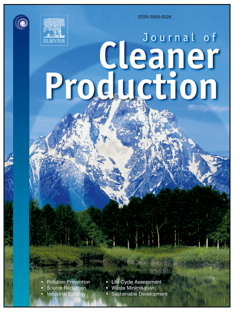
Accepted Manuscript



Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis

A. Ewertowska, A. Galán-Martín, G. Guillén-Gosálbez, J. Gavaldá, L. Jiménez

PII: S0959-6526(15)01832-6

DOI: 10.1016/j.jclepro.2015.11.100

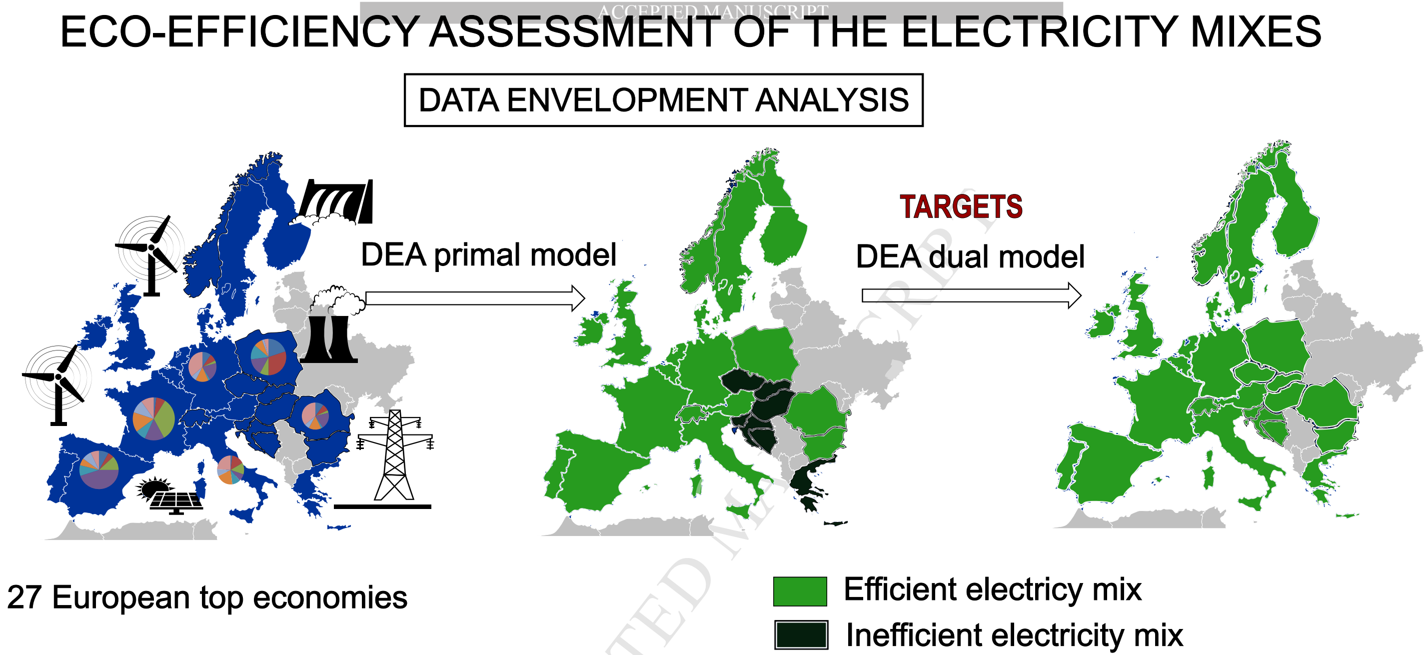
Reference: JCLP 6480

To appear in: *Journal of Cleaner Production*

Received Date: 8 May 2015

Revised Date: 14 August 2015

Accepted Date: 28 November 2015


ECO-EFFICIENCY ASSESSMENT OF THE ELECTRICITY MIXES
DATA ENVELOPMENT ANALYSIS
DEA primal model
TARGETS
DEA dual model
27 European top economies
Efficient electricity mix
Inefficient electricity mix

Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis

Ewertowska[a], A., Galán-Martín[a], A., Guillén-Gosálbez[a,b*], G., Gavaldá[a], J., Jiménez[a], L.

[a]Departament d'Enginyeria Química, Universitat Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain.

[b]Centre for Process Integration, School of Chemical Engineering and Analytical Science, The University of Manchester, Manchester M13 9PL, UK

Corresponding author: Gonzalo Guillén-Gosálbez

E-mail address: gonzalo.guillen@urv.cat

Abstract

Moving towards a more sustainable energy system is a major goal of modern societies that aim to minimize the dependence on fossil fuels and the associated anthropogenic impacts. In this article, the combined use of Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA) is applied to analyse the environmental performance (eco-efficiency) of the electricity mix of the top European economies. This approach allows identifying environmentally efficient and inefficient countries considering as undesirable inputs several environmental impacts associated with the production of 1kWh (regarded as output). The method provides as well targets for the inefficient countries that (if attained) could make them efficient. Our results provide valuable insight for governments and policy makers that aim to satisfy the electricity demand while minimizing the associated environmental impact.

Keywords

Eco-efficiency; Energy assessment; Data envelopment analysis; Life cycle assessment

1. Introduction

Energy transition has recently received increasing public attention because of the role it plays in sustainability (Kern and Smith, 2008). In the last decade, renewable energy sources (e.g. wind energy, biomass, hydropower, solar power, geothermal, and ocean power) have become promising alternatives to reduce the dependence on fossil fuels, as they could lead to significant environmental and economic benefits, including energy security enhancement.

In Europe, several strategies and policies have been recently developed, which highlight the necessity for a clean and efficient energy supply. These policies are aimed to transform the current energy system into a sustainable and low-carbon system, which will have far-reaching implications on how to produce energy. Due to the increased awareness of the role played by energy in our society, it is imperative to find effective ways for assessing the environmental impact of the technologies available for electricity generation in order to move towards an environmentally friendly electricity mix (i.e., eco-friendly mix).

Intensive research efforts are presently being undertaken to seek sustainable alternatives for satisfying the growing electricity demand at minimum environmental impact. In practice, however, it is unlikely that a single technology will show the best performance in every environmental impact category. As an example, nuclear energy contributes marginally to global warming, but shows other impacts, like in ionising radiation (Frischknecht et al., 2000), whereas with coal the opposite occurs. Recognizing that electricity production technologies perform well in some environmental categories and poorly in others, the question that arises is how to identify the best ones (i.e., environmentally efficient ones) and, for the worst, specify targets that (if achieved) would make them efficient. This valuable insight could facilitate the transition towards a cleaner electricity generation system.

The concept of eco-efficiency offers an appealing framework for performing this task. The Eco-efficiency concept was originally introduced in the Earth Summit and later defined as a general management philosophy (Schmidheiny, 1992) during the World Business Council for Sustainable Development. Eco-efficiency is a general instrument for sustainability analysis of products or processes of different nature. It is usually expressed as the ratio between the product value and its environmental burden, thereby indicating the economic creation for a given ecological destruction. This ratio was also called environmental productivity or incremental eco-efficiency by Huppes and Ishikawa (Huppes and Ishikawa, 2005).

The eco-efficiency concept has so far been used in many disciplines. According to Michelsen et al. (Michelsen et al., 2006), the concept of eco-efficiency can be used for measuring the system progress and for communicating the economic and environmental performance of a product or process. The main drawback when constructing eco-efficiency indicators is that there are no agreed rules or standards for the measurement, recognition, and disclosure of environmental information (UNCTAD, 2003).

