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Review

A Review on Economic Input-Output Analysis in the Environmental Assessment of Electricity Generation

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Abstract: This paper aims to review one of the least used, but no less important, approaches in the assessment of the environmental implications of electricity generation: the Economic Input-Output Life Cycle Assessment (EIO-LCA). This methodology is a top-down approach intertwined with the environmental satellite accounts provided by the national statistical office. Through the use of economic input-output (IO) tables and industrial sector-level environmental and energy data, the EIO-LCA analysis allows for broad impact coverage of all sectors directly and indirectly involved with electricity generation. In this study, a brief overview of this methodology and the corresponding assumptions is presented, as well as an updated review of the different applications of the EIO-LCA approach in electricity generation, suggesting a possible classification of the many studies developed in this context. The different ways of overcoming the problem of disaggregation in the electricity sector are also addressed, namely by considering different IO table formats (i.e., symmetric or rectangular tables). This is a particularly relevant feature of our review, as the way in which electricity generation is modeled can result in different calculations of the costs and benefits of environmental policies. In this context, this paper further contributes to the literature by explaining and providing examples of distinct approaches to modeling the electricity sector in IO models on a detailed level.

Keywords: economic input-output analysis; life cycle assessment; environmental impacts; electricity generation

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1. Introduction

There is one less commonly used approach to quantifying the environmental impacts of electricity generation: the Economic Input-Output Life Cycle Assessment (EIO-LCA). It is a top-down technique that explicitly considers the transactions as well as the associated environmental impacts taking place across the entire economy [1–5].

EIO-LCA is a methodology that strives to overcome some of the limitations inherent to the use of the Life Cycle Assessment (LCA) approach. It is built on an input-output (IO) table with transactions across distinct economic sectors that may be supplemented with environmental data, including extra columns and rows that depict the emissions per each activity sector. Because the emissions and flows of all activity sectors are incorporated in the assessment, the EIO-LCA approach overcomes the two key concerns created by Process LCA (P-LCA): the boundary limits are easily established since its boundaries are broad-ranging and comprehensive; and the circularity impacts are considered, because transactions within each activity sector are also contemplated [2–4].

The EIO-LCA approach, while not suffering from truncation like P-LCA, tends to have a higher level of sectoral aggregation [6,7]. This can make it difficult to clearly distinguish between different sectors and understand their specific contributions and interdependencies [2–4].

Table 1 provides a summary of the information that allows for the contrasting of the main features of each approach in the framework of electricity generation, highlighting some of the problems and expected limitations or uncertainties identified.

Table 1. Contrasting EIO-LCA with P-LCA in the framework of electricity generation.

P-LCA	EIO–LCA
Engineering approach Bottom-up approach Entails the processes associated with electricity generation, including infrastructures, transmission and distribution of the electricity generated per source.	Macroeconomic approach Top-down approach Involves the upstream and downstream assessment of the activity sectors engaged with electricity power generation sectors. While the connection of each electricity power generation technology to the national electricity grid is tackled, the transmission and distribution of electricity after connection to the grid are not considered in the analysis.
Main issues: • Establishing the boundary limits of the analysis and the circularity effects. • Inputs required based on the selected processes and inventory systems considered. • Results based on the reference year of the analysis where no technology changes are accounted for. • Considers average processes. • Considers physical flows. • Technological changes involve an update of processes and inventory systems. • Time dependence of data. • Underestimated values due to the cut-off required (Truncation error) • Focus on manufacturing and equipment. • Electricity consumption is measured at the electrical socket. • Waste management, reuse, recycle and remanufacture can be embedded into P-LCA.	Main issues: • The electricity sector is not disaggregated in published IO tables and therefore additional information is required from different sources. • Uses satellite accounts and IO tables for the base year of the analysis and technology changes are not accounted for. • Considers sector averaging technologies. • Requires value-based description of material flows. • Technological changes involve the comparison of IO tables across different years. • Time dependence of data and time lag for availability of data. • The activity sectors within the IO table may diverge from the sectors considered in P-LCA. • Direct information to build an imports matrix is very difficult to obtain. • Capital investments are usually not included as inputs and are usually considered as a part of final demand. • Household electricity consumption is an exogenous variable considered as final demand. • Waste management, reuse, recycle and remanufacture are not apprehended by IO tables.

As a result, using the EIO-LCA approach to analyze the environmental impacts of electricity generation can be challenging because published IO tables do not typically provide sufficient detail to distinguish between the impacts of increased demand for renewable energy sources (RES-E) and conventional electricity (CE). Instead, these tables only evaluate the impacts of an overall increase in demand for global electricity generation [8]. In fact, published IO tables incorporate the entire supply chain of electricity generation and use into a single electricity sector, i.e., generation, transmission, distribution, and supply-related activities [9].

However, disaggregating the electricity sector in IO tables is rather important, particularly for policymakers and researchers who are seeking to understand the impacts of changes in the electricity sector on the overall economy. This is especially relevant in light of the significant technological advancements in the electricity sector, including new fuels and generation technologies, as well as environmental policies targeting specific generation technologies (e.g., nuclear [10] and coal [11] phase-out policies, the unbundling of the electricity sector [12], the carbon tax on prices and emissions of carbon-intensive industries [13], and tax credits for renewables [14]). Overall, the ability to disaggregate the electricity sector in IO tables provides valuable insights into the economic dynamics of the sector and can help policymakers make informed decisions about the sector.

In this context, the disaggregation of the electricity sector is not straightforward, requiring the explicit use of supplementary data exogenous to the information provided in the currently available IO tables [15]. Even if data from official surveys with electricity-related businesses are publicly available, the following two issues might arise [9]: On the one hand, firms directly engaged in electricity generation usually also have other non-generation electricity activities, which biases the conclusions that might be drawn from the survey outcomes since it becomes hard to distinguish what might be assigned to generation activities only; on the other hand, the major firms related to electricity generation normally possess a bundle of different generating technologies. As a result, official published IO data do not clearly identify generating technologies, necessitating alternative approaches. In this context, developing hybrid methodologies that combine the broad stance of an EIO-LCA with the specificity of information for a single product or process of a P-LCA is frequently beneficial [16–18]. However, these types of hybrid models mainly rely on the method of hybridization considered and the quality of the data used and, therefore, may offer restricted help for assessing material flows across product systems [16,18,19]. Finally, as suggested by Han et al. [20], Limmeechokchai and Suksuntornsiri [21], and Lindner et al. [15], there might be a lack of information available on this subject due to the implementation of ad hoc methods.

To sum up, discriminating between different electricity technologies in IO analysis requires specific data that are often unavailable, incomplete, uncertain, or inconsistent [22]. The assumptions and procedures used in such an analysis can vary significantly between research groups, and much of the "educated guesswork" involved in these analyses is not always properly documented or made publicly available [22]. As a result, it can be difficult to compare the results of different IO models that have been developed to analyze the electricity sector, and it can be challenging to identify the most reliable and accurate methods for achieving a detailed understanding of the economic relationships within the sector.

With the foregoing in mind, this paper aims to provide an overview of the use of the EIO-LCA approach in the analysis of the environmental impacts of electricity generation and to review the main studies that have focused on this topic. It also aims to classify these studies and discuss the major challenges associated with their application, as well as to suggest possible ways to overcome these challenges, particularly addressing the disaggregation of the electricity sector within the framework of the EIO-LCA approach. The paper unfolds as follows: Section 2 presents an updated review of the scientific literature on the use of the EIO-LCA approach for the assessment of electricity generation; Section 3 provides an overview of the EIO-LCA methodology in the context of electricity generation; Section 4 presents and discusses the main findings of this review; and Section 5 presents the conclusions and suggests future research directions.

2. Studies with the Application of EIO-LCA to Electricity Generation

Energy analysis emerged in the aftermath of the oil crises of the 1970s as a discipline aimed at computing the total energy requirements to undertake a given activity. Originally, it considered the use of process analysis (PCA), which allows obtaining the energy required to perform the main production processes as well as a detailed assessment of its major supply chain contributors. A drawback that can be found in this approach is the choice of the system boundaries, which might lead to systematic truncation errors [23,24]. One way to overcome such errors is to combine conventional PCA with IO analysis, resulting in a hybrid method [25].

However, unlike P-LCA studies, there is a lack of literature review regarding the application of hybrid and IO approaches to the electricity sector.

Traditional IO analysis can also be used to assess economy-wide direct, indirect, and induced employment effects [8,26–31], economic effects [10,12,20,31–40], energy requirements and pollutant emissions from electricity generation [1,9,21,41], and biodiversity [42].

A hybrid analysis combines process data and IO data into a variety of formats. A possible characterization of such approaches is given below.

2.1. Complement Some Parts of the Life Cycle Lacking Data

Usually, IO analysis is pooled with P-LCA to complement some parts of the life cycle that lack data. In this context, the IO method can either be applied for evaluating materials and non-materials-related processes, or for assessing emissions or energy use. As stressed by Mattila [43], IO is a key tool for complementing the traditionally performed P-LCA with macroeconomic data from the background systems, and, if properly used, it may result in more accurate LCA.

For instance, Voorspools et al. [44] combined PCA with IO analysis to compute greenhouse gas (GHG) emissions and energy use for the different economic sectors engaged in the construction of a power plant. For the operations and maintenance (O&M) of the plant, a hybrid approach is used, though the energy related to the decommissioning stage is obtained by means of a PCA. Their results are significantly different for nuclear plants but are effectively the same for wind farms. This study concluded that the IO-LCA gives an overestimate, since the components of nuclear power plants are more expensive than average products from the other sectors.

Nomura et al. [45] used the IO framework to calculate indirect oxidizing gas emissions from material production for several electricity generation technologies.

Varun et al. [46] used the IO model for assessing the energy requirement for manufacturing steel and aluminum sheet production involved in the life cycle GHG emissions estimation for small hydropower schemes in India.

