UNIVERSITAT ROVIRA I VIRGILI

SYSTEMATIC TOOLS BASED ON DATA ENVELOPMENT ANALYSIS FOR THE LIFE CYCLE SUSTAINABILITY EVALUATION OF TECHNOLOGIES

Anna Ewertowska

DOCTORAL THESIS

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CERTIFY:

That the present study entitled "*Systematic tools based on data envelopment analysis for the life cycle sustainability evaluation of technologies*", presented by Anna Ewertowska for the award of the degree of Doctor, has been carried out under our supervision at the at the Chemical Engineering Department of the University Rovira i Virgili.

Tarragona, 4thMay, 2017

Dr. Jordi Gavaldà Casado Dr. Gonzalo Guillén Gosálbez Dr. Laureano Jiménez Esteller

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SUMMARY

Moving towards a more sustainable energy generation system has been a main challenge of modern societies during the last decades. By minimizing the dependence on fossil fuels and associated anthropogenic impacts, it is possible to improve the sustainability level of anthropogenic activities. Researchers and policy makers confronts the challenge of developing strategies to restructure energy systems into more sustainable forms, which calls for advanced decision-support tools.

With the quick economic and technology growth, several attempts have been put forward in order to define the concept of sustainability and select appropriate measurement tools. The balance of the three main dimensions of sustainable development proposed in Brundland Report [1] referred to the environmental, economic and social aspects of processes/products/systems. In the context of environmental performance, the question that still remains open is how to assess and quantify the environmental eco-efficiency level of a system.

The concept of 'eco-efficiency', introduced in 1991 by the World Business Council for Sustainable Development (WBCSD), soon became a management philosophy geared toward sustainability. Eco-efficiency, which applies to all business aspects, links the economic and environmental performance of a system in order to enable the identification of the most efficient alternatives (*i.e.*, those maximising profits whilst reducing the associated potential ecological damage). A well-established environmental engineering tool, Life Cycle Assessment (LCA) quantifies the impact produced in all of the phases in the life cycle of a system, product or service(*i.e.*, from cradle to grave analysis) using specific environmental indicators.

Environmental metrics can be based on environmental interventions (*e.g.*, emissions, land use, extractions, etc.); midpoint impacts (*e.g.*, global warming, ecotoxicity, acidification, water pollution, ozone depletion, etc.); or endpoints indicators,

which quantify the damage in human health (*e.g.*, morbidity and mortality), ecosystem quality (*e.g.*, biodiversity), and human affluence (*e.g.*, landscape, natural resources, cultural heritage, etc.)

Eco-efficiency can be assessed via data envelopment analysis (DEA), where data on inputs and outputs are based on nominal values that must be perfectly known in advance. From the observed data, DEA determines an efficient frontier containing the efficient units. Furthermore, for each unit deemed inefficient, DEA provided a set of target values (for inputs and outputs) that (if accomplished) would make the inefficient unit efficient.

Unfortunately, in the context of eco-efficiency assessment, environmental scores are affected by numerous sources of uncertainty stemming from imprecise measurements, lack of data and/or modelling choices. Uncertainties are particularly significant in LCA studies [2], as they require large amounts of data from disperse facilities located in different parts of the product's supply chain that might belong to different owners who might be reluctant to share this information (or even lack the necessary measurements).

This doctoral thesis proposes novel methods for the assessment of LCA metrics and for uncertainty analysis that measure the environmental performance (eco-efficiency) of a system under uncertainty. Particularly, a toolkit of techniques including life cycle assessment, the Pedigree matrix, Monte Carlo Simulation and Data Envelopment Analysis are applied to assess the level of sustainability of a system. The main approach is applied to assess the environmental performance of energy production considering several uncertainties.

The work compiled in this PhD dissertation comprises three main parts. The first chapter presents an introduction, an analysis of existing approaches, and a description of methods and tools applied during this thesis.

The second part deals with the combined DEA+LCA technique for the assessment of environmental impacts provoked by energy production, considering how uncertainties affect the results. This part explores the ecological performance (eco-efficiency) of the electricity mix of the top European economies and allows identifying environmentally efficient and inefficient countries considering as undesirable inputs several environmental impacts associated with the production of 1 kWh (regarded as output). Furthermore, the method establishes targets for the inefficient countries that (if attained) would 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 damage. Furthermore, the DEA+LCA method has been extended to deal with the uncertainty, through the implementation of the Pedigree matrix approach and Monte Carlo simulation to enable the eco-efficiency assessment under uncertainty of a system. Additionally, the comparison between the deterministic case and the stochastic cases is made, showing the differences between them and highlighting the importance of the uncertainty assumption in sustainability analysis.

Finally, the last part of this work provides the final conclusions and future work.

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PART I: Introduction

1. Introduction

1.1 Preface

Moving towards a more sustainable global development has become a major goal of modern societies that aim to ensure meeting the needs of present generations without compromising the ability of future generations to meet their own needs. The idea of sustainable development indicate *"not absolute limits but limitations imposed by the present state of technology and social organization on environmental resources and by the ability of the biosphere to absorb the effects of human activities"*[1]. Thus if social organization and technology can be both supervised and improved by governments, as the coordinator of human progress, to make way for a new era of economic growth, it is crucial that sustainability issues have an important role in the agenda.

Furthermore, nowadays, due to the rapidly economic and technology growth, as well as the current environmental friendly trend, governments and worldwide companies face an unending challenge to continually evaluate and measure all aspects of economic and technological development, such as cost reductions, environmental pollution, and impacts damage, among other factors. For those countries/companies that have identified and recognized the need to embrace sustainable development, the understanding and implementation of practical indicators of sustainability is required.

1.2 Sustainability development

With the increase of human actions on the planet, the necessity of sustainability became a crucial objective for present society and future generations. Lindsey has summarized an increasing significance of sustainability research reflected in a growing number of publications [3]. In fact, the perception of sustainability has been the focus of public attention for more than 40 years. Meadows *et al.* alerted in his book titled *"The Limits to Growth"* that our future development is limited by the depletion of natural resources and the growing world population [4]. As cited by Forrester *et al.*[5], three decades ago William Ruckelshaus (1989), the first administrator of the United States Environmental Protection Agency, had already requested: *"Can we move nations and people in the direction of sustainability? Such a move would be a modification of society comparable in scale to only two other changes: the Agricultural Revolution of the late Neolithic and the Industrial Revolution of the past two centuries. These revolutions were gradual, spontaneous, and largely unconscious. This one will have to be a fully conscious operation, guided by the best foresight that science can provide. If we actually do it, the undertaking will be absolutely unique in humanity's stay on Earth."*

For the future development of society we have to look for a sustainable growth, as conceptualized by the World Commission on Environment and Development (WCED) in 1987, which first launched the concept of sustainable development in Our Common Future (also known as the Brundtland Report [1]). The aforementioned works gained public attention in shaping the sustainability and sustainable development concepts, as they explicitly addresses challenges such as the management of the following trade-offs: intra- *versus* intergenerational equity, earth limits *versus* population growth, and collective *versus* individual interests.

Additionally, the critical objectives of sustainable development proposed by the European Commission [6] are: (1) reviving growth; (2) changing the quality of growth; (3) meeting essential needs for job, water, energy, food, and sanitation; (4) reorienting technology and managing risk; (5) ensuring a sustainable level of population; (6) reorienting international economic relations; (7) merging environmental and economics ion decision making; and (8) conserving and enhancing the resource base.

The presented objectives show the mainstream of sustainable development thinking represented by many international environmental agencies such as the World Wildlife Fund (WWF), UNEP [7], the US Agency for International Development, development agencies including World Bank, the Canadian and Swedish international development agencies such as the International Institute for Environmental and Development or the Worldwatch Institute.

Generally, sustainability can be expressed as the ability to sustain [8], maintain [9] or continue [10] something over time. In technical term, this definition refers normally to the maintenance or continuation of some system or process over time [11]. Although sustainability is a relevant concept for society, economics, and the environment, with thousands of annually publications, its definition is still unclear.

For instance, Hannon et al.[12]dispute that *"the diffusion and popularity of the term sustainability with relatively little corresponding rigorous and grounded conceptualization may have created confusion over the basic concepts of sustainability"*. In addition, they advise that *"the lack of a unified and rigorous understanding of sustainability means that sustainability initiatives are often ineffectual*". Although their suggestion was made in a business context, it can be translated into society as a whole.

Sustainability requires a multi-disciplinary approach[13], but unfortunately is still fractured due to disciplinary barriers [8], [11]. Sachs *et al.* [14]considered sustainable development as the great challenge of the 21stcentury. On the other hand, Vollenbroek[15] defined it as a balance between the feasible technologies, strategies of innovation and the policies of governments. As an illustration, there are many distinct research fields that study sustainable development in specialized areas, *e.g.*, development, agriculture, industry, forestry, business, among others (See a more detailed description in Section 2.1).

According to Lélé[16], the main weakness in mainstream formulation of sustainable development are: (i) the characterization of issues of poverty and environmental degradation; (ii) the mentioned unclear definition and conceptualization of the aim of development, sustainability and participation; and (iii) the strategy used against the incomplete knowledge and uncertainty. In his critical review the authors concluded the need to understand the multiple aspects of sustainability and develop measures, benchmarks and principles to deal with them. On the other hand, the author mentioned the urgency to clarify the main definition of sustainability development and to accept the existence of structural, cultural and technological causes of both poverty and environmental degradation and to develop methodologies for sustainability assessment and optimisation.

Several indicators have been put forward to quantify the sustainability level of a system. According to the Brundland Report [1], the sustainability concept refers to the balance of three basic aspects (dimensions) of sustainable development: economic, environmental and social. With the increase of environmental consciousness, stemming from legal and societal pressure, production processes have attempted to improve their ecological performance through process efficiency improvement and waste minimization. Hence, environmental, economic and social benefits are being recognized.On the other hand, Dyllick and Hockerts[17] have framed the three basic aspects (dimensions) of sustainability as the natural case (environmental), the business case (economic) and the societal case (social).

As mentioned above, several attempts have been made to define the methods or indicators for manufacturing operations or processes in order to improve the sustainability level. For instance, the application of two out of the three dimensions of sustainability (economic and environmental) have been implemented by Saling *et al.*[18], as through the use of eco-efficiency metrics. On the other hand, a set of sustainability metrics have been proposed by the Global Reporting Initiative [19] to quantify industrial processes (brief description of other environmental metrics is given in section 1.2.1). The GRI, well known initiative that develops the guidelines for establishment of social, economic and environmental indicators of corporative activities, consists of recommendations and principles of standard reporting format. A total of seventy indicators, introduced in detail in the indicator protocols [20], have been divided into different groups such as economic, environmental, employee, human rights and workplace related or social indicators, among others.

Another authors suggested aggregating the indicators into a single score, thereby helping decision makers[21]–[24]. Other suggestions[25], [26], suitable with the common accepted indicators presented in the Global Reporting Initiative, can be also found in the literature. Afgan *et al.* [27] demonstrates that the decision-making process strongly relies on the preference given to the specific indicators in energy systems evaluation (*e.g.*, acidification potential indicator in Eco99),while Azapagic *et al.* [25] presented useful indicators for the assessment of industrial system.

Unfortunately, although aggregated indicators cover the three dimensions of sustainability, they do not allow the identification of the particular sustainability dimension that should be improved. On the other hand there is an open research question in the selection of the tools to measure sustainability. After the examination of three central steps of index formation: normalization, weighting and aggregation, Böhringer *et al.*[28] find that the normalization and weighting of indicators (associated generally with subject judgments) indicate a high degree of arbitrariness without mentioning or systematically assessing critical assumptions. With regards to aggregation, there are scientific rules which guarantee consistency and meaningfulness of composite indices[29], yet they are still subjective.

1.2.1 Types of sustainability metrics

The selection of suitable indicators or criteria is a crucial issue in sustainability exercise. Several different indicators have been defined besides standard economic, environmental and social aspects, including: technical issues[30], political aspects [31], technological issues[32], institutional aspects[33], community developments[34], or recreational and tourism components [35][36], and indicators for renewable energy systems[37], among others.

According to Schwarz *et al.*[38], there are five basic sustainable indicators: (i) material intensity, (ii) energy intensity, (iii) water consumption, (iv) toxic emissions, and (v) pollutant emissions. Complementary metrics can be developed if other areas of decision support are required.

After an exhaustive analysis of published works on metrics (or indicators) for sustainability, the following issues stand out when obtaining coherent results. According to Martins *et al.*[39] either (i) the selected metrics are not exactly reflective of all three aspects of sustainability; (ii) they are too many and, therefore, are difficult to handle with; or (iii) both limitations apply. The loss of information in the analysis is the principal disadvantage of the use of an aggregated indicator. Consequently, a small set of quantifiable indicators to assess technological or policy changes is an appropriate option [38]. Currently, measurements that consider fewer factors are more versatile and useful for making comparisons between products or processes and therefore more helpful in the decision-making process. Hence, the selection of a suitable set of simple, generally applicable metrics and the construction of complementary metrics, if needed, are the crucial keys in sustainable analysis.

On the other hand, the independency of the chosen indicator, being the requirement in the first selection step, makes easy any changes of description of some indicators or the manner they are calculated, in accordance with the characterization of data available, without influencing others. Economic indicators are usually based on either cost-benefit analysis (CBA) or life-cycle costing (LCC), whereas environmental metrics can be based on environmental interventions (*e.g.*, emissions, extractions, land use, etc.); midpoint impacts (*e.g.*, global warming, toxicity, acidification ozone depletion, etc.); or endpoints indicators. The latter aggregate damages in human health (*e.g.*, morbidity and mortality), ecosystem quality(*e.g.*, biodiversity), and human affluence (*e.g.*, as reflected in production functions, landscape, natural resources, cultural heritage, etc.) [40].

Thus, with the goal of providing an easy and clear method for the implementation of indicators or metrics, the following classification that considers the three dimensions of sustainability (Figure 1.1) has been proposed by Sikdar[41]. The three groups are:

(1) One-dimensional (1D) indicators where only one aspect of sustainability is analysed: economic, social or environmental;

(2) Two-dimensional (2D) indicators where two dimensions are simultaneously taken into account: socio-environmental, socio-economic, or economic-environmental; and

(3) Three-dimensional (3D) sustainability indicators where the three aspects of sustainability are considered simultaneously.

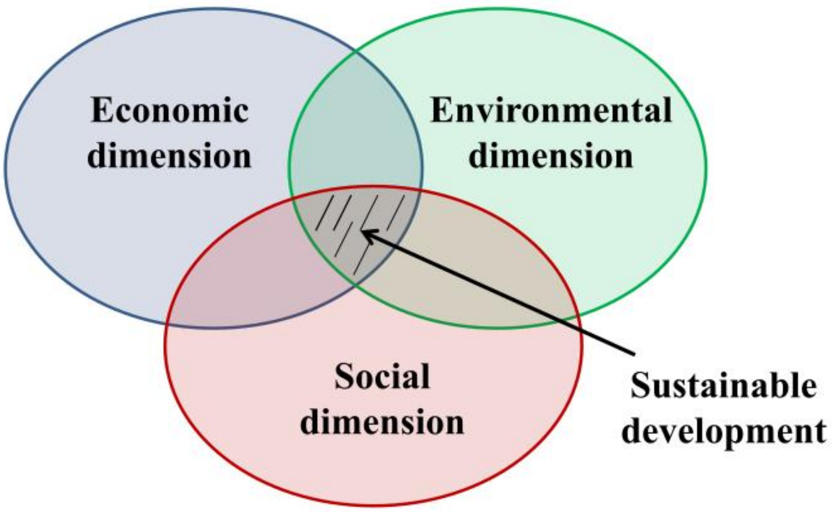


Fig.1.1 Three intersecting circles to illustrate the different dimensions of sustainability.

Ideally, the three dimensional metrics (3D) should be analysed first in order to assess the contribution of manufacturing systems/products to sustainable development. In some cases, when, after application of suitable changes, all the selected 3D metrics increase the efficiency of a system/product, we can assume that the enhanced process is more sustainable. On the other hand, if the outcomes are questionable, the 2D and 1D metrics should be considered for decision making.

This procedure is only a suggestion about what metrics should be taken into account and in which order, but the final election of metrics depends on the system, type of analysis and decision makers. Hence, the types of metrics for a chemical process should be different from those suitable for other manufacturing systems, which may include other services or operations.

Since the metrics should be very carefully chosen, it is crucial to select appropriate indicators according to the type of system under study. For instance, examples of 1D metrics are: "employment rate" (societal), "pollutant emissions" (environmental or ecological), and "gross domestic product (GDP)" (economic).

Several efforts integrating social dimensions into life cycle format have been made in the past decade [42]–[44]. Social life cycle assessments differ from LCA in many aspects, for instance: geographically specific life cycle inventory, employment hours or regional characterisation factors. A key societal indicator such as housing, health care, education or necessities are regionally dependent and lead to polemics when they are measured and compared in order to obtain meaningful results.

1.2.2 Eco-efficiency concept

The concept of eco-efficiency is crucial in corporate environmental management and offers an appealing framework to carry out this task. A new concept can be traced back to 1970s as the concept of "environmental efficiency". Eco-efficiency was introduced in the 1990s as a *"business link to sustainable development"*. Later, it was popularized by The World Business Council for Sustainable Development (WBCSD) for the business sector as a general management philosophy [45].

Eco-efficiency attempts to increase the value through technology and process changes whilst progressively reducing resource intensity and ecological impact throughout the product or service's life. Specially, it has gained important attention because of the important role it plays in indicating how efficient a product or process is regarding to services and nature's goods. More precisely, less waste and pollution emissions generation, improvement of production methods and tools, less virgin resources, water and energy consumption all together convert the businesses/processes/systems based on eco-efficiency principles into more profitable and competitive.

Usually expressed as the ratio between the product value and its environmental burden, eco-efficiency has been applied to all business aspects, from purchasing and production to marketing and distribution. This ratio, called environmental productivity or incremental eco-efficiency [40], indicates the economic creation for a given ecological destruction. The main eco-efficiency aspects are:

- To reduce: energy, water, virgin material use, and waste and pollution levels.
- To increase the product or service value.
- To incorporate the life cycle principles.
- To expand the utility function and therefore product/service life regarding to its usefulness and recyclability at the end of their useful life.

The eco-efficiency concept is an effective method for the business area to increase the economic cost with reduction of environmental impact, which has so far been used in many disciplines. According to Michelsen *et al.*[46], the eco-efficiency concept is a tool for measuring system progress and for communicating the economic and environmental performance of a product or process. On the other hand, Huppes *et* *al.*[40], presents it as an instrument for sustainability analysis underlining the relation between environmental impact and economic value. . The main drawback when constructing eco-efficiency indicators is that there is a lack of accepted regulations or standards recognition, measurement, and disclosure of environmental information [47].

Hence, the way in which the economic and environmental performance values are defined is a key point in eco-efficiency assessment. Environmental indicators provide decision makers an overview of important progress and relevant problem fields. According to Jasch[48], indicators are deemed as comprehensive and concise key data set in a vast sea of environmental information and have the following purposes: (i) overtime comparison and evaluation of environmental performance between firms, processes, systems, services or products; (ii) derivation and pursuit of environmental target, and (iii) the highlighting of optimization potentials, among others.

According to Kuosmanen and Kortelainen[49], pressure indicators can be used to quantify the environmental performance (calculated by weighting the contribution of different pollutants to several damage categories), while the economic value added (the profit) can be applied to measure the economic performance. On the other hand, the environmental performance using life cycle assessment (LCA), proposed by Dyckhoff and Allen [50] quantify the impact caused in all the stages in the life cycle of a product or process (*i.e.*, cradle to grave analysis).

1.3 Life Cycle Assessment

Life Cycle Assessment (LCA) is a well-established and quantitative technique for assessing the environmental aspects of product/systems that has gained wider interest in the recent years. This methodology evaluates various aspects associated with production and development of a product and its potential environmental impact throughout its entire life cycle (Figure 1.2), that is, from raw material acquisition, processing, manufacturing, use, re-use and, finally, its disposal, following defined principles and guidelines [51].

LCA typically focuses on environmental impacts. Indeed, ISO documentation restricts LCA's purview to environmental effects ([51], [52]) underlining resources use, human health and ecological consequences. The ISO 14040 standard [52] describes LCA as "*compilation and evaluation of relevant inputs, outputs, potential environmental impacts of a product system at various points in its life cycle and interpretation of the results of the inventory analysis and impact assessment phases in relation to the objectives of the study*".

