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An AHP-Based Procedure for Model Selection for Eco-Efficiency Assessment

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Abstract: Modelling eco-efficiency is becoming a wide field of research shown by a large body of scientific literature on the subjects concerned. This paper, after performing a systematic literature review (SLR) to identify existing models for process eco-efficiency assessments, provides a methodology, based on the analytic hierarchy process (AHP) method, for choosing the eco-efficiency assessment model to be used for a given application (process, product, or service). For the SLR, papers from the databases Scopus, Web of Science and Science Direct were used. Forty articles were considered for this study, using as the main selection criterion articles that present an eco-efficiency assessment model, since the purpose was to survey the types of existing models that are used to assess processes, products or services for eco-efficiency. With the systematic review carried out, it was possible to identify the types of models that exist and how they are used in different sectors, always aiming to identify if what was analyzed is eco-efficient and what points need to be improved. The proposed AHP-based methodology was applied to a numerical model to outline how to apply the methodology. The approach was easy to use and effective in identifying the proper eco-efficiency model.

Keywords: eco-efficiency; model selection; AHP method

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1. Introduction

In manufacturing processes, one of the main factors to be analyzed is the energy issue, i.e., the energy lost in the form of heat, the emissions into the environment and in relation to the energy costs spent in the process. This causes companies to face pressure from government and society to implement sustainable strategies in their business. To address the economic and environmental challenges, sustainable approaches such as energy efficiency in manufacturing processes are employed to reduce the impacts of wasted energy and emissions on the environment [1].

Given this scenario, from the perspective of sustainability, the concept of eco-efficiency appears to evaluate the environmental and economic conditions of processes, products and services, through the survey and application of indicators that identify the relationship between the results of the processes and sustainable and economic factors.

Eco-efficiency is defined as a relationship between production, expressed by economic values and the ecological impact caused by material consumption or waste generation in the activities involved in the manufacturing operation. It also promotes the idea of minimizing the costs of operating goods and services, maximizing efficiency, while optimizing the use of necessary resources, reducing waste and environmental pollution [2].

An eco-efficiency methodology known and applied in studies in the scientific literature was developed in 1996 by BASF Corporation to assess the economic and environmental impacts of chemicals, processes and products in their life cycle [3]. This methodology has been adapted and follows the ISO 14040 and ISO 14044 standards for life cycle analysis (LCA) [4] and ISO 14045 for Eco-efficiency assessment [5]. BASF's methodology can be used for sustainable decision making at all levels of the consumption chain, from industry to consumer [6].

Lozano and Lozano [7] point out that among the sustainable methodologies, eco-efficiency stands out for providing an explicit and effective evaluation criterion with the use of LCA-based indicators. For environmental impact assessment, six categories are considered: raw material consumption; energy consumption; emissions to air, water and waste; toxicity potential; risk/potential for misuse; and land use. The data and calculations for the first three categories are based on ISO 14040 and 14041 and the others by consulting databases containing these data, for example [4].

There are different tools and methods that can be combined to evaluate the eco-efficiency of products, processes and services; these are established for comparison, with respect to life cycle data, environmental impact assessment and process costs, i.e., such analyses provide only comparative information, without an absolute value. Existing analyses allow the results to be normalized to enable comparison of indicators, providing guidance for the optimal choice of product or process that should be developed from a long-term perspective.

Moreover, eco-efficiency can be used as a decision-making tool, providing the best choice between transformation processes by combining scientific and technical issues with economic issues [7] and can be applied in various sectors, in a specific product, in business, and in industrial processes. Multi-criteria decision analysis (MCDA) can help to make the best decision by evaluating, prioritizing and selecting among several alternatives and distinct criteria that must be considered, in a coherent and transparent way for the stakeholders. The MDCA can be applied following the following phases: define the objective, choose the criteria to measure the objective, specify the alternatives, assign weights to the criteria, apply a mathematical algorithm to rank the criteria and/or choose an alternative and, finally, make the decision or indicate which planning should be followed [8]. There are different MCDA methods, which can be listed as Advanced MCDA: Multi-Attribute Utility Theory (MAUT), probabilistic multi-criteria acceptability analysis (ProMAA), Fuzzy-MAVT (Multi-Attribute Value Theory); Fuzzy-PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations); and Basic MCDA methods: MAVT, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), PROMETHEE, AHP [8]. The method should be selected considering what is most appropriate for the study according to the characteristics of the analyzed problem, which can be in relation to data availability and problem complexity [9].

The development of indicators to compose eco-efficiency is a fundamental strategy to evaluate and monitor the process in a simple but systematic and consistent way, enabling a better understanding of the problem, facilitating decision making and leading towards quality of life and preservation of natural resources [10]. Moreover, eco-efficiency evaluation goes far beyond being introduced as a business concept, and can also be used at regional, national and global levels through evaluation in cities, regions, and countries [11–13].

Thus, studies that present practices, indicators, and methods for evaluating eco-efficiency can contribute to sustainable development in industries, companies, projects and processes. The indicators are employed to measure the economic and environmental data involved in the process and present eco-efficiency results to be discussed and analyzed by the company. Thus, the objectives of this paper are to: (i) identify existing models for processing eco-efficiency evaluation through a systematic literature review (SLR); (ii) provide a procedure, based on the analytic hierarchy process (AHP) method, for choosing the eco-efficiency evaluation model to be used for a given application (process, product, or service). AHP approach is an MCDA method that decomposes a complex multi-factor problem into a hierarchical structure and assigns to each level the related attribute [14]. Consistent with this approach, the AHP method solves complex problems identifying outcomes and developing weights or priorities. A bibliometric study of MCDA fields reveals that AHP has been adopted in more scientific publications than other MCDA methods [15]. According to the scientific literature, the AHP method has been highly acclaimed [16] by a large number of academics for three main reasons: it can be quickly implemented considering a small number of parameters only [15]; it is supported by user-friendly and commercially software packages [17]; and it ensures high reliability avoiding the 'rank reversals problem' by structuring the decision problem before the decision analysis [18]. All these aspects fit with the nature of the issue addressed in this research work.

This paper is structured as follows: Section 2 presents a brief description of eco-efficiency, concepts and applications; Section 3 describes the methodology used to achieve the objectives of the paper; Section 4 presents the analysis of the eco-efficiency evaluation models obtained through SLR, presenting a bibliometric analysis of the articles, followed by a discussion of the eco-efficiency evaluation models; finally, Section 5 presents a suggested procedure for choosing the eco-efficiency model, based on the AHP method.

2. Eco-Efficiency

The term eco-efficiency was first proposed in 1990 by Schaltegger and Sturm. However, it was in 1991 that the World Business Council for Sustainable Development (WBCSD) was responsible for introducing one of the main concepts of eco-efficiency to the world. The term was defined as the delivery of economically competitive goods and services that meet the needs of society in terms of quality of life and that the entire process of manufacturing and availability for consumption, that is, throughout its life cycle, should have the least possible impact on the environment [19].

Eco-efficiency is presented as a combination of the economic and environmental performance of a given system, assessed using a widely applied and easily interpreted framework that can be employed in a wide variety of business sectors, while providing a common set of indicators. Thus, eco-efficiency in the form of Equation (1) is presented as [20]:

$$\text{Eco-efficiency} = \frac{\text{Product or service value}}{\text{Environmental impact}} \tag{1}$$

This concept of eco-efficiency is widely applied to obtain a form that combines environmental and economic performance, for the most diverse product systems, processes and/or companies. It can be understood that the term 'value' present in the eco-efficiency equation can also refer to the related cost in manufacturing up to replacement of the product. The definition of eco-efficiency is given by the ratio between the (added) value of what was manufactured/generated (GDP, income, high quality goods and services offered, etc.) and the (added) impacts of the product or service [21]. For Huppes and Ishikawa [16], eco-efficiency is an instrument to analyze sustainability, in a way that indicates an empirical relationship of economic activities (costs involved) with environmental value (impacts to the environment). Still, it can be pointed out that eco-efficiency presents a role of encouraging business opportunities, allowing companies to become responsible in relation to the environment, while presenting profits [19]. Thus, industrial organizations are expected to produce goods and services by using the least number of resources and generating the least amount of waste and other pollutants [20].

The WBCSD identified seven characteristics that can be considered a guide for companies to become more eco-efficient: reduce material intensity/quantity; reduce energy intensity; increase recyclability; maximize the use of renewable resources; increase product durability; and increase service intensity [19,22].

In the business context, eco-efficiency can be applied at the product, process, corporate or industry level [23,24] and can also be assessed in relation to a specific service [21]. However, the application of this term goes far beyond being introduced as a business concept and can also be used at regional, national and global levels, through the evaluation of the eco-efficiency of cities, regions and countries [11,13,25].

Koskela and Vehmas verified in their work that eco-efficiency can be seen both as an environmental performance indicator and as a business strategy for sustainable development. In their study, the authors pointed out that the definitions and applications of eco-efficiency are associated with some aspects, such as: high production but with lower use of natural resources (produce more with less); produce more added value with lower environmental impact (ratio between economic value and environmental influence); use eco-efficiency as a management strategy (offer companies the possibility to get a new vision of their processes and increase their ability to innovate); a guidance to improve the eco-efficiency of an organization [26].

A wide range of scientific literature is available on eco-efficiency techniques, instruments and models. A systematic review is carried out in the next section.

