UNIVERSITAT ROVIRA I VIRGILI

MULTIREGIONAL SUSTAINABILITY AT A SECTORAL LEVEL: TOWARDS MORE EFFECTIVE ENVIRONMENTAL REGULATIONS

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Towards more effective environmental regulations

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Multiregional sustainability at a sectoral level: Towards more effective environmental regulations

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I STATE that the present study, entitled "Multiregional sustainability at a sectoral level: Towards more effective environmental regulations", presented by Patricia Zurano Cervelló for the award of the degree of Doctor, opting for an International Doctorate Mention, has been carried out under our supervision at the Chemical Engineering Department of the University Rovira i Virgili.

Tarragona, 23rd July 2018,

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SUMMARY

In today's globalized market, where international trade plays a major role, assessing the environmental footprint of anthropogenic activities and allocating the corresponding environmental responsibilities among the parties involved have become very challenging tasks. Anthropogenic activities involve a plethora of interconnected economic transactions among sectors and regions that mask the ultimate impact sources in the life cycle of a product. To solve this problem, substantial research has been aimed at understanding how anthropogenic activities affect the environment from a macroeconomic viewpoint.

In this regard, the environmental footprint assessment is key to identifying the ultimate sources of impact and formulate effective regulations at a sectoral level to mitigate them. Apart from the environmental footprint, there are other aspects also involved in the sustainability evaluation of each economic sector. These aspects belong to the economic and social categories that, together with the environmental one, make up the three main pillars of sustainability.

This thesis is dedicated to the development of tools to assist policy makers in the creation of effective regulations in an efficient and methodical way. To this end, we propose a two stage approach. In the first stage, it is necessary to identify the sectors and burdens that require regulation. Once the inefficient sectors have been pointed out, in a second stage, they are analyzed in detail to provide specific guidelines on how to achieve the targets set in stage one.

This thesis is organized into four main sections. In section 1, we present the introduction, where we establish the background of the methods and data used in this work, as well as the literature gaps on which we rely to base our studies. Section 2 is based on the first work, where we study the eco-efficiency of the EU manufacturing sectors by combining MREEIO tables with the DEA method, following the production and consumption-based approaches. This allows us to identify the sectors requiring regulations in specific burdens. Then, in section 3, we determine the sustainability efficiency of the EU electricity mixes by analyzing the social, economic and environmental features of each portfolio using the DEA method. In a second stage, we use a tailored mathematical model named *EffMixF*

to obtain new electricity mixes for the countries found inefficient. These new mixes can be used as roadmap to devise specific regulations for the sector, indicating which technologies should be boosted and which hindered in each inefficient country. Finally, in section 4, we determine the key driving factors of the environmental impact on a global scale. For this, we first compare two decomposition techniques -the SDA and the Shapley-Sun methods-, establishing their similarities and introducing a simplified general equation that can be used in substitution of both methods. Then, we apply these methods in a case study, where we consider a selection of environmental impacts in a 15-year period, to determine the usefulness of the decomposition methods.

Summarizing the conclusions obtained in this thesis, the work presented in section 2 provides valuable insight into how impacts and wealth are generated at the sectoral level in an economy. The information obtained could be used to develop more effective environmental regulations and investment plans in the transition towards a more sustainable economy. The work in section 3 provides valuable insight into how the electricity portfolios should change in order to improve the nation's sustainability level. Hence, the mathematical program we posed and solved, *EffMixF,* could be a useful tool to aid policy makers in the development of more effective regulations. Specifically, *EffMixF* identifies which technologies should be promoted, or hindered, via tailored policies. Finally, from section 4 we conclude that the *n!* SDA decomposition equations and the Shapley-Sun method are indeed the same approach in mathematical terms. We have formulated a simpler general equation that can be used in substitution of both equations.

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1. INTRODUCTION

1. Introduction

In today's globalized market, where international trade plays a major role, assessing the environmental footprint of anthropogenic activities and allocating the corresponding environmental responsibilities among the parties involved have become very challenging tasks. Anthropogenic activities involve a plethora of interconnected economic transactions among sectors and regions, masking the ultimate impact sources in the life cycle of a product and therefore making it difficult to disentangle them in an objective way.

To solve this problem, substantial research has been aimed at understanding how anthropogenic activities affect the environment from a macroeconomic viewpoint (Martínez-Zarzoso and Maruotti, 2011; Pani and Mukhopadhyay, 2013). Some of these studies are based on the *multiregional environmentally-extended input-output* (MREEIO) tables, which contain very valuable information about how impacts are generated at a global scale (Liu et al., 2017; Schandl et al., 2016). These tables provide the economic transactions among the sectors of different countries, also including the environmental impacts of the goods and services in these transactions from a *life cycle assessment* (LCA) perspective. The MREEIO tables allow to assess the environmental impacts at the production and consumption-based approaches (Dietzenbacher and Lahr, 2008; Miller and Peter D., 2009). The consumption-based impact, also known as footprint (Wackernagel and Rees, 1998), attempts to produce a fairer allocation of the impacts by penalizing consumers rather than producers.

The environmental footprint assessment is key to identifying the ultimate sources of impacts (such as the climate change, the fresh water scarcity, the acidification or the tropospheric ozone depletion, among others (IPCC, 2014)) and formulate effective regulations to mitigate them. Apart from the environmental footprint, there are other aspects that are also involved in the sustainability evaluation of processes and systems within each economic sector. These aspects belong to the economic and social categories that, together with the environmental one, make up the three main pillars of sustainability (Caradonna, 2014).

In order to improve the sustainability of the anthropogenic activities and slow down their environmental footprint, numerous roadmaps have been settled (European commission, 2011; European Union, 2010; Simoes et al., 2017). These guidelines appropriately identify the indicators that have to be improved (e.g., in the EU, reduction of the GHG emissions of 80% below 1990 levels by 2050). However, they do not detail which are the specific changes required to achieve such improvements. In other words, they fail to provide the steps required at a petite scale to improve the sustainability, for example, by pointing the technologies that need to be modified and providing the corresponding alternatives. Particularly, it is still unclear how to use the information on environmental footprints to create effective policies from a multiregional point of view, due to the large amount of data involved. These data are based on international transactions and involve a high number of players and stakeholders in each region and sector, situation that often creates conflicts of interests.

This thesis is dedicated to the development of tools to assist policy makers in the creation of effective policies and regulations in an efficient and methodical way. To this end, we propose a two stage approach. In the first stage, it is necessary to identify the sectors and burdens requiring regulation. One of the methods used for this purpose is *data envelopment analysis* (DEA), a well-established benchmarking method that can be easily combined with MREEIO and LCA data. This technique assesses the relative efficiency of a set of alternatives using a wide number of indicators and in the absence of subjective weights (Cook and Seiford, 2009; Cooper et al., 2011, 2007), providing also improvement targets for inefficient alternatives.

Once the inefficient sectors have been pointed out, in a second stage, they are analyzed in detail to provide specific guidelines on how to achieve their improvement targets. For example, it can be interesting to identify the key factors responsible for an increase in an environmental impact. There are different decomposition analysis methods available in the literature to evaluate the impact drivers (Fernández González et al., 2014). Two of the most commonly used methods in the context of input-output assessment are the *Structural Decomposition Analysis* (SDA) (Dietzenbacher and Los, 1998) and the Shapley-Sun method (Sun, 1998), which allow decomposing the impact changes at a sectoral level. The SDA is a combinatorial method whose complexity increases factorially with the number of factors considered. For this reason, in many studies researchers resorted to the polar decomposition (a subset of the SDA equations) to approximate the whole set of SDA equations. The polar decomposition simplifies the calculations of impact drivers by reducing the number of equations necessary, yet, the results obtained by this method present a certain approximation error.

Apart from the assessment of environmental drivers, in a second stage, it is also possible to perform a rigorous analysis of the sector under study by creating tailored optimization models. These models can include a set of constraints to focus on the sectors at a petite scale (i.e., bottom-up approach), as well as considering the specific characteristics of each region or process under evaluation. For example, in the case of the electricity sector, it would be possible to consider the potential renewable resources in each country, which depend on their orography, climate or hydrography. Furthermore, these methods can include additional restrictions and bounds, being it possible to encompass other existing regulations in the models (e.g., the incorporation of the nuclear reversal policy as a constraint).

This thesis is organized in four main sections. In section 1, we present the introduction, where we stablish the background of the methods and data used in this work, as well as the literature gaps on which we rely to base our studies. Section 2 is based on the first work, where we study the eco-efficiency of the EU manufacturing sectors by combining MREEIO tables with the DEA method, following the production and consumption-based approaches. This allows us to identify the sectors and burdens requiring specific regulations. Then, in section 3, we determine the sustainability efficiency of the EU electricity mixes by analyzing the social, economic and environmental features of each portfolio using the DEA method. In a second stage, we use a tailored mathematical model named *EffMixF* to obtain new electricity mixes for the countries found inefficient. These new mixes can be used as roadmap to devise specific regulations for the sector, indicating which technologies should be boosted and which hindered in each inefficient country. Finally, in section 4, we determine the key driving factors of the environmental impact on a global scale. For that, we first compare two decomposition techniques -the SDA and the Shapley-Sun methods-, establishing their similarities and introducing a simplified general equation that can be used in substitution of both methods. Then, we apply it in a case study to determine its usefulness. In fig. 1.1, we present an overview of the methods and studies we perform in this thesis.

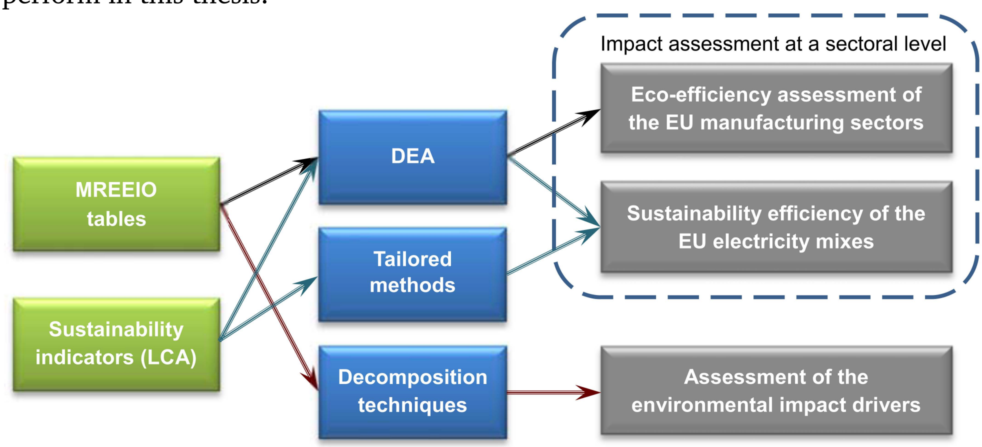

Fig. 1.1. Overview of the methods and studies performed in the thesis.

1.1. Objectives

In this doctoral thesis, there are five main objectives that we aim to achieve. These objectives, addressed in sections 2, 3 and 4, are listed below:

- To assess the EU manufacturing sectors in terms of eco-efficiency by combining MREEIO and DEA methods, following the production and consumption-based approaches in order to identify the sectors and burdens that should be object of environmental regulation.

- To evaluate the sustainability of the EU member countries electricity sector by means of DEA, determining their efficiency with environmental, social and economic indicators.

- To develop a systematic tool to optimize the inefficient electricity mixes of the EU countries, taking into account techno-economic constraints, realistic potentials for renewable sources and the reliability of the supply in each country.

- To demonstrate the equivalence of the Shapley-Sun and the average of the *n!* decomposition SDA equations, highlighting the drawbacks of the polar decomposition in the assessment of environmental drivers at the macro-scale level.

- To develop a simplified general equation to apply the two equivalent decomposition methods, i.e., the Shapley-Sun and the average of the *n!* decomposition SDA equations.

1.2. Life cycle assessment of environmental impacts

Life cycle assessment (LCA) is a well-established method used to evaluate environmental impacts during the product's lifetime, that is, *cradle-to-grave*, (i.e., starting from the raw materials extraction and processing, its manufacture, supply, maintenance and disposal) (Klöpffer and Grahl, 2014). This method, firstly structured by SETAC in 1990 (Klöpffer, 2006), is defined by the ISO 14040 and 14044 standards and is performed in four interdependent phases: i) goal and scope definition, ii) inventory analysis, iii) impact assessment and iv) interpretation. These phases, defined in the ISO 14040, are presented in fig. 1.2.

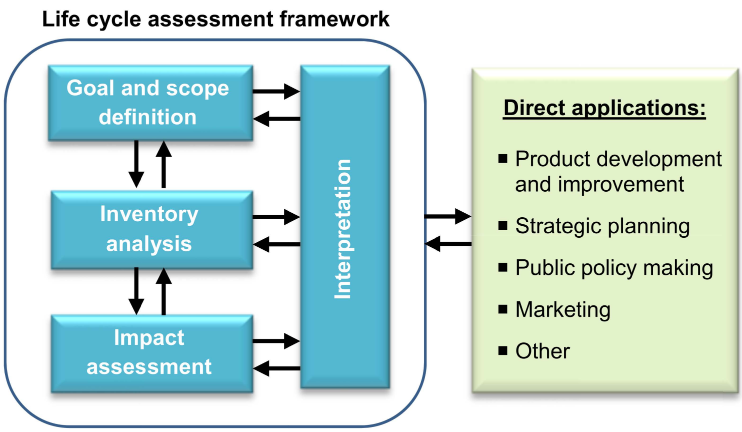

Fig. 1.2. LCA phases by ISO 14040.

The LCA method is of paramount importance in today's globalized markets, as it allows determining the provenance of the burdens in a whole production system, which often spans across different regions. To perform a life cycle impact assessment (LCIA) of an economic sector, it is necessary to gather a large amount of data. These data are available from a variety of databases as are *ecoinvent* (Wernet et al., 2016), *GaBi* (PE-international, 2017) or *IDEA* (Lübkert and Analysis, 1991) among others. At a macroeconomic level, the LCA data is aggregated by sectors in the environmentally-extended input-output (EEIO) models. These models are obtained from the modification of the input-output (IO) tables, where the economic output of each sector is linked to its corresponding environmental impact. With the advent of EEIO models, it is possible to determine the comprehensive environmental footprint of a sector considering its whole life cycle and identifying the role played by the different regions participating in its supply chain.

1.3. Multiregional environmentally-extended input-output models

Multiregional environmentally-extended input-output (MREEIO) tables contain economic and environmental information about the transactions of goods and services taking place among different regions. This information can be used as the basis of a well-established method to study the environmental impact of economic sectors and countries (Dietzenbacher and Lahr, 2008; Miller and Peter D., 2009).

In table 1.1, we present an example of a multiregional input-output (MRIO) table for two regions, each of them with *n* sectors, and the pollution intensity vector, which allows to environmentally extend (EE) the MRIO table. From left to right, we first find the intermediate sales (denoted by *Z*), which provide the economic relationships between sectors and regions in an economy. In this part of the table, the rows provide the sales from a particular sector to all the sectors, while the columns are the purchases. As an example, the first row of region A shows the sales of sector $S_{1,A}$ to all the sectors and regions. All the data in this table is presented in monetary units (e.g., $), allowing the summation of inputs and/or outputs among sectors of different nature. The intermediate sales between sectors of the same region (i.e., domestic intermediate sales) are depicted in blue.

Next to the intermediate sales, we find the demand that the final consumers in each region require from each economic sector (denoted by *DEM*). Then, the total output column (*X*) provides the economic output that each sector generates to satisfy the total demand requirements (i.e., the demand from sectors and final consumers). Finally, the rightmost column, slightly separated from the MRIO table, contains the pollution intensity data, (i.e., the impact generated per unit of money traded in each sector, e.g., tCO_2/$). This column is used to extend the economic data to environmental data (i.e., the environmental extension, EE), making it possible to perform an environmental analysis of a whole economy.

Table 1.1. MRIO table and EE for two regions and *n* sectors in each region.

		Intermediate sales						**Total demand**			**Pollution Intensity**
		Region A			**Region B**			**DEM A**	**DEM B**	**Output**	
		$S_{1,A}$	…	$S_{n,A}$	$S_{1,B}$	…	$S_{n,B}$	y^A	y^B	X	**PI**
Region A	$S_{1,A}$	$z_{1,1,A,A}$	…	$z_{1,n,A,A}$	$z_{1,1,A,B}$	…	$z_{1,n,A,B}$	$y^A_{1,A}$	$y^B_{1,A}$	$X_{1,A}$	$PI_{1,A}$
	…	…	…	…	…	…	…	…	…	…	…
	$S_{n,A}$	$z_{n,1,A,A}$	…	$z_{n,n,A,A}$	$z_{n,1,A,B}$	…	$z_{n,n,A,B}$	$y^A_{n,A}$	$y^B_{n,A}$	$X_{n,A}$	$PI_{n,A}$
Region B	$S_{1,B}$	$z_{1,1,B,A}$	…	$z_{1,n,B,A}$	$z_{1,1,B,B}$	…	$z_{1,n,B,B}$	$y^A_{1,B}$	$y^B_{1,B}$	$X_{1,B}$	$PI_{1,B}$
	…	…	…	…	…	…	…	…	…	…	…
	$S_{n,B}$	$z_{n,1,B,A}$	…	$z_{n,n,B,A}$	$z_{n,1,B,B}$	…	$z_{n,n,B,B}$	$y^A_{n,B}$	$y^B_{n,B}$	$X_{n,B}$	$PI_{n,B}$

There exist a variety of databases that can be used to obtain MRIO tables, depending on the information and level of disaggregation required. Some of these databases are the World Input-Output Database (WIOD) (Timmer et al., 2012), the OECD/WTO trade in value added database (Ahmad, 2002) or the Eora multi-regional IO database (Lenzen et al., 2013). In particular, in this thesis we use the WIOD database that covers macroeconomic transactions for 27 EU countries, 13 other main economies and an aggregated region called "Rest of World", in the period 1995-2009. This database was developed to analyze the effects of globalization on trade patterns, environmental pressures and socio-economic variation considering 35 economic sectors and 70 environmental indicators. More details on this database can be found in section 2.7.

We next present a summary of the method used to analyze MREEIO tables, while further details are available in section 2.2.1. Following Leontief's work (Leontief, 1970, 1936), the total economy output *X* can be calculated as the summation of the intermediate sales (*Z*) and the final consumers' demand (DEM), as expressed in eq. (1.1).

$$X = Z\cdot\vec{1} + DEM = (A\cdot X) + DEM \tag{1.1}$$

where $\vec{1}$ is a "summation vector" (i.e., a column vector of *n* elements equal to one) and *DEM* is a vector where each element represents the total demand required to each sector.

The technical coefficients matrix (*A*) can be obtained by dividing the components of the intermediate sales matrix (*Z*) by the total output vector (*X*). The technical coefficients matrix describes the relationships between sectors in an economy (i.e., the unitary inputs required by the economic sectors). For more details see section 2.2.1.

After appropriate mathematical transformations, the total economic output can be formulated as an explicit function of the final demand:

$$X = (I - A)^{-1} \cdot DEM = LEO \cdot DEM \tag{1.2}$$

where I is the identity matrix and LEO is the Leontief inverse matrix (Dietzenbacher and Lahr, 2008).

Then, by using the pollution intensity vector (PI), it is possible to determine the total impact (IMP) generated by the whole economy (e.g., tCO_2):

$$IMP = PI \cdot (LEO \cdot DEM) \tag{1.3}$$

The calculations carried out up to this point are denominated production-based accounting, as they allocate the emissions to the productive region, regardless of the inputs origin and the final products destination. On the other hand, if it is required to allocate the impact (i.e., environmental responsibilities) to the consumers of such products (consumption-based accounting), it will be necessary to use eq. (1.4).

$$IMP^{CB} = PI \cdot (LEO \cdot DEM^{*}) \tag{1.4}$$

In this equation, the impact consumption-based (IMP^{CB}) is calculated by using the demand of the region or sector under study (DEM^{*}), instead of the total demand (DEM). Following the example in table 1.1, if we want to calculate the impact generated by the products consumed by region A, we should use the *DEM A* column as DEM^{*}. On the other hand, if we want to determine the impact generated (directly and indirectly) by sector $S_{1,A}$, a column vector containing only the demand required to sector $S_{1,A}$ will be DEM^{*} (i.e., the rest of the column will be filled with zeros). Note that when we analyze the consumption-based impact of a sector, we are actually determining all the footprint generated considering all the production phases. These intertwined data are given by the Leontief matrix. Further details can be found in section 2.8.

The consumption-based impact of a region has been deeply studied in the literature being nowadays a well-established method. However, we are interested in analyzing the consumption-based impact of a sector, instead of a region, in order to create more effective regulations. Therefore, one of the objectives in this thesis is to evaluate a set of sectors in the production and consumption-based accounts. Note that in the sectoral evaluation the households' emissions are not considered, contrary to what happens in the regional analysis, where the impacts generated by the activities of the final consumers are also considered (e.g., the emissions generated by the fuel when final consumers use their cars).

1.4. Decomposition methods coupled to input-output tables

The input-output tables can be used to identify the key factors responsible for an increase in an environmental impact in a period of time (e.g., between two years). This analysis, which is particularly useful to guide the efforts of policy makers, is typically performed by using the additive form of structural decomposition techniques (Owen, 2017). In table 1.2, we show a comparison of the main additive structural decomposition techniques available in the literature.

Table 1.2. Comparative of the main additive structural decomposition techniques (adapted from Owen, 2017).

Technique	Exact	Time reversal	Zero value robustness
Laspeyres	No	No	Yes
Marshall-Edgeworth	Not always	Yes	Yes
Paasche	No	No	Yes
Conventional Divisia	Yes	Yes	No
Log-Mean Divisia	Yes	Yes	Require replacements
Adaptive Weighting Divisia	No	No	No
Shapley-Sun	Yes	Yes	Yes
Dietzenbacher and Los	Yes	Yes	Yes

In table 1.2, we compare the different decomposition methods features and show if they are: i) exact or if they present a residual term, as well as if they are ii) time reversal (i.e., the dependence of the result on the order used), and iii) if they present zero value robustness, in case logarithms are involved in the analysis.

Among the different methods considered, only the Dietzenbacher and Los (Dietzenbacher and Los, 1998) and the Shapley-Sun (Sun, 1998) succeed in all these properties without requiring any replacement or data modification, reason why we focus our analysis on these methods. Conversely, the rest of the techniques fail in one or more of these features. In the next subsections, we further explain the Dietzenbacher and Los -also called structural decomposition analysis (SDA)- and the Shapley-Sun methods.

1.4.1. Structural decomposition analysis

As aforementioned, the SDA approach is an additive exact decomposition method which has been widely used to determine which driver contributes the most to an indicator change at a sectoral level (Fernández González et al., 2014; Hoekstra and van der Bergh, 2003). This decomposition employs a non-uniqueness technique that results in *n!* equivalent decomposition forms for *n* determinants (i.e., factors), each of which is considered to be equally valid. For this reason, Dietzenbacher and Los proposed to use the average of the *n!* equivalent decomposition forms in order to obtain the final contribution of each factor towards the impact change.

For systems containing a large number of factors, the polar decomposition method (Dietzenbacher and Los, 1998), and later on, the mirror image decomposition method (De Haan, 2001), were proposed as simpler alternatives requiring only the calculation of a particular subset of the *n!* equivalent decompositions of SDA. Unfortunately, these alternatives simplify the calculations at the expense of producing less accurate results.

In the SDA approach, an indicator change can be decomposed in *n!* different ways, each corresponding to one of the possible combinations of *n* factors and the time period at which they are evaluated. For three factors (*x*, *y* and *z*), the six complete decompositions (3!) are formulated as follows:

$$\Delta IMP = \underbrace{\Delta x y^2 z^2}_{C_3 f_x} + \underbrace{x^1 \Delta y z^2}_{C_3 f_y} + \underbrace{x^1 y^1 \Delta z}_{C_3 f_z} \tag{1.5}$$

$$\Delta IMP = \underbrace{\Delta x y^2 z^2}_{C_3 f_x} + \underbrace{x^1 \Delta y z^1}_{C_3 f_y} + \underbrace{x^1 y^2 \Delta z}_{C_3 f_z} \tag{1.6}$$

$$\Delta IMP = \underbrace{\Delta x y^1 z^2}_{C_3 f_x} + \underbrace{x^2 \Delta y z^2}_{C_3 f_y} + \underbrace{x^1 y^1 \Delta z}_{C_3 f_z} \tag{1.7}$$

$$\Delta IMP = \underbrace{\Delta x y^2 z^1}_{C_3 f_x} + \underbrace{x^1 \Delta y z^1}_{C_3 f_y} + \underbrace{x^2 y^2 \Delta z}_{C_3 f_z} \tag{1.8}$$

$$\Delta IMP = \underbrace{\Delta x y^1 z^1}_{C_3 f_x} + \underbrace{x^2 \Delta y z^2}_{C_3 f_y} + \underbrace{x^2 y^1 \Delta z}_{C_3 f_z} \tag{1.9}$$

$$\Delta IMP = \underbrace{\Delta x y^1 z^1}_{C_3 f_x} + \underbrace{x^2 \Delta y z^1}_{C_3 f_y} + \underbrace{x^2 y^2 \Delta z}_{C_3 f_z} \tag{1.10}$$

Note that, in the context of the MREEIO tables, factors *x*, *y* and *z* could represent: the intermediate sales structure (*LEO* matrix), the final consumers demand (*DEM* vector) and the technological efficiency (given by the *PI* vector).

Eqs. (1.5)-(1.10) are equivalent and can be used indifferently to obtain the contribution of each factor *i* ($C_n f_i$) towards the impact change, leading to the so-called SDA non-uniqueness problem. Dietzenbacher and Los (1998) proposed to deal with this issue by computing the average of all the *n!* decompositions for each factor. That is, following this approach the contribution of factor *x* is given by the average of the first term across the decomposition equations (C_3f_x); for factor *y*, by the average of the second term (C_3f_y) and for factor *z*, by the average of the third term (C_3f_z). Further details on this method are given in section 4.2.2.

The complexity of the SDA method increases factorially with the number of factors being decomposed (e.g., 24 decomposition equations are obtained for four factors, 120 for five and so on). To alleviate the calculations, Dietzenbacher and Los suggested that the average of the polar equations, (i.e., eqs. (1.5) and (1.10)) would be a good estimation. Other authors (De Haan, 2001) considered that the mean of any pair of mirrored decompositions, i.e., equations with the factors analyzed in the opposite periods of time (e.g., eqs. (1.5) and (1.10), eqs. (1.6) and (1.9), and eqs. (1.7) and (1.8) in the three-factor case) are also a good estimation of each factor contribution. Nevertheless, this approximations can present errors as large as the contribution itself, as we demonstrate in section 4.3.

1.4.2. Shapley-Sun method

The Shapley-Sun method, introduced by Sun in 1998 (Sun, 1998), is a variation of the (non-exact) Laspeyres decomposition method (Ang and Zhang, 2000) that applies the '*jointly created and equally distributed*' principle (Ang, 2004; Hoekstra and van der Bergh, 2003). This principle allocates the contribution caused by the factor's interaction among their *ceteris paribus* contributions, achieving an exact decomposition. Albrecht et al. (Albrecht et al., 2002) demonstrated that Sun's method is equivalent to the one proposed by Shapley, so the method was renamed as the Shapley-Sun method (also called refined Laspeyres decomposition (Ang, 2004)).

In contrast with the SDA, in the Shapley-Sun method the contribution of each factor towards the impact change is unambiguous (i.e., there is only one way to obtain the contribution of each factor). In a three-factor model, these contributions are as follows:

$$C_3f_x = \Delta x y^1 z^1 + \tfrac{1}{2}\Delta x \Delta y z^1 + \tfrac{1}{2}\Delta x y^1 \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \quad (1.11)$$

$$C_3f_y = x^1 \Delta y z^1 + \tfrac{1}{2}\Delta x \Delta y z^1 + \tfrac{1}{2} x^1 \Delta y \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \quad (1.12)$$

$$C_3f_z = x^1 y^1 \Delta z + \tfrac{1}{2}\Delta x y^1 \Delta z + \tfrac{1}{2} x^1 \Delta y \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \quad (1.13)$$

Hence, there is no need to calculate any average of terms when using this method.

1.4.3. Similarities between the SDA and the Shapley-Sun method

Hoekstra and van der Bergh observed and pointed out that the additive decomposition results from the Shapley-Sun method and the average of the *n!* decomposition equations from the SDA were identical (Hoekstra and van der Bergh, 2003). Later on, other authors also noticed these similarities (Fengling, 2004; Wang, 2015), yet to the best of our knowledge, no formal mathematical demonstration on their equivalence has been put forward so far. Therefore, in this thesis we present a formal proof on the equivalence of the Shapley-Sun and the average of the *n!* decomposition SDA equations, and we also introduce a simplified general equation to apply these two equivalent decomposition methods in practice. The details can be found in section 4.2.4.

1.5. Mathematical optimization

Mathematical optimization is a specific mathematic technique which aims to find the best available solution for a system or process. The optimization problems are usually expressed in a general form as follows:

$$\begin{aligned} Min/Max \quad & f(x) \\ s.t. \quad & h(x)=0 \\ & g(x)\geq 0 \\ & x \in \Re \end{aligned} \tag{1.14}$$

In the general form, we first find the *objective function, f(x)*, that describes the relation of the *decision variables* and *parameters* of a system (Dutta, 2016; Kallrath, 2013). The *objective function* is the function we want to optimize, that is, we look for a solution, *x*, that minimizes or maximizes this function. Therefore, the objective function provides the scalar according to which we rank the performance of the different available solutions (e.g., the maximum electricity production in a power plant, minimum CO_2 emissions in a system or maximum profit generated in a product manufacture).

There are two types of data in the optimization problems: i) parameters, which are constant data we introduce to the system (e.g., number of people in a country, electricity demand to reach) and ii) variables, data that can adopt different values and distinguish one solution from another (e.g., number of windmills to be installed, total tones of CO_2 released). These variables can be expressed in a variety of forms: continuous, semi-continuous, integer or binary, among others. The *decision variables* are a particular type of variables that can be controlled by a decision maker.

In a mathematical program, we can also find constraints (or restrictions), as are, the equalities, $h(x)=0$, or the inequalities, $g(x)\geq 0$. These constraints can take the form of complex mathematical expressions (e.g., describing the amount of non-dispatchable sources in an electricity portfolio) or simply impose bounds on any variable, e.g., $0\leq x\leq 1$.

1.5.1. Optimization problems classification

Optimization problems can be classified in different categories depending on their mathematical structure, the type of constraints and design variables, as well as the type of algorithms used and application area. In this section, we introduce two main classifications used for optimization problems: i) the linearity and nonlinearity of the problems and ii) the continuous and discrete optimization.

An optimization problem can be defined as linear or non-linear depending on its functions. In a linear problem, all the functions (i.e., equality and inequality constraints as well as the objective function) are linear. On the other hand, if any of the functions is non-linear, then the problem is classified as non-linear.

In the classification of the problem as continuous or discrete, it will be considered continuous if all the decision variables are real continuous numbers (e.g., temperature or operating hours). On the contrary, if all the decision variables are discrete (e.g., number of power plants or number of workers) the problem is defined as a discrete optimization. In case an optimization problem uses both types of variables, continuous and discrete, the optimization problem is defined as *mixed integer*.

With the combination of the two classifications mentioned above, it is possible to obtain a variety of optimization programs: *linear programming* (LP), *non-linear programming* (NLP), *mixed-integer linear programming* (MILP), *mixed-integer non-linear programming* (MINLP), *integer linear programming* (ILP) and *integer non-linear programming* (INLP). These six types of problems are shown in fig. 1.3, where the black lines are constraints and the feasible regions (i.e., surfaces, lines and points) are marked in purple. Note that the lines in the MILP and MINLP, as well as the points in the ILP and INLP are represented here as columns and circles to facilitate their display.

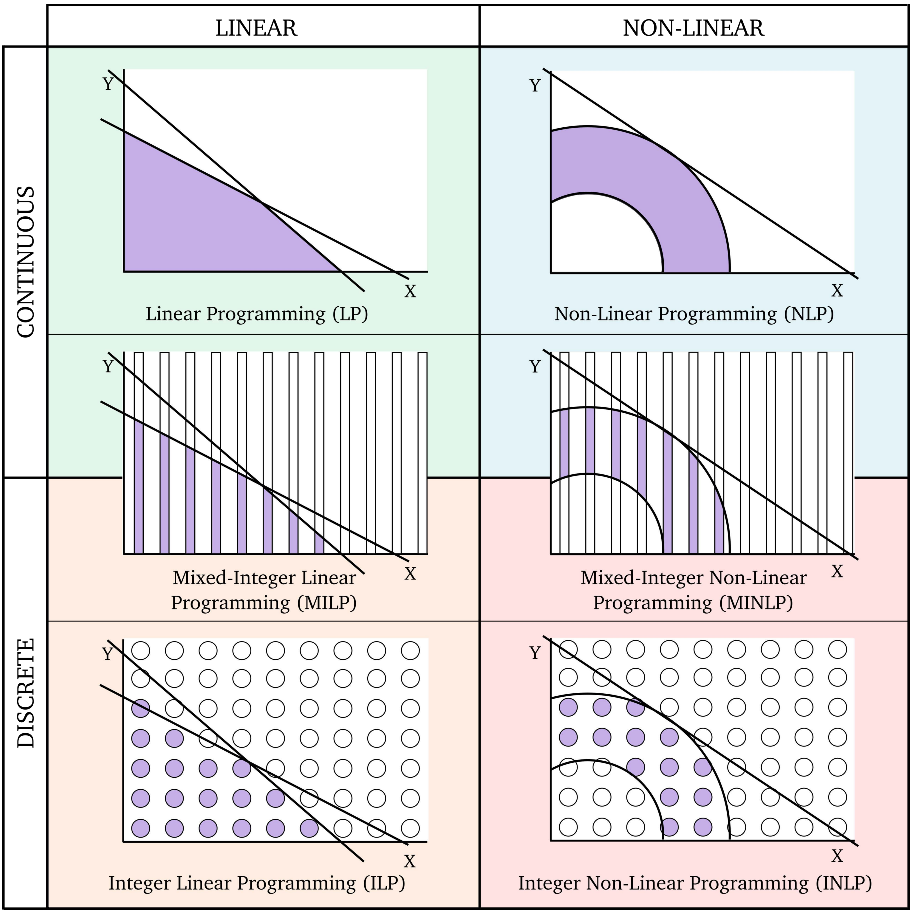

Fig. 1.3. Optimization problems classified by their linearity and continuity.

1.5.2. Optimization applications

Optimization is largely applied to different fields of science and engineering. For example, in chemical engineering optimization is used to project the optimum processes, starting from their design to the synthesis of product, process control or optimization at real time.

Among the potential uses of optimization, we can find well established problems and standard techniques such as DEA (which is described in detail in section 1.6). In other situations, however, standard approaches may proof ineffective and the modeler may need to develop a tailored formulation to tackle a given problem. This is the case of the EffMixF model, an LP model developed in this thesis to optimize electricity portfolios according to DEA. EffMixF takes into account different techno-economic constraints that DEA does not consider (see section 3.2.3 for more details).

1.6. Data envelopment analysis

Data envelopment analysis (DEA) is a non-parametric linear programing (LP) method used to evaluate the relative performance of a set of alternatives named decision making units (DMUs), each converting multiple inputs into multiple outputs (Charnes et al., 1978; Farrell, 1957).

The two main research questions that can be addressed via DEA are: (i) is a DMU performing well in terms of ratio "output to input" compared to the other DMUs?; and (ii) by how much should the inefficient DMUs be improved to become efficient? To answer these questions, DEA calculates, for each DMU, an efficiency score (θ), which is expressed as the ratio of weighted outputs to weighted inputs. The relative efficiency of a DMU is hence evaluated by optimizing the weights attached to every input and output, which has the advantage of not requiring subjective weights when carrying out the analysis. DEA assigns an efficiency score of $\theta = 1$ to efficient DMUs, while inefficient DMUs obtain an efficiency score strictly below, $\theta < 1$. The efficient DMUs form the so-called efficient frontier, where the inefficient DMUs are projected onto. These projections can be used to obtain improvement targets for inefficient DMUs that, if attained, would make them efficient.

The standard DEA model was originally proposed by Charnes et al., in 1978 (Charnes et al., 1978). This model, also called CCR after its creators' names Charnes-Cooper-Rhodes, considers that changes in outputs are proportional to changes in inputs, reason why the model assumes the *constant returns to scale* (CRS) feature. Later on, the original CCR was modified by Banker et al., (Banker et al., 1984) naming it BCC (Banker-Charnes-Cooper) and giving the model the *variable return to scale* (VRS) property. In this thesis, we only use the BCC model, as the VRS formulation can deal with the economies of scale affecting the problems we address.

In fig. 1.4. we show an illustrative example of the application of the CCR and BCC DEA models to a set of six DMUs (A to F). Under the CCR model, the efficient frontier is given by the ray that starts at the origin and passes through the efficient DMUs B and D. In this model, only DMUs B and D are efficient, as none of the others is able to produce a higher output to input ratio. In the case of the BCC model, DMUs B and D remain efficient, and DMUs A and E become efficient due to the variable returns to scale property of the model. The frontier formed by the efficient DMUs is called strongly efficient frontier. In fig. 1.4, we show two more segments as part of the efficient frontier, represented as grey dashed lines. One of them extends from the efficient DMU with the lowest output

(DMU A in the figure) towards the input axis, parallel to the output axis. The other segment goes from the efficient DMU with the highest output (DMU E) towards the infinite, parallel to the input axis. These two segments are called weakly efficient frontier.

On the other hand, DMUs C and F (in yellow) are inefficient regardless of the model used. In order to obtain the improvement targets of these inefficient DMUs, each of them is projected onto a virtual point in the efficient frontier. These virtual points are *C'* and *F'* for DMUs C and F, respectively, as shown in fig. 1.4. The projections used in the BCC model are radial, however, different projections can be used in other DEA models, as shown in section 3.2.2. When we compare the virtual DMUs with the original ones, we are able to determine how their inputs should change to make each DMU efficient. For DMUs C and F, the improvement targets are shown as τ_{ZC} *and* τ_{ZF}. In the case of C, it will become strongly efficient directly by following the radial projection. On the contrary, in the case of F, the radial projection will only shift the DMU towards the weakly efficient frontier (becoming weakly efficient). To become strongly efficient, DMU F needs to go through a second translation that would shift it vertically until reaching the strong frontier and falling exactly in the same position as the DMU A. The distance of this second shift is given by a slack variable on its output (S^{-}_{ZF}). Therefore, in this case DMU F should improve both, input and output to become strongly efficient.

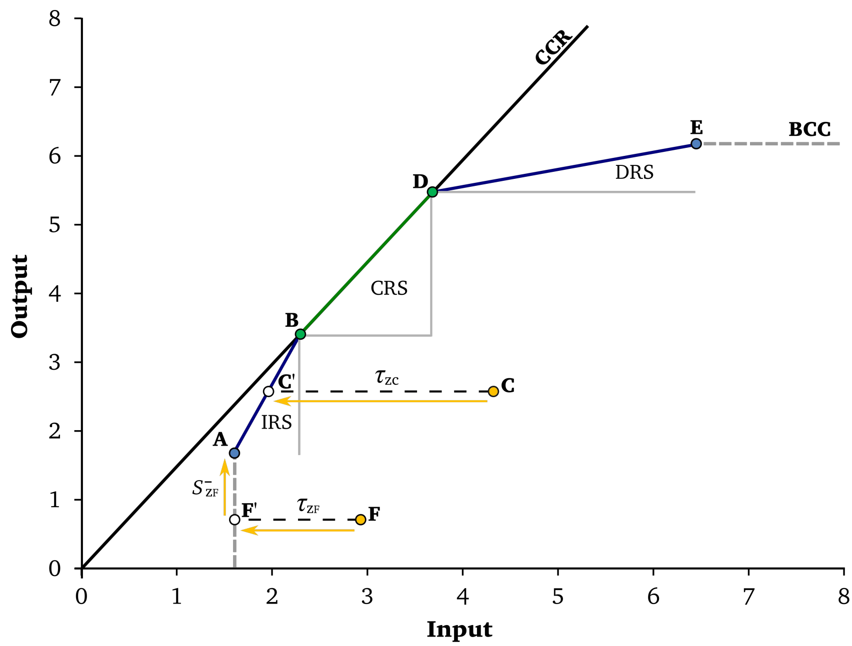

Fig. 1.4. Example for the CCR and BCC DEA models showing the returns to scale zones and the radial projections for the BCC model.

1.6.1. BCC DEA model

The standard DEA determines an efficiency score (θ) for each DMU, expressed as the weighted sum of outputs divided by the weighted sum of inputs. This is evident when looking at the DEA fractional formulation (see eqs. B.1-B.3 in section 2.8). This NLP problem can be linearized using standard mathematical transformations, giving rise to an LP DEA model (see eqs. B.4-B.7 in section 2.8). This LP model, which is said to be in multiplier form, evaluates the efficiency score (θ) of each DMU by optimizing the weights attached to every input and output. Further details about these mathematical transformations are provided in sections 2.2 and 2.8.

While the multiplier DEA model can be used to obtain the efficiency scores, the corresponding dual model (obtained via standard LP duality theory) must be used to obtain the improvement targets for the inefficient DMUs. In fact, this dual model, also called envelopment form, can be used to obtain both: the DMUs efficiency scores and the improvement targets for the inefficient ones (reason why we omit here the fractional and primal DEA formulations). Specifically, in this thesis we resort to the input-oriented dual BCC model (Cooper et al., 2011).

