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Framework for Optimized Analysis of Waste Bioenergy Projects

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Abstract: Over the years, cities have undergone transformations that, invariably, overload and even compromise the functioning of an energy matrix dependent on increasingly scarce resources. The high demand for energy has challenged stakeholders to invest in more sustainable alternatives, such as bioenergy, which, in addition, helps to reduce the pressure for finite resources, enable the energy recovery of waste and contribute to the mitigation of carbon emissions. For these improvements to be successful, stakeholders need specific technological strategies, requiring tools, methods and solutions that support the decision-making process. In this perspective, the current work aimed to develop a framework optimizing the evaluation of waste bioenergy projects through the application of algorithms. Therefore, a literature review was carried out to select the algorithms and identify the sectors/areas and stages in which they are applied. These algorithms were then grouped into two sequential phases. The first targeted the evaluation of region, based on the type and supply of biomass, while the second sought to optimize aspects related to infrastructure and logistics. Both phases were concluded with the application of multi-criteria methods, thus, identifying the areas/regions with the greatest potential for implementing bioenergy projects. In general, it was observed that there are different algorithms and multi-criteria analysis methods that can be suitable in bioenergy projects. They were used to identify and select the regions with the greatest potential for bioenergy plant implementation, focusing on the type, quantity and perpetuity of biomass supply, to assess the operational efficiency of machines, equipment, processes and to optimize the logistics chain, especially the collection and transport of biomass. Thus, the joint work between the use of algorithms and multi-criteria decision methods provides greater assertiveness in choices, helping to identify the most viable projects and mitigating risks and uncertainties for decision-makers.

Keywords: bioenergy; waste; algorithm; circular economy; framework; decision-making

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1. Introduction

The principles of the circular economy have emerged over the years as a regenerative model based on closed-loop system designs and on the reuse of materials, which should configure a sustainable, low-carbon and resource-efficient economy [1,2].

A complementary approach to the circular economy by Molina-Moreno et al. [3] incorporates the reuse and rethinking of materials to be recycled in supply chains, contributing to improving the quality, quantity and sustainability of bioenergy production.

In this sense, Li et al. [4] pointed out that, for this improvement to be effective, decision-makers need to develop specific technological strategies for each location, requiring tools that address mathematical modeling and facilitate this process, as well as algorithms and models based on or oriented to data. These algorithms can adjust, optimize and analyze data, make predictions and model complex non-linear relationships [5], pointing to a more sustainable configuration and favoring the circular economy [4].

Population growth and the demand for quality of life lead to a higher level of energy consumption that cannot be supplied only by conventional sources, which favors the strengthening of renewable energy sources, such as solar, wind and biomass. In Mirkouei et al. [6], the authors considered bioenergy as one of the most sustainable and promising sources to replace traditional sources. It can be said that bioenergy is in an evolutionary process and is currently considered one of the greatest potential sources [6]. This is due, in part, to attractive financial subsidiaries and market forces that promote interests to energy suppliers and fuel producers [7].

Bioenergy can be produced from natural materials, such as forest sources, agricultural residues, algae and energy crops [6,8,9].

For Hagman et al. [10], the agricultural sector, for example, has enormous potential for generating bioenergy, since it produces a large volume of waste, which is often lost. In this context, the authors also highlighted the important role of biorefineries that enable the development and generation of new products, including biofuels and energy, for the bioeconomy, without the need to increase land use. In addition to contributing to adding value to waste, these plants allow for diversified use of inputs, such as agricultural, forestry, aquaculture, municipal solids waste (MSW), among others [11].

Souza et al. [12] stated that, if there are good management practices, bioenergy tends to contribute to energy, food and climate security and to sustainable development. According to Castillo-Villar [13], mathematical optimizations can be applied to solve bioenergy supply chain problems. Optimization algorithms in this field aim to maximize profits and minimize emissions and costs.

In this sense, Thran et al. [14] created a framework to evaluate appropriate options for energy system assessment, considering 29 criteria to build a decision matrix, and applied it to several bioenergy technology pathways. For this purpose, four major steps were considered, namely (a) selection of bioenergy technologies, (b) definition of criteria, (c) creation of an evaluation scale and (d) summarizing the results in a holistic, comprehensible matrix.

Wu et al. [15] proposed a framework for optimum location decisions on agroforestry biomass co-generation (AFBC), considering 3 main criteria and 11 sub-criteria, once again leading to a decision matrix but now adding multi-criteria decision-making (MCDM) techniques, such as analytic network process (ANP), simple additive weighting (SAW) and technique for order preference by similarity to ideal solution (TOPSIS), for alternative ranking.