White and Kulcinski [47] applied the IO method to assess non-materials-related processes regarding coal, fission, wind, and fusion electrical power plants.

Lenzen and Wachsmann [48] used a tiered hybrid LCA, and their results demonstrated the importance of effectively embedding the background system of the local economy in the assessment.

Hondo [49] suggested a PCA analysis for the assessment of carbon dioxide (CO_2) emissions from material production, while IO analysis was considered for the estimation of CO_2 emissions from several manufacturing processes (e.g., the manufacturing of components and assembly).

White [50] used the IO approach for assessing the energy use of the construction and O&M phases of wind farms.

Liu et al. [51] coupled IO analysis with LCA to evaluate the total direct and indirect environmental impacts of the electricity sector in Taiwan. The IO model was used to estimate the environmental impacts generated throughout the upstream supply chain of the electricity sector.

Kumar et al. [52] estimated the GHG emissions throughout the life cycle of wind energy farms by means of the EIO-LCA methodology in the United States. This work incorporates the installation, O&M, and decommissioning stages into the EIO-LCA framework and presents the expected life cycle GHG emissions from O&M activities, identifying uncertainty in the emissions intensity estimates and contributing to the discussion of its causes. The study concludes that, if all costs and a life cycle perspective are incorporated into the analysis, wind energy production is not completely GHG emission-free. In Muangthai and Lin [53], the EIO-LCA approach is applied to estimate the direct and indirect impacts from the power generation sector in Thailand for the years 2005 and 2010. The domestic IO table, excluding the import values, was used to have a more accurate perception of the actual environmental impacts generated by the industrial sectors engaged with the electricity sector. In general, these studies suggest that when using IO instead of P-LCA for the corresponding life cycle phase, the corresponding energy use of that LCA stage becomes larger.

2.2. Express Some IO Sectors in More Detail

P-LCA data can also be tied to IO tables to further decompose some IO sectors [54]. In this framework, Wiedmann et al. [17] used the Ecoinvent database to disaggregate the wind power subsector from the electricity sector in the UK. Crawford [55] disaggregated an IO model into 100 activity sectors, into which available process data was incorporated. By considering this approach, the overall comprehensiveness of the IO model is guaranteed, while more consistent process data can also be integrated whenever it is feasible. In addition to solving the problem of upstream truncation, this also prevents the possibility of obtaining the downstream truncation errors already mentioned.

Nagashima et al. [56] introduced new sectors in the IO table based on data from the production processes of wind turbines, including sectors for manufacturing towers, nacelles, rotors, cables, transformers, and construction. They also used the EIO-LCA analysis method to evaluate the induced production and value-added of all sectors involved in the wind power generation system. Later, Nagashima et al. [57] used the IO approach to study the environment, energy, and economic impacts of a wind power generation system in Japan. The study also evaluated the resulting production and value-added impacts for all sectors related to wind power generation, concluding that these overcompensate the negative effects of replacing conventionally generated electricity with electricity from wind power. In a similar vein, Wolfram et al. [58] used the EIO-LCA approach to assess carbon footprint scenarios for RES-E in Australia. This hybrid approach combined the strengths of both methods, extending the analytical IO framework while preserving the accuracy of P-LCA for crucial processes.

One of the major limitations found regarding the use of this approach is the subjective choice of the data that requires replacement with process data in IO tables, potentially biasing the results obtained. Nevertheless, Lenzen and Munksgaard [59] stated that the use of IO-based hybrid techniques should be preferred whenever system completeness regarding the assessment of the energy content of RES-E systems is to be attained.

An up-to-date and comprehensive review of the most relevant scientific literature regarding the application of the EIO-LCA approach in electricity generation was carried out. Table A1 in the Appendix A provides an overview of the specific features covered by some of these studies.

From the literature review conducted, it can be established that the journals with the highest number of publications on this subject are *Energy*, *Energy Policy*, *Applied Energy*, *Energy Economics* and *Renewable and Sustainable Energy Reviews*, which total nearly half of the reviewed papers (see Figure 1).

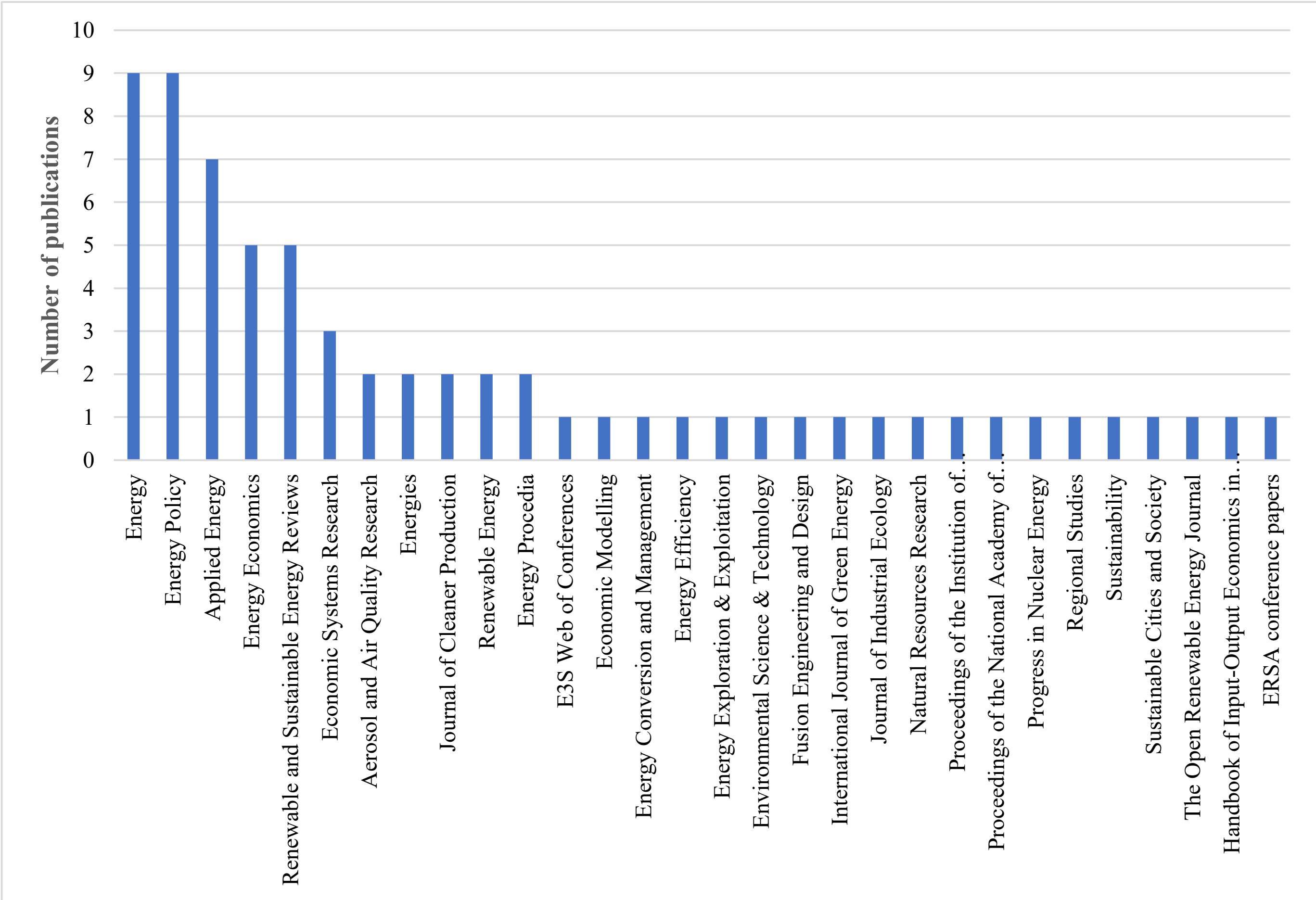

Figure 1. Number of studies per journal.

The interest in this subject has also increased across the time horizon considered, i.e., from 2000 to 2023 (see Figure 2).

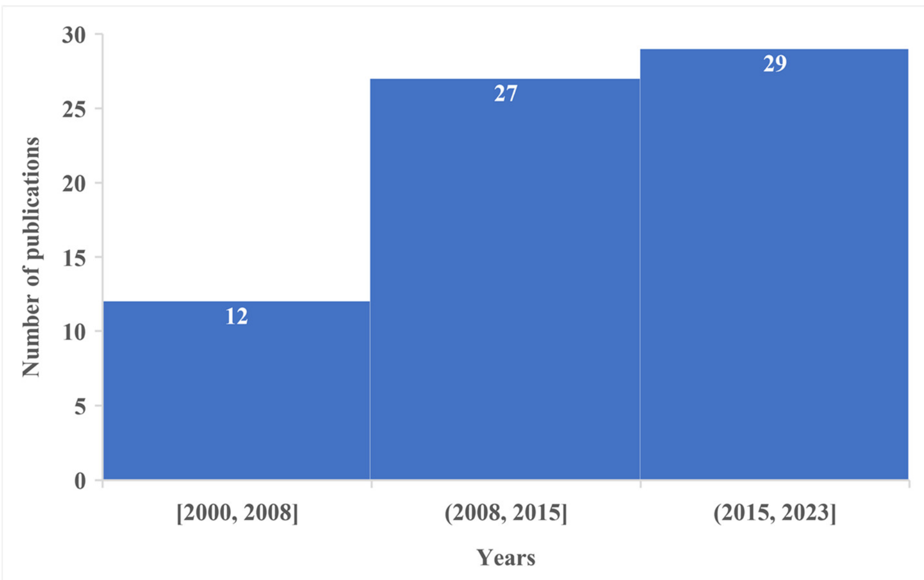

Figure 2. Number of studies for distinct time frames.