In mathematical terms, the problem is described as follows. We consider a set I of $|I|$ DMUs i (i=1,..., $|I|$), each one consuming $|Z|$ inputs χ_{zi} (z=1,..., $|Z|$) to produce $|Y|$ outputs ψ_{yi} (y=1,..., $|Y|$). Under these definitions, the BCC model is formulated as follows:

$$\gamma_o = \min \theta_o - \varepsilon \left(\sum_{y \in Y} S_y^+ + \sum_{z \in Z} S_z^- \right) \tag{1.15}$$

$$\text{s.t.} \quad \sum_{i \in I} \lambda_i \chi_{zi} + S_z^- = \theta_o \chi_{zo} \qquad \forall z \in Z \tag{1.16}$$

$$\sum_{i \in I} \lambda_i \psi_{yi} - S_y^+ = \psi_{yo} \qquad \forall y \in Y \tag{1.17}$$

$$\sum_{i \in I} \lambda_i = 1 \tag{1.18}$$

$$\lambda_i, S_z^-, S_y^+ \geq 0 \qquad \forall i \in I, \forall z \in Z, \forall y \in Y \tag{1.19}$$

Here, θ_o is the relative efficiency of the DMU analyzed (denoted by the subscript o), which can take values from zero (worst value) to one (efficient); ε is a non-Archimedean parameter used to enforce the strict positively of the variables, S^-_z and S^+_y are slack variables for input z and output y, respectively, and λ_i is the linear weight assigned to each DMU i in order to obtain the virtual DMU resulting from the projection of the inefficient unit onto the efficient frontier. Note that in the dual DEA formulation, virtual DMUs are obtained by means of a convex combination of efficient DMUs, the so-called peers or reference set $RS_{i'}$. The peer group of an inefficient DMU is a valuable piece of information as it can be used to obtain guidelines for improvement (Cook and Seiford, 2009).

Then, the improvement targets (reduction for inputs, $\tau_{zi'}$, and increments for outputs, $\delta_{yi'}$) required for the inefficient DMUs *i'* to become efficient are obtained as the difference between their original inputs and outputs and the values of the corresponding virtual DMU (see eqs. (1.20)-(1.21)). Note that the former set of values are given by the reference set $RS_{i'}$ of the inefficient unit *i'* (i.e., efficient units *i* for which the linear coefficient in the projection are strictly positive $\lambda_i^*>0$). In fig. 1.4, the reference set of DMU C is formed by DMUs A and B, whereas the reference set of F is given by DMU A.

$$\tau_{zi'} = \chi_{zi'} - \sum_{i \in RS_{i'}} \lambda_i^* \chi_{zi} = \chi_{zi'} - (\theta_{i'}^* \chi_{zi'} - S_z^{-*}) \qquad \forall z \in Z \, , \forall i' \,|\, \theta_{i'}^* < 1 \tag{1.20}$$

$$\delta_{yi'} = \sum_{i \in RS_{i'}} \lambda_i^* \psi_{yi} - \psi_{yi'} = S_y^{+*} \qquad \forall y \in Y \, , \forall i' \,|\, \theta_{i'}^* < 1 \tag{1.21}$$

Here, λ^*_i are the optimal weights assigned to DMU *i* in the reference set of *i'* ($RS_{i'}$), $\theta^*_{i'}$ is the efficiency score of DMU *i'*, and S_z^{-*} and S^{+*}_y are the optimal values for the slack variables. When $\theta^*=1$ and $S_z^{-*}=0$, $S^{+*}_y=0$, for all *z* and *y*, the DMU is considered to be strongly efficient. On the other hand, if $\theta^*=1$ and $S_z^{-*}\neq0$ or $S^{+*}_y\neq0$, for some *z* and *y*, the DMU is considered to be weakly efficient.

In the VRS DEA model, the DMUs can be situated in three clearly differentiated regions of the frontier, as shown in the example presented in fig. 1.4: the *Increasing Returns-to-Scale* (IRS), defined by segment $\overline{AB}$; the *Constant Returns-to-Scale* (CRS), given by segment $\overline{BD}$; and the *Decreasing Returns-to-Scale* (DRS), corresponding to segment $\overline{DE}$. If a DMU is located in the IRS zone, it can increase its output by a larger proportion than the input increment. On the other hand, if the DMU is in the DRS zone, the opposite happens. In the DRS zone, the "congestion" concept, typical in the economies of scale, becomes evident. This classification can proof useful for decision making, since it provides insight about scale inefficiencies. For more details, see section 3.2.2.

1.6.2. Other DEA models

Since the original model was proposed, DEA has been modified and adapted to new requirements and applications, giving rise to a plethora of different DEA formulations. Some of the DEA features that can be selected to better represent the characteristics of the case study start at the modeling of the DMUs. These models can contain undesirable outputs (i.e., outputs of the process we would like to minimize) apart from the classical desirable outputs and inputs (Chung et al., 1997). Other variations concern the returns to scale (Färe et al., 2008; Zhou et al., 2008a) or the orientation point of view -which, in environment and energy studies, principally consist in output, undesirable output and input-oriented measures- (Zhou et al., 2008b). According to the efficiency measure, the most used in the environment and energy studies are the *Radial* (i.e., the one used in this thesis), *Non-Radial*, *Slacks-based*, *Hyperbolic* and *Directional distance function* (Zhou et al., 2008b). For more details on these methods see section 3.2.2.

1.6.3. Super-efficiency

One of the most significant developments in DEA is the super-efficiency score proposed by Andersen and Petersen 1993 (Andersen and Petersen, 1993). This model aims to overcome the low discrimination capability of DEA to further assess the DMUs deemed efficient. To overcome this limitation, the super-efficiency model ranks efficient DMUs assigning to each of them efficiency scores beyond one. Among the different extensions of the super-efficiency DEA methods, we use the radial VRS input-oriented model (Ray, 2004; Wilson, 1995).

In fig. 1.5 we show an example of the ranking considering four efficient DMUs. In the super-efficiency model, we evaluate the efficiency of every DMU against the efficient frontier that results when the DMU under study is eliminated from the system. For example, when analyzing DMU B, the efficient frontier resulting from its removal would be given by $\overline{ACD}$. In this case, B would be projected onto the “new” efficient frontier at a “ghost” point B’. Since DMU B’ is still efficient, but the original DMU B has additional input savings, this DMU can be denominated as super-efficient.

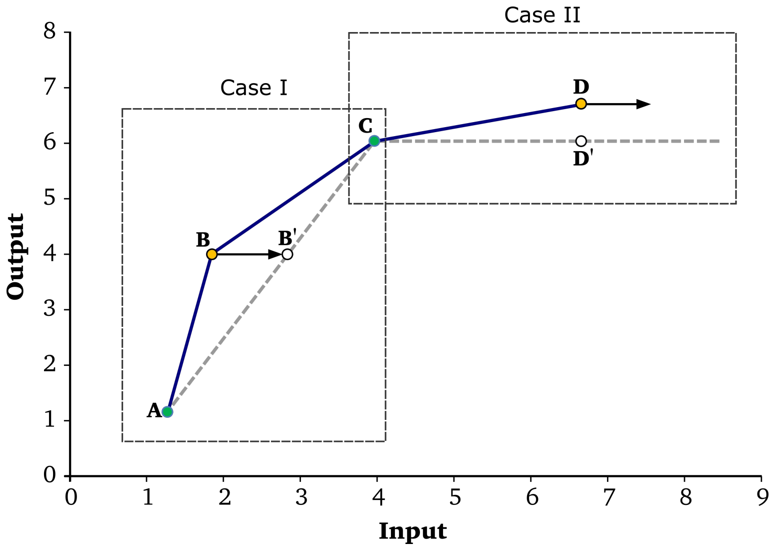

Fig. 1.5. Example of a radial VRS input-oriented super-efficiency method.

The input-oriented super-efficiency allows ranking the efficient units in terms of the extra savings achieved by the DMU in their inputs (as shown above for DMU B) and in terms of stability (i.e., how much can the inputs of the DMU analyzed worsen without losing its efficient condition). Therefore, the higher the super-efficiency value, the higher the input savings attained (see case I in fig. 1.5) and/or the higher the efficiency stability of the efficient DMUs. An exception of this happens, for instance, when the output of the DMU analyzed is larger than in the others. In such case, the DMU analyzed is deemed as the most stable of the group, since its inputs can worsen up to infinity with the DMU remaining efficient, as happens in case II in fig. 1.5. However, this DMU does not show super-efficiency in terms of inputs as it does not present any input savings. In this case, the super-efficiency model results infeasible for this DMU and it is necessary to use other techniques in case of requiring a numerical super-efficiency value (Chen, 2005; Xue and Harker, 2002). More details on this matter are provided in sections 2.2.2 and 2.2.3.

1.7. General conclusions

This thesis is devoted to the development of tools to assist policy makers in the creation of effective policies and regulations in an efficient and systematic way. For this, we studied sustainability aspects at a sectoral level to obtain insight of weaknesses and improvement opportunities. We next provide a set of conclusions that we accomplished in this thesis:

- We assessed the eco-efficiency of the EU manufacturing sectors by combining MREEIO and DEA methods. In this assessment we considered three environmental indicators, the global warming potential, potential acidifying equivalent and tropospheric ozone forming potential, and followed the production and consumption-based approaches. From this assessment we concluded that:
    - There is a significant mismatch between the production and the consumption-based approaches. The reason is that the “primary” manufacturing sectors are indeed used by other “secondary” sectors as inputs. The impact embodied in these inputs is neglected in the production-based approach, while in the consumption-based one it is explicitly incorporated into the calculations (see section 2.3.1 for further details).
    - The efficiency scores in the consumption-based case are generally higher than in the production-based one. This is mainly because the impact caused by primary sectors is allocated among the secondary ones, which leads to a more homogenous distribution of impacts (see section 2.3.2 for further details).
    - In the production-based case, targets allow identifying sectors and pollutants requiring more stringent domestic regulations and/or higher investments in cleaner technologies. Conversely, the consumption-based accounting allows identifying the ultimate sources of impact even when these are embodied in the imports. This information can assist in the selection of alternative “cleaner” suppliers so as to improve the environmental footprint of a sector (see section 2.3.2 for further details).

- We evaluated the sustainability of the 28 EU member electricity sector, determining their efficiency with environmental, social and economic indicators, using the DEA methodology. From this work we evidenced that:
    - The original DEA targets were unattainable in all the cases. The inefficient countries cannot reach the strong frontier due to: (i) the limited availability of renewable sources; and (ii) the existence of other limiting constraints imposed in our model (see section 3.3 for further details).
- We have proposed a methodology that calculates specific mixes and provides more useful insight for policy makers, compared to the standard DEA quantitative improvement targets. Hence, our approach provides clear and attainable country-based roadmaps indicating which technologies should be promoted to improve the sustainability efficiency of the electricity portfolios (see section 3.3.2 for further details).
- We have demonstrated that the average of the *n!* SDA decomposition equations and the Shapley-Sun method are indeed the same approach in mathematical terms (see section 4.2.4 for further details).
- We have formulated a simpler general equation that can be used in substitution of the average of the *n!* SDA decomposition equations and the Shapley-Sun method. Considering that the approximation error of the polar decomposition can be important, we recommend using this general equation as it gives an exact result (see sections 4.2.4 and 4.3.2).

1.8. Future work

Based on the results and conclusions obtained in this thesis, we find some potential research areas to be explored in future works:

- Sectors are highly aggregated in MREEIO tables, so sectoral targets might be unattainable for specific subsectors given the high heterogeneity of activities within them. Further research is still required to better understand how to translate the information obtained for grouped sectors into specific regulations for subsectors. These could be based on bottom-up models or on more detailed MREEIO tables.

- The efficiencies and improvement targets obtained by DEA directly depend on the indicators studied as well as the period analyzed. For this, further research to determine the changes in the country efficiencies when analyzing other indicators and constrains is still required.

- It will be useful to conduct a temporal analysis to study how different policies and regulations affect the efficiencies of the electricity portfolios. This information would be valuable to determine which policies give better results and how to adapt new ones given these results.

- The combination of DEA with tailored models, specific for each economic sector (e.g., *EffMixF* for the electricity sector) will be convenient to generate more insightful DEA targets. The more real the targets we obtain, the better the policies and regulations to improve the sustainability of each sector.

- In the literature, there are a large number of articles about decomposition techniques, which, after all, end up giving very similar (or even identical) results. Therefore, further research to determine the similarities and differences among other decomposition techniques should be performed.

1.9. References

Ahmad, N., 2002. The OECD input-output database. 14th Int. Input-Output Conf. Montr. doi:10.1787/308077407044

Albrecht, J., François, D., Schoors, K., 2002. A Shapley decomposition of carbon emissions without residuals. Energy Policy. doi:10.1016/S0301-4215(01)00131-8

Andersen, P., Petersen, N.C., 1993. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. Manage. Sci. 39, 1261–1264. doi:10.1287/mnsc.39.10.1261

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: Which is the preferred method? Energy Policy. doi:10.1016/S0301-4215(03)00076-4

Ang, B.W., Zhang, F.Q., 2000. A survey of index decomposition analysis in energy and environmental studies. Energy 25, 1149–1176. doi:10.1016/S0360-5442(00) 00039-6

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Manage. Sci. doi:10.1287/mnsc.30.9.1078

Caradonna, J.L., 2014. Sustainability: A history. Oxford University Press, Oxford.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444. doi:10.1016/0377-2217(78)90138-8

Chen, Y., 2005. Measuring super-efficiency in DEA in the presence of infeasibility 161, 545–551. doi:10.1016/j.ejor.2003.08.060

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: A directional distance function approach. J. Environ. Manage. 51, 229–240. doi:10.1006/jema.1997.0146

Cook, W.D., Seiford, L.M., 2009. Data envelopment analysis (DEA) - Thirty years on. Eur. J. Oper. Res. 192, 1–17. doi:10.1016/j.ejor.2008.01.032

Cooper, W.W., Seiford, L.M., Tone, K., 2007. Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software: Second edition, Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software: Second Edition. doi:10.1007/978-0-387-45283-8

Cooper, W.W., Seiford, L.M., Zhu, J., 2011. Data envelopment analysis: History, models, and interpretations, in: International Series in Operations Research and Management Science. pp. 1–39. doi:10.1007/978-1-4419-6151-8_1

De Haan, M., 2001. A structural decomposition analysis of pollution in the Netherlands. Econ. Syst. Res. doi:10.1080/09537320120052452

Dietzenbacher, E., Lahr, M.L., 2008. Wassily Leontief and Input-Output Economics. p. 420.

Dietzenbacher, E., Los, B., 1998. Structural Decomposition Techniques: Sense and Sensitivity. Econ. Syst. Res. doi:10.1080/09535319800000023

Dutta, S., 2016. Optimization in Chemical Engineering. Cambridge University Press, p. 380.

European commission, 2011. Roadmap for moving to a low-carbon economy in 2050. DG Clim. Action portal.

European Union, 2010. Europe 2020 A strategy for smart, sustainable and inclusive growth. Commun. from Comm. doi:10.1016/j.resconrec.2010.03.010

Färe, R., Grosskopf, S., Lovell, C.A.K., 2008. Production Frontiers. Cambridge University Press, Cambridge.

Farrell, M.J., 1957. The Measurement of Productive Efficiency. J. R. Stat. Soc. Ser. A 120, 253–290. doi:10.1016/S0377-2217(01)00022-4

Fengling, L.I.U., 2004. Decomposition Analysis Applied To Energy : Some Methodological Issues.

Fernández González, P., Landajo, M., Presno, M.J., 2014. The Driving Forces of Change in Environmental Indicators, Lecture Notes in Energy.

Hoekstra, R., van der Bergh, J.J.C.J.M., 2003. Comparing structural and index decomposition analysis. Energy Econ. 25, 39–64. doi:10.1016/S0140-9883(02)00059-2

IPCC, 2014. Climate Change 2014: Mitigation of Climate Change, Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. doi:10.1017/CBO9781107415416

Kallrath, J., 2013. Modeling Languages in Mathematical Optimization, in: Applied Optimization. Springer US, p. 408.

Klöpffer, W., 2006. The role of SETAC in the development of LCA. Int. J. Life Cycle Assess. doi:10.1065/lca2006.04.019

Klöpffer, W., Grahl, B., 2014. Life Cycle Assessment (LCA): A Guide to Best Practice, Life Cycle Assessment (LCA): A Guide to Best Practice. doi:10.1002/9783527655625

Lenzen, M., Moran, D., Kanemoto, K., Geschke, A., 2013. BUILDING EORA: A GLOBAL MULTI-REGION INPUT-OUTPUT DATABASE AT HIGH COUNTRY AND SECTOR RESOLUTION. Econ. Syst. Res. doi:10.1080/09535314.2013.769938

Leontief, W.W., 1970. Environmental Repercussions and the Economic Structure. Environ. Reper. Econ. Struct. - An Input-Output Approach 50, 262–271.

Leontief, W.W., 1936. Quantitative Input and Output Relations in the Economic Systems of the United States. Rev. Econ. Stat. 18, 105–125. doi:10.2307/1927837

Liu, X., Klemeš, J.J., Varbanov, P.S., Čuček, L., Qian, Y., 2017. Virtual carbon and water flows embodied in international trade: a review on consumption-based analysis. J. Clean. Prod. 146, 20–28. doi:10.1016/j.jclepro.2016.03.129

Lübkert, B., Analysis, I.I. for A.S., 1991. Life-cycle Analysis IDEA--an International Database for Ecoprofile Analysis: A Tool for Decision Makers, Working paper. International Institute for Applied Systems Analysis. WP. International Institute for Applied Systems Analysis.

Martínez-Zarzoso, I., Maruotti, A., 2011. The impact of urbanization on CO2 emissions: Evidence from developing countries. Ecol. Econ. 70, 1344–1353. doi:10.1016/j.ecolecon.2011.02.009

Miller, R., Peter D., B., 2009. Input–Output Analysis Foundations and Extensions. J. Chem. Inf. Model. 1–784. doi:10.1017/CBO9781107415324.004

Owen, A., 2017. Developments in Input-Output Analysis Techniques for Evaluating the Differences in Multiregional Input- Output Databases.

Pani, R., Mukhopadhyay, U., 2013. Management accounting approach to analyse energy related CO2 emission: A variance analysis study of top 10 emitters of the world. Energy Policy 52, 639–655. doi:10.1016/j.enpol.2012.10.024

PE-international, 2017. GaBi Database & Modelling Principles, thinkstep AG.

Ray, S.C., 2004. Data Envelopment Analysis Theory and Techniques for Economics and Operations Research. Manage. Sci. 42, 1180. doi:10.1017/CBO9780511606731

Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., Owen, A., 2016. Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions. J. Clean. Prod. 132, 45–56. doi:10.1016/j.jclepro.2015.06.100

Simoes, S., Nijs, W., Ruiz, P., Sgobbi, A., Thiel, C., 2017. Comparing policy routes for low-carbon power technology deployment in EU – an energy system analysis. Energy Policy 101, 353–365. doi:10.1016/j.enpol.2016.10.006

Sun, J.W., 1998. Changes in energy consumption and energy intensity: A complete decomposition model. Energy Econ. 20, 85–100. doi:10.1016/S0140-9883(97)00012-1

Timmer, M., Erumban, A., Francois, J., Genty, A., 2012. The World Input-Output Database (WIOD): Contents, Sources and Methods, WIOD Background. doi:10.1111/roie.12178

Wang, T., 2015. Technology, International Trade, and Carbon Emissions from U.S. Industry.

Wackernagel, M., Rees, W., 1998. Our Ecological Footprint: Reducing Human Impact on the Earth, DE-601)212181718: New catalyst bioregional series. New Society Publishers.

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology [WWW Document]. Int. J. Life Cycle Assess. doi:10.1007/s11367-016-1087-8

Wilson, P.W., 1995. Detecting influential observations in data envelopment analysis. J. Product. Anal. 6, 27–45. doi:10.1007/BF01073493

Xue, M., Harker, P.T., 2002. Note: Ranking DMUs with Infeasible Super-Efficiency DEA Models. Manage. Sci. 48, 705–710. doi:10.1287/mnsc.48.5.705.7805

Zhou, P., Ang, B.W., Poh, K.L., 2008a. Measuring environmental performance under different environmental DEA technologies. Energy Econ. 30, 1–14. doi:10.1016/j.eneco.2006.05.001

Zhou, P., Ang, B.W., Poh, K.L., 2008b. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. doi:10.1016/j.ejor.2007.04.042

2. ECO-EFFICIENCY ASSESSMENT OF THE EU MANUFACTURING SECTORS

2. Eco-efficiency assessment of EU manufacturing sectors combining input-output tables and data envelopment analysis following production and consumption-based accounting approaches

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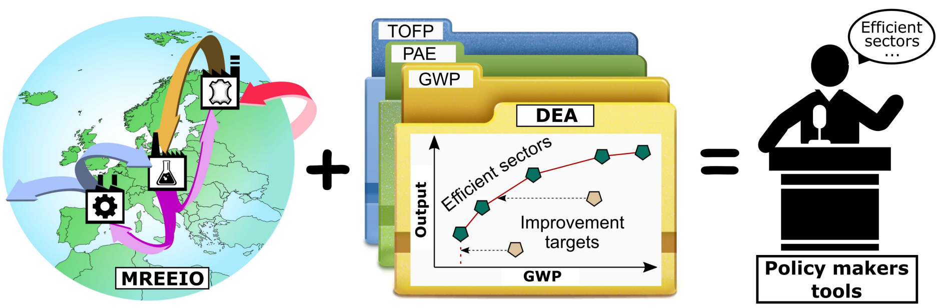
KEYWORDS

MREEIO, DEA, Eco-efficiency, Manufacturing sectors, European Union, Sustainability

ABSTRACT ART



ABSTRACT

Assessing the footprint of anthropogenic activities has become particularly challenging in today's globalized markets, where a large number of economic transactions taking place across the globe need to be disentangled before the most critical sectors are identified. In this work, we present an approach to quantify the eco-efficiency of economic activities that combines multiregional environmentally-extended input-output tables and data envelopment analysis. We employ this method to assess the European Union manufacturing sectors in terms of three inputs -global warming potential, potential acidifying equivalent and tropospheric ozone forming potential- and one output (economic wealth), following both production and consumption-based accounting approaches. Our approach classifies economic sectors as efficient and inefficient, and for the latter it provides improvement targets that if attained would make them efficient. We find that there is a significant mismatch at the sectoral level between both accounting schemes, each providing complementary information for policy-making. In the production-based case, targets allow identifying sectors and pollutants requiring more stringent regulations and/or higher investments in cleaner technologies. Conversely, the consumption-based accounting allows identifying the ultimate sources of impact, an insight that can assist in the selection of alternative "cleaner" suppliers via eco-labelling of products/services and proper taxation schemes.

2.1. Introduction

In recent years, substantial research efforts were aimed at understanding how anthropogenic activities affect the environment from a macro-economic viewpoint (Martínez-Zarzoso and Maruotti, 2011; Pani and Mukhopadhyay, 2013). Unfortunately, the assessment of the environmental footprint of an economic region and the allocation of the corresponding environmental responsibilities has become very challenging in today's globalized market where impacts are embodied in goods and services traded worldwide (Collins and Flynn, 2015; Curry and Maguire, 2011; Fang et al., 2015; Liu et al., 2017; Schandl et al., 2016). This analysis can be carried out using input-output tables (Leontief, 1936; Miller and Peter D., 2009), which cover a wide range of economic transactions taking place between sectors of an economy. Standard input-output tables can be enlarged in scope to incorporate environmental information, thereby leading to environmentally-extended input-output (EEIO) models (Chen et al., 2017; Dietzenbacher and Lahr, 2008; Mi et al., 2017, 2016; Miller and Peter D., 2009; Moran, 2013; Seppälä et al., 2011; Timmer et al., 2012; Wiedmann, 2009a), which link economic transactions to the environmental burdens they generate. At the international level, the relation between trade and environmental pressures can be quantified by combining several domestic EEIO tables into multiregional environmentally-extended input-output (MREEIO) models (Cortés-Borda et al., 2015a, 2015b; González et al., 2014; Pascual-González et al., 2015; Rocco and Colombo, 2016; Weinzettel et al., 2013; Wiedmann, 2009b).

MREEIO models contain very valuable information about how the impact is generated at a global scale. However, their analysis remains challenging as they encompass millions of domestic and international economic transactions embodying a wide variety of environmental burdens. Previous efforts on MREEIO models focused on studying the aggregated impact of economic regions following both production and consumption-based accounting systems (Butnar and Llop, 2007; Croft McKenzie and Durango-Cohen, 2010; Davis and Caldeira, 2010; Ewing et al., 2012; Vetné Mózner, 2013; Wiedmann, 2009a; Wiedmann et al., 2011, 2007). These approaches, however, failed to analyze the trade-offs that naturally arise between economic wealth and impact generated, which could be quantified using the concept of eco-efficiency widely applied in the assessment of industrial systems. Hence, the eco-efficiency of economic sectors is seldom analyzed, as the focus when using EEIO tables is often placed on quantifying the environmental dimension of sustainability in isolation from the economic one.

From a methodological viewpoint, the preferred approach to quantify eco-efficiency relies on the use of data envelopment analysis (DEA) (Charnes et al., 1978), which has been applied to a wide variety of technologies (Ewertowska et al., 2015; Galán-Martín et al., 2016; Limleamthong et al., 2016; Ren et al., 2014; Robaina-Alves et al., 2015; Vázquez-Rowe and Iribarren, 2015). DEA is a methodology originally developed in economics and operations research that allows assessing the relative efficiency of a set of alternatives (usually referred to as decision making units, DMUs) in terms of multiple inputs and outputs. DEA classifies the DMUs into efficient and inefficient, providing an efficiency score for each of them and quantifying the improvement targets required by the inefficient DMUs to become efficient. This technique was already combined with input-output models to assess the efficiency of a single economy with respect to its own potential (Luptáčik and Böhm, 2010; Mahlberg and Luptacik, 2014), but focusing on its aggregated performance rather than on the performance of its sectors, which we aim to analyze herein. Hence, these studies provided very little insight (if any) on how impacts are generated at the sectoral level (i.e., which sectors are ultimately responsible for the impact caused), since they were based on highly aggregated data. In another work, Gokhan Egilmez and co-workers assessed the United States manufacturing sectors by combining EEIO tables with DEA (Egilmez et al., 2013). While covering sectoral burdens, this study focused on a single economy and disregarded interactions with international sectors and the corresponding externalized impacts. Moreover, no ranking of efficient sectors was provided in their analysis.

In this contribution, we combine MREEIO tables with DEA to address knowledge gaps in the literature in three different ways. First, we apply a multiregional analysis that covers the impact of a sector across international supply chains of goods (regardless of the place where such impact takes place). More precisely, we assess the eco-efficiency of the EU manufacturing sectors in terms of three environmental impacts -three undesirable outputs modelled as inputs in DEA: global warming potential (GWP), potential acidifying equivalent (PAE) and tropospheric ozone forming potential (TOFP)- together with the total economic output. We use data from the World Input-Output Database (WIOD) (Timmer et al., 2012), which considers 40 countries (that all together cover 85% of the world's GDP) and an additional aggregated region labelled as Rest of the World (RoW) that represents the remaining countries. Second, we incorporate the consumption-based emissions into the analysis in order to assess the impact produced worldwide to satisfy the demand of the EU final consumers to a given manufacturing sector. The analysis of the mismatch between the traditional production-based accounting and the consumption-based one can help to identify ultimate sources of impact and inefficiencies across inter-sectoral supply chains. Finally, we apply a supper-efficiency analysis to rank efficient sectors depending on their stability and identify those that perform particularly well in the sense that they remain efficient regardless of the values of their inputs.

Overall, our results, discussed in detail later in the article, provide valuable insight into how impacts and wealth are generated at the sectoral level in an economy. We argue that this information could be used to develop more effective environmental regulations and investment plans in the transition towards a more sustainable economy.

2.2. Methods

We next present an approach to assess the eco-efficiency of the EU manufacturing sectors that comprises three main steps. First, the economic and environmental performance of a sector is assessed using MREEIO tables and following both production and consumption-based accounting methods. These values are then used to define the inputs and outputs of an efficiency assessment carried out via DEA, where each EU manufacturing sector is modelled as a DMU. Finally, the results are interpreted in order to generate valuable insight for policy making, with emphasis on identifying sources of inefficiency and suggesting changes for potential improvements. Fig. 2.1 summarizes the proposed methodology, while its three steps are explained in detail in the next subsections. Note that each accounting system requires separate calculations that are described in the ensuing sections.

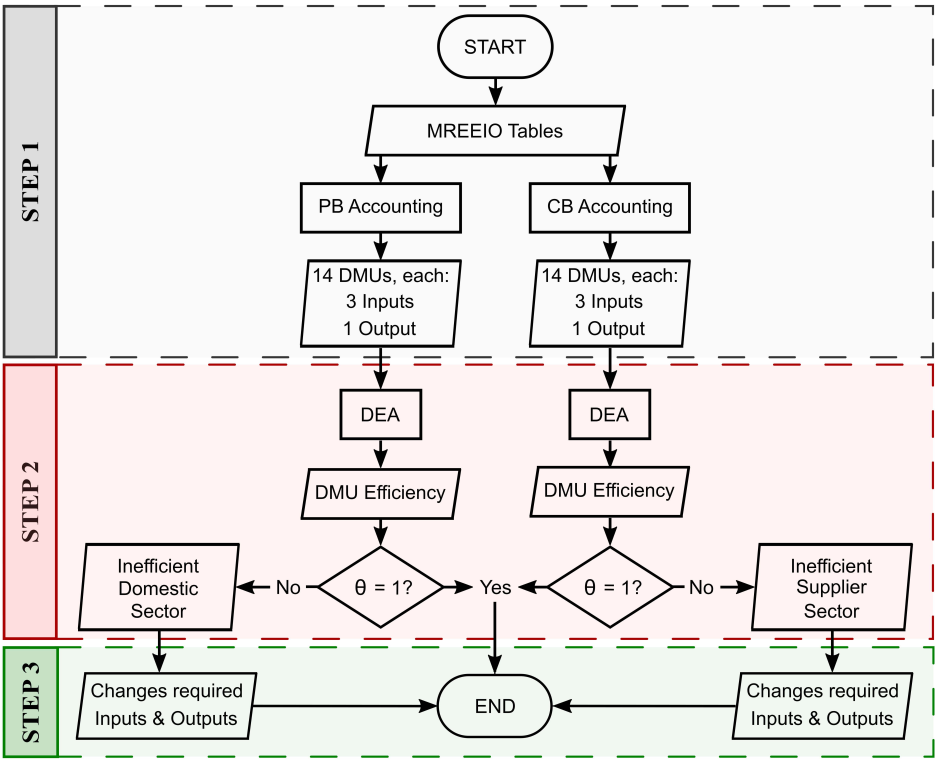


Fig. 2.1. Steps followed in the sectors eco-efficiency assessment.

2.2.1. Step1: Economic output and environmental impact assessment using MREEIO models

The starting point of our analysis is a MREEIO table containing information on economic transactions and associated environmental impacts. In our case, we use data from the World Input-Output Database (WIOD), which covers macroeconomic transactions for 41 regions: 27 EU Countries, 14 other main countries and the aggregated RoW region, for years 1995 to 2009 (we herein use data from year 2009). The WIOD database considers 35 economic sectors in each region, which gives rise to an intermediate sales matrix of 1435x1435 sectors. For every sector, WIOD provides as well the final demand required to the sector, the total output (including both intermediate and final sales) and the environmental accounts (environmental burden per unit of money traded). The detailed list of regions and sectors can be found in tables A1 and A2 in Appendix (Timmer et al., 2015). We next provide details on how the impact caused is calculated.

Production-based impact:

Let sets I/J denote the sectors (indexed by i/j, respectively) of a multi-regional economy (note that each sector belongs to a specific region). In its basic form, an input-output model encompassing n sectors expresses the production-based total economic output (vector X^{PB} containing n elements x_i^{PB}, each corresponding to the total output of an economic sector i expressed in a given currency) as the summation of the inter-sectoral transactions (matrix Z containing n^2 elements z_{ij}, each one denoting the monetary value of goods and services produced by sector i and purchased by sector j), plus the demand of the final end users (vector Y containing n elements y_i, each one denoting the final demand to sector i), as shown in eq. (2.1).

$$X^{PB} = Z \cdot \vec{1} + Y \qquad (2.1)$$

Here, $\vec{1}$ is a "summation vector" (i.e., a column vector of n elements equal to one), while matrixes X^{PB}, Z and Y are defined as follows:

$$X^{PB} = \begin{bmatrix} x_1^{PB} \\ \vdots \\ x_i^{PB} \\ \vdots \\ x_n^{PB} \end{bmatrix}, \quad Z = \begin{bmatrix} z_{11} & \cdots & z_{1j} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{i1} & \cdots & z_{ij} & \cdots & z_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nj} & \cdots & z_{nn} \end{bmatrix}, Y = \begin{bmatrix} y_1 \\ \vdots \\ y_i \\ \vdots \\ y_n \end{bmatrix} \qquad (2.2)$$

The environmental extension of the input-output model translates the economic output of each sector into measurable (production-based) environmental burdens *b* (e.g., Mt of CO_2e emissions). Therefore, the production-based burden *b* generated by sector *i* (denoted by w_{bi}^{PB}, which all together define the elements of vector W_b^{PB}) is obtained from the total output of this sector and its unitary environmental burden (parameter e_{bi}, which all together define vector E_b) as follows:

$$W_b^{PB} = E_b \circ X^{PB} = \begin{bmatrix} w_{b1}^{PB} \\ \vdots \\ w_{bi}^{PB} \\ \vdots \\ w_{bn}^{PB} \end{bmatrix} \qquad \forall b \tag{2.3}$$

$$E_b = \begin{bmatrix} e_{b1} \\ \vdots \\ e_{bi} \\ \vdots \\ e_{bn} \end{bmatrix} \qquad \forall b \tag{2.4}$$

where "$\circ$" is the Hadamard product, i.e., the element-wise product of two matrices of the same dimension. In this work, without loss of generality, we focus on three environmental burdens *b*: global warming potential (GWP), potential acidifying equivalent (PAE) and tropospheric ozone potential (TOFP). The reason why we choose these widely used environmental categories is because they are strongly linked to air emissions coming from industrial sectors. Furthermore, they can be computed by aggregating some emissions data available in the WIOD, as opposed to what would happen with other impacts (e.g., eco-toxicity, eutrophication, etc.) that would require information missing in this database. These indicators are convenient for step 2 to guarantee the discrimination power of the DEA model (i.e., few sectors are identified as efficient). Note that the pollution intensities E_b can be estimated from the information on environmental burdens available in the WIOD (see section *Calculation of environmental intensities*).

Consumption-based impact:

It can be assumed that the ratio between a sector's output and its intermediate purchases remains constant during short periods of time (e.g., one year) (Miller and Peter D., 2009). Such relationships are quantified via technical coefficients a_{ij}, which are calculated as the quotient of intermediate sales from sector i to sector j (z_{ij}) over the total output of sector j (x_j^{PB}), as in eq. (2.5).

$$a_{ij} = \frac{z_{ij}}{x_j^{PB}} \qquad \forall i, j \tag{2.5}$$

In matrix notation, these coefficients are expressed in the form of matrix A as follows:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \tag{2.6}$$

Combining eqs. (2.1) and (2.6), the total economic output can be expressed as an explicit function of the final demand, as shown in eqs. (2.7) and (2.8).

$$X = A \cdot X + Y \tag{2.7}$$

$$X = (I - A)^{-1} \cdot Y = L \cdot Y \tag{2.8}$$

Here, A is the matrix of technical coefficients; I is the identity matrix; and L is the Leontief's matrix containing n^2 elements (Dietzenbacher and Lahr, 2008).

As already mentioned, we assess the production and consumption-based impacts of an economic sector, both of which will be analyzed in conjunction with the economic wealth it generates. The consumption-based environmental pressure of a region (typically referred to as environmental footprint) is well established, but to the best of our knowledge this concept has never been applied to economic sectors rather than regions.

Here we propose to calculate the consumption-based impact of a sector i following a similar approach as the one applied to regions, where in this case the analysis is restricted to one sector at a time. Hence, following this approach, eq. (2.9) is first solved for a demand vector Y^{*i} containing zeros in all its components $y_{i'}^{*i}$ except for the final demand of a given region to sector i. Therefore, in $y_{i'}^{*i}$ the superscript i denotes the sector analyzed, which includes the domestic sector i as well as other sectors of the same type operating in other regions, whereas the subscript i' indicates all the sectors in the economy producing the intermediate goods and services required to cover the demand of i. This implies that $y^{*i}_{i' \neq i}=0$[1]. That is, we aim to assess the impact of covering the final demand of a region (i.e., EU) to a given sector, considering that this demand is covered by both domestic and overseas sectors of the same type. Being even more precise, the population of a region demands goods and services provided by a specific sector, and this demand is satisfied by domestic companies and also by others of the same type but that operate in foreign countries (see Appendix B.1 for further details). The equation applied to quantify the economic output required to satisfy such demand is therefore as follows:

$$X^{CBi} = (I - A)^{-1} \cdot Y^{*i} = L \cdot Y^{*i} \qquad \forall i \tag{2.9}$$

This equation allows computing vector X^{CBi} which contains the total output, generated directly and indirectly from domestic and international activities, respectively, to satisfy the direct demand to sector i. Hence, the summation of the elements of this column vector provides the total economic output generated to satisfy the demand to the sector i being analyzed.

Vector X^{CBi} is finally used in eq. (2.10) to calculate the consumption-based impact W_b^{CBi} of sector i, that is, the one generated in any sector in the world to satisfy the demand to sector i (further details are provided in figs. B1-B2 in Appendix).

$$W_b^{CBi} = E_b \circ X^{CBi} = \begin{bmatrix} w_{b1}^{CBi} \\ \vdots \\ w_{bi'}^{CBi} \\ \vdots \\ w_{bn}^{CBi} \end{bmatrix} \qquad \forall b, i \tag{2.10}$$

The summation of the elements of W_b^{CBi} provides the total environmental burden generated when satisfying the demand to sector i.

After performing the production and consumption-based calculations, we shall use the total economic output and environmental burden generated by every sector to carry out an efficiency analysis following the method described in step 2. For the production-based case, the total output of a sector is denoted by x_i^{PB} and its environmental impact by w_{bi}^{PB}. For the consumption-based, the output corresponds to the summation of the elements of vector X^{CBi}, while the total impact is given by the summation of the elements of W_b^{CBi}.

[1]Note that in this formulation we denote by i all the sectors of the same type in all the regions (e.g., domestic sector M1as well as sectors M1 overseas).

Calculation of environmental intensities:

The WIOD database provides, for several environmental burdens t, the amount of burden generated by the economic sectors (e.g., Mt of CO_2). These burdens are given by vector Q_t, containing n elements q_{ti}, each one denoting the amount of that environmental burden produced in sector i within that region.

$$Q_t = \begin{bmatrix} q_{t1} \\ \vdots \\ q_{ti} \\ \vdots \\ q_{tn} \end{bmatrix} \qquad \forall t \qquad (2.11)$$

These environmental satellites can be used to obtain the environmental intensities of each impact b in each sector i, as indicated by eq. (2.12).

$$e_{bi} = \frac{\sum_{t \in T_b} v_{tb} \cdot q_{ti}}{x_i^{PB}} \qquad \forall b, i \qquad (2.12)$$

Here, T_b is the set of burdens t contributing towards impact b, v_{tb} are the corresponding weighted contributions and x_i^{PB} is the production-based total economic output of sector i. In table 2.1, we provide the weighting factors for the emissions contributing to each of the three impacts (GWP, PAE and TOFP). Specifically, we follow the 100-year GWP from the IPCC Fourth Assessment Report, 2007, (Solomon et al., 2007), while the PAE and TOFP are estimated according to the OECD 2002 calculations.

Table 2.1. Weights v_{tb} for the calculation of environmental intensities from environmental satellites.

	Conversion factor							
	CO (t)	**CO_2 (t)**	**CH_4 (t)**	**N_2O (t)**	**NO_x (t)**	**SO_2 (t)**	**NH_3 (t)**	**NMVOC (t)**
GWP (t CO_2e)	-	1	25	298	-	-	-	-
PAE (t PAE)	-	-	-	-	1/46	1/32	1/17	-
TOFP (t TOFP)	0.110	-	0.014	-	1.22	-	-	1

Finally, the environmental intensities of each impact b in sector i are aggregated in vector E_b as follows:

$$E_b = \begin{bmatrix} e_{b1} \\ \vdots \\ e_{bi} \\ \vdots \\ e_{bn} \end{bmatrix} \qquad \forall b \tag{2.13}$$

2.2.2. Step 2: Efficiency assessment using DEA

Step 1 provides the data required to evaluate how the EU manufacturing sectors perform from an economic and environmental viewpoint, which is analyzed using DEA. DEA is a non-parametric linear programing (LP) method used to evaluate the relative performance of a set of decision making units (DMUs), each converting multiple inputs into multiple outputs (Charnes et al., 1978; Farrell, 1957). In our case, each DMU corresponds to a manufacturing sector of the economy (14 sectors) that contributes towards the total economic wealth (output), while generating specific environmental impacts (undesirable outputs which we model in DEA as inputs (Gomes and Lins, 2008)). Restricting the analysis to three impacts enhances the discriminatory power of DEA. More precisely, there are $|D|$ DMUs, with $|P|$ inputs and $|F|$ outputs (see eq. (2.14)), so the following widely used rule of thumb applied in DEA holds:

$$|D| \geq \max\left(3\left(|P|+|F|\right), |P|\cdot|F|\right) \tag{2.14}$$

The two main research questions we aim to address via DEA are: (i) is an economic sector performing well in terms of ratio "wealth generated to pollution created" compared to the others?; (ii) by how much should the most inefficient sectors be improved to become efficient? To answer these questions, DEA calculates an efficiency score (θ), which is expressed as the ratio of weighted outputs to weighted inputs. The relative efficiency of a system is hence evaluated by optimizing the weights attached to every input and output. This has the advantage of not requiring subjective weights when carrying out the analysis.

We next introduce the mathematical formulation used in DEA. Let us consider a set of $|D|$ DMUs d (d=1,..., $|D|$), each one consuming $|P|$ inputs χ_{pd} (p=1,..., $|P|$) to produce $|F|$ outputs ψ_{fd} (f=1,..., $|F|$). To assess the efficiency of each DMU and establish improvement targets for the inefficient units, we solve the *variable returns to scale* (VRS) input-oriented dual model (Cooper et al., 2011) (see section B.2 in Appendix):

$$\gamma_o = \min \theta_o - \varepsilon \left(\sum_{f \in F} S_f^+ + \sum_{p \in P} S_p^- \right) \tag{2.15}$$

$$\text{s.t.} \quad \sum_{d \in D} \lambda_d \cdot \chi_{pd} + S_p^- = \theta_o \cdot \chi_{po} \qquad \forall p \in P \tag{2.16}$$

$$\sum_{d \in D} \lambda_d \cdot \psi_{fd} - S_f^+ = \psi_{fo} \qquad \forall f \in F \tag{2.17}$$

$$\sum_{d \in D} \lambda_d = 1 \tag{2.18}$$

$$\lambda_d, S_p^-, S_f^+ \geq 0 \qquad \forall d \in D, \forall p \in P, \forall f \in F \tag{2.19}$$

Here, θ_o is the relative efficiency score of DMU o (the one being analyzed), which falls in the range zero-one, being one the best (maximum) efficiency score and zero the worst (minimum); ε is a non-Archimedean value to enforce the strict positively of the variables, S_p^- and S_f^+ are the slack variables for input p and output f, respectively, and λ_d is the weight assigned to each DMU d in order to create a linear combination of peers used to project the inefficient units onto the efficient frontier. A sector will be inefficient if another sector exists generating more wealth and causing less impact simultaneously.