Hence, a key point in the eco-efficiency assessment concerns the manner in which the economic and environmental performance values are defined. Kuosmanen and Kortelainen quantified the environmental performance using pressure indicators (calculated by weighting the contribution of different pollutants to several damage categories), and the economic one through the profit (which measures the economic value added) (Kuosmanen and Kortelainen, 2005). On the other hand, Dyckhoff and Allen (Dyckhoff and Allen, 2001) proposed to quantify the environmental performance using life cycle assessment (LCA), a well-established environmental engineering technique. LCA is an environmental engineering tool that quantifies the impact caused in all of the stages in the life cycle of a product (i.e., cradle to grave analysis), including raw materials acquisition, processing, manufacturing, end-use, disposal and waste management (SETAC, 1993). LCA is generally focused only on environmental impacts. Indeed, ISO documentation restricts LCA's purview to environmental effects (ISO, 2006a)(ISO, 2006b). The ISO 14040 standards (ISO, 2006b) describes LCA as the "compilation and evaluation of the inputs, outputs and potential environmental impacts of a product system throughout its life cycle". Due to the holistic approach it applies(Finnveden et al., 2009), in recent years LCA has expanded rapidly in both industry and academia. In the context of energy systems analysis, LCA considers all aspects associated with energy generation over the entire energy supply chain, that is, throughout the entire life cycle of the production of energy. These include the extraction and combustion of the corresponding fuels (e.g. coal, oil, biomass, natural gas, etc.) the transportation tasks associated with these fuels, the distribution of energy and the impact associated with the construction and maintenance of the facilities that produce energy (e.g. nuclear plants, wind turbines, coal plants, etc.). Further details on this topic can be found in the Ecoinvent database. The main advantage of using LCA in the assessment of energy systems is that it provides a holistic view of each technology, thereby providing clear information on the extent to which is contributes to decrease the impact globally. This comes at the price of requiring large amounts of data, some of which might be difficult to collect in practice. Applications of LCA to electricity production include the assessment of different renewable energy sources (Bhat and Prakash, 2009) and of different emissions associated with electricity production from coal and natural gas in Canada (Zhang et al., 2010), among others. It is worthy to mention that numerous eco-efficiency initiatives are already being undertaken around the world by institutions like the Organization for Economic Co-operation and Development (OECD), or the World Business Council for Sustainable Development (WBCSD), to establish environmental performance indicators.

Eco-efficiency is typically assessed via data envelopment analysis (DEA) (Cooper et al., 2007). DEA is a non-parametric linear programming (LP) based technique that objectively assesses the relative efficiency of a set of units (i.e., products/services). Each of these units is formally defined as an entity that consumes certain amounts of inputs to manufacture certain amounts of outputs. DEA identifies non-dominated (i.e., efficient) (Hongye, 2010) units and for the ones found to be inefficient, it provides both an efficiency score and a set of target values (for its inputs and outputs) that (if attained) would make the unit efficient.

DEA is a very useful analytical tool that can be employed to assess the efficiency and guide retrofit efforts towards an effective enhancement of the environmental performance. Unfortunately, DEA shows some limitations as the results it provides are very sensitive to the inputs and outputs considered and the size of the sample (Bhagavath, 2009).

In the last decade, the combined use of LCA and DEA has developed significantly (Vázquez-Rowe and Iribarren, 2015) as a tool to benchmark the operational and environmental performance of resembling entities (Vázquez-Rowe et al., 2010)(Avadí et al., 2014). Despite being general enough to be applied to any product, the combined use of LCA and DEA have been primarily used to assess agrifood systems (Iribarren et al., 2010). For instance, (Iribarren et al., 2013) have recently carried out an integrated LCA + DEA study of wind farms, showing that this methodology can be useful for the benchmarking of energy conversion systems. This approach has also been applied to assess thermal plants (Liu et al., 2010)(Sarıca and Or, 2007)(Sözen et al., 2010), electric and electronic appliances (Barba-Gutiérrez et al., 2008), U.S manufacturing sectors (Egilmez et al., 2013), building components (Iribarren et al., 2015) and also to evaluate the environmental efficiency of the Chinese industry (Wu et al., 2014), among others.

The combined approach that integrates LCA and DEA proposed by (Vázquez-Rowe et al., 2010) and which entails 5 steps have been applied in this work to assess the environmental efficiency of the electricity mix of the 27 wealthiest economies in Europe. We discuss which countries are efficient and for those found to be inefficient, environmental targets are provided that (if achieved) would make them efficient. Note that we have focused here on analyzing the environmental performance of the electricity generation mixes of the top European countries, which display similar levels of development. Note also that, as it will be discussed in more detail later in the article, economic, social, technological and political aspects have been left out of the analysis. The main reason is that there is a lack of quantitative indicators for describing the performance of a technology in these dimensions (except for the economic case, for which several indicators are available but seldom reflect the true cost of the system due to external regulations). Future work will focus on incorporating some social and economic metrics in the analysis.

The article is organized as follows. The results of an LCA study of the electricity mix of the top economies are first presented. We next describe the DEA methodology, which is employed to quantify the environmental efficiency of the electricity mix of each country. The results of the DEA study are presented afterwards, while the conclusions of the work are drawn in the last section.

2. Environmental Impact Assessment of Energy Production

The environmental performance of the electricity mix of the top economies in Europe (see Table 1) is analyzed first following LCA principles. Particularly, this environmental performance is quantified through the CML 2001(Guinée, 2001)(Van Oers, 2004), an LCA-based methodology that considers 15 damage scores (which in our case are quantified over the entire life cycle of the energy supply chain).

The impacts analysed and the corresponding units are given in Table 2. The results of this LCA analysis have been retrieved from the environmental database EcoInvent v3.1 (Weidema, B.P.; Bauer, Ch.; Hischier, R.; Mutel, Ch.; Nemecek, T.; Reinhard, J.;

Vadenbo, C.O.; Wernet, 2013), which contains LCA data of the main technological processes implemented worldwide.

Table 1 Countries studied in the analysis and their acronyms.

Country	**Acronym**
Austria	AUT
Bosnia & Herzegovina	BIH
Belgium	BEL
Bulgaria	BGR
Switzerland	CHE
Czech Republic	CZE
Germany	DEU
Denmark	DNK
Spain	ESP
Finland	FIN
France	FRA
United Kingdom	GBR
Greece	GRC
Croatia	HRV
Hungary	HUN
Ireland	IRL
Italy	ITA
Luxemburg	LUX
Republic of Macedonia	MKD
Netherlands	NLD
Norway	NOR
Poland	POL
Portugal	PRT
Romania	ROU
Sweden	SWE
Slovenia	SVN
Slovakia	SVK

Table 2 Set of impacts considered in the study (in alphabetic order).

Impact		Unit
1	Acidification potential	kg SO^2 – Eq
2	Climate change	kg CO^2 – Eq
3	Eutrophication potential	kg NOx – Eq
4	Freshwater aquatic eco-toxicity	kg 1.4-DCB-Eq
5	Freshwater sediment eco-toxicity	kg 1.4-DCB-Eq

6	Human toxicity	kg 1.4-DCB-Eq
7	Ionising radiation	DALYs
8	Land use	m^2 times year (m^2 a)
9	Malodorous air	m3 air
10	Marine aquatic eco-toxicity	kg 1.4-DCB-Eq
11	Marine sediment eco-toxicity	kg 1.4-DCB-Eq
12	Photochemical oxidation (summer smog)	kg formed ozone
13	Resources	kg antimony – Eq
14	Stratospheric ozone depletion	kg CFC-11-Eq
15	Terrestrial eco-toxicity	kg 1.4-DCB-Eq

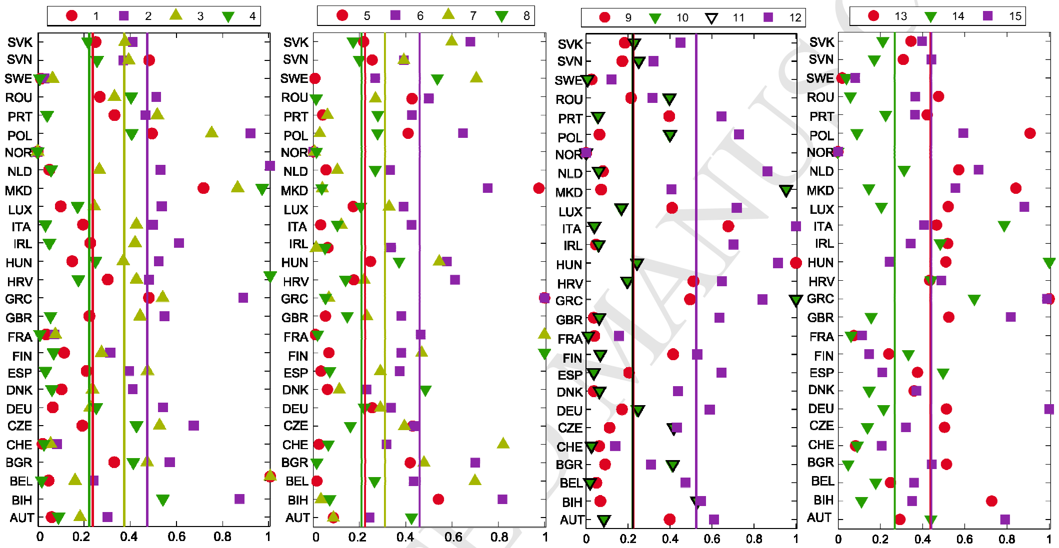


Fig.1. Normalized environmental impact for every country in each category. The values are expressed per kWh and normalized by subtracting the minimum value and dividing by the difference between the maximum and minimum impact attained in every category over all the countries. The horizontal axis displays the values of the 15 impacts described in Table 2 for every country shown in the vertical axis (see acronyms in Table 1). The vertical lines represent the average of each impact.