The study of electricity's environmental and energy impacts has been a constant throughout the entire time horizon, with an increase in the study of economic and employment impacts, particularly since 2007 (see Figure 3).

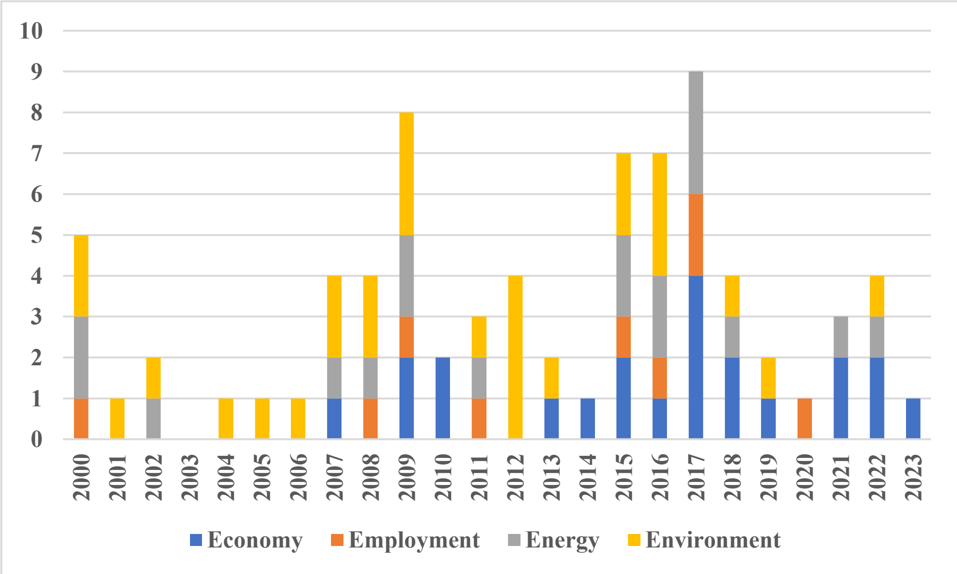

Figure 3. Number of studies per subject addressed.

3. Methodology

The use of the EIO-LCA methodology (For further information on the P-LCA and EIO-LCA conceptual bases, please see Appendices B and C, respectively) to evaluate the impacts of electricity generation can be challenging. In fact, IO tables do not provide detailed information on the environmental and economic impacts of increasing demand for electricity from RES-E or CE. Instead, they only give information about the impact of increasing the overall demand for electricity [8]. IO tables group together all activities related to the production and use of electricity, including generation, transmission, distribution, and supply. Nevertheless, policies often relate to specific technologies or sub-sectors and may not be applicable to the overall sector [60]. Disaggregating the aggregate electricity sectors in IO tables is a crucial step in aligning bottom-up technological detail with top-down data [61,62]. Moreover, although there are already some available IO databases, such as EXIOBASE [63] or the Global Trade Analysis Project (GTAP)-Power database [22,64] that have coefficients for several electricity power technologies, not all sectors and coefficients have been empirically validated [65]. Therefore, it is important to disentangle the different ways to tackle the disaggregation of the electricity sector.

Table 2 briefly describes the main problems and limitation inherent to the application of the EIO-LCA approach.

Table 2. Problems and limitations of EIO-LCA applied to electricity generation technologies.

Problem	Limitations/Uncertainties	Possible Solutions
Published IO tables do not disaggregate the electricity sector.	It is not possible to identify the environmental impacts from the different electricity generation technologies.	(1) Combining P-LCA data with IO tables; (2) Combining IO tables with energy balance data; (3) Combining surveys/technical data with the IO table; (4) Using weight factors; (5) Using RAS methods; (6) Employing mathematical programming models; (7) Employing econometric models

Use matrices include both imported and domestic commodities.	To obtain domestic flow tables, it is necessary to build an imports matrix, which is very difficult to obtain.	Import matrices are built merely by resorting to plausible suppositions.
All products are identified as an average product of the covering sector.	A sector contains many products for which the ratio price/energy-input is not necessarily the same.	Employ the Supply and Use Table (SUT) framework.

A possible classification and characterization of such approaches is provided below.

3.1. Combining P-LCA Data with IO Tables

Heijungs and Suh [54] suggested a methodology in which P-LCA data is tied with IO tables to express some sectors in more detail. This hybrid LCA approach overcomes the truncation errors of the P-LCA and enhances the sector detail of the EIO-LCA. In this context, Wiedmann et al. [17] followed this approach and used the Ecoinvent database to disaggregate the wind power subsector from the electricity sector in the UK. Furthermore, Wolfram et al. [58] studied 16 technology-based power generation technologies for Australia, considering the whole life cycle of power generation from raw material mining to decommissioning. Their work included transportation and energy requirements, construction, O&M, and the end of life. Nagashima et al. [56,57] also combined the strengths of both methods, extending the analytical IO framework while preserving the accuracy of P-LCA for crucial processes.

One of the main disadvantages of these approaches is the extensive amount of data required on the relevant production technologies.

3.2. Combining IO Tables with Energy Balance Data

Bullard et al. [66] proposed an approach that involves using data on the primary energy consumption of different industries. This disaggregation method has also been used by [67] and assumes that all electricity generated is sold to the non-generation activities of the aggregate electricity industry, so that final demands for the electricity-generating sectors are zero by construction. The electricity sector is disaggregated into three sub-sectors: fossil fuel electricity generation, hydroelectricity, and electricity distribution. To perform this disaggregation, it is assumed that the two first generating sub-sectors sell all their output to the distribution sector; the fuel inputs to electricity are entirely attributed to fossil fuel generation; all other inputs are split between the two generating sectors in proportion to their total output; and all purchases of electricity by the remaining sectors and by final demand are supplied by electricity distribution. Allan et al. [9] extend this analysis by disaggregating the electricity sector into several generating sectors. The approach adopted first identifies the IO entries for each of the generating technologies considered by using information from various sources. These estimates are then removed from the original electricity sector in the IO accounts, leaving a residual sector that is considered to capture transmission, distribution, and supply, or non-generation activities. A similar approach is also followed by [51]. In the approaches followed by [21,68], non-generation activities are allocated to generation technologies even though the former, which include transmission, distribution, and supply, would be necessary even in the limiting case of an economy that generates no electricity itself. As a result, this approach to electricity sector disaggregation would be valid only if each generating technology had its own network [9].

3.3. Combining Surveys/Technical Data with the IO Table

Vendries Algarin et al. [1] consider the rectangular version of the IO model and split up the electricity sector into several additional sectors, each representing a specific portion of the electricity industry. Each of these disaggregated sectors includes a supply chain. Since the Use table corresponds to the supply chains for all the industrial sectors in the economy, for every disaggregated sector to be modeled, a listing of the commodities and corresponding monetary values needed to produce the output of the new sector must be created. Moreover, the existing supply chains for every other sector in the model that uses electricity need to be modified as well. Instead of purchasing electricity from a single sector, these activity sectors now purchase from a mix of generation sectors. On the other hand, the Supply table needs to be adjusted for the disaggregated power generation sectors. In the existing Supply tables, the electricity sector provides other commodities besides electricity power generation in the form of delivered steam heat from combined heat and power (CHP) units. However, there are other industries supplying the commodity "electricity power generation" as well. Thus, the monetary values and commodities need to be put into a proper disaggregated sector within the Supply table. Finally, to connect the physical quantities normally associated with electricity, such as kWh, with the monetary units in the IO model, it is important to have good estimates of the costs per kWh. These are the O&M costs that are needed for each type of electricity generation, considering the assumption that all capital investment in the power generation sector, such as new plant construction, will happen outside the model of the economy built with the SUT framework. The author considers construction as an economic activity within the construction sector of the SUT tables, so it is therefore not included in the electricity sector. Hence, explicit consideration of the construction of power plants would require the disaggregation of the construction sector as well. A similar approach might also be found in Allen et al. [9] for Scotland and in Duarte et al. [12] for Spain. In this latter study, data from the Iberian Balances Analysis System (SABI in its Spanish acronym) was used to further disaggregate the electricity sector, obtaining data on wages, social security taxes, value-added, and imports. In a similar vein, Keček et al. [38] obtained survey data to analyze the economic impact of the investments and the O&M costs of RES-E power plants. Lehr et al. [69] added a new vector to the IO table, based on detailed empirical data from a comprehensive survey. This is done by considering different cost structures for the different renewable generation types. The data from the survey are combined with technical data to amend the IO tables.

Breitschopf et al. [70] consider the symmetric version of the IO model and decompose Renewable Electricity Technologies (RETs) into their various activities/components and associated costs, and then match these to the sectors identified in the IO table of the economy under analysis (see Table 3). A similar approach was also followed by [8].

Table 3. Methodology application followed by [70].

Divide into life cycle phase	Manufacturing and Installation; O&M; Fuel (for Biomass).
Decompose life cycle phases into their activities/components	RET activities/components—e.g., large hydropower: • Manufacturing and installation—planning; regulatory activities; construction work; steel hydro construction; hydro turbine; electromechanics; electronic control; installation; electric connection to the grid; other. • O&M—labor costs; waste management; maintenance; spare parts; insurance; other).
Calculate total output of each relevant activity/ component	Total expenditure connected to each life cycle phase cost share of each relevant activity/component as % of life cycle phase.
Match the domestic output of each relevant activity/ component of RET/CE to industry in the IO table.	Match the domestic output of each relevant activity/component of RET to the industries within the IO table.

3.4. Disaggregation Solely Based on Electricity Generation Data

Shrestha and Marapaung [68] and Lindner et al. [71] disaggregated the electricity by only relying on electricity generation data. However, one of the major limitations of this method refers to the assumption of uniform costs of electricity, disregarding the relevant operational characteristics of the electricity sector [72].