A similar study was developed by Maccarini et al. [16], in which a framework to evaluate the feasibility of using pruning residue in power (electricity) generation was presented. However, none of the studied frameworks established a mapping between criteria and algorithms to optimize and increase the accuracy of the assessment.

For Babazadeh et al. [17], the development of bioenergy projects is quite complex and generally involves multiple elements that need to be considered in the final decision. Types of raw material, suppliers, plant location, mode of transport and products are just examples of criteria that need to be analyzed in projects of this nature. Fortunately, today, there are already several models, techniques and algorithms that support this decision-making process.

Gracia et al. [18], for example, used genetic algorithms to optimize the routes and agricultural vehicle fleet between the raw material collection and its packaging in a supply center, while Velázquez-Martí et al. [19] used dendrometric algorithms to estimate the volume of biomass in an olive plantation.

Casanova-Peláez et al. [20] proposed the use of artificial neural networks (ANNs) to improve the drying process of residues generated in the production of olive oil and thereby, optimize the capacity to transport biomass. The optimization of biomass transport logistics is, by the way, one of the recurrent themes in the literature, being also studied by Zamar et al. [21], Matindi et al. [22], Zhu and Yao [23] and Plessen [24].

Therefore, Babazadeh et al. [17] developed a model and applied a Benders Algorithm to design a second-generation biodiesel network that integrates all stages, from supply centers to consumer centers. Zhao and You [25], on the other hand, applied a linear programming model with a global optimization algorithm (parametric algorithm plus a decomposition algorithm) to assess the effectiveness of public policies to encourage the generation of bioenergy.

In large part, this research focuses on the application of a specific type of algorithm, whether these algorithms are genetic, swarm, decomposition, parametric, among others. However, no work, as far as we are aware, proposes an analysis on the role of algorithms in the decision-making process. Therefore, the present study aims to face this gap by evaluating the use of algorithms in bioenergy projects, considering the different types, interaction models and application fields. In particular, it aims to develop a framework for the optimized evaluation of waste bioenergy projects through the application of algorithms.

The article has the following structure: Introduction, with the purpose of placing the reader in the context of the researched topic and offering an overview of the study carried out; Materials and Methods, presenting the techniques and procedures applied to the development of scientific production; Results and Discussions, concerning composition and exposure of relevant data obtained and synthesized in a framework, with critical evaluation of the research itself with its limitations and positive aspects, as well as interpretation of the information found; and, finally, Conclusions, being the representation of the work outcome based on the study results.

2. Materials and Methods

The methodology of this work is divided into two stages: The first refers to the literature search to identify the types of algorithms used and identify the areas/sectors/steps in which the algorithms are used. Next, the structuring of the framework is carried out.

2.1. Bibliometric Review

To carry out the scientific survey, the following databases were used: Science Direct, Scopus and Web of Science. In the three databases, the same combination of keywords was used, employing Boolean operators and respecting the criteria of each database. The combination was: algorithm AND bioenergy AND (waste OR msw).

The search period in the databases was not limited and, therefore, coverage was investigated from the beginning of accounting in 1945 until 15 April 2021 (the effective date of the search). During this phase, it was decided to select only full and review articles.

In total, 59 articles were found, considering the three search bases. Then, two types of filters were applied to select documents. The Mendeley tool supported the first as soon as the documents were downloaded onto the platform and the duplicated jobs were automatically deleted, leaving 40 documents remaining. The second was applied after reading the titles, keywords and abstracts and works identified as not related to the topic were excluded, resulting in 24 articles. In addition, four more articles resulting from snowballing, which consists of selecting other references directly from papers chosen in previous steps, were inserted. The total number of documents found in each database, as well as the result after applying the filters, are shown in Figure 1.

With the result of portfolio analysis, 28 articles were selected for evaluation, whose main information is summarized in Appendix A (Tables A1–A4).

The systematic review was based on the ninth stage of the Methodi Ordinatio [26], which advocates reading and dynamic analysis among the articles in the portfolio. From this process, an electronic spreadsheet was filled with data collected from the literature, such as year, country, objectives, problem, sector, model, type of applied or developed algorithm, application phase, etc.

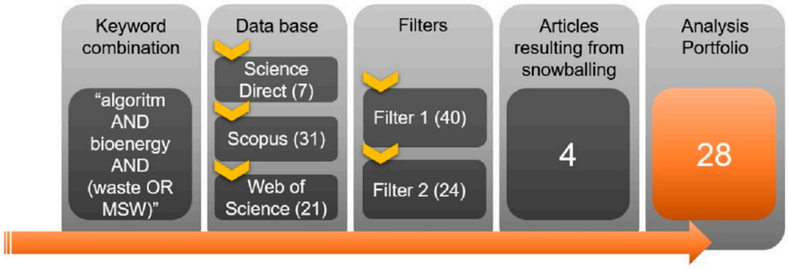

Figure 1. Portfolio analysis composition.

