parameters such as spatial and temporal fluid pressure, temperature, and velocity. These authors evaluated grass drying both experimentally and numerically (CFD) and compared them. In particular, Navier–Stokes equations, mass and energy conservation equations, and Reynolds equations were used. The study revealed the possibility of using the model as a decision support for drying to recommend cutting decisions based on meteorological conditions, the mean variation observed between the analytical and CFD model being only 8%.

Figure 3. Biomass combustion process.

According to Demirbas [22], Van Loo and Koopejan [23] and Rajput et al. [24], moisture and ashes cause ignition problems, reduce the adiabatic temperature of the flame, increase the necessary residence time and exert a negative impact on the stability of the flame.

To reduce the impact of moisture, biomass can be densified through pelleting or briquetting soon after grinding and then be stored. Densification improves biomass quality through the increase in energy density, stability and durability, along with a reduction in handling, storage and transport costs [25]. Pellets are cylinders, typically with a diameter of 6 to 10 mm, and are generally used in automatic feeding boilers due to good fluidity and uniform characteristics in terms of moisture content, size and chemical composition, whereas briquettes are fed manually and have a diameter between 30 and 100 mm [23].

Lixiviation involves the removal of undesirable soluble elements in water through washing. According to Reza et al. [26], lixiviation with hot water can remove 50–90% of inorganics, such as Ca, S, P, Mg and K, from biomass. Rain promotes lixiviation in the weeks prior to use or days after harvest but depends on the climate and increases the risk of degradation [23]. More abundant in agricultural waste and grasses, such as elephant grass, than in forest biomass, inorganic compounds remain in the ash due to their high melting points, thereby reducing boiler efficiency. Significantly greater fouling is expected with grass-type biomass in comparison to wood due to high chlorine and alkaline contents [15,27].

According to Adlakha et al. [17], Ca, K and Mg are the dominant inorganic elements in biomass, with calcium accounting for 80%, while smaller fractions of Na, Al, Si, S, P, Cl, Mn, Fe, Cr, Ni, Cu, Pb and Zn may be found. Their contents depend mainly on the characteristics of the soil in which the biomass is grown and are determined through the analysis of ash composition.

According to Van Loo and Koopejan [23], chlorine concentration in biomass depends on the type and quantity of fertilizer. The application of chlorine-free fertilizers reduces the chlorine content considerably without increasing those of K and S. Another option for minimizing the effect of chlorine is the capture of alkaline compounds to increase the melting point of the ash formed during combustion through the use of additives, such as bauxite, kaolinite, chalk and magnesium oxide [25]. To reduce chlorine content in the ash deposited during the combustion of wood and straw, Mandø [15] applied phosphorus and calcium at an optimal molar ratio of 0.8–0.9.

There are reports of the composition of ash together with sulfur and chlorine as factors related to fouling and corrosion in boilers [25,28–30]. These are mainly alkaline compounds containing K and Na, which form alkaline silicates that melt at lower temperatures, thereby fouling surfaces.

2. Methodology

The literature in the field of biomass is very extensive due to the various possible technologies, types of biomass, and factors involved in BSC. However, literature reviews sometimes are too specific, showing BSC results and advances without highlighting their peculiarities and differences among them.

The present integrative, qualitative review used data collected from several electronic platforms (Science Direct-Germany, SciELO–Brazil, Springer-Germany) available on the Web and specialized research, i.e., scientific papers published between 1997 and 2023. The search was based on comprehensive terms. The following keywords were used in the search for papers: "biomass", "combustion", "biomass supply chain", "linear programming", "neural networks biomass" and "geographic information system biomass".

Articles were selected after reading their abstracts using the following inclusion criteria: thematic publication within the selected period in Portuguese and English. In the refined pass of searches, we initially gave preference to the energy generation process, with no restriction imposed regarding the biomass used. We sought to answer the questions asked in the introduction through recent research considering trends in energy optimization. A summary of the methodology can be seen in Figure 4.