This DEA model is called BCC (Banker-Charnes-Cooper), and generates an efficient frontier embraced by a convex hull. The frontier is formed by linear sections with concave features granting the variable returns-to-scale (VRS) property. We adopt the VRS formulation because manufacturing sectors might show economies of scale (i.e., the ratio wealth generated, modelled as an output, to impact caused, modelled as an input, might change depending on the input level).

Super-efficiency

One of the main limitations of the DEA approach is its low discrimination capabilities to further assess the DMUs deemed efficient (i.e., DMUs with efficiency scores of one are all regarded as efficient and no further ranking is provided). To overcome this limitation, the super-efficiency score, proposed by Andersen and Petersen (Andersen and Petersen, 1993), can be used to discriminate further between the efficient DMUs. Among the different extensions of the super-efficiency DEA methods, we use the radial VRS input-oriented model (Ray, 2004; Wilson, 1995) that is formulated as follows:

$$\min\ \theta_o \tag{2.20}$$

$$\text{s.t.} \quad \sum_{d \in D, d \neq o} \lambda_d \cdot \chi_{pd} \leq \theta_o \cdot \chi_{po} \qquad \forall p \in P \tag{2.21}$$

$$\sum_{d \in D, d \neq o} \lambda_d \cdot \psi_{fd} \geq \psi_{fo} \qquad \forall f \in F \tag{2.22}$$

$$\sum_{d \in D, d \neq o} \lambda_d = 1 \tag{2.23}$$

$$\lambda_d \geq 0 \qquad \forall d \in D,\ d \neq o \tag{2.24}$$

2.2.3. Step 3: Interpretation of results

DEA provides both efficiency scores and reduction targets. The latter, denoted as τ_{op}, are calculated (only for the inefficient units) as the difference between their original inputs and their values in the radial projection on the efficient frontier. Hence, for a reference set *G* of efficient units *d* defined for an inefficient unit *o*, the input reduction targets are calculated as:

$$\tau_{op} = \chi_{po} - \sum_{d \in G} \lambda_d \cdot \chi_{pd} = \chi_{po} - (\theta_o \cdot \chi_{po} - S_p^-) \qquad \forall p \in P, \forall o \in D \qquad (2.25)$$

where λ_d are the weights assigned to DMU *d* in the reference set *G* of *o*, θ_o is the efficiency score of DMU *o* and S_p^- is a slack variable. When $S_p^-=0$ and $\theta_o=1$, DMU *o* is considered strongly efficient. On the other hand, if $S_p^-\neq 0$ and $\theta_o=1$, DMU *o* is considered weakly efficient. Furthermore, the input-oriented super-efficiency allows ranking the efficient units in terms of their stability (i.e., how much can the inputs of the DMU analyzed worsen without losing its efficient condition) and in terms of the extra savings achieved by the DMU in its inputs. Therefore, higher super-efficiency indicates that the DMU is more stable and/or the inputs savings are larger. The only arguable exception for this is given when the model in eqs. (2.20) - (2.24) renders infeasible due to eqs. (2.22) and (2.23). This happens for instance when the output of the DMU analyzed is larger than in the other DMUs, i.e., $\psi_{\mathrm{ro}}>\max\{\psi_{\mathrm{rd}}|\mathrm{d}\neq\mathrm{o}\}$. In such case, the DMU studied is deemed as the most stable of the group, since its inputs can worsen up to infinity with the DMU remaining efficient. In this latter case the DMU is assigned a super-efficiency score of ∞ (Xue and Harker, 2002). Such DMU would not present any extra savings in the inputs, as its super-efficiency would be provided by its outputs (Chen, 2005).

2.3. Results and discussion

We next discuss the results of applying our methodology to the assessment of the EU manufacturing sectors.

2.3.1. Step 1: Data generation for the DEA and preliminary analysis

The production-based and consumption-based emissions of each EU sector are first quantified for three impacts: GWP, PAE and TOFP. Calculations were performed for the 1435 sectors (i.e., 35 sectors in 41 countries) available in the WIOD database, yet for convenience in their presentation countries are aggregated into two regions (see table A1 in Appendix): EU countries (Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden and United Kingdom), and the Rest of Regions (RoR). RoR includes countries from the BRIIAT (Brazil, Russia, India, Indonesia, Australia and Turkey), NAFTA (Canada, Mexico and United States), East Asia (China, Japan, South Korea and Taiwan) and RoW (remaining countries). We consider 14 manufacturing sectors available in the WIOD database (see table 2.2). The other sectors are aggregated into one single category labelled as RS (refer to table A2 in Appendix for further details).

Table 2.2. Manufacturing sectors included in the WIOD and their codes.

Code	Manufacturing sector
M1	Food, Beverages and Tobacco
M2	Textiles and Textile Products
M3	Leather, Leather and Footwear
M4	Wood and Products of Wood and Cork
M5	Pulp, Paper, Paper, Printing and Publishing
M6	Coke, Refined Petroleum and Nuclear Fuel
M7	Chemicals and Chemical Products
M8	Rubber and Plastics
M9	Other Non-Metallic Mineral
M10	Basic Metals and Fabricated Metal
M11	Machinery, Nec
M12	Electrical and Optical Equipment
M13	Transport Equipment
M14	Manufacturing, Nec; Recycling

Fig. 2.2 summarizes in a heatmap the results obtained for the case of GWP (expressed in kt of CO_2e), while figs. C1 and C2 in the Appendix display the same

information for impacts PAE and TOFP. In essence, the heatmap shows the production-based emissions of a sector in the row elements, while the consumption-based ones are provided in the column elements. Hence, the penultimate column displays the w_{bi}^{PB} value, while the bottom row provides the summation of the column elements of W_b^{CBi}. The elements of each column/row provide the breakdown of such amounts among sectors. The economic output is also displayed next to the emissions data (x_{bi}^{PB} for the production-based case and the summation of the column elements of X_b^{CBi} for the consumption-based one).

More precisely, in fig. 2.2 the penultimate column of each row shows the total emissions produced domestically by the sector on the left to satisfy the global demand of the final consumers (production-based emissions, also known as territorial emissions). Internal cells in the heatmap represent the emissions embodied in the goods/services produced in the sector on the left of the row to satisfy the demand of the final consumers of the region on the top of the column. As an example, the total production-based emissions of the EU *Chemicals and Chemical Products* sector (M7) are 170 Mt of CO_2e. From a production-based perspective *Coke, Refined Petroleum and Nuclear Fuel* (M6), *Chemicals and Chemical Products* (M7), *Other Non-Metallic Mineral* (M9) and *Basic Metals and Fabricated Metal* (M10) are the EU manufacturing sectors with the largest CO_2e emissions, as also occurs in the RoR.

Columns in fig. 2.2 provide the total emissions released world-wide to produce the goods and services that the final consumers of the region at the top of the column demand to the sector specified at the same top of the column (i.e., its consumption-based emissions). In the heatmap, the elements of the column display the breakdown of those emissions among sectors. For instance, the total consumption-based emissions of sector M7 of the EU are 200 Mt of CO_2e. These are the total emissions that all the sectors in the world release all together in order to cover the demand that the EU final consumers (i.e., EU citizens) require from M7. These total emissions correspond to the summation of the column elements under the label “7” in fig. 2.2. As an example, to satisfy the demand that the EU requires from the world sector M7, it is necessary to generate 280 kt of CO_2e in the *Food, Beverages and Tobacco* (M1), 54 kt of CO_2e in *Textiles and Textile Products* (M2), and so on so forth until the total emissions sum up 200 Mt of CO_2e (note that some emissions come from overseas sectors covered in the RoR category, like 190 kt of CO_2e from sector *Food, Beverages and Tobacco*). Results reveal that most of the emissions embodied in the goods consumed by a sector are generated within the same region and sector, indicating preference for domestic products (i.e., local consumption), which reduces transportation costs and improves reliability.

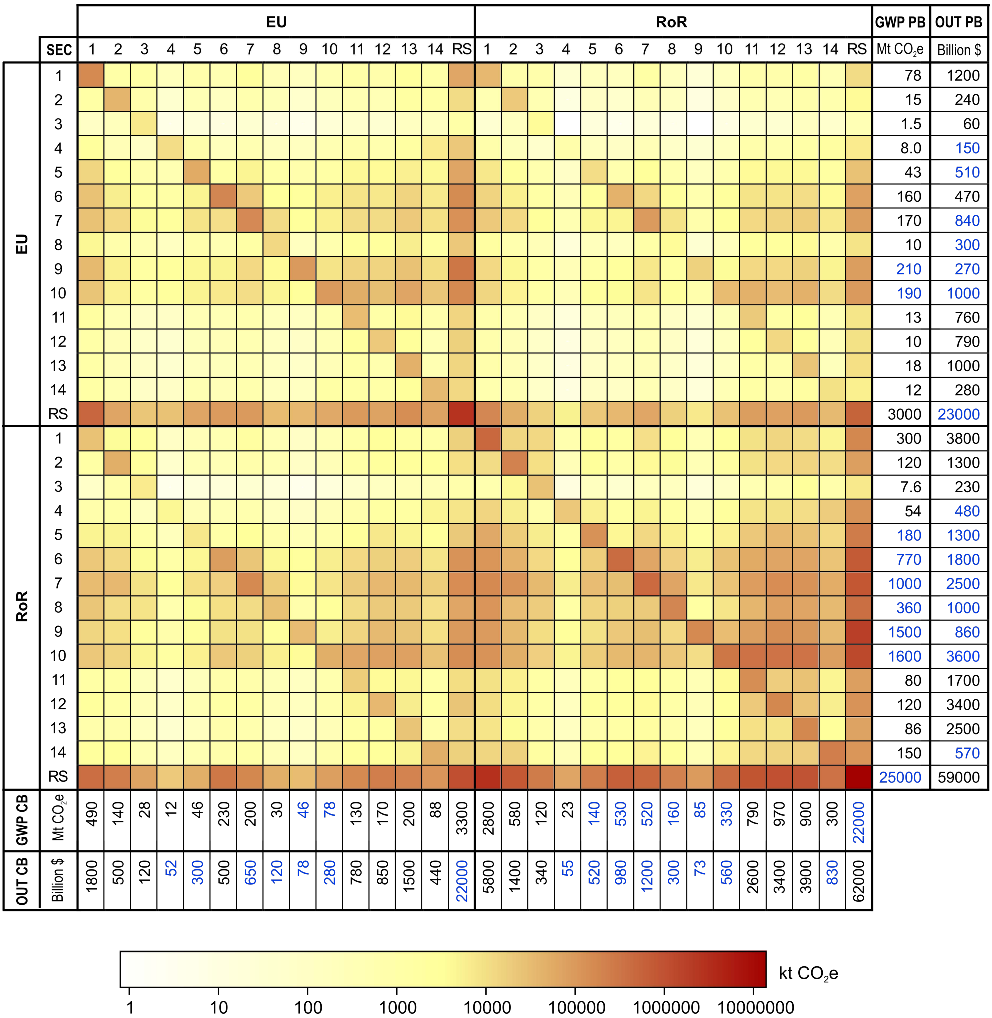


Fig. 2.2. Heatmap of the CO_2e emissions by regions and sectors. Total emissions and outputs highlighted in blue indicate that the sector is net exporter of the corresponding commodity. Rows and columns labeled as 1 to 14 correspond to manufacturing sectors M1 to M14, whereas RS denotes the remaining sectors.

There are significant mismatches between production and consumption-based accounting systems when one analyzes the economic output and CO_2e emissions of the EU manufacturing sectors (see fig. C7 in Appendix). There are two sectors where production-based emissions are larger than consumption-based ones (and 12 in which the opposite situation occurs), while we find six where the production-based economic output exceeds the consumption-based one (and eight showing the opposite pattern). This mismatch can be as high as in sector *Leather, Leather and Footwear* (M3), where the consumption-based emissions are 19 times the production-based ones. Generally speaking, the production-based emissions tend to be higher than the consumption-based ones in the case of "primary" manufacturing sectors (i.e., M9 and M10). This is because the products manufactured by primary sectors are consumed as inputs by other manufacturing sectors, which increase their environmental footprint when one considers the impact embodied in their feedstocks.

2.3.2. Steps 2 and 3: DEA results for three inputs and one output

We discuss next the results obtained by following the DEA methodology described above. All the models were coded in GAMS and solved with CPLEX 12.6.2.0 on a computer Intel Core i7-4790 CPU 3.6GHz. The VRS dual model contains 20 variables and six constraints and was solved in less than one CPU second in all the instances.

Two analyzes were carried out. The first assesses the eco-efficiency of the EU manufacturing sectors considering a single-input (GWP) and a single-output (economic output), and following production (Case A) and consumption-based (Case B) accountings. For simplicity and clarity in the presentation of the results, these calculations are discussed in section C.4 in the Appendix. In the second analysis, which is presented next, we evaluate the eco-efficiency of the same sectors, but this time with three environmental indicators (GWP, PAE and TOFP) along with the economic output for the production (Case C) and consumption-based (Case D) cases.

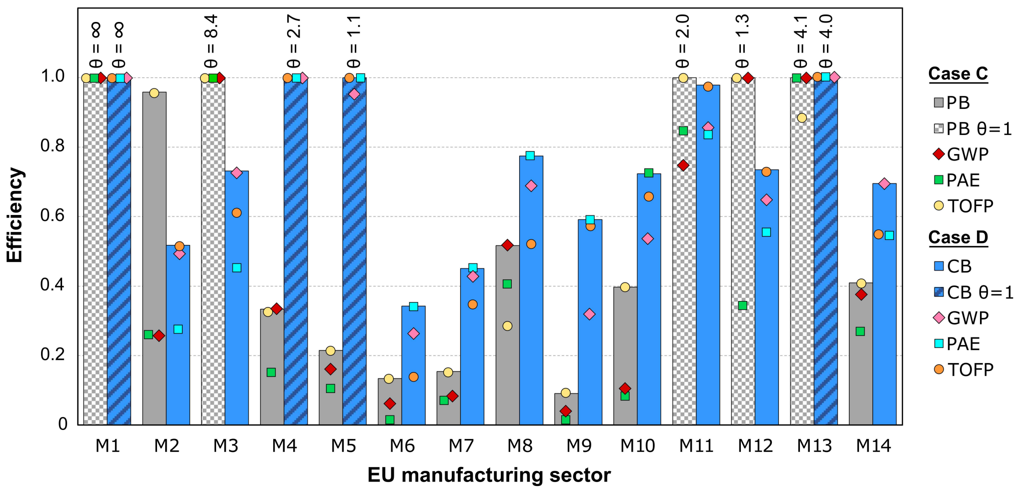


Fig. 2.3. Input-oriented efficiencies and super-efficiencies of the EU manufacturing sectors for Case C (production-based, PB, gray bars) and Case D (consumption-based, CB, blue bars). Efficient sectors are identified with a pattern and include the input-oriented super-efficiency on the top of the corresponding bar. Makers above each bar illustrate the efficiencies attained when only one of the inputs and the economic output are considered.

The results are shown in fig. 2.3, where we display the efficiency values for the different cases (Cases C and D corresponding to the production and consumption-based accounting systems, respectively), including additional calculations of single-input single-output DEAs that consider each environmental burden separately (see the figure caption for details). This information is further complemented with figs. C10 to C23 in the Appendix, which show the contribution of each sector (in the EU and in the RoR) towards the total impact and total economic output of each EU manufacturing sector.

Case C: production-based

In Case C (production-based), there are five efficient sectors (θ = 1, see fig. 2.3): *Food, Beverages and Tobacco* (M1), *Leather, Leather and Footwear* (M3), *Machinery, Nec* (M11), *Electrical and Optical Equipment* (M12) and *Transport Equipment* (M13). Sectors M1 and M13 show high economic output, generating, respectively, 15% and 13% of the total output of the EU manufacturing sectors. Sector M11 shows the third lowest TOFP impact (87 kt TOFP, see fig. C2 in Appendix) and an output significantly higher than the average output of the EU manufacturing sectors (760 Billion $ compared to 560 Billion $ on average). For this sector we find that most of the TOFP impact and economic output are associated with the demand to the same sector. That is, the EU demand to M11 is responsible for 40% of the impact on TOFP, whereas that of the RoR is responsible for 22%. Furthermore, 39% and 26% of the economic output are generated when satisfying the demand of the EU and the RoR, respectively (fig. C20 in Appendix). On the other hand, sector M3 is deemed as efficient despite showing a low economic output, because this poor performance is offset by its low environmental impact (lowest impact in all the categories). Furthermore, sector M12 emerges as efficient mainly due to its good performance in the categories GWP and TOFP (see markers in fig. 2.3).

Among the inefficient sectors, the *Textiles and Textile Products* (M2) is almost efficient (θ_d > 90%), due to its low TOFP impact. This may be the result of the EU regulations establishing upper limits for ozone precursors, acidification and eutrophying pollutants [Directive 2001/81/EC October 2001 on National Emissions Ceilings (NECs)](Christie, 2007). The other inefficient EU manufacturing sectors show efficiencies lower than 0.6 and, among them, the most inefficient ones (θ_d < 20%) are *Coke, Refined Petroleum and Nuclear Fuel* (M6), *Chemicals and Chemical Products* (M7) and *Other Non-Metallic Mineral* (M9), which were also the most inefficient manufacturing sectors in Case A (see fig. C8A in Appendix).

Case D: consumption-based

In Case D (consumption-based), the sectors identified as efficient are *Food, Beverages and Tobacco* (M1), *Wood and Products of Wood and Cork* (M4), *Pulp, Paper, Paper, Printing and Publishing* (M5) and *Transport Equipment* (M13). Sectors M1 and M13, which were also deemed as efficient from a production-based accounting, emerge as efficient again in the consumption-based analysis. This is mainly due to their high economic output (1800 and 1500 Billion $, respectively), which compensates for their high impact (for instance, sector M1 shows the largest impact on GWP and TOFP). On the other hand, sectors M4 and M5 were inefficient in Case C, but become efficient in Case D. These sectors lead to low economic outputs (52 and 300 Billion $, respectively) and low impacts (see fig. 2.2 and figs. C1 and C2 in Appendix). Note that M4 emerges as efficient when DEA is applied considering each environmental indicator separately and M5 does so also when considering the PAE and TOFP indicators (markers in fig. 2.3).

Regarding inefficient sectors, M11 (with efficiency above 0.9) is very close to the efficient frontier, while sectors M6 and M7 are the most inefficient ones, with efficiencies lower than 0.5. In particular, sector M6 shows low efficiency mainly due to its high emissions, as it happened in the production-based accounting. However, the drivers behind these low efficiencies are significantly different in both accountings (see section C.5 in Appendix).

Overall, we find that eight sectors increase their efficiency score when moving from production to consumption-based, two remain the same and four worsen. This may happen because the consumption-based approach allocates the impact of the primary sectors among the others, which in general leads to a more homogenous distribution of impacts (see figs. C3-C6 in Appendix).

Super-efficiency assessment:

In order to further discriminate between efficient DMUs, we finally applied the super-efficiency analysis previously described. The following super-efficiency values and associated rankings are obtained for Case C: M1(∞) > M3(8.4) > M13(4.1) > M11(2.0) > M12(1.3). Sector M1 is the one showing the best stability, which indicates that the sector will remain efficient regardless of how much its inputs are worsened. This is explained by its output value, which is the highest among the EU manufacturing sectors, rather than by its input values, which are similar to the average (between 0.94 and 1.36 times the average impacts). Conversely, sectors M3, M13, M11 and M12 do show extra savings in their inputs, which become smaller as the super-efficiency of the sectors decreases.

The input-oriented super-efficiency scores for Case D are as follows: M1(∞) > M13(4.0) > M4(2.7) > M5(1.1). Sector M1, which obtained a super-efficiency score of ∞ in the production-based perspective, shows the same result in the consumption-based case. This occurs because its economic output is the largest among the EU manufacturing sectors, thereby featuring the best efficiency stability (i.e., its inputs can worsen, yet the sector will remain efficient). Note however that, as previously discussed, this sector does not show any extra savings in its inputs, since its super-efficiency is mainly given by the economic output. Conversely, the other super-efficient sectors (M13, M4 and M5) do present extra savings in their inputs.

Improvement targets:

We finally calculated improvement targets using the dual model (fig. 2.4). As an example, for the consumption-based perspective (Case D), the *Manufacturing, Nec; Recycling* sector (M14) deemed as inefficient should reduce its GWP by 31%, its PAE by 42% and its TOFP by 39% to become a strongly efficient sector. The improvement targets required in the inefficient manufacturing sectors tend to be higher in the production-based accounting (Case C) than in the consumption-based one (Case D). The reason behind this might be the same one discussed before, namely, that in the consumption-based approach the impact of the primary sectors is distributed more fairly among the other sectors.

		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
CASE C	GWP		70%		67%	79%	95%	87%	48%	98%	72%				59%
	PAE		72%		71%	88%	97%	85%	48%	98%	63%				59%
	TOFP		4%		67%	79%	87%	85%	48%	91%	60%				59%
CASE D	GWP		48%	27%			69%	55%	29%	67%	43%	15%	32%		31%
	PAE		73%	55%			66%	55%	23%	41%	28%	17%	45%		42%
	TOFP		48%	35%			86%	63%	47%	41%	34%	2%	27%		39%

Colour scale: 0%, 20%, 40%, 60%, 80%, 100%

Fig 2.4. Reduction in each impact category required by each inefficient EU manufacturing sector to become efficient in the production-based (Case C) and consumption-based (Case D) cases.

Efficiency scores and improvement targets provide valuable insight into how sectors contribute towards the total wealth and impact of an economic region and could therefore aid policy makers in developing more effective regulations. These implications are different for each of the two accounting schemes. In the production-based case, targets allow to spot the sectors and pollutants requiring more stringent regulations and/or higher investments in cleaner technologies.

Conversely, regulations aimed at reducing domestic emissions may not be sufficient to achieve the consumption-based targets, since part of these consumption-based emissions may come from overseas via trade of goods/services. Hence, it might be necessary to identify the ultimate impact sources and propose alternative “cleaner” suppliers in order to enhance the footprint impact of goods/services of a sector (see figs. C10-C23 in Appendix). This could be done through taxes on imports that should be established according to the pollution intensity of the exporting region and sector. Another way to decrease the consumption-based impact of the sectors could rely on eco-labelling strategies across supply chains that would make final consumers aware of the true impact of the goods and services they consume, ultimately driving their consumption-patterns towards more sustainable choices. It seems clear that proper taxation schemes and eco-labelling could become valuable tools in the transition towards a more sustainable economy, yet the specific regulations based on these strategies remain unclear. We argue here that this topic requires further research combining input-output tables with additional macro-economic tools.

We also note that the target values provided by DEA might be unrealistic in some sectors, as they are based on the performance of other sectors that are often inherently different. The high level of aggregation of MREEIO tables constitutes another limitation of this approach, as one sector might include a wide variety of subsectors requiring more specific targets. As an example, subsectors within the chemical industry show very different environmental footprints and economic performance, yet they are treated in the same manner when aggregated into a single lumped sector. Hence, more detailed models would be required for specific sectors in order to determine more realistic targets.

2.4. Conclusions

In this contribution we assessed the eco-efficiency of the 14 EU manufacturing sectors, for the year 2009, considering three environmental impacts (i.e., GWP, PAE and TOFP) and the economic output. To this end, we followed a three-step approach that integrates different tools for environmental analysis. We first evaluated the economic and environmental performance of the sectors under study through the use of MREEIO tables using production and consumption-based accountings. Our results show that there is a significant mismatch between both impact values, as "primary" manufacturing sectors (i.e., M9 and M10) produce outputs that are indeed used by other "secondary" sectors as inputs. The impact embodied in these inputs is neglected in the production-based approach, while in the consumption-based one it is explicitly incorporated into the calculations.

The impacts and economic outputs obtained in the previous step were then used to assess the eco-efficiency of the EU manufacturing sectors via DEA. Five of these sectors were efficient ($\theta = 1$) from a production-based perspective, whereas four were deemed efficient from a consumption-based one. Only sectors M1 (*Food, Beverages and Tobacco*) and M13 (*Transport Equipment*) were efficient in both accountings. We found that the efficiency scores in the consumption-based case are generally higher than in the production-based one. This is mainly because the impact caused by primary sectors is allocated among the secondary ones, which leads to a more homogenous distribution of impacts (and in turn eco-efficiencies).

Using the super-efficiency concept, we ranked the efficient manufacturing sectors, finding that M1 (sector *Food, Beverages and Tobacco*) presents the highest input-oriented efficiency stability in both accountings, essentially because its economic output is the largest among the EU manufacturing sectors.

Finally, we obtained the improvement percentage required by the inefficient sectors to become efficient. These improvement targets along with the information contained in the MREEIO tables can be used to support policy making. More precisely, in the production-based case targets allow identifying sectors and pollutants requiring more stringent regulations and/or higher investments in cleaner technologies. Conversely, the consumption-based accounting allows identifying the ultimate sources of impact (considering domestic and overseas production). This information can assist in the selection of alternative "cleaner" suppliers so as to improve the environmental footprint of a sector.

It should be emphasized that the manufacturing sectors are inherently different from each other and play well-defined and specific roles in the economy.

Hence, attempting to make them all efficient via taxes schemes might not be a sensible strategy. Furthermore, sectors are highly aggregated in MREEIO tables, so aggregated sectoral targets might be unattainable for specific subsectors given the high heterogeneity of activities within them. Despite these limitations, we still think that quantifying the wealth and impact generated by sectors (via production and consumption-based approaches) can help develop more effective environmental regulations.

Further research is therefore still required to better understand how this information could be best translated into specific regulations aiming at a more sustainable development and based on a deeper understanding on how impacts are generated in an economy.

2.5. Acknowledgements

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2.6. Nomenclature

a	Elements of technical coefficients matrix
A	Technical coefficients matrix
D	Set denoting DMUs
e	Elements of environmental load vector
E	Environmental load vector
F	Set denoting outputs
I	Set denoting sectors
J	Set denoting sectors
L	Leontief matrix
P	Set denoting inputs
q	Elements of the burdens vector
Q	Burdens vector
S	Slack variable
T	Set of burdens contributing towards an impact
w	Elements of environmental impacts vector
W	Environmental impacts vector
x	Element of an output vector
X	Output vector
y	Elements of the final demand vector
Y	Final demand vector
z	Elements of inter-sectoral transactions matrix
Z	Inter-sectoral transactions matrix

Acronym

BRIIAT	Brazil, Russia, India, Indonesia, Australia and Turkey region
DEA	Data envelopment analysis
DMU	Decision making unit
EEIO	Environmental-extended input-output
EU	European Union
GDP	Gross domestic product
GWP	Global warming potential
LP	Linear programing
MREEIO	Multiregional environmentally-extended input-output
NAFTA	North American Free Trade Agreement
PAE	Potential acidifying equivalent
RoR	Rest of regions
RoW	Rest of world
RS	Rest of Sectors
TOFP	Tropospheric ozone forming potential
WIOD	World input-output database

Greek letters

γ	Technical efficiency
ε	Non-Archimedean value
θ	Relative efficiency
λ	Weight assigned to a DMU
τ	Reduction target
χ	Input of the DMU
ψ	Output of the DMU

Indices

*	Only one sector under study
b	Environmental pressure
CB	Consumption-based
d	DMU
f	Output
i	Sector
j	Sector
o	DMU being analyzed
p	Input
PB	Production-based
t	Environmental burden

2.7. Appendix A. Data used

In this work we use the WIOD database, which considers 41 regions and 35 economic sectors in each of them. This gives rise to an intermediate sales matrix of 1435x1435 sectors. For every sector, WIOD provides as well its final demand, total output and environmental accounts (Timmer et al., 2015). The demand is disaggregated in five parts: 1. the final consumption expenditure by households; 2. final consumption expenditure by non-profit organizations serving households; 3. final consumption expenditure by government; 4. gross fixed capital formation; and 5. changes in inventories and valuables. We grouped the demands in order to obtain a single column for each region. Next, in table A1 and A2 we present the countries and sectors aggregation that we used. The region labeled as the Rest of Regions includes countries from BRIIAT, NAFTA, East Asia and the Rest of the World.

Table A1. Aggregation used for the countries included in the WIOD database.

European Union (EU)			**Rest of Regions (RoR)**	
Austria	Germany	Netherlands	**BRIIAT**	**NAFTA**
Belgium	Greece	Poland	Brazil	Canada
Bulgaria	Hungary	Portugal	Russia	México
Cyprus	Ireland	Romania	India	United States
Czech Republic	Italy	Slovak Republic	Indonesia	**East Asia**
Denmark	Latvia	Slovenia	Australia	China
Estonia	Lithuania	Spain	Turkey	Japan
Finland	Luxemburg	Sweden	**RoW**	South Korea
France	Malta	United Kingdom	Rest of countries	Taiwan

Table A2. WIOD sectors and their aggregation per groups.

Code	Group	Sector
M1	Manufacturing Sectors	Food, Beverages and Tobacco
M2		Textiles and Textile Products
M3		Leather, Leather and Footwear
M4		Wood and Products of Wood and Cork
M5		Pulp, Paper, Paper, Printing and Publishing
M6		Coke, Refined Petroleum and Nuclear Fuel
M7		Chemicals and Chemical Products
M8		Rubber and Plastics
M9		Other Non-Metallic Mineral
M10		Basic Metals and Fabricated Metal
M11		Machinery, Nec
M12		Electrical and Optical Equipment
M13		Transport Equipment
M14		Manufacturing, Nec; Recycling
RS	Rest of Sectors	Agriculture, Hunting, Forestry and Fishing
		Mining and Quarrying
		Construction
		Electricity, Gas and Water Supply
		Other Inland Transport
		Other Water Transport
		Other Air Transport
		Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
		Post and Telecommunications
		Hotels and Restaurants
		Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
		Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
		Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
		Financial Intermediation
		Real Estate Activities
		Renting of Machinery and Equipment and Other Business Activities
		Public Admin and Defense; Compulsory Social Security
		Education
		Health and Social Work
		Other Community, Social and Personal Services
		Private Households with Employed Persons

2.8. Appendix B. Methodology

B.1. Consumption-based calculations

In figs. B1 and B2 we show how we obtain the economic output and environmental impact of a sector according to the consumption-based approach.

$$
\begin{array}{cc|ccc|ccc}
 & & & \mathbf{R1} & & & \mathbf{R2} & \\
 & & \mathbf{S1} & \mathbf{S2} & \mathbf{S3} & \mathbf{S4} & \mathbf{S5} & \mathbf{S6} \\
\hline
 & \mathbf{S1} & L_{11} & L_{12} & L_{13} & L_{14} & L_{15} & L_{16} \\
\mathbf{R1} & \mathbf{S2} & L_{21} & L_{22} & L_{23} & L_{24} & L_{25} & L_{26} \\
 & \mathbf{S3} & L_{31} & L_{32} & L_{33} & L_{34} & L_{35} & L_{36} \\
\hline
 & \mathbf{S4} & L_{41} & L_{42} & L_{43} & L_{44} & L_{45} & L_{46} \\
\mathbf{R2} & \mathbf{S5} & L_{51} & L_{52} & L_{53} & L_{54} & L_{55} & L_{56} \\
 & \mathbf{S6} & L_{61} & L_{62} & L_{63} & L_{64} & L_{65} & L_{66}
\end{array}
\times
\begin{array}{c}
\mathbf{Y^{*i}} \\ \hline y_1^{*i} \\ 0 \\ 0 \\ \hline y_4^{*i} \\ 0 \\ 0
\end{array}
=
\begin{array}{c}
\mathbf{X^{CBi}} \\ \hline x_1^{CBi} \\ x_2^{CBi} \\ x_3^{CBi} \\ \hline x_4^{CBi} \\ x_5^{CBi} \\ x_6^{CBi}
\end{array}
$$

Fig. B1. Calculation example of the consumption-based output of sector i in an input-output table of two regions and three sectors in each region.

In fig. B1, vector Y^{*i} contains zeros in all its components $y_{i'}^{*i}$ except for the final demand of a given region to the sector analyzed in all the regions. Therefore, in this example, i entails domestic and overseas sectors of the same type (i.e., S1 and S4, respectively).

Vector X^{CBi} can then be used to calculate the consumption based impact as in fig. B2.

$$
\begin{array}{c}
\mathbf{E_b} \\ \hline e_{b1} \\ e_{b2} \\ e_{b3} \\ \hline e_{b4} \\ e_{b5} \\ e_{b6}
\end{array}
\circ
\begin{array}{c}
\mathbf{X^{CBi}} \\ \hline x_1^{CBi} \\ x_2^{CBi} \\ x_3^{CBi} \\ \hline x_4^{CBi} \\ x_5^{CBi} \\ x_6^{CBi}
\end{array}
=
\begin{array}{c}
\mathbf{W_b^{CBi}} \\ \hline W_{b1}^{CBi} \\ W_{b2}^{CBi} \\ W_{b3}^{CBi} \\ \hline W_{b4}^{CBi} \\ W_{b5}^{CBi} \\ W_{b6}^{CBi}
\end{array}
$$

Fig. B2. Example of calculation of the environmental impact consumption-based.

B.2. DEA fractional and primal model

The original BCC model considers that changes in inputs are not proportional to increases in outputs, reason why this model is known as *variable returns to scale* (VRS) model.

DEA solves the following input-oriented linear fractional programming model:

$$Max\,\theta_o = \left(\sum_{f \in F} u_f \cdot \psi_{fo} - u_o \right) / \sum_{p \in P} v_p \cdot \chi_{po} \tag{B.1}$$

$$\text{s.t.} \quad \sum_{f \in F} u_f \cdot \psi_{fd} - u_o - \sum_{p \in P} v_p \cdot \chi_{pd} \le 0 \qquad \forall d \in D \tag{B.2}$$

$$u_f, v_p \ge 0 \qquad \forall f \in F, \forall p \in P \tag{B.3}$$

where θ_o is the relative efficiency score of DMU o, u_f denotes the linear weight assigned to output f and v_p represents the linear weight assigned to input p and u_o is a free variable. Note that the efficiency scores fall in the range 0-1, being one the best (maximum) efficiency score and zero the worst (minimum). The problem defined in eqs. (B.1-B.3) determines whether DMU o is efficient or not based on the efficiency scores: efficient DMUs show efficiency scores of one (θ_o = 1), while inefficient ones show efficiency values strictly below one (θ_o < 1).

The non-linear and non-convex programming formulation shown above can be reformulated into the following linear programming (LP) model as follows:

$$Max\theta_o = \sum_{f \in F} \mu_f \cdot \psi_{fo} - \mu_o \tag{B.4}$$

$$\text{s.t.} \quad \sum_{p \in P} v_p \cdot \chi_{po} = 1 \tag{B.5}$$

$$\sum_{f \in F} \mu_f \cdot \psi_{fd} - \mu_o - \sum_{p \in P} v_p \cdot \chi_{pd} \le 0 \qquad \forall d \in D \tag{B.6}$$

$$\mu_f, v_p \ge 0 \qquad \forall f \in F, \forall p \in P \tag{B.7}$$

where the DMU being evaluated is denoted by o, μ_f and v_p are related to u_f and v_p by means of a variable change, and μ_o is a free variable. In this work, we solve the dual formulation of this problem (i.e., eqs. 2.15-2.19), which provides not only the efficiency score θ_o but also the slack variables S_p^- and the weights λ_d associated to the DMU d in the reference G of d.

2.9. Appendix C. Supplementary results

C.1. Heatmaps for PAE and TOFP

In figs. C1 and C2 we show two heatmaps with the results obtained for the PAE and TOFP (expressed in t of PAE and kt of TOFP). The rows provide the provenance of the emissions (production-based accounting) which are directly generated from the sector specified on the left. The columns show the consumption-based emissions generated in all the regions and sectors to satisfy the demand of the final consumers of a region to the world sector indicated on the top of the figure.

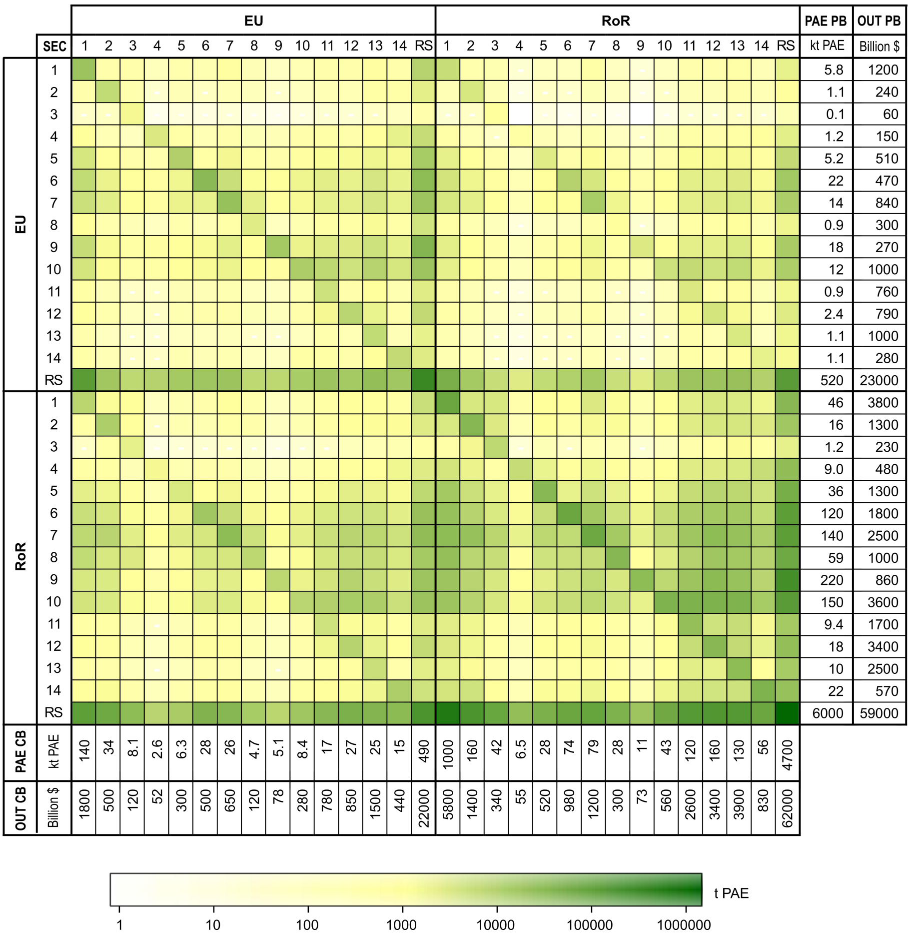


Fig. C1. Heatmap of the PAE by regions and sectors. Rows and columns labeled as 1 to 14 correspond to manufacturing sectors M1 to M14.

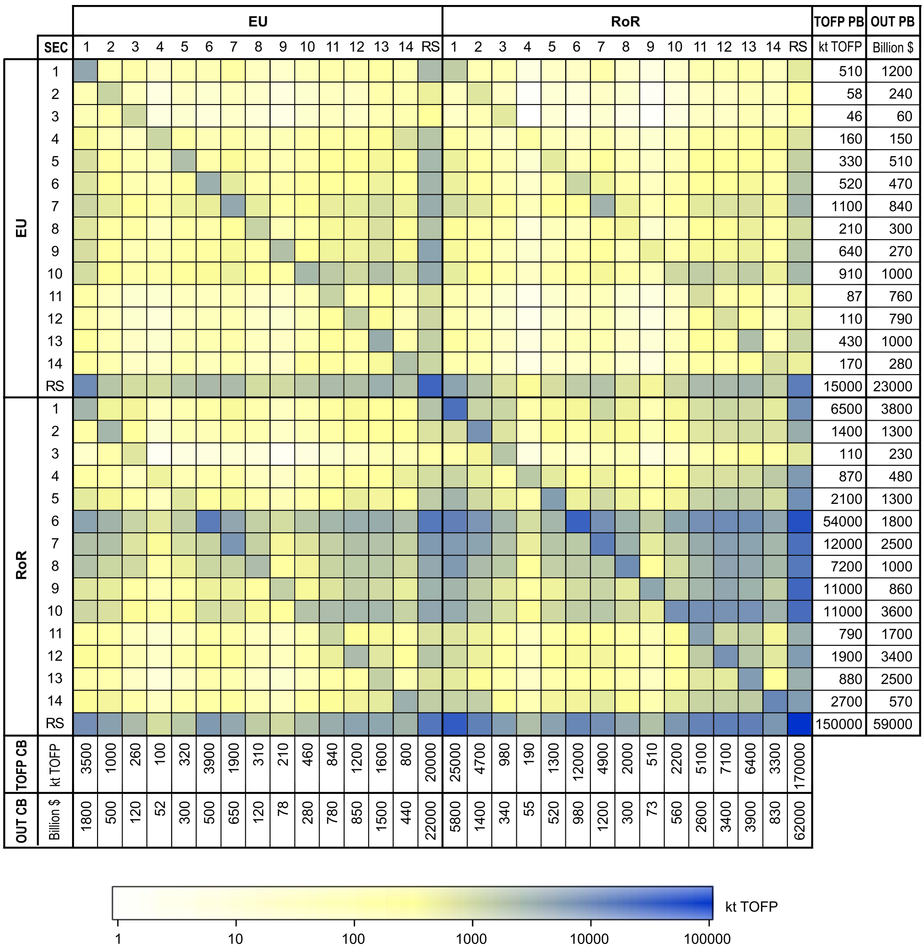


Fig. C2. Heatmap of the TOFP by regions and sectors. Rows and columns labeled as 1 to 14 correspond to manufacturing sectors M1 to M14.

C.2. Staked histograms of the GWP, PAE, TOFP and Output

Figs. C3-C6 display four staked histograms with the distributions of the GWP, PAE, TOFP and output in the production and consumption-based accountings.