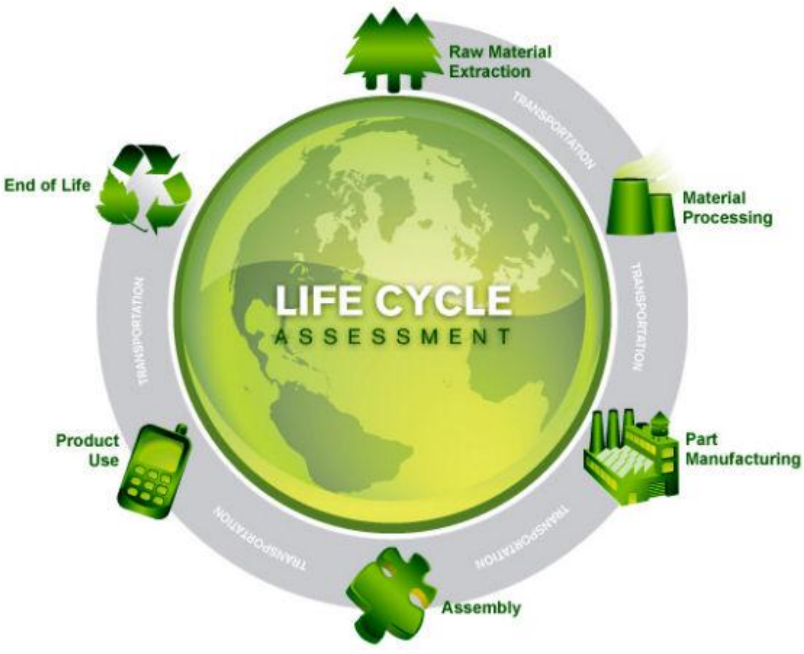


Fig.1.2 Interpretation of Life Cycle Assessment.

The main applications of LCA are:

(i) *Identification of possibilities to improve the environmental aspects* of products throughout their life cycle;

(ii) *Informing decision-makers* in industry, government or non-government organizations (*e.g.*, strategic planning, priority setting, product or process design or redesign);

(iii) *The choice of significant indicators* of environmental performance, including measurement methods, and

(iv) *Marketing* (*e.g.*, implementation of ecolabelling schemes, making an environmental claim, or producing an environmental product declaration).

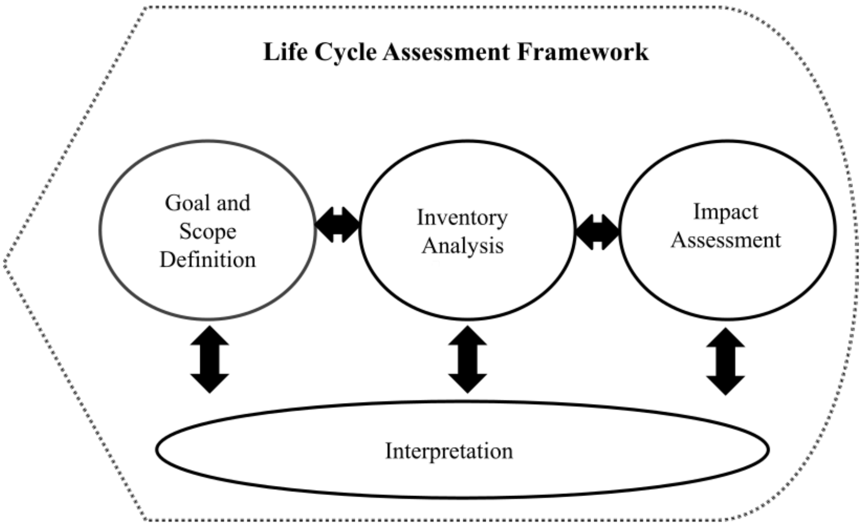


Fig.1.3 The phases of Life Cycle Assessment.

The Life Cycle Assessment (LCA) application is typically divided into four phases as shown in Figure 1.3.

1. *Goal and scope definition:* This first step determines which processes, environmental impacts and economic or social good provided by the goods or services in question, will be included in the analysis. It also fixes the frontiers of the study.

2. *Inventory analysis:* Life Cycle Inventory (LCI) is the compilation of relevant energy and material and environmental inputs and outputs involved in the life cycle

assessment. This includes modeling, data collection and verification of input data (*i.e.*, materials, energy…) and output data (*i.e.*, air and water emissions or solid waste…).

3. *Life Cycle Impact Assessment (LCIA):* the evaluation of the potential ecological damage associated with defined inputs and releases. The typical list of impact indicators contains: human toxicity, climate change, stratospheric ozone depletion, acidification, ecotoxicity, natural resources, among others. Various LCIA methodologies that differ in impacts categories and indicators selection can be applied (*i.e.*, CML 2001, Eco-indicator 99 or ReCiPe, among others).

4. *Interpretation:* The interpretation of results aims to help decision-making so as to improve the human health and environmental impacts of products, processes, systems or activities. Measures derived from this phase can be used to modify the previous aspects, thus improving the environmental performance of the system.

However, these phases show some limitations. After a critical review of more than twenty software and twenty-five databases Zamagni *et al.*[53] concluded that each of the aforementioned stages have several inaccuracies. The authors identified that the current developments of life cycle approaches are oriented towards:

(1) The improvement of the most debated issues such as system boundaries and allocation and
(2) The understanding on how to extend the present LCA methodology into more comprehensive problems related to sustainability and development of these methods.

The inventory and impact assessment phases typically focus on environmental aspects only, disregarding the economic and social dimension of sustainability. The authors suggested that future developments would involve other disciplines fields and expertise at several levels. Hence, the combination of environmental analysis with different disciplines could improve the sustainability assessment of products and processes. Nowadays, many authors underlay that this involvement could be useful to reduce the uncertainty, the collection of more representative data or the improvement of system modeling.

1.4 Uncertainty of LCA

Uncertainty is one of the important issues, often mentioned as an increasingly accepted component of LCA, which complicates the interpretation of results. According to Huijbregts[54], there are three types of uncertainty: (i) parameter uncertainty, (ii) model uncertainty and (iii) uncertainty due to choices.

Parameter uncertainty: Uncertainty of a large amount of data used in the inventory analysis and in the models which determine the weighting factors in the impact assessment also causes uncertainty in the outcome of an LCA. The main sources of parameter uncertainty are: imprecise measurements, incomplete or outdated measurements and lack of data. A comprehensive procedure for improving the LCA results considering major uncertainties is described by Weidema and Wesnæs [55], who estimate the imprecise and incomplete inventory data, both qualitatively and quantitatively. The authors recognize that uncertainty analysis is usually complex and hampered by a lack of knowledge on the uncertainty distributions and/or correlations between parameters. Several methods have been suggested in order to deal with parameters uncertainty in LCA outcomes such as [56]:

- Parameter variation and scenario analysis;
- Bootstrapping, Monte Carlo simulations and other sampling approaches;
- Classical theory on the basis of probability distributions, tests of hypothesis, etc.;
- Applying qualitative uncertainty techniques, for example, by relying on data quality indicators;

- Using conventional methods, like Bayesian analysis [57] or non-parametric statistic or fuzzy set theory [58];
- Implementing analytical methods, using first order error propagation.

The study of uncertainties in LCA studies typically focuses on parameter uncertainty. Some databases (*e.g.*, the Ecoinvent inventory data) include probability distributions for almost all the data involved. The most widely used tools for LCA incorporate algorithms for handling uncertainties, including Monte Carlo analysis, while some programs permit the application of analytical approaches or fuzzy techniques.

Model uncertainty: According to Huijbregts[54], some aspects are difficult or impossible to model within the present LCA structure. For example, the aggregation of emissions in the inventory analysis causes the loss of temporal and spatial attribution. Additionally, the assumption of linear behavior in the environmental interventions of ecological processes is neglected in the impact assessment phase [59]. Furthermore, the derivation of characterization factors computed using simplified environmental models introduces model uncertainty.

Uncertainty due to choices: When implementing LCAs, choices are inevitable. These include the choice of the functional unit in the inventory analysis and/or allocation procedure and the choice of the weighting scheme. The standardization of procedures ISO[51] allows the reduction of uncertainties due to choices to a universally established level. In case of inability to apply the standard procedures, these uncertainties may be treated with a scenario analysis, which can display the results on LCA outcomes for different combinations of choices.

1.5 Data Envelopment Analysis

Methods for measuring efficiency emerged in 1960s. As cited by Cook *et al.*[60], sixty years ago Farrell [61] stated in his paper on the measurement of productive efficiency: *''The problem of measuring the productive efficiency of an industry is important to both the economic theorist and the economic policy maker. If the theoretical arguments as to the relative efficiency of different economic systems are to be subjected to empirical testing, it is essential to be able to make some actual measurements of efficiency. Equally, if economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources."*

Unfortunately, the principal reason of the failure of his attempts was the lack of success combining the calculations of the multiple inputs into any tangible measure of efficiency. For instance, the formation of an average productivity input ignoring all other inputs or the comparison between the weighted average of inputs with the output.

Twenty years after Farrell's idea, Charnes *et al.*[60] introduced and developed a powerful service management and benchmarking technique coined as data envelopment analysis (DEA) to assess the relative efficiency of multi-input multi-output production units. Originally developed to evaluate public and nonprofit organizations, this powerful methodology has been applied in many different research fields, including the assessment of the environmental performance of industrial plants, economic sectors, countries, and products, among others (see a more detailed description in Section 2.3).

DEA estimates the relative efficiency of a number of homogeneous units, commonly defined as decision making units (DMUs). As a non-parametric linear programming method (LP), DEA assesses objectively the efficiency of a set of units (*i.e.*, products/services). Non-parametric estimation means that it does not assume any specific functional form for data. The inputs and outputs have to be known and from those, DEA identifies a set of non-dominated units (*i.e.*, efficient) [63] and for the ones found to be inefficient provides both an efficiency score and a set of target values that would make the unit efficient. The main advantages and information provided from DEA are:

(1) The comparison of all units (*i.e.*, branches, services provided) – directly against peers - without any assumption allows identifying the most efficient ones, while showing for the inefficient units, which improvements are required in order to become efficient.

(2) DEA can handle multiple inputs and outputs calculating the amount and type of cost and resources savings that can be achieved by making the inefficient ones as efficient as the most efficient units.

(3) While the inputs and outputs can have very different units, DEA identifies the specific changes in the inefficient units that can be implemented to achieve potential targets.

(4) The information obtained about performance of service units can help decision makers or management understand which improvements in the productivity of inefficient units are required, providing insight into how reduce operating costs and increase profitability.

As any other technique, DEA has some weaknesses. For example the results provided are very sensitive to the number of inputs and outputs (measurement error can cause significant problems), as well as the size of the sample (large problems can be computationally intensive)[64]. Errors in the data and the measurement of an efficiency score only relative to the best practice within a particular sample can both lead to lack of meaningful results. On the other hand, DEA estimates “the relative efficiency” of a DMU but avoids the absolute efficiency. For instance, although DEA can show how well the DMU is, in comparison with other peers, “the possible theoretical maximum” to achieve is not taken into account. Additionally, there are some difficulties in statistical hypothesis tests because of the nonparametric character of this technique.

1.6 Uncertainty of DEA

In the standard DEA, data describing inputs and outputs are based on nominal values that must be perfectly known in advance (i.e., without uncertainty). From these observed data, DEA determines a convex frontier containing the efficient units. For each unit deemed inefficient, DEA establishes in turn a set of target values (for inputs and outputs) that, if attained, would make the inefficient unit efficient.

Unfortunately, environmental calculations are affected by numerous uncertainties stemming from imprecise measurements, lack of data and/or modelling choices. These uncertainties critically affect the outcome of LCA studies. Hence, these uncertainties should be accounted for in the analysis if meaningful results are sought.

1.7 DEA + LCA framework

In recently years, the combined use of LCA and DEA has developed significantly. Presented in 2009 by Lozano *et al.* the LCA+DEA methodology has attracted growing attention ever since. The LCA+DEA methodology has been applied in two different manners: (1) "five-step LCA+DEA method" that is recommended to undertake eco-efficiency verification through the quantification of environmental consequences [66]; and (2) "three-step LCA+DEA method" that estimate environmental impacts and parameters directly [67].

1.7.1 Five-steps LCA + DEA method

The combined approach of operational and environmental assessment of multiple inputs and outputs has been defined by Vázquez-Rowe *et al.* [68] in five steps (Figure 1.6):

(i) Description and development of the Life Cycle Inventory (LCI) for each unit of assessment (*i.e.*, DMU). Data collection of inputs and outputs is required for the system assessed.

(ii) The characterization of Life Cycle Impact Assessment (LCIA) for every unit (*i.e.*, DMU) from the LCI data selected in the first step.

(iii) The calculation of a efficiency score for each unit (DMU) and determination of targets by applying DEA to inputs/outputs from LCIs.

(iv) LCIA of the target DMUs from the new LCI data obtained from the third step. As a result, the determination of potential environmental impacts associated with virtual units is achieved.

(v) Quantification of the environmental consequences of operational inefficiencies (eco-efficiency verification). The comparison between potential environmental impacts for the virtual DMUs and those corresponding to the current DMUs quantifies the environmental damage generated by inadequate operational practices.

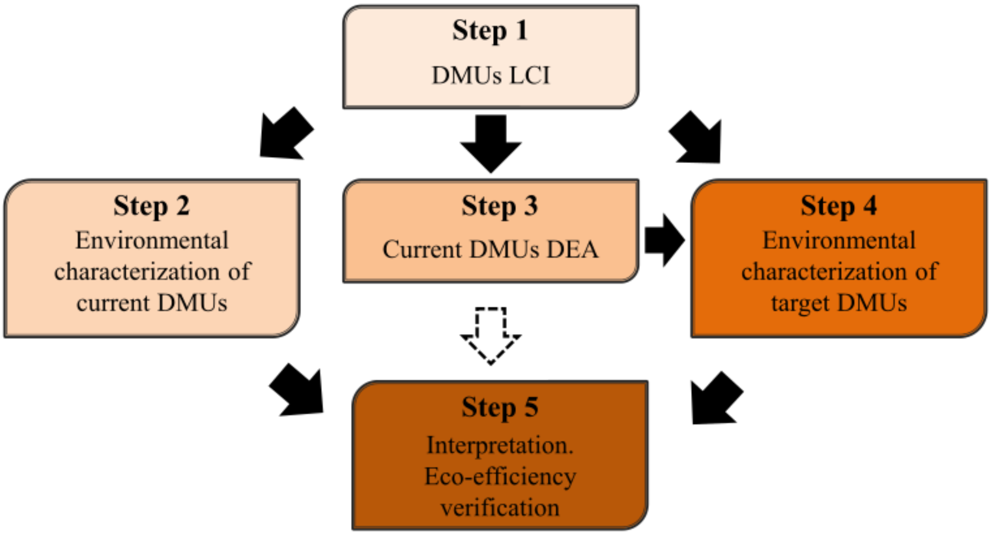


Fig.1.6. Representation of five-step LCA+DEA method

1.7.2 Three steps LCA + DEA method

A simplified alternative LCA+DEA method is composed of three steps [65]. The first two stages are similar to those in the five-step method. In the third phase, however, the estimation of targets for both inputs/outputs and potential environmental impacts is made. Hence, as opposed to the five-step method, the three-step alternative implements environmental impacts as inputs when resolving DEA. Hence, this method avoids the environmental characterization of targets DMUs. As shown in Figure 1.7, this approach consists of the following stages:

(i) LCI for each of the units (DMUs). Data collection of inputs and outputs for the units being assessed.

(ii) LCIA applied for each of the units (DMUs) from the first step. The environmental characterization of current DMUs is made.

(iii) DEA applied to the LCIs from the first step and the characterization results obtained in the second phase. The environmental and operational impact efficiency of each unit (DMU) is determined and the target DMUs are established. In this stage, the comparison of the current and target values for each environmental category is calculated.

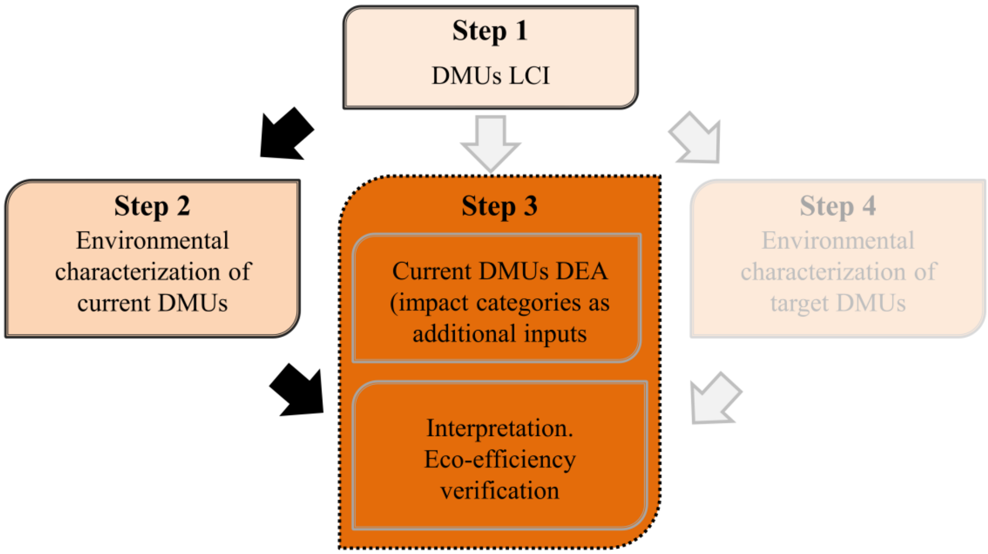


Fig.1.7. Representation of three-step LCA+DEA method.

1.7.3 Illustrative example of the application of DEA + LCA methodology

Based on the definitions of efficiency by Farrell (1957), technical efficiency means producing a given output with minimum amount of inputs or alternatively, producing the maximum amount of output from a given quantities of input. Hence, a firm/system/process is technically efficient when operates on its production frontier, reaching its maximum potential.

These efficiency concepts can be illustrated by considering a single output (equal to 1) value for all DMUs being produced from two inputs, X_1 and X_2 (Figure 1.9). Red circles in the figure represent the efficient values, while blue circles depict the inefficient ones. The Pareto condition is that the efficient technologies cannot be improved in one DMU without worsening the other one. The efficient frontier is the “imaginary” line that links the efficient units on the convex envelope of the DMUs.

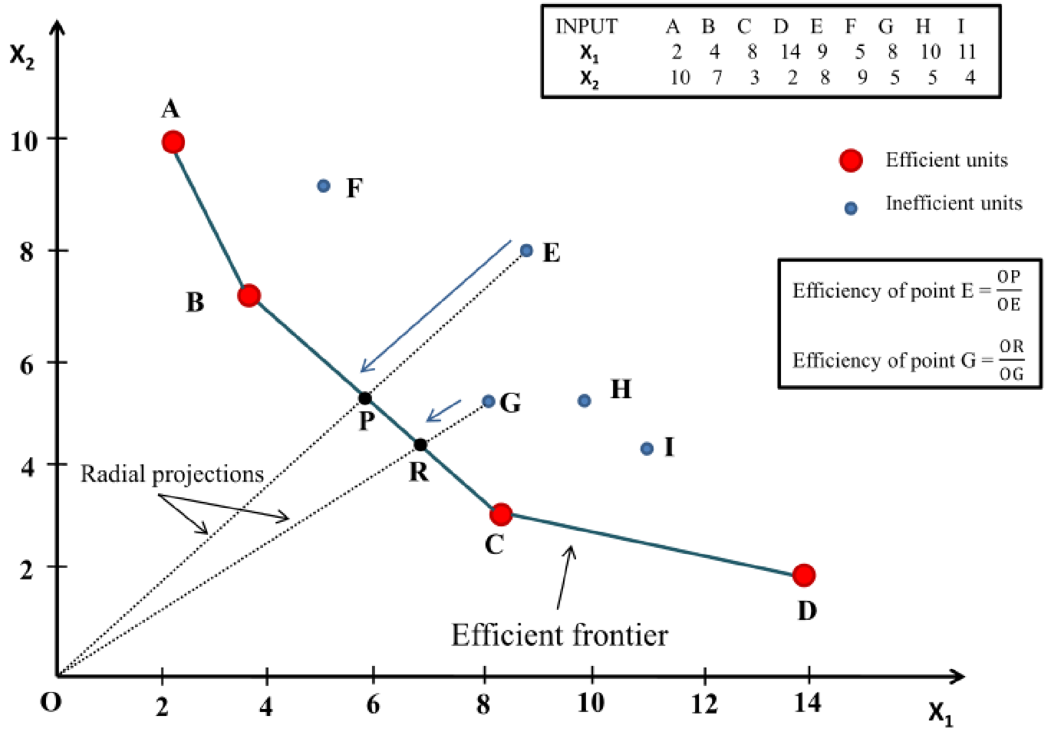


Fig. 1.8 A two input illustration of DEA projection.