In the next subsection, the main parameters for the development of the proposed framework methodology are presented.

2.2. Composition of the Analysis Framework Review

From the information collected as explained earlier, the identification of similarities among data, as well as distinct application purposes for the algorithms found, began. The identification of these key elements fed the connection between the applied techniques and offered subsidies for the construction of the framework.

As application step, type and category of the algorithm used, as well as criteria for evaluating the alternatives through multi-criteria methods provided by each of the articles, made up the final portfolio.

The framework was divided into two phases, namely Biomass and Region Assessment and New Biorefinery or Retrofit, comprising three steps each. Therefore, its structure was as follows: Phase 1 step 1, definition of the region and type of biomass; Phase 1 step 2, application of algorithms for optimized valuation of each criterion raised during the bibliometric review (Biomass Seasonality, Biomass Generation Estimate, Disposal Rate, Investment Subsidies, Social Impact and Environmental Impact); Phase 1 step 3, application of multi-criteria methods, namely Analytic Hierarchy Process (AHP), TOPSIS, Fuzzy TOPSIS and Fuzzy Višekriterijumsko Kompromisno Rangiranje (VIKOR), to rank the alternatives based on region/biomass optimized by the application of the respective algorithms per criterion; Phase 2 step 1, selection of the first three placed in the ranking of Phase 1 step 3; Phase 2 step 2, application of specific algorithms for optimized valuation of each criterion raised during the bibliometric review for this specific phase (Drying of Biomass, Energy Return on Energy Invested (EROEI), Biomass Logistics, Biorefinery Location and Optimization of Production and Cost); and Phase 2 step 3, final ranking through the application of the above multi-criteria methods.

3. Results and Discussion

The proposal developed in this work aims to develop a framework to evaluate, in an optimized way, bioenergy projects from waste by applying machine learning algorithms. In general, it is a conceptual structure intended to serve as a support or guide for potential project evaluation on waste management targeting to minimize cost, maximize benefits in a faster way and increase accuracy compared to traditional approaches.

For the development of this work, a comprehensive mapping of waste bioenergy projects and the best practices adopted was carried out, considering agricultural, industrial or urban waste management approaches.

In this process, a gap was identified for models that simultaneously work with multiple sources of waste, including qualitative and quantitative data. It also considers the opinion of decision-makers, allowing comparisons and optimization and driving a better choice in more complex scenarios of possibilities. First, the existing studies evaluated specific parts of the process, focusing on just one source, such as agricultural, industrial or urban residues. Second, by advancing deeply in the literature to describe how the variables found in quantitative studies are carried out in reality, this new global view resulted in best practices that can positively influence the overall efficiency of the sector.

Among the works analyzed, we found a series of projects that use algorithms in different phases and contexts. To facilitate the analysis and understanding of these applications, it was preferred to group the research findings into two large sequential phases, which, in a way, summarize the most frequent occurrences in the literature. Figure 2 shows a representation of these phases. The first aim is to assess the region (R), as a function of the type and supply of biomass (B), while the second is more oriented to infrastructure and logistics issues. Both phases are concluded with the application of multi-criteria methods, thus, obtaining the rankings of areas/regions with the greatest potential for implementing bioenergy projects.

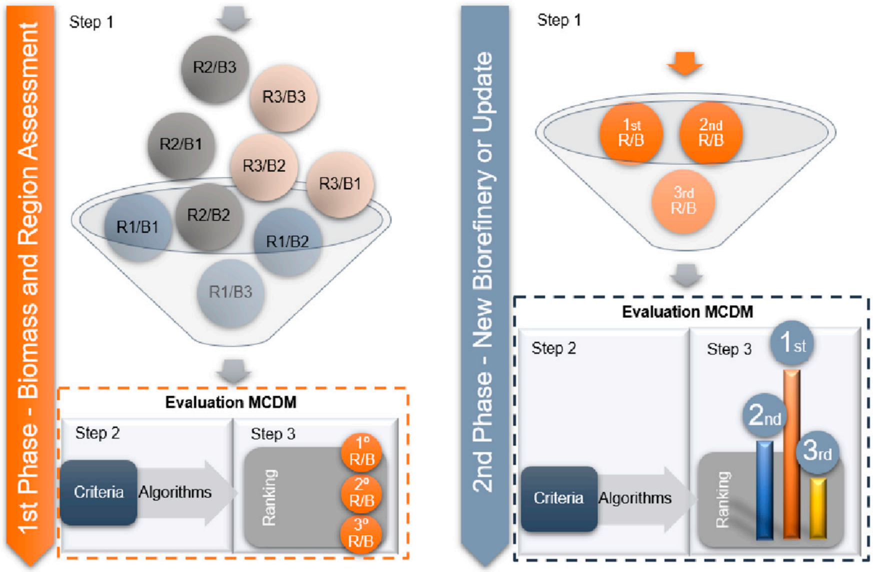

Figure 2. Framework for analyzing the role of algorithms in bioenergy projects. Note. R1/B1, R2/B1, R3/B1 refer to the ratio between region and type of biomass analyzed.