3.5. Using Weight Factors

Lindner et al. [15] proposed a method for breaking down the electricity by considering weight factors. According to their approach, the consumption of electricity by different sectors in a region is proportional to the mix of power generation sources in that region's grid system. This enables them to create sector-specific electricity consumption mixes, where every sector in the IO table uses electricity from a particular power mix. Lindner et al. [15] derived two sets of weight factors: input weight factors that divide all inputs into the new electricity production sectors from the common sectors, and output weight factors that distribute the output of the new electricity production sectors among all the other sectors, consistent with the regionally weighted industry consumption mixes. They calculated the input weight factors for each common sector by employing the weighted sum of the O&M costs and the annual electricity generation output of the power plants using a method described in [1]. To obtain the output weight factors, they used a regionally weighted industry coefficient method based on the simple location quotient (SLQ) method [73]. The SLQ method is a non-survey technique for regionalizing national coefficients using adjustments based on regional employment, income, or output by industry. Lindner et al. [15] apply this method by extracting information from regional tables detailing the electricity purchased by the common sectors and relating it to the national table.

Overall, Lindner et al. [15] primarily handle row shares by allocating input costs to new technologies based on generation and other basic assumptions, without considering the final cost structure of the technologies. In essence, this *pro rata* distribution-based methodology may not provide a reliable, systematic method for adding additional data [60].

3.6. Using a Mathematical Programming Approach

Sue Wing [61] developed a positive mathematical programming approach [74] to include the cost structure and detailed bottom-up data (e.g., thermal efficiency and power generation). Although this model formulation efficiently introduces further detailed information, it disregards the preservation of input intensities (i.e., row shares) with the new technologies [60].

Linder et al. [71] used a random walk algorithm [75] to explore the range of feasible combinations for the unknown technical coefficients with the purpose of disaggregating the IO table. Nevertheless, this approach has the disadvantage of taking a long time to build the bottom-up energy and emissions database by fuel type [15].

The rectangular choice-of-technology (RCOT) model [76–78] is another model that is particularly developed to account for distinct technologies within an industry that uses a mathematical programming approach. It uses rectangular tables with potentially multiple columns (i.e., production technologies) per industry and includes constraints on the availability of primary inputs. The model uses linear programming to find the optimal mix of production. In this context, Kätelhön et al. [79] combined the RCOT model with consequential LCA and included stochastic elements in their analysis.

3.7. The share Preserving Cross-Entropy (SPCE) Approach

Peters and Hertel [60] consider that in the process of disaggregation of the electricity sector, it is necessary to reconcile detailed sub-sector information with the overall sector using a matrix balancing method.

In this context, in a review conducted by Wang et al. [80], the authors concluded that the RAS method (this method consists of an iterative scaling and rescaling of the rows and columns of an IO table until they equal the new row and column totals) and the improved normalized squared differences method (INSD) developed by Friedlander [81] would be more suitable for balancing IO tables. In this context, it is worth noting that the GRAS method developed by [82] is also a variant of RAS that can be used with the same purpose. In a latter review by [83] on the mainstream methods for projecting SUTs, it was also ascertained that RAS, INSD, and the method developed by Kuroda [84] outperform their alternatives.

Nevertheless, according to Peters and Hertel [60], Kuroda's method [84] is the only one that can effectively handle cases where the total costs are unknown, or that do not require the imposition of fixed constraints on total costs. Without a strict constraint on total costs, both the RAS and INSD methods become equivalent to the *pro rata* distribution, which only considers the proportion of each row and neglects the cost structure.

The approach developed by Peters and Hertel [60] guarantees that both the cost structure and row shares are preserved in the disaggregation of the electricity, particularly when the replacement of technologies is at stake (e.g., the phase-out of nuclear power, the replacement of coal power and the introduction of RES-E).

3.8. Using Econometric Methods and Panel Data

Wimmer et al. [65] proposed the use of econometric methods and panel data to compute future input coefficients for the energy sector. They claimed that their methodology has several advantages over other methods, including the fact that it is easily applicable to many countries and does not depend on experts' judgments. Furthermore, their method is more adaptable than a single-country trend analysis because it includes information about technological changes that have taken place in other countries. It can also be used to disaggregate the energy sector and cross-validate and corroborate predictions made by other methods. The authors derived input coefficients and the energy mix for their econometric model using Eurostat data. Their research concentrated on the relative monetary shares of inputs and value-added in sector D35, which is officially designated as "electricity, gas, steam and air conditioning supply".

4. Discussion of Results

In summary, it is possible to conclude that most of the studies reviewed are devoted to wind power generation technologies, in particular onshore wind farms, while the rarest ones are on ocean and biogas generation technologies—see Figure 4. In fact, information on the life cycle GHG emissions from wave power is extremely limited (only three studies refer to this form of electricity generation—see [45,58,85]). Only seven studies have taken into account the transmission and distribution of electricity, which is an additional issue that needs to be addressed—see Table A1 in Appendix A.

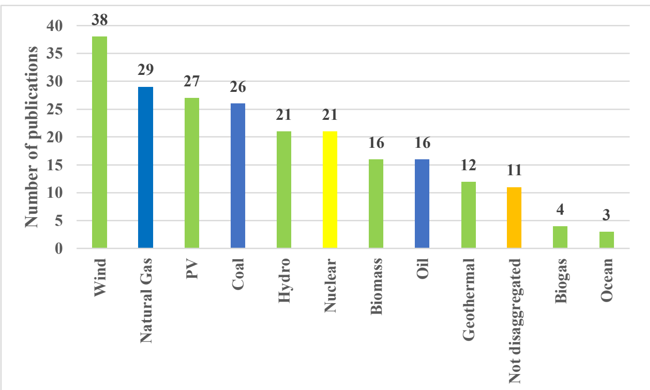

Figure 4. Number of studies per technology assessed.

Studies using EIO-LCA methods have focused mostly on the manufacturing and O&M phases (22 studies refer the consideration of this stage—see Table A1 in the Appendix A), assuming that most of the emissions occur during those life cycle events, neglecting the decommission phase (only eight studies refer the consideration of this stage—see Table A1 in the Appendix A) that can be particularly relevant in the phase-out of technologies (e.g., nuclear power and coal power).

Furthermore, it is observed that most studies developed have focused on European (with particular focus on Germany and Spain), Asian (specifically, Japan, China, and South Korea) and North American countries (with emphasis on the USA)—see Figure 5.

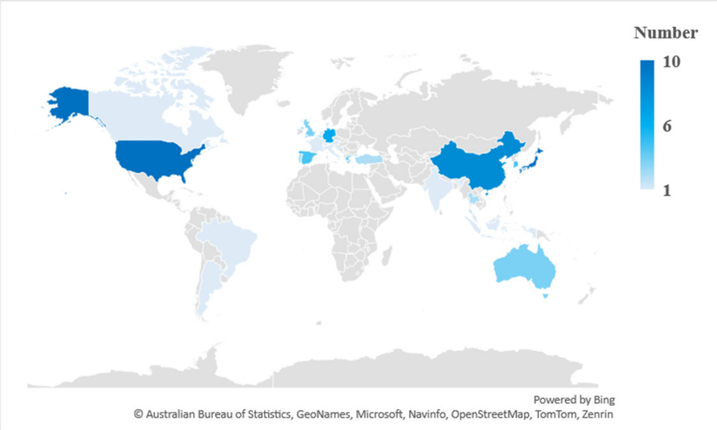

Figure 5. Number of studies by country.

The literature review also suggests that while the impacts of promoting renewable energy have been estimated at the national level using IO models, there is a limited number of sub-national studies due to the challenges in applying these models to micro-level analyses [40].

Additionally, the studies reviewed and analyzed also indicate that EIO-LCA assessments provide systematically higher impacts than P-LCA assessments [58]. In fact, when using IO instead of P-LCA, studies suggest that the energy use of that LCA stage becomes significantly higher (see [50,55]). In effect, relying only on P-LCA outcomes might lead to underestimated figures for energy use, but it is also possible that IO analysis overestimates energy use. Therefore, several methodological options for the application of IO-based hybrid LCA should be further explored by contrasting the use of these methodologies, thus obtaining further insights into the availability and robustness of approaches for informing energy and environmental policy.

Several limitations have also been found in the studies that used IO analysis at the macroeconomic level. One issue is that the magnitude and extent of each electricity sub-sector are technically defined by scholars because these sub-sectors have not been openly reported from a sectoral standpoint and are not frequently completely separated from other industry sectors in IO tables. Because the IO analysis involves the consideration of complex interactions among industry sectors, the outcomes of the direct and indirect spill-over assessments may vary. Due to the disparities in data and evaluation methods used by different researchers, there is also a limitation in clarifying the identification of the distinct technologies. Out of the 68 papers examined (as shown in Table A1 in Appendix A), 11 studies did not include the disaggregation of the electricity sector in their assessments, as illustrated in Figure 4. These studies treated the electricity sector as a final demand sector. Even studies that utilized IO analysis to supplement the PCA missing data and conducted separate evaluations of various electricity technologies did not disaggregate the electricity sector in the IO table.

In addition, there are several methodologies available to handle the disaggregation of the electricity sectors, all of which have their merits and demerits. The disaggregation can be performed by obtaining the input coefficients for the distinct technologies according to surveys and technical data (the most popular approach with 24 publications), P-LCA data (with six studies), energy balance data, and experts' opinions (the third most popular approach with 10 studies) [65]—see Figure 6. Nevertheless, to conduct such approaches, a substantial amount of information is usually required. When the disaggregation is solely based on electricity generation data, relevant operational characteristics of the electricity sector are usually neglected [72]. The use of mathematical programming approaches to account for the detailed cost structure of the electricity sector generally disregards the preservation of the row shares in the new technologies [60]. The RAS method and its several variants also have inherent limitations, namely when the total costs are unknown [60]. In this context, to overcome these limitations, Peters and Hertel [60] suggested an approach that preserves both the cost structure and row shares in the disaggregation of the electricity sector. Finally, more recently, Wimmer et al. [65] suggested the use of econometric methods and panel data to further disaggregate the electricity sector, which can cross-validate other methods. However, their method concentrated on the shares of inputs.