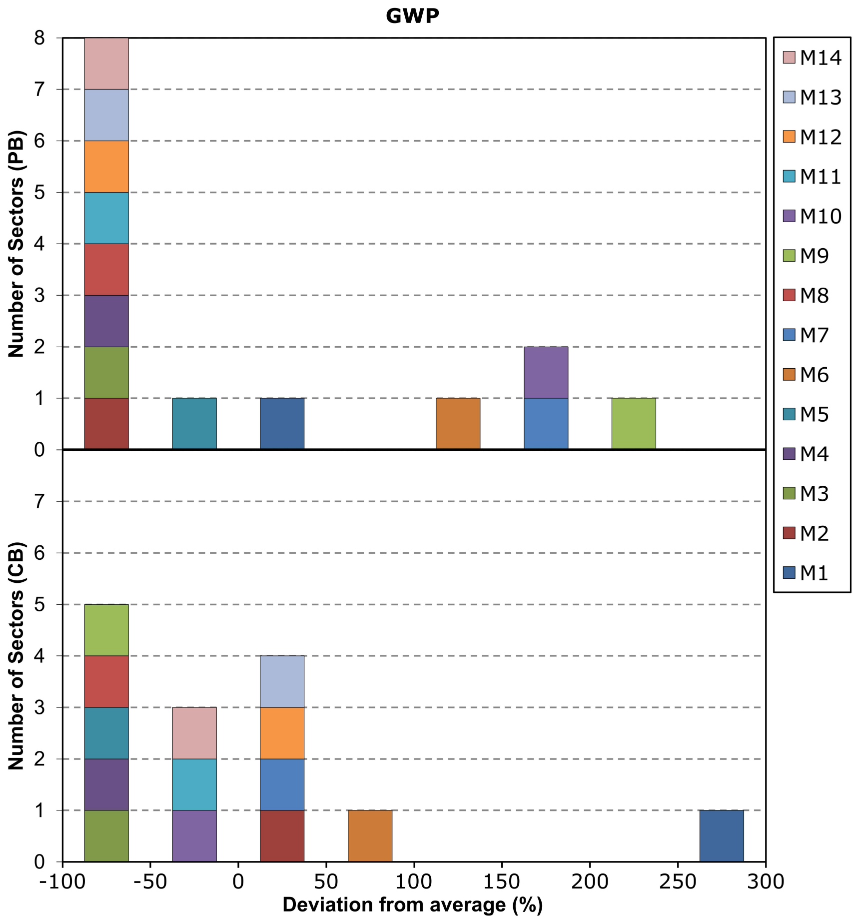


Fig. C3. GWP distribution of the EU manufacturing sectors in the production and consumption-based assessments.

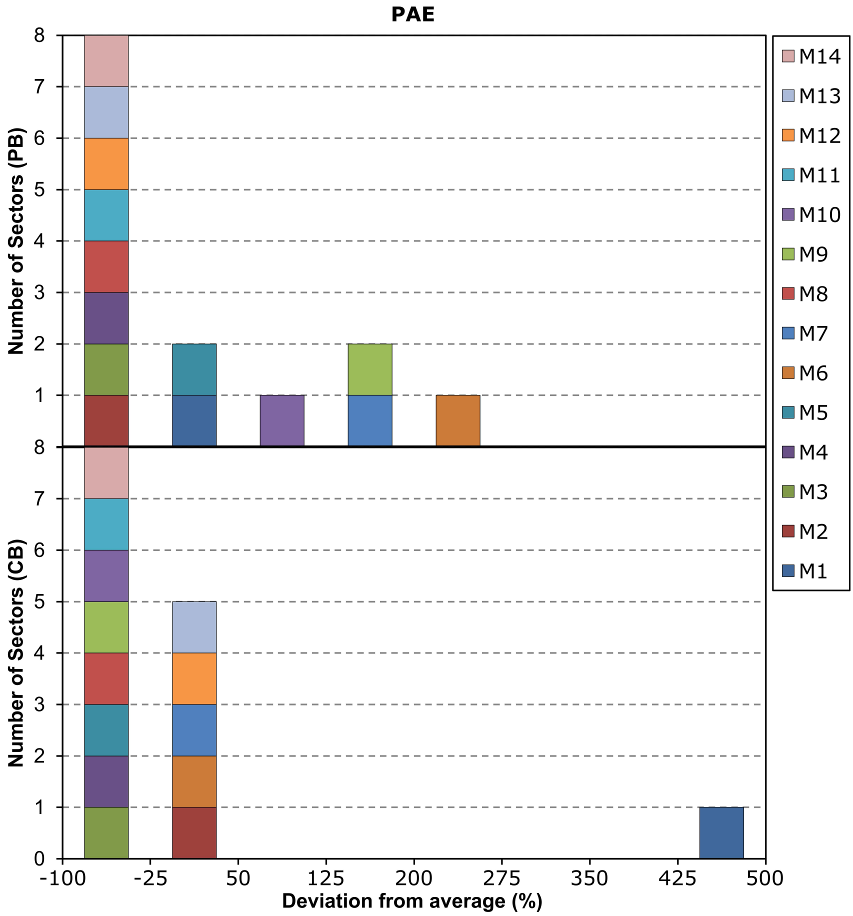


Fig. C4. PAE distribution of the EU manufacturing sectors in the production and consumption-based assessments.

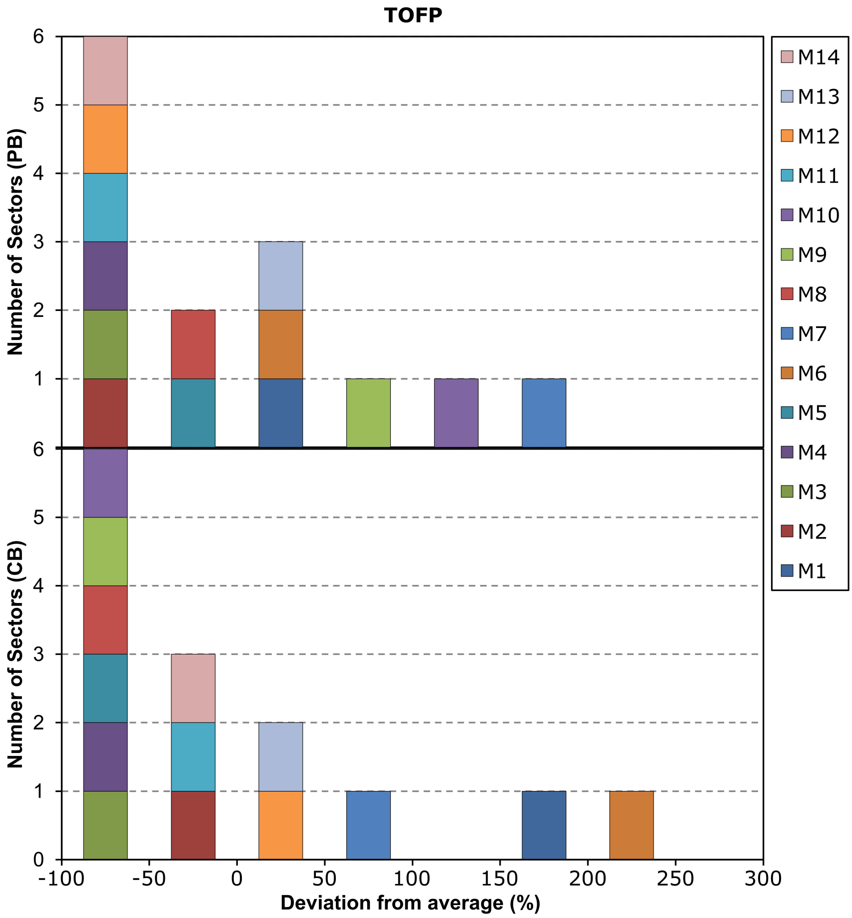


Fig. C5. TOFP distribution of the EU manufacturing sectors in the production and consumption-based assessments.

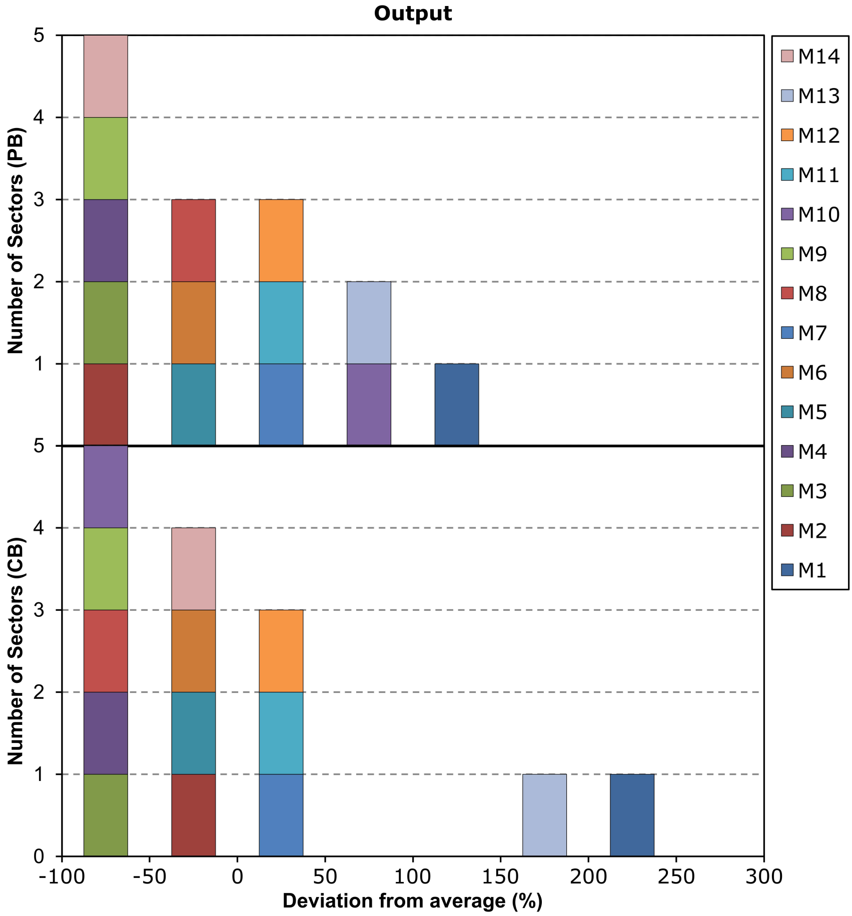


Fig. C6. Output distribution of the EU manufacturing sectors in the production and consumption-based assessments.

C.3. Results for the GWP-Output

We analyzed the mismatch in the GWP and economic output between the production and consumption-based accounting approaches.

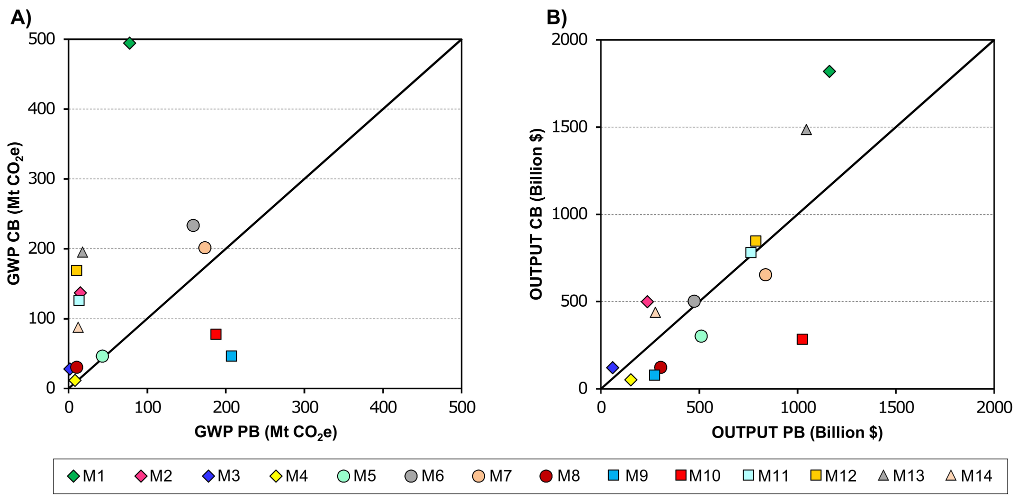


Fig. C7. Scatter plot contrasting the consumption and production-based GWP (subplot A) and economic output (subplot B) for the 14 manufacturing sectors of the EU in 2009.

Note that there are significant mismatches between both accounting systems in the manufacturing sectors of the EU. In order to illustrate this, we plot in fig. C7 the consumption-based GWP (subplot A) and the economic output (subplot B) of each manufacturing sector within the EU against the production-based ones. In fig. C7A, 12 out of the 14 EU manufacturing sectors lie above the diagonal. Some of these sectors present a large mismatch between both accounting approaches, as happens in M12 and M13, with consumption-based emissions 16 and 11 times, respectively, larger than the production-based ones. In both cases, consumption-based emissions are imported mainly from the RS (64% and 58% for M12 and M13, respectively) and sector M10 (14% for M12, with 11% imported from the RoR and 3% from the EU; and 18% for M13, with 10% from the RoR and 8% from the EU; see figs. C10 and C23 in the Appendix). This evidences the significant amount of emissions embodied in the inputs that sectors M12 (*Electrical and Optical Equipment*) and M13 (*Transportation Equipment*) require from the primary sector M10 (*Basic Metals and Fabricated Metal*). On the other hand, there are other sectors such as M5 and M7 where this difference is rather small, despite the differences in their emission patterns in both accounting perspectives (see figs. C14 and C16 in the Appendix).

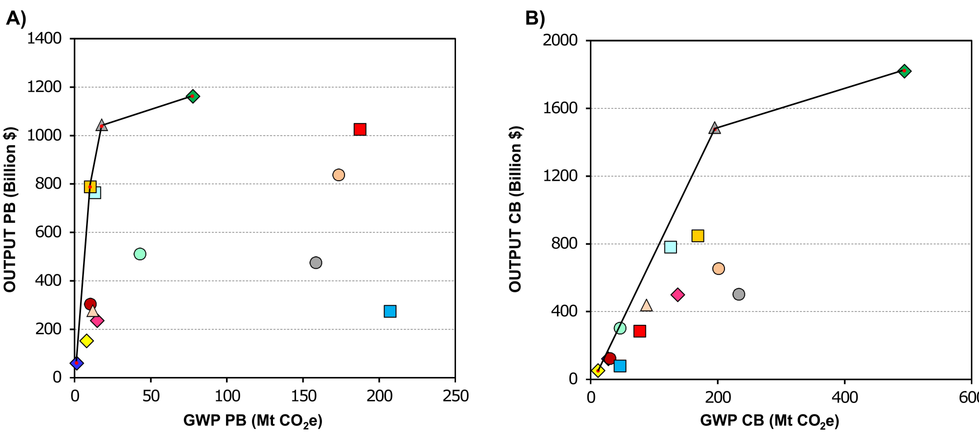
The only two EU manufacturing sectors which lie below the diagonal are the *Other Non-Metallic Mineral* (M9) and the *Basic Metals and Fabricated Metal* (M10) sectors. In these sectors the consumption-based impact on GWP is four and two times the production-based one, respectively. In the case of M9, the contribution from the RS, which is the highest from a production-based (71%, with exports of 11% to the RoR and 60% to the EU) is reduced by 91% in the consumption-based case (with a 95% reduction in exports to RoR and a 75% in exports to EU), thus yielding an overall reduction of 78% in the GWP impact of the sector (see fig. C18 in the Appendix). Similar figures can be observed in the case of sector M10 (see fig. C19 in the Appendix), where the contribution of the RS of both the RoR (14%) and the EU (28%) in the production-based perspective is reduced by 55% in the consumption-based case (a 21% in RoR and an a 73% in EU). Overall, these figures are explained by the fact that these are primary sectors whose outputs are consumed as inputs in other manufacturing sectors.

We next turn our attention to the mismatch between production-based and consumption-based output (fig. C7B). We find that eight out of the 14 EU manufacturing sectors lie above the diagonal (i.e., M1, M2, M3, M6, M11, M12, M13 and M14), yet the difference between the production and consumption-based output is smaller than that for the GWP (the average of the relative error between the production and consumption-based GWP is 110% compared to 54% for the output). These eight sectors generate more economic output indirectly in sectors around the world than the one they produce directly through their intermediate and final sales. For example, in *Transport Equipment* (M13) the consumption-based output is 42% higher than the production-based one, mainly because this sector requires inputs from other sectors. Specifically, a 200% higher output is produced in the RS in the EU, and a 60% higher output in the primary sector M10 in both, the EU and the RoR (see fig. C22), which provides metal-based raw materials for the manufacturing of transportation equipment. On the other hand, there are six sectors below the diagonal (i.e., M4, M5, M7, M8, M9 and M10). As an example, in *Chemicals and Chemical Products* (M7) the output consumption-based is 22% lower than the production-based one because this sector provides outputs to other sectors. Specifically, the higher reductions are caused by sectors M7 (37% lower) and the RS (31% lower), both in the RoR (see fig. C16 in the Appendix).

C.4. DEA results: Case A and B

We next determine which of the 14 EU manufacturing sectors (M1 to M14, see table A1) can be deemed efficient considering only one input (the CO_2e emissions) and one output (the economic output) using the BCC dual input-oriented model.

We divide the analysis in two cases, one for each accounting approach: Case A uses a production-based perspective and Case B the consumption-based one (see fig. C8). In Case A, the input is the production-based GWP of the EU manufacturing sector (as calculated by eq. (2.3) in the manuscript), while the output corresponds to the economic output of such sector, that is, the summation of the sales of this sector to all the sectors (manufacturing and RS in EU and RoR) and final households (as obtained from eq. (2.1) in the main manuscript). Case B conversely, employs a consumption-based perspective, so that the input is the consumption-based GWP, that is, the one generated indirectly in the whole world (sectors M1-M14 and RS, in EU and RoR) to satisfy the direct EU demand of the manufacturing sector under study, covered either domestically or from overseas (eq. (2.10) in the main manuscript). Furthermore, the output is the economic activity generated indirectly to satisfy the direct demand of the EU sector, regardless of whether this demand is satisfied domestically or from abroad (eq. (2.9) in the main manuscript). Note, however, that the methodology proposed herein is general enough to handle other possible definitions of consumption-based emissions of sectors.



	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
θ PB	1	0.25	1	0.33	0.16	0.04	0.07	0.43	0.02	0.09	0.76	1	1	0.34
θ CB	1	0.50	0.73	1	0.94	0.30	0.44	0.68	0.32	0.53	0.83	0.67	1	0.69

Fig. C8. Total economic output as a function of the GWP indicator for each of the 14 manufacturing sectors in the EU in Case A (subplot A: Production-based) and Case B (subplot B: Consumption-based).

In Case A, the following four sectors emerge as efficient: *Food, Beverages and Tobacco* (M1), *Leather and Leather products* (M3), *Electrical and Optical Equipment* (M12) and *Transport Equipment* (M13). Among the inefficient ones, those which are most notably deviated from the efficient frontier (efficiency score θ_d < 10%) are: *Coke, Refined Petroleum and Nuclear Fuel* (M6), *Chemicals and Chemical Products* (M7), *Other Non-Metallic Mineral* (M9) and *Basic Metals and Fabricated Metal* (M10). These are the four sectors with the highest production-based emissions, being sector M9 the top emitter. In the case of the *Chemicals and Chemical Products* sector, these emissions are released during the production of a wide variety of organic and inorganic chemicals following processes involving energy-intensive steps (i.e., distillation columns, evaporators, furnaces, etc.). The IEA estimated the energy consumption in the chemical and petrochemical industries in 2012 to be 15 EJ/yr, which explains its high GHG emissions as most of this energy comes from fossil fuels (IEA and ICCA, 2013). Similarly, sector M6 consumes large amounts of energy in processes such as coke oven products, the refined petroleum and the processing of nuclear fuel (World Bank Group, 1999). Regarding the GHG emissions generated in the metallurgic industry (sector M10), these are mainly caused by the large quantity of energy used in the metals production, and the use of carbon-based fuels and reductants (Carpenter et al., 2012). Sector M9 covers the manufacture of glass, fibers, ceramics or cement, among others. These industries consume as well large amounts of energy to melt, dry or cook their products.

In Case B (consumption-based) three efficient sectors emerge, two of which are also efficient in Case A (M1 and M13) and one not (M4): *Food, Beverages and Tobacco* (M1), *Wood and Products of Wood and Cork* (M4) and *Transport Equipment* (M13). Note that the consumption-based CO_2e emissions of sectors M1 and M13 are six to 11 times higher than their production-based ones, but despite this they manage to remain efficient in Case B thanks to their high total economic output (1800 and 1500 billion $ respectively). Hence, these sectors consume significant inputs from other sectors that contribute towards their global environmental and economic performance. Conversely, sector *Wood and Products of Wood and Cork* (M4) is efficient from a consumption-based accounting, but was found to be inefficient on a production basis. In the consumption-based accounting, the GWP of M4 increased by 45% (8 Mt CO_2e more in the consumption-based vs the production-based) and its output diminished by 66% with respect to the production-based case (i.e., 150 Billon $ less in the consumption-based vs the production-based). However, these changes are compensated with changes in the other sectors (i.e., other sectors increase their GWP even more, so M4 emerge as efficient on a consumption-based basis).

In Case B, the four sectors that are most notably deviated from the efficient frontier (showing efficiencies below 40%) are *Textiles and Textile Products* (M2), *Coke, Refined Petroleum and Nuclear Fuel* (M6), *Chemicals and Chemical Products* (M7) and *Other Non-Metallic Mineral* (M9). From them, sectors *Coke, Refined Petroleum and Nuclear Fuel* (M6), *Chemicals and Chemical Products* (M7) and *Other Non-Metallic Mineral* (M9) were also found among the most inefficient sectors in Case A, despite the differences in the specific efficiency scores obtained in each case (e.g., the *Chemicals and Chemical Products* efficiency improves from 0.1 in production-based to 0.4 in consumption-based). The main reason of this efficiency improvement is that most of the remaining EU manufacturing sectors (M1-M3 and M11-M14) worsen more in terms of GWP (from six to 19 times worse when moving from production-based to consumption-based GWP, see fig. C7A), whilst the improvement in the output is not that significant (at most three times better consumption-based than production-based output, see fig. C7B).

One of the drivers behind this impact increase is that the EU imports significant volumes of goods from other regions with less stringent environmental regulations, and the emissions embodied in such trades are not considered in the production-based accounting. As an example, in 2009, the EU imported roughly 26% from the textile sector and around a 45% from the clothing industry (% of million $) (Nuttall et al., 2010) from foreign countries. From these percentages, 85% and 87%, respectively, correspond to imports from Asia, where weaker environmental regulations are in place.

Comparing production and consumption-based efficiencies, we can see how the latter are higher than the former (average efficiency of 0.46 in production-based versus 0.69 in consumption-based). This indicates that inefficient DMUs are on average closer to the efficient frontier in the consumption-based case.

We next analyze the improvement targets required for the inefficient units to become efficient. Fig. C9 provides the input (i.e., impact in GWP) reduction targets (expressed as a percentage referred to the original input) required by inefficient manufacturing sectors to become efficient from both a production (Case A) and a consumption (Case B) based perspective. Efficient sectors in each case are identified with a blank cell.

		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
CASE A	GWP		75%		67%	84%	96%	93%	57%	98%	91%	24%			66%
CASE B	GWP		50%	27%		6%	70%	56%	32%	68%	47%	17%	33%		31%

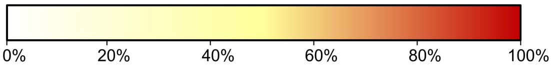


Fig. C9. Reduction in the impact on GWP required by each inefficient EU manufacturing sector to become efficient.

As seen, the targets in Case A (production-based case) are higher than in Case B (consumption-based case). These results are consistent with fig. C8, where it became clear than the efficiency values are higher in Case B. This might be due to the fact that the impact of primary sectors is distributed among other sectors, which leads to a more homogenous distribution of impacts. The sectors that require larger reductions in Case A are M6, M7, M9 and M10 while in Case B are M2, M6, M7 and M9.

C.5. Impacts and outputs patterns

In figs. C10 to C23, we show the contribution of each sector in the EU and in the RoR towards the GWP, PAE and TOFP and the total economic output of each EU manufacturing sector. In these figures, on the top of each bar we show the total impact in each category (GWP in Mt CO_2e, PAE in kt PAE, TOFP in kt TOFP) and the total economic output (in billion \$). The black lines separate the contributions of sectors within the EU (below the line) from those within the RoR (above the line).

These patterns can help to identify the ultimate sources of inefficiency. As an example, sector M6 shows low efficiency mainly due to its high emissions in both accountings, but the drivers behind these low efficiencies are significantly different. In the production-based one, both the environmental indicators and the output showed a very similar pattern. More precisely, burdens are mostly generated to satisfy the demand of its own sector (i.e., between 36-37% of the total impact in each of the three categories, and 37% of the total economic output are caused by the transactions within the same sector), followed by transactions between the sector and the rest of sectors (RS) in the EU (30% of the total impact for each of the three indicators and 29% of the total economic output) and in the RoR (12% for each of the three impacts and the total economic output, see fig. C15). However, the pattern is quite different in Case D, where the domestic contribution of the same sector (i.e., sector EU M6), which is the same for both accountings, represents only a 25% of the total GWP impact, 29% of the total PAE and 5% of the total TOFP. Conversely, the RS of the RoR is now the sector that most affects the GWP and PAE indicators (49% and 45% respectively), whilst in the TOFP the main contribution comes from overseas sectors M6 (73%). This is because the EU sector M6 shows lower pollution intensities in these three impact categories than the sectors it imports from. On the other hand, the main output contribution in consumption-based comes still from the domestic consumption of its own sector (but it now represents a 35% of the total economic output rather than a 29% in the production-based), followed by the RS of the RoR and the EU (30 and 19%, respectively). In sector M7, the pattern differences between the two accountings is not as pronounced as in M6, yet they are still present (fig. C16), with sectors contributing the most towards the three impacts being RS and M7 in both, RoR and EU. In the case of the impact on TOFP, these emissions are also affected by sector M6 in the RoR (17%), which provides raw materials to sector M7, and which shows a significantly worse pollution intensity in this impact category.

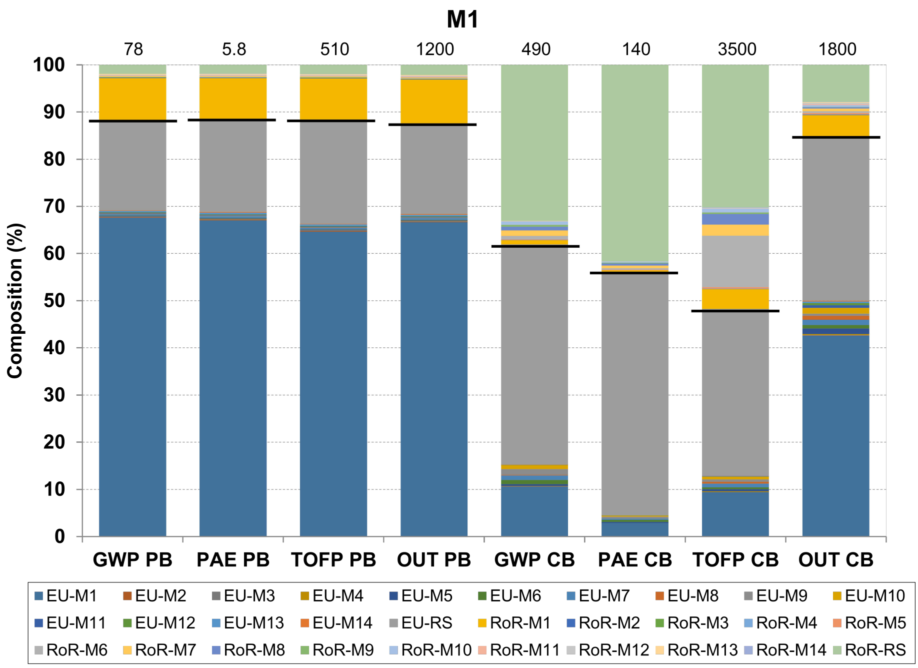


Fig. C10. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M1, production and consumption-based.

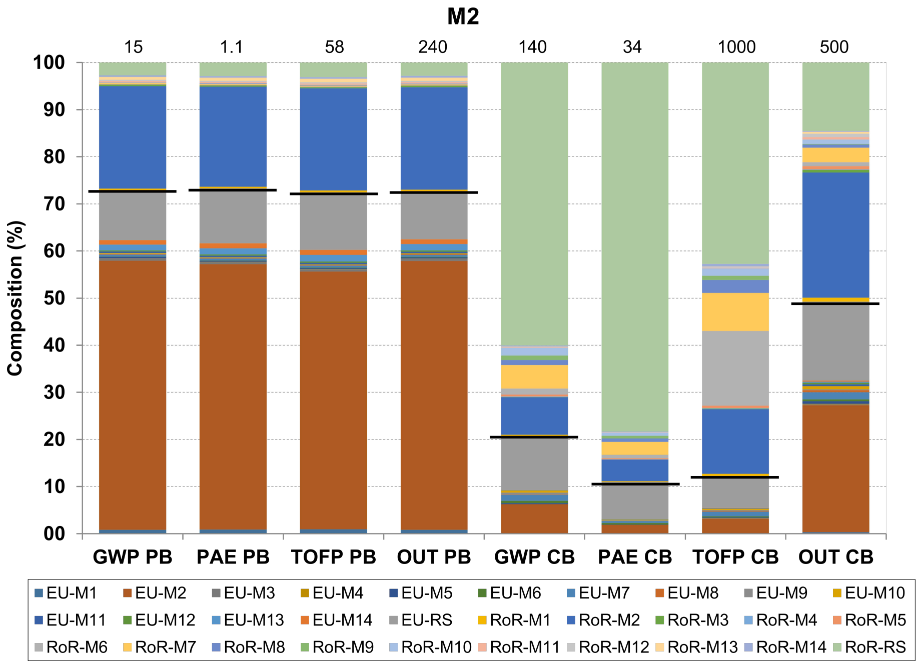


Fig. C11. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M2, production and consumption-based.

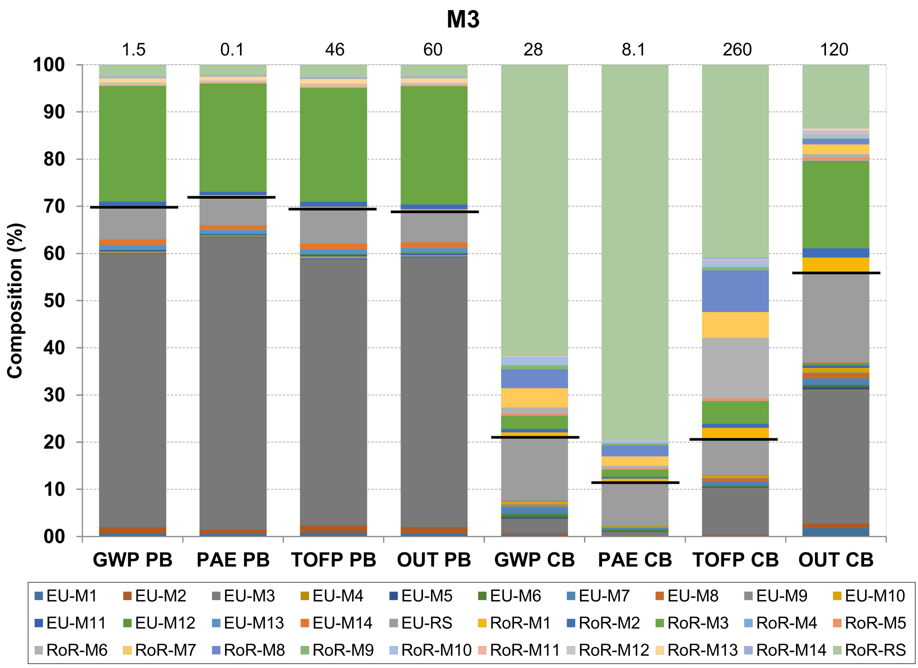


Fig. C12. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M3, production and consumption-based.

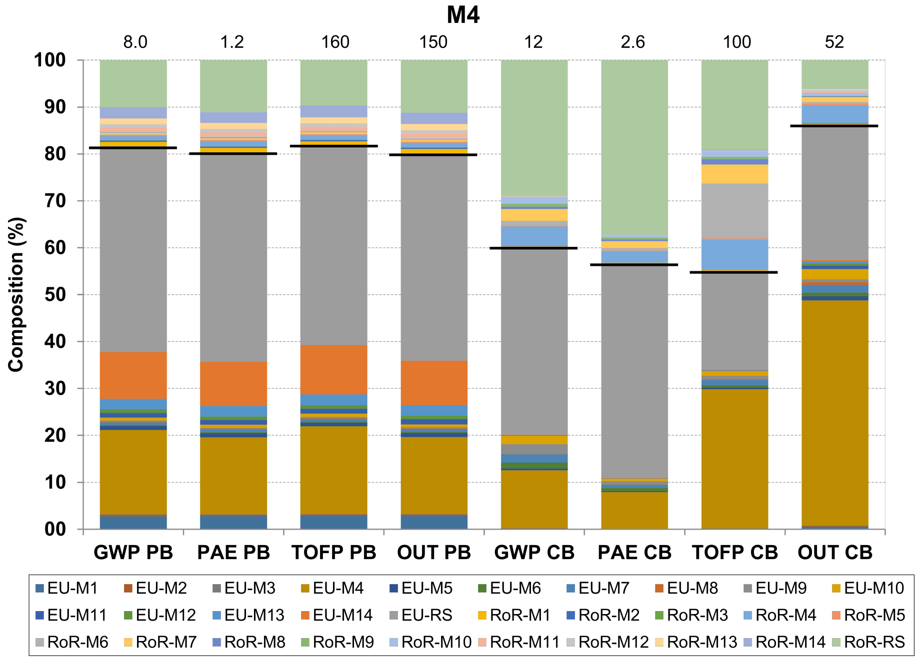


Fig. C13. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M4, production and consumption-based.

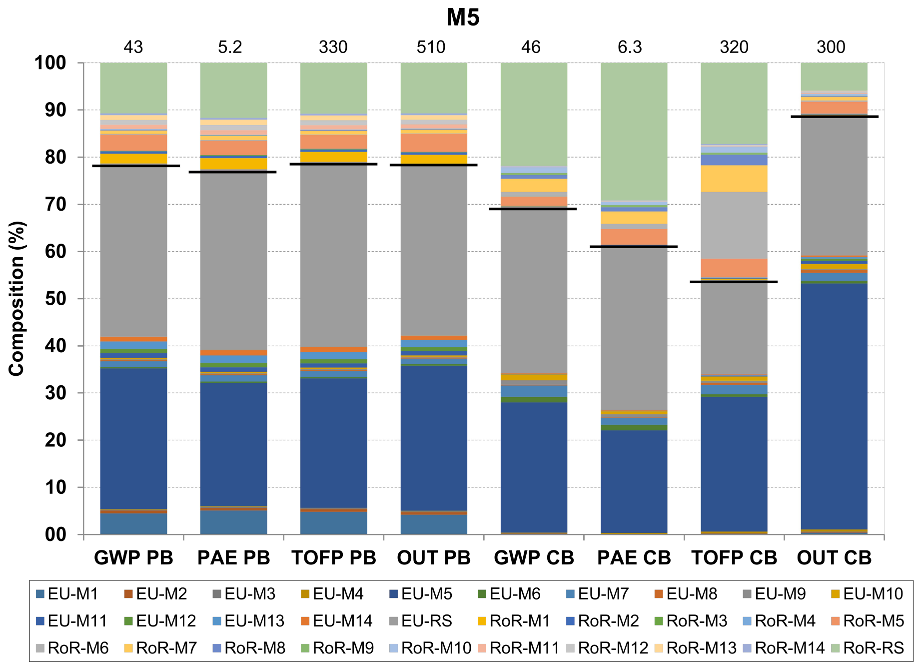


Fig. C14. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M5, production and consumption-based.

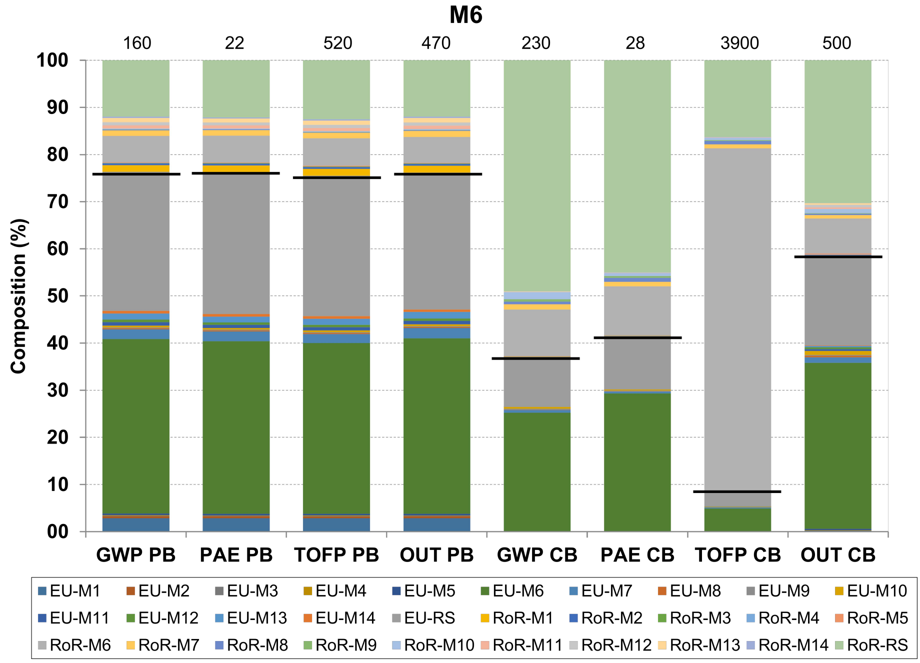


Fig. C15. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M6, production and consumption-based.

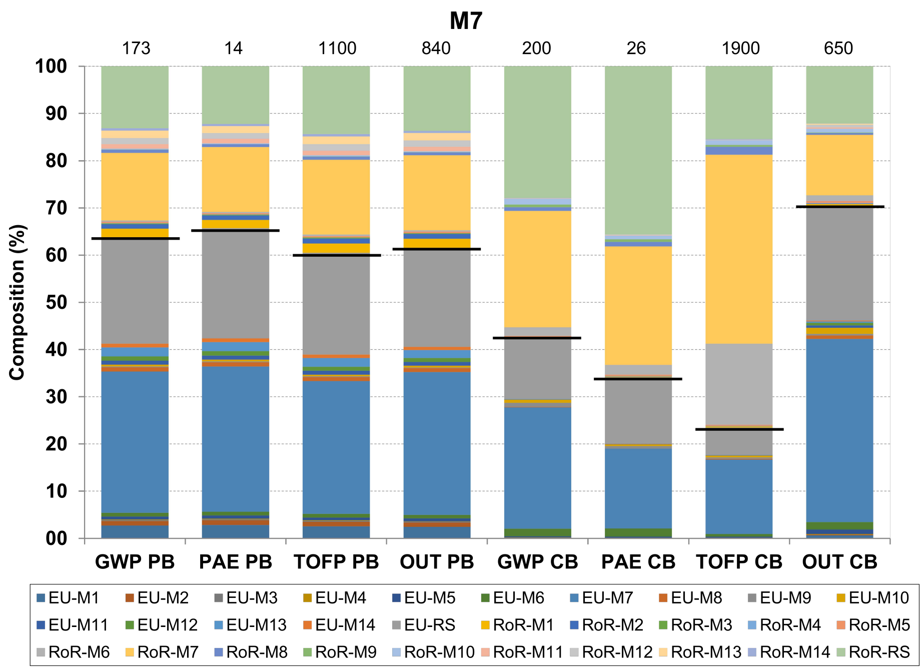


Fig. C16. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M7, production and consumption-based.

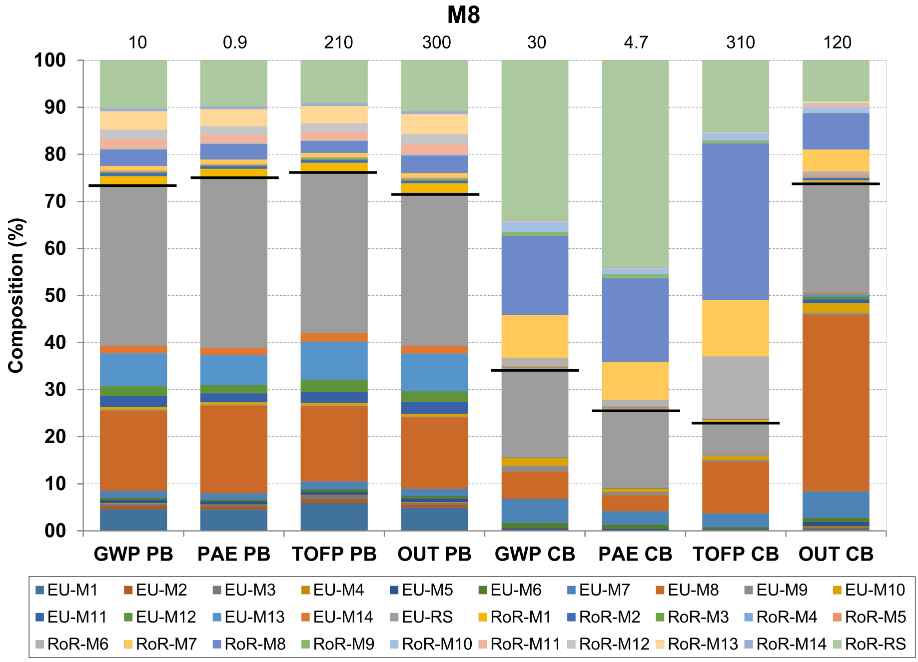


Fig. C17. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M8, production and consumption-based.