The phases and steps that make up the framework are detailed below.

- Phase 1: Biomass and Region Assessment.

The use of algorithms as support tools in this phase refers to the identification and selection of the best regions for bioenergy projects, based, above all, on the analysis of biomass supply. In general terms, it comprises elements, such as the supply, quantity and type of biomass available in each region, the perpetuity of the supply of raw material and strategies for evaluating public policies to encourage bioenergy projects (Figure 3).

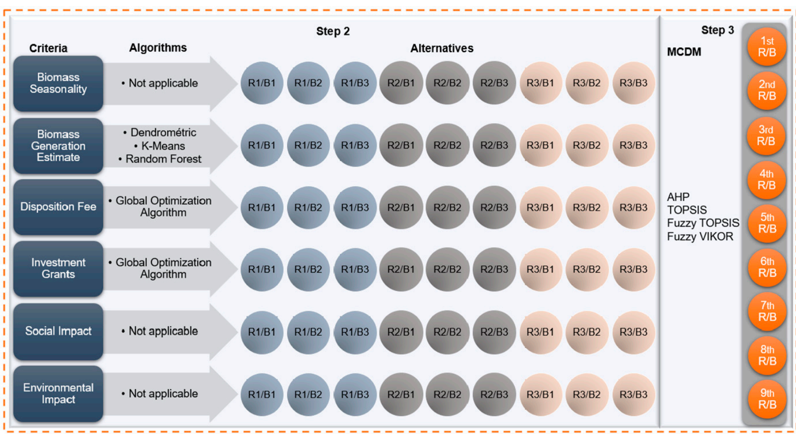

Figure 3. Detailed illustration of steps 2 and 3 in Phase 1. Note. R1/B1, R2/B1, R3/B1 refer to the ratio between region and type of biomass analyzed.

This phase is divided into three steps. In the first step, the potential areas for the implementation of bioenergy projects are listed, which can be a neighborhood, city, state or country. Likewise, the different types of biomasses present in this area/region are identified and analyzed. It is noteworthy that this is not necessarily just one type of input. In fact, it can be considered a composition of different types of biomasses, according to their local availability.

After identifying these potential regions and the types of biomasses present in these areas, represented by the R/B ratio in Figure 3, the second step of analysis begins with the application of a series of specific algorithms. Among the algorithms mapped in the literature and that can be used in this phase are the dendrometric [19,27] and the random forest [28] ones, which aim to estimate the amount of biomass in each area or region, in addition to those with potential for global optimization that can be applied to measure the effectiveness of public incentive policies, such as final disposal fees and subsidies for bioenergy projects [25].

Further, in this second step, other important criteria for bioenergy projects can be identified and listed, such as the seasonality of biomass supply and parameters that aim to assess social and environmental impacts [29]. From the perspective of this work, these criteria are not analyzed through algorithms, but through other strategies, such as the comparative assessment carried out by regional experts on biomass seasonality as environmental engineers and agronomists. Thus, the analysis would be performed for each R/B using linguistic terms for later application of a fuzzy set.

Then, after applying the algorithms and evaluation by elected experts, the results are forwarded to a multi-criteria decision matrix (step 3), with each R/B combination being an alternative. At the end of this stage, a ranking of the regions with the greatest potential is obtained, considering the choices and weights defined by the decision-makers. For the next phase, only the three best-positioned regions in the ranking follow.

- Phase 2: Construction or Retrofit of Biorefinery Units.

With a closer look at the predefined regions in the previous phase, the use of algorithms in this phase aims to optimize the evaluation of the listed criteria, which are oriented to operational issues, such as infrastructure and logistics.

The application of algorithms aimed to improve the operational efficiency of machines, equipment and processes is contemplated in this phase. The optimization of the logistics chain, especially for the collection and transport of biomass, helps decision-makers to decide between expansion or construction of transformation plants and for the optimization of aspects related to costs and productivity. The algorithms mapped in the literature, which are part of step 2, are shown in Figure 4.