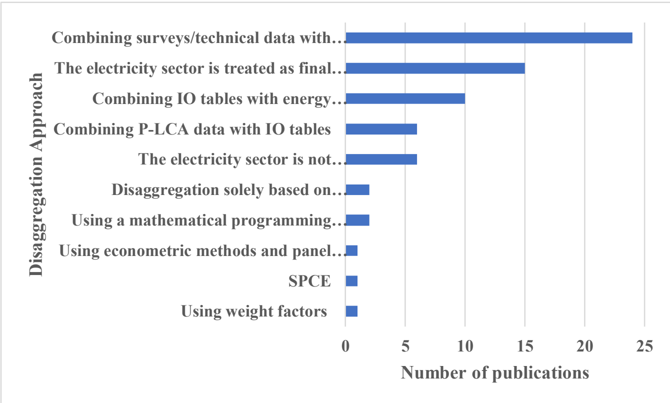

Figure 6. Number of studies by disaggregation methodology.

In effect, tailored surveys and IO tables are the sole reliable sources of information; however, they are constrained by the fast-paced developments in the sector, implying that frequent updates are imperative despite the method's reliability.

Finally, studies frequently only consider one year of data for the IO estimations; however, the replacement of electricity technologies will have a significant impact on the overall industrial structure of the economy, not only when the replacement takes place, but also in the future. As a result, it is also necessary to perform prospective assessments of the electricity industry from a macroeconomic point of view that can offer relevant guidelines to energy policymakers.

5. Conclusions

The evaluation of the environmental impacts associated with different electricity generation technologies is particularly relevant for supporting energy and environmental policy. P-LCA and EIO-LCA are two techniques that can be used in this regard. A significant number of LCA analyses of electricity generation technologies can be found in the scientific literature. However, published LCA studies present a wide variability of results, and some methodological challenges persist regarding the application of P-LCA and EIO-LCA. To overcome their corresponding shortcomings on final assessments, different methods have been suggested to hybridize these two techniques. In the present paper, a selected and critical review of more than a hundred papers that consider the application of the EIO-LCA approach to wind power, solar PV, hydropower, geothermal, ocean, biomass, coal-fired, oil-fired, natural gas, and nuclear power was performed, which clearly highlights data variability and its causes.

Our paper contributes to the literature on the study of a broad range impacts of electricity generation in different ways. First, it provides a classification and characterization of the main studies devoted to the assessment of the impacts of the electricity sector in the framework of the EIO-LCA framework, hence, contributing to the theoretical understanding of electricity modelling in the IO framework. Second, the paper presents several methods for disaggregating the input and output structure of the electricity sector in IO tables to account for technological diversity.

In summary, the reviewed studies focused mainly on wind power generation technologies, particularly onshore wind farms, while ocean and biogas generation technologies received little attention. Information on the life cycle GHG emissions from wave power is particularly limited, with only three studies considering it. Studies using EIO-LCA methods have mostly focused on the manufacturing and O&M phases, neglecting the decommissioning phase that can be relevant in the phase-out of technologies. Moreover, most studies were conducted in Europe, Asia, and North America.

The literature review also indicates that IO models have been used to estimate the impacts of promoting renewable energy at the national level, but there are limited sub-national studies due to the challenges of applying these models to micro-level analyses. Additionally, EIO-LCA assessments provide systematically higher impacts than P-LCA assessments. However, relying solely on P-LCA outcomes might lead to underestimated figures for energy use, and IO analysis might overestimate energy use. Thus, several methodological options for the application of IO-based hybrid LCA should be further explored to inform energy and environmental policy.

Several limitations were found in the studies that used IO analysis at the macroeconomic level. The magnitude and extent of each electricity sub-sector are not always reported, and there is a limitation in identifying distinct technologies. Additionally, there are several methodologies available to handle the disaggregation of the electricity sector, all of which have their merits and demerits. Tailored surveys and IO tables are the most reliable sources of information, but they are constrained by the fast-paced developments in the sector. Moreover, studies often only consider one year of data for the IO estimations, while the replacement of electricity technologies will have a significant impact on the overall industrial structure of the economy, making prospective assessments necessary.

In conclusion, there is a need for further studies that consider a broader range of renewable energy generation technologies, particularly those that have received little attention, such as ocean and biogas generation technologies. Moreover, more studies at the sub-national level are necessary to inform local energy policy. Finally, the use of IO-based hybrid LCAs should be further explored, and tailored surveys and IO tables should be updated frequently to reflect the fast-paced developments in the sector.

Finally, the scope with regards to environmental impacts should also be broadened, encompassing more detailed explorations of social and human health impacts.

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Data Availability Statement: Data is entirely available in Appendix A.

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

Appendix A

Table A1. Studies with the application of IO analysis to electricity generation.

Objectives	Country/Region	Years Covered	Technologies Assessed	LCA Stages	Disaggregation Approach	Methodologies	Reference
GHG emissions and energy inputs of the different economic sectors engaged in the construction of power plants	Belgium, Netherland, Northern France, and Northern Germany	1996	Nuclear, Wind and PV	Fuel, construction, operation and maintenance (O&M) and decommission	The electricity sector is not disaggregated in the IO matrix	IO and PCA techniques (IO used to complement some parts of the life cycle that lack data)	[44]
Assessment of non-materials related processes	United States of America (USA)	Not specified	Coal, Wind and Nuclear	Fuel, construction, O&M, decommission and waste disposal	The electricity sector is not disaggregated in the IO matrix	IO and PCA techniques (IO used to complement some parts of	[47]

						the life cycle that lack data)	
Net employment effects	Federal Republic of Germany	1999–2017	Coal, Natural Gas and Oil vs RES-E	Not available	The electricity sector is treated as final demand	Symmetric IO framework	[26]
NO_x and SO_2 emissions for materials production	Japan	1985	Natural Gas, Coal, Hydro, PV, Wind, and Ocean	Fuel, construction and O&M	The electricity sector is not disaggregated in the IO matrix	IO and PCA techniques (IO used to complement some parts of the life cycle that lack data)	[45]
Energy and CO_2 LCAs	Germany, Argentina, Belgium, UK, USA, Denmark, Switzerland, and Japan	1980–2001	Wind	Not available	Not applicable	Review that includes hybrid IO life cycle assessment	[59]
Role of electricity sector in economy	South Korea	1985, 1990, 1995, 1998	Hydro, Coal, Oil, Natural Gas and, Nuclear	Not available	The electricity sector is treated as final demand	Input-output Symmetric framework, Demand-driven model, and supply-driven model and Leontief price model	[20]
Energy and CO_2 embodied in a particular wind turbine manufactured	Brazil and Germany	1999	Wind	Material extraction, Manufacture and O&M	The electricity sector is not disaggregated in the IO matrix	IO and PCA techniques (IO used to complement some parts of the life cycle that lack data)	[48]
CO_2 emissions from various manufacturing processes involved in power generation	Japan	1990s	Coal, Oil, Natural Gas, Nuclear, Hydro, Geothermal, Wind and PV	Fuel (extraction, manufacture and transportation), O&M and waste disposal	The electricity sector is not disaggregated in the IO matrix	IO and PCA techniques (IO used to complement some parts of the life cycle that lack data)	[49]
Economic and environmental impacts of integrated resource planning in the power sector	Java, Madura, Bali, Indonesia	2000	Thermal and Hydro	Not available	Combining IO tables with energy balance data and disaggregation solely based on electricity generation data	Decomposition IO Analysis (structural change, fuel mix, final demand, and joint impacts)	[68]
Economic consequences and CO_2 emissions of changes in electricity generating capacity and mix	Scotland	2000	Electricity distribution transmission and Nuclear, coal, Hydro, Natural Gas, Biomass, Wind, Biogas and Marine	Not available	Combining IO tables with energy balance data and combining surveys/technical data with the IO table	IO Symmetric framework	[9]
CO_2 emissions affected by the substitution of the conventional coal technology with cleaner technologies	Thailand	IO Table of 1998, years covered 2006–2016	Coal, Natural Gas, Oil, Biomass, Hydro, Small Hydro, Wind, PV, and solar thermal	Not available	Combining IO tables with energy balance data	IO Symmetric framework	[21]
Energy requirements	USA	Not specified	Wind energy	Construction, O&M and decommission	The electricity sector is not disaggregated in the IO matrix	IO and PCA techniques (IO used to complement some parts of the life cycle that lack data)	[50]