3. Systematic Literature Review (SLR) Methodology and Procedures

For the development of the work, theoretical research was conducted based on a systematic literature review (SLR), to substantiate and level the knowledge about the subjects involved in the proposal. The SLR process involves three main phases: planning the review, conducting the review and reporting the review [27,28]. In each phase there are specific steps that are further detailed in this section.

In Planning the Review there are two steps to be performed: formulating the research problem and developing and validating the review protocol. Thus, the research question was specified and the review protocol was developed.

In the Conducting the Review phase there are five steps: searching the literature, screening for inclusion, assessing quality, extracting data, analyzing and synthesizing data.

To search the literature, the databases Scopus, Web of Science, Science Direct were used and the following keywords were used: "Eco-efficiency", "Assessment" and "Model".

In the screening phase for inclusion, the articles were screened excluding the articles according to the exclusion criteria established according to the research question. Initially, the titles and abstracts were read to select the articles. Table 1 presents the research protocol, containing the aspects used for searching and selecting articles for the RSL.

Table 1. Research protocol.

Aspects for Article Selection	
Database	Scopus, Web of Science, Science Direct
Search strings used	"Eco-efficiency" AND "Assessment" AND "Model"
Research fields	Article title, abstract and keyword
Language	English
Publication date range	No limit was set for the date range
Exclusion Criteria	- It is not in the scope of the research (in title, abstract); - Duplicate articles; - Conference papers or book chapter - It does not present development and/or application of eco-efficiency evaluation models.

Subsequently, in the step of assessing the quality of the selected texts, the texts were read in full and it was considered whether the articles provide clear and objective information about eco-efficiency assessment models.

Thus, primary studies were identified and selected and extracted (extract step) and the data referring to the theme were analyzed and synthesized (analyze step), according to the criteria established in Table 1.

The last phase, the Review Report, is composed of the step of reporting the findings to describe in a systematized way the information obtained from the literature review.

The results obtained from the literature search screening and quality assessment are presented in the flow chart shown in Figure 1.

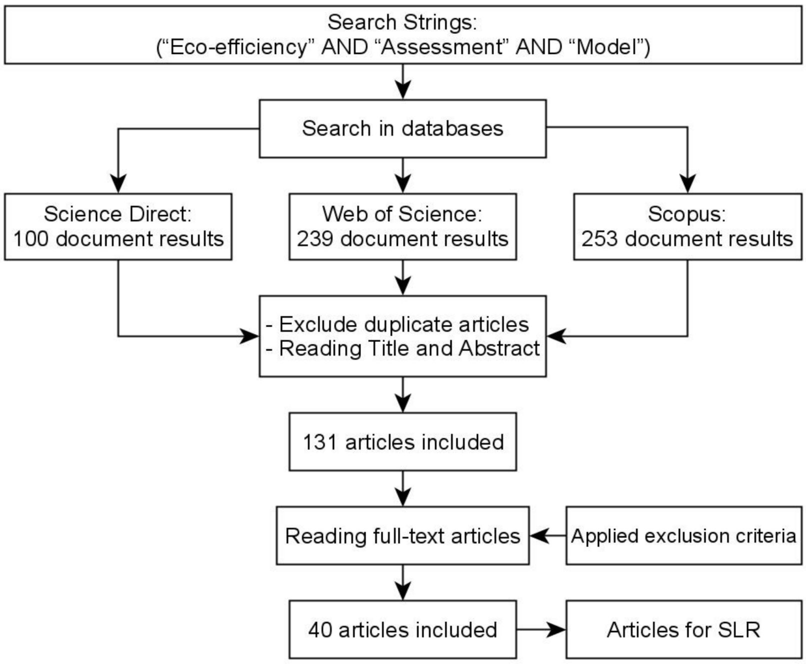

Figure 1. Literature search and evaluation for inclusion of articles for SLR.

Initially, with searches in the three databases, as shown in Figure 1, 592 articles were found. Articles were exported to the StArt® (State of the Art through Systematic Review) software, a tool that provides support to carry out the systematic review process, facilitating the classification of articles to select which ones will be used for SLR [29]. Out of the 592 initial articles, 200 articles were excluded for duplication. By reading of the title and abstracts, 131 articles out of the 392 articles were selected as most aligned with the objective of the present research. Finally, 40 articles were selected as having a complete an eco- efficiency evaluation model and related application to evaluate processes, products, or services for eco-efficiency.

4. Analysis of Eco-Efficiency Assessment Models

The term eco-efficiency has gained greater visibility through the definition established by the WBCSD in 1991, aimed directly at business orientation. Since then, studies aimed at assessing eco-efficiency have gained space in organizations and in the scientific community. Eco-efficiency has been analyzed in different applications, with concepts focused on analyses of production and consumption, with the relationship between 'value' and 'environmental impact'. Eco-efficiency models began to be developed and applied to understand how a product or service could be more or less eco-efficient [29].

The selected articles were analyzed in terms of the application area of the eco-efficiency assessment models, as shown in Figure 2. Nine areas were identified, with eco-efficiency assessment of cities and regions being the focus of study in 23% of the total articles analyzed, followed by construction and manufacturing sectors each of them with about 18% of the articles.

In the following section, the analysis and discussion of the articles surveyed that resulted from the systematic literature review is shown.

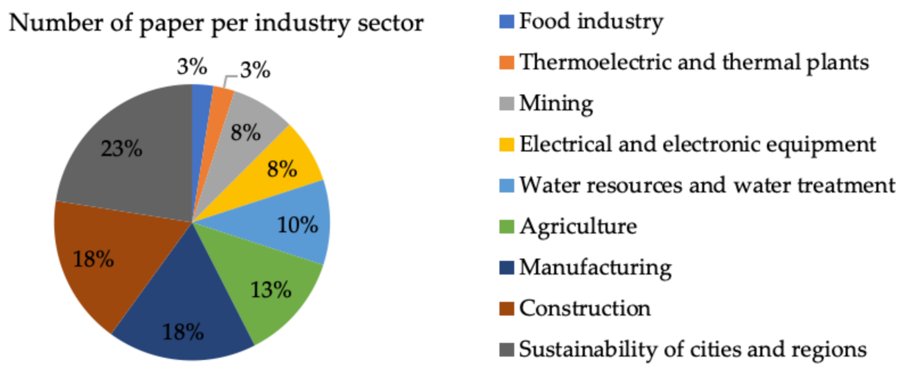

Figure 2. Publications by industry sector.

Discussion of Eco-Efficiency Assessment Models

The evaluation of the eco-efficiency (EE) of products, services or processes is carried out through different approaches, methods and models offering an appropriate way to measure eco-efficiency, with measurable indicators and indexes.

According to Yang and Zhang [30], the assessment of eco-efficiency can be performed through the ratio between the economic value of the goods or services that are produced and the environmental impacts they have. It is required that the numerator and denominator are normalized so that a meaningful ratio of compared quantities is obtained. Still, according to the authors, other approaches can be used to evaluate EE, incorporating life cycle analysis (LCA) for environmental assessment, for example and even using data envelopment analysis (DEA), incorporating different inputs and outputs in different dimensions, this being the approach most often adopted by some researchers [31,32].

Based on the systematic literature review conducted in this work, it was observed that eco-efficiency is evaluated in different areas and industrial sectors to achieve minimal environmental impact in relation to the economic gain obtained.

In analyses conducted in the field of electrical and electronic equipment, Barba-Gutierrez, Adenso-Diaz and Lozano [33] presented an evaluation of EE to present reference products adopted for improving eco-efficiency in the production of electrical and electronic equipment. These analyses were performed using an approach based on DEA, which consists of solving a simple linear programming model to help support decision making, that considers as output the average retail price of the products, and as input the LCA data for the environmental impact. DEA is used to measure the efficiency of a set of decision-making units (DMUs) when there are multiple inputs and outputs in the production process. In this context, both Kondo and Nakamura [34] and Lozano et al. [23] showed EE evaluation methods that allow the identification of better strategies for the use of electrical and electronic products.

EE assessment has also been studied in the construction sector, aiming to analyze the eco-efficiency of building materials [35–39] and of processes involved in this industrial sector [40,41]. In the studies conducted in [35] and [36], eco-efficiency evaluation models based on a DEA framework were presented to evaluate EE of building materials. For this, the concepts of life cycle cost (LCC) and life cycle assessment (LCA) were used to calculate the eco-efficiency index. Furthermore, DEA was used in the modeling, considering input data acquired by LCA and output as data obtained by LCC. The approach supports decision making by comparing the eco-efficiency of building materials.

Perera et al. [39] calculated eco-efficiency by means of the ratio between LCC and LCA to select which material is more eco-efficient to be used in construction. In this case, the economic score, referring to the EE equation, was identified based on life cycle cost (LCC), while the environmental score was obtained by using life cycle assessment (LCA).

The LCC is the entire cost (initial and future) of the product, from purchase, installation, maintenance, repair and replacement. The approach that uses the LCC to represent the economic value added in the numerator of the eco-efficiency equation is commonly used, as it is possible to estimate all the costs that are related to the environmental effects of the life cycle, that is, to obtain an economic value for the entire life cycle. As for the denominator, the LCA is used to obtain data from the environmental effect categories.