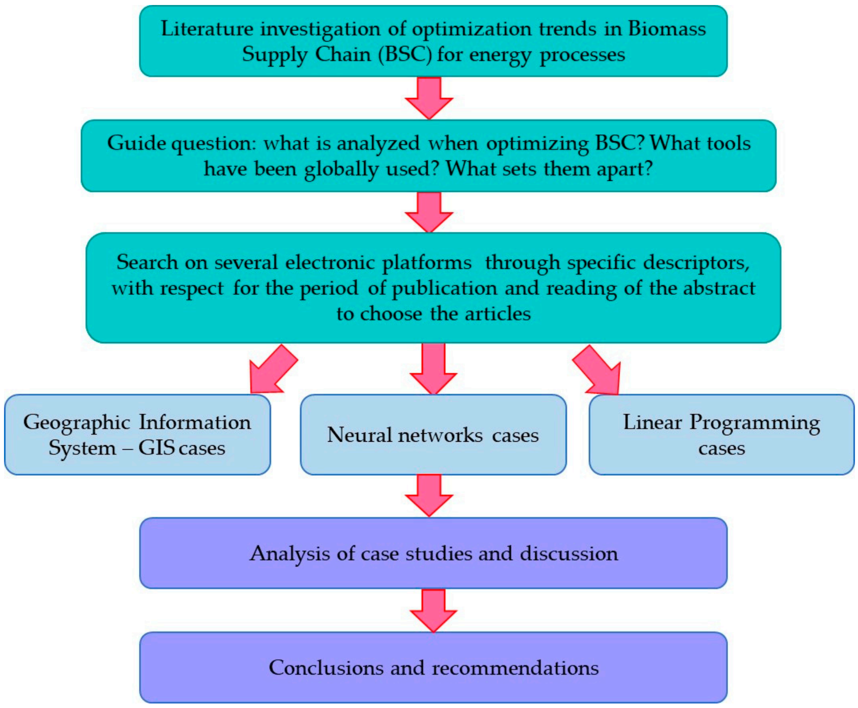

Figure 4. Research methodology.

3. Modeling and Biomass Supply Chain

The use of modeling of the biomass supply chain for energy purposes has been widely explored in the literature and can assist in strategic, tactical and operational decision making. Differences exist in the comprehensiveness of the levels of decision. Regarding long-term aspects (e.g., annual), strategic decisions include the design of the boiler itself, investments, selection of suppliers, allocation of installations, etc. Medium-term aspects involving transport routes and seasonal inventories are tactical decisions. Operational problems require more frequent adjustments and involve transport planning and short-term demands [31].

According to Sun and Fan [32], the BSC problems relating to the harvesting process are those regarding scheduling forest and crop harvest, as well as the necessary equipment. There are location and shipping scheduling problems (related to storage), while network design with material flows and vehicle routes is expected to generate transport problems.

In general, there is a preponderance of the economic focus in optimization of the biomass supply chain, with limited attention given to the reduction in the carbon emissions of this chain [33].

Modeling of the biomass supply chain could be single-objective or multi-objective, with various goals to be optimized at the same time [34]. According to Albashabsheh and Stamm [35], the use of deterministic methods presupposes prior knowledge of all parameters. In contrast, other researchers take into consideration uncertainties and more realistic random parameters relating to the supply, transport and demand for biofuels as well as the prices of biofuels and biomass, thus characterizing a stochastic or hybrid model when combined with the deterministic model. The need emerges to make the optimal solution feasible, independently of the uncertainty (distributions of probability), and sensitivity analysis could be performed with variation in the input parameters [35,36]. For instance, Sajid [37] observed the impact on the quality, collection and transport of biomass through uncertainties of the conditions of the 2019 coronavirus pandemic.

The solutions of the model include distinct methods that can be associated with each other: multi-criteria decision analysis (MCDA), simulation methods, heuristic methods, geographic information systems (GIS), mathematical programming such as mixed integer linear programming (MILP), etc. [38]. Considering the multiple possibilities of objectives and attributes, the model based on MCDA enables ordering the decision criteria in an explicit way according to relative weights in order to select the most adequate solution [39]. Due to the complexity of real problems, such as those relating to energy and sustainability, modeling by linear programming can sometimes produce insufficient results, with fuzzy modeling being more adequate in the use of uncertainties [40]. Heuristic methods, such as genetic algorithms (GA), are generally used for the treatment of practical examples on a large scale, aggregating agility in comparison to mathematical modeling [31,38].