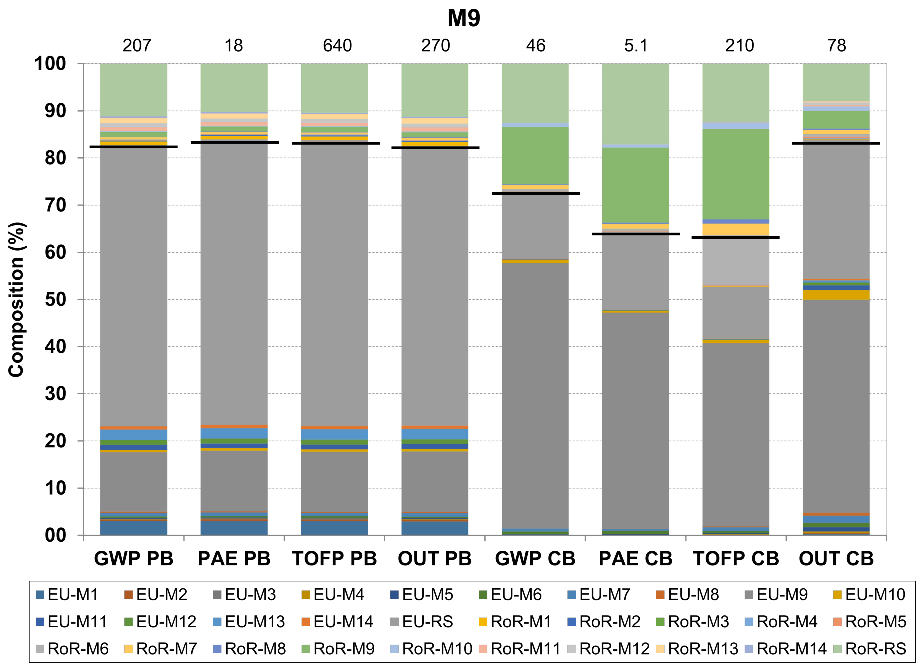


Fig. C18. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M9, production and consumption-based.

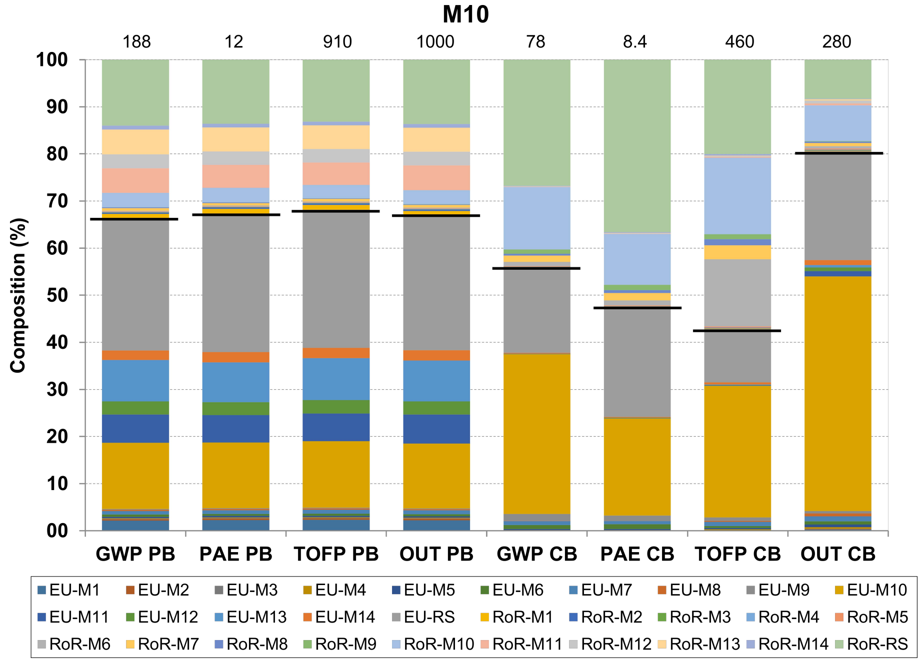


Fig. C19. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M10, production and consumption-based.

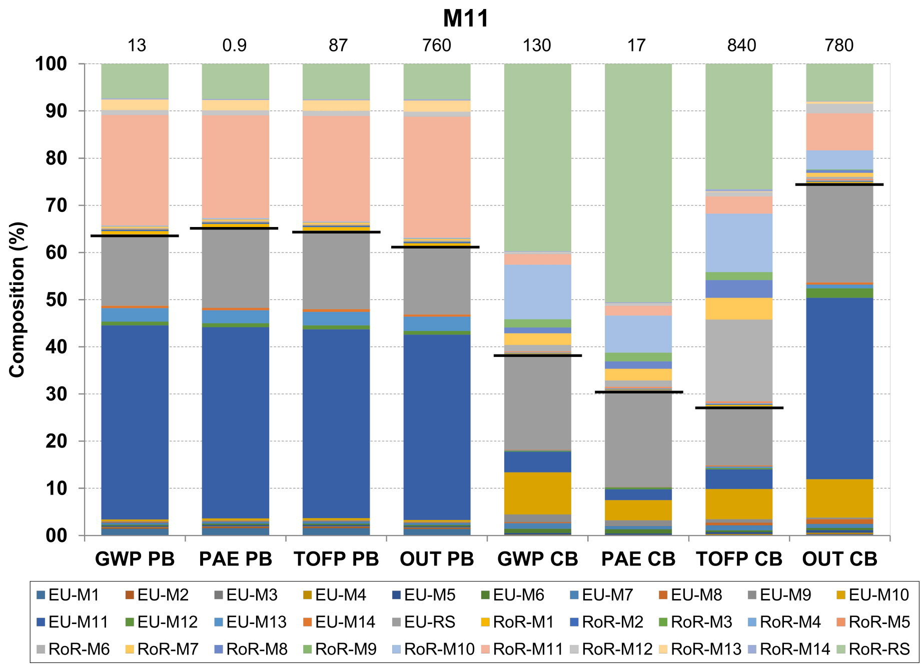


Fig. C20. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M11, production and consumption-based.

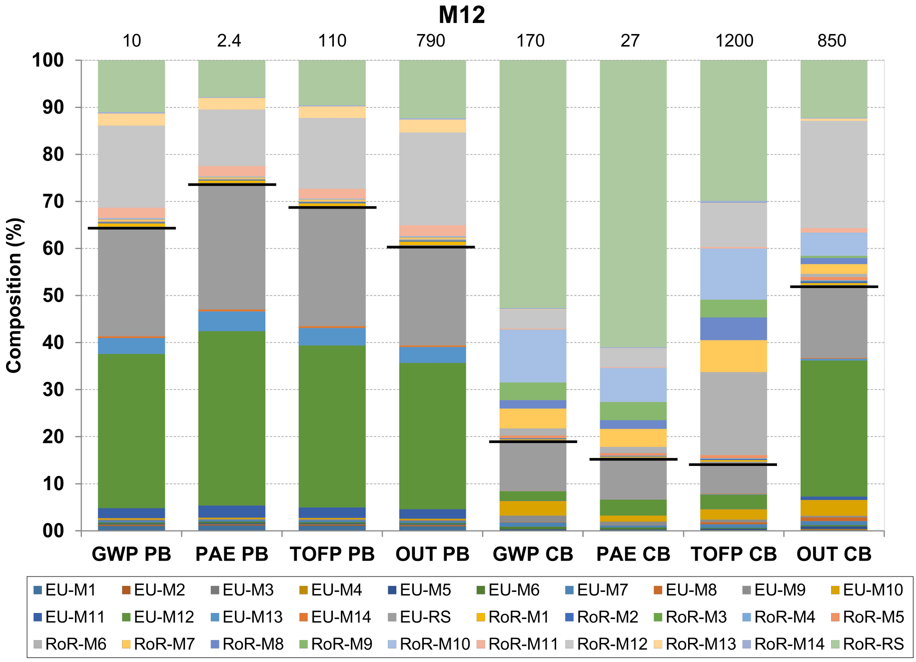


Fig. C21. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M12, production and consumption-based.

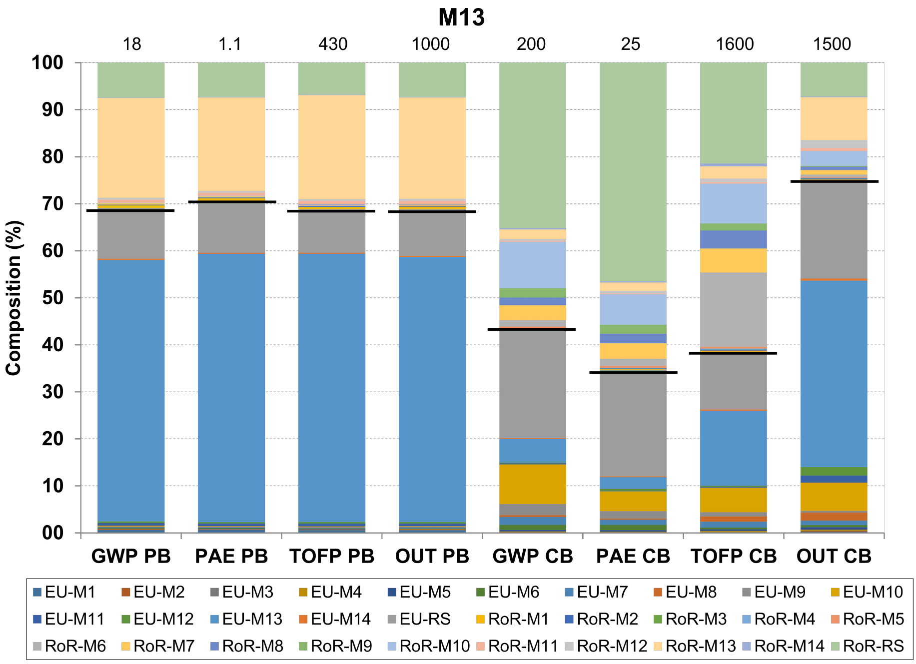


Fig. C22. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M13, production and consumption-based.

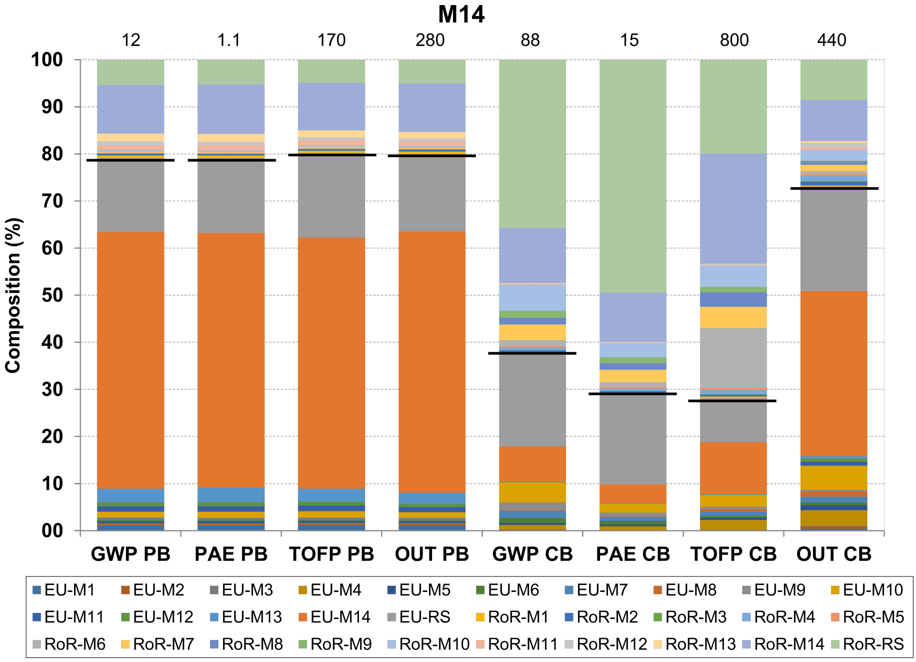


Fig. C23. Composition of the impacts (GWP, PAE and TOFP) and total economic output of EU manufacturing sector M14, production and consumption-based.

2.10. References

Andersen, P., Petersen, N.C., 1993. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. Manage. Sci. 39, 1261–1264. doi:10.1287/mnsc.39.10.1261

Butnar, I., Llop, M., 2007. Composition of greenhouse gas emissions in Spain: An input-output analysis. Ecol. Econ. 61, 388–395. doi:10.1016/j.ecolecon.2006.03.005

Carpenter, A., Carvalho, A. De, Workshop, G.G., Cavenati, S., Grande, C.A., Rodrigues, A.E., Leckel, D., Dry, M.E., 2012. CO2 abatement in the iron and steel industry. Energy & Fuels 77, 43–50. doi:10.1021/ef900064c

Collins, A., Flynn, A., 2015. The ecological footprint: New developments in policy and practice, The ecological footprint. doi:10.4337/9780857936967

Cooper, W.W., Seiford, L.M., Zhu, J., 2011. Data envelopment analysis: History, models, and interpretations, in: International Series in Operations Research and Management Science. pp. 1–39. doi:10.1007/978-1-4419-6151-8_1

Cortés-Borda, D., Guillén-Gosálbez, G., Jiménez, L., 2015a. Assessment of nuclear energy embodied in international trade following a world multi-regional input-output approach. Energy 91, 91–101. doi:10.1016/j.energy.2015.07.117

Cortés-Borda, D., Ruiz-Hernández, A., Guillén-Gosálbez, G., Llop, M., Guimerà, R., Sales-Pardo, M., 2015b. Identifying strategies for mitigating the global warming impact of the EU-25 economy using a multi-objective input-output approach. Energy Policy 77, 21–30. doi:10.1016/j.enpol.2014.11.020

Croft McKenzie, E., Durango-Cohen, P.L., 2010. An input-output approach for the efficient design of sustainable goods and services. Int. J. Life Cycle Assess. 15, 946–961. doi:10.1007/s11367-010-0227-9

Curry, R., Maguire, C., 2011. The use of Ecological and Carbon Footprint Analysis in regional policy making: application and insights using the REAP model. Local Environ. Int. J. Justice Sustain. 16, 917–936. doi:10.1080/13549839.2011.615306

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444. doi:10.1016/0377-2217(78)90138-8

Chen, B., Li, J.S., Chen, G.Q., Wei, W.D., Yang, Q., Yao, M.T., Shao, J.A., Zhou, M., Xia, X.H., Dong, K.Q., Xia, H.H., Chen, H.P., 2017. China's energy-related mercury emissions: Characteristics, impact of trade and mitigation policies. J. Clean. Prod. 141, 1259–1266. doi:10.1016/j.jclepro.2016.09.200

Chen, Y., 2005. Measuring super-efficiency in DEA in the presence of infeasibility 161, 545–551. doi:10.1016/j.ejor.2003.08.060

Christie, R., 2007. Environmental Aspects of Textile Dyeing. Woodhead Publ. Text. doi:10.1533/9781845693091.93

Davis, S.J., Caldeira, K., 2010. Consumption-based accounting of CO2 emissions. Proc. Natl. Acad. Sci. U. S. A. 107, 5687–5692. doi:10.1073/pnas.0906974107

Dietzenbacher, E., Lahr, M.L., 2008. Wassily Leontief and Input-Output Economics. p. 420.

Egilmez, G., Kucukvar, M., Tatari, O., 2013. Sustainability assessment of U.S. manufacturing sectors: An economic input output-based frontier approach. J. Clean. Prod. 53, 91–102. doi:10.1016/j.jclepro.2013.03.037

Ewertowska, A., Galán-Martín, A., Guillén-Gosálbez, G., Gavaldá, J., Jiménez, L., 2015. Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis. J. Clean. Prod. 116. doi:10.1016/j.jclepro.2015.11.100

Ewing, B.R., Hawkins, T.R., Wiedmann, T.O., Galli, A., Ertug Ercin, A., Weinzettel, J., Steen-Olsen, K., 2012. Integrating ecological and water footprint accounting in a multi-regional input–output framework. Ecol. Indic. 23, 1–8. doi:10.1016/j.ecolind.2012.02.025

Fang, K., Heijungs, R., Duan, Z., De Snoo, G.R., 2015. The environmental sustainability of nations: Benchmarking the carbon, water and land footprints against allocated planetary boundaries. Sustain. 7, 11285–11305. doi:10.3390/su70811285

Farrell, M.J., 1957. The Measurement of Productive Efficiency. J. R. Stat. Soc. Ser. A 120, 253–290. doi:10.1016/S0377-2217(01)00022-4

Galán-Martín, Á., Guillén-Gosálbez, G., Stamford, L., Azapagic, A., 2016. Enhanced data envelopment analysis for sustainability assessment: A novel methodology and application to electricity technologies. Comput. Chem. Eng. 90, 188–200. doi:10.1016/j.compchemeng.2016.04.022

Gomes, E.G., Lins, M.P.E., 2008. Modelling undesirable outputs with zero sum gains data envelopment analysis models. J. Oper. Res. Soc. 59, 616–623. doi:10.1057/palgrave.jors.2602384

González, J.P., Gosálbez, G.G., Esteller, L.J., 2014. Multi-objective optimization of US economy via multi-regional input-output analysis. Comput. Aided Chem. Eng. 33, 1015–1020. doi:10.1016/B978-0-444-63455-9.50004-0

IEA, ICCA, 2013. Technology Roadmap Energy and GHG Reductions in the Chemical Industry via Catalytic Processes 1–60.

Leontief, W.W., 1936. Quantitative Input and Output Relations in the Economic Systems of the United States. Rev. Econ. Stat. 18, 105–125. doi:10.2307/1927837

Limleamthong, P., Gonzalez-Miquel, M., Papadokonstantakis, S., Papadopoulos, A.I., Seferlis, P., Guillén-Gosálbez, G., 2016. Multi-criteria screening of chemicals considering thermodynamic and life cycle assessment metrics via data envelopment analysis: application to CO2 capture. Green Chem. 18, 6399–6696. doi:10.1039/c6gc01696k

Liu, X., Klemeš, J.J., Varbanov, P.S., Čuček, L., Qian, Y., 2017. Virtual carbon and water flows embodied in international trade: a review on consumption-based analysis. J. Clean. Prod. 146, 20–28. doi:10.1016/j.jclepro.2016.03.129

Luptáčik, M., Böhm, B., 2010. Efficiency analysis of a multisectoral economic system. Cent. Eur. J. Oper. Res. 18, 609–619. doi:10.1007/s10100-010-0175-2

Mahlberg, B., Luptacik, M., 2014. Eco-efficiency and eco-productivity change over time in a multisectoral economic system. Eur. J. Oper. Res. 234, 885–897. doi:10.1016/j.ejor.2013.11.017

Martínez-Zarzoso, I., Maruotti, A., 2011. The impact of urbanization on CO2 emissions: Evidence from developing countries. Ecol. Econ. 70, 1344–1353. doi:10.1016/j.ecolecon.2011.02.009

Mi, Z., Wei, Y.M., Wang, B., Meng, J., Liu, Z., Shan, Y., Liu, J., Guan, D., 2017. Socioeconomic impact assessment of China's CO2 emissions peak prior to 2030. J. Clean. Prod. 142, 2227–2236. doi:10.1016/j.jclepro.2016.11.055

Mi, Z., Zhang, Y., Guan, D., Shan, Y., Liu, Z., Cong, R., Yuan, X.C., Wei, Y.M., 2016. Consumption-based emission accounting for Chinese cities. Appl. Energy 184, 1073–1081. doi:10.1016/j.apenergy.2016.06.094

Miller, R., Peter D., B., 2009. Input–Output Analysis Foundations and Extensions. J. Chem. Inf. Model. 1–784. doi:10.1017/CBO9781107415324.004

Moran, D., 2013. The Eora MRIO, in: The Sustainability Practitioner's Guide to Multi-Regional Input-Output Analysis. pp. 66–71.

Nuttall, C., Allen, R.G.D., Ely, J.E., 2010. International Trade Statistics 2010, World Trade Organization International Trade Statistics. doi:10.2307/2985456

Pani, R., Mukhopadhyay, U., 2013. Management accounting approach to analyse energy related CO2 emission: A variance analysis study of top 10 emitters of the world. Energy Policy 52, 639–655. doi:10.1016/j.enpol.2012.10.024

Pascual-González, J., Guillén-Gosálbez, G., Mateo-Sanz, J.M., Jiménez-Esteller, L., 2015. Statistical analysis of global environmental impact patterns using a world multi-regional input-output database. J. Clean. Prod. 90, 360–369. doi:10.1016/j.jclepro.2014.11.065

Ray, S.C., 2004. Data Envelopment Analysis Theory and Techniques for Economics and Operations Research. Manage. Sci. 42, 1180. doi:10.1017/CBO9780511606731

Ren, J., Tan, S., Dong, L., Mazzi, A., Scipioni, A., Sovacool, B.K., 2014. Determining the life cycle energy efficiency of six biofuel systems in China: A Data Envelopment Analysis. Bioresour. Technol. 162, 1–7. doi:10.1016/j.biortech.2014.03.105

Robaina-Alves, M., Moutinho, V., MacEdo, P., 2015. A new frontier approach to model the eco-efficiency in European countries. J. Clean. Prod. 103, 562–573. doi:10.1016/j.jclepro.2015.01.038

Rocco, M. V., Colombo, E., 2016. Evaluating energy embodied in national products through Input-Output analysis: Theoretical definition and practical application of international trades treatment methods. J. Clean. Prod. 139, 1449–1462. doi:10.1016/j.jclepro.2016.09.026

Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., Owen, A., 2016. Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions. J. Clean. Prod. 132, 45–56. doi:10.1016/j.jclepro.2015.06.100

Seppälä, J., Mäenpää, I., Koskela, S., Mattila, T., Nissinen, A., Katajajuuri, J.M., Härmä, T., Korhonen, M.R., Saarinen, M., Virtanen, Y., 2011. An assessment of greenhouse gas emissions and material flows caused by the Finnish economy using the ENVIMAT model. J. Clean. Prod. 19, 1833–1841. doi:10.1016/j.jclepro.2011.04.021

Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L., 2007. IPCC, 2007: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, D Qin M Manning Z Chen M Marquis K Averyt M Tignor and HL Miller New York Cambridge University Press pp.

Timmer, M., Erumban, A., Francois, J., Genty, A., 2012. The World Input-Output Database (WIOD): Contents, Sources and Methods, WIOD Background. doi:10.1111/roie.12178

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production. Rev. Int. Econ. 23, 575–605. doi:10.1111/roie.12178

Vázquez-Rowe, I., Iribarren, D., 2015. Review of life-cycle approaches coupled with data envelopment analysis: Launching the CFP + DEA method for energy policy making. Sci. World J. 2015. doi:10.1155/2015/813921

Vetné Mózner, Z., 2013. A consumption-based approach to carbon emission accounting-sectoral differences and environmental benefits. J. Clean. Prod. 42, 83–95. doi:10.1016/j.jclepro.2012.10.014

Weinzettel, J., Hertwich, E.G., Peters, G.P., Steen-Olsen, K., Galli, A., 2013. Affluence drives the global displacement of land use. Glob. Environ. Chang. 23, 433–438. doi:10.1016/j.gloenvcha.2012.12.010

Wiedmann, T., 2009a. A review of recent multi-region input–output models used for consumption-based emission and resource accounting. Ecol. Econ. 69, 211–222. doi:10.1016/j.ecolecon.2009.08.026

Wiedmann, T., 2009b. A review of recent multi-region input-output models used for consumption-based emission and resource accounting. Ecol. Econ. doi:10.1016/j.ecolecon.2009.08.026

Wiedmann, T., Lenzen, M., Turner, K., Barrett, J., 2007. Examining the global environmental impact of regional consumption activities — Part 2: Review of input–output models for the assessment of environmental impacts embodied in trade. Ecol. Econ. 61, 15–26. doi:10.1016/j.ecolecon.2006.12.003

Wiedmann, T., Wilting, H.C., Lenzen, M., Lutter, S., Palm, V., 2011. Quo Vadis MRIO? Methodological, data and institutional requirements for multi-region input–output analysis. Ecol. Econ. 70, 1937–1945. doi:10.1016/j.ecolecon.2011.06.014

Wilson, P.W., 1995. Detecting influential observations in data envelopment analysis. J. Product. Anal. 6, 27–45. doi:10.1007/BF01073493

World Bank Group, 1999. Pollution Prevention and Abatement Handbook Toward Cleaner Production.

Xue, M., Harker, P.T., 2002. Note: Ranking DMUs with Infeasible Super-Efficiency DEA Models. Manage. Sci. 48, 705–710. doi:10.1287/mnsc.48.5.705.7805

3. SUSTAINABILITY ASSESSMENT OF THE EU ELECTRICITY MIXES

3. Sustainability efficiency assessment of the electricity mix of the 28 EU member countries combining data envelopment analysis and optimized projections

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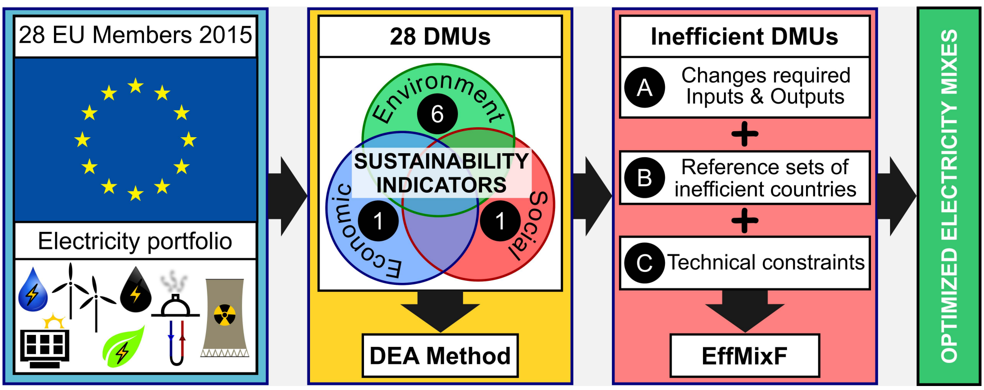
KEYWORDS

Sustainability, Data envelopment analysis (DEA), Electricity mix, European Union, Eco-efficiency, Optimization

ABSTRACT ART



ABSTRACT

Assessing the sustainability level of electricity mixes is a necessary step in the transition towards a more sustainable energy system. In this contribution, we propose a novel approach for the sustainability assessment and optimization of electricity mixes, and apply it to the 28 EU members in 2015. The approach presented combines life cycle assessment, data envelopment analysis (DEA) and rigorous mathematical programming tools in three main steps. Firstly, DEA is applied to assess the efficiency level of the electricity mixes of the 28 EU countries considering the three dimensions of sustainability (economic, environmental and social). Then, the electricity mix of the inefficient countries is optimized by solving an optimization model named EffMixF that seeks to attain the targets provided by DEA while simultaneously considering the technical constraints that govern the electricity generation within each country. This second model, which constitutes the cornerstone of our approach, complements the standard DEA by ensuring that the improvement targets reflect meaningful and realistic results for policy-making. Finally, in the third step, we re-evaluate the optimized electricity portfolios previously obtained by rerunning the DEA model. We find that 20 countries are efficient, while eight are inefficient. Among the inefficient ones, the lowest efficiency scores are present in Lithuania, Finland and Latvia. Our results confirm that DEA targets might indeed be unattainable in practice when constraints on electricity generation are considered. In this context, our framework provides valuable insight on how to improve the sustainability efficiency of electricity mixes in an effective and realistic manner by spotting the technologies that should be object of regulations. As a general trend, we find that non-renewable electricity sources should be reduced by 9% on average with respect to the total electricity generated within the EU members. Furthermore, *Hydropower* and *Wind* should be promoted in order to reduce the environmental impact, while deploying more *Coal* and *Solar* could enhance the economic and social performance, respectively.

3.1. Introduction

Transitioning towards a more sustainable energy system is one of the major challenges facing the world today. In Europe, numerous plans and policies have been settled, denoting the importance of deploying more sustainable electricity mixes (European Union, 2010; Simoes et al., 2017). For example, the *Europe 2020 targets* (European Union, 2010) aim to lead Europe to a more sustainable future considering environmental (i.e., greenhouse gas emissions reduction, increment of renewable energy sources and improvement in energy efficiency) and social (i.e., employment, poverty, education, R&D) pillars. In this context and given the important role that electricity production plays in our society, it is necessary to find effective ways to assess the sustainability level of the technologies used in electricity production as well as of the electricity mixes implementing them (Fong and Lee, 2012; Galán-Martín et al., 2016; Li and Tao, 2017; Limleamthong and Guillén-Gosálbez, 2017; Olabi, 2016).

Sustainability encompasses economic, environmental and social aspects, each of which can be quantified by a wide variety of indicators (Li et al., 2017; Lo Piano and Mayumi, 2017; Matino et al., 2017; Schlör et al., 2013). Hence, the main difficulty when assessing the level of sustainability attained by a system consists in finding a way to combine a plethora of metrics into a single score in a systematic and objective manner so that it can assist policy-making. This is particularly challenging when assessing energy systems, whose performance can be quantified using a wide range of indicators covering the three sustainability dimensions. In this context, data envelopment analysis (DEA) (Charnes et al., 1978) arises as a promising methodology (Cristóbal et al., 2016; Ewertowska et al., 2017; Zurano-Cervelló et al., 2017). This approach assesses the relative efficiency of a set of entities (known as decision making units, DMUs) according to several indicators classified as either inputs or outputs and without the need to define subjective weights on them (Cook and Seiford, 2009; Cooper et al., 2011, 2007). Specifically, DEA classifies DMUs into efficient and inefficient, assigning an efficiency score to each of them. The model also provides improvement targets for the inefficient DMUs that if attained would make them efficient.

DEA, was firstly used by Färe *et al.* (Färe et al., 1986) in the context of environmentally efficiency. Since then, substantial research has applied DEA to environmental problems, including the eco-efficiency assessment of energy mixes (Kuosmanen and Kortelainen, 2005; Sueyoshi et al., 2017; Zhou et al., 2008a). Sueyoshi and Goto (Sueyoshi and Goto, 2015) applied DEA to determine the new fuel mix required in Japan after the Fukushima Daiichi nuclear power plan disaster. They pointed out inconsistencies between the electricity mix they calculated and the one proposed by the Japanese government. Bampatsou *et al.* (Bampatsou et al., 2013) applied DEA to assess the Technical Efficiency Index of the energy mix of each of the 15 EU countries between 1980 to 2008. Furthermore, Chang and Yu (Chang and Yu, 2017) studied the energy productivity change from 1995 to 2010 of the 27 EU members (Baltic Sea and non-Baltic sea States) using a Malmquist-DEA approach. They selected real capital stock, labor and energy usage as inputs, and real GDP as output. Ewertowska *et al.* (Ewertowska et al., 2015) combined Life Cycle Assessment with DEA in order to evaluate the electricity mix of the top European countries along with the changes needed to make the inefficient regions efficient. Other applications of DEA in environmental studies include the screening of solvents (Limleamthong and Guillen Gosalbez, 2018) and process flowsheets (Mio et al., 2018), as well as the related to the power energy technologies (Iribarren et al., 2014, 2013; Vázquez-Rowe and Iribarren, 2015).

More recently, social aspects have been incorporated in DEA studies (together with economic and environmental indicators) to assess the sustainability efficiency of energy systems and, more specifically, technologies for electricity generation. Jinchao Li *et al.* (Li et al., 2016) compared the sustainability level of the G20 countries from 2005 to 2014. To this end, they proposed an index composed by a set of desirable (electricity generation and job creation) and undesirable outputs (supply risk and environmental and health costs) that was studied using DEA. Sueyoshi and Yuan (Sueyoshi and Yuan, 2016) used DEA to compare the marginal rate of transformation and rate of substitution of different production factors in the North American and European nations. They used the GDP as desirable output, the air pollution -PM 2.5 and CO_2- as undesirable output, and the total population and total energy supply as inputs. Other contributions of DEA in the context of sustainability assessment include the study of the urban development of Chinese provincial capital cities by using eco-efficiency as an indicator for sustainability (Yin et al., 2014) and the incorporation of the social and environmental dimensions of sustainability into project management (Sánchez, 2015). Zhou *et al.* (Zhou et al., 2008a) presents a survey covering DEA studies applied to energy and the environment, classifying them according to the type, model used and underlying assumptions, e.g., scale used, inputs and outputs disposability or efficiency measures.

In parallel to novel applications, new developments in DEA have also been made in order to deal with the specific features of the sustainability assessment of systems. These include the use of cross-temporal measures -as the Malmquist index- to assess the progress made in technology development (Song et al., 2017a), as well as the emergence of cross-efficiency methods to handle the self-evaluation issue (Song et al., 2017b), among others (Cooper et al., 2007). In the context of environmental efficiency, one of the main advances has been the introduction of the undesirable output concept (Chung et al., 1997).

However, despite all these advances, some issues still remain unsolved. One general limitation of DEA is that it fails to provide specific roadmaps on how to achieve the improvement targets. That is, no guidelines are offered on the changes that need to be implemented to make inefficient electricity systems efficient. In the electric power sector, some authors suggested to overcome this limitation by using linear coefficients to generate new electricity portfolios that would combine the technologies of their peers in an optimal manner (Ewertowska et al., 2015). However, these mixes may still be unattainable, since neither the amount of available resources (e.g., limited potential for renewables) nor the reliability of the supply (e.g., excessive dependence on intermittent resources) are considered in the analysis. Moreover, another DEA limitation is that the improvement targets are rigid, as projections are made onto a point of the efficient frontier rather than on a region. Tailored DEA models can be used to calculate targets in alternative ways that differ in the orientation point of view (e.g., input or output-oriented), RTS condition (e.g., constant or variable returns to scale) and/or efficiency measures used. Unfortunately, they all offer little flexibility (if any) on how to turn inefficient units into efficient. This is because these approaches force the inefficient units to display specific input and output values instead of providing intervals within which these values should fall. In the context of electricity systems, this limitation is particularly critical as targets might point towards unattainable solutions due to technical constraints that govern the design of electricity mixes.

In this contribution, we propose an enhanced DEA for the electric power sector where a projection step is carried out using optimization tools that ensure achievable improvement targets. More precisely, we first assess the efficiency of the 28 EU members in 2015 taking into account eight indicators covering the three dimensions of sustainability: the economic (i.e., the annualized cost of electricity), the environmental (i.e., six life-cycle impact indicators) and the social (i.e., number of direct Job-Yr and electricity generation). Then, we study whether DEA targets are indeed attainable and suggest the best-possible electricity mix for each inefficient country. To this end, we solve an optimization problem, named EffMixF, which is the cornerstone of our approach. This model considers: (i) techno-economic constraints; (ii) real potentials for the use of renewable sources; and (iii) the reliability of the supply. Instead of directing the projection to a specific point of the efficient frontier, as occurs in the traditional DEA (e.g., radial projection), EffMixF model allows the projection to point towards the more convenient -the more easily attainable- point of a facet of the efficient frontier. This provides higher flexibility to the inefficient countries to become efficient. Therefore, while the targets proposed might not necessarily guarantee efficiency (i.e., it might not be possible to attain the efficient frontier), they will always improve the current situation by pointing towards the "best" feasible alternative (i.e., the feasible point lying closest to a facet). The method we present provides valuable insight into how the electricity portfolios should change in order to improve the nation's sustainability level. Hence, EffMixF could be a useful tool to aid policy makers in the development of more effective regulations by identifying which technologies should be promoted (or hindered) via tailored policies.

3.2. Methods

The proposed methodology to assess the sustainability efficiency of electricity mixes encompasses three main steps (see algorithm in fig. 3.1). In step 1, we apply DEA based on a set of indicators to classify the electricity portfolios of the 28 EU countries in 2015 (*Current* mix) as efficient or inefficient. These indicators cover the three main pillars of sustainability (i.e., economy, environment and society). Then, in step 2, we optimize the *Current* electricity mix of the inefficient DMUs identified in step 1 (*Optimized* mixes), so that they can become efficient, or near efficient if full efficiency cannot be attained within the boundaries imposed by physical limits. To this end, we solve a customized optimization problem, named EffMixF, which considers techno-economic data (e.g., the levelized cost of electricity (LCOE), the feasibility of the proposed portfolio and its reliability in terms of intermittency of non-dispatchable sources), together with sustainability aspects. Finally, we apply DEA again (step 3) to evaluate the efficiency of the *Optimized* electricity mixes obtained in step 2, reassessing their gains in efficiency after making the proper changes in the electricity portfolios.

In the next section, we first provide the data used in this work, including indicators associated with the electricity mix of each country (inputs and outputs for DEA), as well as domestic potentials for electricity generation and capacity factors of technologies (used in model EffMixF). We then explain in detail the main steps of the proposed methodology.

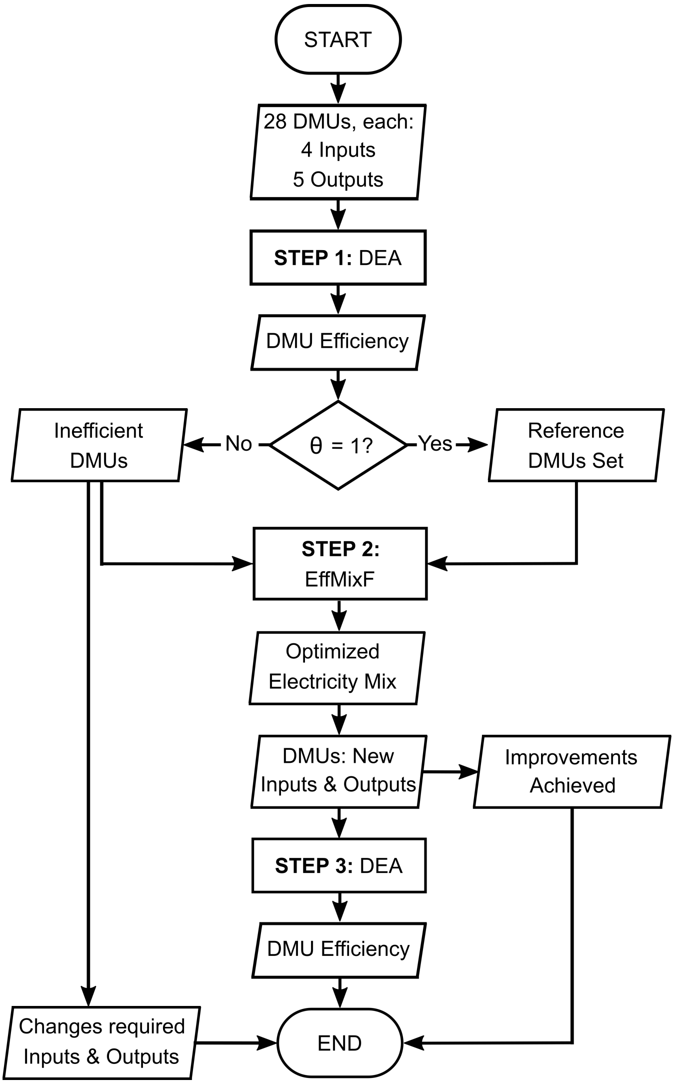


Fig. 3.1. Algorithm showing the steps of the methodology used in this paper.

3.2.1. Data used

We divide the data used in this study into two main blocks: (i) sustainability indicators; and (ii) potentials and capacity factors. In section 3.2.1.1, we explain the data used and the calculations required to obtain the sustainability indicators fed into the DEA (section 3.2.2) and EffMixF models (section 3.2.3). Furthermore, potentials for electricity generation and capacity factors data are described in section 3.2.1.2.

3.2.1.1. Sustainability indicators

In this work, we use the electricity mix data of the 28 EU member countries (see table 3.1) for 2015. More precisely, we use data from the Eurostat Energy Statistics -energy datasheets- (European Union, 2016). These datasheets disaggregate the electricity production into 12 energy sources; of which nine are considered here (see table 3.2). Hence, *Tide, Wave and Ocean* energy production is omitted because it only represents a 0.1% of the electricity mix at most (France). We also discard *Wastes*, *Non-Renewable* as well as *Other,* because they represent less than 2% of the electricity mix of any country and also because there is no further information on the specific technologies embedded within these categories. For simplicity, only the most representative technology within each category is considered (see table 3.2).

Table 3.1. 28 EU member countries by ISO 3166-2 code and country name.

Code	**Country**	**Code**	**Country**	**Code**	**Country**
AT	Austria	FR	France	MT	Malta
BE	Belgium	GB	United Kingdom	NL	Netherlands
BG	Bulgaria	GR	Greece	PL	Poland
CY	Cyprus	HR	Croatia	PT	Portugal
CZ	Czech Republic	HU	Hungary	RO	Romania
DE	Germany	IE	Ireland	SE	Sweden
DK	Denmark	IT	Italy	SI	Slovenia
EE	Estonia	LT	Lithuania	SK	Slovak Republic
ES	Spain	LU	Luxembourg		
FI	Finland	LV	Latvia		

Table 3.2. Technologies and assumptions used in our study.

Name used [a,b]	Technology
Natural Gas	**Natural gas CCGT plant**
Nuclear	**Pressure water reactor**
Oil	**Petroleum, heavy fuel oil**
Coal	**Coal plant**
Biomass and Renewable wastes	**Biomass CCGT plant**
Geothermal	**Deep geothermal**
Hydropower	Run-of-river
Solar	Photovoltaic open ground installation
Wind	Onshore wind

a) In bold dispatchable technologies (DP).
b) In gray non-renewable technologies, in white renewable ones.

In table 3.2, we distinguish between dispatchable and non-dispatchable technologies. The dispatchable technologies (DP) -displayed in bold- are operative and generate electricity at request. On the other hand, the non-dispatchable technologies (i.e., *Hydropower*, *Solar* and *Wind*) rely on intermittent sources that can only generate electricity when the environmental conditions allow it; e.g., if there is no wind, or if the wind is too strong, electricity cannot be generated via wind turbines. Note that, depending on the plant type, hydropower facilities could be considered as either dispatchable (as happens with hydropower plants with reservoir) or non-dispatchable. In this study, we categorize hydropower plants as non-dispatchable, as they are assumed to be based on the run-of-river technology. Many facilities of this type have already been deployed across European countries ("AQUARET, Run-of-river.," 2012), while many others are at present in the planning phase (Gallagher et al., 2015). Furthermore, these power plants cause less environmental and ecological damage than the storage hydroelectric facilities (Bilotta et al., 2016).

With the electricity portfolios of every country at hand, we next calculate their corresponding environmental, economic and social performance using the indicator coefficients shown in table 3.3. We next describe the data sources used in the analysis.

Table 3.3. Environmental, economic and social indicators specified by name, symbol, unit and source.

Indicator name [a]	Abbreviation	Unit	Source
Climate change[1]	GWP100	kg CO_{2e}	(Wernet et al., 2016)
Fossil depletion[1]	FDP	kg Oil_e	(Wernet et al., 2016)
Human toxicity[1]	HTPinf	1,4-DCB_e	(Wernet et al., 2016)
Ozone depletion[1]	ODPinf	kg CFC-11_e	(Wernet et al., 2016)
Total land occupation[1]	TLOP	m^2yr	(Wernet et al., 2016)
Water depletion[1]	WDP	m^3	(Wernet et al., 2016)
Annualized cost of electricity[2]	ACOE	USD	(Alberici et al., 2014; NEA et al., 2015)
Total job-years[3]	Job-Yr	Job-yr	(Wei et al., 2010)
Electricity generated[3]	EGen	TWh	(European Union, 2016)

[1] Environmental, [2]economic and [3]social.