We find that DMUs A, B, C and D are efficient (equal to 1), while DMUs E, F, G, H and I are inefficient. For DMU E and G, the efficiency scores are 0.64 and 0.85, respectively, calculated as a ratio between the distances (*e.g.*, efficiency of point E is the ratio between |OP| and |OE|). In case of DMU E, its projected (frontier) value is represented by point P, while point R denotes DMU G. In addition, the same proportionality reduction factor is used in each input of every inefficient DMU.

As illustrated by this example, the deterministic assumption of DMUs is made and the radial projection is used (a detailed discussion about the influence of the projection is presented in section 4.4.1). The crucial key is what happens when the values assumed as deterministic, in fact, are stochastic: How should the efficiency be measured? We will deal with this issue through this thesis.

1.8 Main objectives and thesis outline

In the current context of more sustainable development, improving the efficiency of European energy systems is an essential issue.

The overall goal of this thesis is the application of Life Cycle Assessment and Data Envelopment Analysis as a useful tool in sustainability assessment and analysis of methods taking into account data uncertainty. In order to achieve this aims, the following objectives need to be accomplished:

- To analyze and compare energy systems.
- To consider the uncertainty in the input data.

This thesis has been organized in order to introduce progressively the application of Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA) into sustainability assessment. Figure 1.8 illustrates the outline of the thesis, which has been structured in three main parts.

Part I includes the introductory view of the problem to be addressed (Chapter 1), a detailed state of the art of the techniques and applications used (Chapter 2), and the methods and tools used through this thesis (Chapter 3).

Part II represents the combined applications of LCA and DEA methodologies to the case-studies. Chapter 4 aims to assess the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis under deterministic conditions. Assuming the uncertain aspects of the environmental impacts, Chapter 5 extends the approach to handle such uncertainties.

Finally, in Part III, the main contributions of this thesis has been summarized and conclusions with future work remarks are presented.

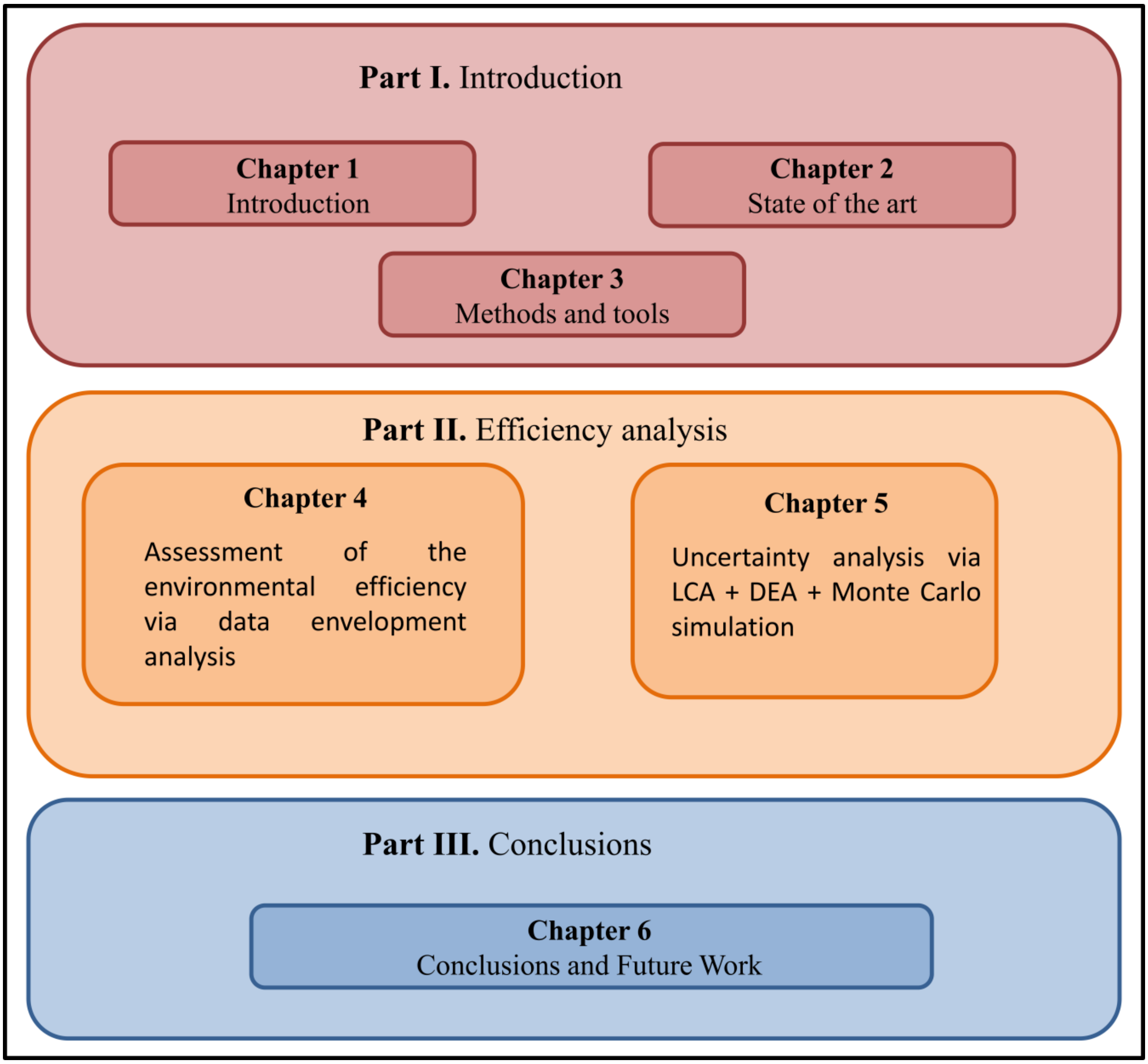


Fig 1.8 Thesis outline

2. State of the art

Our world is facing at present crucial environmental problems such a deterioration of environmental systems or a non-sustainable exploitation of natural resources that affect the quality of life. The need for collaboration between governments and companies (through legislation) is motivating our society into the adaptation of an environmentally friendlier attitude.

Life Cycle Assessment and Data Envelopment Analysis are powerful tools which benchmark the systems/processes or products in order to obtain meaningful improvements.

This chapter summarises major contributions made until now in the topics developed throughout this thesis. Notably, the most important works related to the improvement of sustainability using LCA and LCA+DEA are reviewed.

2.1 Brief historical outline of sustainability development

Enhancing the quality of life by improving the environmental, social and economic conditions for present and futures generations is the main aim of sustainable development.

According to Linton *et al.*[70], although the first attempt toward sustainability can be found in many ancient cultures, recently many researches of philosophers and economists focus on its development [71]. The increase of awareness and the consideration of sustainability in the management literature continued in the 1990s, but the transition from the technical concept into mainstream took part with the publication of the Brundtland Report.

Since the world commission on environment and development (WCED), entitled *Our Common Future*[1], the term sustainable development has gained world's attention as an strategy that links united environmental performance and development in order to enable the identification and to develop the policy for meeting the needs of future generations.

The main research fields that considered sustainability until 2006 were [70]: Environmental science (more than 12000 papers); social science (more than 9000 articles); engineering (8000 papers); Agriculture and Biological Science (6000 articles); Earth and Planetary Science (more than 5000 papers); Economics, Business, and Management (4000 publications); Energy and Medicine (more than 2000 each one); Chemical Engineering (2000) and Material Science (more than 1000 papers).

As mentioned above, the sustainability development assessment has been applied in many distinct research fields such as:

- Global and regional assessment such as a European strategies for sustainable development [72], sustainable urban development [73]; Mascarenhas *et al.*[74] developed sustainability indicators within regional context allowing local sustainability benchmarking and enhancing the analysis of a region whereas Polido *et al.*[75] applied it into European small island analysis. A conceptual framework proposed by Coelho *et al.*[76] developed a set of sustainability indicators for regional assessment in Portugal, while the indicators for analysis of local public services were suggested by Domingues *et al.*[77].
- Universities or public institutions: Making higher education more sustainable was the purpose of the research proposed by Alghamdi *et al.* [78] [78], who investigated which indicators are crucial in the assessment of universities sustainability. The role and potential values of sustainability indicators has been analysed for high education [79] or public institutions [80].
- Tourism sector: The role of indicators in tourism development and planning in the transition to sustainability [35].
- Energy sector: Several energy systems have been assessed in terms of sustainable development such as: hydrogen energy systems [27], geothermal energy [81];

Chu *et al.*[82] described the challenges of our sustainable energy future considering both renewable and non-renewable energy systems; Bhowmik *et al.*[83] reviewed more than 200 studies in energy planning for sustainable development carried out during the last sixty years.

- Transport sector: Ramanathan *et al.*[84] provided a review of the Indian transport sector using a scenario approach in order to achieve the goals of various policy options; while Garza-Reyes *et al.*[85] studied how to improve the transport operations in México.
- Industry sector: Methods for sustainable development in the construction are discussed in [86]
- Agriculture sector: The challenges for the next 50 years in agricultural sustainability and production practices are described in [87].
- Supply chain: Seuring *et al.*[88] reviews the literature on sustainable supply chain management, underlining that the research field is still dominated by green/environmental aspects whereas the three dimensions analysis is still rare.

2.2 Life Cycle Assessment applied to sustainability

The life cycle assessment is an internationally accepted method for evaluating the environmental impacts/effects of products, processes or materials. LCA evaluates the direct and indirect environmental burdens related with a product or activity in comparative analysis quantifying energy and material use and environmental performance at each stage of a product’s life cycle. This comprehensive view makes LCA unique and the best tool because it examines the full range of impacts over all product/process phase[89].

2.2.1 Historical review of LCA methodology

The concepts that later become ecological LCA first appeared in the 1960s[90]. Initial studies were uncomplicated and mostly restricted to calculating energy demand and solid wastes, with slight importance given to evaluating potential environmental impacts.

According to [91], the study of environmental impact can be divided into three main parts: past, present and future.

<u>Past of LCA:</u>

In the past stage of LCA (1970-2000), two periods can be distinguished:

1970-1990: Decades of conception, where environmental issues like energy efficiency, pollution control and solid waste become public attention. During the crisis oil of the early 1970s, expanded energy researches based on life cycle inventories were extended into industrial systems (Fava et al., 1992). In 1980s, principally private companies in Sweden, Switzerland and the USA implemented numerous studies following LCA principles [93];de Haes and Huppes, 1993).

1990-2000: Decade of standardization, where the first LCA guides and handbooks appears. Also the first scientific publications started to appear in the most important journals. Until the early 1990s, several names were established to undertake an assessment of the material, energy or waste flows of product's/process's life cycle. Many researchers used terms such as ecobalance, environmental profile analysis or environmental analysis and environmental profiles. The Society of Environmental Toxicology and Chemistry (SETAC) started to play a leading and coordinating role in bringing LCA users and scientists together to collaborate on the improvement and standardization of LCA framework, terminology and methodology [95]. Parallel to SETAC, the International Organization for Standardization (ISO) has been involved in LCA since 1994. SETAC groups focused at the development and harmonization of methods, while ISO adopted the formal task of standardization of methods and procedures. Currently, two international standards are established:

✓ ISO 14040 [52]: " Environmental management – Life cycle assessment - Principles and framework";

✓ ISO 14044 [51]: "Environmental management – Life cycle assessment - Requirements and guidelines".

During this decade, several well-known life cycle impact assessment method were developed, such as CML 1992 [96] or end point (Eco-indicator 99) approaches (Goedkoop et al., 2001).

Present of LCA:

2000-2010: Decade of elaboration: An increasing attention of LCA methodology could be noted in the first decade of the 21st century. An international Life Cycle Partnership, known as the Life Cycle Initiative was launched by the SETAC and United Nations Environmental Programme (UNEP) in 2002 [98]. The main goal was to formulate and promote the life cycle thinking into practice improving the data and indicators in European Policy (*e.g.*, European Commission of the European Communities on Integrated Product Policy, IPP)[99]. Incorporated on the Prevention and Recycling of Waste[100] and in the thematic strategies on the Sustainable Use of Resources[101], life cycle thinking grew in importance and was promoted among the collaborators of IPP[99].

This period is characterized by a divergence in methods due to no common agreement on interpretation and standardization of LCA. Several methods have been developed such as allocation methods [54,102], dynamic LCA[103,104], risk-based LCA [104] or environmental input-output based LCA based on hybrid LCA[105], among others. Besides this, life cycle costing (LCC) [106], used by the U.S. Department of Defense in the 1960s [107] and social life cycle assessment (SLCA) [108] studies have been introduces and implemented that may have consistency issues with environmental

LCA in terms of calculation procedure, system boundaries, etc. Although several textbooks [90][109] have been published in order to clarify the LCA framework, the need of more specifications of types of externalities (in particular for social and economic impacts) and other techniques (analysing behaviour, price effect, rebound) lead to CALCAS (Co-ordination Action for innovation in Life Cycle Analysis for Sustainability) project. Introduced by the European Commission in 2006 for define and structure the varying fields of LCA approaches [110] finished with the establishment of a framework for Life Cycle Sustainability Analysis(LCSA). The LCSA links the life cycle assessment questions to the expertise required for addressing them, describing research programs and recognizing available models. During this decade, was made an effort to update and harmonize LCA data via the development of the Swiss Ecoinvent database, where more than 4000 products and services are available[111], among others.

Additionally, several attempts have been made in order to describe the appropriate LCA types (in goal and scope definition phases where the hypotheses or question are formulated). The most accepted are: attributional and consequential [112]. The difference between these is that the former focuses on the description of environmentally relevant physical flows to and from a life cycle and its subsystems while the latter aims to describe how the possible decisions change the environmentally relevant flows.

<u>Future of LCA:</u>

2010-2020: Decade of Life Cycle Sustainability Analysis: The LCSA is considered the future of LCA approach. It extends the area of current LCA from primarily environmental impacts to cover all three dimensions of sustainability (economic, environmental and social). Additionally, it broadens the view from product-related (product level) questions to sector related questions (sector level) or economy-wide levels (economy level). On the other hand, the future LCA considers more relations in analysis approach (including physical relations and limitations for resources or land use, economic and behavioural relations, etc.). Due to the intensive character of LCA data and that the lack of data can limit the conclusions; more efforts in databases development have been taken into account [56]. On the other hand, even though many efforts have been made in model development for specific types of impacts (*e.g.*, impact assessment of land use including freshwater resources or of human health aspects are problematic), there is still a need to better method to make future assessments more comprehensive and more reliable. According to Finnveden *et al*.[56], further development of tools for consequential LCA, methods for assessment of impacts from water use, weighting methods, developments and maintenance of data bases should be a prioritised area in LCA.

2.2.2 LCA application fields

Since the first apparition in the 1960s, LCA methodology, applied for industrial products primarily has been adapted for the construction industry and has gained progressively acceptance. The pioneers sectors in LCA investigation were plastics, automobiles, detergents, and personal care products, followed by agriculture, gas extraction, mining and oil, construction/building sector, industry sector and recently by infrastructure industries (transport, electricity, gas and water supply and communication). Additionally, this method was recognized as one of the best tools for the development, balancing and integration of environmental policies[113].

There are multiplied fields in which LCA can be implemented in the microscale areas as well as in macro-scale analysis, in private sector as well as in public organizations, in product engineering, among others. The largest applications are in the following areas:

- *Industry sector*: there are many approaches applied to the LCA to determinate the consequences of biofuels generations (palm oil biodiesel production [114][115]; algae biomass production[116]; sugarcane bagasse for methanol production[117] and alcohol industry[118], biodiesel production from microalgae [119], among others). There are many applications into industry analysis of particular country (*e.g.*, Swedish [120]) or material production (such as steel[121], industry materials [122], cotton shopping bags [123] or wool textiles and clothing [124]). Jacquemin *et al.*[125]made the important review of past, present and future application of LCA in processing and manufacturing industry.

- *Building sector*: LCA has been used in the building sector since 1990 and is an important tool for assessing buildings (Taborianski and Prado, 2004; Fava, 2006). The compilation of LCA studies, from 2000 to 2007 within the building sector can be found in [128]. More than ever, the differences between the LCA of building materials and components *versus* the LCA of all building life cycle has been discussed. In addition, the applications of LCA studies evaluating only the impacts of different construction materials and solutions have been reviewed by Khasreen et al. (2009). On the other hand, there were numerous studies published in which LCA was applied to analysis environmental impacts of residential and commercial buildings [130]. Recently, more than 100 publications of LCA for environmental evaluation of buildings and building related to industry and sector including construction products and systems have been summarized by Cabeza et al. (2014).
- *Urban settlement:* Herfray *et al.*[132] applied LCA to study two settlements including all relevant impacts related to production of energy, water, materials, etc., and four stages of settlements life cycle: construction, operation, renovation and finally dismantling of the settlement.
- *Products:* Roy *et al*.[133]reviewed LCA studies applied on several industrial food products. One of the important food products that have been studied by many researches is bread[134]–[136]. The research field included crop production method, milling technologies, bread production processes, packaging and cleaning phases. It is interesting that the production and manufacturing of the

packing elements in the cases of beer production[137], [138] accounts the most of the emissions. Additionally, LCA of other agricultural products the LCA was studied in order to improve its environmental performance such as: tomato ketchup[139]–[141], rice [142], sugar beet production [148,149], sugar industry[145] or potatoes[146], among others.

The dairy industry was another important sector that has been studied in order to define the environmental impact caused in several European regions. Milk, as one of the most produced dairy product in Europe, has been examined to reduce the potential impact in system production [147]–[151]. Another important sector that causes a major impact on the environment and has been studied by several authors is livestock production. Vries *et al.*[152]reviewed 16 peer studies assessing the environmental impact of production of pork, chicken, beef, milk and eggs based on the type of LCA methodology selected.

- *Packaging and food management systems:* an important source of environmental waste and the fundamental element of every food production are associated with the packaging phase. Several approaches have been reported in order to reduce environmental impacts ([152],[153]). On the other hand, the way to improve energy efficiency, reduce raw material use or water consumption is waste minimization[153]–[156].

According to Udo de Haes *et al.*[157], energy is a substantial part of environmental impacts that LCA analysis throughout full life-cycle of product/process/services. The three main connections between LCA and energy are:

- Indeed the energy is involved in all life cycle stages: from inventory issues like extraction of raw materials, emissions of carbon dioxide, through production or transport stage, to impact assessment like climate change or depletion of resources. When the products or services are compared, the energy aspect should be always incorporated if appropriate quantitative results are expected.

- The separate analysis of only energetic aspects of a life cycle phase has been performed and developed earlier than LCA and is recognized as energy analysis. For instance, process analysis *versus* Input-output-based energy analysis can be compared with LCA[158] and some attempts to establish the connections between exergy analysis and LCA have been made[159].
- It is well-known that LCA can be applied into the analysis of energy systems. From the comparison of small scale products like two types of batteries, to the comparison of electricity generation structures of countries. For instance, an important field of research is the comparison of fossil fuels with biofuels[160].

At present, the LCA of energy systems represent an active domain of study. The completely review of renewable energy for electricity generation system was made by Varun *et al.*[161] including wind energy systems [162]–[164], solar photovoltaic system[165]–[168], solar thermal system[169]–[171], biomass system[172]–[174] and hydro power[175]–[177].One of the most promising renewables energy alternatives is the use of biomass (*i.e.*, bioenergy). The growing interest, at both national and global levels provoked recent creation of policies and publication of several LCA bioenergy studies (94 studies from 1995 to 2010[178] in this field). On the other hand, Turconi *et al.*[179] reviewed more than 160 LCA case studies of electricity generation focused on non-fossil and fossil fuels including hard coal[180]–[183], lignite[187,189], natural gas[183]–[185], oil[183], [184], nuclear[186], [187], wind[163], [188], [189], solar[190], hydropower[175]–[177], and others energy sources.

Recently, Mälkki *et al.*[191], synthesized the application of LCA for renewable and sustainable energy education by examining LCA as an investigation tool for evaluating the sustainability of renewable energy systems.

2.3 Data Envelopment Analysis framework

Since the first publication in 1957 by Farrell[61] on The Measurement of Productive Efficiency, being the background for Data Envelopment Analysis (DEA), Charnes, Cooper and Rhodes developed a relative efficiency model known by the initials of its developers - CCR[192]. Thus DEA started being a useful method to measure efficiency of public sector organizations (using the same inputs to produce the same outputs by estimating the efficiency of homogeneous organizational units called DMUs). Among many application fields, DEA has been proposed to analyze environmental performance of industrial plants, economic sectors, countries, products, universities, metropolises, hospitals, public and commercial companies or energy production, among others. According to Emrouznejad *et al.*[193] the most popular research fields until 2007 were: banking, education (including higher education), hospital and health care efficiency assessment.