Hamid and Shafiq [37] used the ratio of economic score (cost of material and labor used) and environmental score (data of the amount of carbon emission during the material manufacturing) to define the eco-efficiency index of reinforced concrete structures, in the decision-making process for selecting the best sustainable design for reinforced concrete structure. For Kim et al. [38], to evaluate eco-efficiency in the performance and use of concrete, it is necessary to also consider the durability of the material used in reinforced concrete structures, in addition to the environmental load (EC is the environmental cost) and manufacturing costs (MC is the manufacturing cost and SL is the service life of concrete).

Studies have showed that evaluating the EE for selecting the most eco-efficient material requires understanding the entire context involved in manufacturing, from the material resources involved, which generate environmental impacts, to the costs of transformation (e.g., the labor involved, logistics, etc.). Hu and Liu [40] explored data of the Australian construction industry between the years 1990 and 2013 to feed DEA models so as to identify in a quantitative way the eco-efficiency of Australian industries and point out key measures to improve EE, such as the implementation of advanced and eco-efficient construction technologies.

Eco-efficiency analyses applied in construction can both facilitate the circulation of information to the different stakeholders that are involved in this industry and help in the identification and procurement of environmentally and economically efficient materials [41]. Eco-efficiency can be considered an important factor to assess sustainability and the application and interpretation of the proposed models are able to show a path to be followed that integrates economic growth, resource conservation and environmental protection [40].

For systems involving water resources, EE evaluation was performed by [42–45]. The studies aimed to evaluate systems that use water as the main resource, analyzing efficiency, economic performance, pollutants, among other factors necessary to obtain an eco-efficiency index of the analyzed water system.

Liu et al. [42] analyzed the eco-efficiency of water systems in regions located in China by combining the input–output index obtained by the rough set theory (RST) and DEA to analyze the eco-efficiency of water systems.

Mehmeti et al. [43] estimated a set of proposed EE indicators to identify the best alternatives for improving irrigation system eco-efficiency.

In [44,45], the eco-efficiency of wastewater treatment plants (WWTPs) was evaluated. A WWTP is defined as a production facility that uses material and energy resources to remove pollutants from wastewater and discharge the water that has been treated into the environment [45]. With the evaluation performed by Molinos-Senante et al. [44], using a Weighted Russell Directional Distance Model (WRDDM), it was possible to identify the variables with a direct impact on EE, making it possible to focus on them to improve the eco-efficiency of the system. In the EE evaluation presented by Gómez et al. [45], data envelopment analysis (DEA) was used, which allowed for the integration of desirable or undesirable outputs and inputs.

Sanjuan et al. [46] state that different models are proposed to measure eco-efficiency, with the main difference between these being the weighting system used to aggregate environmental outputs.

Approaches using LCA are often used to evaluate EE, as shown in the studies of [47–50]. Life cycle assessment of a product or service consists of a methodology that evaluates the environmental burdens associated with a product, process, or activity, identifying energy and materials used and waste released into the environment. LCA encompasses all the different stages of the life cycle of goods: extraction and processing of raw materials, manufacturing, transportation, distribution, use, reuse, maintenance, recycling and final disposal [51,52].

In [47], an eco-efficiency modeling method for cattle feedlot systems was presented. In the eco-efficiency assessment model proposed, producers become aware of the feed costs and other expenses involved in keeping the animals, as well as in relation to the impacts on the environment, with enteric, air and water emissions.

LCA was also used to survey the total environmental impact (considering the categories of human health damage, ecosystem quality, climate change and resources) to obtain a single indicator of eco-efficiency in the manufacture of light fixtures [50]. Eco-efficiency was calculated as the ratio of total fixture cost (TFC) to total environmental impact (TEI: human health, ecosystem quality, climate change and resources).

In other studies, LCA was combined with LCC to obtain standardized EE indicators and be able to assess which product (standard and redesigned disposable diapers) was more eco-efficient [48]. LCA, focusing on carbon footprint, was used in conjunction with DEA to assess eco-efficiency in raspberry production in Chile [49].

In research aimed at evaluating the EE of cities, considering the common definition of eco-efficiency (ratio between economic value and environmental pressures), DEA-based models (linear programming analysis) have been presented to evaluate the EE of cities in China [11,53,54]. A city's eco-efficiency is in line with its level of economic development, with continuous cleaner production, circular economy, energy conservation moves and emissions reduction [53]. By using the DEA model, it was possible to compare samples and observe changing trends in use of resources, environmental impact and economic performance over the years, finding that cities with higher eco-efficiencies tend to show considerable technological progress [30]. Furthermore, more eco-efficient cities focus on cleaner production while developing the region's economy [11].

Another study applied a super-slack-based measure (Super-SBM) model, which, unlike DEA, considers undesirable production indicators, to assess the eco-efficiency and its influential factors of Chinese cities [12]. In Wang et al. [13] the eco-efficiency of some European countries was evaluated, as they consume a large share of global energy annually. DEA and slacks-based measure (SBM) were used to evaluate the eco-efficiency of decision-making units (DMUs) and the Malmquist Productivity Index (MPI) to analyze the efficiency change, technological change and total productivity change for DMUs.

Masternak-Janus and Rybaczewska-Błażejowska [25] presented DEA for eco-efficiency evaluation of Polish regions to promote sustainable transformation of the regions. In another study, the authors adopted the same economic and environmental factors to assess regional eco-efficiency by using a combined application of LCA and DEA, complementing this with the input-oriented BCC model proposed by Banker, Charnes and Cooper's [55,56] so as to compare regions and countries with respect to their economic and environmental performance.

Ecoefficiency evaluation methods have also been used in coal mine production, considering earnings before interest and taxes (EBIT) as an economic indicator [57], to measure of eco-efficiency of world-class mining companies, using an enhanced optimization model based on a directional distance function (DDF) [58,59].

In agricultural activities, EE assessment has been conducted to quantify the potential environmental impacts through LCA combined with economic benefits using DEA, in this way calculating eco-efficiency scores of an agricultural production [60]. In Cheng et al. [61], the EE of agricultural activity in China was evaluated using the DEA-CCR method developed by Charnes, Cooper and Rhodes [62].

In this same vein, to evaluate EE in agricultural production, Masuda [63] considered eco-efficiency in his study as agricultural revenue divided by potential global warming. In Song and Chen [64], a method combining water footprint (WF) analysis and stochastic frontier approach (SFA) was developed to estimate the eco-efficiency of grain production in China. The WF analysis was employed to quantify the resource consumption and environmental impacts associated with grain production and the SFA model quantified the capital present.

In industrial sectors, an eco-efficiency model assessment was provided by Egilmez et al. [65]. Here, economic input–output life cycle assessment (EIO-LCA) and DEA were integrated to analyze the eco-efficiency of manufacturing in the United States.

In Zheng and Peng [66], the eco-efficiency of energy-intensive industries, chains and industry clusters was evaluated. Data from the chemical industry, building materials industry, metallurgical industry and thermal energy industry from 2004 to 2015 were analyzed. DEA was used, by means of a classical input-oriented CCR model, at given outputs, focusing more attention on inputs.

Finally, studies that presented models to evaluate EE in industrial processes were reviewed. Ng et al. [67] analyzed the eco-efficiency of technologies used to bond copper to copper. Low temperature copper to copper bonding (LTCCB) technology was compared with the conventional method (CM), using the cost of production (C) and the carbon footprint (CFP) to assess eco-efficiency. A graphical representation was adopted to present the eco-efficiency analysis performed for both processes.

In Leme Jr. et al. [68], eco-efficiency indicators were used to measure the performance of a production system. To analyze the eco-efficiency of a machining center, a Lean-Green model combining single minute exchange of die (SMED) with carbon footprint (CF) was proposed. The eco-efficiency evaluation was performed by dividing the product value by the environmental impact, aiming to reduce waste of time, resources and greenhouse gas emissions.

In another study that evaluated the eco-efficiency of a manufacturing process, Lucato et al. [24] presented a conceptual proposal in which indicators were combined to obtain a single eco-efficiency index for a piece of equipment, making it possible to later expand and evaluate eco-efficiency for a production area. The authors proposed a model that allows evaluating the eco-efficiency of the process through a radar chart.

Based on the analysis and discussion above, we concluded that eco-efficiency can be evaluated in different industrial sectors, in addition to evaluating products, processes and services by applying an appropriate model consistent with the aim of the EE analysis. To this end, in the following section, a procedure for choosing an eco-efficiency model is proposed; the procedure is based on the AHP (analytic hierarchy process) decision-making process.

In Table 2, the 40 selected articles discussed above are classified according to the application sector, field of application (Product/Process/Service) and the type of model used to assess EE.

Table 2. Articles surveyed based on the systematic literature review.