Figure 1 shows the normalized environmental impacts associated with the generation of 1kWh in the different damage categories. The interval within which the impact values fall is very large, which leads to numerical problems during the application of the DEA approach. The goal of normalization is to refer the impact scores to a common interval ([0,1], where 0 is the minimum value and 1 is the maximum). This facilitates the comparison of different environmental impacts and their visual analysis (see Figure 1), while at the same time avoiding the numerical difficulties that may arise when solving the LP models of the DEA for impact values that differ in several orders of magnitude.

The average of each impact is depicted by a vertical line (note that the values of the average of impact 9, 10 and 11 are very similar; 0.2235, 0.2227 and 0.2240, respectively, and cannot be properly distinguished in the figure).

As seen in Figure 1, there are countries that perform poorly in one impact and well in others. As an example, France, Switzerland and Sweden show low environmental impacts in all of the damage categories, except for ionising radiation. This is because in these countries nuclear energy represents a significant proportion of the production mix (see Figure 2), and this technology performs very well in many environmental categories except for ionising radiation. Hence, there is no single country that shows the best performance in all of the indicators simultaneously.

Furthermore, as seen in Figure 1, some impacts behave similarly, that is, when one takes high values in one country so do others and vice-versa. To further study the relationships between metrics, we carried out a statistical analysis based on the p-value between damage categories (Table 3). This analysis shows that water pollution metrics (impacts 4, 5, 10, 11) are highly correlated (p-value above 0.99 between them and above 0.72 with climate change, acidification, resources and human toxicity). Other strong dependences arise between climate change and resources (p-value of 0.975) and climate change and eutrophication potential (p-value of 0.886), between acidification and eutrophication potential (p-value above 0.91) and between malodorous air and stratospheric ozone depletion (p-value above 0.84). In addition, human toxicity shows a strong correlation with climate change and acidification potential (p-values of 0.715 and 0.732, respectively). Moderate correlations are observed as well between climate change and ionising radiation (p-value of 0.588) and photochemical oxidation (p-value of 0.563), and between malodorous air and photochemical oxidation (p-value of 0.628). These results suggest that countries performing well in some impacts will automatically display low impacts in those damage categories correlated with the former.

Table 3 Correlation between impacts (with significance level of 0.05).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	**0.754**	**0.919**	**0.721**	**0.720**	**0.732**	-0.438	-0.296	-0.036	**0.723**	**0.722**	0.164	**0.685**	-0.044	0.172
2	**0.754**	1	**0.886**	**0.777**	**0.777**	**0.715**	**-0.588**	-0.229	0.127	**0.778**	**0.780**	**0.563**	**0.975**	0.197	**0.547**
3	**0.919**	**0.886**	1	**0.679**	**0.679**	**0.720**	**-0.515**	-0.237	0.054	**0.682**	**0.682**	0.396	**0.810**	0.100	0.238
4	**0.721**	**0.777**	**0.679**	1	**1.000**	**0.795**	-0.311	-0.302	0.066	**1.000**	**1.000**	0.126	**0.770**	0.032	0.401
5	**0.720**	**0.777**	**0.679**	**1.000**	1	**0.794**	-0.312	-0.303	0.064	**1.000**	**1.000**	0.125	**0.770**	0.030	0.401
6	**0.732**	**0.715**	**0.720**	**0.795**	**0.794**	1	-0.064	-0.266	0.234	**0.804**	**0.803**	0.318	**0.729**	0.195	0.310
7	-0.438	**-0.588**	**-0.515**	-0.311	-0.312	-0.064	1	0.123	-0.064	-0.314	-0.317	-0.454	-0.586	-0.176	-0.396
8	-0.296	-0.229	-0.237	-0.302	-0.303	-0.266	0.123	1	0.220	-0.306	-0.307	0.104	-0.236	0.109	-0.112
9	-0.036	0.127	0.054	0.066	0.064	0.234	-0.064	0.220	1	0.073	0.072	**0.628**	0.181	**0.844**	0.143
10	**0.723**	**0.778**	**0.682**	**1.000**	**1.000**	**0.804**	-0.314	-0.306	0.073	1	1.000	0.134	**0.773**	0.041	0.403
11	**0.722**	**0.780**	**0.682**	**1.000**	**1.000**	**0.803**	-0.317	-0.307	0.072	**1.000**	1	0.135	**0.775**	0.039	0.406
12	0.164	**0.563**	0.396	0.126	0.125	0.318	-0.454	0.104	**0.628**	0.134	0.135	1	**0.631**	**0.767**	**0.532**
13	**0.685**	**0.975**	**0.810**	**0.770**	**0.770**	**0.729**	**-0.586**	-0.236	0.181	**0.773**	**0.775**	**0.631**	1	0.265	**0.634**
14	-0.044	0.197	0.100	0.032	0.030	0.195	-0.176	0.109	**0.844**	0.041	0.039	**0.767**	0.265	1	0.157
15	0.172	**0.547**	0.238	0.401	0.401	0.310	-0.396	-0.112	0.143	0.403	0.406	0.532	**0.634**	0.157	1

To shed further light on the environmental impact patterns of energy generation, we next analyzed the electricity mix of the top European countries (Figure 2).

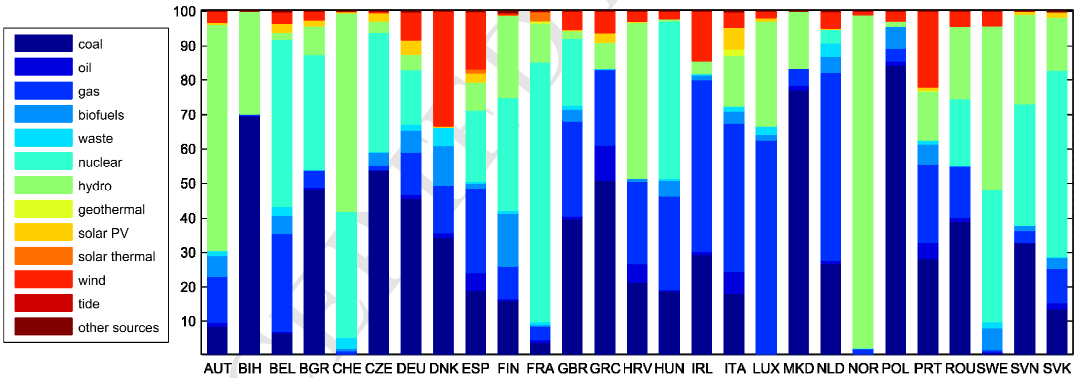


Fig.2. Mix of electricity generation for the 27 studied countries. Source: IEA statistics, electronic version, 2012.

From this analysis we can draw the following conclusions:

- Norway shows the lowest impact in all of the categories due to the high share of hydro power (i.e., 96.7%), which is a very clean production technology.
- Countries with high share of nuclear energy present high impacts in ionising radiation. For instance, France attains the maximum ionising radiation impact, as nuclear energy represents 75.3% of its total mix. Other countries with high

ionising radiation impacts are Slovakia, Belgium and Hungary. On the other hand, countries with little or no nuclear energy show low impacts in ionising radiation (i.e., Austria, Bosnia & Herzegovina, Denmark, Greece, Ireland, Poland, Portugal and Republic of Macedonia).

- Countries with high share of fossil fuels (coal and oil) show high impacts on climate change, eutrophication potential and human and terrestrial eco-toxicity, among others. This happens for instance in Greece, Bosnia & Herzegovina, Poland and Republic of Macedonia, which use large amounts of coal.
- Countries with large shares of fossil, nuclear and renewable sources in their electricity mixes show large environmental impacts in many categories (i.e. Germany, Portugal, Romania and Spain).

As observed, countries tend to perform well in some damage categories and poor in others. This is because the environmental impact is given by the technologies they implement (i.e., fossil, nuclear or renewable), which have large impacts in some categories and low in others as well. Hence, there is no single nation attaining the lowest impact in all of the environmental damage categories, that is, there is no single "best" electricity mix in environmental terms, but rather a set of "efficient" technologies that feature the property that they cannot be improved simultaneously in all of the environmental categories without necessarily worsening at least one of them. Bearing this in mind, we next address the following points:

- Considering the current electricity mixes, we would like to know which nations are environmentally efficient and which are inefficient.
- For the countries that are inefficient (i.e., they cannot be improved simultaneously in all of the impact categories), we would like to answer the following questions: (i) Which efficient countries should be taken as benchmark to improve the environmental performance of the inefficient one? (ii) By how much we should reduce the impact in every category to make the inefficient country efficient?

In the following sections, DEA is used to shed light on these fundamental questions.