The environmental indicator coefficients are retrieved from the *Ecoinvent* database (Wernet et al., 2016), specifically from version 3.0 of the *Allocation at the point of substitution* system model. The data collected is based on the ReCiPe 2008 Midpoint Hierarchist (H). Note that TLOP values are not directly provided by the database, but rather obtained by aggregating the *Agricultural land occupation* (ALOP) and the *Urban land occupation* (ULOP) potentials available therein.

The *Annualized cost of electricity* (ACOE) is obtained from the LCOE, which considers the unitary costs of a technology over its operating life time as well as the amount of electricity generated with each technology in each country. We gather the LCOEs for each technology and country from the *Projected Costs of Generating Electricity 2015 Edition* published by the International Energy Agency and the Nuclear Energy Agency (NEA et al., 2015), assuming an investment cost of 7%. The *Oil* LCOE, missing in that document, is estimated from the *Subsides and costs of EU energy* by Ecofys (Alberici et al., 2014).

Finally, we obtained the total Job-Yr for each technology, defined as the full-time employment for a person in one year (Wei et al., 2010). Data for the *Oil* is assumed to be the same as that for the *Natural Gas* technology, as they share similar processes. Note that the coefficient for the total Job-Yr indicator is the same for the 28 EU countries.

When possible, we obtain the indicator coefficients applicable to each technology (j), EU country (i) and category (c). When indicator coefficients (CT_{ijc}) are missing for a particular country and/or technology, we use the average value for that technology across all the available countries. These indicator coefficients are then multiplied by the amount of electricity generated (Mix_{ij}) to obtain an aggregated indicator value per country i and category c ($AInd_{ic}$):

$$\sum_j (CT_{ijc} Mix_{ij}) = AInd_{ic} \qquad \forall i,c \tag{3.1}$$

The corresponding values for the aggregated indicators are presented in fig. 3.2.

	TLOP (m^2yr)	**FDP** (kg Oil_e)	**WDP** (m^3)	**ACOE** (USD)	**GWP100** (kg CO_{2e})	**HTP** (1,4-DCB_e)	**ODP** (kg CFE-11_e)	**Job-Yr** (Job-yr)	**EGen** (TWh)
AT	$1.04\cdot10^{10}$	$3.53\cdot10^{9}$	$2.79\cdot10^{7}$	$7.85\cdot10^{9}$	$9.81\cdot10^{9}$	$3.70\cdot10^{9}$	$2.09\cdot10^{3}$	$1.50\cdot10^{4}$	$6.45\cdot10^{1}$
BE	$1.30\cdot10^{10}$	$4.99\cdot10^{9}$	$1.23\cdot10^{8}$	$7.23\cdot10^{9}$	$1.25\cdot10^{10}$	$5.01\cdot10^{9}$	$4.01\cdot10^{3}$	$1.18\cdot10^{4}$	$6.89\cdot10^{1}$
BG	$1.50\cdot10^{9}$	$1.08\cdot10^{10}$	$1.78\cdot10^{8}$	$4.68\cdot10^{9}$	$4.67\cdot10^{10}$	$1.36\cdot10^{10}$	$2.09\cdot10^{3}$	$8.02\cdot10^{3}$	$4.92\cdot10^{1}$
CY	$1.36\cdot10^{8}$	$1.56\cdot10^{9}$	$4.69\cdot10^{6}$	$1.50\cdot10^{9}$	$4.45\cdot10^{9}$	$4.40\cdot10^{8}$	$7.99\cdot10^{2}$	$6.13\cdot10^{2}$	$4.53\cdot10^{0}$
CZ	$1.22\cdot10^{10}$	$1.35\cdot10^{10}$	$2.20\cdot10^{8}$	$7.95\cdot10^{9}$	$5.49\cdot10^{10}$	$1.79\cdot10^{10}$	$4.10\cdot10^{3}$	$1.27\cdot10^{4}$	$8.37\cdot10^{1}$
DE	$1.24\cdot10^{11}$	$9.95\cdot10^{10}$	$1.15\cdot10^{9}$	$5.94\cdot10^{10}$	$3.35\cdot10^{11}$	$7.44\cdot10^{10}$	$2.19\cdot10^{4}$	$1.16\cdot10^{5}$	$6.38\cdot10^{2}$
DK	$9.99\cdot10^{9}$	$2.71\cdot10^{9}$	$2.55\cdot10^{7}$	$2.74\cdot10^{9}$	$1.01\cdot10^{10}$	$4.69\cdot10^{9}$	$6.90\cdot10^{2}$	$4.83\cdot10^{3}$	$2.82\cdot10^{1}$
EE	$1.94\cdot10^{9}$	$2.53\cdot10^{9}$	$2.46\cdot10^{7}$	$9.99\cdot10^{8}$	$9.92\cdot10^{9}$	$2.52\cdot10^{9}$	$1.97\cdot10^{2}$	$1.26\cdot10^{3}$	$1.03\cdot10^{1}$
ES	$1.52\cdot10^{10}$	$3.14\cdot10^{10}$	$4.34\cdot10^{8}$	$3.10\cdot10^{10}$	$1.06\cdot10^{11}$	$2.64\cdot10^{10}$	$1.40\cdot10^{4}$	$5.16\cdot10^{4}$	$2.80\cdot10^{2}$
FI	$2.68\cdot10^{10}$	$4.34\cdot10^{9}$	$1.13\cdot10^{8}$	$7.44\cdot10^{9}$	$1.52\cdot10^{10}$	$1.01\cdot10^{10}$	$4.85\cdot10^{3}$	$1.21\cdot10^{4}$	$6.80\cdot10^{1}$
FR	$1.47\cdot10^{10}$	$1.07\cdot10^{10}$	$1.43\cdot10^{9}$	$5.13\cdot10^{10}$	$3.24\cdot10^{10}$	$2.31\cdot10^{10}$	$4.95\cdot10^{4}$	$9.22\cdot10^{4}$	$5.65\cdot10^{2}$
GB	$7.04\cdot10^{10}$	$3.81\cdot10^{10}$	$5.73\cdot10^{8}$	$4.07\cdot10^{10}$	$1.25\cdot10^{11}$	$4.61\cdot10^{10}$	$1.26\cdot10^{4}$	$5.16\cdot10^{4}$	$3.36\cdot10^{2}$
GR	$1.17\cdot10^{9}$	$1.06\cdot10^{10}$	$8.97\cdot10^{7}$	$6.63\cdot10^{9}$	$3.74\cdot10^{10}$	$7.38\cdot10^{9}$	$2.66\cdot10^{3}$	$9.94\cdot10^{3}$	$5.18\cdot10^{1}$
HR	$6.79\cdot10^{8}$	$1.12\cdot10^{9}$	$1.02\cdot10^{7}$	$1.36\cdot10^{9}$	$3.88\cdot10^{9}$	$9.93\cdot10^{8}$	$2.18\cdot10^{2}$	$2.42\cdot10^{3}$	$1.14\cdot10^{1}$
HU	$5.18\cdot10^{9}$	$3.06\cdot10^{9}$	$7.65\cdot10^{7}$	$2.97\cdot10^{9}$	$1.03\cdot10^{10}$	$3.54\cdot10^{9}$	$2.67\cdot10^{3}$	$4.18\cdot10^{3}$	$3.01\cdot10^{1}$
IE	$1.28\cdot10^{9}$	$4.28\cdot10^{9}$	$3.83\cdot10^{7}$	$2.91\cdot10^{9}$	$1.32\cdot10^{10}$	$2.79\cdot10^{9}$	$6.64\cdot10^{2}$	$3.73\cdot10^{3}$	$2.83\cdot10^{1}$
IT	$4.70\cdot10^{10}$	$3.80\cdot10^{10}$	$3.26\cdot10^{8}$	$3.43\cdot10^{10}$	$1.20\cdot10^{11}$	$2.96\cdot10^{10}$	$1.36\cdot10^{4}$	$5.94\cdot10^{4}$	$2.80\cdot10^{2}$
LT	$1.05\cdot10^{9}$	$7.09\cdot10^{8}$	$4.53\cdot10^{6}$	$5.93\cdot10^{8}$	$1.84\cdot10^{9}$	$4.10\cdot10^{8}$	$3.78\cdot10^{2}$	$8.19\cdot10^{2}$	$4.61\cdot10^{0}$
LU	$2.99\cdot10^{8}$	$1.87\cdot10^{8}$	$1.60\cdot10^{6}$	$3.25\cdot10^{8}$	$4.60\cdot10^{8}$	$1.12\cdot10^{8}$	$9.75\cdot10$	$6.39\cdot10^{2}$	$2.70\cdot10^{0}$
LV	$1.80\cdot10^{9}$	$6.19\cdot10^{8}$	$5.18\cdot10^{6}$	$6.60\cdot10^{8}$	$1.51\cdot10^{9}$	$5.43\cdot10^{8}$	$3.50\cdot10^{2}$	$9.92\cdot10^{2}$	$5.53\cdot10^{0}$
MT	$2.54\cdot10^{7}$	$5.20\cdot10^{8}$	$1.58\cdot10^{6}$	$4.36\cdot10^{8}$	$1.48\cdot10^{9}$	$1.42\cdot10^{8}$	$2.67\cdot10^{2}$	$2.15\cdot10^{2}$	$1.30\cdot10^{0}$
NL	$1.23\cdot10^{10}$	$2.00\cdot10^{10}$	$1.77\cdot10^{8}$	$1.09\cdot10^{10}$	$5.75\cdot10^{10}$	$8.21\cdot10^{9}$	$2.48\cdot10^{3}$	$1.37\cdot10^{4}$	$1.07\cdot10^{2}$
PL	$2.59\cdot10^{10}$	$4.12\cdot10^{10}$	$3.99\cdot10^{8}$	$1.59\cdot10^{10}$	$1.61\cdot10^{11}$	$3.97\cdot10^{10}$	$3.08\cdot10^{3}$	$2.02\cdot10^{4}$	$1.65\cdot10^{2}$
PT	$7.57\cdot10^{9}$	$6.28\cdot10^{9}$	$5.86\cdot10^{7}$	$5.76\cdot10^{9}$	$2.28\cdot10^{10}$	$6.36\cdot10^{9}$	$1.33\cdot10^{3}$	$8.94\cdot10^{3}$	$5.21\cdot10^{1}$
RO	$1.71\cdot10^{9}$	$7.62\cdot10^{9}$	$1.07\cdot10^{8}$	$6.92\cdot10^{9}$	$2.71\cdot10^{10}$	$5.99\cdot10^{9}$	$2.43\cdot10^{3}$	$1.23\cdot10^{4}$	$6.63\cdot10^{1}$
SE	$2.52\cdot10^{10}$	$9.77\cdot10^{8}$	$1.81\cdot10^{8}$	$1.81\cdot10^{10}$	$3.35\cdot10^{9}$	$9.21\cdot10^{9}$	$7.04\cdot10^{3}$	$3.36\cdot10^{4}$	$1.61\cdot10^{2}$
SI	$7.28\cdot10^{8}$	$1.40\cdot10^{9}$	$3.10\cdot10^{7}$	$1.51\cdot10^{9}$	$5.48\cdot10^{9}$	$1.50\cdot10^{9}$	$6.82\cdot10^{2}$	$2.72\cdot10^{3}$	$1.51\cdot10^{1}$
SK	$3.96\cdot10^{9}$	$1.50\cdot10^{9}$	$5.98\cdot10^{7}$	$2.74\cdot10^{9}$	$5.21\cdot10^{9}$	$2.64\cdot10^{9}$	$2.14\cdot10^{3}$	$4.61\cdot10^{3}$	$2.68\cdot10^{1}$

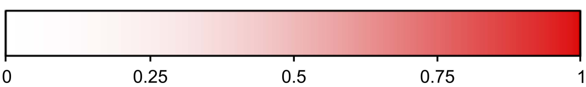


Fig. 3.2. Inputs and outputs data per country used in the DEA method for the year 2015. The heatmap color indicates the normalized value for the indicator, from zero (white) to one (dark red).

3.2.1.2. Potentials and capacity factors

Our study considers country potentials (*PT*) for the electricity generated with renewable technologies (i.e., the amount of kWh that can be generated annually with a given technology in a given region). This applies to all renewable technologies except for *Biomass and renewable wastes*, for which there is no limiting potential. This is because the resources consumed by this technology -the biomass and renewable waste- can be purchased from overseas. Therefore, we define set *RP*, whose elements correspond to renewable sources for which generation potentials are considered.

The *Geothermal* potential for every country is obtained from *A prospective study on the geothermal potential in the EU* (van Wees et al., 2013), considering the 2030 potential for a LCOE < 150 EUR/MWh. The electricity generation potential for *Hydropower* is retrieved from the report *Hydro in Europe: Powering Renewables* (Pirker et al., 2011), which provides the technologically feasible *Hydropower* potential in Europe. The *Solar* potential is sourced from the renewable electricity projections in 2020 in the *Mapping renewable energy pathways toward 2020* (EREC, 2011). Lastly, the *Wind* potential is obtained from the technical potential for onshore wind in 2030, as published in an EEA Technical report *Europe's onshore and offshore wind energy potential* (Eea, 2009). In order to improve the consistency among all the databases, all these potentials are compared with the data for current (i.e., 2015) electricity generation, choosing always the higher value under the premise that current generation is certainly achievable.

For each technology and country, the capacity factor (*Cf*), defined as the ratio between the electricity generated to the one that could have been generated at full-power process in the same period of time, is retrieved from the *Projected Costs of Generating Electricity 2015 Edition* by the International Energy Agency and the Nuclear Energy Agency (NEA et al., 2015). Data gaps for particular technology-country pairs are covered using average capacity factors among countries available for the corresponding technology, similarly as was done with the indicator coefficients. The *Oil* capacity factor is assumed to be the same as that for *Natural Gas*, as both are quite similar in practice.

3.2.2. Step 1: Efficiency assessment using DEA

After gathering the necessary data, DEA is applied to assess the efficiency of the electricity mixes. This approach studies the relative performance of a set of decision making units (DMUs), each converting multiple inputs into multiple outputs (Charnes et al., 1978; Farrell, 1957). In our study, each DMU models the electricity mix of an EU country that contributes towards the social wellbeing by creating jobs and producing electricity, while causing environmental impacts and incurring in some economic cost (see fig. 3.3).

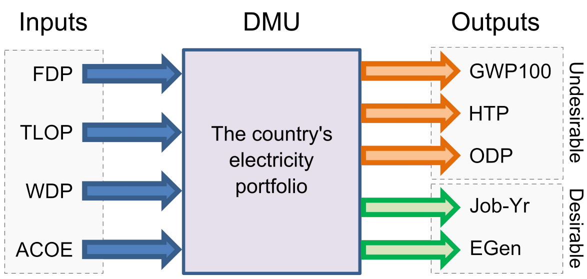


Fig. 3.3. Inputs and outputs included in the DMUs analyzed.

Here, ACOE is the annualized cost of electricity, an economic input needed to build, maintain and operate all power plants of each country. Regarding the environmental impacts, some of them are inputs to the system (i.e., resources). This is the case of the FDP, TLOP and WDP indicators, which are connected to the fuel, land and water requirements, respectively, along the life cycle of the electricity production. On the other hand, the GWP, HTP and ODP impact indicators are considered undesirable outputs as are produced by the emissions released by the system (Gomes and Lins, 2008). The Job-Yr could be considered as an input (Tsai et al., 2016; Wolde-Rufael, 2009). However, in sustainability studies this indicator is commonly treated as an output, as it denotes the number of jobs generated, that are assumed to be good for the society (Galán-Martín et al., 2016; Li et al., 2016). Finally, EGen is modelled as a social indicator, as it is a commodity involved in social development and quality of life (Mazur, 2011; Pasten and Santamarina, 2012). In this study, we force EGen to remain unchanged, as we aim to optimize the country's electricity portfolio while maintaining its level of electricity generation constant. To this end, we model it as a non-discretionary output; see eqs. (3.5)-(3.6) (Cook and Seiford, 2009).

Before applying DEA, we checked the isotonicity of the data using the Pearson coefficient correlation as an indicator. All the Pearson coefficients obtained indicate a positive correlation between all the attributes (see fig. 3.4), being all of them significant at a level of alpha equal to 0.05. Hence, these results satisfy the isotonicity principle in the DEA method, which requires a non-erratic relationship between inputs and outputs, i.e., an increase in input does not result in the decrease of output (Xie and Huang, 2014). In particular, the desirable outputs (Job-Yr and EGen) present a strong correlation with inputs and also with the undesirable outputs, with correlation coefficients in the range from 0.771 to 0.990.

	FDP	TLOP	WDP	ACOE	GWP100	HTP	ODP	Job-Yr	EGen
FDP	1.000								
TLOP	0.908	1.000							
WDP	0.676	0.660	1.000						
ACOE	0.795	0.816	0.927	1.000					
GWP100	0.997	0.891	0.665	0.773	1.000				
HTP	0.957	0.917	0.775	0.872	0.961	1.000			
ODP	0.437	0.460	0.940	0.855	0.415	0.560	1.000		
Job-Yr	0.795	0.811	0.930	0.986	0.772	0.848	0.862	1.000	
EGen	0.790	0.797	0.963	0.990	0.771	0.860	0.884	0.991	1.000

*All the values are different from 0 with a significance level alpha=0.05

Fig. 3.4. Pearson correlation coefficient of input and output variables. The inputs are marked in blue, the undesirable outputs in grey and the desirable outputs in yellow.

With the DMU representation at hand, the next step consists in selecting an appropriate DEA model. Since the original model was proposed, DEA has been modified and adapted to new requirements. Some of the DEA features that can be selected to best represent the characteristics of the case study concern the returns to scale (Färe et al., 2008; Zhou et al., 2008b) or the orientation point of view -which, in environment and energy studies, principally consist in output, undesirable output and input-oriented measures- (Zhou et al., 2008a). According to the efficiency measure, the most used in the environment and energy studies are the *Radial*, *Non-Radial*, *Slacks-based*, *Hyperbolic* and *Directional distance function* (Zhou et al., 2008a). Specifically, there are two interlinked aspects which play a very important role on the selection of a particular DEA model: (i) the classification of outputs as desirable or undesirable; and (ii) the separability or non-separability property of the inputs and outputs. Different ways of proceeding when there are undesirable outputs in the model have been thoroughly described in the literature (Liu et al., 2010). Some examples of these procedures are the transformation proposed by Koopmans (Koopmans, 1951) to convert undesirable outputs into desirable, and the linear transformation for undesirable factors introduced by Seiford and Zhu (Seiford and Zhu, 2002). Unfortunately, the data transformed can produce unexpected untoward results, deforming the efficient frontier (Liu and Sharp, 1999). Other methods comprise the use of the extended *Slack-based* measure of efficiency (Cooper et al., 2007) that includes undesirable outputs and takes into account the input and output slacks to produce the efficiency measure, the *Hyperbolic* efficiency measure (Färe et al., 2008), which increases the desirable output while decreasing the undesirable outputs, and the *Directional distance function* efficiency measure (Chung et al., 1997) that expands the desirable outputs while reducing the inputs and undesirable outputs considering a direction vector.

On the other hand, other approaches avoid the use of intricate efficiency measures or data transformation by shifting undesirable outputs as inputs (Cooper et al., 2007; Liu et al., 2010). This approach is largely used in energy and environment modelling mainly by the simplicity and its application in traditional DEA models, but it requires undesirable and desirable outputs to be separable, which might not always be the case (Cooper et al., 2007; Ray, 2004). For example, in a coal plant, the carbon consumed (input) will be non-separable from the CO_2 released (undesirable output) or the electricity generated (desired output), being the latter ones 'joint' outputs. In our case study, we consider that the undesirable outputs are separable from the desirable ones because our system is based on the electricity portfolio of a nation comprising a wide variety of technologies (see table 3.2). For example, we can generate electricity (desirable output) almost without producing GWP (undesirable output) if we rely on hydropower, thus evidencing the separability between desirable and undesirable outputs. Therefore, due to the properties of the data we analyze, we proceed to treat the undesirable outputs as inputs (Beltrán-Esteve et al., 2014; Dakpo et al., 2014; Li et al., 2016; Liu et al., 2010; Sueyoshi et al., 2017; Yin et al., 2014).

The final number of inputs and outputs satisfy the rule of thumb ensuring a minimum discriminatory power in the DEA results. Specifically, there are $|I|$ DMUs, with $|Z|$ inputs and $|Y|$ outputs, satisfying that:

$$|I| \geq \max\left(3\left(|Z|+|Y|\right), |Z|\cdot|Y|\right) \tag{3.2}$$

Given these data, DEA determines an efficiency score (θ) for each DMU, expressed as the weighted sum of outputs divided by weighted sum of inputs. The efficiency score (θ) is evaluated by optimizing the weights attached to every input and output. In mathematical terms, the problem is described as follows. We consider a set I of $|I|$ DMUs i (i=1,…, $|I|$), each one consuming $|Z|$ inputs χ_{zi} (z=1,…, $|Z|$) to produce $|Y|$ outputs ψ_{yi} (y=1,…, $|Y|$). To calculate the efficiency scores and obtain the improvement targets for the inefficient ones, we apply the *Variable Returns-to-Scale* (VRS) model. The choice of a VRS model is motivated by the fact that electricity technologies are affected by economies of scale. Specifically, we use the following input-oriented dual model, inspired in the original BCC model (Cooper et al., 2011), which considers a non-discretionary output set (*ND*):

$$\gamma_o = \min \theta_o - \varepsilon \left(\sum_{y \in Y \setminus ND} S_y^+ + \sum_{z \in Z} S_z^- \right) \tag{3.3}$$

$$\text{s.t.} \quad \sum_{i \in I} \lambda_i \chi_{zi} + S_z^- = \theta_o \chi_{zo} \qquad \forall z \in Z \tag{3.4}$$

$$\sum_{i \in I} \lambda_i \psi_{yi} - S_y^+ = \psi_{yo} \qquad \forall y \in Y \setminus ND \tag{3.5}$$

$$\sum_{i \in I} \lambda_i \psi_{yi} \geq \psi_{yo} \qquad \forall y \in ND \tag{3.6}$$

$$\sum_{i \in I} \lambda_i = 1 \tag{3.7}$$

$$\lambda_i, S_z^-, S_y^+ \geq 0 \qquad \forall i \in I, \forall z \in Z, \forall y \in Y \tag{3.8}$$

Here, θ_o is the relative efficiency of the DMU analyzed, which can take values from zero (worst value) to one (efficient); ε is a non-Archimedean parameter used to enforce the strict positively of the variables, S^-_z and S^+_y are slack variables for input z and output y, respectively, *ND* is the subset of non-discretionary outputs and λ_i is the linear weight assigned to each DMU i in order to create a convex combination of peers used to project the inefficient units onto the efficient frontier. A country will be deemed inefficient if there is another country generating higher output and simultaneously showing less inputs.

Then, the improvement targets (reduction for inputs, $\tau_{zi'}$, and increments for outputs, $\delta_{yi'}$) required for the inefficient DMUs i' to become efficient are obtained as the difference between their original inputs and outputs and the values achieved when they are projected onto the efficient frontier (see eqs. (3.9)-(3.10)). Note that the projection for an inefficient unit i' is given by its reference set $RS_{i'}$ (efficient units i for which the linear coefficient in the projection are strictly positive $\lambda^*_i > 0$).

$$\tau_{zi'} = \chi_{zi'} - \sum_{i \in RS_{i'}} \lambda_i^* \chi_{zi} = \chi_{zi'} - (\theta_{i'}^* \chi_{zi'} - S_z^{-*}) \qquad \forall z \in Z, \forall i' \mid \theta_{i'}^* < 1 \tag{3.9}$$

$$\delta_{yi'} = \sum_{i \in RS_{i'}} \lambda_i^* \psi_{yi} - \psi_{yi'} = S_y^{+*} \qquad \forall y \in Y \setminus ND, \forall i' \mid \theta_{i'}^* < 1 \tag{3.10}$$

Here, λ^*_i are the weights assigned to DMU i in the reference set of i' ($RS_{i'}$), $\theta^*_{i'}$ is the efficiency score of DMU i' and S_z^{-*} and S^{+*}_y are the slack variables. When

$\theta^*=1$ and $S_z^{-*}=0$, $S^{+*}_y=0$, the DMU is considered to be strongly efficient. On the other hand, if $\theta^*=1$ and $S_z^{-*}\neq 0$ or $S^{+*}_y\neq 0$, the DMU is considered to be weakly efficient. Note that in eq. (3.10) the output that belongs to the *ND* subset is not included.

The VRS model shown above is called BCC (*Banker-Charnes-Cooper*) (Cooper et al., 2007), and creates an efficient frontier given by the convex hull of efficient DMUs. These linear segments with concave characteristics guarantee the VRS proprieties of the frontier. In the example shown in fig. 3.5, the segments in blue and green form the VRS frontier (i.e., segments $\overline{AB}$, $\overline{BD}$ and $\overline{DE}$).

Three differentiated regions can be distinguished in the VRS frontier: the *Increasing Returns-to-Scale* (IRS), defined by segment $\overline{AB}$; the *Constant Returns-to-Scale* (CRS), given by segment $\overline{BD}$; and the *Decreasing Returns-to-Scale* (DRS), corresponding to segment $\overline{DE}$. If a DMU is located in the IRS zone, it can increase its output by a larger proportion than the input increment. On the other hand, if the DMU is in the DRS zone, the opposite happens: a decrease in the output provides a larger decrease in the input.

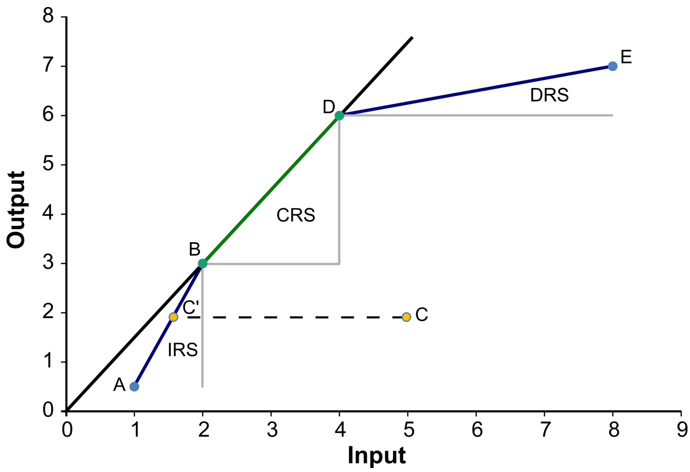


Fig. 3.5. Example of VRS, CRS and NIRS models.

To determine where a DMUs lies (DRS, CRS or IRS zone), we combine the results of the VRS, CRS and NIRS (Non-Increasing Returns-to-Scale) models. In the CRS model, it is assumed that the ratio outputs to inputs is independent of the level of inputs. The CRS model is essentially the same as the VRS model, but the latter includes eq. (3.7) that is omitted in the former. In fig. 3.5, the ray that goes from the origin through points B and D is the CRS efficient frontier.

Conversely, in the NIRS model the output to input ratio of the DMUs in the efficient frontier does not increase with the input values. This model is obtained by replacing eq. (3.7) in the VRS formulation by eq. (3.11). The resulting NIRS frontier is given by the segments from the origin to DMU B ($\overline{OB}$), $\overline{BD}$, and $\overline{DE}$.

$$\sum_{i \in I} \lambda_i \leq 1 \tag{3.11}$$

By comparing the efficiency scores obtained with the three models (i.e., VRS, CRS and NIRS), it is possible to determine the zone where a DMU lies. In this example (fig. 3.5), the green segment, $\overline{BD}$ is shared by the three models CRS, NIRS and VRS. Therefore, DMUs B and D are efficient ($\theta^*=1$) in the three models. On the other hand, DMU E is efficient ($\theta^*=1$) in the VRS and NIRS models, but inefficient in the CRS one ($\theta^*<1$), since it is located in the DRS zone. DMU A lies in the IRS zone, which is part of the efficient frontier ($\theta^*=1$) in the VRS zone, but it is inefficient ($\theta^*<1$) in the CRS and NIRS models. DMU C, inefficient in all of the models ($\theta^*<1$), belongs to the IRS zone (assuming we apply an input-oriented projection).

Note that in the proposed methodology the VRS model is applied twice (see fig. 3.1): firstly, to assess the efficiency of the *Current* electricity mixes of the EU countries (step 1), and finally to re-evaluate the efficiency of the *Optimized* portfolio obtained by the EffMixF model (step 3).

3.2.3. Step 2: New *Optimized* mix using EffMixF

The standard DEA provides specific improvement targets for inefficient DMUs which, if attained, would make the DMU efficient. However, these targets, obtained using a particular projection (e.g., input or output-oriented radial projection, minimum distance, etc.), just reflect one possible pathway to attain the efficient status. Furthermore, such targets may be unrealistic, since they omit technical constraints.

In this step, we determine a new electricity mix for those countries found inefficient in step 1. To obtain such new portfolios for the EU countries, we formulate an auxiliary model named EffMixF, ensuring that the new mix is feasible while at the same time lies as close as possible to the facet of the efficient frontier defined by its reference set. By allowing the DMU to get projected onto a facet of the efficient frontier rather than onto a specific point, we provide more flexibility for inefficient countries to become efficient.

In fig. 3.6 we illustrate the basics of the EffMixF method for a hypothetical DMU A in a two inputs and a constant dummy output case. When the input-oriented BCC model is used (steps 1 and 3), the inefficient DMU A is projected into the point A' of the efficient frontier. This point is located in the intersection between the radial projection $\overline{AO}$ and the reference facet (i.e., the facet of the efficient frontier defined by the reference set of DMU A). On the other hand, when using the EffMixF model (step 2 of our framework), the DMU A can be projected to any other point of the reference facet provided that the non-worsening constraint is fulfilled (i.e., enforcing that the original value of inputs and outputs do not worsen in the projection, eqs. (3.19)-(3.20)), region shaded in green. Furthermore, EffMixF ensures a feasible solution by identifying a feasible point (point B in the figure), even in the case an inefficient DMU cannot reach the reference facet in light of the technical constraints. This is achieved by minimizing the remaining distance to the reference facet, defined by the slacks $S^N{}_1$ and $S^N{}_2$ (distance between points B and B').

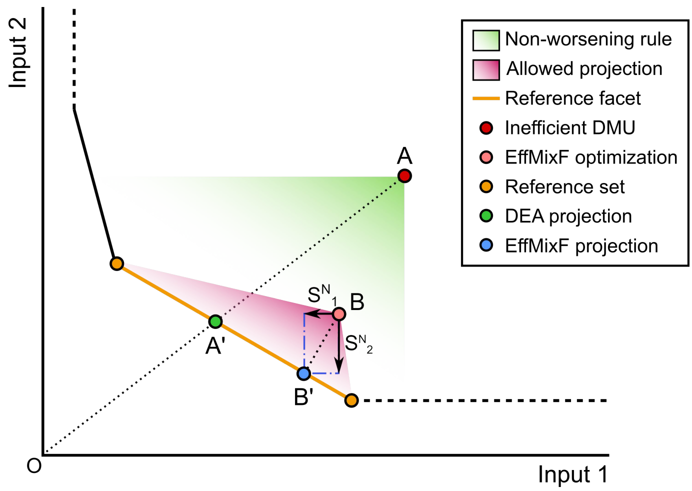


Fig. 3.6. Example for two inputs and a dummy output for the EffMixF and DEA model projections.

This model, defined by eqs. (3.12)-(3.24), considers the main technical aspects related with electricity systems. The model is individually formulated for each inefficient country i (note that in step 1, inefficient countries are indexed by i' to differentiate them from the others). Therefore, the equations of the model are applied to one country at a time, yet we have kept subscript i in the parameters and variables to indicate the country studied in each case (in the same spirit as we do with subscript o for the DMU being analyzed in DEA). This model contains two main sets of equations: (i) those related with electricity generation; and (ii) those related with the DEA targets we aim to achieve.

3.2.3.1. Electricity generation

The total electricity generated ($EGen_i$) within each country i has to be kept constant (i.e., the same amount of electricity as in the current situation needs to be ensured). To enforce this condition, we use an electricity mix combining standard (Mix_{ij}^{ST}) and back-up (Mix_{ij}^{BU}) generation with the available technologies j, as indicated by eq. (3.12).

$$\sum_j \left(Mix_{ij}^{ST} + Mix_{ij}^{BU} \right) = EGen_i \tag{3.12}$$

Note that we do not consider electricity trade between countries, since we aim to improve the efficiency of the electricity generated rather than consumed within each EU country, i.e., we are performing a production-based study.

The reliability of the supply is ensured by firm technologies, also called dispatchable sources of electricity (DP), such as *Nuclear*, *Natural Gas*, *Coal*, *Oil*, *Geothermal* or *Biomass and Renewable wastes* (see table 3.2). We use the back-up parameter (BUP) to indicate the capacity of dispatchable sources required to back-up each unit of non-dispatchable installed in the mix (see table 3.2), as shown in eq.(3.13). In the literature, reported values for the BUP oscillate from 15-100% of the non-dispatchable installed capacity (Gross et al., 2006; Heuberger et al., 2016). In this contribution, we use an intermediate value of 50%.

$$\sum_{j \in DP} Cap_{ij}^{BU} \geq BUP \sum_{j \notin DP} Cap_{ij}^{ST} \tag{3.13}$$

Here, Cap_{ij}^{ST} and Cap_{ij}^{BU} are the capacities installed for technologies acting as standard and back-up, respectively. Note that only the dispatchable technologies can participate as back-up sources:

$$Cap_{ij}^{BU} = 0 \qquad \forall j \notin DP \tag{3.14}$$

The amount of electricity generated for both standard and back-up purposes (Mix_{ij}^{ST} and Mix_{ij}^{BU}) are given by the product between the corresponding installed capacities (Cap_{ij}^{ST} and Cap_{ij}^{BU}, respectively) the capacity factor (Cf_{ij}) and the total number of hours in a year (H).

$$Mix_{ij}^{ST} = Cap_{ij}^{ST} Cf_{ij} H \qquad \forall j \tag{3.15}$$

$$Mix_{ij}^{BU} = Cap_{ij}^{BU} Cf_{ij} H \qquad \forall j \tag{3.16}$$

Furthermore, we take into account the available potential (PT_{ij}) for electricity generation of each renewable technology included in the set RP (i.e., all renewable technologies, except *Biomass and renewable wastes,* as discussed in section 3.2.1.1). This prevents unrealistic solutions where electricity generation from these sources surpasses the environment limits dictated by the hydrography, orography and climate characteristics of each country (eq. (3.17)).

$$Mix_{ij}^{ST} + Mix_{ij}^{BU} \leq PT_{ij} \qquad \forall j \in RP \tag{3.17}$$

We also impose that the amount of electricity produced by *Nuclear* technology cannot be higher than the current one (Mix_{ij}^{2015}) (eq. (3.18)). This assumption is consistent with the nuclear energy policy reversal of some western Europe countries such as Austria, Belgium, Germany, Italy, Switzerland, Sweden and Spain (Müller and Thurner, 2017), as well as with the acceleration of the nuclear phase-out policies in some of the European countries (NEA and OECD, 2017).

$$Mix_{ij}^{ST} + Mix_{ij}^{BU} \leq Mix_{ij}^{2015} \qquad j = NCL \tag{3.18}$$

3.2.3.2. DEA targets

In this section, we describe the equations used to link the electricity mixes within each country with the DEA targets obtained from step 1 of the methodology. Firstly, we force inputs and outputs (left-hand side of the equations) to be equal or better than the original ones (Inp_{iz} and Out_{iy}):

$$\sum_j \left(CT_{ijz}^{INP} \left(Mix_{ij}^{ST} + Mix_{ij}^{BU} \right) \right) \leq Inp_{iz} \ \forall z \tag{3.19}$$

$$\sum_j \left(CT_{ijy}^{OUT} \left(Mix_{ij}^{ST} + Mix_{ij}^{BU} \right) \right) \geq Out_{iy} \ \forall y \setminus ND \tag{3.20}$$

where CT_{ijz}^{INP} and CT_{ijy}^{OUT} are the inputs (z) and outputs (y) coefficients for country i and technology j.

For consistency with section 3.2.1.1, $c = z \cup y$ and $AInd_{ic} = Inp_{iz} \cup Out_{iy}$. The target in the *ND* output is not enforced (see eq. (3.20)) since it is already imposed via eq. (3.12) which fixes the total electricity generated.

Eqs. (3.21)-(3.23) provide the distance (slacks S_{iz}^{N} and S_{iy}^{P}) between the facet of the efficient frontier, defined by the reference set of the country being analyzed (left-hand side of the equations), and the inputs and outputs achieved with the new *Optimized* electricity mix (right-hand side) (see fig. 3.6):

$$\sum_{i' \in RS_i} \left(\lambda_{i'} Inp_{i'z} \right) + S_{iz}^{N} = \sum_{j} \left(CT_{ijz}^{INP} \left(Mix_{ij}^{ST} + Mix_{ij}^{BU} \right) \right) \quad \forall z \tag{3.21}$$

$$\sum_{i' \in RS_i} \left(\lambda_{i'} Out_{i'y} \right) - S_{iy}^{P} = \sum_{j} \left(CT_{ijy}^{OUT} \left(Mix_{ij}^{ST} + Mix_{ij}^{BU} \right) \right) \forall y \setminus ND \tag{3.22}$$

$$\sum_{i' \in RS_i} \lambda_{i'} = 1 \tag{3.23}$$

where $\lambda_{i'}$ is the linear coefficient for countries i' belonging to the reference set of country i (RS_i), and S_{iz}^{N} and S_{iy}^{P} are the input (z) and output (y) slacks for country i. Note that the linear coefficients in eqs. (3.21)-(3.23) might differ from those calculated by the DEA model in step 1. These linear coefficients, which are positive values between zero and one, define the point in the efficient facet where the projected mix will either lie (all slacks are zero) or attempt to lie (some slacks will be greater than zero). Furthermore, slack variables ensure the feasibility of all models, even when the target facet cannot be attained due to the need to satisfy all the technical constraints defined in eqs. (3.12)-(3.18) (see fig. 3.6).

Finally, we present the overall model that seeks for each country a solution that satisfies the physical constrains related with the electricity supply while, at the same time, approaching as much as possible to the facet of the efficient frontier provided by the original DEA.

$$\text{minimize} \qquad ObjFun_i = \sum_{z} (S_{iz}^{N} / Inp_{iz}) + \sum_{y} (S_{iy}^{P} / Out_{iy}) \tag{3.24}$$

$$s.t. \qquad Eqs.\ 12\text{-}23$$

$$Mix_{ij}^{ST}, Mix_{ij}^{BU}, Cap_{ij}^{ST}, Cap_{ij}^{BU}, S_{iz}^{N}, S_{iy}^{P}, \lambda_i \geq 0 \qquad \forall y, z, j$$

Note that, in the objective function, slacks are normalized using the *Current* values of inputs and outputs.

3.3. Results and discussion

We divide this section in three main parts. Firstly, we show the results from the DEA application to the *Current* electricity portfolios, determining the efficiency of the EU countries and their improvement targets (step 1). In the second part, we present the new EU electricity mixes obtained for the inefficient countries by solving model EffMixF and analyze the improvements they attain with respect to the *Current* case (step 2). Finally, we assess the efficiency gains achieved by the *Optimized* electricity mixes (step 3).

3.3.1. Step 1: *Current* EU electricity mixes

We first calculate the efficiency of the EU member countries for 2015 using the VRS DEA method (step 1) and considering the indicators provided in table 3.3. These efficiencies are presented in fig. 3.7, and range from 0.85 to one. Of the 28 countries analyzed, 20 were found efficient (θ^*=1, dark green in the figure) and eight inefficient (θ^*<1, remaining colors). Among the latter, Lithuania has the lowest efficiency (θ^*=0.86), followed by Finland (θ^*=0.91) and Latvia (θ^*=0.92).

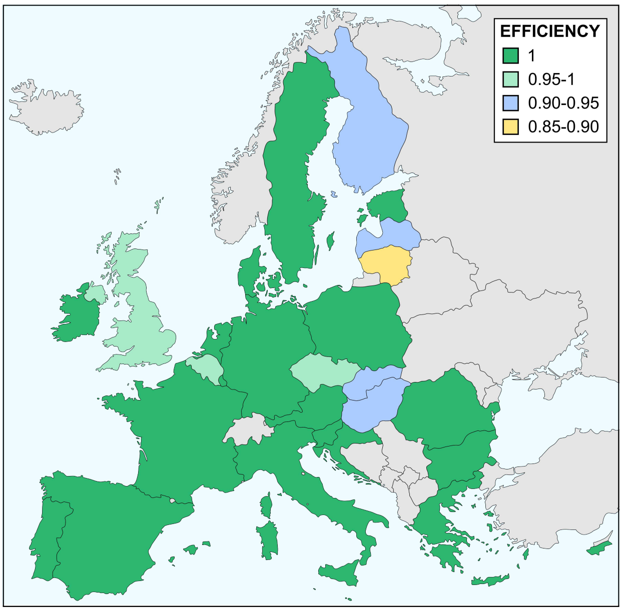


Fig. 3.7. Efficiencies of the 28 EU countries using the VRS DEA model.

In order to determine the sources of inefficiency of these countries, we study the improvement percentages required in each indicator to make them efficient (see fig. 3.8). Note that the output *EGen* is not included in the improvement percentage figures of the results section (figs. 3.8 and 3.12) because we enforce it to remain unchanged (eq. (3.12)).

In Lithuania, reductions are required in all the inputs. The largest improvements are needed in the ODP (54%), FDP (54%), GWP (47%) and TLOP (24%) categories, while the rest of inputs require reductions of 14%. This country also needs to increase its Job-Yr (19%) to become strongly efficient. This poor performance is mainly given by two factors: (i) the large share of *Natural Gas* (43%), which is the 3rd worst technology in terms of ODP, FDP and GWP compared to the others, and which shows in turn a low employment rate; and (ii) the share of *Biomass and Renewable wastes* (10%), the worst technology in the TLOP category, with an impact around nine times the average unitary impact in this category across technologies.