Application Sector	Product/Process/Service	Author/Year	Model for EE Evaluation
Electrical and electronic equipment	Product	Barba-Gutierrez; Adenso-Diaz; Lozano (2009) [33]	DEA
	Product	Lozano et al. (2011) [23]	DEA
	Process/Service	Kondo and Nakamura (2006) [34]	WIO-LP
Civil construction	Product	Tatari and Kucukvar (2011) [35]	DEA
	Product	Tatari and Kucukvar (2012) [36]	DEA
	Product/Service	Hu and Liu (2017) [40]	DEA
	Product	Hamid and Shafiq (2016) [37]	Economic Score/Environmental Score
	Product	Kim et al. (2016) [38]	(EC + MC) /SL
	Product	Perera et al. (2017) [39]	Economic Score/Environmental Score
	Product/Service	Belucio et al. (2021) [41]	DEA

Table 2. *Cont.*

Application Sector	Product/Process/Service	Author/Year	Model for EE Evaluation
Water resources and water treatment	Process/Service	Gómez et al. (2018) [45]	DEA
	Process/Service	Molinos-Senante et al. (2016) [44]	DEA
Food industry	Process	Sanjuan et al. (2011) [46]	Economic Score/Environmental Score
Farming	Product/Process	Hengen et al. (2016) [47]	Economic Score/Environmental Score
	Process/Service	Rebolledo-Leiva et al. (2019) [49]	DEA
	Process	Zhong et al. (2020) [60]	DEA
	Process/Service	Cheng et al. (2012) [61]	DEA
	Service	Song; Chen (2019) [64]	SFA
	Process/Service	Masuda (2016) [63]	LP-linear programming
Thermoelectric and thermal power plants	Process/Service	Guo et al. (2017) [69]	DEA-SBM
Sustainability of cities and regions	Product/Process/Service	Xu et al. (2017) [11]	DEA
	Product/Process/Service	Zhou et al. (2018) [12]	DEA
	Product/Process/Service	Wang et al. (2020) [13]	DEA
	Product/Process/Service	Xu and Chen (2015) [70]	DEA
	Product/Process/Service	Yang and Zhang (2018) [30]	DEA
	Product/Process/Service	Yin et al. (2014) [53]	DEA
	Product/Process/Service	He et al. (2016) [71]	DEA
	Product/Process/Service	Zhang (2020) [54]	DEA
	Product/Process/Service	Masternak-Janus and Rybaczewska-Błażejowska (2016) [25]	DEA
	Product/Process/Service	Rybaczewska-Błażejowska and Masternak-Janus (2018) [56]	DEA
Mining	Process	Czaplicka-Kolarz et al. (2015) [57]	EBIT/LCA
	Service	Oliveira et al. (2017) [58]	DEA
	Service	Oliveira et al. (2015) [59]	DEA
Manufacturing	Process	Ng et al. (2014) [67]	C/CFP
	Process	Egilmez et al. (2013) [65]	EIO-LCA + DEA
	Process/Service	Zheng and Peng (2019) [66]	DEA
	Process	Lucato et al. (2013) [24]	Product value/Ecological influence
	Product/Process	Mendoza et al. (2019) [48]	Economic Score/Environmental Score
	Product/Process	Vukelic et al. (2019) [50]	TFC/TEI
	Process	Leme Jr. et al. (2018) [68]	Lean-Green Model: SMED/CF

5. AHP-Based Procedure for Selecting an Appropriate Eco-Efficiency Model

As observed in the previous section, a wide variety of EE models are available in the scientific literature. The choice of a proper model depends on several factors including the area of application and the aim of the assessment. Consistently, it needs a systematic and simple approach to address the choice of an appropriate EE model. To this end, the authors propose a simplified procedure for choosing the eco-efficiency evaluation model to ensure that the evaluation and its result are consistent with context and purpose. To this end, the AHP (analytic hierarchy process) method proposed by Saaty [72] was used. It consists of a hierarchical analysis method to support multicriteria decision making. Considered as one of the main mathematical models used to support decision making, the AHP method is used in situations to prioritize criteria and select alternatives, obtaining as a result a hierarchical logic.

The AHP method is widely employed in decision making when involving sustainable issues due to its comprehensibility in theory and simplicity in application, which makes it the most popular comprehensive method [73]. Five main steps are included to solve the multi-objective decision-making problem with the AHP algorithm. The first consists of problem definition. The second consists of dividing the decision-making solution into three levels: the target, criteria and program. The matrix on the criteria selected is thus identified by pairwise comparison of the weights by means of eigenvector method (third step). Afterwards, the single-level sequencing allowing estimation of the corresponding weights is defined (fourth step). Finally, the general hierarchy ranking calculates the total weights of each alternative [74].

In [75], the authors point out that the AHP method offers advantages when compared to other classical decision-making methods, such as the possibility to decompose the decision problem hierarchically and use subjective and verbal expressions to determine the relative importance of the established criteria [76]. Furthermore, Jamwal et al. 2021 identified as strengths of AHP: ease of being adapted to the objectives, suitable and flexible to support decision, can be applied in numerous areas and can measure consistency based on expert opinion and provide a simple and flexible model to analyze problems [77].

Thus, AHP is a widely employed method due to its flexibility [78] and is considered a simple and flexible technique when it is necessary to analyze criteria quantitatively and qualitatively [77].

Wang and Yang analyzed three multicriteria decision making methods (AHP, SMART and FM) for theoretical validity, predictive and perceived performance. As results, the AHP was indicated as the preferred one in terms of performance and was considered easier to apply.

For this study, the AHP method was considered due to its approach to the problem, being possible to analyze the criteria (EE indicators) in a qualitative and in a quantitative way. This is considered an adequate point, given the simplicity of using the AHP.

5.1. Fundamentals of Analytic Hierarchy Process—AHP

Mu and M. Pereyra-Rojas [79] summarize in six steps how a decision analysis should be conducted by using the analytic hierarchy process (AHP):

i. Developing a decision model: decision is structured into a hierarchy of objectives, criteria and alternatives;
ii. Derive the priorities (weights) for the established criteria: in this step, the importance of the criteria is made by a pair comparison of criteria to derive their weights. The consistency of the judgments provided by experts is quantified so as to review the judgments and ensure that a reasonable level of consistency with respect to proportionality and transitivity is met;
iii. Derive the local priorities (preferences) for the alternatives: at this point, the derivation of the priorities or the alternatives in relation to each criterion separately is done (this process is like the previous step, since the comparison of the alternatives in pairs with respect to each criterion should be performed). Then, consistency is checked and adjusted when necessary;
iv. Derive the general priorities (this is the model's synthesis): in this step, all priorities of the alternatives obtained must be combined as a weighted sum, considering the weight of each criterion and establishing the general priorities of the alternatives. By this analysis, the alternative that presents the highest overall priority is considered as the best choice;
v. Sensitivity analysis: a study is conducted to analyze how changes in the weights of the criteria can affect the result. The sensitivity analysis allows us to understand the reason that led to the results obtained;
vi. Final decision making: decision-making is based on the results of the model synthesis and the sensitivity analysis.

Based on the steps described above, it can be observed that this process does not determine the decision to be made; in fact, the results should be interpreted as a project of preferences and alternatives that are based on the level of importance obtained for the defined criteria, in which the comparative judgments of the decision maker are considered. This means that the AHP method allows determining the alternative that is most consistent with the criteria and the level of importance that are given by the individual who is conducting the decision-making process [72,79,80].

5.2. *Applying AHP for Selecting the Appropriate Eco-Efficiency Model*

The survey of EE models proposed in Section 4 allows identifying a set of models for each of the nine production sectors: Electrical and electro-electronic equipment; Civil construction; Water resources and water treatment; Food industry; Farming; Thermoelectric and thermal power plants; Sustainability of cities and regions; Mining; and Manufacturing.

The survey addresses the first choice of the set of models: for example, an analyst interested in evaluating the EE performance of a manufacturing process will initially focus on the set of corresponding models classified as the 'Manufacturing' group in Table 2.

This directs them to a smaller number of model options, to be later analyzed by the AHP decision making method, according to the established criteria, and thus define which model is the most appropriate to be applied in his scenario.

Applying AHP requires carrying out a survey of all the eco-efficiency indicators (EE) (environmental and economic) considered in each model of the sector concerned.

After these initial analyses, an AHP can be performed, according to the six steps described earlier in Section 5.1 [79].

The first step is defining the hierarchy of the decision making process (Figure 3): At the first level the objective of the decision is set as "Choose an eco-efficiency evaluation model"; the second level of the hierarchy pertains the most suitable criteria identified to select the EE model, i.e., the EE indicators belonging to the sector concerned; finally, the third level of the hierarchy is located the models among which selecting the most appropriate for the case under investigation.

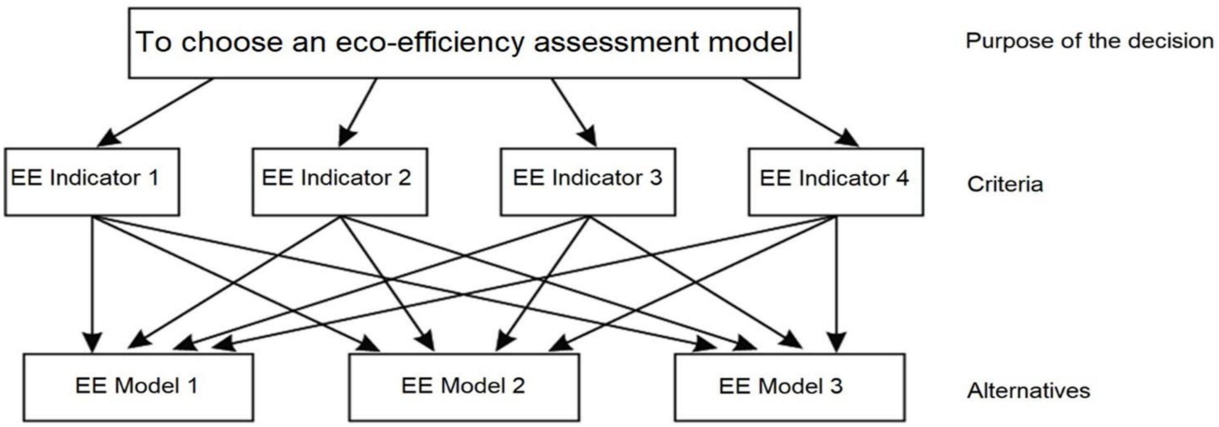

Figure 3. Structure of the AHP method for choosing the EE model.