Additionally, 620 papers that use the DEA application into financial sector were reviewed by Kaffash *et al.*[194] examining the period time from 1985 to 2016 analyzing the diffusion of DEA in three categories: (1) banking groups, (2) money market funds, and (3) insurance groups. On the other hand, Fethi *et al*.[195] reviewed almost 200 studies that used operational research and artificial intelligence techniques in the assessment of banking performance. Other important applications of DEA in banking sector have been developed by Othman *et al*.[196], Thanassoulis[197] or Golany *et al*.[198], among others.

As mentioned above, DEA was applied in order to measure the efficiency in education sector or universities. For instance, the higher education institutions/universities were examined in different countries, like: Johnes[199] analyzed a set of more than 100 English institutions; Ng *et al.*[200] researched more than 80 Chinese universities whereas Ramírez *et al.*[201] took a sample data of more than 300 Colombian higher education institutions, among others. We can underlining the following works: the measurement of performance efficiency of the academic departments[202], evaluation of secondary schools in Portugal[203], a review of DEA in secondary and tertiary education[204] and the estimation of the parameters assessing the performance and efficiency of university professors[205].

Eco-efficiency evaluation [206]was the other important research field where DEA has been applied jointly with the efficiency assessment of several power plants[207]–[209].

Among other field where the DEA has been applied we can underline the following:

- *Airport assessment:* Fasone *et al*.[210] presented a critical review of approximately 60 peer-reviewed publications on business performance measurement in the airport industry published during the last 15 years;
- *Water companies assessment:* the estimation of potential cost savings at water companies [211]; the measurement of the efficiency of water and wastewater companies of 17 municipalities of Iran[212]; the measurement and assessing of several water utility companies in Chile ([213],[214]), Italy [215], Portugal[216], United Kingdom ([218],[219]), Australia[219]and USA[220], among others;
- *Hospital assessment:* Several approaches have been published for assess health care and their contributions to local economies in various countries, like USA[221], [222], Brazil[223], China[224], Canada[225], Ghana[226] or Kenya[227], among others;
- *Resorts assessment:* Besides several studies of hotels performance[228]–[230], or French ski resorts analysis[231];
- *Park assessment:* Various analysis assessing the efficiencyof several parks or industrial parks have been published[232]–[235];
- *Supply chains assessment:* Several DEA approaches have been published in order to examine buyer-supplier supply chain settings allowing efficiency evaluation [236]–[238].

2.3.1 DEA studies of energy

Since the first paper treated to energy efficiency issues and published in 1983 by Färe *et al.*[239], numerous studied employing DEA methods have been developed. Several approaches evaluated energy efficiency due to the implementation of DEA in developed economies such as the US[240], Japan[241], Canada[242], the APEC countries[243], among others.

In the last decade, this tool has been employed to assess the efficiency and guide retrofit efforts towards an effective enhancement of the environmental performance. A literature survey on the application of DEA to energy and environmental (E&E) studies, presented by Zhou *et al.*[244] accumulates more than 100 publications in this field from 1983 to 2006. On the other hand, a comprehensive review published by Mardani *et al.* [245] accounted 144 published papers between 2006 and 2015 of DEA application in energy efficiency. The analyzed papers can be segregated according to:

- *Country/regions energy efficiency analysis*: Several regions have been assessed such as 30 regional industrial systems in China ([246],[247]) or its environmental efficiency[248], 95 countries[249], 47 Japanese regional industries [250] or 54 Turkish provinces [251], among others. Additionally, the energy-environmental efficiency have been studied for 10 regions in Japan [252], 29 administrative regions of China [253], APEC countries [254], BRICS countries [255], 22 OECD countries [256] and the comparison of efficiency factors for energy technologies utilized by New York region [257] have been made.After DEA analysis of 23 developing countries during the period of 1980-2005, Zhang *et al.*[258] concluded that Panama, Botswana and Mexico reveal the best energy efficiency, while Kenya, Philippines and Syria the worst. Recently, Li *et al.*[259] compared an electricity generation systems in sustainability analysis of 23 G20 countries between 2005 and 2014. The inputs indexes were generation capacity, cost and land use while the desirable outputs: total energy generation and job creation.

- *Industrial sector*: Among other approaches, we can underlay the following: the measurement of energy efficiency for French agricultural farms [260], the energy efficiency in steel and iron sector of Swedish production [261] or of Chinese production [262], the evaluation of farmers energy efficiency for Iranian potato production sector [263] and energy efficiency of 260 wheat farms [264].
- *Energy sectors:* District heating plants ([265], [266]), oil and gas industries [267], [268], 48 Iranian thermal power plants [269] and coal mines ([270], [271]).

On the other hand, the DEA approaches based on *renewable and sustainable energy* can be classified as follows:

- *Countries:* after analysis of 45 economies, Chien *et al.*[272] concluded that the increase of use of renewable energies simultaneously enhances its technical efficiency. Additionally, the environmental efficiency differs regarding to geographical region according to Woo *et al.*[273] which used DEA to assess 31 OECD countries. Some results of sustainable energy analysis for countries are: the countries with high income represents the best performance in sustainable energy (analysis of 109 worldwide countries)[274]; the OECD countries have large opportunities in creation of more sustainable systems in agricultural production [275]; and US manufacturing eco-efficiency analysis is very sensitive to the energy use [276], among others.
- *Production and industrial sector:* the results of sustainable and efficient energy consumption reveals that: the current corn production is not sustainable (analysis of 89 Iranian corn farmers)[277]; and the textile sector is the most efficient Brazilian sectors while metallurgical is the least one [278], among others.

According to *European countries in DEA analysis*, the following approaches underlie in the last decade. In 2013, Bampatsou *et al.*[279] analysed 15 European (EU-15) countries from 1980 to 2008 using cross-country comparison. The authors used

Technical Efficiency Index (which represents the GDP for a given level of total energy input) determined from energy mix (nuclear, fossil and non-fossil fuels energy) of each country studied. They repeated analysis before and after the integration of nuclear energy in the electricity mix of each country and concluded that nuclear energy has a negatively influence in the technical efficiency. Moreover, in 2015 Robaina-Alves *et al.*[280]used DEA for assessing the environmental and resource efficiency issues in 26 European countries. They used capital, labour, fossil fuels and renewable energy consumption as inputs and maximized GDP/GHG ratio as output. The results showed Ireland, Hungary Slovakia and Portugal as efficient countries while the least efficient were Denmark, Bulgaria and Romania. On the other hand, Chang [281] utilized DEA to develop an indicator to improve energy intensity by measuring the difference between the target level of energy intensity and the actual energy intensity. The author used three inputs (capital, labour and energy use) and one output (*e.g.*, real GDP) for each one of 27 EU members and concluded that (i)energy intensity improvement does not fully depend on a decline in energy intensity and (ii) Denmark and Luxemburg were always located on *"the best-practice energy frontier"*. As you can see, some of the results point in different directions, depending on the approach followed.

Additionally, after the analysis of 87 worlds countries during 2004-2010, Pang *et al.*[282] concluded that the European countries were more efficient in terms of economic growth, emission reduction and energy conservation when compared with others world countries.

2.4 Combined use of LCA and DEA

Combined LCA and DEA methodology was introduced in 2009 [66] but formally presented in 2010 by Vázquez-Rowe *et al.* (2010)[67] to measure the environmental and operational performance of resembling entities. According to Vázquez-Rowe and

Iribarren (2015)[283], the five-step LCA+DEA method was found to be the approach most often selected by LCA+DEA practitioners.

To date, this approach has been mainly applied to the primary sector such as:

- *Agriculture*: Benchmarking of environmental impacts for best-performing 72 Galician's dairy farms [284]; analysis of 40 vine-growing exploitations belonging to the Rias Baixas appellation (NW Spain) [285]; identification and recommendation of improvement for a total of 94 soybean farms in Iran [286]; the estimation of technical efficiency of a 82 rice paddy fields for spring and summer growing seasons in Iran [287]; Recently, using the aforementioned DEA and LCA model, Soteriades *et al.*[288] calculated eco-efficiency scores for 185 French specialized dairy farms;
- *Aquaculture*: Direct link between operational and environmental efficiency illustrated with mussel cultivation in rafts case study [66];
- *Fishing*: Link between environmental and socioeconomic assessment of fishers using a Spanish coastal trawl fishery as an example [68]; intra- and inter assessment of fishing fleets in Galicia [289] or of Peruvian anchoveta fishery [290];
- *Energy sector*: Furthermore, the application of this approach in other sectors (e.g., the energy sector) has already been demonstrated [138]. Moreover, a group of 113 wastewater treatment plants (WWTPs) located in regions across Spain have been analysed by Lorenzo-Toja et al. (2015)[291] determining the operational efficiency of each unit in order to obtain environmental benchmarks for inefficient plants.

In addition, the first study focused on the implementation of social parameters into LCA + DEA approaches was attempted by Iribarren et al. in 2013. The authors concluded that labor (social indicator) is a suitable input in LCA+DEA studies but requires very cautious result interpretation. Moreover, the LCA+DEA method has been implemented for 40 relevant socio-economic indicators [293] in order to improve this dimension for sustainability assessment and for assessment of sustainability efficiency [294] with the three dimensions of sustainability considered.

On the other hand, the three-step LCA+DEA approach leads to a relatively rapid environmental benchmarking and allows the simultaneous benchmarking of operational issues [65]. The direct use of life cycle assessment indicators as DEA inputs accounts an important number of publications such as:

- *Agriculture*: an analysis of 16 scenarios of Mahon-Menorca cheese production in order to determinate the most eco-efficient production technique [295]; the economic and environmental performance of the 56 Swiss dairy farms in the alpine area [296];
- *Aquaculture*: an environmental impact efficiency analysis of a set of 83 mussel cultivation rafts [65];
- *Products/materials*: a comparative eco-efficiency analysis of electronic devices [297]; eco-efficiency measure of a sample of electric/electronic products [298]; an assessment of construction materials in order to select the most eco-efficient exterior wall finish for a building [299].

2.5 The framework of uncertainty analysis of DEA

DEA was initially formulated as a deterministic model, but there have been numerous developments that take into account uncertainties following a wide array of methods. These include, to name a few, fuzzy theory[300]–[302], stochastic frontier analysis (SFA) ([303], [304]), imprecise DEA (IDEA) [305], chance-constrained programming ([306], [307]), bootstrapping([308], [309]), robust DEA approach[310] and Monte Carlo simulation ([237], [311]). Dyson *et al.* (2010)[312]examined five different DEA models

(SFA, chance-constrained, bootstrapping, IDEA and Monte Carlo simulation) to deal with uncertainty in DEA.

Recently, the uncertainty analysis of DEA has been developed using the mainly following aforementioned methods:

- *Fuzzy theory:* the sustainability performance assessment of the 33 U.S. food manufacturing sectors [313];the management of uncertainty in vendors section [314]; to measure transport systems [315];
- *Imprecise DEA:* to evaluate and rank the operational performance of firms of cement industry [316];
- *Bootstrapping:* productive efficiency of banks [317];
- *Monte Carlo simulation:* to measure the quality for health care provider and pay-for-performance of USA nursing homes [318]; the application for Supply Change management[319]–[321]; to evaluate the relative technical efficiency of small health care areas [322].

3. Methods and tools

3.1 Introduction

The major goal of sustainability assessment is the development and application of decision-support tools to help in the recognition, selection and environmental evaluation of products, processes and/or systems.

The application of the combined use of LCA and DEA in sustainability described in this thesis is a complex task due to the many aspects that should be considered. In this chapter, the Data Envelopment Analysis used for the efficiency assessment analysis is illustrated and explained. First, the theoretical concepts of these tools are discussed, followed by the DEA under uncertainty approach with the characterization of uncertainty, solvers and databases.

3.2 Decision making

The decision-making approaches are usually classified as descriptive (concern with the identification of the observed nature of a problem) and normative (concern with the solution of a problem based on a set of rules)[323]. Among the former approaches distinguish *forecasting* based on future projections and *simulation* based on the analysis of behavior of a system with several degrees of accuracy to imitate a real system. On the other hand, the later uses *mathematical programming* based on the optimization of decision-making problems with real or integer variables within constraints or *heuristic methods* based on feasible approximate solutions without the guaranty of optimality. In this thesis we concentrate of mathematical programming methods.

3.3 Mathematical models

A mathematical model can be defined as a representation or approximation of the behavior of real objects in mathematical terms. This model generally combines the following variables/equations: (i) the relevant information about balances (*i.e.*, mass and energy), states (dynamic or stationary), etc. and (ii) Equations representing functional relationships, boundary conditions and other specifications.

The mathematical model usually includes continuous and discrete variables in its formulations. According to Grossmann *et al.*[324], the general formulation of an optimization problem is presented in the following form:

$min\ or\ max\ f(x)$	Objective function	
subject to		
$h(x) = 0$	Equality constrains (*e.g.*, process equation)	(3.1)
$g(x) \leq 0$	Inequality constraints (*e.g.*, specifications)	
$x = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^n$	Decision variables	

where: *f(x)*, *h(x)* and *g(x)* represent scalar functions of vector *x*, being *f(x)* – the objective function (that can minimize or maximize cost, environmental impact, etc.). The independent decision variables (the components of vector *x*) can be discrete or continuous variables (*e.g.*, storage amounts, prices, production levels, etc.). In optimization processes, the values of the aforementioned variables are determined. The mathematical form generally includes several restrictions for decision variables: equalitiesor inequalities constrains (*e.g.*, mass balances, correlations between variables, production, purchase, etc.). The classification of mathematical problem due to its characteristics is explained in Table 3.1.

Table 3.1. Type of mathematical problems according to the variables and functions included.

Type of problem	Vector *x*	Functions *f(x)*, *h(x)* and *g(x)*
Linear	Continuous	Linear
Non-linear	Continuous	At least one is non-linear
Mixed integer linear	At least one ofthe x_i elements is integer (or binary)	Linear
Mixed integer non-linear	At least one of x_i elements is integer (or binary)	At least one is non-linear

In this thesis, we focus on Data Envelopment Analysis, a tool that uses linear programming models.

3.4 Optimization methods and tools

The programming models can be classified as deterministic or probabilistic. As mentioned above, the former can be subdivided into four main mathematical classes: linear, nonlinear, mixed-integer linear and mixed-integer non-linear models whereas the latter can be subdivided into two classes: (1) where an unpredictable nature is involved (knowing or unknowing the probability distribution) and (2) those against an unfriendly opponent (*e.g.*, two or multi person games).

According to Daraio *et al.* [198], the linear programming theory is *"a milestone of efficiency analysis"*. The project SCOOP (Scentific Compiting of Optimum Programs, started in June 1947 by US Air Force, counted with the contribution of Dantzing[325], developed: (i) an initial mathematical model of the general linear programming problem and (ii) a general method of solution named the Simplex method. Since then, the simplex method which is the basic computational algorithm and linear programming initiated to be the solution in efficiency analysis. On the other hand, Charnes and Cooper, after the contribution to theory and applications in the development of linear programming[326], popularized its utilization in DEA in the 1970s [62].

3.4.1 Continuous optimization

In order to solve the linear and nonlinear problems, continuous optimization is the common way. There are two most accepted methods to solve linear problems (LP): (i) simplex and (ii) interior points.

In continuous optimization, the parameters used in order to solve linear problems are only the objective function, the continuous variables and linear constrains.

3.4.1.1 Linear programming

Linear programming (LP) method builds a model that can be applied to a broad class of decision making problems encountered in industry, engineering, management/government or economics. This method is considered with the simplest mathematical structure solving practical scheduling problems associated with the aforementioned areas. LP studies the behavior of all systems and distinguishes feature of operations research or management science. As cited by Dantzig[325], sixty years ago Herrmann and Magee, stated to considerate the operations as an entity and defined the subject matter studied as: *"the combination of equipment used, the morale of participant and the physical properties of the output as an economic process"*.

Since 1940, the development of the applications of LP followed in different activities, such as input-output analysis[327], [328]or microeconomic production programming models[329], [330]. In these models, detected as the outputs and inputs of production units, the activities presented as intensity variables or coefficients of activity, form a sequence of linear inequalities, producing a piecewise linear frontier technology.

The description of the procedure of linear programming method:

Suppose that the system under study (one actually existing or one only designed), that is, on what kind of activities will be implemented, what will be the size of these operations, is complex of a number of various factors, such as people, materials, technological equipment, money, supplies etc. Suppose that we are able to identify specific purpose of this system. Looking at it from the linear programing point of view consist in decomposing system into a number of certain elementary functions named *activities* (*e.g.*, process of the raw material processing for a particular technology installation, process of raw material storage or product, the process of selling a product, etc).

Each activity thought of as a kind of "black box", is affected by several factors which flow into the inputs such as, men, raw materials and which flow out named outputs such as products of manufacture. Details of what happens to the inputs during the activity are not important in order to formulate the linear programming task, only the rates of flow into and out of the activity and are taken into account. Various forms of inputs and outputs are the *items* of activity. After determining a set of activities that composes a system, magnitudes that clearly define its intensity should be selected for each of them among its components (*e.g.*, one of the inputs). These magnitudes are called generally *decision variables*. The quantity of each activity is named the *activity level*. The changes in the flows into and out of the activity change the activity level.

Additionally, if the system is a linear programming model, the following assumptions must be satisfied: proportionality, nonnegativity, additivity and the objective function must be linear:

- *Proportionality:* the quantities of contributions into and out of the activity are always proportional to the activity level. For instance, if the doubling of activity level is required, all the corresponding flows for the unit activity level need have to be doubled. A change in a variable causes a proportionate change in that variable's contribution to the value of the function.

- *Nonnegativity:* the variables are required to be nonnegative.
- *Additivity:* The system of activities should be complete. Precisely, it is requires that for each item, the total amount indicated by the system as a whole equals the sum of the amounts flowing into the different activities minus the sum of the amounts flowing out.
- *Linear Objective Function:* the constraints and objective function are required to be linear. Linearity requires (i) the proportionality of the value of the objective function and the responses of each resources expressed by the constraints to the activity levels expressed in the variables, and (ii) the additivity of objective function and variables, that means that there are no interactions between the effects of different activities.

Model building: the outline for the procedure of the formulation of the linear programming model based on the basic assumptions mentioned above is as follows:

Step 1: The definition of Activity Set by the decomposition of the entire system under study into all of its elementary functions called *activities* and for each of them choose a unit of quantification or *level* of measurement.

Step 2: The definition of Item Set by determination of a set of decision units that measure the consumption or production of activities.

Step 3: The determination of input-output coefficients and exogenous flows that describe the system inside (inputs and outputs of the items between system) and outside.

Step 4: The creation of linear objective function of system.

LP technique uses a linear objective function subject to the linear equality and/or inequality constraints. The LP method finds a point, if such point exists, in a polytope with real-valued function defined in it, by examining all polytope vertices. The intersection of halfspaces and hyperplanes of the constraints is a feasible region (Figure 3.1).

The set of mathematical relationships that characterizes the feasible region of the system is the result of the model building and is *linear programming model.*

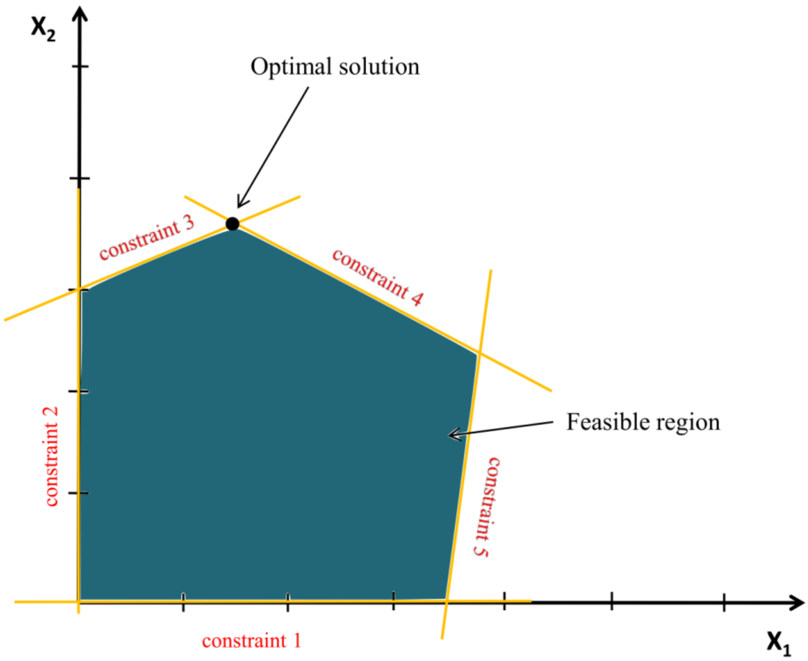


Fig. 3.1. Linear programming representation.