Employment impacts	Germany	2004–2030	Wind, PV, Hydro, Geothermal and Biomass	Not available	Combining surveys/technical data with the IO table	Scenarios for future development of RES-E and macro-econometric model PANTA RHEI	[69]
Review of life cycle energy and GHG emissions	World	1975–2006	Nuclear power	Not applicable (review)	Not applicable (review)	Review that includes hybrid IO life cycle assessment	[86]
Allocation of the inputs to the electricity sector in a social accounting matrix	USA	2000	Coal, Natural Gas, Oil, Hydro, Nuclear, Wind, Biomass, Geothermal and PV	Not available	Using a mathematical programming approach	Social Accounting Matrix (SAM) IO framework	[61]
Pollution emission from electric power industries	Malaysia	1991–2000 (projections for 2020)	Oil, Coal, Natural Gas and Hydro	Not available	Combining IO tables with energy balance data	IO Symmetric framework	[41]
Direct employment of wind power	EU	2008	Wind	Manufacture, construction and O&M	Combining surveys/technical data with the IO table	IO Symmetric framework	[87]
Embodied energy values of the wind turbines	Australia	1996–1997 (2000–2001)	Wind	Fuel, construction, O&M, decommission and waste disposal	Combining P-LCA data with IO tables	IO and PCA techniques	[55]
Economy, energy, and environment impacts	Portugal	1992	Fossil fuel (coal, oil and natural gas), Hydro and electricity distribution	Not available	Combining IO tables with energy balance data	IO symmetric framework	[67]
Employment benefits of power-generation technologies	Greece	2000–2006	Coal and Natural Gas	Construction and O&M	Combining surveys/technical data with the IO table	IO symmetric framework	[28]
Role of nuclear power generation in the economy	South Korea	2003	Nuclear and non-nuclear	Not available	Combining surveys/technical data with the IO table	Demand-driven model, inter-industry linkage effect analysis, supply-driven model, and Leontief price model	[32]
Identify sectors that contribute most to electricity consumption	Spain	2004	The electricity sector is not disaggregated	Not available	The electricity sector is treated as final demand	IO symmetric framework and backward and forward effects	[88]
Estimate the effects of a carbon tax on prices and emissions of carbon-intensive industries	USA	2002	Hydro, Coal, Natural Gas, Oil, Nuclear and others	Not available	Combining surveys/technical data with the IO table	IO SUT framework. Introduces the concept of price elasticity of demand into IO analysis to capture the effect of a price change on consumer demand	[13]
Electricity demand	China	2002	The electricity sector is not disaggregated	Not available	The electricity sector is treated as final demand	IO symmetric framework	[89]
Employment benefits of RES-E	Greece	2005	Wind, PV, Hydro, Geothermal and Biomass	Manufacturing, Fuel extraction, Construction and O&M	Combining surveys/technical data with the IO table	IO symmetric framework	[27]
Indirect GHG emissions of energy technologies using wind power generation	UK	2004	Wind power and Transmission of electricity	Construction, grid-connecting and decommission	Combining P-LCA with IO to express some sectors in more detail	IO based hybrid LCA (SUT framework) and Integrated Hybrid LCA	[17]
Forward and backward linkage effects of the electricity sector	Taiwan	2004–2006	The electricity sector is not disaggregated.	Not available	Combining IO tables with energy balance data	Forward and backward linkage effects obtained from analysis of sensibility index of dispersion and	[90]

						power index of dispersion	
Disaggregate the IO table	China	2007	Hydro, Nuclear, Wind, Biomass, Coal and Natural Gas	Not available	Using a mathematical programming approach and disaggregation solely based on electricity generation data	IO Symmetric framework combined with a random walk algorithm	[71]
Environmental impacts of electricity sector	Taiwan	2001, 2004 and 2006	The electricity sector is not disaggregated	Cradle to gate	Combining IO tables with energy balance data	Simillar to Carnegie Mellon EIO-LCA model	[51]
Energy requirements of manufacturing materials for small hydropower plants	India	2004–2005	Small Hydro	Construction, O&M	Combining surveys/technical data with the IO table	Carnegie Mellon EIO-LCA model	[46]
Technological responsibility of productive structures in electricity consumption	Spain	2005	The electricity sector is not disaggregated	Not available	The electricity is treated as final demand	Structural Decomposition Analysis (SDA) and IO symmetric framework	[91]
Disaggregating the electricity sector in the IO table	China	2007	Transmission and distribution, Coal, Wind, PV, Nuclear, Hydro and Natural Gas	Not available	Using weight factors	IO symmetric framework	[15]
Macroeconomic effects associated with several energy conservation measures	Greece	2010–2020	Wind offshore and onshore, PV, Small Hydro, Geothermal and Biomass	Not available	The electricity sector is treated as final demand	IO symmetric framework	[33]
Identify key sectors that promote energy savings in the production and distribution of electricity	Spain	2007	The electricity sector is not disaggregated	Not available	The electricity sector is treated as final demand	IO symmetric framework, Classical Multiplier Method, and Hypothetical Extraction Method	[92]
Amount of solar energy embodied in trade	Top ten wealthiest economies	1995–2009	Solar energy	Not available	The electricity sector is treated as final demand	IO symmetric framework	[93]
Socio-economic impacts of geothermal power generation	Japan	2005	Geothermal power generation	Not available	The electricity sector is treated as final demand	IO Symmetric framework	[29]
Economic, energy and environment impacts	Japan	2005	Wind	Manufacturing, construction and installation	Combining P-LCA with IO to express some sectors in more detail	IO Symmetric framework combined with PCA	[56]
Economic evaluation of small hydroelectric generation project with citizen participation	Iida City, Japan	2010	Small Hydro	Not available	Combining surveys/technical data with the IO table	Regional IO analysis in which willingness to work is incorporated.	[34]
CO_2 emissions for conventional and RES-E for several regions	USA	2002	Coal, Natural Gas, Oil, Nuclear, Hydro, Geothermal, Biomass, Wind and PV power; transmission and distribution	O&M	Combining surveys/technical data with the IO table	SUT framework	[1]
Evaluate the impacts of coal-to-gas switching in electricity generation	China	Not available	Coal, Oil, Natural Gas, Nuclear, Hydro, Wind, PV, and Other	Not available	Not available	Symmetric IO framework, GTAP	[11]

Employment impacts of electricity sector	Portugal	2008–2020	Wind, PV, Hydro, Geothermal, Biomass, Coal, and Natural Gas	Manufacturing, Installation and O&M	Combining surveys/technical data with the IO table	IO Symmetric framework (quantity and price models)	[8]
HiDisaggregate the electricity sector	USA	2007	Nuclear, Coal, Gas Natural, Oil, Hydro, Wind and PV	Not available	SPCE	IO Symmetric framework	[60]
GHG emissions of wind energy farms	USA	2010	Wind power	Manufacturing, Installation, O&M, and decommission	Combining surveys/technical data with the IO table	Carnegie Mellon EIO-LCA model and Monte Carlo simulation	[52]
Carbon footprint of renewable electricity generation	Australia	2008 and 2009	Wind onshore, Wind offshore, PV, Geothermal, Hydro, Coal, Natural Gas, Oil, Biomass and Ocean	From raw material mining to decommission (no recycling)	Combining P-LCA with IO to express some sectors in more detail	Consequential LCA, SUT framework and Multi-Regional IO (MRIO) tables	[58]
Embodied energy analysis for coal-based power generation	China	2005 and 2007	Coal	Construction and O&M	Combining P-LCA with IO to express some sectors in more detail	IO and PCA techniques (IO used to complement some parts of the life cycle that lack data)	[94]
Economic impacts of wind and PV power	China	2012	Wind and PV	Not available	Combining surveys/technical data with the IO table	IO symmetric framework	[95]
Analysis of the energy return on investment	UK	1997–2012	Coal, Oil, Natural Gas, Nuclear, Hydro, PV, Biomass and Wind	Not available	The electricity sector is treated as final demand	MRIO symmetric framework	[36]
Regional employment generated by investments in electricity-generation	Wales	2007	Coal, Natural Gas, Nuclear, Wind, PV, Tidal and Wave power	Not available	Combining surveys/technical data with the IO table	IO symmetric framework	[85]
Structure analysis of the electricity sector	Spain	2013	Wind, Nuclear, Conventional Thermal, Hydro, PV and other power generation,	Not available	Combining surveys/technical data with the IO table	Uses the SAM IO symmetric framework departing from the SUT framework,	[12]
Comparison of employment impacts between RES-E, CE and energy efficiency	USA	2013	Wind, PV, Biomass, Geothermal, Hydro, Oil, Natural Gas, and Coal	Manufacturing, construction, Installation and O&M	Combining surveys/technical data with the IO table	IO symmetric framework	[30]
Environment, energy and economic impacts	Japan	2005	Wind power	Manufacturing, construction, and O&M	Combining P-LCA with IO to express some sectors in more detail	IO SUT framework and PCA techniques	[57]
Economic impacts and the feed-in tariff system	Japan	2005	Nuclear, Thermal, Hydro, and Transmission and Distribution	Not available	Combining surveys/technical data with the IO table	IO symmetric framework	[14]
Net energy analysis	Australia	1998/99 to 2006/07	Transmission, Distribution, Onselling and Generation	Construction, O&M, and decommission	Combining IO tables with energy balance data	IO symmetric framework and Energy Return on Investment (EROI)	[96]
Economic and environmental impacts of increasing indigenous coal	Turkey	1990, 2000, 2010 and 2015	Coal, Natural Gas, Oil, Hydro, Wind, and other,	Not available	Combining surveys/technical data with the IO table	IO symmetric framework	[97]