3. Methodology – DEA application

After performing the preliminary analysis of environmental performance shown above, we next describe the methodology followed to assess the environmental efficiency of the electricity mix of the countries. In essence, we follow here the combined method of

LCA and DEA, which was applied to quantify the eco-efficiency of wind farms(Iribarren et al., 2013). In this approach, DEA is used to measure the environmental efficiency, while LCA principles are applied to quantify the environmental performance. The fundamentals of DEA are presented first through the use of a small illustrative example before explaining in detail how it has been applied to our particular case.

3.1. Fundamentals of DEA

DEA makes use of an LP model to estimate the efficiency of a set of decision making units (DMUs) (in our case, electricity generation technologies). The ultimate goal is to determine an efficiency score that takes into account multiple inputs and outputs simultaneously. This efficiency indicator can be mathematically expressed as follows:

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} \quad (1)$$

According to Cooper (Charnes et al., 1978), a full (100%) efficiency is attained by any DMU if and only if none of its inputs or outputs can be improved without worsening some of its other inputs or outputs. DEA performs a multi-factor productivity analysis that measures the relative efficiencies of a homogenous set of DMUs.

As previously mentioned, the efficiency of a unit *j* (denoted by θ_j) is defined as the weighted sum of outputs to the weighted sum of inputs:

$$\theta_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \quad \forall j \quad (2)$$

Where variable u_r is the weight associated with the *r*-th output, variable v_i represents the weight given to the *i*-th input, parameter x_{ij} is the amount of input *i* utilized by DMU_j, and parameter y_{rj} is the amount of output *r* produced by DMU_j, wherein $i = 1, \dots, m; j = 1, \dots, n; r = 1, \dots, s.$

Consider *n* DMUs, each with *m* inputs and *s* outputs. Assuming that $x_{ij} \geq 0, y_{rj} \geq 0$ and for the test object with index 0, the relative efficiency score of DMU *j'* ($\theta_{j'}$) is obtained by solving the following LP model proposed by Charnes et al. (Charnes et al., 1978):

$$\theta_{j'} = \max \frac{\sum_{r=1}^{s} u_r y_{rj'}}{\sum_{i=1}^{m} v_i x_{ij'}} \qquad (3)$$

$$s.t. \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \ \ \forall j$$

$$u_r \geq 0 \ \ \forall r, v_i \geq 0 \ \forall i$$

The fractional program shown in (3) can be reformulated into the following linear program (for more details see Charnes et al. (Charnes et al., 1978)):

$$\theta_{j'} = \max \sum_{r=1}^{s} u_r y_{rj'}$$

$$s.t \sum_{i=1}^{m} v_i x_{ij'} = 1 \qquad (4)$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \ \ \forall j$$

$$u_r \geq 0 \ \ \forall r, v_i \geq 0 \ \forall i$$

This model (4) is known as input-oriented CCR DEA (Charnes et al., 1978). The term “input-oriented” indicates that the linear programming model is configured so as to determine that an inefficient unit is made efficient thought the proportional reduction of inputs while the output is held constant. Moreover, the CCR model is referred to constant return to scale (CRS) which assumes that all DMUs operate at the same scale and the output will change at the same proportion as the inputs are changed.

By running the above problem *n* times (each time for a different DMU unit), we obtain the relative efficiency score of each DMU. In addition, the LP determines the input and output weights that maximize the efficiency score of a DMU. A DMU is considered to be efficient if the LP provides a score equal to 1, while a score lower than 1 indicates that the DMU is inefficient.

For every inefficient DMU, DEA determines a set of efficient units that can be used as benchmarks for improving the inefficient unit. The benchmarks can be obtained by solving the following dual problem:

$$\min \theta_{j'}$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} - \theta_{j'} x_{ij'} \leq 0, \quad \forall i \qquad (5)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{rj'} \geq 0, \quad \forall r$$

$$\lambda_j \geq 0, \forall j$$

Observe that decision variable λ_j represents the weight for DMU_j. Note that a DMU is inefficient if a composite DMU (linear combination of units in the set) can be recognized which maintains at least the same output level while utilizing less input than the test DMU.

The dual problem (5) provides as output the necessary improvements required in the inefficient unit's input to make it efficient. An inefficient DMU can be made more efficient by projection into the efficiency frontier. Efficiency can be improved through reduction of inputs. The existing gap from any inefficient DMU to the efficiency frontier shows the extent to which the DMU should be further improved to reach the optimal efficiency level. Hence, more precisely, the input reduction required for a DMU to become efficient, corresponds to the difference between the current input value in the inefficient unit, and the input value in the aggregated DMU obtained as a linear combination of the efficient units selected by the dual problem. Note that the variables of the dual problem represent the linear coefficients of such combination of efficient units. Each composite unit represents hypothetical targets for future attainment which could be useful guides for decision and policy-makers makers in order to improve the efficiency of the inefficient unit. Further details on this issue can be found elsewhere (Cooper et al., 2007). Note that DEA is primarily a diagnostic tool and does not prescribe any reengineering strategies to make inefficient units (countries) efficient.

3.2. Integrated use of LCA and DEA.

(Vázquez-Rowe et al., 2010) developed a “five step LCA+DEA method” for the direct estimation of environmental impact efficiency of DMUs and the simultaneous benchmarking of operational and environmental parameters. In our case, we have adapted this approach by omitting some steps that are not required because the environmental profiles are obtained from LCIA data retrieved from an environmental database (i.e., Ecoinvent 3.1) rather than calculated from mass and energy balances. Hence the following steps are applied in our case:

i) Data collection. Environmental LCIA data is gathered for each DMU using environmental databases. If the necessary data are missing for some technologies, specific LCA calculations based on mass and energy balances will be carried out in order to obtain the impact values required for the analysis.

ii) The primal DEA is solved for each DMU in order to determine whether it is efficient or not.

iii) Quantification of the environmental consequences of operational inefficiencies (eco-efficiency verification). The comparison between the potential environmental impacts for the virtual DMUs and those for the current DMUs quantifies the environmental impacts generated by inadequate operational practices. Clear guidelines are therefore proposed for the inefficient units that could in turn be used to develop more efficient environmental regulations.

3.3. DEA in the context of our study: illustrative example.

To further clarify the concept of efficiency and the use of the primal and dual LP models in the context of our problem, we next introduce an illustrative example that considers 9 technologies for electricity generation and 2 environmental impacts. For simplicity, we assume that all the technologies have the same cost, but differ in the values of the environmental impacts associated with the generation of 1 kWh. Hence, for this case the inputs are the environmental impacts, and the output is 1 kWh.

Table 4 Example of 9 technologies with 2 environmental inputs (i.e., impacts) and one output (i.e., 1 kWh).

Technologies		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
Impact 1 [units·kWh^{-1}]	x_{1j}	4.0	7.0	8.0	4.0	2.0	5.0	6.0	5.5	6.0
Impact 2 [units·kWh^{-1}]	x_{2j}	3.0	3.0	1.0	2.0	4.0	2.0	4.0	2.5	2.5
Output [kWh]	y_{1j}	1	1	1	1	1	1	1	1	1

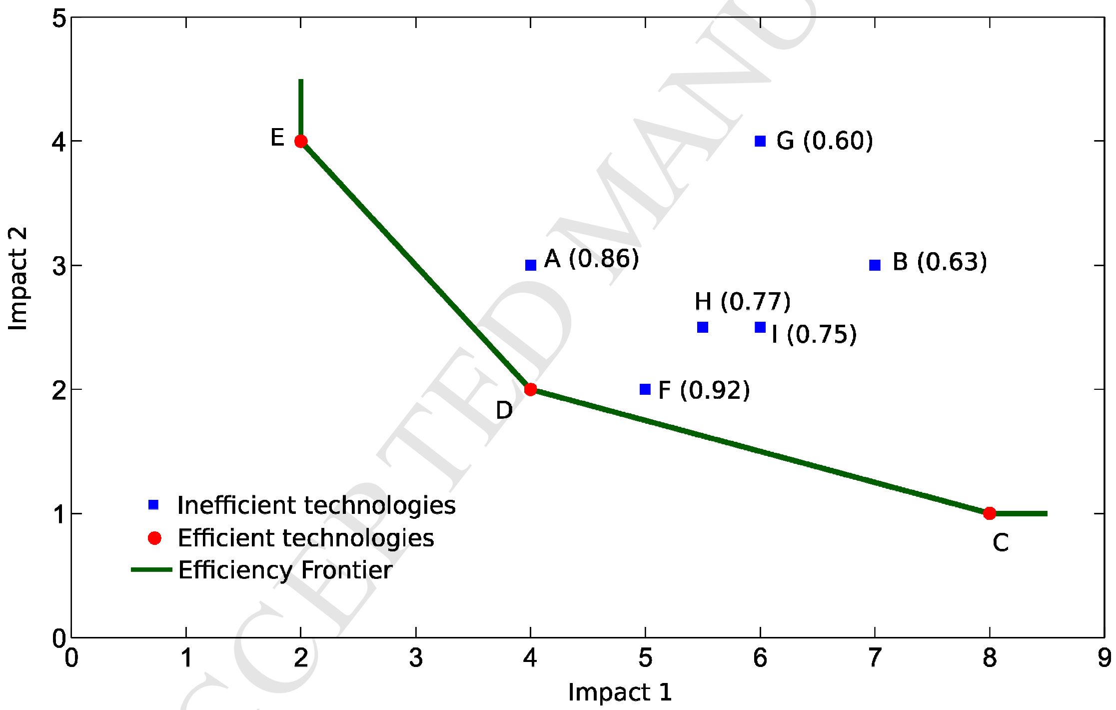


Fig. 3. Interpretation of the DEA eco-efficiency measure for the alternatives in Table 4 as a radial distance to the frontier. The efficient value of each technology is shown into brackets (note that E, D and C has an efficiency score of 1).