All LP problems can be mathematically expressed as follows:

$$z = f(x_1, \dots, x_n) = \sum_{j=1}^{n} c_j x_j \tag{3.1}$$

subject to

$$g_i(x_1, \dots, x_n) = \sum_{j=1}^{n} a_{ij} x_j \leq b_i, \quad i = 1, \dots, m \tag{3.2}$$

where the coefficients c_j, b_i, a_{ij}, $j=1,\dots,n$, $i=1,\dots,m$ are the parameters of the problem, while x_j , $j=1, \dots, n$, are the decision variables.

3.4.1.1.1 Simplex method

There are several methods to solve the linear problems. The simplest one is a graphic method, but it's practical application limits to problems with only two decision variables. The most used algorithm for solving LP problems is the simplex method, proposed in 1947 by George Dantzig[325]. The simplex method requires to convert LP problem into its standard form, where the object function is maximized, the variables are nonnegative and the constraints are equalities. The general expression of LP problem in standard form is presented as follows:

$$\max \quad z = f(x_1, \dots, x_n) = \sum_{j=1}^{n} c_j x_j \tag{3.3}$$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j = b_i, \quad i = 1, \dots, m \tag{3.4}$$

$$x_1, \dots, x_n \geq 0 \tag{3.5}$$

Where $b_i \geq 0$, $i=1,\dots,m$.

Each linear program is intimately connected into a dual linear program. We start first with the duality of the standard problem. The dual of the standard maximum problem (3.3)-(3.5) is defined to be the standard minimum problem as follows:

$$\min \quad w(y_1, \dots, y_m) = \sum_{i=1}^{m} b_i y_i \tag{3.6}$$

subject to

$$\sum_{i=1}^{m} a_{ij} y_i = c_j, \quad j = 1, \dots, n \tag{3.7}$$

$$y_1, \dots, y_m \geq 0 \tag{3.8}$$

Koopmans and Shephard [329], [330] imposed convexity on the reference technology in his work, thus the DEA estimator depend on the convexity assumption. The programming model affirms the structure of frontier technology without requiring a special functional form by the envelopment of data points with linear segments. A simple means of calculating the distance to the frontier is provided by frontier technology and it is a maximum feasible radial expansion of specific activity. The interpretation of efficiency or performance as maximal-minimal proportionate feasible changes in an activity of given technology explains the measurement of the distance to the frontier and this explanation agrees with Farrell's definition of efficiency measurement[61]. However, the first formulation of efficiency measurement as a linear programming problem took place later (1966) by Boles[331], Bressler[332], Seitz[333] and Sitorius[334] (the development of piecewise linear case) and by Timmer[335] who extended the piecewise log-linear case.

Linear programming methods are utilized also in production analysis for nonparametric "tests", which are the quantitative indicators, but not a real statistical test procedure. These techniques consist on the regulation of conditions and the behaviour of objectives. Additionally, a series of consistency "tests", developed by Afriat[336] in 1972, assumed an increase of more restrictive regulatory hypotheses on production technology. Theses "tests" are based on linear programming formulations. On the other hand, Diewert *et al.*[337]proposed this series of tools as *"a screening device in the construction of frontiers and efficiency measurement of data related to frontier construction"*.

3.4.2 Frontier analysis methods

According to Simar and Wilson [338] the efficiency frontier models can be classified in accordance with the following criteria:

1. The specification of the (functional) form for the frontier function: *Parametric* and *nonparametric* models;
2. The presence of noise in the sample data: *Deterministic* and *stochastic* models;
3. The type of data analyzed: *cross-sectional* and *panel data* models.

Several models have been analyzed in the literature by the combination of the three criteria:

- *Parametric deterministic models.*
- *Parametric statistic models.*
- *Nonparametric deterministic models.*
- *Nonparametric stochastic models.*

The parametric methods are based on statistical concepts. The model of dependence between studied values identifies which parameters are subject to estimation based on empirical data. A classic problem of parametric method is the model of production function. On the other hand, in the case of nonparametric methods, the basis for assessing efficiency is the ratio between its actual productivity to the highest possible productivity. The main advantage of nonparametric methods is the lack of need of behavioural assumptions for measuring technical efficiency[339]. Looking from a technical point of view, both the inputs and the outputs distance function can be applied to measure the technical efficiency. The variation of the direction in which distance to the technology is calculated is the only difference. On the other hand, from the context of the study depends the way in which the frontier is assessed. If the external outputs are not under the decision makers control, the efficiency of inputs (the only elements controlled by managers) will be examined.

The most common methods used in research works are the nonparametric (deterministic) frontier approach such as DEA (Data Envelopment Analysis), FDH (Free Disposal Hull) and the (parametric) stochastic frontier approach such as SFA (Stochastic Frontier Analysis). The FDH is used in the analysis of production efficiency or the evaluation of public funds spending due to the comparison of the individual performance to the limit production capacity. In this method the convexity assumption is not imposed and FDH method is treated as a special variant of the method DEA.

3.4.2.1 Data Envelopment Analysis

DEA method, originally proposed in 1978 by Charnes *et al.*[62], is a decision making technique based on linear programming for assessing the relative efficiency of a set of comparable units called DMUs (Decision Making Units). The initial inspiration for DEA was to examine the productive efficiency of similar institutions like public organizations (DMUs), but it has been extended to banks, cars, hospitals, schools, engineering components, among others. In order to securing relative comparisons, the evaluation of a group of DMUs is as follows: each other with each DMU have a certain degree of freedom in decision making.

Let's be n DMUs: DMU_1, DMU_2,…,DMU_n. The following input and output items characterize each of these $j=1,\ldots,n$ DMU [340]:

- For each input and output the data are assumed to be positive and available.

- The data that flow into and out and the election of DMUs should be selected very carefully in order to obtain appropriate results.
- The preference of small input amounts and large output amounts is required.
- There is no necessary for inputs and output measurement to be compatible. For instance, the units may be numbers of persons, cost amount or areas of wall space, etc.

The basic model, known as the CCR model due to the initials of the developers, now is widely known as the *constant return to scale* (CRS) model. On the other hand, the other basic frontier model, known as BCC (Banker, Charnes and Cooper initials), represents the *variable return to scale* (VRS) model, which includes the convexity condition in its constraints, that is, an increase in inputs does not result in a proportional change in the outputs. According to the orientation, the basic envelopments of DEA model are presented in Figure 3.2.

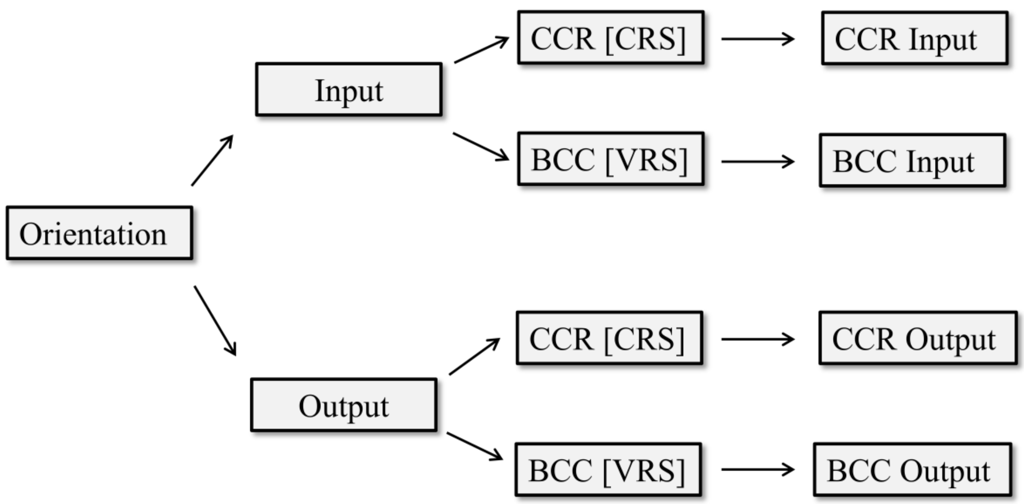


Fig. 3.2. The classification of basic envelopments DEA models

Some definitions and properties are defined before the description de CCR models.

Assumption 3.1 (Nonnegativity)

Given a vector (x_j,y_j) of a nonnegative inputs and outputs where j=1,..,n of n DMUs. The nonnegative assumption (called semipositive by Cooper et al. [341]*) means that: for some j=1,…,n the following conditions are fulfilled:* $x_j \geq 0, x_j \neq 0$ *and* $y_j \geq 0, y_j \neq 0$. *Thus, each DMU has at least one positive value in both input and output.*

Definition 3.1 (Activity)

A pair (x,y), where semipositive input $x \in R_m^+$ *and semipositive output* $y \in R_p^+$ *is called an activity. Note that m and s specify the number of vector dimensions space for inputs and outputs, respectively.*

Definition 3.2 (Production possibility set)

The set of feasible activities is named the production possibility set and is denoted by P.

$P = \{(x, y): x \epsilon R_m^+ \,;\ y \epsilon R_p^+;\ y\ can\ be\ produced\ from\ x\}$

An input-output pair (*x*,*y*) is called *feasible* if and only if $(x, y) \in P$.

The typical production set for the CCR model with the single input and single output case (the two dimensions are *m*=1 and *p*=1) is represented in Figure 3.3. As shown, the possibility set is determined by B point and the line connecting the origin and going through B is called the efficiency frontier.

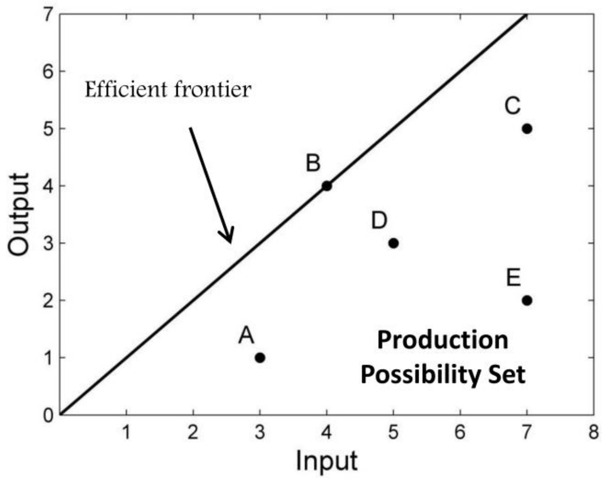


Fig. 3.3. Representation of the production possibility set for point B.

Model orientation

There are two versions of CCR model: *input-oriented* and *output-oriented*. The former aims to minimize inputs satisfying at least the given outputs at the same time, while the later attempts to maximize outputs without needing more of any of the inputs values.

We illustrate the difference between those two models via the following small-scale example by considering the case of one input and one output (Table 3.2).

Table 3.2. Explanatory example of one input and one output case.

DMU	input (x)	output (y)
A	3	1
B	4	4
C	7	5
D	5	3
E	7	2

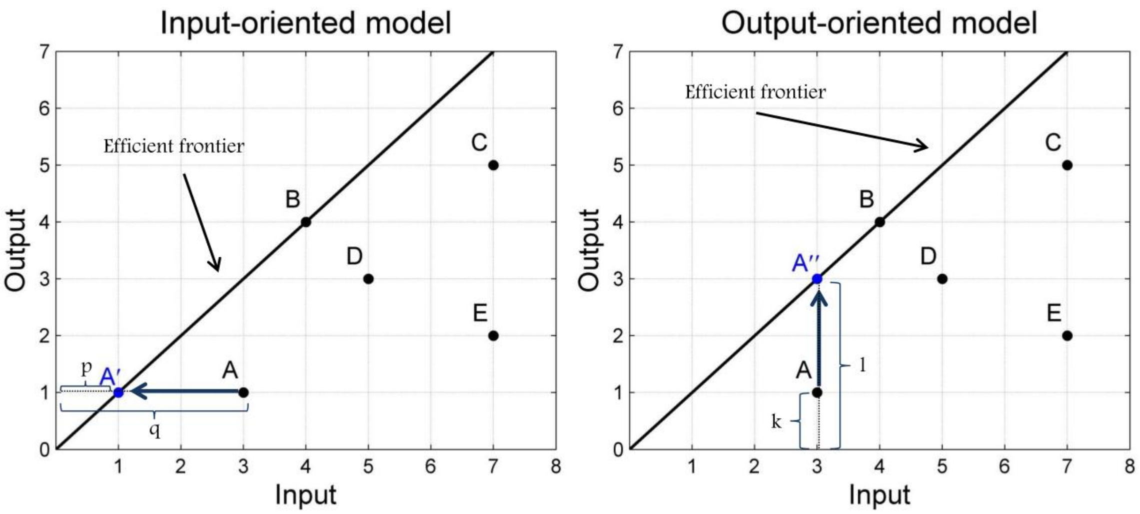


Fig. 3.4. The graphical representation of explanatory example.

Table 3.2 shows five DMUs with one input and one output while the graphical representation of efficient frontier for the simplest version of CCR model is presented in Figure 3.4. The inputs and outputs of five hypothetical decision making units A, B, C, D and E have been depicted, which use one input *x* (in different quantities) in order to obtain one output *y* (with different levels). Among the studied DMUs, the unit B represents *"the best"* ratio between output and input, thus this unit is considered as a *referent set* for others DMUs.

The relative efficiency of unit B equals 1, whereas the relative efficiency of the remaining DMUs is calculated as a ratio between the studied units to the *"best"* unit. For instance, the relative efficiency of DMU A equals$\frac{y_A/x_A}{y_B/x_B}$. The line connecting unit B with the beginning of coordinate system determinates the efficient frontier. His gradient equals the efficiency value of unit B, that is,$y_B/x_B = 1$.According to the model orientation, the following two cases can be applied for inefficient units in order to achieve efficiency:

- The *input-oriented model (CCR-I):*The unit A, which is inefficient, can achieve the relative efficiency equal 1, if producing y_A units of product will reduce the input x_A by *q – p,* that is, by reaching the point A'. The relative efficiency of unit A can be depicted as a ratio between the segments *p* and q. Thus, the ratio $p/_q = \frac{y_A x_B/y_B}{x_A}$represents the relative efficiency score in input-oriented model.
- The o*utput-oriented model (CCR-O):* The inefficient unit A, in order to achieve efficiency value 1, using the input x_A should obtain the results about *l – k* higher (*i.e.*, point A''). The relative efficiency of unit A can be depicted as a ratio between the segments *k* and *l*. Thus, the ratio $k/_l = \frac{y_A}{x_A y_B/x_B}$ represents the relative efficiency score in output-oriented model.

In DEA models with the constant return to scale assumption (CCR-models), the relative efficiency (θ) of any DMU is equivalent for input-oriented (CCR-I) and output-oriented (CCR-O) model (Table 3.3).

Table 3.3. Results of explanatory example of one input and one output case.

DMU	input (*x*)	output (*y*)	CCR-I (θ)	CCR-O(θ)	Reference Set
A	3	1	0.333	0.333	B
B	4	4	1.000	1.000	B
C	7	5	0.714	0.714	B
D	5	3	0.600	0.600	B
E	7	2	0.286	0.286	B

3.4.2.1.1. The Charnes, Cooper and Rhodes model

As mentioned above, the most basic DEA model is CCR model, which was proposed by Charnes, Cooper and Rhodes in 1978. The original problem formulation for assessing efficiency was constructed as a task of fractional programming (FP), while the solution procedure consists of linear programming (LP) usage for each of the units under assessment.

Let x_{ij} be the observed magnitude of i – type input for entity j (where $x_{ij}>0$, $i=1,\ldots,m$, $j=1,\ldots,n$) and y_{rj} – the observed magnitude of r – type output for entity j (where $y_{rj}>0$, $r=1,\ldots,p$, $j=1,\ldots,n$). Suppose that DMU_j is evaluated on any trial formed as DMU_o where o ranges over $1,\ldots,n$. Therefore, the virtual input and output is created for each DMU with the corresponding weights (v_i) and (u_r), where:

$$Virtual\ input = v_1 x_{1o} + \cdots + v_m x_{mo} \tag{3.6}$$

$$Virtual\ output = u_1 y_{1o} + \cdots + u_s y_{so} \tag{3.7}$$

Therefore, the commonly measure of efficiency is defined as a ratio of the weighted sums of the outputs (virtual output) and the weighted sums of the inputs (virtual inputs):

$$\frac{\boldsymbol{Virtual\ output}}{\boldsymbol{Virtual\ input}} \tag{3.8}$$

The Charnes-Cooper-Rhodes (CCR) model is defined in the following structure for the chosen entity o.

$$(FP_o) \quad max\ \theta = \frac{\sum_{r=1}^{p} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{3.9}$$

Subject to

$$\frac{\sum_{r=1}^{p} u_r y_j}{\sum_{i=1}^{m} v_i x_j} \leq 1, \ \forall j = 1, 2, \ldots, j_o, \ldots, n \tag{3.10}$$

$$u_r \geq 0, \ r = 1, 2, \ldots, p \tag{3.11}$$

$$v_i \geq 0, \ i = 1,2, \ldots, m \tag{3.12}$$

As for the relative efficiency θ of one decision making unit o, the maximum in objective function (3.9) is desired and assuming the condition (3.10), the conclusion that $0 \leq \theta \leq 1$ for each DMU_o is obviously. Additionally, the weight values may vary from one DMU to another and the calculation of weights (v_i) and (u_r) maximizing the ratio of DMU_o is the objective of each evaluated DMU. On the other hand, if the condition (3.10) is true for every DMU, each of them belongs to the efficiency frontier or beyond it. When max $\theta = \theta^* = 1$, that indicates the achievement of efficiency and means that $\mathrm{DMU_o}$ is efficient. The case when $\theta^* < 1$ means that $\mathrm{DMU_o}$ is inefficient.

The most used and widely known model is input-oriented CCR (in primal and dual form) despite the several modifications that have been developed. The CCR models assume that all DMUs operate under *constant returns to scale (Property 3.1)*. In other words, an increase in the input values results in a proportional increase in the output levels.

Property 3.1. (Constant returns to scale)

If (x,y) is a feasible point, then for any positive t, (tx, ty)is also feasible.

<u>Input-oriented model</u>

The fractional problem ($\mathrm{FP_o}$) is nonconvex, nonlinear, has linear and fractional objective function and constrains and is being replaced by the following linear program ($\mathrm{LP_o}$). This two problems are equivalent (the theorem and its proof is demonstrated in Cooper *et al.* [340]). Thus, the input oriented CCR primal model is:

$$(\mathrm{LP_o}) \qquad \max \theta = \sum_{r=1}^{p} u_r y_{ro} \tag{3.13}$$

Subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{3.14}$$

$$\sum_{r=1}^{p} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, (\forall j = 1, \dots, n) \tag{3.15}$$

$$u_r \geq 0,\ r = 1, 2, \dots, p \tag{3.16}$$

$$v_i \geq 0,\ \mathrm{i} = 1,2, \dots, \mathrm{m} \tag{3.17}$$

First, suppose that (θ^*, v^*, u^*) is an optimal solution of ($\mathrm{LP_o}$) where v^* and u^* represents values with constrains given in (3.16) and (3.17). The *CCR-efficiency* has been defined as follows:

Definition 3.3 (CCR-Efficiency)

1. *If* $\theta^* = 1$, *then DMU*$_o$ *is CCR-efficient and exists at least one optimal solution* (v^*, u^*), *where* $v^* > 0$ *and* $u^* > 0$.
2. *Otherwise, DMU*$_o$ *is CCR-inefficient.*

The (LP_o) model is linear and is associated with dual model (as mentioned in 3.4.1.1 that each linear programming model is connected with his dual form and can be solved by simplex method) as follows:

$$(DLP_o) \quad \min \quad \theta - \varepsilon\left(\sum_{r=1}^{p} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \qquad (3.18)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} (\forall r = 1, \dots, p) \qquad (3.19)$$

$$\theta x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = 0 \quad (\forall i = 1, \dots, m) \quad (3.20)$$

$$\lambda_j, s_r^+, s_i^- \geq 0 \quad \forall j = 1, \dots, n \qquad (3.21)$$

Where the s^- values (slack) represents the input excesses while the s^+ values (slack) are the output shortfalls in (3.19) and (3.20), respectively.

The concept of DEA is explained in the dual CCR model (DLP_o). For each inefficient unit, the hypothetical composite of existing and efficient units is constructed, where the efficient DMUs and the segments that interconnect them form the efficient frontier. In the input-oriented model, the inefficient units envelope below the frontier while in output-oriented – it is located above the frontier.