Each study presents a particular context that includes the type of available data, the quality and quantity of data and the general objectives of the study. Basically, all techniques are used in the BSC, but with different approaches, that is, in different stages of the chain. Neural networks focus on the biomass feed stage because that is where you have a larger volume of data, and it is impossible to do so in other steps that envision installation, mapping and conversions, for example. In this sense, this article is important because it reinforces the trends in approaches and applications reported in the literature. The context indicates the most appropriate optimization model. Three of the main types of modeling are presented below.

3.1. Geographic Information Systems—GISs

Geographic information systems (GISs) use interactive maps for managing geographic and spatial data, helping decision makers analyze processes. Geographical issues are a factor that can affect the feasibility of a project due to the location provided by longitude and altitude parameters [41,42].

GISs are a useful tool for identifying, selecting and optimizing locations of bioenergy plants considering physical, biological, social and economic criteria [11]. GIS systems enable superimposing data from different disciplines, such as vegetation cover and demographic density, on useful maps for BSC managers of BSC. According to Kim et al. [43], GISs have been used for the precise analysis of transport distances, costs and impacts of different projects; facilitating the selection of sites as sources of biomass and their yields; determining suitable areas to build facilities (strategic decisions); calculating changes in routes (road network) and regions of demand and high densities; and considering factors such as water flows, electricity networks for infrastructure, and population for labor. They are used to help design, plan and manage problems in the BSC [32,42]. This type of consideration and simulation helps to achieve, for example, minimization of costs in the BSC.

Wang et al. [11] used a GIS in their scenario-defining phase, selecting potential plant candidates found to be highly suitable according to criteria such as biomass availability, distance from main roads, distance from electric substations, distance from water bodies, and the flood risk of potential sitings. Vukašinović and Gordić [42] mapped potential storage locations and potential locations of biomass plants (forest residues) in a municipality of Serbia using geographic information system technologies. They concluded that only 6% of the available potential could be used in an economically optimal way. Lozano-García et al. [44] assessed the potential to use residues of crops (maize, wheat, sugarcane, barley, sorghum, agave, paddy rice, and pecan nut) in several regions across Mexico for generating energy by gasification and combustion. Hu et al. [45] developed a linear complementarity model to simulate the rice straw cofiring system in the electric power market of Taiwan, making use of GIS spatial analysis to evaluate and describe rice straw collection, transportation and CO_2 reduction. Sahoo et al. [46] integrated GISs to identify optimal plant sites and calculate the delivered cost with neural network models to assess sustainably available crop residues. The authors assessed the use of cotton stalks to produce fuel pellets in the state of Georgia (USA) while maintaining long-term soil health. Zyadin et al. [47] applied GISs and data from a field survey of farmers to produce land use maps for forest and agricultural surpluses in two Polish provinces. These were used as a tool to optimize the locations of future investments in biomass-based power plants. The calculated amounts of surplus residues of corn, wheat, rye, barley, rapeseed, triticale, and grass indicated that 30% of the surplus biomass could be safely used for energy generation.

According to Charis et al. [48], problems of BSC and the management of urban solid waste share a "common denominator": both depend on the spatial distribution of supply points and variability in the quantity of resources. The authors pointed out that GISs are an important tool that can be used to capture the spatiotemporal dynamics of biomass and waste.

Solid waste management could make good use of maps with GISs. For instance, eco-points could be strategically located near the neighborhoods with considerable generation of waste and interest on the part of the population in selective waste collection. Solid waste management in Brazil has an important legal framework: the National Solid Waste Policy instituted by Law nº 12.305/2010 and regulated by Decree nº 10.936/2022 [49]. This policy elicits services or research, development and innovation projects related to the use of technical-economic optimization tools, such as GIS, linear programming and other methods also associated with BSC optimization. However, the discussion on optimization methods that apply to solid waste management and BSC are beyond the scope of this article.

GIS separately or combined with other optimization tools described below could be applied to the management of BSC or urban solid waste.

3.2. Neural Networks

Neural networks are mathematical models of stochastic nature composed of units or nodes called neurons that can predict system outputs with high precision, low cost, and short processing time [50]. They are based on two stages: training and validation. A set of input data and respective output data are provided in the training step. The modeled neural network is formed by a set of layers and weights. The input layer receives the input data, the output layer provides the result, and the hidden layers enable the neural network to operate through activation functions [51].