Reductions in all the inputs are also required in Finland, particularly in TLOP (51%), HTP (34%) and ODP (33%). These impacts are mainly caused by two factors: (i) the large share of *Biomass and Renewable wastes* (17%, being the EU member country with the largest share in this technology), which is the worst technology in the TLOP and HTP indicators; and (ii) the large share of *Nuclear* (34%), the 2nd worst technology in ODP.

In the case of Latvia, ODP (44%), TLOP (38%) and FDP (34%) are the inputs requiring the highest reductions, while the Job-Yr generated also needs to be improved (15%) to become strongly efficient. As happened in Lithuania, this is the consequence of deploying an electricity mix with a strong dependence on (i) *Natural Gas* (50%) and (ii) *Biomass and Renewable wastes* (14%).

	BE	CZ	FI	GB	HU	LT	LV	SK
TLOP	34%	2%	51%	13%	49%	24%	38%	34%
GWP100	4%	32%	9%	1%	6%	47%	16%	20%
FDP	23%	20%	10%	3%	16%	54%	34%	15%
HTP	4%	47%	34%	28%	12%	14%	8%	32%
ODP	4%	2%	33%	1%	26%	54%	44%	14%
WDP	4%	20%	9%	7%	6%	14%	8%	8%
LCOE	4%	2%	9%	18%	6%	14%	8%	8%
Job-Yr	2%	12%	1%	24%	10%	19%	15%	0%

Fig. 3.8. Improvement percentage required for each inefficient country to become efficient considering its *Current* mix using the VRS DEA model.

Remarkably, there are other inefficient countries showing strong targets but attaining higher efficiency levels than the three analyzed above. This happens in Czech Republic, which requires a reduction of 47% in HTP, 32% in GWP, 20% in FDP and WDP, and an increase of 12% in the employment indicator. However, this country only requires an improvement of 2% in TLOP, ODP and ACOE, a value significantly below the minimum targets required in the previous three countries (Lithuania, Finland and Latvia, with all their targets above 8%).

To obtain further insight on the efficiency assessment, we solve the CRS and NIRS models (see section 3.2.2). We find 16 counties which are efficient in the three models, thereby lying in the CRS region. In fig. 3.9 we show the remaining countries (i.e., $\theta < 1$ at least for one of these models), as well as their efficiencies in the VRS method. The efficiency scores obtained in three of these countries (Belgium, Latvia and Lithuania) are the same in the three models, indicating that they are also situated in the CRS (constant returns to scale) zone. Four of the countries (Czech Republic, Estonia, Hungary and Slovakia) are located in the IRS (increasing returns to scale) zone, while the remaining five (Spain, Finland, United Kingdom, Italy and Portugal) belong to the DRS (decreasing returns to scale) zone. Furthermore, it can be seen how four of the efficient countries in the VRS (Estonia, Spain, Italy and Portugal) are not efficient in the CRS, whereas the remaining eight countries are inefficient regardless of the returns-to-scale model applied. Note that the VRS efficiencies are higher than the CRS ones. This happens because the VRS takes into account the economies of scale, and therefore the variation in inputs does not necessarily result in the same percentage change in outputs. Note that larger differences between efficiencies in the different models indicate further distances from the CRS zone. In this case, the largest differences are observed in United Kingdom, Italy and Spain.

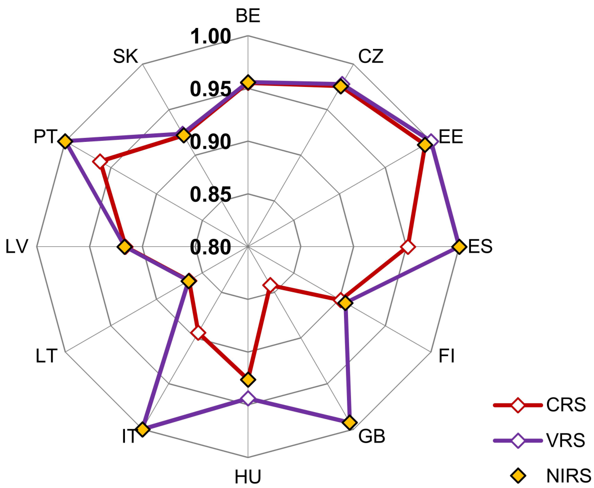


Fig. 3.9. Difference in efficiencies between VRS, CRS and NIRS for the *Current* mixes.

Additionally, the VRS DEA provides the linear coefficients of the reference set defining the radial projection of inefficient countries onto the efficient frontier (fig. 3.10). Remarkably, only nine out of the 20 efficient countries appear in the reference set of the inefficient countries; these include: Austria, Belgium, Germany, Denmark, Estonia, France, Luxemburg, Netherlands, and Sweden. The most likely reason for this is that the mix of the remaining efficient countries differs quite significantly from those of the inefficient ones. On the other hand, the countries that are most highly used as peers are France and Denmark (eight and six countries, respectively), very likely because they deploy similar portfolios as those in the inefficient countries. Note that these linear coefficients can lead to unrealistic projections, as they overlook the actual potential for electricity generation within countries, e.g., a country cannot deploy *Hydropower* technology in absence of mighty rivers. This limitation is overcome here by posing and solving the EffMixF model, which considers the main technical aspects of the electricity supply problem, ensuring the feasibility of the suggested portfolios.

Inefficient Countries

Reference Countries	BE	CZ	FI	GB	HU	LT	LV	SK
AT	9%					1%	1%	
BG		4%						
DE		8%	1%	37%				0%
DK	38%		84%		5%	4%	7%	14%
EE		84%			80%			
FR	5%	4%	3%	0%	4%	0%	0%	3%
LU	32%				11%	95%	92%	83%
NL	9%							
SE	8%		11%	63%				

Fig. 3.10. Reference set linear coefficients of the inefficient countries in the EU using the VRS DEA model.

3.3.2. Step 2: *Optimized* EU electricity mixes

In this section, we propose new electricity mixes for the inefficient countries identified in section 3.3.1 by solving the facet projection model EffMixF (step 2 of the methodology, section 3.2.3).

Each new electricity mix is generated by projecting the inefficient country onto an efficient facet. Note that the facet is defined by the reference set of the inefficient country under study, yet the projection might not imply the same linear coefficient values provided by the standard DEA. In fig. 3.11 we present the *Current* and *Optimized* mixes for each inefficient country, indicating the total amount of electricity generated within the country on the top of the bars.

None of the inefficient countries is able to achieve the associated efficient facet ($ObjFun_i > 0 \ \forall i$), yet a new electricity mix improving the original portfolio is obtained in all the cases (see section 3.3.3). Hence, our results clearly highlight the need to incorporate additional constraints in DEA models applied to electric power systems, as otherwise the improvement targets might be unrealistic.

An overall analysis of the new electricity mixes reveals that the non-renewable electricity sources still constitute the largest share of the portfolio (average of 61%), despite being displaced to some extent by renewable sources (9% with respect to the total electricity production). In particular, the use of non-renewable sources is reduced in countries such as Lithuania (by 18%, from 49% to 31%), Latvia (15%) and Finland (13%), while it remains almost unchanged in Czech Republic (1%) and United Kingdom (4%). The next sub-sections describe in detail the most significant changes required in the mixes of the inefficient countries.

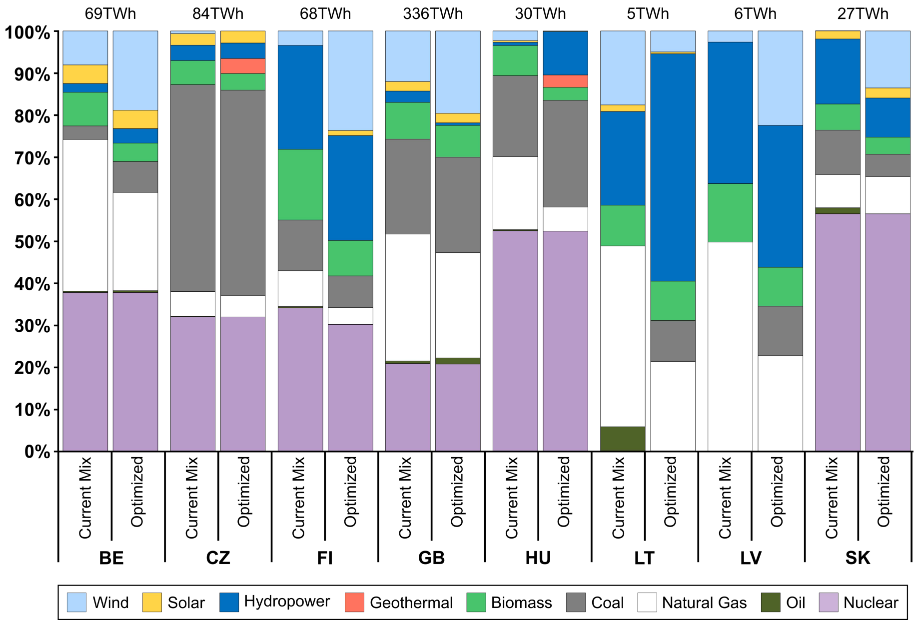


Fig. 3.11. *Current* and *Optimized* electricity mixes of the inefficient countries.

3.3.2.1. Renewable sources

There is a general tendency to slightly displace the *Biomass and Renewable Wastes* technology, with an average reduction across inefficient countries of 4% (with respect to the total electricity generation) without taking into account Lithuania, where it remains the same. The largest reductions in that technology are found in Finland (8%), Latvia (5%) and Hungary (4%). This happens because these countries need to reduce their TLOP and HTP impacts, being *Biomass and Renewable Wastes* the technology contributing the most towards both indicators.

As a general trend, the *Geothermal* and *Hydropower* electricity sources increase their share in the electricity portfolios. Specifically, *Geothermal* is increased in Czech Republic and Hungary (4% and 3%, respectively). On the other hand, *Hydropower* increases a 1% in Belgium and a 10% in Hungary, with the highest increment occurring in Lithuania (32%), where it becomes the dominant source of power. In contrast, Slovakia and United Kingdom diminish their *Hydropower* contribution by 2% and 6%, respectively, while Latvia, Czech Republic and Finland keep it almost constant (increments lower than 1%).

The *Wind* and *Solar* technologies show no clear pattern. The *Wind* technology is increased in Belgium, Finland, United Kingdom, Latvia and Slovakia (14% in average) and decreased in the remaining countries. There are countries where this change is small, as in Czech Republic and Hungary, which have an average reduction of 1%. On the other hand, Lithuania is the country with the highest reduction (13%), replacing most of its *Wind* share by *Hydropower*. This happens because *Hydropower* performs better in all the indicators except for the ACOE. Furthermore, the back-up restriction (eq. (3.13)) limits the total use of non-dispatchable sources, being it necessary to swap between renewable sources to reduce the level of intermittency in the power generation system, i.e., enforcing the reduction of *Wind* to leave room for *Hydropower*. The changes in the *Solar* electricity production mixes are below 2% in all the cases.

3.3.2.2. Non-renewable sources

The trends in the non-renewable sources are not as clear as in the renewable ones, being boosted in some countries and displaced in others. This happens because non-renewable sources are highly used (i.e., 70% in average of the inefficient countries in the *Current* mix) and therefore they are more likely to be affected by DEA targets. Hence, depending on the improvement needed in each country, their proportions within the electricity mix will change in order to attain the sustainability requirements of each of them.

Natural Gas is reduced in all of the countries except for Slovakia, where it is increased to 1% in the new *Optimized* portfolio. Specifically, the highest reductions of *Natural Gas* occur in Latvia (27%, from a 50% of the share in the *Current* mix to 23% in the *Optimized* one), Lithuania (22%) and Belgium (13%). This is motivated by the improvement required in the FDP impact (34% Latvia, 54% Lithuania and 23% Belgium), in which *Natural Gas* plays a key role (3rd worst technology).

The electricity production with *Oil* already represented a marginal fraction of the original electricity mix of the inefficient countries (1% on average). In the new *Optimized* mixes, it is further displaced down, with the highest reductions found in Lithuania (6%) and Slovakia (1%). On the other hand, there is a 1% increment of *Oil* in the electricity mix of the United Kingdom, where *Oil* partially replaces *Natural Gas*. This increment is explained by the *Oil* capacity factor, which is slightly greater than that of *Natural Gas*.

Coal electricity production presents no clear pattern. This technology is one of the worst in all the inputs except for ACOE (where it is the best) and ODP (the 2nd best dispatchable and the best non-renewable source). This makes it the preferred alternative to backup intermittent renewable sources when improvements on ACOE or ODP indicators are required. The highest reduction in the share of *Coal* occurs in Slovakia (5%), while the highest increment takes place in Latvia (12%), where *Coal* allows to mitigate the impact on ODP (this country needs a reduction of 44% in such impact).

Regarding *Nuclear* electricity, only Finland reduces its use by 4% (from 34% in the *Current* mix to 30% in the *Optimized* one), whilst the rest of countries remain the same; this is due to eq. (3.18) that forces the amount of nuclear-based electricity to be at most equal to the current value (see section 3.2.3).

3.3.2.3. Optimized electricity mixes improvements

We next show the improvements achieved in inputs and outputs by the *Optimized* electricity mixes of the inefficient countries (fig. 3.12). Note that these improvements may differ from the targets obtained in step 1, as here the inefficient DMUs are allowed to get projected onto any point in the facet defined by their peers. Furthermore, the inefficient DMUs might be unable to reach the facet, thereby activating the slacks and showing lower improvements in some indicators.

In general, the countries with lower efficiencies are the ones that more changes present. This is the case of Lithuania or Finland, with efficiencies in the *Current* Mix of 0.86 and 0.91, respectively, which show reductions in some attributes above 50%. Conversely, other countries such as Czech Republic or United Kingdom with higher efficiencies in the *Current* Mix (0.98 and 0.99, respectively) show reductions always below 30%.

Another factor to highlight is that some of the reductions attained in the *Optimized* solution are higher than those required in step 1 (underlined cells in fig. 3.12). In other words, there are countries which clearly exceed the requirements in some indicators, but invest much less efforts in improving others. This is for example the case of Hungary, which “over-improves” its impact on TLOP at the expense of more modest (and in some cases insufficient) improvements in other indicators.

	BE	CZ	FI	GB	HU	LT	LV	SK
TLOP	<u>44%</u>	<u>28%</u>	50%	<u>13%</u>	<u>55%</u>	3%	32%	34%
GWP100	0%	1%	<u>41%</u>	<u>1%</u>	0%	40%	2%	<u>35%</u>
FDP	11%	2%	<u>43%</u>	<u>3%</u>	11%	49%	23%	<u>32%</u>
HTP	<u>20%</u>	5%	<u>40%</u>	3%	11%	0%	0%	<u>33%</u>
ODP	<u>11%</u>	<u>6%</u>	31%	0%	24%	<u>62%</u>	<u>49%</u>	4%
WDP	4%	1%	<u>23%</u>	3%	2%	<u>29%</u>	<u>16%</u>	6%
LCOE	0%	1%	4%	0%	3%	6%	4%	6%
Job-Yr	<u>3%</u>	3%	<u>7%</u>	0%	9%	<u>19%</u>	4%	0%

Fig. 3.12. Input and output improvements attained by the *Optimized* electricity mixes with respect to the *Current* mixes of inefficient countries. Percentage reductions higher than required are underlined.

3.3.3. Step 3: *Current* and *Optimized* electricity mixes efficiency

We finally use DEA once more to assess the 28 EU countries (step 3) using the *Current* mixes for countries found efficient in step 1 and the *Optimized* mixes (step 2) for the inefficient ones. We find that all the countries originally deemed inefficient improve their efficiencies (fig. 3.13), with three of them moving from inefficient to weakly efficient (i.e., their efficiency is one, yet they present slack values greater than zero). Hence, out of eight inefficient countries, only three are able to reach the facet defined by their peers, while five are not.

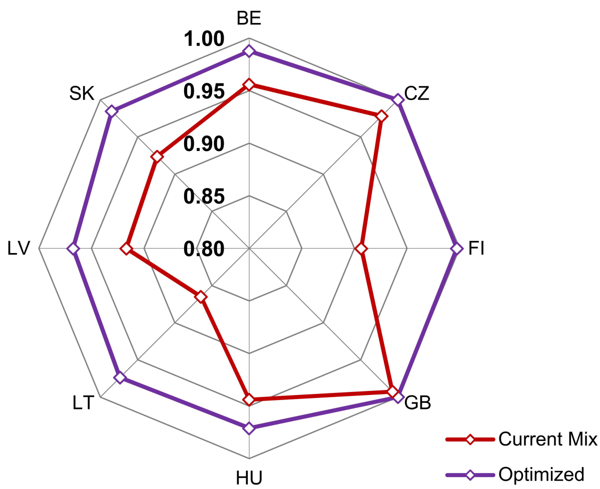


Fig. 3.13. Radar plot comparing the efficiency of the *Current* and *Optimized* mixes for countries originally deemed inefficient.

The countries that improve their efficiencies the most are Lithuania and Finland (increments of 0.11 and 0.09 in efficiency scores, respectively). Lithuania enhances all its indicators except HTP, with the highest abatements occurring in the ODP (62%), FDP (49%) and GWP (40%) indicators. Finland, improves in all its indicators, being these above 40% in four of them (TLOP, GWP, FDP and HTP). Some of the largest reductions in the indicators listed above are higher than the ones calculated with DEA in step 1 (see underlined values in fig. 3.12).

The efficiencies of Czech Republic, United Kingdom and Hungary are the ones that change the least. In the case of Czech Republic and United Kingdom, the countries already have high efficiency scores in the *Current* mix (0.98 and 0.99, respectively), leaving in many cases little room for the improvement of some impacts without worsening others (a requirement imposed in our model via eqs. (3.19)-(3.20)). On the other hand, Hungary does not achieve the large reductions demanded by the original DEA, despite improving its indicators almost proportionally to such requirements. In this case, *Solar* is the limiting technology as it reaches the total potential of Hungary. This technology has the best performance in the Job-Yr indicator, which requires an improvement of 10% in Hungary (see fig. 3.8).

3.4. Conclusions

Electricity production is one of the most important sectors in any economy, playing a crucial role in the climate change mitigation. In this contribution, we assessed the current sustainability efficiency of the electricity mixes of the 28 EU members, providing a roadmap towards higher efficiency based on changes in their portfolios. To this end, we integrated DEA with an auxiliary optimization model that considers detailed techno-economic aspects. This approach was applied to the 28 EU members in 2015 covering the three sustainability dimensions: the economic, environmental and social.

Firstly, we applied DEA to the EU countries, finding that eight are inefficient, being Lithuania, Finland and Latvia the ones with the lowest efficiency scores. Then, we solved the auxiliary optimization model named EffMixF to calculate new mixes for improving the inefficient countries. This model enhances the traditional DEA approach by providing more flexibility to the inefficient countries to become efficient. This is accomplished by projecting the inefficient countries onto a facet rather than on a single point of the efficient frontier. Furthermore, model EffMixF takes into account the main technical constraints modeling electricity generation within each country, e.g., the domestic generation potentials from renewable sources and the reliability of the supply. This prevents unrealistic solutions which can eventually arise in the standard approach, where DEA targets are not based on technical constraints.

In fact, we found that none of the inefficient countries assessed was indeed able to reach the strongly efficient frontier, evidencing that the original DEA targets were unattainable in all the cases. The reasons why the inefficient countries cannot reach the strong frontier include: (i) the limited availability of renewable sources (mainly *Hydropower*, that performs well in most of the environmental indicators); and (ii) the existence of other limiting constraints imposed in our model (e.g., Hungary cannot improve some impacts without worsening others). However, the efficiencies of the *Optimized* mixes were always above the ones of the *Current* mixes, as demonstrated by the second DEA applied, where three of the eight originally inefficient countries became weakly efficient.

As a general trend, we found that non-renewable electricity sources should be reduced an average of 9% with respect to the total electricity production (from 70% in the *Current* mix to 61% in the *Optimized* one). *Hydropower* and *Wind* should be deployed to improve the environmental performance, while *Coal* and *Solar* are preferred to improve the economic and the social performance, respectively. On the other hand, the *Biomass and Renewable Wastes* technology would need to be displaced due to its significant impact in TLOP and HTP, despite being attractive from the GWP viewpoint.

It is important to note that the efficiencies and the portfolios obtained directly depend on the indicators studied as well as the year analyzed. For example, the LCOE of the newest technologies may vary according to learning curves. Nevertheless, the framework we propose is flexible enough to accommodate other indicators and constrains, always rendering feasible and reasonable solutions.

Standard DEA determines quantitative improvement targets but fails to provide specific actions to attain them; in contrast, the proposed methodology calculates specific mixes and provides more useful insight for policy makers. Hence, our approach provides clear and attainable roadmaps indicating which technologies should be promoted to improve the sustainability efficiency. Such regulations already exist for specific technologies, like the nuclear energy policy reversal active in Austria, Belgium, Germany, Italy, Switzerland, Sweden and Spain. Therefore, our framework can help to formulate better regulations and policies in the transition towards a more sustainable energy system.

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3.6. Nomenclature

AInd	Aggregated indicator value per country
BUP	Back-up parameter
Cap	Capacity installed
Cf	Capacity factor
CT	Indicator coefficient
DP	Set of dispatchable sources of electricity
EGen	Total electricity generated
H	Hours in a year
I	Set denoting DMUs
Indicator	Unitary indicator value for country
Inp	Original input
Mix	Electricity generated
ND	Set denoting non-discretionary Outputs
ObjFun	Objective function
Out	Original output
PT	Available generation potential
RP	Set of technologies with generation potential
RS	Reference set
S	Slack variable
Y	Set denoting Outputs
Z	Set denoting Inputs

Acronym

ACOE	Annualized cost of electricity
ALOP	Agricultural land occupation potential
BCC	Banker-Charnes-Cooper
CCGT	Combined cycle gas turbine
CRS	Constant returns-to-scale
DEA	Data envelopment analysis

DMU	Decision making unit
DRS	Decreasing returns-to-scale
EU	European Union
FDP	Fossil depletion
GDP	Gross domestic product
GWP100	Climate change
HTPinf	Human toxicity
IRS	Incrasing returns-to-scale
LCOE	Levelized cost of electricity
NCL	Nuclear
NIRS	Non-increasing returns-to-scale
ODPinf	Ozone depletion
TLOP	Total land occupation potential
ULOP	Urban land occupation potential
VRS	Variable Returns-to-Scale
WDP	Water depletion

Greek letters

δ	Increment target for outputs
χ	Input of the DMU
ε	Non-Archimedean value
γ	Technical efficiency
λ	Weight assigned to a DMU
θ	Relative efficiency
τ	Reduction target for inputs
ψ	Output of the DMU

Indices

BU	Back-up
c	Indicator
i	EU country
j	Technology
o	DMU being analyzed
ST	Standard
y	Output
z	Input

3.7. References

Alberici, S., Boeve, S., Breevoort, P. Van, Deng, Y., Förster, S., Gardiner, A., van Gastel, V., Grave, K., Groenenberg, H., de Jager, D., Klaassen, E., Pouwels, W., Smith, M., de Visser, E., Winkel, T., Wouters, K., 2014. Subsidies and costs of EU energy. Final report.

AQUARET, Run-of-river. [WWW Document], 2012. URL http://www.aquaret.com/indexc744.html?option=com_content&view=article&id=82&Itemid=198&lang=en (accessed 9.26.17).

Bampatsou, C., Papadopoulos, S., Zervas, E., 2013. Technical efficiency of economic systems of EU-15 countries based on energy consumption. Energy Policy 55, 426–434. doi:10.1016/j.enpol.2012.12.021

Beltrán-Esteve, M., Gómez-Limón, J.A., Picazo-Tadeo, A.J., Reig-Martínez, E., 2014. A metafrontier directional distance function approach to assessing eco-efficiency. J. Product. Anal. 41, 69–83. doi:10.1007/s11123-012-0334-7

Bilotta, G.S., Burnside, N.G., Turley, M.D., Gray, J.C., Orr, H.G., 2016. The effects of run-of-river hydroelectric power schemes on invertebrate community composition in temperate streams and rivers. PLoS One 12. doi:10.1371/journal.pone.0171634

Cook, W.D., Seiford, L.M., 2009. Data envelopment analysis (DEA) - Thirty years on. Eur. J. Oper. Res. 192, 1–17. doi:10.1016/j.ejor.2008.01.032

Cooper, W.W., Seiford, L.M., Tone, K., 2007. Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software: Second edition, Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software: Second Edition. doi:10.1007/978-0-387-45283-8

Cooper, W.W., Seiford, L.M., Zhu, J., 2011. Data envelopment analysis: History, models, and interpretations, in: International Series in Operations Research and Management Science. pp. 1–39. doi:10.1007/978-1-4419-6151-8_1

Cristóbal, J., Limleamthong, P., Manfredi, S., Guillén-Gosálbez, G., 2016. Methodology for combined use of data envelopment analysis and life cycle assessment applied to food waste management. J. Clean. Prod. 135, 158–168. doi:10.1016/j.jclepro.2016.06.085

Chang, M.-C., Yu, C.-H., 2017. Estimation of energy productivity change in Baltic Sea and EU non-Baltic Sea states. Balt. J. Econ. 17, 78–102. doi:10.1080/1406099X.2017.1309785

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444. doi:10.1016/0377-2217(78)90138-8

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: A directional distance function approach. J. Environ. Manage. 51, 229–240. doi:10.1006/jema.1997.0146

Dakpo, K.H., Jeanneaux, P., Latruffe, L., Paper, W., Lereco, S., 2014. Inclusion of undesirable outputs in production technology modeling : The case of greenhouse gas emissions in French meat sheep farming.

Eea, 2009. Europe's onshore and offshore wind energy potential, EEA Technical report. doi:10.2800/11373

EREC, 2011. Mapping Renewable Energy Pathways towards 2020. Eur. Renew. Energy Counc. 28.

European Union, 2016. EU energy in Figures, Statistical pocketbook. doi:10.2833/03468

European Union, 2010. Europe 2020 A strategy for smart, sustainable and inclusive growth. Commun. from Comm. doi:10.1016/j.resconrec.2010.03.010

Ewertowska, A., Galán-Martín, A., Guillén-Gosálbez, G., Gavaldá, J., Jiménez, L., 2015. Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis. J. Clean. Prod. 116. doi:10.1016/j.jclepro.2015.11.100

Ewertowska, A., Pozo, C., Gavaldà, J., Jiménez, L., Guillén-Gosálbez, G., 2017. Combined use of life cycle assessment, data envelopment analysis and Monte Carlo simulation for quantifying environmental efficiencies under uncertainty. J. Clean. Prod. 166, 771–783. doi:10.1016/j.jclepro.2017.07.215

Färe, R., Grosskopf, S., Lovell, C.A.K., 2008. Production Frontiers. Cambridge University Press, Cambridge.

Färe, R., Grosskopf, S., Pasurka, C., 1986. Effects on relative efficiency in electric power generation due to environmental controls. Resour. Energy 8, 167–184. doi:10.1016/0165-0572(86)90016-2

Farrell, M.J., 1957. The Measurement of Productive Efficiency. J. R. Stat. Soc. Ser. A 120, 253–290. doi:10.1016/S0377-2217(01)00022-4

Fong, K.F., Lee, C.K., 2012. Towards net zero energy design for low-rise residential buildings in subtropical Hong Kong. Appl. Energy 93, 686–694. doi:10.1016/j.apenergy.2012.01.006

Galán-Martín, Á., Guillén-Gosálbez, G., Stamford, L., Azapagic, A., 2016. Enhanced data envelopment analysis for sustainability assessment: A novel methodology and application to electricity technologies. Comput. Chem. Eng. 90, 188–200. doi:10.1016/j.compchemeng.2016.04.022

Gallagher, J., Styles, D., McNabola, A., Williams, A.P., 2015. Current and future environmental balance of small-scale run-of-river hydropower. Environ. Sci. Technol. 49, 6344–6351. doi:10.1021/acs.est.5b00716

Gomes, E.G., Lins, M.P.E., 2008. Modelling undesirable outputs with zero sum gains data envelopment analysis models. J. Oper. Res. Soc. 59, 616–623. doi:10.1057/palgrave.jors.2602384

Gross, R., Green, T., Leach, M., Skea, J., Heptonstall, P., Anderson, D., 2006. The Costs and Impacts of Intermittency: An assessment of the evidence on the costs and impacts of intermittent generation on the British electricity network. doi:10.1016/j.enpol.2008.06.013

Heuberger, C.F., Staffell, I., Shah, N., Mac Dowell, N., 2016. Quantifying the value of CCS for the future electricity system. Energy Environ. Sci. 9, 2497–2510. doi:10.1039/C6EE01120A

Iribarren, D., Martín-Gamboa, M., Dufour, J., 2013. Environmental benchmarking of wind farms according to their operational performance. Energy 61, 589–597. doi:10.1016/j.energy.2013.09.005

Iribarren, D., Vázquez-Rowe, I., Rugani, B., Benetto, E., 2014. On the feasibility of using emergy analysis as a source of benchmarking criteria through data envelopment analysis: A case study for wind energy. Energy 67, 527–537. doi:10.1016/j.energy.2014.01.109

Koopmans, T.C., 1951. An Analysis of Production as an Efficient Combination of Activities, in: Activity Analysis of Production and Allocation. pp. 225–87.

Kuosmanen, T., Kortelainen, M., 2005. Measuring eco-efficiency of production with data envelopment analysis. J. Ind. Ecol. 9, 59–72. doi:10.1162/108819805775247846

Li, J., Geng, X., Li, J., 2016. A comparison of electricity generation system sustainability among G20 countries. Sustain. 8, 1–11. doi:10.3390/su8121276

Li, M.J., Tao, W.Q., 2017. Review of methodologies and polices for evaluation of energy efficiency in high energy-consuming industry. Appl. Energy 187, 203–215. doi:10.1016/j.apenergy.2016.11.039

Li, T., Roskilly, A.P., Wang, Y., 2017. Life cycle sustainability assessment of grid-connected photovoltaic power generation: A case study of Northeast England. Appl. Energy. doi:10.1016/j.apenergy.2017.07.021

Limleamthong, P., Guillén-Gosálbez, G., 2017. Rigorous analysis of Pareto fronts in sustainability studies based on bilevel optimization: Application to the redesign of the UK electricity mix. J. Clean. Prod. 164, 1602–1613. doi:10.1016/j.jclepro.2017.06.134

Limleamthong, P., Guillen Gosalbez, G., 2018. Mixed-Integer Programming Approach for Dimensionality Reduction in Data Envelopment Analysis: Application to the Sustainability Assessment of Technologies and Solvents. Ind. Eng. Chem. Res. acs.iecr.7b05284. doi:10.1021/acs.iecr.7b05284

Liu, W., Sharp, J., 1999. DEA Models via Goal Programming, in: Westermann, G. (Ed.), Data Envelopment Analysis in the Service Sector. Deutscher Universitätsverlag, Wiesbaden. doi:https://doi.org/10.1007/978-3-663-08343-6_5

Liu, W.B., Meng, W., Li, X.X., Zhang, D.Q., 2010. DEA models with undesirable inputs and outputs. Ann. Oper. Res. 173, 177–194. doi:10.1007/s10479-009-0587-3

Lo Piano, S., Mayumi, K., 2017. Toward an integrated assessment of the performance of photovoltaic power stations for electricity generation. Appl. Energy 186, 167–174. doi:10.1016/j.apenergy.2016.05.102

Matino, I., Colla, V., Baragiola, S., 2017. Quantification of energy and environmental impacts in uncommon electric steelmaking scenarios to improve process sustainability. Appl. Energy. doi:10.1016/j.apenergy.2017.06.088

Mazur, A., 2011. Does increasing energy or electricity consumption improve quality of life in industrial nations? Energy Policy 39, 2568–2572. doi:10.1016/j.enpol.2011.02.024

Mio, A., Limleamthong, P., Guillén-Gosálbez, G., Fermeglia, M., 2018. Sustainability evaluation of alternative routes for fine chemicals production in an early stage of process design adopting process simulation along with data envelopment analysis. Ind. Eng. Chem. Res. doi:10.1021/acs.iecr.7b05126

Müller, W.C., Thurner, P.W., 2017. The Politics of Nuclear Energy in Western Europe. Oxford University Press. doi:10.1093/oso/9780198747031.001.0001

NEA, IEA, OECD (Eds.), 2015. Projected Costs of Generating Electricity. OECD Publishing.

NEA, OECD, 2017. Impacts of the Fukushima Daiichi Accident on Nuclear Development Policies 1–67.

Olabi, A.G., 2016. Energy quadrilemma and the future of renewable energy. Appl. Energy 108, 1–6. doi:10.1016/j.energy.2016.07.145

Pasten, C., Santamarina, J.C., 2012. Energy and quality of life. Energy Policy 49, 468–476. doi:10.1016/j.enpol.2012.06.051

Pirker, O., Argyrakis, I., Babkin, V., Chudy, M., Crosnier, G., Dahlback, N., Gianatt, R., Gomez-Martin, P., Gudnason, E., Hellsten, K., Kreiss, G., Nikolov, I., Oesch, P., O'Mahony, B., Pala, R., Reinig, L., Kreikenbaum, D., Polak, D., Romer, N., Saturka, Z., Stanojevic, V., Stettler, A., Marin, C., Teixeira Freitas, J.C., Lobacz, J., Weisrock, G., Jenko, J., Seelos, K., Timm, M., 2011. Hydro in Europe: Powering renewables. Renew. Action Plan 66.

Ray, S.C., 2004. Data envelopment analysis: Theory and techniques for economics and operations research, Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research. doi:10.1017/CBO9780511606731

Sánchez, M.A., 2015. Integrating sustainability issues into project management. J. Clean. Prod. 96, 319–330. doi:10.1016/j.jclepro.2013.12.087

Schlör, H., Fischer, W., Hake, J.F., 2013. Methods of measuring sustainable development of the German energy sector. Appl. Energy 101, 172–181. doi:10.1016/j.apenergy.2012.05.010

Seiford, L.M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. Eur. J. Oper. Res. 142, 16–20. doi:https://doi.org/10.1016/S0377-2217(01)00293-4

Simoes, S., Nijs, W., Ruiz, P., Sgobbi, A., Thiel, C., 2017. Comparing policy routes for low-carbon power technology deployment in EU – an energy system analysis. Energy Policy 101, 353–365. doi:10.1016/j.enpol.2016.10.006

Song, M., Zheng, W., Wang, S., 2017a. Measuring green technology progress in large-scale thermoelectric enterprises based on Malmquist–Luenberger life cycle assessment. Resour. Conserv. Recycl. 122, 261–269. doi:10.1016/j.resconrec.2017.03.001

Song, M., Zhu, Q., Peng, J., Santibanez Gonzalez, E.D.R., 2017b. Improving the evaluation of cross efficiencies: A method based on Shannon entropy weight. Comput. Ind. Eng. 112, 99–106. doi:10.1016/j.cie.2017.07.023

Sueyoshi, T., Goto, M., 2015. Japanese fuel mix strategy after disaster of Fukushima Daiichi nuclear power plant: Lessons from international comparison among industrial nations measured by DEA environmental assessment in time horizon. Energy Econ. 52, 87–103. doi:10.1016/j.eneco.2015.09.001

Sueyoshi, T., Yuan, Y., 2016. Marginal Rate of Transformation and Rate of Substitution measured by DEA environmental assessment: Comparison among European and North American nations. Energy Econ. 56, 270–287. doi:10.1016/j.eneco.2016.01.017

Sueyoshi, T., Yuan, Y., Goto, M., 2017. A literature study for DEA applied to energy and environment. Energy Econ. 62, 104–124. doi:10.1016/j.eneco.2016.11.006

Tsai, W.-H., Lee, H.-L., Yang, C.-H., Huang, C.-C., 2016. Input-output analysis for sustainability by using DEA method: A comparison study between European and Asian countries. Sustain. 8. doi:10.3390/su8121230

van Wees, J.-D., Boxem, T., Angelino, L., Dumas, P., 2013. A prospective study on the geothermal potential in the EU 42.

Vázquez-Rowe, I., Iribarren, D., 2015. Review of life-cycle approaches coupled with data envelopment analysis: Launching the CFP + DEA method for energy policy making. Sci. World J. 2015. doi:10.1155/2015/813921

Wei, M., Patadia, S., Kammen, D.M., 2010. Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US? Energy Policy 38, 919–931. doi:10.1016/j.enpol.2009.10.044

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology [WWW Document]. Int. J. Life Cycle Assess. doi:10.1007/s11367-016-1087-8

Wolde-Rufael, Y., 2009. Energy consumption and economic growth: The experience of African countries revisited. Energy Econ. 31, 217–224. doi:10.1016/j.eneco.2008.11.005

Xie, L., Huang, D. (Eds.), 2014. Advanced Engineering and Technology. Taylor & Francis Group, London.

Yin, K., Wang, R., An, Q., Yao, L., Liang, J., 2014. Using eco-efficiency as an indicator for sustainable urban development: A case study of Chinese provincial capital cities. Ecol. Indic. 36, 665–671. doi:10.1016/j.ecolind.2013.09.003

Zhou, P., Ang, B.W., Poh, K.L., 2008a. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. doi:10.1016/j.ejor.2007.04.042

Zhou, P., Ang, B.W., Poh, K.L., 2008b. Measuring environmental performance under different environmental DEA technologies. Energy Econ. 30, 1–14. doi:10.1016/j.eneco.2006.05.001

Zurano-Cervelló, P., Pozo, C., Mateo-Sanz, J.M., Jiménez, L., Guillén-Gosálbez, G., 2017 Eco-efficiency assessment of EU manufacturing sectors combining input-output tables and data envelopment analysis following production and consumption-based accounting approaches. J. Clean. Prod. 174, 1161–1189. doi:10.1016/J.JCLEPRO.2017.10.178

4. DECOMPOSITION METHODS IN THE STUDY OF IMPACT DRIVERS

4. On the equivalence between the structural decomposition analysis and the Shapley-Sun methods in the study of environmental impact drivers

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KEYWORDS

Shapley-Sun, Structural Decomposition Analysis (SDA), Impact drivers

ABSTRACT

The identification of the key driving factors responsible for environmental impacts is of paramount importance when developing effective mitigation strategies. This analysis can be performed using decomposition techniques, some of which provide very similar (or even identical) results as is the case of the Shapley-Sun and the SDA methods. In this contribution, we demonstrate that the average of the $n!$ SDA additive decomposition equations and the Shapley-Sun method are indeed the same approach in mathematical terms. We compare the patterns from the decomposition of the two- and three-factor cases and formulate a simpler general equation which can be used in substitution of both methods. Furthermore, we present a case study considering 25 environmental indicators from the WIOD, whose changes between 1995 and 2009 are decomposed into three, four and five factors using the SDA, polar decomposition and Shapley-Sun methods. We find that, as expected, the results from the SDA and Shapley-Sun method are identical, but different from the polar decomposition average, which can produce errors up to the 21.9%. Finally, we recommend the use of the general equation we present, since it is as simple as the polar approximation and provides no errors.

4.1. Introduction

Environmental pressures, mainly caused by anthropogenic activities, are wreaking havoc on the environment damaging ecosystems and producing resource scarcity (Ghinea et al., 2017). The consequences of these activities are further aggravated by different factors such as the growth of global population, the increase in per-capita consumption and goods demand, and the high energy dependence of modern societies (Harte, 2007).

Therefore, the identification of the factors responsible for environmental impact is of paramount importance, especially when developing effective mitigation strategies. This task requires quantifying environmental burdens on a life cycle basis of a vast number of economic transactions. This data is typically given by the multiregional input-output (MRIO) tables, containing the economic interactions among sectors and regions worldwide (Liu et al., 2017; Schandl et al., 2016). The MRIO tables were originally employed only for economic assessments (Leontief, 1936; Miller and Peter D., 2009). However, this tables can include environmental data leading to multiregional environmentally extended input-output tables (MREEIO), which can be used to quantify the environmental burdens linked to the economic activities (Cortés-Borda et al., 2015b, 2015a; Guan et al., 2009; Pascual-González et al., 2015; Rocco and Colombo, 2016; Wiedmann, 2009; Zurano-Cervelló et al., 2017). As a consequence, the MREEIO analysis has recently attracted increasing interest as an environmental assessment tool for the development of policies and regulations (Chen et al., 2017; Mi et al., 2017, 2016; Seppälä et al., 2011), by identifying which drivers contribute more towards the total impact.

Two of the most commonly used methods to evaluate the impact drivers using the input-output tables are the structural decomposition analysis (SDA) (Dietzenbacher and Los, 1998) and the Shapley-Sun method (Sun, 1998). The SDA approach is an additive exact decomposition method which has been widely used to determine which driver contributes the most to an indicator change at a sectoral level (Fernández González et al., 2014; Hoekstra and van der Bergh, 2003). This decomposition employs a non-uniqueness technique that results in $n!$ equivalent decomposition forms for n determinants (i.e., factors), each of which is considered to be equally valid. For that reason, Dietzenbacher and Los proposed to use the average of the $n!$ equivalent decomposition forms in order to obtain the final contribution of each factor. For systems containing a large number of factors, the polar decomposition method (Dietzenbacher and Los, 1998), and later on, the mirror image decomposition method (De Haan, 2001), were proposed as simpler alternatives requiring only the calculation of a particular subset of the $n!$

equivalent decompositions of SDA. Unfortunately, these alternatives may simplify the calculations at the expense of producing less accurate results. We note that, despite this limitation, this method is still frequently used in practice (Distefano et al., 2014; Gui et al., 2014; Nie et al., 2016; Pei et al., 2011; Weber, 2009; Xiao et al., 2016; Yunfeng and Laike, 2010).

The Shapley-Sun method, introduced by Sun in 1998 (Sun, 1998), is a variation of the (non-exact) Laspeyres decomposition method (Ang and Zhang, 2000) that applies the '*jointly created and equally distributed*' principle. This principle allocates the contribution caused by the factor's interaction among their *ceteris paribus* contributions, achieving an exact decomposition. In 2002, Albrecht et al., (Albrecht et al., 2002) noticed that Sun's method yielded the same results as the ones proposed by Shapley. Later, Ang et al., (Ang et al., 2003) demonstrated that both methods were indeed the same, renaming the method as the Shapley-Sun approach (this method is also known by other names, such as refined Laspeyres index (Ang, 2004)).

In turn, Hoekstra and van der Bergh observed that the additive decomposition results obtained by the Shapley-Sun method and the average of the $n!$ decomposition equations from the SDA were identical (Hoekstra and van der Bergh, 2003). In fact, the strong similarities between the Shapley-Sun and the average of the $n!$ SDA decompositions in the additive form have been already pointed out in the literature (Fengling, 2004; Wang, 2015), yet to the best of our knowledge, no formal mathematical proof on their equivalence has been put forward so far.