Definition 3.4 (CCR-Efficiency, Radial Efficiency, Technical Efficiency)

Due to the association between (LP_o) and (DLP_o) and duality theorem, DMU_o is called CCR-efficient if and only if for an optimal solution $(\theta^*, \lambda^*, s^{-*}, s^{+*})$ *the following conditions must be satisfied (if full efficiency is to be attained):*

(i) $\theta^* = 1$

(ii) $s^{+*} = s^{-*} = 0$ *(zero-slack)*

The first condition refers to *radial* or *technical efficiency* due toif $\theta^* < 1$, then all the inputs can be reduced at the same time without the alternation of the proportion in which they are used. Thus, $(1 - \theta^*)$ represents the maximal proportionate reduction admitted by production possibility set. Any additional reductions connected with nonzero slack condition will inevitably change the input proportions.

Additionally, the CCR-efficiency concept given in Definition 3.3 is equivalent to that given in Definition 3.4 (The proof of this theorem is demonstrated in Cooper *et al.*[340]).

However, if only the first condition (i) is satisfied, then it refers to *weak efficiency* term. Furthermore, the two conditions (i) and (ii) describe the *Pareto-Koopmans* or *strong* definition of efficiency.

Definition 3.5 (Pareto-Koopmans Definition of Efficiency)[329]*The performance of a DMU is efficient if and only if it is not possible to improve any input or output without worsening any other input or output.*

Hence, the dual problem if the full efficiency is required is:

$$(DLP_o - full\ \ efficiency)\ \ \min\ \ \theta \qquad (3.22)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro} \geq 0 \qquad (\forall r = 1, \dots, p) \qquad (3.23)$$

$$\theta x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad (\forall i = 1, \dots, m) \qquad (3.24)$$

$$\lambda_j \geq 0 \quad \forall j = 1, \dots, n \qquad (3.25)$$

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 (DLP_o *full efficiency*) 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 a useful guide for decision and policy-makers. Further details on this issue can be found elsewhere [341].

3.4.2.1.2. The Banker Charnes Cooper model

The most relevant extension of the CCR-model is BCC (Banker-Charnes-Cooper) model, developed by Banker *et al.*[192] in 1984. The only difference between CCR and BBC model is that the latter includes the convexity condition (*i.e.*,$\sum_{j=1}^{n} \lambda_j,\ \lambda_j \geq 0, \forall j$).

Suppose that we have *n* DMUs (decision making units) where: each DMU_j, *j=1,...,n* produces the same *s* outputs in different amounts (y_{rj} ; $r = 1,..,p$) consuming the same *m* inputs in different amounts (x_{ij} ; $i = 1,..,m$). The efficiency of a specific DMU_o for the input-oriented BCC model can be presented as the solution of the following linear program:

$$(\mathrm{BBC_o}) \quad \max \theta = \sum_{r=1}^{p} u_r y_{ro} - u_0 \tag{3.26}$$

Subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{3.27}$$

$$\sum_{r=1}^{p} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0, (\forall j = 1, \dots, n) \tag{3.28}$$

$$u_r \geq 0, \ r = 1, 2, \dots, s \tag{3.29}$$

$$v_i \geq 0, \ \mathrm{i} = 1,2, \dots, \mathrm{m}; \ \ u_0 \text{ free in sign} \tag{3.30}$$

wherex_{ij} and y_{rj}(being nonnegative) are the inputs and outputs of the *j*th DMU, while v_i and u_r represent the input and output weights. For the DMU_o, x_{io} and y_{ro} are the corresponding inputs and outputs.

The free variable u_0, associated with the constraint $\sum_{j=1}^{n} \lambda_j = 1$ is the unique difference between the CCR and BCC models and does not appear in the CCR.
The dual form of this linear program *(BBCo)* is expressed as follows:

$$(BCC_o - dual) \ \ \min \ \ \theta - \varepsilon \left(\sum_{r=1}^{p} s_r^+ + \sum_{i=1}^{m} s_i^- \right) \tag{3.31}$$

Subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} (\forall r = 1, \dots, p) \tag{3.32}$$

$$\theta x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = 0 \quad (\forall i = 1, \dots, m) \tag{3.33}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{3.34}$$

$$\lambda_j, s_r^+, s_i^- \geq 0 \quad \forall j = 1, \ldots, n \tag{3.35}$$

Definition 3.6 (BCC-Efficiency)

1. *If $\theta_B^* = 1$, then DMUₒ is BCC-efficient and exists at least one optimal solution (v^*, u^*), where $v^* > 0$and $u^* > 0$.*
2. *Otherwise, DMU_o is BCC-inefficient.*

Definition 3.7 (BCC-Full Efficiency)

If for an optimal solution $(\theta_B^*, \lambda^*, s^{-*}, s^{+*})$ obtained from the (BCC_o) and (BCC_o-dual) models the following conditions are satisfied:

(i) $\theta_B^* = 1$

(ii) $s^{+*} = s^{-*} = 0$ *(zero-slack)*

Then the DMU_o is called BBC-full efficient, otherwise it is BBC-inefficient.

Hence, the dual problem if the full efficiency is required is:

$$(BBC_o - full\ \ efficiency)\ \ \min\ \ \theta \tag{3.36}$$

Subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro} \geq 0 \quad (\forall r = 1, \ldots, p) \tag{3.37}$$

$$\theta x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad (\forall i = 1, \ldots, m) \tag{3.38}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{3.39}$$

$$\lambda_j \geq 0 \quad \forall j = 1, \ldots, n \tag{3.40}$$

The output-oriented models for both CCR and BBC models are presented in Table 3.4.

Table 3.4. Output- oriented models for CCR and BBC.

Model CCR – primal	**Model BCC – primal**
$(CCR-\ O_o)\ \min\ \eta=\sum_{i=1}^{m} v_i x_{io}$ Subject to $\sum_{r=1}^{p} u_r y_{ro}=1$ $\sum_{r=1}^{p} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij}\le 0, (\forall j=1,\dots,n)$ $u_r\ge 0, \quad r=1,2,\dots,p$ $v_i\ge 0, \quad \mathrm{i}\ =\ 1{,}2,\dots,\mathrm{m}$	$(BCC-O_o)\ \min \eta_B=\sum_{i=1}^{m} v_i x_{io}-u_0$ Subject to $\sum_{r=1}^{p} u_r y_{ro}=1$ $\sum_{r=1}^{p} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij}+u_0\le 0, (\forall j=1,\dots,n)$ $u_r\ge 0, \quad r=1,2,\dots,p$ $v_i\ge 0,\ \mathrm{i}\ =\ 1{,}2,\dots,\mathrm{m};\ \ u_0$ free in sign
Model CCR – dual	**Model BCC – dual**
$(CCR-O_o\ dual)\ \max\ \ \eta$ Subject to $\sum_{j=1}^{n} \lambda_j y_{rj}-\eta y_{ro}\ge 0 \quad (\forall r=1,\dots,p)$ $x_{io}-\sum_{j=1}^{n} \lambda_j x_{ij}\ge 0 \quad (\forall i=1,\dots,m)$ $\lambda_j\ \ge 0 \quad \forall j=1,\dots,n$	$(BCC-O_o\ dual)\ \max\ \ \eta_B$ Subject to $\sum_{j=1}^{n} \lambda_j y_{rj}-\eta_B y_{ro}\ge 0 \quad (\forall r=1,\dots,p)$ $x_{io}-\sum_{j=1}^{n} \lambda_j x_{ij}\ge 0 \quad (\forall i=1,\dots,m)$ $\sum_{j=1}^{n} \lambda_j=1$ $\lambda_j\ \ge 0 \quad \forall j=1,\dots,n$

Note, that for the CCR- model, an optimal solution of output-oriented model relates to that of input-oriented model as follows: $\eta^*={}^{1}\!/_{\theta^*}$.

It is important to remark that DEA is primarily a diagnostic tool and does not prescribe any reengineering strategies to make inefficient units efficient.

3.4.2.1.3. Explanatory example between CCR and BCC model (1input and 1 output)

In order to clarify the differences between the two models presented above and the two orientation cases, we use the same explanatory example introduced in Table 3.2. The example represents five different DMUs, each one with one input and one output (Fig. 3.5). The thinnest line on Figure 3.5 that links point B from the origin is the efficient frontier of the CCR model. On the other hand, the bold line that connects A, B and C represents the frontiers of the BBC model. The area below the efficiency frontier that includes observed and possible activities jointly with a shortfall in outputs and/or excess of inputs when comparing to the frontiers is the production possibility set. Additionally, B is CCR-efficient whereas A, B and C are BCC-efficient and all point leading on the solid line connecting them are also BCC-efficient.

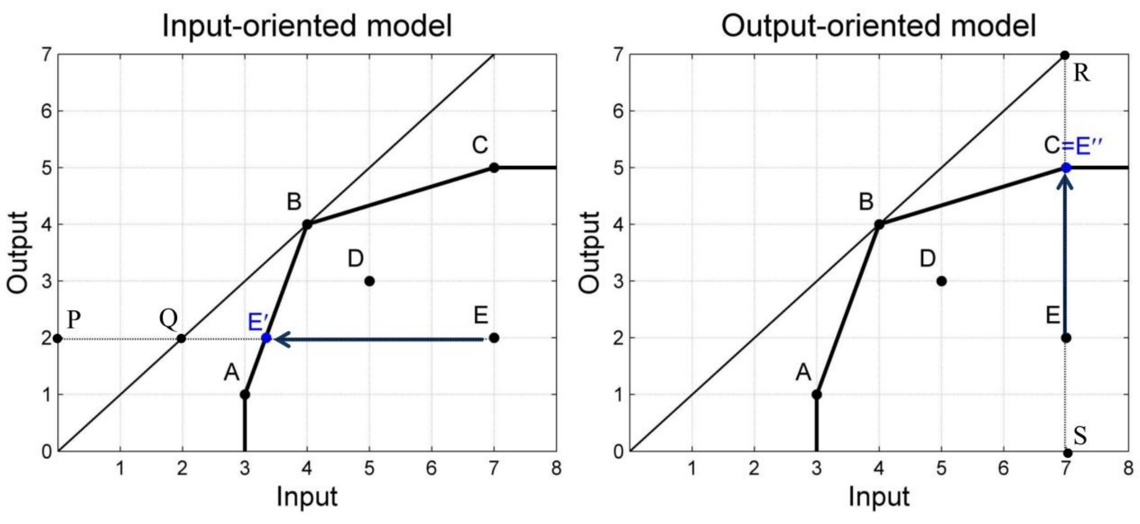


Fig. 3.5. The graphical representation of explanatory example between CCR and BCC models.

The CCR- efficiency of point E for the input-oriented model is evaluated by

$$\theta = \frac{PQ}{PE} = \frac{2}{7} = 0.285 \qquad (3.50)$$

While the BCC-efficiency is higher with value

$$\frac{PE'}{PE} = \frac{3.35}{7} = 0.478 \quad (3.51)$$

On the other hand, the CCR efficiency for output-oriented model is calculated by

$$\theta^* = \frac{RS}{ES} = \frac{7}{2} = 3.5 \quad (3.52)$$

While the BCC-efficiency is smaller and equals

$$\frac{SE''}{SE} = \frac{5}{2} = 2.5 \quad (3.53)$$

This means that for the point E the increase of output from the observed value to achieve efficiency equals: (Eq. 3.53) $2.5 \times 2 = 5$ units for BBC model and (Eq. 3.52) $3.5 \times 2 = 7$ units for CCR model. Additionally, as mentioned before, there is a relationship between input and output-oriented for CCR model, that is the output efficiency could be obtained from input efficiency value ($\frac{1}{0.285} = \frac{1}{\theta^*} = \eta^* = 3.5$). Note that this "reciprocal relation" between input and output efficiencies is available only for CCR model, but not for BBC models. The efficiency values for both DEA models and both input and output oriented cases are presented in Table 3.5.

Table 3.5. Results of explanatory example for the CCR and BBC models

DMU	input (*x*)	output (*y*)	CCR-I (θ)	CCR-O(η)	BCC-I (θB)	BCC-O (ηB)
A	3	1	0.333	0.333	1.000	1.000
B	4	4	1.000	1.000	1.000	1.000
C	7	5	0.714	0.714	1.000	1.000
D	5	3	0.600	0.600	0.750	0.690
E	7	2	0.286	0.286	0.464	0.400

Note that generally the CCR-efficiencies are lower than BBC-efficiencies.

3.5 Uncertainty approaches

Despite the fact that many relevant advances in optimization tools have been made during the last decades, the complexity of models when several sources of uncertainty are considered in the study produces important problems to the decision makers in order to ensure the solution. The variability of parameters, like manufacturing time or conditions of reaction; uncertainty in prices, demand or resources; and other external uncertainties (*e.g.*, different types of errors) are one of the principal challenges nowadays.

The sources of uncertainty can be classified as [342]: (i) exogenous such as supply, demand, etc., and (ii) endogenous such as capacity, yield, etc. On the other hand, one of the classifications of the approaches treated the problems under uncertainty are reactive and preventive procedures[343]. Reactive approaches consist of modifications of deterministic model in order to obtain the reaction and response to the uncertain events. Some of the reactive approaches that tackle with uncertainty are the Model Predictive Control and the multi-programming, among others. On the other hand, the preventive approaches incorporate the uncertainty parameters and for all possible cases find a good solution. The main advantage of this approach is that for all considered scenarios, a feasible solution is achieved. The most relevant techniques are: (i) Stochastic programming, (ii) Chance-constrained programming, (iii) robust optimization, and (iv) fuzzy programming, among others.

3.5.1 Data Envelopment Analysis with uncertainty

The main tool in preventive technique that handles with the uncertainty is stochastic programming. This technique is based on the optimization of the expected performance metrics such as maximizing the expected profits or minimizing the environmental impact or expected costs. Due to being a scenario-based method, the uncertain parameters are included as random scenarios (*e.g.*, impact values, demand, price, etc.) with the probability distribution of each of them[344]. The goal is to obtain the optimal expected decisions/values and to analysis how changes the efficiency with the influence of some uncertain assumptions.

In the model detailed in 3.4.2.1, the inputs and outputs are assumed to take nominal variables. Let us now consider the case in which they are stochastic variables modelled via specific probability functions. To account for this, a stochastic model (3.54)-(3.58) is formulated taking the deterministic formulation (3.13)-(3.17) as a basis (the input-oriented CCR model). Consider *t* scenarios belonging to the set of scenarios S, each corresponding to a different materialization s of the uncertain parameters ($s=1,\dots,t;$ $s \in S$), that is, inputs and outputs take different values in each scenario. For each such scenario, we aim to quantify the efficiency of *n* DMUs, each with *m* inputs and *p* outputs. We use the following notation: variable u_{rs} is the weight associated with the *r*-th output in scenario *s*, variable v_{is} represents the weight given to the *i*-th input in scenario *s*, parameter x_{ijs} is the amount of input *i* utilized by DMU_jin scenario s, and parameter y_{rjs} is the amount of output *r* produced by DMU_jin scenario s, wherein $i = 1, \dots, m$; $j = 1, \dots, n$; $r = 1, \dots, p$; $s = 1, \dots, t$. Assuming that $x_{ijs} \geq 0$,$y_{rjs} \geq 0$ and for the test object with index *j'*, the relative efficiency score in scenario *s* of DMU *j'* ($\theta_{j's}$) is given by the following LP model defined for every scenario:

$$\theta_{j's} = \max \sum_{r=1}^{p} u_r y_{rj's} \qquad (3.54)$$

Subject to

$$\sum_{i=1}^{m} v_i x_{ij's} = 1 \qquad (3.55)$$

$$\sum_{r=1}^{p} u_r y_{rjs} - \sum_{i=1}^{m} v_i x_{ijs} \leq 0, \ \forall j \qquad (3.56)$$

$$u_{rs} \geq 0, \ \forall r, s \qquad (3.57)$$

$$v_{is} \geq 0, \ \forall i, s \qquad (3.58)$$

This model is known as input-oriented CCR DEA [62]. By running the above model for each DMU and scenario, we can obtain the relative efficiency score of each

DMU for each possible outcome of the uncertain parameters. For every inefficient DMU and scenario, we can in turn determine the corresponding improvement targets by projecting such unit onto the efficient frontier. This is done by solving the following dual problem defined for every scenario:

$$\min \theta_{j's} \qquad (3.59)$$

Subject to

$$\sum_{j=1}^{n} \lambda_{js} y_{rjs} - y_{rj's} \geq 0 \quad \forall r \qquad (3.60)$$

$$\theta_{j's} x_{ij's} - \sum_{j=1}^{n} \lambda_j x_{ijs} \geq 0 \quad \forall i \qquad (3.61)$$

$$\lambda_{js} \geq 0, \forall j, s, \ \theta_{j's} \ unconstrained \quad (3.63)$$

Decision variable λ_{js} represents the weight for DMU_j defined as peer of *j'* in scenario *s*. Note that a DMU is inefficient if a composite DMU (linear combination of units in its peer group) can be recognized which maintains at least the same output level while utilizing less input than the DMU tested. The dual problem (3.59)-(3.63) 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 onto the efficiency frontier. Further details on this issue can be found elsewhere [341]. As mentioned above, DEA is primarily a diagnostic tool and does not prescribe any reengineering strategies to make inefficient units (technologies) efficient. Note that the same transformation from deterministic values to stochastic ones can be done for BBC model and for all orientation cases.

3.5.1.1 Monte Carlo sampling

The Monte-Carlo sampling method consists of a repeated random sampling of uncertain parameters and has many applications such as: simulation, optimization, regression, probability distribution and risk analysis, etc.

Jens Krüger[345] presented the Monte Carlo approach for old and new frontier methods for the measurement of efficiency. Several situations with different return to scale regimens were studied and concluded that the stochastic frontier analysis(SFA) and data envelopment analysis (DEA) should be cross-checked first before the use of new methods in efficiency analysis.

The first study that initiated a unstopped stream of Monte Carlo method application for efficiency analysis was proposed in 1987 by Banker *et al.*[346].Some of the further studies are presented in this section in chronological order.

Later, in 1993, Banker *et al.*[347] compared de DEA and SFA models for samples size of 25, 50, 100 and 200 and measurement errors. The results showed that DEA performs better for the smallest size. Three years later, Banker *et al.*[348] using deviations as error measure concluded that DEA under VRS performs better than DEA under CRS. The weakness of this approach was very low number of 25 Monte-Carlo simulations.

Moreover, after the analysis of five different DEA models (SFA, chance-constrained, bootstrapping, IDEA and Monte Carlo simulation) to deal with uncertainty in DEA, Dyson *et al.*[312] concluded that Monte Carlo simulation is an effective approach to handle uncertainties in DEA, yet it is computationally greedy. They used 100, 200, 500, 1000 and 2000 replications and concluded that with more than 500 replications, the study is reliable.

In this thesis, Monte Carlo simulation has been used in scenario generation for stochastic DEA model. The use of Monte-Carlo sampling method in this thesis helps in obtaining the replications of environmental impacts in uncertainty analysis of DEA.The procedure of Monte Carlo simulation requires the parameters based on the following variables:

(i) *The value* – arithmetical mean amount.

(ii) *The distribution function* – the type of uncertainty distribution.

(iii) *The uncertainty type* – for the measurement of dispersion.

According to Huijbregts *et al.*[349], an increase of the incorporation of uncertainty information for LCA provoked that the representation of statistical distribution became ambiguous. The most used distribution are: i) the uniform, ii) the triangular, iii) the normal or Gaussian and iv) the lognormal. The authors described the relationship between the mathematical formulations, their representation in Ecoinvent databases and in CMLCA software (which is an advanced tool that includes analysis under uncertainty via Monte Carlo method).

In this thesis, the lognormal distribution have been used for Monte Carlo simulation with uncertainty level calculated from the Weidema model for LCA impacts retrieved from the Ecoinvent database.

3.5.1.2 Data quality management (Weidema model)

The Weidema model has been used to measure the type of uncertainty for Monte Carlo simulation. The Pedigree matrix approach ([55], [350]) allows translating quality indicators into quantitative information. This methodology relies on the assumption that the uncertain parameters can be described using lognormal distributions [351]. Data sources can be expressed according to[55]: *uncertainty* (spread and pattern of distribution), *reliability* (different methods used for calculations, measurement and quality control data), *completeness* (number of data collection points, periods and their representativeness of the total population), *age* (year of the original measurement), *the geographical area* and *the technological level* for which the data is representative. Thus, the five general items in which the data is assessed are: “reliability”, “completeness”, “temporal correlation”, “geographical correlation” and “further technological correlation” (see Table 3.6). Each characteristic of the data is divided into five quality levels with a score between one and five.