A neural network needs data collection, pre-processing of data, optimizing of the network design (number of hidden layers, neurons and activated transfer functions, algorithm selection). The linear transfer functions (Purelin and Poslin), Log-Sigmoid function (Logsig), and Tan-Sigmoid function (Tansig) are often reported in the literature. To train the network and obtain the best weights of neurons, algorithms such as quasi-Newton (QN), sealed conjugate (SC) and Levenberg–Marquardt (LM) are cited by Yatim et al. [50] and Güleç et al. [52].

Neural networks can be applied in the context of seasonal variability in the composition and supply of biomass for production chain situations in which the volume of data enables computational algorithms to learn from varied examples. According to Yatim et al. [50], artificial neural networks are one of the most applicable and widely used algorithms in the field of waste-to-energy (combustion) design and optimization as a tool for higher heating value (HHV) estimation based on ultimate analysis. The correlations developed make the process cheaper by consuming less time and equipment. In this sense, the study, conducted in Morocco, used compositions from the literature of 114 different biomasses to make such correlations.

As "machine learning" establishes, the program is capable of providing outputs based on new inputs—like a human brain would do—after having learned to relate inputs and outputs that are related in a highly nonlinear, complex way. In this regard, artificial neural networks were utilized to predict biomass pyrolysis behavior without known reaction mechanisms [53]. Zhang et al. [54] reported the use of neural networks to predict HHV, enthalpies of combustion and other exergetic data based on biomass composition. Uzun et al. [55], Estiati et al. [56] and Hosseinpour et al. [57] were also able to accurately infer the higher calorific values of biomass based on fixed carbon, volatile matter, moisture and ash content (proximate analysis). Meanwhile, Güleç et al. [52] investigated and evaluated a model to predict HHV from combined ultimate and proximate analyses as a better method than using them separately. They compared different biomasses, algorithms, activation functions and hidden layers. According to Jakšić et al. apud Güleç et al. [52], any mixture of biomass feedstocks using proximate analysis can have their calorific values determined using an artificial neural network.

Deep neural network algorithms, an advanced version of artificial neural networks for Big Data analysis, were able to predict and verify the slagging tendency of 571 types of biomass, indicating that they are a useful tool for the selection of biomass fuels to increase the life, efficiency, and safety of combustion boilers [58].

3.3. Linear Programming

The optimization method known as linear programming is widely employed because it also helps in decision making with regards to production planning. This mathematical model of deterministic origin involves an objective function to be either maximized or minimized (the objective function generally regards the overall operating cost of a plant when applied to the optimization of biomass supply chains for energy purposes) and a set of restrictions (mathematical expressions, such as linear equations or inequations) that address the selected decision variables (outputs) and parameters (inputs) [59,60]. In the context of BSC, restrictions in linear programming problems may be related to the thermal demand required by the boiler, admissible moisture content of biomass (40 to 50%, according to Annevelink et al. [61]), available pretreatments, prevention of natural degradation, prevention of boiler corrosion (generally associated with sulfur and chlorine contents in biomass), limits of pollutant emissions generated during combustion, capacities of the available stocks, load capacity of transporters of biomass to storage, supply limits (sensitive to crops and other factors), contractual conditions, such as the minimum purchased from suppliers, etc. If one or more decision variables are integers, this is known as mixed integer linear programming (MILP) [38,62].

The objective may be to understand the maximization of profit, minimization of operating costs, environmental impact or fuel consumption. The general restrictions of a supply chain model regard the availability of biomass, processing capacities and market demands, establishing limits to be met [34].

According to Wu et al. [38], the main cost involved in the supply chain is transport, followed by the cost of biomass acquisition. Regarding operational costs, the highest one is that of labor (35.92%), followed by the costs of purchasing and equipment (30.70 and 24.25%, respectively). The large contribution of the purchasing cost with the variability in the biomass supply pattern and associated uncertainties require well-designed modeling.

Zahraee et al. [39] stressed the importance of MILP in the resolution of problems involving modeling due to the occurrence of discrete phenomena. However, in the case of biomass chain modeling and optimization, linearity may only reflect specific conditions, and the model deviates from reality when there are changes in these conditions [63].

The application of linear programming generally occurs in supply chains still to be established and in which the restrictions (storage limit, transport capacity limit, supply, demand, etc.) can be expressed by linear expressions that involve input parameters and decision variables. In most cases, the decision maker adopts linear restrictions after simplifying the problem.