Figure 3 displays the values of the 2 impacts (inputs) for each technology. Red circles in the figure denote the efficient technologies, while blue squares represent the inefficient ones. The efficient technologies satisfy the condition that they cannot be improved in one impact without necessarily worsening the other one. In the figure, the efficient units lie on the convex envelope of the points.

The figure shows also the efficiency values of each technology, which are obtained from the primal LP model. The dual problem is solved for the inefficient technologies (i.e., those for which the efficiency score is lower than one) in order to obtain further guidelines on how to improve them using as a basis the efficient ones.

We identify the line connecting C,D and E as the efficient frontier. The efficiency of technology A (note that this point does not belong to the efficiency frontier) can be measured as follows. Let $\overrightarrow{OA}$ be the line from zero to A, which crosses the frontier line at P (see Fig.4). The efficiency of A corresponds to $\frac{OP}{OA} = 0.86$. This means that the efficiency of A is to be evaluated by a combination of D and E, because point P is on the line connecting these two points. D and E are called the *reference set* for A. The reference set for an inefficient technology may differ from one technology to another. For example, the reference set of B is composed of C and D in Figure 4. We can also observe that many technologies are close to D, so it can be therefore said that D is an efficient technology which is also “representative”. On the other hand, C and E are also efficient, but display different features compared to the other units, and for this reason they are far from them.

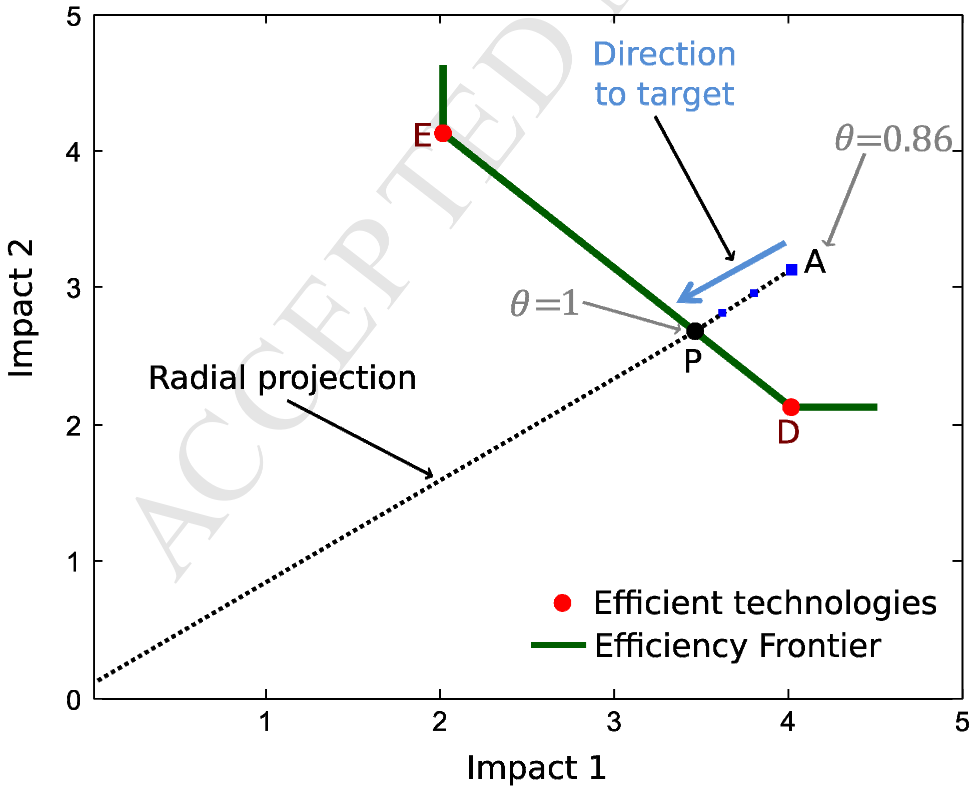


Fig.4. Improvement of an inefficient point (technology) to make it efficient.

We extend the analysis in Figure 4 to identify improvements for the inefficient units so they can become efficient and lie in the efficient frontier. For each inefficient technology, a composite efficient one belonging to the frontier is determined. This composite unit reflects the hypothetical targets that should be achieved by the inefficient unit in order to become efficient. Each inefficient technology should try to get as close as possible to its targets, because by doing so it increases its efficiency. Note that there are different possible ways in which we can project the inefficient unit onto the efficient frontier. Among them, we have selected in this paper the radial projection because it is the most widely used one. However, we could have applied instead the minimum distance projection that finds the point in the efficient frontier with minimum distance to the inefficient unit. In general, there are an infinite number of possible projections, and the targets set on the inefficient units depend on the one chosen. For example, A can be improved by moving towards P with $Inputx_1 = 3.4$ and $Inputx_2 = 2.6$ (which corresponds to the coordinates of P, that is, the coordinates of the point on the efficient frontier identified with the line segment $\overrightarrow{OA}$ in Figure 3 that connects A with the origin). In practice, this means that A needs to reduce impact 1 by 15% and impact 2 by 13.3% so as to become efficient.

4. Numerical results and discussion

The combined approach that integrates DEA with LCA was applied to determine the environmental efficiency of the electricity production mix of the 27 European top economies. The countries, and therefore the electricity production mix associated to each of them are the DMUs considered in the DEA (whose eco-efficiency will be assessed via DEA). As output, we consider the electricity production of 1 kWh, while the environmental impacts associated with the mix (undesirable outputs) are considered as inputs.

The results obtained by applying the input-oriented CCR DEA model are presented in the radar chart of Fig 5. Results reveal that 3 countries are found to be eco-efficient (efficiency equal to 1). These are Ireland, Norway and Romania. On the other hand, 24 countries are inefficient (efficiency lower that 1), with some of them showing very low efficiency scores (like Hungry, Finland, Luxemburg and Germany).

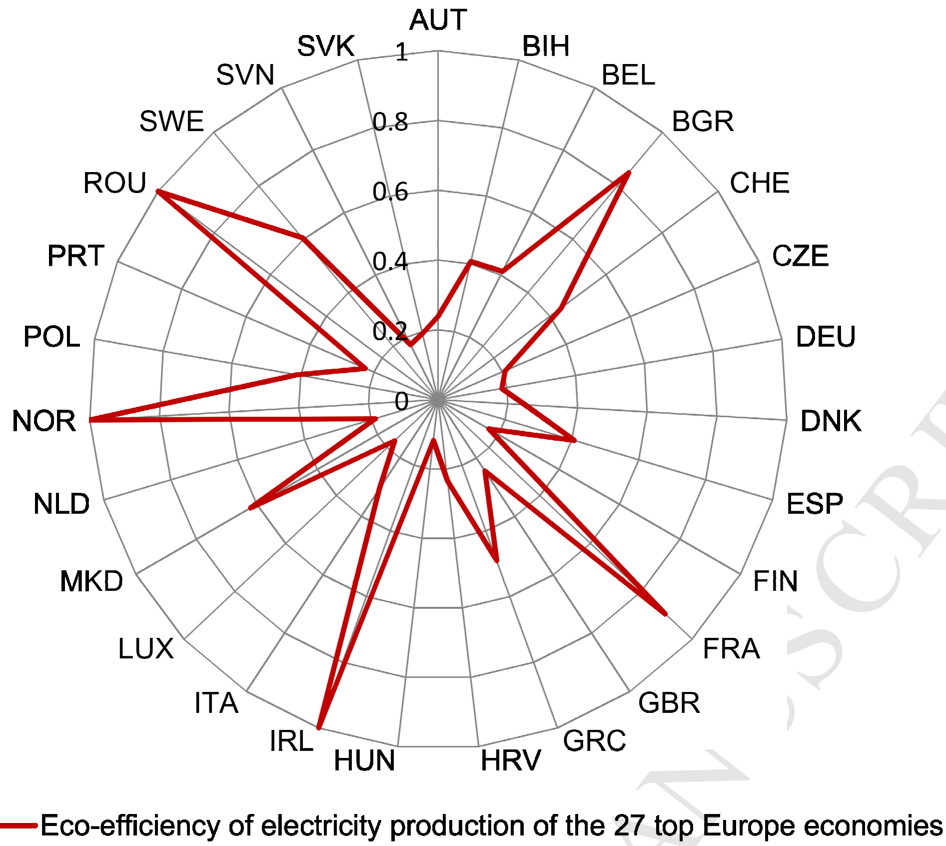


Fig. 5. Eco-efficiency of the electricity production mix of the 27 European top economies.