Accordingly, a set of five indicator scores is attributed to each individual input and output exchange (except the reference products), reported in a data source.

Tabe 3.6. Pedigree matrix used to assess the quality of data sources, modified from [55][350].

Indicator score	**1**	**2**	**3**	**4**	**5 (default)**
Reliability	Verified data based on measurements	Verified data partly based on assumptions or non-verified data based on measurements	Non-verified data partly based on qualified estimates	Qualified estimate (*e.g.*, by industrial expert)	Non-qualified estimate
Completeness	Representative data from all sites relevant for the market considered, over an adequate period to even out normal fluctuations	Representative data from >50% of the sites relevant for the market considered, over an adequate period to even out normal fluctuations	Representative data from only some sites (<<50%) relevant for the market considered ***or*** >50% of sites but from shorter periods	Representative data from only one site relevant for the market considered ***or*** some sites but from shorter periods	Representativeness unknown or data from a small number of sites ***and*** from shorter periods
Temporal correlation	Less than 3 years of difference to the time period of the dataset	Less than 6 years of difference to the time period of the dataset	Less than 10 years of difference to the time period of the dataset	Less than 15 years of difference to the time period of the dataset	Age of data unknown or more than 15 years of difference to the time period of the dataset
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown ***or*** distinctly different area (North America in-stead of Middle East, OECD-Europe instead of Russia)
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study (*i.e.*, identical technology) but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials	Data on related processes on laboratory scale ***or*** from different technology
Sample size	> 100, continous measurement, balance of purchased products	> 20	>10, aggregated in environental report	>= 3	unknown

Table 3.7 represents the example of data quality indicators for German electricity production. In this example, the use of hard coal plants is reported for production of 1 kWh of energy. After the investigation of background of this data in Ecoinvent database, is pedigree can be quantified as follows: (1,1,1,1,1). The explanation of each indicator is shown in Table 3.6.

Table 3.7. The example of determining data quality indicators

Data quality indicator for electricity production of hard coal (Germany)	Score	Explanation
Reliability	1	The data source are official German impact values obtained from the constructed hard coal power plant ready to produce electricity including analysis from grave : the reception of hard coal and operating materials at power plant gate to cradle, i.e. including all upstream activities.
Completeness	1	The data are determined for Germany hard power plants for the period 1980-2015.
Temporal correlation	1	The data period are from 1980 to 2015
Geographical correlation	1	The information values have been derived from German data.
Further technological correlation	1	This dataset represents the production of high voltage electricity in an average hard coal power plant in Germany.

The method of uncertainty measurement using Pedigree Matrix is next presented.

To generate a given number of scenarios, two parameters of the distribution (mean and standard deviation) are required. The nominal value of the impact retrieved from EcoInvent provides the expected value of the distribution, which can then be used together with the standard deviation to obtain the mean parameter. On the other hand, the outcome of the Pedigree matrix is used to determine the standard deviation. First, the geometric standard deviation is calculated as follows: the variance σ_g^2 is computed using the Pedigree Matrix (eq. 3.64) by answering questions regarding the reliability (U_1), completeness (U_2), temporal correlation (U_3), geographical correlation (U_4), further technological correlation (U_5), and sample size (U_6) of the LCI data (see Table 3.8). Parameter U_b is an uncertainty factor that depends on the environmental burden (see Table 3.9).

$$\sigma_g^2 = \exp\left(\sqrt{(lnU_1)^2 + (lnU_2)^2 + (lnU_3)^2 + (lnU_4)^2 + (lnU_5)^2 + (lnU_6)^2 + (lnU_b)^2}\right) \quad (3.64)$$

Two uncertainty levels (low and high) are calculated in the following way: the low level considers the lowest scores of the Pedigree factors, while the high level considers the highest (1 and 5, based on Table 3.8, respectively).

Parameter U_b varies from one impact to the other, but for a given impact category remains the same across technologies (*e.g.* acidification potential expressed in kg SO_2e as an uncertainty factor U_b corresponding to SO_2= 1.05 from Table 3.8 regardless of the technology being assessed). For instance, the variance σ_g^2 of acidification potential impact when considering the quality score 1 (being the pedigree (1,1,1,1,1,1)) is calculated as follows:

$$\sigma_g^2 = \exp\left(\sqrt{(ln1)^2 + (ln1)^2 + (ln1)^2 + (ln1)^2 + (ln1)^2 + (ln1)^2 + (ln1.05)^2}\right) = 1.05$$

Note that the uncertainty factor U_b corresponds to SO_2 and equals 1.05 (Table 3.9) whereas the standard deviation is 1.025. On the other hand, when the quality score of 5 is considered (represented by pedigree (5,5,5,5,5,5)), the standard deviation equals 7.18 (for the same uncertainty factor $U_b = 1.05$).

Table 3.8. Uncertainty factors for the pedigree matrix scores

Indicator score	**1**	**2**	**3**	**4**	**5**
Reliability	1	1.05	1.1	1.2	1.5
Completeness	1	1.02	1.05	1.1	1.2
Temporal correlation	1	1.03	1.1	1.2	1.5
Geographical correlation	1	1.01	1.02	---	1.1
Further technological correlation	1	---	1.2	1.5	2
Sample size	1	1.02	1.05	1.1	1.2

Table 3.9. Basic uncertainty factors (U_b).

Input / output group	**c**	**p**	**a**	**Input / output group**	**c**	**p**	**a**
Demand of:				**Pollutants emitted to air:**			
Thermal energy, electricity, semi-finished products, working material, waste treatment services	1.05	1.05	1.05	CO_2	1.05	1.05	
Transport services (tkm)	2	2	2	SO_2	1.05		
Infrastructure	3	3	3	NMVOC total	1.5		

Resources:				NO_X, N_2O	1.5		1.4
Primary energy carriers, metals, salts	1.05	1.05	1.05	CH_4, NH_3	1.5		1.2
Land use, occupation	1.5	1.5	1.1	Individual hydrocarbons	1.5	2	
Land use, transformation	2	2	1.2	PM>10	1.5	1.5	
Pollutants emitted to water:				PM10	2	2	
BOD, COD, DOC, TOC, inorganic compounds (NH4+, PO43-, NO3-, Cl-, Na+, etc...)		1.5		PM2.5	3	3	
Individual hydrocarbons, PAH,		3		Polycyclicaromatic hydrocarbons (PAH)	3		
Heavy metals		5	1.8	CO, heavy metals	5		
Pesticides			1.5	Inorganic emissions, others		1.5	
NO_3 , PO_4			1.5	Radionuclides (*e.g.*, Radon-222)		3	
Pollutants emmited to soil:							
Oil, hydrocarbon total		1.5					
Heavy metals		1.5	1.5				
Pesticides			1.2				

3.5.1.3 Combined use of Monte Carlo simulation and Pedigree matrix

We used the lognormal distribution function which is the most commonly used distribution[349] to present the Monte Carlo simulation via the Pedigree matrix approach.

As mentioned in chapter 3.5, to generate a given number of scenarios, the Monte Carlo method requires two parameters of the lognormal distribution (mean (ξ) and standard deviation (ϕ).). The nominal value of the LCI entry provides the expected value of the LCI entry (retrieved from Ecoinvent database), on the other hand, the outcome of the Pedigree matrix (presented above) gives the standard deviation value as follows[349]:

$\xi = \ln(1 + \frac{Var[\tilde{X}]}{(E[\tilde{X}])^2})$(3.65)

$\phi = \ln\left(E[\tilde{X}]\right) - \frac{1}{2}\xi$ (3.66)

Where $E[\tilde{X}]$is the expected value of the LCI entry, which can be retrieved from environmental databases such as Ecoinvent, $Var[\tilde{X}]$is its variance, and ξ and ϕ are the mean and standard deviation of the natural logarithm of the stochastic variable (which by definition follows a normal distribution). The varianceσ_g^2 is computed using the Pedigree Matrix, which builds the underlying lognormal distribution according to the quality of the data available.

As mentioned above, the expected mean value ($E[\tilde{X}]$) is first retrieved from Ecoinvent v3 and we assume that it represents the population arithmetic mean of the random variable. The "true" mean can be estimated by the expected value of a set of independent replications (*i.e.*, scenarios). The same norm holds for the geometric standard deviation that is next calculated using the Pedigree Matrix (Eq. 3.64) and converted into the arithmetic standard deviation ($\sigma = \ln(\sigma_g)$). It should by mention that the true mean and standard deviation of uncertain parameters should correspond to the expected value and standard deviations of replications (*i.e.*, scenarios) for an infinite number of those.

Formerly the distribution is defined; the random values of the uncertain parameters using sampling methods can be generated. Figure 3.6 represents the procedure. The multivariate sampling methods typically consider that the uncertain data follows distributions other than *lnN* (*i.e.*, mainly normal distributions). A random number-generator with the so-called inverse transform sampling method is used to generate the values for lognormal from normal distribution. This procedure consist in that if *F(x)* is the cumulative distribution function (CDF) of random variable *x*, and the stochastic variable *y* follows a uniform distribution between 0 and 1, then the stochastic variable $z=F^{-1}(y)$ will follow the distribution of *x*. Hence, we generate the scenarios assuming that the uncertain parameters follow normal distribution (N from here on). The mean (ϕ^N) and standard deviation (σ^N) are obtained as follows

$$\phi^N = E^N[\tilde{X}] \quad (3.67)$$

$$\sigma^N = \sqrt{Var^N[\tilde{X}]} \quad (3.68)$$

Where $E^N[\tilde{X}]$ is the expected value of the uncertain parameter and $Var^N[\tilde{X}]$ represents its variance. Without loss of generality, we assume that the expected mean value and variance of normal distribution to be the same as those of lognormal distribution

$$E^N[\tilde{X}] = E[\tilde{X}] \quad (3.69)$$

$$Var^N[\tilde{X}] = Var[\tilde{X}] \quad (3.70)$$

As mentioned before, the $E^N[\tilde{X}]$ of the *lnN* distribution can be retrieved from Ecoinvent databases, while $Var^N[\tilde{X}]$ is obtained from the transformation of eq. (3.65) and (3.66) as follows:

$$Var[\tilde{X}] = \left[E[\tilde{X}]\right]^2 \left(e^{\xi} - 1\right) = (e^{2\phi+\xi})\left(e^{\xi} - 1\right) \quad (3.71)$$

We next calculate standard deviation (σ^N) of the normal distribution and covariance matrix ($Cov = (\sigma^N)^2$). In case of correlation between impacts, we multiply the covariance matrix by the correlation matrix.

The generation of multivariate normal random scenarios is made from the multivariate normal distribution with expected mean ($E^N[\tilde{X}]$) and covariance parameters. The transformation of normal into lognormal distribution is done in two steps:

(1) Firstly, we apply the normal cumulative distribution function (CDF) to obtain a uniform distribution in the interval [0,1].

(2) Next, we undo the inverse CDF, but this time, into lognormal distribution instead of a normal distribution.

Finally, the selected number of scenarios is generated with a lognormal distribution.

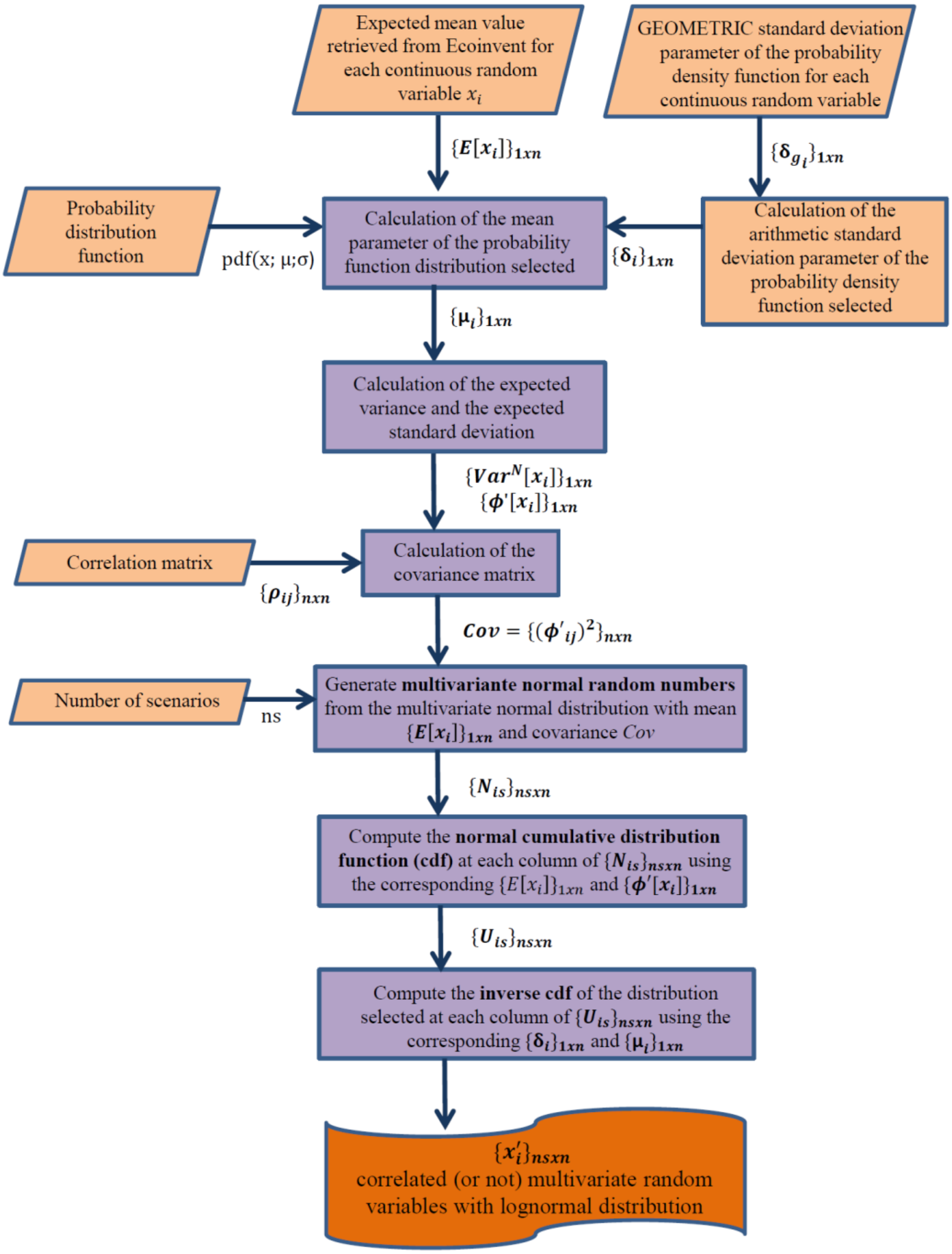


Fig. 3.6. The procedure of the Monte Carlo simulation process.

3.6 Modelling systems

Various commercial tools can be used to implement the mathematical models (deterministic, stochastic, etc) including GAMS (General Algebraic Modeling Systems), AMPL (A Mathematical Programming Language)[352], AIMMS (Advanced Interactive Multidimensional Modeling Software)[353], OPL (Open Programming Language)[354] or MATLAB (MATrixLABoratory).

3.6.1 GAMS – General Algebraic Modeling System

The modeling system used in this thesis is GAMS, which is one of the most important software used in optimization problems[355]. Originally developed through a World Bank funded study in 1988, achieved the reputation as one of the most flexible and popular language. The programming language that GAMS uses, allows not only the modeling of optimization problems but also its optimization. Some important aspects have been pointed out by Castillo *et al.*[356]:

- The separation between the modeling and solving procedure. After the development of a model, several solvers are available to optimize the problem.
- The mathematical description of the problem is similar to the representation of model in GAMS.
- Without varying the code, it is possible to transform the small size problem into large-scale one.
- It is easy for both machines and humans to read the algebraic statements because of very compact and concise description of models
- The unambiguous statements of algebraic relationship are allowed
- Allows the changes in model specifications in very simple and safe way.
- Allows to export and import data from/to Microsoft Excel files.
- Allows the connection between MATLAB and GAMS.

Moreover, it is worthy to mention that optimization algorithms mentioned above are embedded in some of the different GAMS solvers. Each solver is usually developed to tackle a specific type of program (*i.e.*, LP, NLP, MILP, MINLP, etc.).

According to Chattopadhyay [357], although that the GAMS is easy and flexibly in implementing a wide variety of optimization problems, some situations are not advisable when choosing the optimization models. First of all, the GAMS program is not freeware. Next, when the problems have an inherent inflexibility of modeling language, the application of GAMS does not admit full exploitation of power system capacities and is prohibited. Additionally, GAMS models are not a substitute for commercial power system software. The simplistic GAMS model performs inferior when compared with power system properties and expertise of a number of company years.

3.6.2 ECOINVENT database

The Ecoinvent database v.3.2 [358] is used to retrieve the environmental data required to perform the calculations. As mentioned before, this database contains LCA data of 4087 products associated with human activities organized by region, economic sector and product type. Additionally, Ecoinvent database is a set of information of various thousands of life cycle inventory datasets in several fields such as: energy supply, biofuels and biomaterials, agriculture, transport, chemicals, basic and precious metals, packing materials, ICT (information and communication technologies), waste treatment, and electronic devices, among others. The main advantages of this database results of its:

- *Consistency*: the database is fully interlinked with unit processes and presents the common data requirements and guidelines;
- *Reliability*: Ecoinvent database has been continuously developed and improved for over 18 years by several independent expert and reviewers for all datasets;

- *Transparency*: Each dataset contain individual documentation and the unit process data with all calculation results are fully accessible.

The main disadvantages are the license cost. Additionally, the datasets provides information for only for a limited number of regions or countries (mostly refers to the European and US countries). On the other hand, due to the limited number of the elementary flows for specific processes (*e.g.*, earth movement in agriculture and silviculture or countries with unused mining and extraction processes for specific substances), in some cases it is impossible to consider the regional differences in the analysis.

Despite de Ecoinvent database, several national and international public databases have been created such as: the Swedish SPINE@CPM [359], the Japanese JEMAI [360], the US NREL[361], the German PROBAS (UBA) [362], the Australian LCI database [363] or the European Reference Life Cycle Database (ELCD) [364], among others. Additionally, some of the databases alternative to Ecoinvent are: GaBi[365] or ELCD[366], among others.

PART II. Ecoefficiency analysis

4. Assessment of the environmental efficiency of the electricity mix of the top European economies via DEA

4.1 Introduction into sustainable development of energy system

Moving towards a more sustainable energy system or company converts into a major goal of modern societies that aim to minimize the dependence on fossil fuels and the associated anthropogenic impacts.

With the recent increase of awareness that the role plays energy in sustainability has suffered major changes. There is a clear need for systematic approaches for sustainability analysis, including tools to quantify the eco-efficiency level attained by a system.

The 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 the European Union, several environmental strategies and policies have been recently developed, which highlight the necessity for a clean and efficient energy supply. These policies aim 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 a specific character of energy generation in each country and that any energy transition is a very slow process, the World Energy Council has summed up the challenges in their "energy trilemma" concept which involves balancing three conflicting objectives:

(i) Energy security: The reliability of energy supply must be ensured to meet current and future demand,

(ii) Energy equity: The accessibility of energy around the world at affordable cost,

(iii) Environmental sustainability: The improvement of energy efficiency through the lowering of greenhouse gas emissions, pollution, and fossil fuel dependence.

Several scenarios (Figure 4.1) have been developed by IEA experts analyzing how the energy mix could change by 2035. The common trend to minimize the fossil fuels dependence and at the same time, to increase the use of renewable energy has been proposed to achieve the goals.

As mentioned above, significant energy reduction strategies have been enacted in order to minimize energy consumption improving energy efficiency. For instance, a binding legislation approbated by the European Union (EU) in March 2007, which purposes the ambitious 2020 Energy Strategy plan combating climate change and air pollution. By 2020, the EU aims to reduce its greenhouse gas emissions by at least 20% from 1990 levels, increase the share of renewable energy to at least 20% of consumption, and achieve energy savings of 20% or more [367]. In addition, EU countries have agreed to meet the following objectives by 2030:

(i) Reduction of at least a 40% in greenhouse gas emissions, compared to 1990.