Case Studies of Linear Programming in the Context of Biomass Supply Chains

The literature describes some linear programming (LP) case studies related to BSCs, as listed below.

Cundiff et al. [64] used linear programming to minimize costs related to transport and expansion capacity in warehouses, performing an uncertainty study with regards to the climate and applying it to a plant whose chain involved 20 producers, in the Piedmont region of Virginia (USA), each with four to seven storage locations.

In the year 2000, Nienow et al. [65] used LP to optimize the optimal cofiring mixture of coal and wood biomass in the state of Indiana (USA), minimizing costs.

Bruglieri and Liberti [66] adopted LP to generate a preexisting network of the supply, transport and processing of biomass in Italy. The authors also used MILP to optimize the decision-making process of the allocation of processing centers and network management.

Rocco and Morabito [67] proposed an optimization model in Brazil using LP to support decision making in the steam production process involving the management (purchasing, storage and use) of fuels (sugarcane bagasse, wood chips, firewood, rice straw and oil with a low fluidity point) and the mode of functioning of one or multiple boilers (switching on, heating and switching off). The optimization software was the General Algebraic Modeling System (GAMS), and the global cost was minimized.

Saghaei et al. [68] presented an optimization model in the USA that was initially nonlinear (presenting multiplication of continuous and binary parameters and the demand parameter following a normal distribution) but subsequently linearized to minimize the total cost of the electricity production chain using different biomasses. Biomass flows from suppliers to storage and from storage to plants were identified as well as stored volumes (and stored excesses), electricity production at each plant and distribution plan of electricity from the plants to consumers. In this approach, the energy demand was presumed to follow a normal distribution. It is to be noted that instead of using a stochastic programming approach, the writers adopted an interesting linearization technique. The algorithm also featured different scenarios whose demands had different means and variances and whose biomass availability also differed.

Wang et al. [11] developed a model using MILP to optimize the harvest of different biomasses and the logistics of BSCs, quantifying and mapping (13 states of the USA) costs in different scenarios, with sensitivity analysis of availability, harvesting rate, moisture content, acquisition ratio and installation capacity.

Abdelhady et al. [69] used MILP to design a national biomass supply chain network in Egypt with the aim of maximizing profit through an optimal configuration. The decision of whether or not to install a power plant with different capacity levels in each location available was an output (decision variable) of the algorithm.

Ferretti [70] used a mathematical model to maximize profits in Italy with the definition of optimal weekly quantities of wood scraps for different purposes: combustion, reintegration to the production cycle, sale and storage, assisting in decision making from the strategic standpoint. An approximately 15% increase was achieved in profits from this process.

Starting from the premise that a BSC is stochastic by nature, Aghalari et al. [71] used mathematical modeling (MILP and a hybrid algorithm) to assess the impact of quality (ash and moisture content) while optimizing the production of biomass pellets in the USA.

Yahya et al. [33] applied MILP in a case study in Malaysia with 491 variables, 143 integers and 437 restrictions, addressing different scenarios, with the assessment of the total supply of nine plants fueled with biomass and an investigation stage to achieve a reduction in carbon emissions. During the mathematical programming phase, values for CAPEX and OPEX of different technologies were used as parameters in certain constrains. The study aided in the decisions of the "operational state of each technology", in other words, whether or not a power plant with certain conversion technology should be installed.

Paes et al. [72] performed modeling of the Brazilian energy system, aggregating explicitly environmental parameters to the most commonly addressed socioeconomic parameters and imputing penalties, the restriction of greenhouse gas emissions or a carbon tax, relating a cost to environmental pollution within the objective function. The authors studied scenarios with and without the application of penalties.

Using a multidisciplinary analysis that included MILP, GIS, economic analysis and sensitivity analysis, Wu et al. [38] optimized the biomass supply chain in China from the strategic standpoint in the search for lower costs.