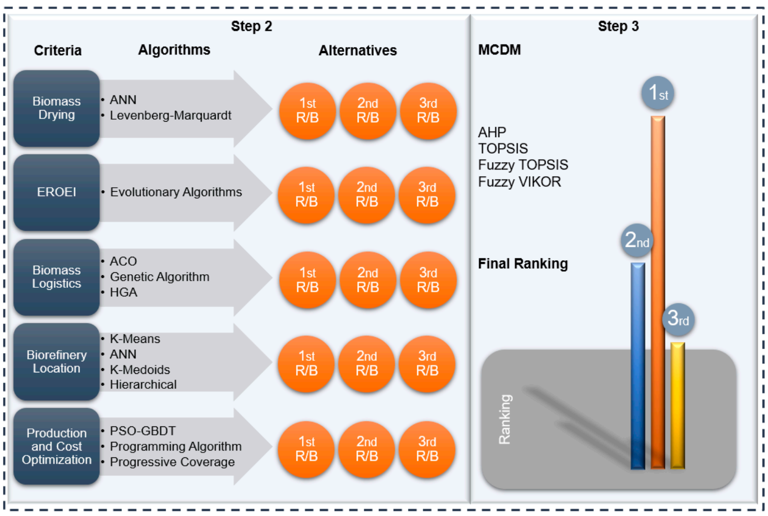

Figure 4. Detailed illustration of steps 2 and 3 in Phase 2.

As in the previous phase, in the second stage, the respective algorithms are applied to optimize the values of each criterion in its corresponding combination of biomass and region.

It is worth noting that the algorithms considered and applied in this step were all mapped in the literature related to this topic. Among the several listed for bioenergy projects, the following stand out: Levenberg–Marquardt [20], Evolutionary Algorithms [29], Ant Colony Optimization (ACO) [30], Genetic Algorithms (GAs) [31–33], K-Means [34], Particle Swarm Optimization and Decision Tree Gradient Increase PSO-GBDT [35], Programming Algorithm, Scheduling Algorithm [36], Progressive Coverage Algorithm [37], Artificial Neural Networks (ANNs) [38], Hybrid Genetic Algorithms (HGAs) [18,39,40], Evolutionary Algorithms [41], K-Medoids [42] and Agglomerative Hierarchical Algorithm [43].

At the end of this phase, the best alternatives, which were optimized by the algorithms, are directed to a multi-criteria decision matrix (Figure 4, step 3), which, in turn, makes it possible to list the regions with the greatest potential.

Multi-criteria analysis methods (MCDMs) can be thought of as tools that deal with the evaluation alternatives set in terms of decision criteria, often conflicting. Thus, given a set of options and a criteria series, the objective of a MCDM is to provide a choice that, in most cases, lists alternatives in order of preference [44]. It is important to highlight the need to harmonize the criteria that often have different units of measurement, which can cause an undesirable effect, polarizing the model's responses to the most significant criterion.

In both phases considered in this work (Figure 1), the different authors worked with multi-criteria methods [17,25,30–33,45,46], with the most cited ones being AHP, TOPSIS, Fuzzy TOPSIS and Fuzzy VIKOR.

Below, there is a brief description of each method.

- AHP is based on the use of pairwise comparisons, both to estimate criteria weights and to compare alternatives against decision criteria. On the other hand, it has a higher computational cost compared to other methods [44];
- TOPSIS is based on an aggregation function that represents the proximity of reference points. It addresses an MCDM problem considering that the optimal alternative must have the shortest distance from the ideal solution and the longest distance from the anti-ideal [44];
- VIKOR is a multi-criteria decision method based on the commitment to the solution, that is, obtaining a satisfactory solution closer to the ideal solution to the problem [44];
- Fuzzy numbers, or more precisely Fuzzy Sets, are represented by sets whose limits are not precise: an element presents a degree of membership about the set [44].

In general, it is noted that there are different algorithms and multi-criteria methods that can be applied in bioenergy projects. The application of algorithms is quite wide and diverse. It is observed they can be used to analyze the potential of crops and raw materials in each region [27], to point out the most suitable location for the installation of a transformation plant and to help in the improvement of the bioenergy generation logistics chain [33]. The use of these tools enables optimization techniques focused on combinatorial analysis to meet specific characteristics and project challenges [18].

The implementation of bioenergy projects can bring several benefits to a given region. The creation and consolidation of the logistics chain for energy production from biomass enables the development of a more competitive and sustainable production system with economic, social and environmental gains [17]. Projects of this nature favor the development of a more circular economy, as they allow the use and aggregation of waste value and generation of income and energy, which can either be commercialized or used by the producers themselves [47].

From this perspective, the role of algorithms is of paramount importance, as they optimize the results that serve as input for the construction of decision matrices [48]. Thus, the joint use of algorithms and multi-criteria decision methods provides greater assertiveness in choices, helping to identify the most viable projects and mitigating risks and uncertainties for decision making [30].