In the second step, judgments concerning the relative importance between each couple of criteria are provided and priorities (normalized weights) calculated. It is worth noting that the aim is to choose an EE evaluation model that is optimal for the scenario under investigation. In the case of the example of the 'Manufacturing' sector, EE indicators to be considered in the AHP were identified in article classified in Table 2; indicators are summarized in Table 3.

Table 3. Alternatives and criteria to be evaluated in the AHP for the Manufacturing sector.

Author/Year		Model for EE Evaluation (Alternatives)	Composition of EE Indicators (Criteria)
Ng et al. (2014) [67]	A1	C/CFP	C is the cost of production CFP is the carbon footprint
Egilmez et al. (2013) [65]	A2	EIO-LCA + DEA (CCR)	EIO is economic input–output (total economic output) GHG emissions, energy use, water use, hazardous waste generation and toxic emissions)
Zheng and Peng (2019) [66]	A3	DEA (CCR)	Resource efficiency (comprehensive energy consumption, unit labor output, unit product capital input) environmental efficiency (gas emission and waste)
Leme Jr. et al. (2018) [68]	A4	Lean-Green Model: SMED/CF	SMED is single minute exchange of die CF is the carbon footprint
Lucato et al. (2013) [24]	A5	Product value/ Ecological influence	number of pieces consumed energy material resources of equipment consumed
Mendoza et al. (2019) [48]	A6	Economic Score/Environmental Score	raw material cost, manufacturing cost, transportation cost and waste management cost) Element abiotic depletion potential (ADP), fossil fuel abiotic depletion potential (ADP), acidification potential (AP), eutrophication potential (EP), freshwater aquatic ecotoxicity potential (FAETP), global warming potential (GWP), human toxicity potential (HTP), marine aquatic ecotoxicity potential (MAETP), ozone depletion potential (ODP), photochemical oxidant creation potential (POCP) and terrestrial ecotoxicity potential (TETP)
Vukelic et al. (2019) [50]	A7	TFC/TEI	TFC is the total fixture cost TEI is the total environmental impact: human health, ecosystem quality, climate change and resources

Once the initial survey of indicators is performed, the pairwise judgments of the criteria (indicators extracted from the models) is carried out, according to weights, from 1 to 9, of the Saaty scale (see Table 4). Experts provide a pairwise comparison, C_{ij}, of each couple of criteria C_i vs. C_j, $i, j = 1, n$, $i > j$. In each case of $i < j$ the reciprocal value $C_{ji} = 1/C_{ij}$ is set to guarantee consistency between the couple of criteria compared. Finally, in case of $i = j$, $C_{ii} = 1$, $i = 1, n$.

Table 4. Saaty's pairwise comparison scale.

Verbal Judgment	Numeric Value
Extremely important	9 8
Very strongly more important	7 6
Strongly more important	5 4
Moderately more important	3 2
Equally important	1

Source: [79].

In Table 5, an example with four criteria, i.e., four EE indicators, is considered. EE indicator C2 is considered by experts as 'very strongly more important' than EE indicator C1 according to the scale of Table 4. Consistently, $C_{21} = 7$, $C_{12} = 1/7$. The same line of reasoning applies for each couple of criteria (EE indicators) considered.

Table 5. Example of pairwise judgments: four criteria (EE indicators) adopted.

	Indicators						
	Criteria	**C1**	**C2**	**C3**	**C4**	**Weight C_i**	**Normalized Weight C_{in}**
Indicators	**C1**	1	1/7	1/9	1	2.25	0.05
	C2	7	1	1/3	7	15.33	0.37
	C3	9	3	1	9	22.00	0.53
	C4	1	1/7	1/9	1	2.25	0.05
	Total					41.84	

The normalized weight Ci of the i-th criterium can be obtained as:

$$C_{in} = \frac{\sum_{j=1}^{n} C_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}} \tag{2}$$

In the example developed, the normalized weight of each criterium is shown in the last column.

Next, the consistency ratio (CR) of the judgments is calculated as in Equation (3) [79]:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3}$$

i.e., as the ratio between the level of coherence (CI–Consistency Index) provided in the judgements (level of importance attributed by pairwise comparison) over the random index (RI) that would be achieved in a limit case where the judgements were provided by a pure random judgement generation; RI only depends on the order of the comparison matrix (Table 5) and can be obtained by numerical simulation where random judgements in the scale of Saaty are generated.

The coherence index (CI) can be calculated as [79]:

$$\mathrm{CI} = \frac{(\lambda_{max} - \mathrm{n})}{(\mathrm{n} - 1)} \tag{4}$$

where

n is the order of the comparison matrix;

λ_{max} is the maximum eigenvalue of the comparison matrix as described in Mu and Pereyra–Rojas [79], which can be determined by averaging on the n criteria the ratio of vectorial product of the i-th vector of the judgement matrix and the vector of normalized weights (Table 5) over the i-th component of the vector of normalized weights as:

$$\lambda_{max} = \underset{\{\mathrm{i=1,n}\}}{\mathrm{Average}} \left\{ \frac{\left(\overline{D_i} * \overline{C_{in}}\right)}{C_{in}} \right\} \tag{5}$$

where

$\overline{D_i}$ is the i-th row vector of the judgment matrix;

$\overline{C_{in}}$ is the vector of normalized weights;

C_{in} is the i-th component of the vector of the normalized weights.

CR has the purpose of analyzing whether the judgment was made in a way that ensures a reasonable level of consistency in terms of proportionality and transitivity [79].

To calculate the RI value, according to Saaty, for a square matrix of order 4 is equal to 0.90. Therefore, the researcher should use the tabulated RI value according to the order of his matrix. Following the example presented in Table 5, calculations were made to analyze consistency (CR–Consistency Ratio), using Equations (3)–(5). Results are in Table 6.

Table 6. Criteria consistency analysis (EE indicators).

C_i	$\lambda max = \left\{ \frac{(\overline{D_i} * \overline{C_{in}})}{C_{in}} \right\}$	λ_{max} (Mean)	IR	CI	CR
C1	4.06	4.16	0.90	0.053	0.058
C2	3.54				
C3	4.94				
C4	4.06				

The acceptance of the coherence of judgement expressed in Table 5 is checked by verifying that CR is lower than an acceptable limit value (usually set equal to 0.10). If it is higher, a new trial should be performed. In the case example of Table 6, it has a consistency of 0.058 < 0.10 which means that the judgment performed is coherent.

In the third step, judgments must be made for the alternatives: considering the same example cited above, for this step the seven models for EE evaluation (ranked A1 to A7, Table 3) are the seven alternatives that should be judged, following the same procedure described in step ii. The judgments should be based on preferences for each EE indicator (criterion) for each model. Thus, the seven alternatives for each criterion (EE indicator) must be judged separately, that is, seven matrices must be built.

The weights for the alternatives must be placed in relation to each criterion and then the weights must be normalized. The consistency of each matrix can be checked, by using Equations (3)–(5) where the judgment matrix presented (Table 7) refers to the judgments of the alternative models.

Table 7. Pairwise judgment of alternatives (EE models) and consistency (CR) analysis for criterion (C1).

	Alternatives										
C1	**A1**	**A2**	**A3**	**A4**	**Weight** C_a	**Normalized Weight** $C_{i,an}$	$\lambda_{max} = \left\{ \frac{(\overline{D_i} * \overline{C_{i,an}})}{C_{i,an}} \right\}$	λ_{max} **(Mean)**	**IR**	**CI**	**CR**
A1	1	1/5	1/2	1/7	1.84	0.06	4.13	4.12	0.90	0.040	0.045
A2	5	1	2	1	9.00	0.30	4.51				
A3	2	1/2	1	1/6	3.67	0.12	3.91				
A4	7	1	6	1	15.00	0.51	3.93				
Tot					29.51						

As an example, we considered analyzing four alternatives (A1 to A4). The couples of alternatives were subject to pairwise comparison with reference to each of the four criteria (C1 to C4) (previously analyzed in Table 5): the decision maker must consider how important each criterion is for each alternative. In the example developed, when judging the preference of the first two alternatives (A1 and A2) in relation to criterion C1, it is evaluated that alternative A2 is strongly important (scale 5) over alternative A1, then A2 in relation to alternative A1 is weighted with value 5 on the Saaty scale; consistently, A1 in relation to A2 weighted by the reciprocal value 1/5. The complete comparison matrix of the four alternatives (the EE models) evaluated each other with reference to criterion C1 is in Table 7.

Tables 8–10 show the comparison matrix of the four alternatives compared each other with reference to the criteria C2, C3 and C4, respectively.

Table 8. Pairwise judgment of alternatives and consistency analysis for criterion (C2).