The articles of this section can be subdivided into different applicability groups:

- The first group involves studies that focus in the harvest stage of the BSC. Wang et al. [11] is included in this group, with applicability reserved for early stages in the biomass conversion planning. Usually, in this stage the resource availability is promising but conversion technology has not been considered yet;
- A second group involves Cundiff et al. [64], Bruglieri and Liberti [66], Rocco and Morabito [67], Abdelhady et al. [69], Yahya et al. [33] and Saghaei et al. [68]; their models aid the decision maker in the process of power plant location and/or storage location definition and multiple-facility operational status definition. Some of them also allow for uncertainty in the model (Saghaei et al. [68], Cundiff et al. [64]);
- A third group focuses on the optimization for different uses for the considered biomasses; Ferretti [70] and Aghalari et al. [71] could be included in this group;
- A fourth group involves the research of Paes et al. [72] that, despite optimizing the BSC from an economic standpoint, also uses explicit environmental constrains. Nienow et al. [65] could also be placed in this group, since their research also helps the power plant comply with environmental regulations;
- A fifth group involves Wu et al. [38] whose research focuses on holistic approaches giving great attention to multidisciplinarity (geographic information systems and mathematical modeling with technical economic analysis and sensitivity analysis).

The studies include cases from America (USA, Mexico and Brazil), the European Union (Italy, Serbia and Poland), Africa (Egypt and Morocco) and Asia (Malaysia, Taiwan and China), demonstrating broad applicability of the described tools.

Most optimization strategies, such as LP, aid in the optimal management of the chain, indicating quantities, purchase schedule, and routes. The physical aspect of the conversion, whether it is combustion, gasification or pyrolysis, is considered as a black box, and the algorithms usually require that conversion efficiencies and heating values are given as input parameters. For instance, Saghaei et al. [68] claimed that heating values and power plant efficiencies should be known a priori, while Rocco and Morabito [67] used as an input parameter the steam that could be generated in each power plant after combustion; therefore, the second incorporated both the heating value and efficiency in a single input parameter.

The aforementioned parameters usually come from practice, but it is to be noted that CFD tools can help for simulating lower heating values of biomass after combustion, burner efficiency and other parameters. They may be present in optimization algorithms, such as those required in the start-up phases of power plants.

CFD simulation for solid biomass combustion, gasification or pyrolysis is far from trivial. It usually involves heterogeneous reactions with turbulent flows. Bermúdez et al. [73] used the software Ansys Fluent to perform CFD simulations of solid biomass combustion (consisting of pyrolysis, gasification, and combustion). The solid part of the domain was modeled using porous media and used defined scalars and the respective transport equations, while the gas phase was simply used homogeneous reactions. This shows the complexity of combining this type of tool with modeling, as well as the complexity of biomass conversion processes.

Table 1 summarizes some applications of mathematical modeling relating to biomass, especially linear programming, which is often used with other tools and techniques. Through these models, there has been a broad approach to programming, with most of them minimizing the global cost. It can be noted that at this stage, the biorefinery or plant does not have a large enough volume of data to allow it to use other techniques. In general, the previous integrated use of GIS makes it possible to indicate the vegetation cover and its space–time variability, supporting the definition of locations for the installation of thermoelectric conversion plants and biorefineries.

Table 1. Summary of studies involving the use of mathematical modeling of biomass supply chain.

Authors	Type of Modeling/Solver	Factors Considered	Objective
Cundiff et al. [64]	Linear programming (LP) optimization software package CPLEX	Storage Transport Losses with storage and handling Production uncertainty due to weather	Minimize costs relating to transport and expansion capacity in warehouses
Nienow et al. [65]	Linear programming (LP)	Cofiring Production of wood biomass Transport Use	Minimize cost of production of particular demand for electricity while meeting environmental regulations
Bruglieri and Liberti [66]	Mixed integer nonlinear programming (MINLP) Mixed integer linear programming (MILP) optimization software package CPLEX	Different biomass transformation processes Commodities Transport Processing	Minimize costs of commodities, transport and processing
Rocco and Morabito [67]	Mixed Integer linear programming (MILP)	Purchasing Transport Storage Multiple boilers with different aspects (switch on, heating and switch off)	Minimize costs of biomass supply chain for steam production: purchasing, fuel transport, storage and switching on and heating of boilers
Saghaei et al. [68]	Stochastic programming MINLP Metaheuristics Genetic algorithms (GAs) Chaos theory Tent maps CE (ICE) algorithm	Suppliers Storage Energy plants Consumers	Minimize costs; identify optimal size and location, flow between sectors, volumes of stored and converted materials, and distribution strategy