Each of the specific algorithms has it own goal, such as to maximize material waste collection and optimize transport (Scheduling Algorithm), minimize distance implementing an optimized logistic routing from waste sourcing (Ants Colony Optimization (ACO)), define improved location to build waste conversion industry, among others, thus, maximizing the overall return of each potential project and allowing decision-makers to take a decision with a lower level of risk.

Another point to highlight is the strategy considering a data-driven analysis framework that splits the evaluation into two phases, which was developed by integrating multi-methods and leveraging multi-source data for any waste source.

At first, the method focuses on more general characteristics, such as biomass seasonality, biomass generation, disposition fee, investment grants, social impact and environment impact. As shown in Figure 3, these factors are ranked considering potential return aspects. Second, more technical data, such as biomass drying, EROEI, biomass logistics, biorefinery location and logistics and cost optimization, are considered to increase the efficiency and investment return (Figure 4).

This integrated analysis framework allows for assessing the potential performance of complex projects and provides a comprehensive picture of the regional bioenergy development in any application area. Using adapted modifications of biomass sources and bioenergy products, this holistic analysis framework can also be extended to the use of other biomasses for other bioenergy products in other regions.

From this perspective, this work sought to structure a decision-making model that shows the necessary steps and highlights the tools and methods used in each process step. This work does not aim to point out the most suitable method or tool since there are multiple possibilities. The definition of these variables depends on the context of each region where the bioenergy project will be implemented.

It is expected that this project will be very useful in the evaluation of different bioenergy projects, increasing the chances of better assessment in the economic, social and environmental sectors, meeting and enhancing the best practice analysis of circular economy, job creation, etc., in addition to energy recovery. This is a potential option for analyzing and accelerating projects focused on incorporating renewable bioenergy sources into the energy matrix of any region, in addition to providing a guideline for evaluating different economically viable solid waste solutions. At the same time, composing this generation circularly, it is expected to allow the study of the decentralized use of biomass to take place, which can generate more jobs and better distribution of social wealth compared to traditional methods concentrated in a single large bioenergy plant, serving a macro-region concerning the supply of biomass. It also offers a mathematical modelling tool for known problems with algorithm optimization in several areas, such as logistics, chemical composition and biofuel application [49–51].

This work aims to be applied to all sources of bioenergy from solid waste. In general, with the attention of the government and the private sector, it is expected that this framework will offer opportunities for entrepreneurship, raising both private and public financial resources to expand the energy matrix with respect to traditional methods of generation, such as wind power, solar, hydraulic, fossil fuels, nuclear, etc.

4. Conclusions

Mathematical modeling and algorithms are increasingly being developed and applied to evaluate and optimize the implementation of waste bioenergy projects. In this perspective, this work proposed to build a framework for the optimized evaluation of waste bioenergy projects through the application of algorithms. The idea is that this framework makes it possible to analyze the application of algorithms, aimed at optimizing and evaluating different stages.

As seen throughout this work, the application of algorithms is quite broad and diversified and contributes to different stages within bioenergy projects. They are used to identify and select the regions with the greatest potential for implementing bioenergy plants, focusing on the type, quantity and perpetuity of biomass supply, to assess the operational efficiency of machines, equipment, processes and to optimize the logistics chain, especially the collection and transport of biomass.

Therefore, this framework can act as a guide for evaluating potential projects with a focus on the formation of clusters for bioenergy projects, maximizing both their financial and socio-environmental returns, especially by optimizing resources, integrating logistics and the supply chain. It is also worth highlighting the possibility of evaluating government incentives for the implementation of these projects.

The decision-maker would then be asked to identify clusters and regions that would be suitable for building a community biodigester. Here, a great challenge is identified, as the greater the region and the variability of biomass, the greater will be the obstacles related to potential conflicts of interest of the formed group, which may involve farmers, entrepreneurs, society and public authorities. The model, then, would provide information to the decision-maker in a more agile and assertive way. Thus, by evaluating multiple alternatives and reducing the possibilities, it is believed that the use of algorithms and multi-criteria decision methods provides greater assertiveness in choices, helping to identify the most viable projects and mitigating risks and uncertainties for decision-making.

As future works, the framework can be applied in a real case study, evaluating the potential and new opportunities, since both the multi-criteria methods and the algorithms are in constant evolution. As for possible limitations, it is believed that the proposed model does not act in the definition of incentive policies, since it only evaluates and considers the existing policies in the chosen study region, which may restrict the location of the biodigester.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The algorithm models identified in the analysis portfolio as well as their applications and expected results are presented in Table A1 (papers from 2009 to 2013), Table A2 (papers from 2014 to 2017), Table A3 (papers from 2018 to 2019) and Table A4 (papers from 2020 to 2021).