			transmission and distribution				
Exergy LCA of electricity generation	Milan, Italy	2010	The electricity sector is not disaggregated	Construction, O&M and disposal	The electricity sector is treated as final demand	Carnegie Mellon EIO-LCA model and Exergy Return on Investment	[98]
Analysis of energy policy	Canada	2013	Renewable energy	Not available	Combining IO tables with energy balance data	Multi-factor IO analysis	[37]
Influence on terrestrial biodiversity	USA	2010	Coal, Oil, Natural Gas, Nuclear, Hydro, PV, wind, and other	Not available	Combining surveys/technical data with the IO table	Uses MRIO tables from GTAP	[42]
Economic spillover effects of investment in RES-E	Croatia	2010	Wind, PV, biomass, biogas, and small-scale hydro	Installation and O&M	Combining surveys/technical data with the IO table	IO symmetric framework	[38]
Environmental impacts	Thailand	2005–2010	The electricity sector is not disaggregated	Not available	The electricity sector is treated as final demand	Similar to Carnegie Mellon EIO-LCA	[53]
Gross employment (direct and indirect employment)	Germany	2000 and 2018	Wind, PV, Hydropower, Geothermal, Biogas and Biomass	Fuels, Manufacturing, Installation and O&M	Combining surveys/technical data with the IO table	Data based on surveys and O&M data based on questionnaire-interviews with experts	[99]
Macroeconomic effects of investments in RES-E	Croatia	2015 (projections 2021–2030)	Hydro, Wind, PV, Geothermal, Biomass, Natural Gas	Not available	Combining surveys/technical data with the IO table	IO symmetric framework	[35]
Economic effects of replacing nuclear power with RES-E	South Korea	2015	Nuclear, PV, and onshore/ offshore wind	Not available	Data publicly available in the 384 IO Table	IO symmetric framework	[10]
RES-E consumption policy	Turkey	2014	The electricity sector is not disaggregated	Not available	The electricity sector is treated as final demand	IO symmetric framework	[100]
Economic spillover effects	South Korea	2010, 2015 and 2020	RES-E	Not available	Data publicly available in the 384 IO Table	IO symmetric framework	[39]
Economic effects	Island of Tsushima in Japan	2011–2020	PV and Wind	Construction and O&M	Combining surveys/technical data with the IO table	IO symmetric framework	[40]
Explore the temporal dynamics of energy and emission embodiments	China	2018	The electricity sector is not disaggregated	Not available	Combining surveys/technical data with the IO table	SDA and IO symmetric framework (annual electricity consumption disaggregated into monthly consumption)	[101]
Evaluate energy consumption and intensity	Shanxi Province, China	2002–2017	The electricity sector is not disaggregated	Not available	The electricity sector is treated as final demand	SDA and IO symmetric framework	[102]
Predicting Structural Changes	Austria	2010 to 2020	Coal, Natural Gas, Oil, PV, Wind, Hydro power, Biomass, Biogas, Nuclear and Other	Not available	Using econometric methods and panel data	Combine econometric methods and panel data with the SUT framework	[65]

Appendix B

Appendix B.1. P-LCA Conceptual Basis

LCA is a methodological approach which aims at evaluating the environmental impacts, all stages of the life cycle of a product, service, or sector from “cradle to grave” [103]: from resource extraction and processing, through construction, manufacturing and retail, transportation and use, repair, and maintenance, and disposal/decommissioning and re-use/recycling. LCA procedures are usually based on environmental management standards (ISO 14040/14044) and are conducted in four steps:

(1) Goal and scope definition—the goal and scope definition comprise the purpose of the study, the aimed application, and the intended audience (ISO 14040). At this stage the system boundaries of the study are established and the functional unit is defined. The functional unit is a quantitative measure of the tasks that the goods (or service) provide.
(2) Life Cycle Inventory (LCI)—the outcomes of the LCI are a compilation of the inputs (resources) and the outputs (emissions) from the product over its life cycle regarding its functional unit. According to ISO 14044, electricity inventories shall consider electricity mixes, fuel efficiencies, as well as transmission and distribution losses.
(3) Life cycle impact assessment—the P-LCA is aimed at understanding and assessing the extent and implications of the potential environmental impacts of the studied system (ISO 14040).
(4) Interpretation—in the interpretation phase, the results from the previous steps are evaluated regarding the goal and scope to achieve conclusions and recommendations (ISO 14044).

As already noted, the system boundary identification has great influence on the emission factors estimation in the LCA process, and it is an important task of the first step of this approach. Therefore, a standard system boundary must be used to guarantee the comparability of the results obtained. The LCA system boundaries of different electricity generation technologies usually include impacts from extraction, processing, and the transportation of fuels, the building of power plants and the generation of electricity, and are briefly described in Table A2.

Table A2. LCA system boundaries of different electricity generation technologies.

Electricity Technology	Upstream	Operation	Downstream	Reference
Thermal power	Coal—open cut mining operations, deep mining operations, preparation plant for all mines includes crushing, screening, sizing, washing, blending, and loading onto trucks and conveyors and spontaneous combustion. Natural gas/oil—exploration and test drilling; gas/water separation, condensate separation, dehydration, compression, and other initial processing on offshore platforms; stripping of CO2 and other impurities from raw gas pipeline transmission to the onshore processing plant; construction phase—building material production, such as steel and cement; facilities installation	Fuel combustion; fuel provision	Power plant decommissioning process	[104–106]
Hydropower	Building material production processes, such as steel and cement, equipment installation	Reservoir emissions, period of drought and maintenance	Power plant decommissioning process	[5,106]
Nuclear	Supply of materials (production of steel, cement, copper, and aluminium) and facility construction	Uranium mining, milling, conversion, enrichment, fuel rod fabrication, transportation, facility O&M, and reprocessing	Facility decommissioning; nonradioactive waste disposal/recycling; and temporary, long-term, and permanent radioactive waste storage after electricity generation and facility lifetime	[86,106–108]
Wind	Raw materials extraction, materials manufacturing, component manufacturing, transportation from the manufacturing facility to the construction site, and on-site construction and related machinery, concrete, iron, and steel	Maintenance activities such as replacement of worn parts and lubricating oils, and transportation to and from the turbines during servicing	Turbine and site decommissioning, disassembly, transportation to the waste site, and ultimate disposal and/or recycling of the turbines and other site materials	[106,109]
Biomass	Processes of planting, harvesting, and transportation, the manufacture of equipment, the building material production	Fuel combustion process	Equipment recycling and scrapping process	[106]

Solar PV	Mining, refining and purification all of the silicon and/or other required metals and minerals for the cells, glass, frame, inverters, and other required electronics; petroleum extraction for plastics, natural gas extraction used for heating, and effectively any other material extraction and processing needed to create the PV module and finished electronics; wiring, encapsulation and any other processes by which the modules and electronics are fabricated and finished (up until the point of transportation to the site of operation); on-site construction of the generator and transportation of materials to the site	Maintenance and cleaning	Equipment recycling and scrapping process	[106,110,111]
Geothermal	Exploration, drilling, well installation, surface plant construction with all buildings	O&M, cooling facilities	Plant decommissioning and recycling	[112]

Currently, LCA is an entrenched framework, established on internationally agreed environmental management standards and supported by international initiatives (ISO 14040/14044). The outcomes of P-LCA may be obtainable as inventories of individual stressors, or as environmental impact category indicators at 'midpoint' or 'endpoint' levels of aggregation. The midpoint indicators (e.g., substance emissions) allow for environmental effects of several individual stressors to be integrated into a single impact type (e.g., Global Warming Potential, Acidifying Potential, and Photochemical Ozone Creation Potential). Endpoint indicators quantify impact potentials by endpoints in the effect chain. Ecosystem (e.g., atmosphere, water, and land), natural resources, solid waste and human health are usually considered as such endpoints, but occasionally even one single indicator of environmental impact is used [5].

Several studies are aimed at exploring the main challenges and opportunities at stake in applying LCA to electricity generation technologies (see, for example, [5,104,113–115]). We briefly refer to some of these challenges below.

Appendix B.1.1. Data

Data representativeness is an important aspect when conducting an LCA because of the heterogeneity of electricity LCI data.

(1) Geographic Coverage
  a. Sometimes no regionalized electricity data is available—gaps in LCI data still exist and are usually more evident in non-OECD countries.
  b. Grid delimitation—it is difficult to know where the electricity is coming from.

(2) Temporal Aspects of Electricity

Predicting and capturing changes in time—a relevant task in consequential LCA—is a challenging task for both temporal scopes: the short-term and long-term horizon.
  a. Short-Term: Price bids are not always publicly available. Additionally, not all electricity markets have the same extent of de-regulation.
  b. Long-Term: Additional capacity would need to be installed to cover increases in demand. Changes in the electricity sector depend on political, environmental, and economic considerations that are substantially uncertain and country specific.

(3) Technology Coverage

The main challenges in technology data coverage concern currently used technologies and those which will be installed in the future and are not yet commercially available.
  a. Current Technologies: There is a wide variation among generation stations in terms of emissions and inputs per unit generation across and even within fuel types.
  b. Prospective Technologies: Modelling how technology performance will change over time is particularly difficult for nascent technologies such as organic PV panels or carbon capture and storage. Moreover, disruptive technologies can

bring improvements in efficiency, but also have implied changes in infrastructure and user behavior, which are more difficult to predict.

Appendix B.1.2. Using Electricity LCI Data

LCI data should represent the actual local or regional/national power supply as close as possible to be useful for LCA practitioners.

In Table A3, some of the problems and expected limitations/uncertainties identified in regarding the application of P-LCA to electricity generation and corresponding possible solutions are identified.

Table A3. Problems and limitations of LCAs applied to electricity generation technologies.

Problem	Limitations/Uncertainties	Possible Solutions
Mainstream literature based on "attributional" LCA, with average product or technology lifecycle.	LCA cannot capture the dynamics of changing electricity markets and technologies.	Consequential LCA would allow the full effects of electricity generation technologies to be assessed simultaneously.
LCA usually considers a static nature and addressing individual power plants.	Assumptions and changing characteristics of the background energy system	Use scenario-consistent assumptions of technical improvements in key energy and material production technologies.
LCA usually does not consider a number of important criteria such as social aspects, acceptability, or security of supply.	Attempts to incorporate those elements in turn lead to other limitations and uncertainties.	To foster such aspects in the LCA guidelines, theSocial LCA of products were developed in 2009 by UNEP.
LCA is often considered a long and onerous process and focuses on existing installations. Modelling a new product or process is difficult and expensive.	Outdated values are often used that fail to reflect evolutions in the power sector.	LCA can also be prospective. LCAs may include future scenarios.
Defining system boundaries for LCA is arbitrary and controversial.	Incomplete assessments or expensive costs.	Hybrid LCA methodologies should be employed in order to achieve system completeness.
There is lack of comprehensive data for LCA.	Equally credible analyses can produce different results	Make process-level inventory input data available together with LCA publications.
Lack of harmonization and transparency and eventually to a wide variety of results.	Not possible to make comparisons across different studies.	Conduct regular and continuous meta-analysis with the normalization of results.
Electricity grids are increasingly becoming interconnected, and selecting a grid mix boundary becomes a complex task.	There is potential for double counting when assessing large, interconnected energy systems	Use national electricity mixes and accounting for imports from the neighbouring jurisdictions. Create clusters of data according to the congestion status and its location.