Norway was expected to be environmentally efficient because it shows very good performance in almost all of the impact categories. This is because its share of hydro power is quite large. The other 3 efficient countries perform well in very few categories in which Norway fails to attain the best performance. This happens because some energy sources responsible for few specific impacts are missing in their mixes (i.e., nuclear, fossil fuels or renewable sources). For instance, the share of hydro power in Romania is lower than in Norway, and for this reason Romania shows better performance in land use, which is mainly given by hydro power (i.e., as they require large amounts of land). Similarly, Ireland has not nuclear energy, and therefore its ionising radiation impact is lower than that of Norway.

We address next the issue of how to make the inefficient countries efficient. As already mentioned, besides the efficiency score, DEA provides guidelines on how to improve the inefficient countries taking as a basis the efficient ones. Figure 6 shows the heat map of the linear coefficients that should be assigned to each efficient country so as to make every inefficient nation efficient. The rows correspond to the efficient countries taken as benchmark in the improvement of the inefficient nations, while the columns display the inefficient countries. Each cell is colored according to the value of the linear coefficient assigned to the efficient nation (in the corresponding row), which is taken as a basis to improve the efficiency score of the inefficient one (in the corresponding column). Light colors indicate low coefficients, while dark colors indicate the opposite.

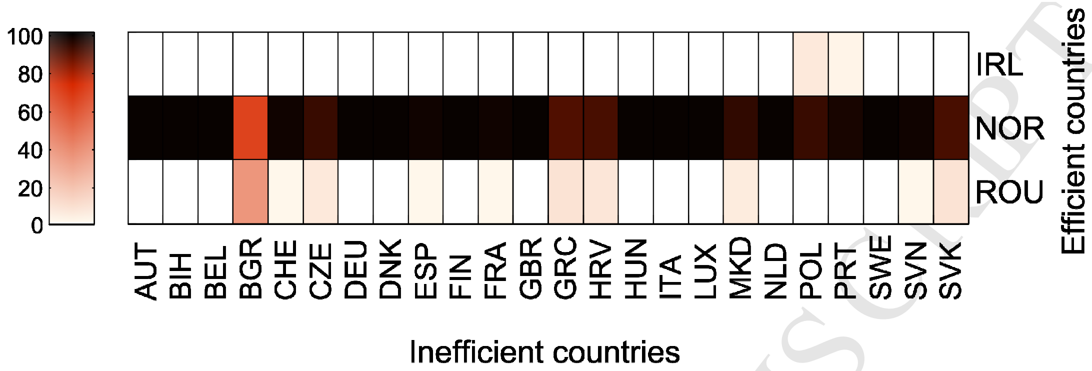


Fig. 6. Heat map of linear coefficients used for improving the inefficient countries considering 27 European top economies.

As observed, Norway is the most employed country (it shows the highest weights). This is because Norway produces most of its electricity from hydro power. Inefficient countries could become eco-efficient by reducing its inputs (environmental impacts) drastically in order to resemble to Norway. This would be accomplished by replacing their current electricity production mix by one based on hydroelectric power. Note, however, that this strategy is quite unrealistic, as the orography of the country plays a key role in the establishment of hydro plants. In other words, it might be impossible (or extremely expensive) to build hydro plants in flat countries (e.g., The Netherlands).

As suggested by Atici and Podinovski(Atici and Podinovski, 2015), there are several ways of dealing with applications in which DMUs have different specializations or production profiles, as happens in our case. One way is to select a subset of inputs on the basis of which the analysis is performed. Another possible manner is to use weight restrictions on the inputs (environmental impact categories). Both these methods have the drawback of being based on value judgements. In this work we follow an alternative method that consists of removing the outliers from the analysis (Golany and Storbeck, 1999; Thanassoulis, 1999). In our study, Norway shows very specific profiles of electricity production that differ significantly from those displayed by the other countries. Since Norway produces more than 96.7% of its electricity using hydro power, it can be regarded as an outlier and it is therefore removed from the analysis in order to generate more meaningful results.

The results obtained by applying the input-oriented CCR DEA model without considering Norway are presented in the radar chart of Figure 7. 19 countries were found to be eco-efficient, while 7 countries are inefficient. Ireland and Romania still appear as eco-efficient, as they do not have nuclear facilities (and therefore show very good performance in ionising radiation).

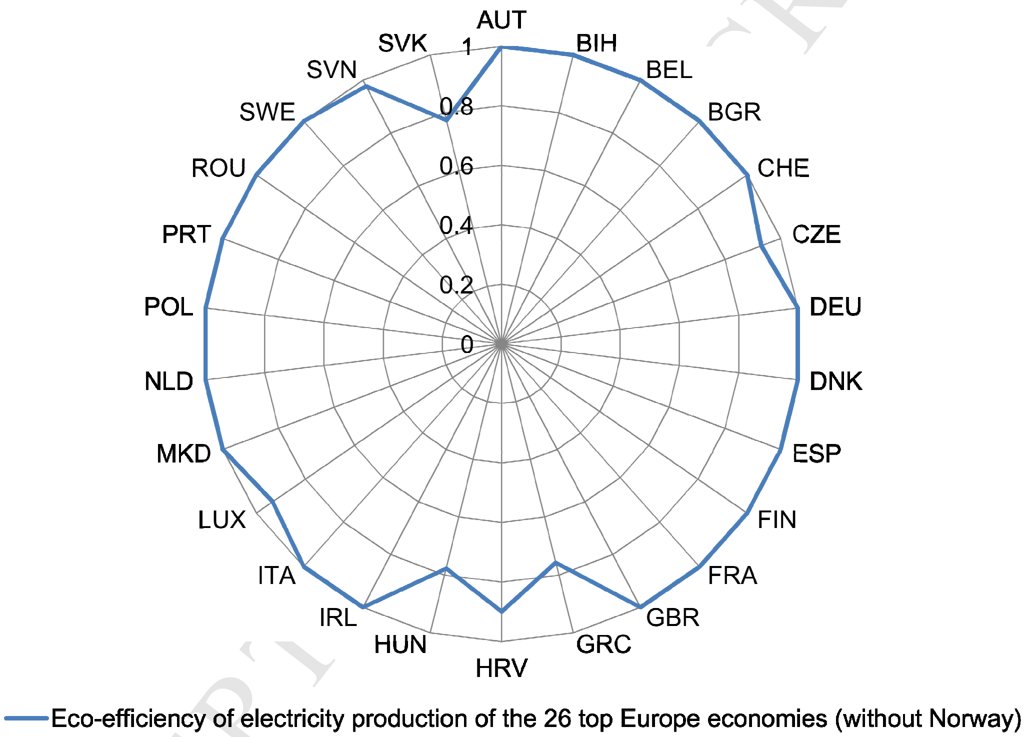


Fig. 7. Eco-efficiency of the electricity production mix of the 26 European top economies without considering Norway.

The inefficient countries are Czech Republic, Greece, Croatia, Hungary, Luxemburg, Slovenia and Slovakia. The efficiency value obtained determines to what extent these countries should reduce their inputs (environmental impacts) to become eco-efficient considering a fixed output of 1 kWh of electricity. Following the previous order, they should reduce their impacts (compared to the current level) in 6.94%, 24.31%, 9.97%, 22.23%, 6.73%, 2.27% and 22.57%, respectively.

We address next the issue of how to make the inefficient countries efficient taking as a basis the eco-efficient ones. Figure 8 shows the heat map of the linear coefficients that should be assigned to each efficient country so as to make every inefficient nation efficient. The rows correspond to the efficient countries (taken as benchmark in the improvement of the inefficient nations), while the columns display the inefficient countries. Each cell is colored according to the value of the linear coefficient assigned to the efficient nation (in the corresponding row), which is taken as a basis to improve the efficiency score of the inefficient one (in the corresponding column). Light colors indicate low coefficients, while dark colors indicate the opposite.