Table A1. Algorithm models identified in the analysis portfolio as well as their applications and expected results from 2009 to 2013.

Authors	Year/Ref.	Technique	Application
Ayoub et al.	2009/[31]	Genetic Algorithm (GA)	Integrates the bioenergy supply chain. As a result of the development of the bioeconomy, the extension of the life of natural resources has been allowed, reducing the environmental burden and providing a better human living condition, besides adding value to products thanks to the use of waste.
Zhu and Yao	2011/[23]	Mixed Integer Linear Programming (MILP)	The model, produced as mixed-integer linear programming, determined the storage locations, the number of people for the harvest team, and the quantity and type of biomass harvested for purchase, storage, and processing each month. It has proven that there are advantages to using various kinds of biomass raw materials rather than working with just one type. In addition, it analyzed the relationship between the supply capacity of biomass raw material with the production and the cost of biofuel.
Muth Jr. et al.	2012/[36]	Scheduling Algorithm	Optimization of the biomass collection process. In addition to including geoprocessing tools and integration of different spatial scales of data.
Chen and Fan	2012/[37]	Progressive Coverage Algorithm	Optimizes the ethanol production chain, focusing on cost reduction. Through the proposed model, it was possible to conclude that bio-waste-based is as an alternative solution for the sustainable energy of the future.
Ren et al.	2013/[49]	Design the most sustainable bioethanol supply chain	Design of a more sustainable bioethanol supply chain. The proposed method studied several ethanol raw material systems, thus finding the best solution to obtain an ecological footprint.
Kaundinya et al.	2013/[42]	K-Medoids	This method divides the entire region into clusters and locates the biomass energy generation systems in the medoids. A Geographical Information System (GIS) map has represented the results of the clusters.
Velázquez-Martí et al.	2013/[27]	Dendrometric Algorithm	The model calculates the estimated biomass generation. From the regression equations and the dendrometric characteristics of the trees, it was possible to assume the biomass available per tree and hectare. From the results of these equations, it is possible to implement GIS maps and estimate the amount of biomass generated in each area.

Table A2. Algorithm models identified in the analysis portfolio as well as their applications and expected results from 2014 to 2017.

Authors	Year/Ref.	Technique	Application
Gracia et al.	2014/[18]	Hybrid Genetic Algorithm—HGA	Responsible for optimizing logistics to route equipment and collect agricultural waste. A real case study was developed through a hybrid approach based on genetic algorithms and local search methods. With the application of algorithms from the industrial engineering domain, results have been obtained that show a significant improvement in operational efficiency.
Velázquez-Martí et al.	2014/[19]	Dendrometric Algorithm	It estimated the volume of biomass in an olive orchard. Correlated productivity and fruit quality, the quantity of residual pruning biomass with Light Detection and Ranging (LIDAR) data obtained an efficient and accurate method to predict biomass.
Muir et al.	2015/[50]	14C flue gas analysis by accelerator mass spectrometry (AMS) and liquid scintillation counting (LSC).	Defined the biomass fraction of mixed waste located in an operational energy-from-waste plant. Concluded that 14Ctechniques are advantageous for data acquisition and the accuracy and reliability of the electricity generator and industry regulator.
Casanova-Peláez et al.	2015/[20]	Artificial Neural Network (ANN) and Levenberg-Marquardt Algorithm	It optimized the process of drying and transporting biomass. It was defined that ANN is the most appropriate method to get a mathematical function for CO drying kinetics and to open new perspectives for the use of waste as energy.
Enitan et al.	2017/[30]	Computational Optimization Methods	Distinct approach models to improve the anaerobic digestion processes. Optimization strategies and controls were performed for advanced actor performance and biogas production through evolutionary algorithms.
Zamar et al.	2017/[21]	Evolutionary Algorithm	Responsible for optimizing the biomass transportation logistics. With this, a stochastic vehicle routing problem was solved by a combination of scenario analysis and heuristics. The performance of the proposed model revealed approximately 6 GJ energy savings compared to the reference method.

Table A3. Algorithm models identified in the analysis portfolio as well as their applications and expected results from 2018 and 2019.