	Alternatives										
C1	**A1**	**A2**	**A3**	**A4**	**Weight** C_a	**Normalized Weight** $C_{i,an}$	$\lambda_{max} = \left\{ \frac{(D_i{}^*C_{i,an})}{C_{i,an}} \right\}$	λ_{max} **(Mean)**	**IR**	**CI**	**CR**
A1	1	1/4	5	2	8.25	0.22	3.67	4.10	0.90	0.033	0.037
A2	4	1	9	9	23.00	0.63	4.56				
A3	1/5	1/9	1	1/2	1.81	0.05	4.32				
A4	1/2	1/9	2	1	3.61	0.10	3.85				
Tot					36.67						

Table 9. Pairwise judgment of alternatives and consistency analysis for criterion (C3).

	Alternatives										
C1	**A1**	**A2**	**A3**	**A4**	**Weight** C_a	**Normalized Weight** $C_{i,an}$	$\lambda_{max} = \left\{ \frac{(D_i{}^*C_{i,an})}{C_{i,an}} \right\}$	λ_{max} **(Mean)**	**IR**	**CI**	**CR**
A1	1	1/6	1/2	1/2	2.17	0.09	3.96	4.02	0.90	0.008	0.009
A2	6	1	2	3	12.00	0.52	3.92				
A3	2	1/2	1	1	4.50	0.20	4.26				
A4	2	1/3	1	1	4.33	0.19	3.96				
Tot					23.00						

Table 10. Pairwise judgment of alternatives and consistency analysis for criterion (C4).

	Alternatives										
C1	**A1**	**A2**	**A3**	**A4**	**Weight** C_a	**Normalized Weight** $C_{i,an}$	$\lambda_{max} = \left\{ \frac{(D_i{}^*C_{i,an})}{C_{i,an}} \right\}$	λ_{max} **(mean)**	**IR**	**CI**	**CR**
A1	1	1/6	1/4	1/4	1.67	0.07	4.10	4.18	0.90	0.059	0.066
A2	6	1	1/2	1	8.50	0.34	3.47				
A3	4	2	1	1	8.00	0.32	4.83				
A4	4	1	1	1	7.00	0.28	4.31				
Tot					25.17						

In the fourth step, the decision maker analyzes the general priority of the alternatives (global performance) for the choice of the most adequate EE model. After performing the judgments, checking consistency, making the weighted total with the weights and determining the normalized weights for the criteria and alternatives, it is possible to obtain the overall priorities, defined in this study as overall performance, followed by the overall ranking (Table 11). To obtain the results to be filled in Table 11 we adopted the normalized weights of the criteria (C_{in}: Table 5) and alternatives ($C_{i,}$: Tables 7–10). The global performance is determined by the total sum of the corresponding row. The alternative with the highest overall performance will have the best score.

Table 11. Overall performance of the alternatives for each criterion analyzed in the example.

	C1	**C2**	**C3**	**C4**	**Overall Performance**	**Classification**
A1	0.003	0.082	0.050	0.004	0.139	4
A2	0.016	0.230	0.274	0.018	0.539	1
A3	0.007	0.018	0.103	0.017	0.145	3
A4	0.027	0.036	0.099	0.015	0.178	2

In the numerical example, the value of 0.003 (A1 × C1) was obtained by multiplying the 0.05 (C_{in}: Table 5) by 0.06 ($C_{i,an}$: Table 7). The same approach was followed to complete the final matrix in Table 11.

The overall performance was obtained by summing up the values of each row.

The result obtained allows the decision maker to identify the alternative A2 as the best choice, i.e., the most appropriate eco-efficiency evaluation model to be applied.

Fifth step consists of sensitivity analysis of the choice of alternative (EE model).

To perform a sensitivity analysis, the decision maker changes criteria weights (by changing the judgments, i.e., changing the scale weight assigned to each criterion) and seeing how they change the overall performance of the alternatives.

The last step consists of the choice of the EE assessment model: After analyzing the result of the overall priority (step iii) and sensitivity (step iv), the final decision is made and the EE assessment model to evaluate the scenario (e.g., a given production process) is obtained. In the view of the proposed procedure for selecting the ideal EE model, the flow chart in Figure 4 contains all the steps to be followed sequentially.

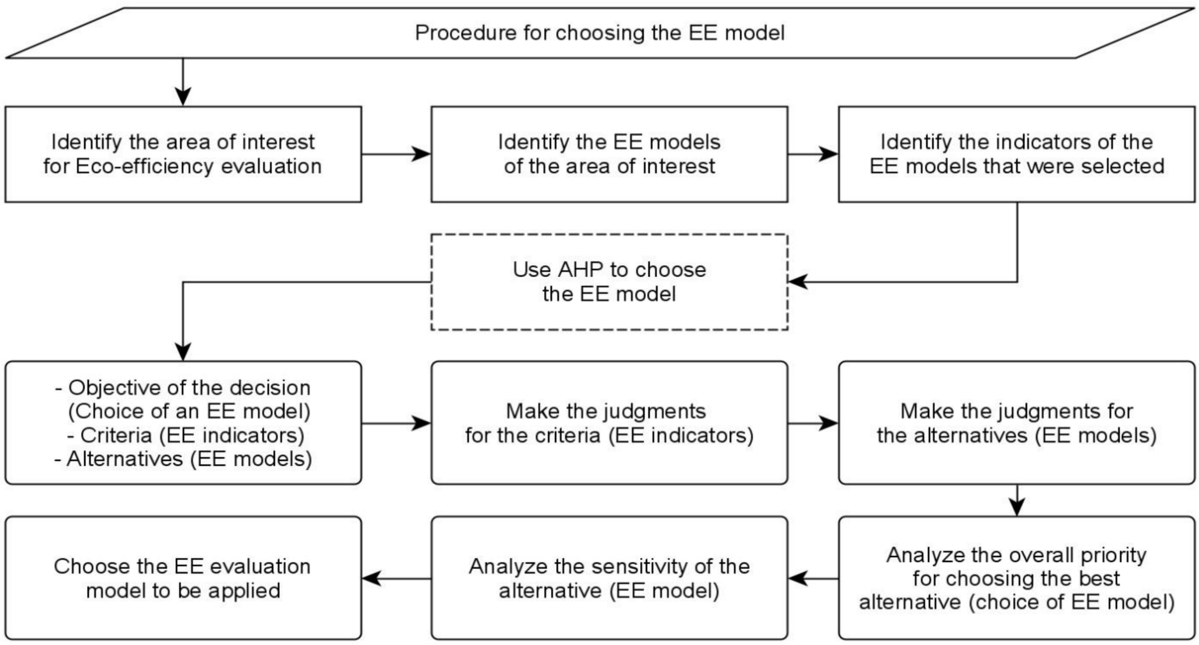

Figure 4. Steps in the procedure to choose the EE evaluation model.

Due to the diverse EE evaluation models existing in the literature, it is understood that the analyses proposed in this article can facilitate the understanding of how the choice of a model that is more aligned with the area to be explored by the decision maker should be made. AHP is an established decision-making method, clear and with well-defined steps to be followed. The judgments and calculations that should be made in each step of the AHP can be seen in greater depth in [79–81], since the purpose of this work was to show how the structure should be outlined, in relation to the objective of the decision (choice of EE model), the criteria (EE indicators) and the alternatives (EE models).

6. Conclusions

Eco-efficiency is an approach used to evaluate environmental and economic aspects in an integrated manner, through the identification of indicators capable of providing sufficient data to be considered when using an evaluation model.

By the systematic review performed, it was possible to identify the types of models available in the scientific literature and how they are applied in different industrial sectors. It was also possible to identify which eco-efficiency indicators are used in the models and which are necessary for analysis according to the area to be explored to evaluate the eco-efficiency of a product or process. EE evaluations require, among other things, the identification of material and energy involved in the processes which generate environmental impacts as well as their costs.

Greater environmental concerns and pressures from governments and society mean industries are seeking to demonstrate that their processes increasingly cause less impact on the environment. Eco-efficiency can verify such impacts, encompassing not only the environmental impact, but also the cost involved in the process.

Finally, the proposal of a procedure for choosing the EE evaluation model was carried out with the objective of facilitating the understanding of how the decision-making process should be carried out for the selection of an EE model that guarantees an adequate analysis, according to the area being evaluated. The AHP method can provide an exploration in a systematic way, with judgments that come closest to a convenient choice. This procedure is considered an affordable alternative for conducting analysis, which can be used in many different areas to evaluate eco-efficiency. It is pointed out that studies such as this one can contribute to researchers continued exploration of sustainability-related issues necessary for the development of a conscious and industrially developed society.