Our purpose in this work is threefold: (i) highlight the potential pitfalls of using the polar decomposition when assessing drivers at the macro-scale level using MREEIO tables; (ii) present a formal proof on the equivalence of the Shapley-Sun and the average of $n!$ decomposition SDA equations; and (iii) introduce a simplified general equation to apply these two equivalent decomposition methods in practice. To support our discussion, we use data from the WIOD database for years 1995 and 2009 to calculate the main drivers behind changes in 25 environmental indicators for three, four and five factors, using the SDA, the polar decomposition and the Shapley-Sun method. Our results demonstrate that the polar decomposition can lead to high errors (up to 21.9%), reinforcing the need to carry out more detailed calculations, which can be simplified using our compact equation presented herein.

4.2. Methods

We organize the methods section in five main parts. Firstly, we introduce the input-output fundamentals which are relevant to the application of the different decomposition methods. Secondly, we describe the SDA as well as the polar and mirror decompositions for the general three-factor case. Then, we present the Shapley-Sun method (in the context of the same three-factor case) to afterwards, in part four, demonstrate its similarity with the average of the $n!$ SDA decomposition forms. Finally, we present the case study to compare both methods (which are indeed the same) with the polar decomposition, using data from the WIOD database.

4.2.1. Multiregional input-output models

In our analysis, we rely on MREEIO tables, regarded as a well-established method to study the environmental impact of economic sectors and countries. Here we present a brief summary of the method, while further details are available elsewhere (Dietzenbacher and Lahr, 2008; Miller and Peter D., 2009).

Following Leontief's work (Leontief, 1970, 1936), the total economy output X can be calculated as the summation of the intermediate sales ($A \cdot X$) and the final consumers' demand (DEM), as expressed in eq. (4.1).

$$X = A \cdot X + DEM \tag{4.1}$$

Here, A is the matrix of technical coefficients describing the relationships between sectors in an economy (i.e., the unitary inputs required by the economic sectors). After appropriate mathematical transformations, the total economic output can be formulated as an explicit function of the final demand:

$$X = (I - A)^{-1} \cdot DEM = LEO \cdot DEM \tag{4.2}$$

where I is the identity matrix and LEO is the Leontief inverse matrix (Dietzenbacher and Lahr, 2008).

Finally, by using the pollution intensity vector (PI) (containing the impact generated per unit of money traded in each sector, e.g., $tCO_2/\$$), it is possible to determine the total impact (IMP) generated by the whole economy (e.g., tCO_2):

$$IMP = PI \cdot (LEO \cdot DEM) \tag{4.3}$$

Eq. (4.3) relates the impact caused with its three driving factors (LEO, DEM and PI). Therefore, we shall decompose changes in impact between two consecutive periods (ΔIMP) using this expression in conjunction with the methods presented in the following sections: the SDA, the polar decomposition and the Shapley-Sun method.

4.2.2. Structural decomposition analysis

The SDA method assesses the driving forces contributing towards the change of a specific economic, social or environmental indicator in a given period. This method, first proposed by Dietzenbacher and Los in 1998 (Dietzenbacher and Los, 1998), is an exact decomposition technique -typically focused on the additive form-, that uses information from input-output data. In this approach, an indicator change can be decomposed in $n!$ different ways, each corresponding to one of the possible combinations of n factors and the time period at which they are evaluated. For three factors (x, y and z), the six complete decompositions (3!) are formulated as follows:

$$\Delta IMP = \underbrace{\Delta x y^2 z^2}_{C_3 f_x} + \underbrace{x^1 \Delta y z^2}_{C_3 f_y} + \underbrace{x^1 y^1 \Delta z}_{C_3 f_z} \tag{4.4}$$

$$\Delta IMP = \underbrace{\Delta x y^2 z^2}_{C_3 f_x} + \underbrace{x^1 \Delta y z^1}_{C_3 f_y} + \underbrace{x^1 y^2 \Delta z}_{C_3 f_z} \tag{4.5}$$

$$\Delta IMP = \underbrace{\Delta x y^1 z^2}_{C_3 f_x} + \underbrace{x^2 \Delta y z^2}_{C_3 f_y} + \underbrace{x^1 y^1 \Delta z}_{C_3 f_z} \tag{4.6}$$

$$\Delta IMP = \underbrace{\Delta x y^2 z^1}_{C_3 f_x} + \underbrace{x^1 \Delta y z^1}_{C_3 f_y} + \underbrace{x^2 y^2 \Delta z}_{C_3 f_z} \tag{4.7}$$

$$\Delta IMP = \underbrace{\Delta x y^1 z^1}_{C_3 f_x} + \underbrace{x^2 \Delta y z^2}_{C_3 f_y} + \underbrace{x^2 y^1 \Delta z}_{C_3 f_z} \tag{4.8}$$

$$\Delta IMP = \underbrace{\Delta x y^1 z^1}_{C_3 f_x} + \underbrace{x^2 \Delta y z^1}_{C_3 f_y} + \underbrace{x^2 y^2 \Delta z}_{C_3 f_z} \tag{4.9}$$

Eqs. (4.4) - (4.9) are equivalent and can be used indifferently to obtain the contribution of each factor i ($C_n f_i$) towards the impact change, leading to the so-called SDA non-uniqueness problem. Dietzenbacher and Los (1998) proposed to deal with this issue by computing the average of all the $n!$ decompositions for each factor. That is, following this approach the contribution of factor x is given by the average of the first term across the decomposition equations ($C_3 f_x$); for factor y, by the average of the second term ($C_3 f_y$) and for factor z, by the average of the third term ($C_3 f_z$). Further details on this method are given in section 4.2.4.

The complexity of the SDA method increases factorially with the number of factors being decomposed (e.g., 24 decomposition equations are obtained for four factors, 120 for five and so on). To alleviate the calculations, Dietzenbacher and Los suggested that the average of the polar equations, (i.e., eqs. (4.4) and (4.9)) would be a good estimation. Other authors (De Haan, 2001) considered that the mean of any pair of mirrored decompositions, i.e., equations with the factors analyzed in the opposite periods of time (e.g., eqs. (4.4) and (4.9), eqs. (4.5) and (4.8) and eqs. (4.6) and (4.7) in the three-factor case) are also a good estimation of the contribution of each factor. In this contribution, we compare the average of the polar equations with the average of the $n!$ SDA decomposition forms, showing that the former simplification can lead to significant errors.

4.2.3. Shapley-Sun method

The Shapley-Sun method, first introduced by Sun in 1998 (Sun, 1998), is an exhaustive and nonparametric decomposition technique entailing no residual terms. This is accomplished by reallocating the residual term of the Laspeyres decomposition among the different factors involved in it, following the '*jointly created and equally distributed*' principle (Ang, 2004; Hoekstra and van der Bergh, 2003). According to this principle, the residual (described as the interaction between factors), is equally distributed among the causing factors and added to their *ceteris paribus* contribution towards the impact change. Albrecht et al. (Albrecht et al., 2002) demonstrated that Sun's method is equivalent to the one proposed by Shapley, so the method was renamed as the Shapley-Sun method (also called refined Laspeyres decomposition (Ang, 2004)).

In contrast with the SDA, in the Shapley-Sun method the contribution of each factor towards the impact change is unambiguous (i.e., there is only one way to obtain the contribution of each factor). In a three-factor model, these contributions are as follows:

$$C_3 f_x = \Delta x y^1 z^1 + \tfrac{1}{2}\Delta x \Delta y z^1 + \tfrac{1}{2}\Delta x y^1 \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \tag{4.10}$$

$$C_3 f_y = x^1 \Delta y z^1 + \tfrac{1}{2}\Delta x \Delta y z^1 + \tfrac{1}{2} x^1 \Delta y \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \tag{4.11}$$

$$C_3 f_z = x^1 y^1 \Delta z + \tfrac{1}{2}\Delta x y^1 \Delta z + \tfrac{1}{2} x^1 \Delta y \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \tag{4.12}$$

Hence, there is no need to calculate any average of terms when using this method.

4.2.4. The similarity between the average of the *n!* SDA decomposition forms and the Shapley-Sun method

In this section, we discuss the equivalence between the average of the *n*! SDA decomposition forms and the Shapley-Sun method, showing that they are indeed the same for the two- and three-factor cases. Then, we complete the proof by deriving the general formula for the *n*-factor case and finally, we apply this general equation in order to obtain the corresponding expression for the four- and five-factor cases.

Therefore, we start by showing the equivalence of both methods in the two-factor case (*x* and *y*). Using the SDA method, the impact change (ΔIMP) can be decomposed in two (2!) different ways:

$$\Delta IMP = \underbrace{\Delta x y^1}_{C_2 f_x} + \underbrace{x^2 \Delta y}_{C_2 f_y} \tag{4.13}$$

$$\Delta IMP = \underbrace{\Delta x y^2}_{C_2 f_x} + \underbrace{x^1 \Delta y}_{C_2 f_y} \tag{4.14}$$

Then, the contribution of each factor *i* ($C_2 f_i$) towards the impact change is determined as the average of its contribution among the two decompositions. For factor *x,* such average contribution is given by eq. (4.15).

$$C_2 f_x = \Delta x (y^1 + y^2)/2 \tag{4.15}$$

Conversely, in the Shapley-Sun method, the general contribution of factor *x* is given as follows:

$$C_2 f_x = \Delta x y^1 + \tfrac{1}{2} \Delta x \Delta y \tag{4.16}$$

Eq. (4.16) can be rearranged as in eq. (4.17) via standard algebraic manipulations:

$$C_2 f_x = \Delta x (y^1 + y^2)/2 \tag{4.17}$$

where eq. (4.17) is the same as eq. (4.15).

For the three-factor decomposition (*x*, *y* and *z*), the contribution of factor *x* ($C_3 f_x$) is given by the average of the 3! SDA decompositions (average $C_3 f_x$ for eqs. (4.4) to (4.9)).

$$C_3 f_x = \Delta x (2 y^2 z^2 + y^2 z^1 + y^1 z^2 + 2 y^1 z^1)/6 \tag{4.18}$$

In the case of the Shapley-Sun method, the contribution for the same factor (x) is obtained from the general equation:

$$C_3 f_x = \Delta x y^1 z^1 + \tfrac{1}{2}\Delta x \Delta y z^1 + \tfrac{1}{2}\Delta x y^1 \Delta z + \tfrac{1}{3}\Delta x \Delta y \Delta z \tag{4.19}$$

that expands as follows:

$$C_3 f_x = (6\Delta x y^1 z^1 + 3\Delta x \Delta y z^1 + 3\Delta x y^1 \Delta z + 2\Delta x \Delta y \Delta z)/6 \tag{4.20}$$

$$C_3 f_x = \Delta x (6 y^1 z^1 + 3\Delta y z^1 + 3 y^1 \Delta z + 2\Delta y \Delta z)/6 \tag{4.21}$$

$$\begin{aligned} C_3 f_x = \Delta x(&6y^1z^1 + 3y^2z^1 - 3y^1z^1 + 3y^1z^2 - 3y^1z^1 + \\ &+ 2y^2z^2 - 2y^1z^2 - 2y^2z^1 + 2y^1z^1)/6 \end{aligned} \tag{4.22}$$

$$C_3 f_x = \Delta x (2y^2z^2 + y^2z^1 + y^1z^2 + 2y^1z^1)/6 \tag{4.23}$$

Here, eq. (4.23), obtained from the Shapley-Sun method, is the same as eq. (4.18) from the SDA, demonstrating again that performing the average of the $n!$ SDA decomposition forms is indeed the same as the Shapley-Sun method.

The results from the two- and three-factor decompositions unveil several patterns that can be used to propose the following simplified eq. (4.24) for the contribution of each factor in the general n-factor case:

$$C_n f_i = \frac{\Delta f_i}{n!}\left[\sum_{k=0}^{n-1}\left(\sum_{j\in r_{n,k}}\left(\left((n-1)!\Big/\binom{n-1}{k}\right)\prod_{i'\neq i}\left(f_{i'}^{a_{i',j}}\right)\right)\right)\right] \forall i \tag{4.24}$$

Here f_i is the factor under study, n is the total number of factors and k is a scalar that indicates the number of factors evaluated in time instant 2 in a specific factor combination, e.g., k=2 for x^2y^2, k=1 for x^1y^2 and x^2y^1, and k=0 for x^1y^1. The set j denotes each of the possible permutations of indexes (either 1 or 2) for each k, all of them embedded in set $r_{n,k}$. The superscript $a^{i'j}$ denotes the time period where each factor i' has to be evaluated in permutation j. In table 4.1 we provide an example showing how set $r_{n,k}$ and superscript $a^{i'j}$ would work in the evaluation of factor x in a n=4 factors (x, y, z and t).

Table 4.1. Example of $r_{n,k}$ and $a^{i'j}$, for factor x and k=2 in a n=4 factors (x, y, z and t).

		$a^{i'j}$		
	$r_{n,k}$	y	z	t
j = 1	$y^2z^2t^1$	2	2	1
j = 2	$y^2z^1t^2$	2	1	2
j = 3	$y^1z^2t^2$	1	2	2

Following eq. (4.24), we derive the formulae for the contribution of factor x in four- and five-factor systems:

$$\begin{aligned} C_4 f_x = \Delta x(&6y^2z^2t^2 + 2y^2z^2t^1 + 2y^2z^1t^2 + 2y^1z^2t^2 + \\ &+ 2y^2z^1t^1 + 2y^1z^2t^1 + 2y^1z^1t^2 + 6y^1z^1t^1)/24 \end{aligned} \tag{4.25}$$

$$\begin{aligned} C_5 f_x = \Delta x(&24y^2z^2t^2u^2 + 6y^2z^2t^2u^1 + 6y^2z^2t^1u^2 + 6y^2z^1t^2u^2 + \\ &+ 6y^1z^2t^2u^2 + 4y^2z^2t^1u^1 + 4y^2z^1t^2u^1 + 4y^2z^1t^1u^2 + \\ &+ 4y^1z^2t^2u^1 + 4y^1z^2t^1u^2 + 4y^1z^1t^2u^2 + 6y^2z^1t^1u^1 + \\ &+ 6y^1z^2t^1u^1 + 6y^1z^1t^2u^1 + 6y^1z^1t^1u^2 + 24y^1z^1t^1u^1)/120 \end{aligned} \tag{4.26}$$

The expression for the contribution of the remaining factors in each case (e.g., y, z and t in the case of the four-factor) can be obtained analogously using eq. (4.24).

While we were unable to provide a rigorous proof that this equation shall apply for the general n-factor case, we observed from numerical examples that it indeed holds for up to five factors, and we believe it is likely to be valid for any number of factors.

4.2.5. Case study

In our case study, we decompose the total change in burdens generated worldwide (Δ*IMP*) for different environmental categories using the different methods presented in this section: the SDA, the polar decomposition and the Shapley-Sun method, which are applied to the three-, four- and five-factor decomposition cases. The three-factor case (i.e., *LEO*, *DEM* and *PI*) is given directly by eq. (4.3). To generate the four- and five-factor decompositions, we further disaggregate the final demand (*DEM*), as shown in table 4.2. Specifically, in the four-factor decomposition, the demand vector is disaggregated into the per-capita demand (vector) and the population (scalar) factors. In the five-factor decomposition, the per-capita demand is further disaggregated into the total per-capita demand and a structural demand vector (obtained by dividing the per-capita demand vector by the total per-capita demand scalar).

Table 4.2. Three, four and five factors considered in the decompositions.

<table>
<tr><th>Code</th><th>Three factors</th><th>Code</th><th>Four factors</th><th>Code</th><th>Five factors</th></tr>
<tr><td>LEO</td><td>Leontief structure</td><td>LEO</td><td>Leontief structure</td><td>LEO</td><td>Leontief structure</td></tr>
<tr><td rowspan="3">DEM</td><td rowspan="3">Demand</td><td>POP</td><td>Population</td><td>POP</td><td>Population</td></tr>
<tr><td rowspan="2">DEM_{PC}</td><td rowspan="2">Per-capita demand</td><td>DEM_S</td><td>Structural demand</td></tr>
<tr><td>TD_{PC}</td><td>Total per-capita demand</td></tr>
<tr><td>PI</td><td>Pollution Intensity</td><td>PI</td><td>Pollution Intensity</td><td>PI</td><td>Pollution Intensity</td></tr>
</table>

We retrieve the MREEIO data for years 1995 and 2009 from the World Input-Output Database (WIOD). This database encompasses macroeconomic transactions for 41 regions: 40 main countries and an aggregated region (ROW). In each region, 35 economic sectors are considered, giving rise to a 1435x1435 intermediate sales matrix (i.e., 41 regions multiplied by 35 sectors each). Furthermore, for every sector, the WIOD provides the final demand, the total output and the environmental accounts for 70 environmental burdens (Timmer et al., 2015).

We select a subset of 25 of these indicators (see table 4.3), spanning across the water (code 1-3), air emissions (code 4-11), land (code 12-15) and material (code 16-25) categories, yielding a total of 300 different instances analyzed: 75 in the three-factor case (25 indicators x 3 factors), 100 in the four-factor case (25 indicators x 4 factors), and 125 in the five-factor case (25 indicators x 5 factors). Note that for materials (i.e., biomass, fossil and minerals), the database contains two different indicators for each burden: *used*, i.e., considering the portion of burden entering the economy, and *unused,* i.e., materials extracted but not consumed in any economic activity. Here, we aggregate the *used* and *unused* data into a single indicator to take into account the total burden for each material considered. For more details on how the WIOD is built, see Timmer et al. (Timmer et al., 2015).

Table 4.3. Environmental indicators considered in the decompositions.

Code	Burden	Code	Burden	Code	Burden
1	Water blue	**10**	NMVOC	**19**	Biomass forestry
2	Water green	**11**	NH_3	**20**	Fossil coal
3	Water grey	**12**	Arable Area	**21**	Fossil gas
4	CO_2	**13**	Permanent Crops	**22**	Fossil oil
5	CH_4	**14**	Pastures	**23**	Minerals construction
6	N_2O	**15**	Forest	**24**	Minerals industrial
7	NO_x	**16**	Biomass animals	**25**	Minerals metals
8	SO_x	**17**	Biomass feed		
9	CO	**18**	Biomass food		

4.3. Results and discussion

In this section, we first discuss in detail the results obtained for the CO_2 indicator in the five-factor decomposition (fig. 4.1) and then we proceed to present the overall results for the 300 instances (i.e., all the cases).

4.3.1. Illustrative case: Five-factor CO_2 case

In fig. 4.1, we show the results of the five-factor CO_2 case (see table 4.2) in order to illustrate how the results obtained from the decomposition work. In this figure, the shapes of the five violins result from the distribution of each factor's contribution towards the total burden change, as given by the decomposition equations in the SDA. As explained in the methodology section, when we decompose a burden change using the SDA method, the total number of decomposition equations is 5! (120 equations). Since each of these equations can potentially yield a different contribution for each factor (non-uniqueness problem), we end up with a distribution of contributions rather than with a specific value for each factor. The average of all the SDA equations for each factor is also depicted with dashed lines on the violins. It can be seen how these averages give the same results as the Shapley-Sun method (white diamonds), but different from the polar decomposition (black stars). Note that the contributions of the TD_{PC} and *POP* factors show similar distributions, with most of the values situated around the SDA mean. Conversely, the contribution of the *LEO*, DEM_S and *PI* factors display elongated violins, exhibiting few values around the SDA mean. Moreover, the dispersion of the *PI* factor is higher than in the other factors (note that its negative scale is twice as big as the one for positive factors in the figure), being the difference between the most extreme results around 120%.

When we compare the SDA average (and the Shapley-Sun method) versus the polar decomposition average, the *PI* factor presents the highest absolute difference (8.1%: -84.3% for the SDA average and the Shapley-Sun method compared to -92.4% for the polar decomposition average). On the other hand, when we analyze the relative difference, it is higher for the TD_{PC} factor (-28.6%: 26.2% for the SDA average and Shapley-Sun compared to 33.8% for the polar decomposition average).

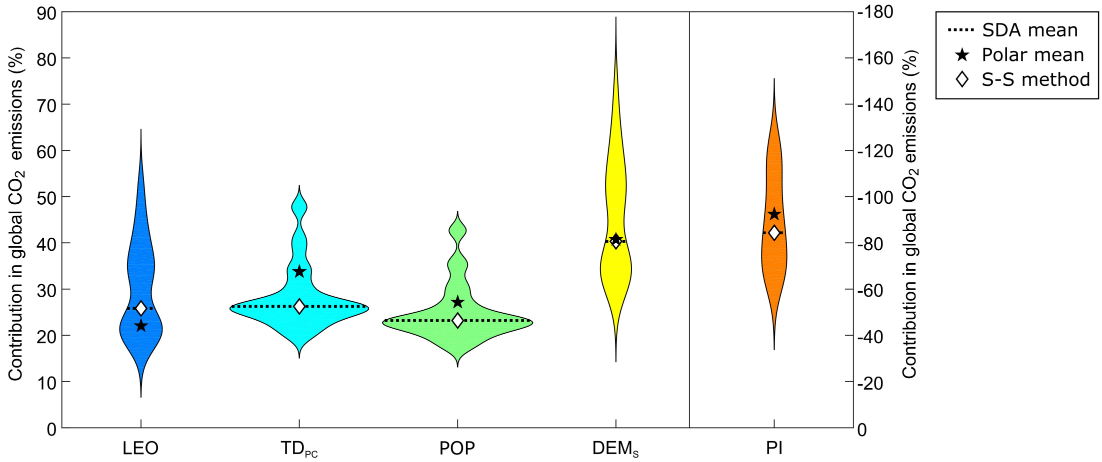

Fig. 4.1. Violin plot providing the % contribution of each factor towards the change in global CO_2 emissions between 1995 and 2009 from the n! SDA equations. The SDA and polar means, and the result from the Shapley-Sun method are marked on the violins. The *PI* contribution is provided by the right-hand side y axis.

4.3.2. Overall results of the 25 environmental indicators

We next present the overall results for the 300 instances analyzed, which are given in fig. 4.2. This figure provides the % contribution (obtained as the average of the SDA equations and the Shapley-Sun method) of each factor towards the total impact of indicators 1 to 25 in the three-, four- and five-factor cases. The labelling of the different factors and indicators is as follows: the first number denotes the number of factors, then the letters represent the factor analyzed as indicated in table 4.2, and finally, the last number provides the indicator whose burden is being decomposed (see table 4.3). For example, 3LEO1 corresponds to the result of the Leontief factor (i.e., *LEO*) in the three-factor decomposition for the first indicator (i.e., water blue). The absolute and relative differences between the % contribution computed from the SDA average (and Shapley-Sun method) and the polar decomposition average are shown in colors. The columns in blue, white and yellow correspond to the absolute differences, while those in red, white and green depict the relative ones.

	Contrib. SDA & S-S (%)	Polar abs. difference	Polar rel. difference		Contrib. SDA & S-S (%)	Polar abs. difference	Polar rel. difference		Contrib. SDA & S-S (%)	Polar abs. difference	Polar rel. difference		Contrib. SDA & S-S (%)	Polar abs. difference	Polar rel. difference		Contrib. SDA & S-S (%)	Polar abs. difference	Polar rel. difference		Contrib. SDA & S-S (%)	Polar abs. difference	Polar rel. difference
3LEO1	22			3PI1	-73			4POP1	23			4PI1	-71			5TD$_{PC}$1	25			5DEM$_{S}$1	29		
3LEO2	-3			3PI2	-20			4POP2	22			4PI2	-19			5TD$_{PC}$2	24			5DEM$_{S}$2	12		
3LEO3	-1			3PI3	-23			4POP3	24			4PI3	-22			5TD$_{PC}$3	27			5DEM$_{S}$3	32		
3LEO4	27			3PI4	-88			4POP4	23			4PI4	-86			5TD$_{PC}$4	26			5DEM$_{S}$4	40		
3LEO5	12			3PI5	-74			4POP5	21			4PI5	-73			5TD$_{PC}$5	24			5DEM$_{S}$5	33		
3LEO6	0			3PI6	-46			4POP6	20			4PI6	-45			5TD$_{PC}$6	23			5DEM$_{S}$6	16		
3LEO7	18			3PI7	-81			4POP7	22			4PI7	-79			5TD$_{PC}$7	25			5DEM$_{S}$7	32		
3LEO8	48			3PI8	-155			4POP8	24			4PI8	-152			5TD$_{PC}$8	27			5DEM$_{S}$8	61		
3LEO9	33			3PI9	-128			4POP9	21			4PI9	-126			5TD$_{PC}$9	23			5DEM$_{S}$9	34		
3LEO10	35			3PI10	-114			4POP10	23			4PI10	-112			5TD$_{PC}$10	26			5DEM$_{S}$10	39		
3LEO11	-1			3PI11	-41			4POP11	21			4PI11	-40			5TD$_{PC}$11	23			5DEM$_{S}$11	16		
3LEO12	-6			3PI12	-45			4POP12	19			4PI12	-45			5TD$_{PC}$12	21			5DEM$_{S}$12	9		
3LEO13	0			3PI13	-34			4POP13	20			4PI13	-34			5TD$_{PC}$13	23			5DEM$_{S}$13	10		
3LEO14	-1			3PI14	-52			4POP14	19			4PI14	-51			5TD$_{PC}$14	21			5DEM$_{S}$14	10		
3LEO15	-5			3PI15	-40			4POP15	19			4PI15	-40			5TD$_{PC}$15	21			5DEM$_{S}$15	6		
3LEO16	0			3PI16	-38			4POP16	21			4PI16	-38			5TD$_{PC}$16	23			5DEM$_{S}$16	14		
3LEO17	-2			3PI17	-41			4POP17	20			4PI17	-41			5TD$_{PC}$17	22			5DEM$_{S}$17	10		
3LEO18	-3			3PI18	-22			4POP18	22			4PI18	-22			5TD$_{PC}$18	25			5DEM$_{S}$18	16		
3LEO19	-4			3PI19	-44			4POP19	19			4PI19	-43			5TD$_{PC}$19	21			5DEM$_{S}$19	7		
3LEO20	31			3PI20	-86			4POP20	24			4PI20	-84			5TD$_{PC}$20	27			5DEM$_{S}$20	38		
3LEO21	55			3PI21	-87			4POP21	23			4PI21	-86			5TD$_{PC}$21	26			5DEM$_{S}$21	21		
3LEO22	69			3PI22	-127			4POP22	22			4PI22	-126			5TD$_{PC}$22	25			5DEM$_{S}$22	24		
3LEO23	48			3PI23	-87			4POP23	28			4PI23	-85			5TD$_{PC}$23	31			5DEM$_{S}$23	71		
3LEO24	-10			3PI24	-53			4POP24	19			4PI24	-52			5TD$_{PC}$24	22			5DEM$_{S}$24	7		
3LEO25	61			3PI25	-138			4POP25	22			4PI25	-136			5TD$_{PC}$25	25			5DEM$_{S}$25	36		
3DEM1	78			4LEO1	22			4DEM$_{PC}$1	55			5LEO1	22			5POP1	22			5PI1	-70		
3DEM2	58			4LEO2	-3			4DEM$_{PC}$2	36			5LEO2	-3			5POP2	22			5PI2	-19		
3DEM3	83			4LEO3	-1			4DEM$_{PC}$3	59			5LEO3	-1			5POP3	24			5PI3	-22		
3DEM4	93			4LEO4	26			4DEM$_{PC}$4	68			5LEO4	26			5POP4	23			5PI4	-84		
3DEM5	80			4LEO5	12			4DEM$_{PC}$5	57			5LEO5	12			5POP5	21			5PI5	-72		
3DEM6	60			4LEO6	0			4DEM$_{PC}$6	39			5LEO6	-1			5POP6	20			5PI6	-45		
3DEM7	81			4LEO7	18			4DEM$_{PC}$7	57			5LEO7	18			5POP7	22			5PI7	-78		
3DEM8	117			4LEO8	47			4DEM$_{PC}$8	90			5LEO8	47			5POP8	24			5PI8	-149		
3DEM9	81			4LEO9	32			4DEM$_{PC}$9	59			5LEO9	32			5POP9	21			5PI9	-124		
3DEM10	90			4LEO10	34			4DEM$_{PC}$10	65			5LEO10	34			5POP10	23			5PI10	-110		
3DEM11	61			4LEO11	-1			4DEM$_{PC}$11	40			5LEO11	-1			5POP11	20			5PI11	-40		
3DEM12	50			4LEO12	-6			4DEM$_{PC}$12	31			5LEO12	-6			5POP12	19			5PI12	-45		
3DEM13	53			4LEO13	0			4DEM$_{PC}$13	33			5LEO13	0			5POP13	20			5PI13	-34		
3DEM14	51			4LEO14	-1			4DEM$_{PC}$14	32			5LEO14	-1			5POP14	19			5PI14	-51		
3DEM15	47			4LEO15	-5			4DEM$_{PC}$15	28			5LEO15	-5			5POP15	19			5PI15	-39		
3DEM16	59			4LEO16	0			4DEM$_{PC}$16	38			5LEO16	0			5POP16	21			5PI16	-37		
3DEM17	53			4LEO17	-2			4DEM$_{PC}$17	33			5LEO17	-2			5POP17	20			5PI17	-40		
3DEM18	63			4LEO18	-3			4DEM$_{PC}$18	41			5LEO18	-3			5POP18	22			5PI18	-21		
3DEM19	48			4LEO19	-4			4DEM$_{PC}$19	29			5LEO19	-4			5POP19	19			5PI19	-43		
3DEM20	90			4LEO20	31			4DEM$_{PC}$20	65			5LEO20	31			5POP20	23			5PI20	-83		
3DEM21	71			4LEO21	54			4DEM$_{PC}$21	47			5LEO21	54			5POP21	23			5PI21	-86		
3DEM22	73			4LEO22	68			4DEM$_{PC}$22	50			5LEO22	68			5POP22	22			5PI22	-125		
3DEM23	132			4LEO23	47			4DEM$_{PC}$23	103			5LEO23	47			5POP23	28			5PI23	-84		
3DEM24	50			4LEO24	-10			4DEM$_{PC}$24	30			5LEO24	-10			5POP24	19			5PI24	-51		
3DEM25	84			4LEO25	60			4DEM$_{PC}$25	61			5LEO25	60			5POP25	22			5PI25	-135		

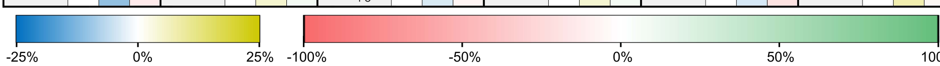

Fig. 4.2. Comparison of the results obtained for the decomposition using the different methods for indicators 1 to 25 in the three-, four- and five-factor cases. The numbers provide the % contribution of each factor calculated from the average of the SDA and the Shapley-Sun method. The heatmap shows the absolute and relative difference between these contributions and the one obtained with the polar decomposition method.

We obtained identical contributions for the different factors with the average of the SDA and the Shapley-Sun method, as demonstrated in the methodology section 4.2.4 (see *Contrib. SDA & S-S (%)* column). On the other hand, when we compare these results with those obtained from the polar decomposition average, we find that the absolute difference means (in absolute value, i.e., without considering if this absolute difference is positive or negative), is 3.0% ± 0.4%, using a significance level of 5%. While the absolute difference might seem small in average, it can be as high as 21.9%, as given by the *DEM* factor for the SO_X indicator (code 8) in the three-factor case. There are also high differences for the *PI* (17.5%) and the TD_{PC} (-14.9%) factors for the same indicator in the five-factor case. The factors with the lowest maximum differences are *DEMs*, *POP* and *LEO* in the five-factor case, being their highest values -3.4%, -8.6% and 9.4%, respectively (all occurring in the SO_X indicator). In the remaining factors, the maximum absolute difference fluctuates between a 10.0% and 14.5%.

Regarding the relative difference, it is 10.1% ± 1.7% in average, reaching particularly high values for the factors with lower contributions, where the relative difference can be as high as the contribution itself. This is the case of the permanent crops indicator (code 13) in all the *LEO* factors (i.e., 3LEO13, 4LEO13 and 5LEO13), showing a relative difference of 98.2% (from a 0.1% contribution in the SDA average and Shapley-Sun to a 0.0% in the polar decomposition average). This also happens in the *LEO* factor for the N_2O indicator (code 6) in the three- and four-factor case (-88.2% and -79.4% relative difference, respectively).

As a general trend, the average of the polar decomposition overestimates the contribution of the *LEO* and *PI* factors, being this difference higher than 5% for the SO_X, CO and NMVOC indicators (codes 8, 9 and 10). Conversely, the factors relative to the demand and population (i.e., *DEM*, DEM_{PC}, DEM_S, TD_{PC} and *POP*) are underestimated by the average of the polar decomposition, especially in the SO_X, CO and NMVOC indicators. The analysis of this case study evidences that the use of the polar decomposition average is a good estimation only in the case where a certain error (a 21.9% in our case) is allowed. Since the general equation (eq. (4.24)) we present in the methods section 4.2.4 is as affordable as the polar equations, and it gives an exact result (in contrast with the estimation provided by the average of the polar decomposition), we recommend the use of the general equation.

4.4. Conclusions

In the literature, there are a large number of articles about decomposition techniques, which, after all, end up giving very similar (or even identical) results. This is the case of the Shapley-Sun and the SDA methods. In this contribution, we demonstrate that, despite their very different origins, the average of the $n!$ SDA decomposition equations and the Shapley-Sun method are indeed the same approach in mathematical terms. With the patterns observed in the decomposition of the two- and three-factor cases, we formulate a simpler general equation which can be used in substitution of both methods.

Furthermore, we present a case study considering 25 environmental indicators, whose change between 1995 and 2009 is decomposed into three, four and five factors using the SDA, polar decomposition and Shapley-Sun method. We find that, as expected, the results from the SDA and Shapley-Sun method are identical, but different from the polar decomposition average, obtaining an absolute difference of 3.0% ± 0.4%, where, in some cases, these differences can be as high as 21.9%. Among the different indicators, SO_x (code 8) is the one with the largest differences: 21.9% in the *DEM* factor in the three-factor case, and 17.5% and -14.9% in the *PI* and TD_{PC} factors, respectively, in the five-factor case. Among all the factors, *LEO* and *PI* are the ones whose contributions tend to be overestimated by the average of the polar decomposition, more notoriously in the SO_x, CO and NMVOC indicators (codes 8, 9 and 10). On the other hand, the factors relative to the demand and population (i.e., *DEM*, DEM_{PC}, DEM_S, TD_{PC} and *POP*) are underestimated by this method in the same indicators.

As a final conclusion, considering that the approximation error of the polar decomposition can be important (up to 21.9% in our case study), we recommend to use the general equation we present in this article (eq. (4.24)) as it gives an exact result and is as affordable as the average of the polar decomposition equations.

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4.6. References

Albrecht, J., François, D., Schoors, K., 2002. A Shapley decomposition of carbon emissions without residuals. Energy Policy. doi:10.1016/S0301-4215(01)00131-8

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: Which is the preferred method? Energy Policy. doi:10.1016/S0301-4215(03)00076-4

Ang, B.W., Liu, F.L., Chew, E.P., 2003. Perfect decomposition techniques in energy and environmental analysis. Energy Policy. doi:10.1016/S0301-4215(02)00206-9

Ang, B.W., Zhang, F.Q., 2000. A survey of index decomposition analysis in energy and environmental studies. Energy 25, 1149–1176. doi:10.1016/S0360-5442(00)00039-6

Chen, B., Li, J.S., Chen, G.Q., Wei, W.D., Yang, Q., Yao, M.T., Shao, J.A., Zhou, M., Xia, X.H., Dong, K.Q., Xia, H.H., Chen, H.P., 2017. China's energy-related mercury emissions: Characteristics, impact of trade and mitigation policies. J. Clean. Prod. 141, 1259–1266. doi:10.1016/j.jclepro.2016.09.200

Cortés-Borda, D., Guillén-Gosálbez, G., Jiménez, L., 2015a. Assessment of nuclear energy embodied in international trade following a world multi-regional input-output approach. Energy 91, 91–101. doi:10.1016/j.energy.2015.07.117

Cortés-Borda, D., Ruiz-Hernández, A., Guillén-Gosálbez, G., Llop, M., Guimerà, R., Sales-Pardo, M., 2015b. Identifying strategies for mitigating the global warming impact of the EU-25 economy using a multi-objective input-output approach. Energy Policy 77, 21–30. doi:10.1016/j.enpol.2014.11.020

De Haan, M., 2001. A structural decomposition analysis of pollution in the Netherlands. Econ. Syst. Res. doi:10.1080/09537320120052452

Dietzenbacher, E., Lahr, M.L., 2008. Wassily Leontief and Input-Output Economics. p. 420.

Dietzenbacher, E., Los, B., 1998. Structural Decomposition Techniques: Sense and Sensitivity. Econ. Syst. Res. doi:10.1080/09535319800000023

Distefano, T., Riccaboni, M., Marin, G., 2014. Global Virtual Water Trade: Integrating Structural Decomposition Analysis with Network Theory.

Fengling, L.I.U., 2004. Decomposition Analysis Applied To Energy : Some Methodological Issues.

Fernández González, P., Landajo, M., Presno, M.J., 2014. The Driving Forces of Change in Environmental Indicators, Lecture Notes in Energy.

Ghinea, C., Campean, T., Gavrilescu, M., 2017. Integrating sustainability indicators for tracking anthropogenic pressure on the earth-the footprint family. Environ. Eng. Manag. J. 16, 935–948.

Gui, S., Mu, H., Li, N., 2014. Analysis of impact factors on China's CO2 emissions from the view of supply chain paths. Energy. doi:10.1016/j.energy.2014.06.116

Harte, J., 2007. Human population as a dynamic factor in environmental degradation. Popul. Environ. 28, 223–236. doi:10.1007/s11111-007-0048-3

Hoekstra, R., van der Bergh, J.J.C.J.M., 2003. Comparing structural and index decomposition analysis. Energy Econ. 25, 39–64. doi:10.1016/S0140-9883(02)00059-2

Leontief, W.W., 1970. Environmental Repercussions and the Economic Structure. Environ. Reper. Econ. Struct. - An Input-Output Approach 50, 262–271.

Leontief, W.W., 1936. Quantitative Input and Output Relations in the Economic Systems of the United States. Rev. Econ. Stat. 18, 105–125. doi:10.2307/1927837

Liu, X., Klemeš, J.J., Varbanov, P.S., Čuček, L., Qian, Y., 2017. Virtual carbon and water flows embodied in international trade: a review on consumption-based analysis. J. Clean. Prod. 146, 20–28. doi:10.1016/j.jclepro.2016.03.129

Mi, Z., Wei, Y.M., Wang, B., Meng, J., Liu, Z., Shan, Y., Liu, J., Guan, D., 2017. Socioeconomic impact assessment of China's CO2 emissions peak prior to 2030. J. Clean. Prod. 142, 2227–2236. doi:10.1016/j.jclepro.2016.11.055

Mi, Z., Zhang, Y., Guan, D., Shan, Y., Liu, Z., Cong, R., Yuan, X.C., Wei, Y.M., 2016. Consumption-based emission accounting for Chinese cities. Appl. Energy 184, 1073–1081. doi:10.1016/j.apenergy.2016.06.094

Miller, R., Peter D., B., 2009. Input–Output Analysis Foundations and Extensions. J. Chem. Inf. Model. 1–784. doi:10.1017/CBO9781107415324.004

Nie, H., Kemp, R., Vivanco, D.F., Vasseur, V., 2016. Structural decomposition analysis of energy-related CO2 emissions in China from 1997 to 2010. Energy Effic. doi:10.1007/s12053-016-9427-x

Pascual-González, J., Guillén-Gosálbez, G., Mateo-Sanz, J.M., Jiménez-Esteller, L., 2015. Statistical analysis of global environmental impact patterns using a world multi-regional input-output database. J. Clean. Prod. 90, 360–369. doi:10.1016/j.jclepro.2014.11.065

Pei, J., Dietzenbacher, E., Oosterhaven, J., Yang, C., 2011. Accounting for china's import growth: A structural decomposition for 1997-2005. Environ. Plan. A. doi:10.1068/a43396

Rocco, M. V., Colombo, E., 2016. Evaluating energy embodied in national products through Input-Output analysis: Theoretical definition and practical application of international trades treatment methods. J. Clean. Prod. 139, 1449–1462. doi:10.1016/j.jclepro.2016.09.026

Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., Owen, A., 2016. Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions. J. Clean. Prod. 132, 45–56. doi:10.1016/j.jclepro.2015.06.100

Seppälä, J., Mäenpää, I., Koskela, S., Mattila, T., Nissinen, A., Katajajuuri, J.M., Härmä, T., Korhonen, M.R., Saarinen, M., Virtanen, Y., 2011. An assessment of greenhouse gas emissions and material flows caused by the Finnish economy using the ENVIMAT model. J. Clean. Prod. 19, 1833–1841. doi:10.1016/j.jclepro.2011.04.021

Sun, J.W., 1998. Changes in energy consumption and energy intensity: A complete decomposition model. Energy Econ. 20, 85–100. doi:10.1016/S0140-9883(97)00012-1

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production. Rev. Int. Econ. 23, 575–605. doi:10.1111/roie.12178

Wang, T., 2015. Technology, International Trade, and Carbon Emissions from U.S. Industry.

Weber, C.L., 2009. Measuring structural change and energy use: Decomposition of the US economy from 1997 to 2002. Energy Policy. doi:10.1016/j.enpol.2008.12.027

Wiedmann, T., 2009. A review of recent multi-region input-output models used for consumption-based emission and resource accounting. Ecol. Econ. doi:10.1016/j.ecolecon.2009.08.026

Xiao, B., Niu, D., Guo, X., 2016. The driving forces of changes in CO2 emissions in China: A structural decomposition analysis. Energies. doi:10.3390/en9040259

Yunfeng, Y., Laike, Y., 2010. China's foreign trade and climate change: A case study of CO2 emissions. Energy Policy. doi:10.1016/j.enpol.2009.09.025

Zurano-Cervelló, P., Pozo, C., Mateo-Sanz, J.M., Jiménez, L., Guillén-Gosálbez, G., 2017. Eco-efficiency assessment of EU manufacturing sectors combining input-output tables and data envelopment analysis following production and consumption-based accounting approaches. J. Clean. Prod. 174. doi:10.1016/j.jclepro.2017.10.178

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