Authors	Year/Ref.	Technique	Application
Matindi et al.	2018/[22]	Optimization Algorithm LDS	Work developed to optimize the logistics of biomass transportation. In this study, the Bounden Discrepancy Search algorithm was adapted with the integration of other algorithms developed for scalable transport. The algorithms were encoded using the Optimization Programming Language (OPL) to optimize the transportation time of sugarcane and its residues.
Cui et al.	2018/[34]	K-Means	Used to point out potential sites for the installation of biodigestion plants based on the analysis of biomass availability in a given region. The results showed that, by converting 10% of pasture and agricultural land to sorghum, about 37% of the 214 existing corn ethanol biorefineries could be adapted or expanded to work with cellulosic feedstocks and that additional 71 new biorefineries could be built.
Babazadeh et al.	2019/[17]	Benders Decomposition Algorithm (BDA)	Applied to perform the projection of a supply network for second generation biodiesel production. The efficiency of the accelerated decomposition algorithm and the performance of the proposed programming model were validated through a computational analysis using data from a real case in Iran.
Zhao and You	2019/[25]	Global Optimization Algorithm	The use of this algorithm aimed to evaluate the effectiveness of the implementation of incentive policies for the generation of bioenergy. The applicability of the proposed model was validated through a case study that aimed to monitor the rate of adoption of biodigesters in dairy farms in the state of New York. The results obtained showed the effectiveness of public policies in promoting bioelectricity.
Sarker et al.	2019/[32]	Genetic Algorithm—GA	Optimization of the supply chain for biomethane production. The application of this algorithm allowed the resolution of representative problems in an efficient way and with better quality when compared to other solutions found in the market.
Khishtandar	2019/[39]	Hybrid Genetic Algorithm—HGA	Employed to design the formation of a supply network for biogas production. The results indicated that the proposed algorithm effectively contributes to solving the biogas plant location allocation model within an interesting computational time.
Chakraborty et al.	2019/[28]	Random Forest Algorithm	Estimate of bioenergy generation potential from surplus crop residues. The mapping results, which can be used for planning public policies, indicated the type and quantity of surplus waste that can be used as inputs for bioenergy generation in each region of India.

Table A4. Algorithm models identified in the analysis portfolio as well as their applications and expected results from 2020 and 2021.

Authors	Year/Ref.	Technique	Application
Kokkinos et al.	2020/[46]	Analysis and Optimization Algorithms	Analysis of all social actors involved to assess the impacts of the use of biowaste for the energy transition. A decision-making tool was presented that uses optimization algorithms to guide the involved actors on aspects related to sustainable energy transition towards decarbonization.
Yu et al.	2020/[35]	Particle Swarm Optimization and Gradient Boosting Decision Tree (PSOGBDT) Algorithm	Optimization of energy production through the combined pyrolysis of agricultural residues and sludge from the pharmaceutical industry. The results contributed to evaluate the behavior of the mixture at different heating rates, to the optimization and to increase the efficiency of the bioenergy production system.
Geng et al.	2020/[51]	Clustering Algorithm	The application of the algorithm in this process aimed to assist the projection and optimization of a biodiesel supply chain and to identify the best location for the installation of a biorefinery to produce this resource. The results indicated that the optimization of the chain can contribute significantly to increase biodiesel production and reduce costs. In relation to the installation site of the plant, the model results showed that the current location is the most appropriate because of the large supply of inputs and low transportation costs.
Gorokhova et al.	2020/[47]	Bioeconomy Support Algorithm	Development and strengthening of bioenergy projects in Ukraine. The research results showed that bioeconomy development can contribute to the diversification of the local economy, to the development of renewable commodities, to the strengthening of territories and regions, and to the extension of the life span of natural resources.
De Jesus et al.	2021/[29]	Multicriteria—GIS	Development and application of a methodology that enables the identification of suitable locations for the implantation of biodigesters. The results showed that the definition of biodigesters' location is a fundamental step for the project's viability, since, in addition to meeting environmental issues and legal requirements, it directly influences issues related to biomass transport costs.
De Jesus et al.	2021/[43]	Agglomerative hierarchical algorithm/multi criteria analysis/(GIS)	Identification of opportunities to create strategic partnerships for the generation of bioenergy. The results, obtained through a case study, showed that it is perfectly viable to build clusters to produce bioenergy using geographic coordinates of raw material suppliers and the volume of biomass residues supplied by each actor. In addition, with the input of environmental, economic, social, and legal criteria and requirements, it is also possible to identify the best location for installing the biodigesters.
Geng and Sun	2021/[33]	Genetic Algorithm—NSGAII	Optimization of the biodiesel supply chain. The efficiency of the method and the optimal solution were verified by a case study.
Lomazov et al.	2021/[45]	Genetic Algorithm—GA	Optimization of construction costs for a biogas plant. The use of evolutionary algorithms in this process aims, together with other classic tools and methods, to optimize the construction steps of a bioenergy generation plant. The research results showed the development of a mathematical model that contributes to increase the efficiency of the system and that provides a reduction in the construction costs of a biogas plant.

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