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References

1. Taheri, K.; Gadow, R.; Killinger, A. Exergy Analysis as a Developed Concept of Energy Efficiency Optimized Processes: The Case of Thermal Spray Processes. *Procedia CIRP* **2014**, *17*, 511–516. [CrossRef]
2. Bidoki, S.M.; Wittlinger, R.; Alamdar, A.A.; Burger, J. Eco-efficiency analysis of textile coating materials. *J. Iran. Chem. Soc.* **2006**, *3*, 351–359. [CrossRef]
3. Saling, P.; Kicherer, A.; Dittrich-Krämer, B.; Wittlinger, R.; Zombik, W.; Schmidt, I.; Schrott, W.; Schmidt, S. Eco-efficiency analysis by basf: The method. *Int. J. Life Cycle Assess.* **2002**, *7*, 203–218. [CrossRef]
4. Uhlman, B.W.; Saling, P. Measuring and communicating sustainability through Eco-efficiency analysis. *Chem. Eng. Prog.* **2010**, *106*, 12.
5. Bradlee, C.A.; Saling, P.; Uhlman, B. Submission for NSF Protocol P352 Validation and Verification of Eco-efficiency Analyses, Part A. *BASF's Eco-Effic. Anal. Methodol.* **2009**, *1*, 1–38.
6. Wall-Markowski, C.A.; Kicherer, A.; Wittlinger, R. Eco-efficiency: Inside BASF and beyond. *Manag. Environ. Qual. An Int. J.* **2005**, *16*, 2.
7. Lozano, F.J.; Lozano, R. Assessing the potential sustainability benefits of agricultural residues: Biomass conversion to syngas for energy generation or to chemicals production. *J. Clean. Prod.* **2018**, *172*, 4162–4169. [CrossRef]
8. Suter, G.W. *Multi-Criteria Decision Analysis: Environmental Applications and Case Studies*; CRC Press: Boca Raton, FL, USA, 2011.
9. Talukder, B.; Blay-Palmer, A.; Hipel, K.W.; VanLoon, G.W. Elimination Method of Multi-Criteria Decision Analysis (MCDA): A Simple Methodological Approach for Assessing Agricultural Sustainability. *Sustainability* **2017**, *9*, 287. [CrossRef]
10. Van Caneghem, J.; Block, C.; Cramm, P.; Mortier, R.; Vandecasteele, C. Improving eco-efficiency in the steel industry: The ArcelorMittal Gent case. *J. Clean. Prod.* **2010**, *18*, 807–814. [CrossRef]
11. Xu, T.; Gao, P.; Yu, Q.; Fang, D. An Improved Eco-Efficiency Analysis Framework Based on Slacks-Based Measure Method. *Sustainability* **2017**, *9*, 952. [CrossRef]

12. Zhou, C.; Shi, C.; Wang, S.; Zhang, G. Estimation of eco-efficiency and its influencing factors in Guangdong province based on Super-SBM and panel regression models. *Ecol. Indic.* **2018**, *86*, 67–80. [CrossRef]
13. Wang, C.-N.; Hsu, H.-P.; Wang, Y.-H.; Nguyen, T.-T. Eco-Efficiency Assessment for Some European Countries Using Slacks-Based Measure Data Envelopment Analysis. *Appl. Sci.* **2020**, *10*, 1760. [CrossRef]
14. Mokarram, M.; Mokarram, M.J.; Gitizadeh, M.; Niknam, T.; Aghaei, J. A novel optimal placing of solar farms utilizing multi-criteria decision-making (MCDA) and feature selection. *J. Clean. Prod.* **2020**, *261*, 121098. [CrossRef]
15. Sarraf, R.; McGuire, M.P. Integration and comparison of multi-criteria decision making methods in safe route planner. *Expert Syst. Appl.* **2020**, *154*, 113399. [CrossRef]
16. Oliveira, M.; Fontes, D.; Pereira, T. Multicriteria Decision Making: A Case Study in the Automobile Industry. *Ann. Manag. Sci.* **2014**, *3*, 109–128. [CrossRef]
17. Ferrari, S.; Zagarella, F.; Caputo, P.; Bonomolo, M. Assessment of tools for urban energy planning. *Energy* **2019**, *176*, 544–551. [CrossRef]
18. Vakilipour, S.; Sadeghi-Niaraki, A.; Ghodousi, M.; Choi, S.-M. Comparison between Multi-Criteria Decision-Making Methods and Evaluating the Quality of Life at Different Spatial Levels. *Sustainability* **2021**, *13*, 4067. [CrossRef]
19. Council for Sustainable Development (WBCSD). Measuring eco-efficiency: A guide to reporting company performance WBCSD. 2000, pp. 1–39. Available online: https://www.gdrc.org/sustbiz/measuring.pdf (accessed on 30 September 2021).
20. WBCSD. Introduction to the learning module WBCSD. 2006, pp. 1–231. Available online: https://docs.wbcsd.org/2006/08/EfficiencyLearningModule.pdf (accessed on 30 September 2021).
21. Zhang, B.; Bi, J.; Fan, Z.; Yuan, Z.; Ge, J. Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach. *Ecol. Econ.* **2008**, *68*, 306–316. [CrossRef]
22. Diebold, W.; Schmidheiny, S. Changing Course: A Global Business Perspective on Development and the Environment. *Foreign Aff.* **1992**, *71*, 202. [CrossRef]
23. Lozano, S.; Adenso-Diaz, B.; Barba-Gutiérrez, Y. Russell non-radial eco-efficiency measure and scale elasticity of a sample of electric/electronic products. *J. Frankl. Inst.* **2011**, *348*, 1605–1614. [CrossRef]
24. Lucato, W.C.; Júnior, M.V.; Santos, J.C.D.S. Measuring the ecoefficiency of a manufacturing process: A conceptual proposal. *Manag. Environ. Qual. Int. J.* **2013**, *24*, 755–770. [CrossRef]
25. Masternak-Janus, A.; Rybaczewska-Błażejowska, M. Comprehensive Regional Eco-Efficiency Analysis Based on Data Envelopment Analysis: The Case of Polish Regions. *J. Ind. Ecol.* **2016**, *21*, 180–190. [CrossRef]
26. Koskela, M.; Vehmas, J. Defining Eco-efficiency: A Case Study on the Finnish Forest Industry. *Bus. Strat. Environ.* **2012**, *21*, 546–566. [CrossRef]
27. Kitchenham, B. Guidelines for performing systematic literature reviews in software engineering. *Tech. Rep. EBSE* **2007**, *1*, 1–65.
28. Brereton, P.; Kitchenham, B.; Budgen, D.; Turner, M.; Khalil, M. Lessons from applying the systematic literature review process within the software engineering domain. *J. Syst. Softw.* **2006**, *80*, 571–583. [CrossRef]
29. Fabbri, S.; Silva, C.; Hernandes, E.M.; Octaviano, F.; Di Thommazo, A.; Belgamo, A. Improvements in the StArt tool to better support the systematic review process. *ACM Int. Conf. Proceeding Ser.* **2016**, *21*, 5. [CrossRef]
30. Yang, L.; Zhang, X. Assessing regional eco-efficiency from the perspective of resource, environmental and economic performance in China: A bootstrapping approach in global data envelopment analysis. *J. Clean. Prod.* **2018**, *173*, 100–111. [CrossRef]
31. Kuosmanen, T.; Kortelainen, M. Measuring Eco-efficiency of Production with Data Envelopment Analysis. *J. Ind. Ecol.* **2005**, *9*, 59–72. [CrossRef]
32. Lorenzo-Toja, Y.; Vázquez-Rowe, I.; Chenel, S.; Marín, D.; Moreira, M.T.; Feijoo, G. Eco-efficiency analysis of Spanish WWTPs using the LCA + DEA method. *Water Res.* **2015**, *68*, 651–666. [CrossRef]
33. Gutiérrez, Y.B.; Adenso-Díaz, B.; Lozano, S. Eco-Efficiency of Electric and Electronic Appliances: A Data Envelopment Analysis (DEA). *Environ. Model. Assess.* **2008**, *14*, 439–447. [CrossRef]
34. Kondo, Y.; Nakamura, S. Waste input–output linear programming model with its application to eco-efficiency analysis. *Econ. Syst. Res.* **2005**, *17*, 393–408. [CrossRef]
35. Tatari, O.; Kucukvar, M. Evaluating Eco-Efficiency of Construction Materials: A Frontier Approach. *Congr. Comput. Civ. Eng. Proc.* **2011**, 736–743. [CrossRef]
36. Tatari, O.; Kucukvar, M. Eco-Efficiency of Construction Materials: Data Envelopment Analysis. *J. Constr. Eng. Manag.* **2012**, *138*, 733–741. [CrossRef]
37. Hamid, M.S.A.; Shafiq, N. Eco-efficiency index model for reinforced concrete structural design: Malaysia case study. *ARPN J. Eng. Appl. Sci.* **2016**, *11*, 8.
38. Kim, T.; Tae, S.; Chae, C.U.; Lee, K. Proposal for the Evaluation of Eco-Efficient Concrete. *Sustainability* **2016**, *8*, 705. [CrossRef]
39. Perera, P.; Hewage, K.; Alarti, M.S.; Sadiq, R. Eco-efficiency analysis of recycled material for residential construction: A case study of Okanagan (BC). In Proceedings of the 6th CSCE-CRC International Construction Specialty Conference 2017-Held as Part of the Canadian Society for Civil Engineering Annual Conference and General Meeting 2017, Vancouver, BC, Canada, 31 May–3 June 2017; Volume 1.
40. Hu, X.; Liu, C. Slacks-based data envelopment analysis for eco-efficiency assessment in the Australian construction industry. *Constr. Manag. Econ.* **2017**, *35*, 11–12.