Appendix C

EIO-LCA Conceptual Basis

IO analysis is a method for analyzing the interlinkages between distinct activity sectors within an economy that can be employed to compute total factor multipliers, which can be used to evaluate the economic spillover effects inherent to the investment in RES-E, for example, while also accounting for the corresponding energy and environmental impacts [39]. It considers the use of tables that show the flows of goods and services between different sectors of the economy, including both the production and consumption of each sector. These tables can have various formats depending on three main criteria [116]: symmetric or rectangular formats; total or domestic-use flows; and basic or purchaser's prices.

The symmetric format of IO tables represents industries or commodities in both the rows and columns and considers that each industry produces a single commodity. This format shows industry-by-industry or commodity-by-commodity interrelations [116]. Nevertheless, as each industry may produce multiple secondary commodities, the rectangular format, also called the supply and use tables (SUT) format, is more appropriate [73]. In this format, the rows of the supply table represent the various industries and their contributions to the output of different commodities, while the columns of the use table show the consumption of different commodities by industries and final users. The SUT format is particularly useful, as it allows for the inclusion of a larger number of commodities than industries in the model.

The symmetric IO framework given in (A1) depicts the distribution of the total output of each sector at basic prices:

$$x_i = \sum_{j=1}^{n} x_{ij} + \sum_{f=1}^{m} y_{if} \tag{A1}$$

where x_i is the output of sector *i*, x_{ij} is the sales from sector *i* to sector *j*, and y_{if} is the sales of sector *i* to final demand sector *f* (households, government, firms, and foreign countries).

Considering the constant returns to scale hypothesis, Equation (A1) becomes:

$$x_i = \sum_{j=1}^{n} a_{ij} x_j + \sum_{f=1}^{m} y_{if} \tag{A2}$$

in which a_{ij} is the sales of input *i* to sector *j* per unit of sector *j*'s output (or direct coefficients).

From (A2), and aggregating final demand into a vector, the basic IO system of equations is obtained in its matrix form (A3):

$$\mathbf{x} = \mathrm{A}\mathbf{x} + \mathbf{y}, \tag{A3}$$

where A is the technological coefficients matrix, **y** is the final demand vector, and **x** is the output vector.

To compute the output multipliers, the Leontief inverse matrix needs to be obtained as:

$$\mathbf{x} = (\mathrm{I} - \mathrm{A})^{-1}\,\mathbf{y}, \tag{A4}$$

where I is an identity matrix and $(\mathrm{I} - \mathrm{A})^{-1}$ is the Leontief inverse. Each element of $(\mathrm{I} - \mathrm{A})^{-1}$ corresponds to the total amount of good or service *i* directly and indirectly required to produce a unit of final demand of good or service *j* [73]. Therefore, this matrix is also called the multiplier matrix.

The concept of multipliers is based on the difference between the initial impact of an exogenous change (final demand) and the overall impact of that change. Direct effects refer to the response of a particular industry to a change in final demand for that industry [73]. Indirect effects represent the response of all the industries that supply to a particular industry to a change in final demand for that industry [73]. Induced effects refer to the response of all industries to increased (or decreased) household spending and inter-industry transfers that result from the direct and indirect effects of a change in final demand for a particular industry [73]. To calculate the pollution resulting from inter-industry activity, we can use a matrix of pollution output or direct impact coefficients, R, where each element, r_{kj}, represents the amount of pollutant type *k* produced per unit of output from industry *j* [2–4]. This allows us to express the level of pollution associated with a given vector of total outputs as:

$$\mathbf{r} = \mathrm{R}\mathbf{x}, \tag{A5}$$

where **r** is the pollution vector. Hence, from (A4) and (A5), we can compute vector **r** as the total pollution of each type directly and indirectly produced for providing a given final demand:

$$\mathbf{r} = \mathrm{R}\,(\mathrm{I} - \mathrm{A})^{-1}\,\mathbf{y}, \tag{A6}$$

Finally, from (A6) we can establish that $\mathrm{R}\,(\mathrm{I} - \mathrm{A})^{-1}$ is a matrix of total environmental impact coefficients, i.e., an element of this matrix is the total pollution impact generated per monetary unit of final demand.

According to the SUT framework, the total demand of product *i* at purchaser's prices is:

$$q_i = \sum_{j=1}^{k} u_{ij} + \sum_{f=1}^{m} y_{if} = \sum_{j=1}^{k} m_{ji} + i_i + d_i + l_i, i = 1, \ldots, n \tag{A7}$$

where q_i is the total demand of commodity *i*; u_{ij} (each element of the Use table) is the amount of commodity *i* used to generate the output of industry *j* (intermediate consumption of commodities); y_{if} is the input of product *i* to final demand *f*; m_{ji} (each element of the Supply table) is the amount of commodity *i* produced by industry *j* in a given year (both primary and secondary commodities); i_i is the amount of imports of commodity *i*; d_i is the amount of margins of commodity *i* and l_i is the amount of net taxes of commodity *i*.

On the other hand, the total output of industry *j* at basic prices is:

$$g_j = \sum_{i=1}^{n} m_{ji} = \sum_{i=1}^{n} u_{ij} + \sum_{q=1}^{p} z_{qj}, j = 1, \ldots, k \tag{A8}$$

where g_j is the total output of industry *j* and z_{qj} is the primary input *q* to industry *j*;

Analogously to the traditional IO model, the basic IO system of equations is also obtained in its matrix form, providing the industrial balance as:

$$\mathbf{g} = \mathrm{M}\mathbf{e}_1 = \mathrm{U}'\mathbf{e}_1 + \mathrm{Z}'\mathbf{e}_2, \tag{A9}$$

where $\mathbf{e}_1$ and $\mathbf{e}_2$ are column vectors filled with ones with convenient dimensions, $\mathbf{g}$ is the vector of the total output per industrial sector at basic prices, M is the supply table, U is the Use table, and ′ designates the transpose and Z is the matrix of value-added inputs. At the product level, the balance can be expressed as:

$$\mathbf{q} = \mathrm{U}\,\mathbf{e}_3 + \mathrm{Y}\,\mathbf{e}_4 = \mathrm{M}'\,\mathbf{e}_3 + \mathbf{i}' + \mathbf{d}' + \mathbf{l}', \tag{A10}$$

where $\mathbf{e}_3$ and $\mathbf{e}_4$ are column vectors filled with ones with convenient dimensions, Y is the matrix of final demand, $\mathbf{i}$ is the vector of imports, $\mathbf{d}$ is the vector of margins, and $\mathbf{l}$ is the vector of net taxes.

The SUT framework offers two options for technology assumptions: industry technology and product technology. In the industry technology assumption, the input structure of an industry is kept constant regardless of its product mix, and all secondary products of the industry are produced using the technology used for the primary product. This assumption requires that each industry has a fixed share in the production of a given product. The product technology assumption, on the other hand, states that a given product always has the same input structure, irrespective of the industry in which it is produced. There is no agreement on which assumption is more appropriate, but the commodity technology assumption is generally favored from an axiomatic point of view [117]. Nevertheless, this assumption can lead to negative values, which are not allowed conceptually [117]. As a result, the industry technology assumption may be preferred in some cases.

Thus, for practical reasons we consider the industry technology assumption (for further developments on the product technology model please see [116]) by dividing all the elements of U and M by the corresponding column totals of industrial output and the demanded products, respectively. Subsequently, we obtain the following partitioned matrix, composed by the matrices Q and S and two zero-filled matrices:

D = $\begin{bmatrix} 0 & \mathrm{Q} \\ \mathrm{S} & 0 \end{bmatrix}$, where each element of Q is given by $\frac{u_{ij}}{g_j}$ (amount of product *i* consumed by industry *j* per unit of output of industry *j*) and each element of S is obtained by $\frac{m_{ji}}{q_i}$ (amount of product *i* produced by industry *j* per unit of total demand of product *i*).

From D and considering final demand aggregated into a single vector, it is possible to write the following matrix system:

$$\begin{bmatrix} 0 & Q \\ S & 0 \end{bmatrix}\begin{bmatrix} \mathbf{q} \\ \mathbf{g} \end{bmatrix}+\begin{bmatrix} \mathbf{y} \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} \mathbf{q} \\ \mathbf{g} \end{bmatrix} \Leftrightarrow \begin{bmatrix} \mathbf{q} \\ \mathbf{g} \end{bmatrix} = \begin{bmatrix} I & -Q \\ -S & I \end{bmatrix}^{-1}\begin{bmatrix} \mathbf{y} \\ \mathbf{0} \end{bmatrix}. \tag{A11}$$

When applying the general formulas for computing the inverse of a partitioned matrix, we obtain (for further details see [64]):

$$\begin{bmatrix} I & -Q \\ -S & I \end{bmatrix}^{-1} = \begin{bmatrix} (I-QS)^{-1} & (I-QS)^{-1}Q \\ S(I-QS)^{-1} & I+S(I-QS)^{-1}Q \end{bmatrix} \tag{A12}$$

or

$$\begin{bmatrix} I & -Q \\ -S & I \end{bmatrix}^{-1} = \begin{bmatrix} I+Q(I-QS)^{-1} & Q(I-QS)^{-1} \\ (I-QS)^{-1}S & (I-QS)^{-1} \end{bmatrix} \tag{A13}$$

From the rectangular IO model, it is possible to derive expression (A14), which is analogous to expression (A6), since it allows for the measuring of the impact on an industry's output due to changes in final demand. Therefore, if we consider the rectangular version of the IO model instead of expression (A6), we obtain:

$$\mathbf{r} = R\,[S(I-QS)^{-1}]\,\mathbf{y}, \tag{A14}$$

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