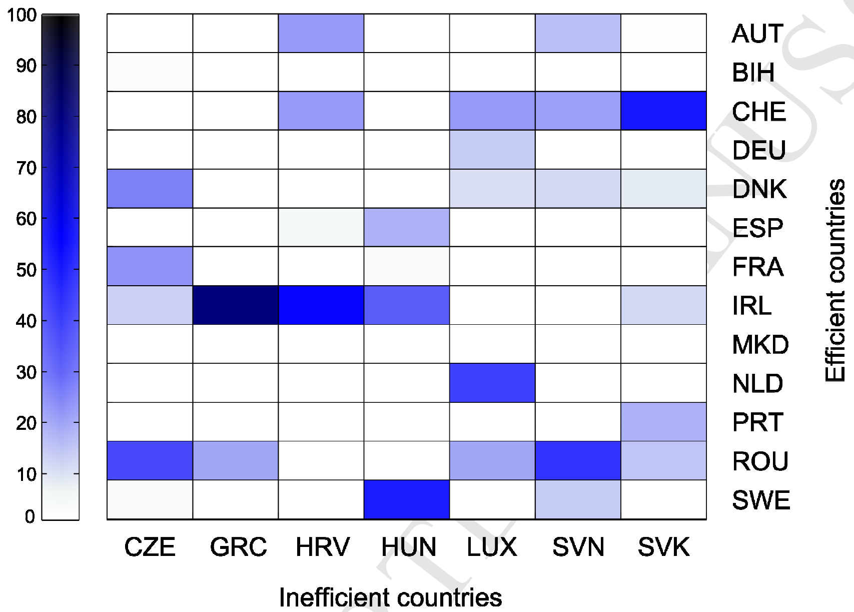


Fig. 8. Heat map of linear coefficients used for improving the inefficient countries considering 26 European top economies (analysis without Norway).

As an example on how to interpret the coefficients shown in Fig.8, Luxemburg would be eco-efficient making a linear combination of the countries in its efficiency reference set, which is composed by Switzerland, Germany, Denmark, Netherlands and Romania. The inputs and outputs of the efficiency reference set are multiplied with the coefficients shown in Fig.8, and then added together to create a composition (i.e., new electricity mix), which determines the hypothetical inputs that Luxemburg should show so as to become eco-efficient.

The eco-efficiency composition for each inefficient country (obtained as explained previously for Luxemburg) can then be compared with the current inputs and outputs.

This analysis allows determining the excesses of inputs (excesses in environmental impact) of the inefficient countries and the way in which they should change their electricity production mix in order to become eco-efficient.

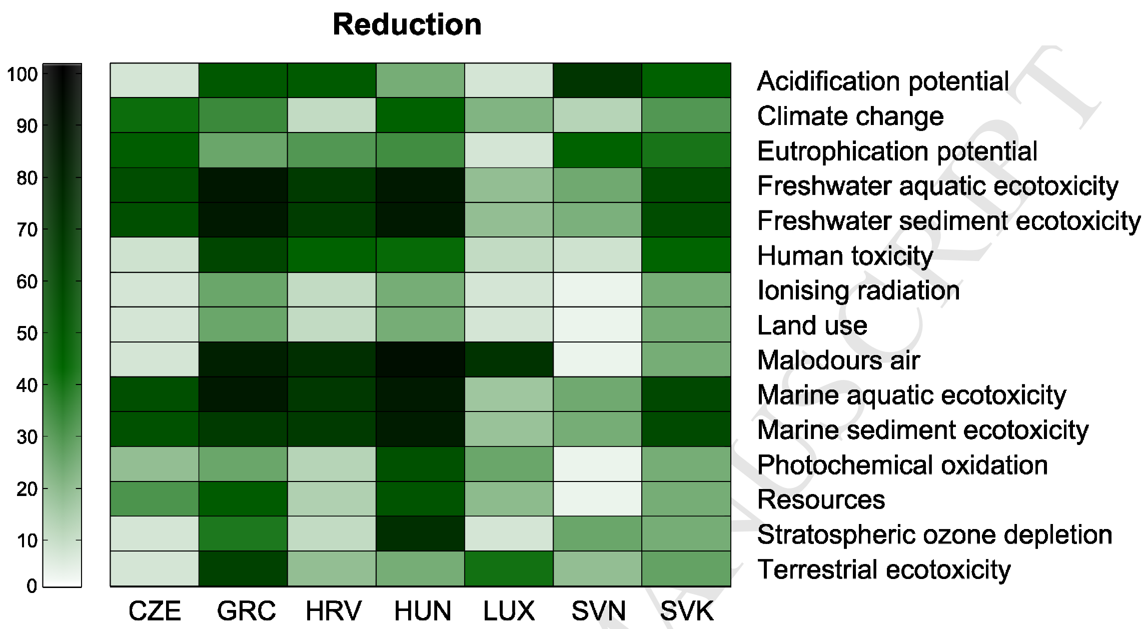


Fig. 9. Heat map of environmental impact reductions (%) for the inefficient countries.

Figure 9 shows the reductions in each environmental impact category that are necessary to make the inefficient countries efficient. Every cell in the heat map represents the impact reductions (% with respect to the current situation) required by each inefficient country in every damage category so as to make it efficient. Light colors indicate low reductions, while dark colors represent the opposite. As an example, in Luxemburg, significant reductions in malodours air, terrestrial eco-toxicity, photochemical oxidation (summer smog) and climate change (71.4%, 39.8%, 24.1% and 20.5%, respectively) have to be attained to become eco-efficient.

These reductions are further explained by the change that should be implemented in the electricity production mix. Figure 10 shows a comparison between the current electricity production mix of the inefficient countries and the hypothetical mix which makes them eco-efficient. There are two columns per country; the first one corresponds to the current production electricity mix and the second one, bordered with a bold line, corresponds to the hypothetical mix that would make the inefficient country eco-efficient.

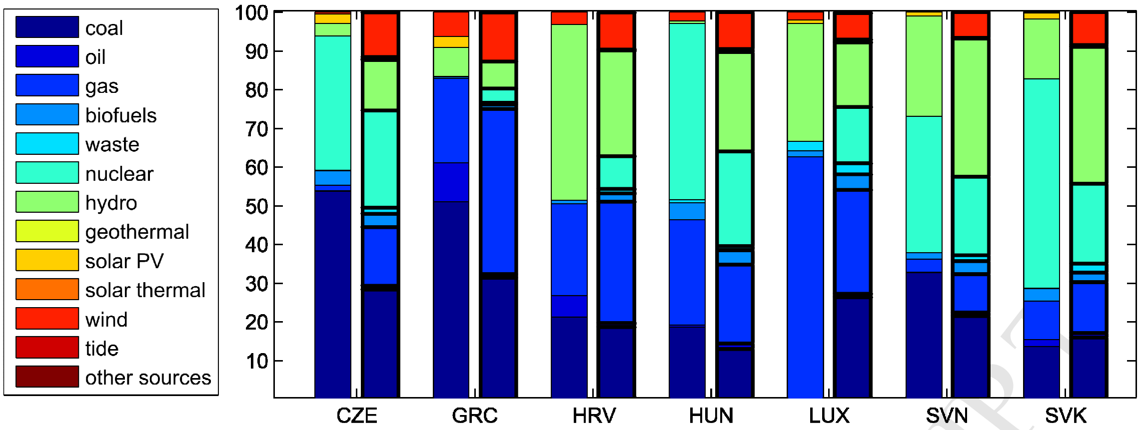


Fig. 10. Comparison between the current and hypothetical efficient electricity production mix of inefficient countries.

As observed in Figure 10, there is a repeated pattern in all the countries. Particularly, the share of hydro power should increase and the share of fossil fuels reduced. Each of these "hypothetical" eco-efficient electricity production mixes provides valuable insight for governments and policy-makers as to which targets need to be met in the future to ensure a better transition towards a cleaner energy system. In practise, the targets could be reached by progressively replacing some technologies by others. More precisely, fossil fuels should be replaced by cleaner and environmentally friendlier electricity production technologies.

5. Conclusions

Moving towards environmentally friendly energy systems has become a major goal of modern societies, which seek to satisfy the growing electricity demand at minimum environmental impact.

In this paper we assessed the eco-efficiency of the electricity mix of the top 27 European's economies using an approach that combines LCA and DEA. Each European country satisfies the electricity demand with different mixes of technologies that cause specific impacts. In this context, the integrated methodology that combines LCA and DEA allows assessing the level of eco-efficiency attained by a country, that is, the extent to which it is able to cover its electricity demand while keeping the impact in several categories as low as possible. Our approach provides clear environmental targets that should be attained by inefficient countries in order to become eco-efficient.