41. Belucio, M.; Rodrigues, C.; Antunes, C.H.; Freire, F.; Dias, L.C. Eco-efficiency in early design decisions: A multimethodology approach. *J. Clean. Prod.* **2020**, *283*, 124630. [CrossRef]
42. Liu, Y.; Sun, C.; Xu, S. Eco-Efficiency Assessment of Water Systems in China. *Water Resour. Manag.* **2013**, *27*, 4927–4939. [CrossRef]
43. Mehmeti, A.; Todorovic, M.; Scardigno, A. Assessing the eco-efficiency improvements of Sinistra Ofanto irrigation scheme. *J. Clean. Prod.* **2016**, *138*, 208–216. [CrossRef]
44. Molinos-Senante, M.; Gémar, G.; Gómez, T.; Caballero, R.; Sala-Garrido, R. Eco-efficiency assessment of wastewater treatment plants using a weighted Russell directional distance model. *J. Clean. Prod.* **2016**, *137*, 1066–1075. [CrossRef]
45. Gómez, T.; Gémar, G.; Molinos-Senante, M.; Sala-Garrido, R.; Caballero, R. Measuring the eco-efficiency of wastewater treatment plants under data uncertainty. *J. Environ. Manag.* **2018**, *226*, 484–492. [CrossRef]
46. Sanjuan, N.; Ribal, J.; Clemente, G.; Fenollosa, M.L. Measuring and Improving Eco-efficiency Using Data Envelopment Analysis: A Case Study of Mahón-Menorca Cheese. *J. Ind. Ecol.* **2011**, *15*, 4.
47. Hengen, T.J.; Sieverding, H.L.; Cole, N.A.; Ham, J.M.; Stone, J.J. Eco-Efficiency Model for Evaluating Feedlot Rations in the Great Plains, United States. *J. Environ. Qual.* **2016**, *45*, 4.
48. Mendoza, J.M.F.; D'Aponte, F.; Gualtieri, D.; Azapagic, A. Disposable baby diapers: Life cycle costs, eco-efficiency and circular economy. *J. Clean. Prod.* **2019**, *211*, 455–467.
49. Rebolledo-Leiva, R.; Angulo-Meza, L.; Iriarte, A.; González-Araya, M.C.; Vásquez-Ibarra, L. Comparing two CF+DEA methods for assessing eco-efficiency from theoretical and practical points of view. *Sci. Total. Environ.* **2018**, *659*, 1266–1282. [CrossRef]
50. Vukelic, D.; Agarski, B.; Budak, I.; Simunovic, G.; Buchmeister, B.; Jakovljevic, Z.; Tadic, B. Eco-Design of Fixtures Based on Life Cycle and Cost Assessment. *Int. J. Simul. Model.* **2019**, *18*, 72–85. [CrossRef]
51. ISO. 14040: Environmental management–life cycle assessment—Principles and framework. *Int. Organ. Stand.* **2006**, *3*, 28.
52. Finnveden, G.; Hauschild, M.Z.; Ekvall, T.; Guinée, J.; Heijungs, R.; Hellweg, S.; Koehler, A.; Pennington, D.; Suh, S. Recent developments in Life Cycle Assessment. *J. Environ. Manag.* **2009**, *91*, 1–21. [CrossRef]
53. Yin, K.; Wang, R.; An, Q.; Yao, L.; Liang, J. Using eco-efficiency as an indicator for sustainable urban development: A case study of Chinese provincial capital cities. *Ecol. Indic.* **2014**, *36*, 665–671. [CrossRef]
54. Zhang, X. Estimation of eco-efficiency and identification of its influencing factors in China's Yangtze River Delta urban agglomerations. *Growth Chang.* **2020**, *51*, 2.
55. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 9.
56. Rybaczewska-Błażejowska, M.; Masternak-Janus, A. Eco-efficiency assessment of Polish regions: Joint application of life cycle assessment and data envelopment analysis. *J. Clean. Prod.* **2018**, *172*, 1180–1192. [CrossRef]
57. Czaplicka-Kolarz, K.; Burchart-Korol, D.; Turek, M.; Borkowski, W. Model of Eco-Efficiency Assessment of Mining Production Processes. *Arch. Min. Sci.* **2015**, *60*, 2.
58. Oliveira, R.; Camanho, A.; Zanella, A. Eco-efficiency assessment at firm level: An application to the mining sector. In *Operations Research and Big Data: IO2015-XVII Congress of Portuguese Association of Operational Research (APDIO)*; Springer: Berlin/Heidelberg, Germany, 2015; Volume 15.
59. Oliveira, R.; Camanho, A.; Zanella, A. Expanded eco-efficiency assessment of large mining firms. *J. Clean. Prod.* **2017**, *142*, 2364–2373. [CrossRef]
60. Zhong, F.; Jiang, D.; Zhao, Q.; Guo, A.; Ullah, A.; Yang, X.; Cheng, Q.; Zhang, Y.; Ding, X. Eco-efficiency of oasis seed maize production in an arid region, Northwest China. *J. Clean. Prod.* **2020**, *268*, 122220.
61. Cheng, C.Y.; Ren, J.M.; Wang, R.S.; Liu, F. Eco-Efficiency Assessment of Farming Activity in China. *Adv. Mater. Res.* **2011**, *361-363*, 1776–1779. [CrossRef]
62. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
63. Masuda, K. Optimization Model for Mitigating Global Warming at the Farm Scale: An Application to Japanese Rice Farms. *Sustainability* **2016**, *8*, 593. [CrossRef]
64. Song, J.; Chen, X. Eco-efficiency of grain production in China based on water footprints: A stochastic frontier approach. *J. Clean. Prod.* **2019**, *236*. (accessed on 30 September 2021). [CrossRef]
65. Gumus, S.; Egilmez, G.; Kucukvar, M.; Park, Y.S. Integrating expert weighting and multi-criteria decision making into eco-efficiency analysis: The case of US manufacturing. *J. Oper. Res. Soc.* **2016**, *67*, 616–628. [CrossRef]
66. Zheng, J.; Peng, X. Does an Ecological Industry Chain Improve the Eco-Efficiency of an Industrial Cluster? Based on Empirical Study of an Energy-Intensive Industrial Cluster in China. *Sustainability* **2019**, *11*, 1651. [CrossRef]
67. Ng, R.; Nai, S.; Chan, H.L.I.; Shi, C.W.P.; Song, B. Comparative Eco-efficiency Analyses of Copper to Copper Bonding Technologies. *Procedia CIRP* **2014**, *15*, 96–104. [CrossRef]
68. Leme, R.D.; Nunes, A.O.; Costa, L.B.M.; Silva, D.A.L. Creating value with less impact: Lean, green and eco-efficiency in a metalworking industry towards a cleaner production. *J. Clean. Prod.* **2018**, *196*, 517–534. [CrossRef]
69. Guo, Y.; Liu, W.; Tian, J.; He, R.; Chen, L. Eco-efficiency assessment of coal-fired combined heat and power plants in Chinese eco-industrial parks. *J. Clean. Prod.* **2017**, *168*, 963–972. [CrossRef]
70. Xu, T.; Chen, Y. Eco-efficiency assessment of Wuhan based on data envelopment analysis approach. In Proceedings of the 2015 27th Chinese Control and Decision Conference CCDC, Qingdao, China, 23–25 May 2015.

71. He, J.; Wan, Y.; Feng, L.; Ai, J.; Wang, Y. An integrated data envelopment analysis and emergy-based ecological footprint methodology in evaluating sustainable development, a case study of Jiangsu Province, China. *Ecol. Indic.* **2016**, *70*, 23–34.
72. Karayalcin, I.I. The analytic hierarchy process: Planning, priority setting, resource allocation. *Eur. J. Oper. Res.* **1982**, *9*, 1.
73. Wang, J.J.; Jing, Y.Y.; Zhang, C.F.; Zhao, J.H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renew. Sustain. Energy Rev.* **2009**, *13*, 9.
74. Ge, Y. Research on green suppliers' evaluation based on AHP & genetic algorithm. In Proceedings of the 2009 International Conference on Signal Processing Systems, Singapore, 15–17 May 2009.
75. Sadok, W.; Angevin, F.; Bergez, J.; Bockstaller, C.; Colomb, B.; Guichard, L.; Reau, R.; Doré, T. Ex ante assessment of the sustainability of alternative cropping systems: Implications for using multi-criteria decision-aid methods. A review. *Agron. Sustain. Dev.* **2008**, *28*, 163–174. [CrossRef]
76. Macharis, C.; Springael, J.; de Brucker, K.; Verbeke, A. PROMETHEE and AHP: The design of operational synergies in multicriteria analysis. *Eur. J. Oper. Res.* **2004**, *153*, 2.
77. Jamwal, A.; Agrawal, R.; Sharma, M.; Kumar, V. Review on multi-criteria decision analysis in sustainable manufacturing decision making. *Int. J. Sustain. Eng.* **2020**, *14*, 202–225. [CrossRef]
78. Kurttila, M.; Pesonen, M.; Kangas, J.; Kajanus, M. Utilizing the analytic hierarchy process (AHP) in SWOT analysis—A hybrid method and its application to a forest-certification case. *For. Policy Econ.* **2000**, *1*, 41–52. [CrossRef]
79. Mu, E.; Pereyra-Rojas, M. Practical Decision Making using Super Decisions v3. 2018. In *An Introduction to the Analytic Hierarchy Process*; Springer: Berlin/Heidelberg, Germany. [CrossRef]
80. Saaty, T.; Vargas, L. *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*; Springer: Boston, MA, USA, 2012.
81. Labib, A. Introduction to the Analytic Hierarchy Process. In *Learning from Failures*; Elsevier: Amsterdam, The Netherlands, 2014; pp. 33–44. [CrossRef]