Table 1. *Cont.*

Authors	Type of Modeling/Solver	Factors Considered	Objective
Wang et al. [11]	Mixed integer linear programming (MILP) General algebraic modeling system (GAMS)/ optimization software package CPLEX Geographic information systems (GISs)	Supply Harvest Storage Transport Pre-processing	Optimize biomass supply chain in 13 states of USA, with sensitivity analysis
Abdelhady et al. [69]	MILP SAM software	Capital costs of plant Harvest and pre-processing Logistics Operation and maintenance Size of variable capacity Costs of capital and variable organization and methods (O&M) Efficiency of variable plants Unknown location of plants Taking climate conditions into consideration	Establish optimal configuration of national biomass supply chain network in Egypt to maximize profit with regard to generation of electricity
Ferretti [70]	Modeling for use of decision support system State task network Genetic algorithms (GAs) Particle swarm optimization (PSO)	Decision strategy between selling residual biomass, use for production of plywood, storage or production of thermal energy	Maximize profit and optimize quantities of biomass waste for different purposes
Aghalari et al. [71]	Stochastic programming MILP Hybrid algorithm with sample average approximation Progressive hedging	Harvest Storage Transport Quality inspection Production decisions	Generate yield and quality of biomass supply chain for production of pellets
Paes et al. [72]	MILP IBM ILOG CPLEX optimization software package Optimization programming language	Costs of operation and expansion Availability of plants Energy specifications Meteorological data	Minimize economic costs of operation, investment and emissions
Wu et al. [38]	MILP	Purchasing and harvesting Pretreatment Costs of loading and unloading /transport No losses during transport	Minimize costs of agricultural biomass supply through design of optimal supply chain

In a way, the literature has contemplated several modeling methods for various technologies of conversion of biomass into energy and bioproducts. However, there is limited addressing of governmental regulations and policies in BSCs. Different aspects have been considered in recent studies, with growing attention given to environmental issues. The current challenge is to ensure the applicability of academic studies to the industrial environment as well as the efficient and global reuse of multiple residual biomasses.

4. Conclusions

Biomass supply chains generally involve supply, logistics, pre-treatment, storage and conversion. The achievement of more sustainable production models can be linked to the execution of more optimized processes as well as the development of more efficacious technologies from the energy standpoint. First, it is necessary to consider and analyze the yield and energy conferred by the types of biomass available, as well as whether there is a need for pre-treatment.

The main trends and directions were discussed with reference to modeling the BSC. The optimization methods shown here, i.e., GIS, LP (and its variant, mixed integer linear programming) and artificial neural networks, among others, such as multi-criteria decision analysis (MCDA), simulation methods, heuristic methods, fuzzy modeling, and CFD, can be successfully used in different processes.

The issues raised in the introduction were evaluated. The difference among the methods lies in the degree of complexity, uncertainty and volume and type of data available. In this regard, linearity was discussed. The levels of decisions that each type of modeling encompasses, the focus given to the objective functions, and the aspects of modeling found in the literature were addressed. This makes us conclude that combined analyses through more than one tool, enrich modeling.

A preponderance of the use of GISs for spatial analyses of biomass in order to reduce uncertainties associated with spatial and temporal variations was observed, while neural networks were found to be widely used for HHV correlations. Linear programming generally aims to minimize the costs and emissions of the global chain, sometimes using these other tools in conjunction. Prevention of corrosion appeared timidly in the approaches, demonstrating a gap to be incorporated into the approaches. Rotting time for stored biomasses and pre-treatment elapsed time before storage are required parameters in more realistic BSC linear programming models; no article reviewed considered these aspects.

It is important to say that advantages and disadvantages among the three methods discussed can be pointed out regardless of whether there are similar approaches or not, but as explained throughout the article, the approaches usually differ from each other.

Therefore, there are still some challenges to consider in the future research. This study recommends, as an improvement, compliance with the socio-environmental criteria of current processes and helping processes respect policies and legislation, as well as the consideration of climate change as an aggravating factor of uncertainty in the complexity of the BSC. It is also suggested that regulatory targets are achieved with the use of environmental restrictions due to emissions.

In conclusion, the literature has attested to the applicability of the methods cited, achieving advances with regards to the optimization of the BSC through mathematical modeling.

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