After removing outliers, we found that there are 7 eco-inefficient countries out of 26. For the inefficient countries, we determined the changes in their mixes that need to be performed so as to make them efficient. These changes imply reductions of different magnitude in the share of fossil fuels, which cause significant environmental impacts. Therefore, our results provide valuable insight for decision and policy makers on how to set environmental targets on electricity production. However, when making decisions for the future electricity mix other considerations of economic and social nature should be considered.

The combined approach LCA+DEA provides valuable insight during the development of effective regulations that aim to ensure that electricity demand is satisfied at minimum environmental impact.

Note that the results obtained in this work may change according to the variability and uncertainty of the input data. Uncertainty factors were missing for some LCIA data, and for this reason we decided to concentrate on the analysis of the nominal performance. Future work, however, will deal with this aspect of the problem.

We should also clarify that economic, social, technological and political aspects have been left out of the analysis, mainly because there is a lack of quantitative indicators for describing the performance of a technology in these dimensions (except for the economic case, for which several indicators are available but as already mentioned they seldom reflect the true cost of the system due to external regulations). Future work will focus on incorporating some social and economic metrics in the analysis.

Acknowledgements

The authors wish to acknowledge support from the Spanish Ministry of Education and Science (Projects (CTQ2012-37039-C02, DPI2012-37154-C02-02, and ENE2011-28269-C03-03) and the Generalitat de Catalunya (FI programs).M.T. acknowledges the support from TUBITAK with Grant104M322. Authors express special thanks to Dr. Carlos Pozo (SUSCAPE, URV) for carefully reviewing and improving this manuscript.

References

Atici, K.B., Podinovski, V. V., 2015. Using data envelopment analysis for the assessment of technical efficiency of units with different specialisations: An application to agriculture. Omega 54, 72–83. doi:10.1016/j.omega.2015.01.015

Avadí, Á., Vázquez-Rowe, I., Fréon, P., 2014. Eco-efficiency assessment of the Peruvian anchoveta steel and wooden fleets using the LCA+DEA framework. J. Clean. Prod. 70, 118–131. doi:10.1016/j.jclepro.2014.01.047

Barba-Gutiérrez, Y., Adenso-Díaz, B., Lozano, S., 2008. Eco-Efficiency of Electric and Electronic Appliances: A Data Envelopment Analysis (DEA). Environ. Model. Assess. 14, 439–447. doi:10.1007/s10666-007-9134-2

Bhagavath, V., 2009. Technical Efficiency Measurement by Data Envelopment Analysis: An Application in Transportation. Alliance J. Bus. Res. 60–72.

Bhat, I.K., Prakash, R., 2009. LCA of renewable energy for electricity generation systems—A review. Renew. Sustain. Energy Rev. 13, 1067–1073. doi:10.1016/j.rser.2008.08.004

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

Cooper, W.W., Seiford, L.M., Tone, K., 2007. Data Envelopment Analysis, Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software: Second Edition. Springer US, Boston, MA. doi:10.1007/978-0-387-45283-8

Dyckhoff, H., Allen, K., 2001. Measuring ecological efficiency with data envelopment analysis (DEA). Eur. J. Oper. Res. 132, 312–325. doi:10.1016/S0377-2217(00)00154-5

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

Finnveden, G., Hauschild, M.Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., Koehler, A., Pennington, D., Suh, S., 2009. Recent developments in Life Cycle Assessment. J. Environ. Manage. 91, 1–21. doi:10.1016/j.jenvman.2009.06.018

Frischknecht, R., Braunschweig, A., Hofstetter, P., Suter, P., 2000. Human health damages due to ionising radiation in life cycle impact assessment. Environ. Impact Assess. Rev. 20, 159–189. doi:10.1016/S0195-9255(99)00042-6

Golany, B., Storbeck, J.E., 1999. A data envelopment analysis of the operational efficiency of bank branches. Interfaces (Providence). 29, 14–26.

Guinée, J., 2001. Handbook on life cycle assessment - Operational guide to the ISO standards. Int. J. Life Cycle Assess. 6, 255.

Hongye, S., 2010. Generalized Additive Models of DEA and Generalized Non-Dominated Solution in Multi-objective Programming, in: 2010 International Conference on Computational Intelligence and Security. IEEE, pp. 596–600. doi:10.1109/CIS.2010.136

Huppes, G., Ishikawa, M., 2005. A Framework for Quantified Eco-efficiency Analysis. J. Ind. Ecol. 9, 25–41. doi:10.1162/108819805775247882

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., Marvuglia, A., Hild, P., Guiton, M., Popovici, E., Benetto, E., 2015. Life cycle assessment and data envelopment analysis approach for the selection of building components according to their environmental impact efficiency: a case study for external walls. J. Clean. Prod. 87, 707–716. doi:10.1016/j.jclepro.2014.10.073

Iribarren, D., Vázquez-Rowe, I., Moreira, M.T., Feijoo, G., 2010. Further potentials in the joint implementation of life cycle assessment and data envelopment analysis. Sci. Total Environ. 408, 5265–72. doi:10.1016/j.scitotenv.2010.07.078

ISO, 2006a. ISO 14044 Environmental management—life cycle assessment—requirements and guidelines.

ISO, 2006b. ISO 14040 Environmental management—life cycle assessment—principles and framework.

Kern, F., Smith, A., 2008. Restructuring energy systems for sustainability? Energy transition policy in the Netherlands. Energy Policy 36, 4093–4103. doi:10.1016/j.enpol.2008.06.018

Kuosmanen, T., Kortelainen, M., 2005. Measuring Eco-efficiency of Production with Data Envelopment Analysis. J. Ind. Ecol. 9, 59–72. doi:10.1162/108819805775247846

Liu, C.H., Lin, S.J., Lewis, C., 2010. Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. Energy Policy 38, 1049–1058. doi:10.1016/j.enpol.2009.10.057

Michelsen, O., Fet, A.M., Dahlsrud, A., 2006. Eco-efficiency in extended supply chains: a case study of furniture production. J. Environ. Manage. 79, 290–7. doi:10.1016/j.jenvman.2005.07.007

Sarıca, K., Or, I., 2007. Efficiency assessment of Turkish power plants using data envelopment analysis. Energy 32, 1484–1499. doi:10.1016/j.energy.2006.10.016

Schmidheiny, S., 1992. Changing course - a global business perspective for development and environment. MIT Press, Cambridge.

SETAC, 1993. Guidelines for life-cycle assessment. A code or practice., in: SETAC Workshop. Sesimbra.

Sözen, A., Alp, İ., Özdemir, A., 2010. Assessment of operational and environmental performance of the thermal power plants in Turkey by using data envelopment analysis. Energy Policy 38, 6194–6203. doi:10.1016/j.enpol.2010.06.005

Thanassoulis, E., 1999. Data envelopment analysis and its use in banking. Interfaces (Providence). 29, 1–13.

UNCTAD, 2003. A manual for the preparers and users of eco-efficiency indicators. United Nations Conference on Trade and Development.

Van Oers, L., 2004. CML-IA–Database Containing Characterization Factors for Life Cycle Impact Assessment (Centre of Environmental Science (CML)), in: [CML 2004]. Leiden.

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, 1–10. doi:10.1155/2015/813921

Vázquez-Rowe, I., Iribarren, D., Moreira, M.T., Feijoo, G., 2010. Combined application of life cycle assessment and data envelopment analysis as a methodological approach for the assessment of fisheries. Int. J. Life Cycle Assess. 15, 272–283. doi:10.1007/s11367-010-0154-9

Weidema, B.P.; Bauer, Ch.; Hischier, R.; Mutel, Ch.; Nemecek, T.; Reinhard, J.; Vadenbo, C.O.; Wernet, G., 2013. The ecoinvent database: Overview and methodology, Data quality guideline for the ecoinvent database version 3.

Wu, J., An, Q., Yao, X., Wang, B., 2014. Environmental efficiency evaluation of industry in China based on a new fixed sum undesirable output data envelopment analysis. J. Clean. Prod. 74, 96–104. doi:10.1016/j.jclepro.2014.03.054

Zhang, Y., McKechnie, J., Cormier, D., Lyng, R., Mabee, W., Ogino, A., Maclean, H.L., 2010. Life cycle emissions and cost of producing electricity from coal, natural gas, and wood pellets in Ontario, Canada. Environ. Sci. Technol. 44, 538–44. doi:10.1021/es902555a

- We analyze the eco-efficiency of the electricity mix of the top 27 European economies.
- Moving toward ecofriendly electricity production mixes is the target of this study.
- The targets for eco-inefficient countries are provided and compared with actual mixes.
- The study focus on satisfy electricity demand with minimum environmental impact.
- Useful guide for governments on how to improve environmental performance.