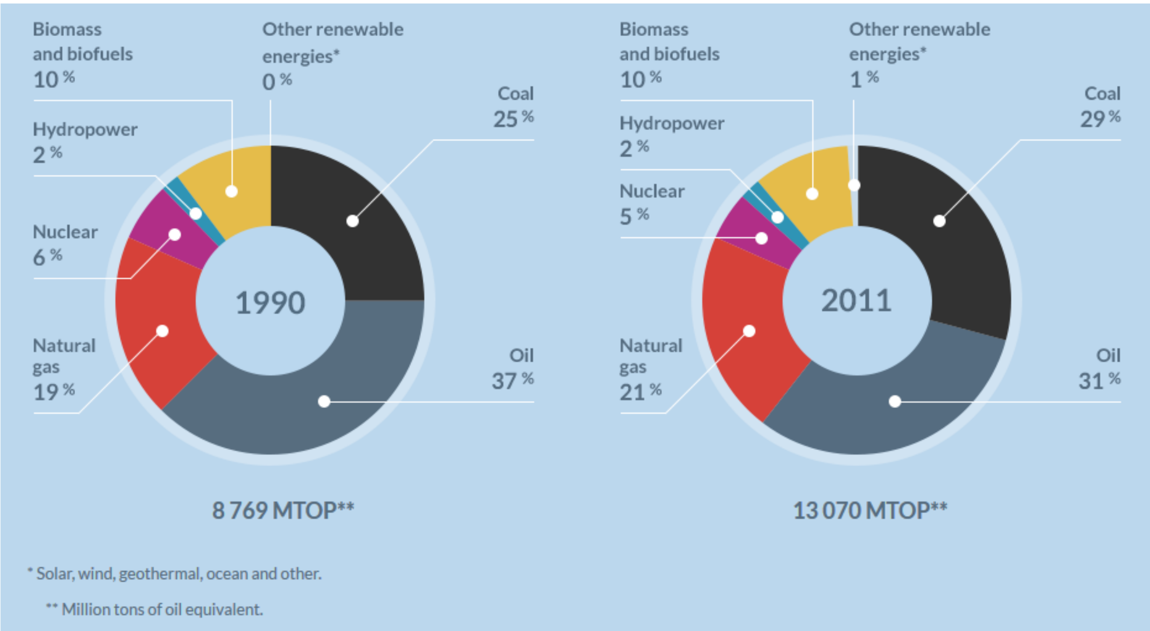
(ii) Achieve a binding target of at least 27% of renewable energy.

(iii) An energy efficiency increase of at least 27%, to be reviewed by 2020 potentially raising the target to 30%.

(iv) A completion of the internal energy market by reaching an electricity interconnection target of 15% between EU countries, and pushing forward important infrastructure projects.

The finally EU aim is to achieve an 80% to 95% reduction in greenhouse gasses compared to 1990 levels by 2050. Indeed, the transformation of the current energy system into a sustainable, low-carbon and greenhouse gas emissions system seems to be the significant energy efficiency strategy to achieve the reduction goals presented above. 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).

As the significant role of energy in sustainability is evident, intensive research efforts are presently being undertaken to seek sustainable alternatives for satisfying the growing electricity demand at minimum environmental impact. In practice, it is unlikely that a single technology will show the best performance in every environmental impact category of interest. As an example, nuclear energy contributes marginally to global warming, but shows high impact in ionising radiation [368], whereas with coal the opposite situation occurs. Understanding that electricity production technologies may 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) and, for the worst, obtain the specify targets that (if achieved) would make them efficient. This valuable insight could facilitate the transition towards a cleaner electricity generation system.



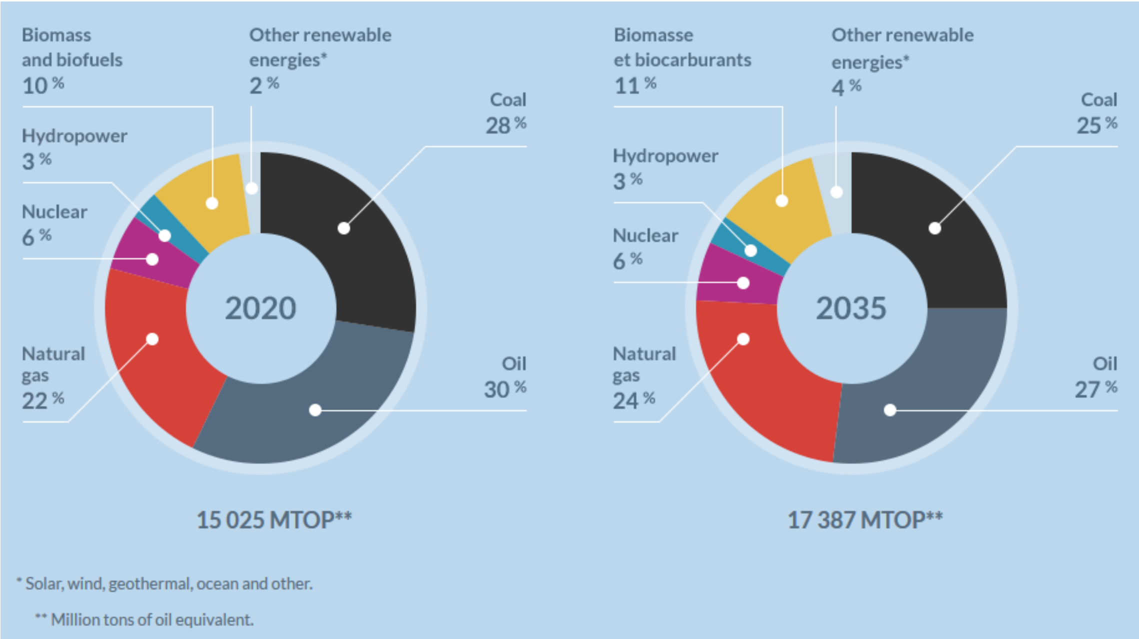


Fig.4.1 Global energy mix from 1990 to 2035. Several scenarios have been developed by International Energy Agency (IEA) that project energy trends through to 2035. *Source: IEA*[369].

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 lifecycle stages 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.). The main advantage of using LCA in the assessment of energy systems is that it provides a holistic view of each technology, thereby informing on the extent to which it contributes to decrease the impact globally. This comes at the cost 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 [161] and of several emissions associated with electricity production from coal and natural gas in Canada [370], among others. More information is presented in subsection 2.2.2.1.

4.2 Problem statement

The combined approach that integrates LCA and DEA proposed by Vázquez-Rowe *et al.*[67] has been applied in this work to assess the environmental efficiency of the electricity mix of the 27 wealthiest economies in Europe (Figure 4.2). We discuss in this chapter which countries are efficient and for those found to be inefficient, we obtain the quantitative environmental targets are provided to 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 this chapter, economic, social, technological and political aspects have been left out of the analysis. The main reason for this 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 they seldom reflect the true cost of the system due to external regulations).

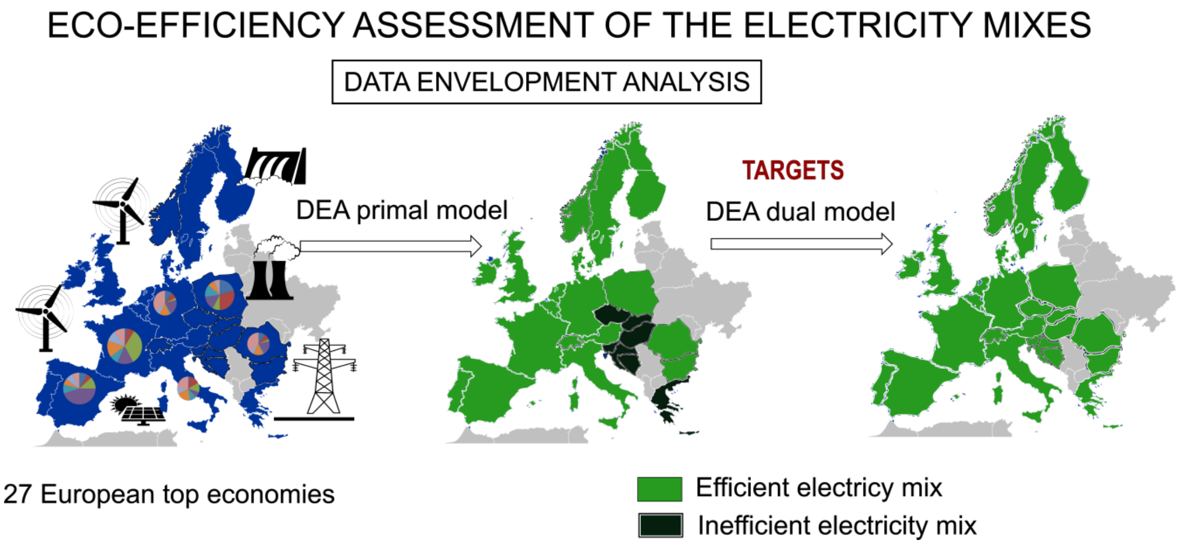


Fig. 4.2 Graphical abstract of DEA study case.

The chapter is organized as follows. The results of applying LCA to 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.

4.3 Environmental impact assessment of energy productions

The environmental performance of the electricity mix of the top economies in Europe (see Table 4.1) is analyzed first following LCA principles. Particularly, this environmental performance is quantified through the CML 2001 [109], [371], an LCA-based methodology that considers 15 damage scores (which are quantified over the entire life cycle of the energy supply chain).

Table 4.1 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

The impacts analysed and the corresponding units are given in Table 4.2. The results of the LCA analysis have been retrieved from the environmental database EcoInvent v3.2[372], which contains LCA data of the main technological processes implemented worldwide.

Table 4.2 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 NO_x – 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^2a)
9	Malodorous air	m^3 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. 4.3 shows the normalized environmental impacts associated with the generation of 1 kWh 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. Hence, to enhance the numerical robustness of the models solved

by DEA, we first normalize the data prior to its application. The goal of normalization is to refer the impact scores to a common interval (*e.g.*, [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 Fig. 4.3), while at the same time avoiding the numerical difficulties that may arise when solving the LP models of the DEA approach using the original raw data.

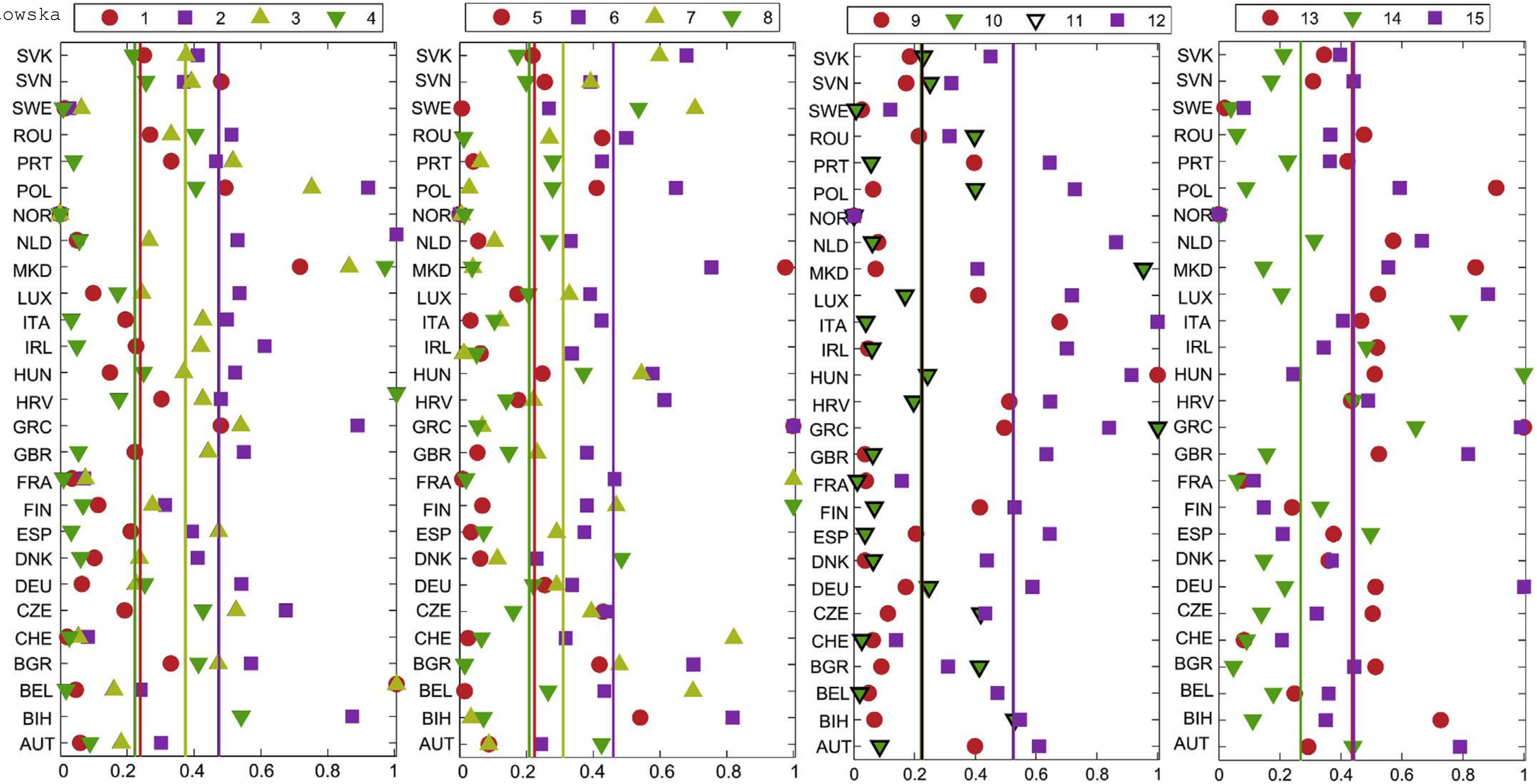


Fig. 4.3 Normalized environmental impact for every country in each category. The values are expressed per kWh and normalized by subtracting the minimum value and dividing bythe difference between the maximum and minimum impact attained in every category over all the countries. The horizontal axis displays the values of the 15 impacts described inTable 4.2 for every country shown in the vertical axis (see acronyms in Table 4.1). The vertical lines represent the average of each impact.

In Fig. 4.3, 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, 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, which performs very well in many environmental categories except for ionising radiation, represents a significant proportion of the electricity production mix (see Figure 4.4). Hence, there is no single country that shows the best performance in all indicators simultaneously.

Furthermore, as seen in Fig. 4.3, 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 *r*-value (Pearson correlation coefficient) between damage categories (Table 4.3). This analysis shows that water pollution metrics (impacts 4, 5, 10, 11) are highly correlated (*r* -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 (*r*-value of 0.975) and climate change and eutrophication potential (*r*-value of 0.886), between acidification and eutrophication potential (*r*-value above 0.91) and between malodorous air and stratospheric ozone depletion (*r*-value above 0.84). In addition, human toxicity shows a strong correlation with climate change and acidification potential (*r*-values of 0.715 and 0.732, respectively). Moderate correlations are observed as well between climate change and ionising radiation (*r*-value of 0.588) and photochemical oxidation (*r*-value of 0.563), and between malodorous air and photochemical oxidation (*r*-value of 0.628).

Table 4.3 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**	**0.527**	**0.757**	**0.729**	**0.728**	0.376	**-0.418**	-0.198	-0.218	**0.723**	**0.722**	-0.099	**0.514**	-0.222	**0.412**
2	**0.527**	**1**	**0.779**	**0.713**	**0.713**	**0.539**	**-0.601**	0.141	0.197	**0.717**	**0.718**	**0.601**	**0.976**	0.230	**0.642**
3	**0.757**	**0.779**	**1**	**0.561**	**0.561**	**0.493**	**-0.541**	0.085	0.008	**0.567**	**0.567**	**0.383**	**0.730**	0.080	**0.564**
4	**0.729**	**0.713**	**0.561**	**1**	**1.000**	**0.642**	-0.353	-0.222	-0.091	**0.999**	**0.999**	-0.005	**0.754**	-0.147	**0.694**
5	**0.728**	**0.713**	**0.561**	**1.000**	**1**	**0.643**	-0.353	-0.222	-0.091	**0.999**	**0.999**	-0.005	**0.754**	-0.148	**0.694**
6	0.376	**0.539**	**0.493**	**0.642**	**0.643**	**1**	0.049	-0.147	0.159	**0.661**	**0.664**	0.218	**0.579**	0.154	**0.862**
7	**-0.418**	**-0.601**	**-0.541**	-0.353	-0.353	0.049	**1**	-0.137	-0.186	-0.359	-0.358	**-0.473**	**-0.596**	-0.235	-0.351
8	-0.198	0.141	0.085	-0.222	-0.222	-0.147	-0.137	**1**	-0.031	-0.229	-0.229	0.284	0.106	-0.055	-0.139
9	-0.218	0.197	0.008	-0.091	-0.091	0.159	-0.186	-0.031	**1**	-0.075	-0.074	**0.719**	0.175	**0.963**	0.206
10	**0.723**	**0.717**	**0.567**	**0.999**	**0.999**	**0.661**	-0.359	-0.229	-0.075	**1**	**1.000**	0.010	**0.759**	-0.129	**0.717**
11	**0.722**	**0.718**	**0.567**	**0.999**	**0.999**	**0.664**	-0.358	-0.229	-0.074	**1.000**	**1**	0.011	**0.760**	-0.128	**0.720**
12	-0.099	**0.601**	**0.383**	-0.005	-0.005	0.218	**-0.473**	0.284	**0.719**	0.010	0.011	**1**	**0.587**	**0.805**	0.294
13	**0.514**	**0.976**	**0.730**	**0.754**	**0.754**	**0.579**	**-0.596**	0.106	0.175	**0.759**	**0.760**	**0.587**	**1**	0.215	**0.674**
14	-0.222	0.230	0.080	-0.147	-0.148	0.154	-0.235	-0.055	**0.963**	-0.129	-0.128	**0.805**	0.215	**1**	0.189
15	**0.412**	**0.642**	**0.564**	**0.694**	**0.694**	**0.862**	-0.351	-0.139	0.206	**0.717**	**0.720**	0.294	**0.674**	0.189	**1**

To shed further light on the environmental impact patterns of energy generation, we next analyzed the electricity mix of the top European countries (Fig 4.4). 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 ionizing 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).

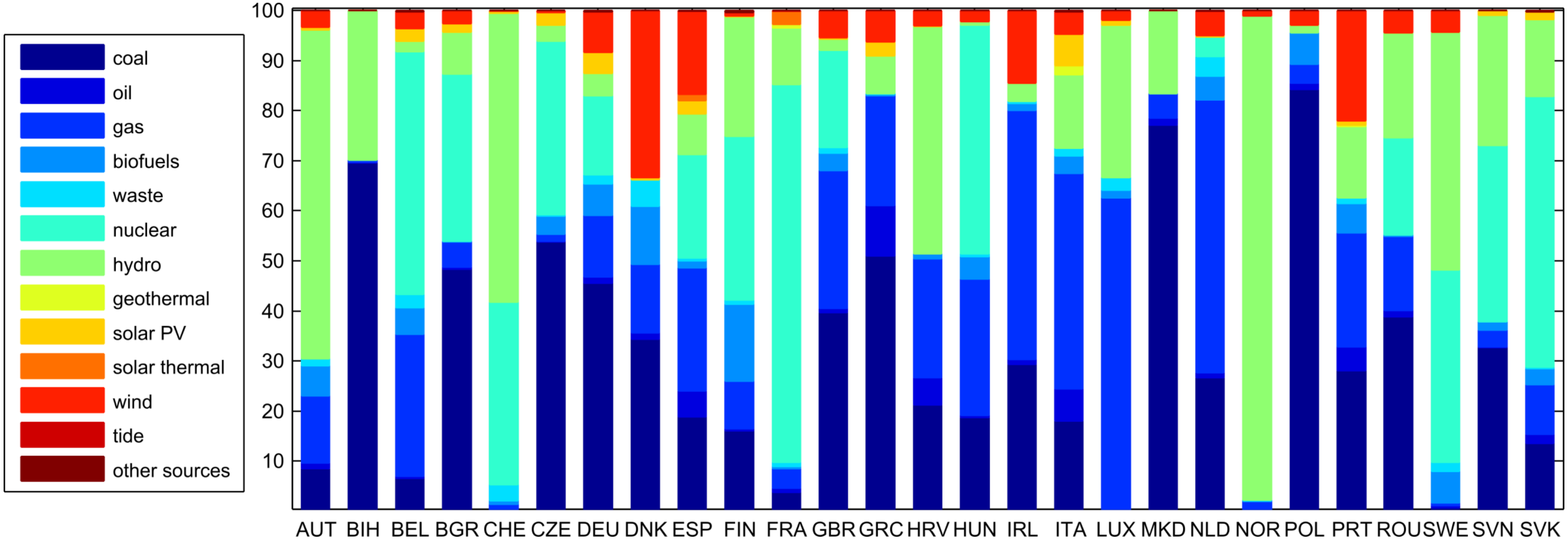


Fig.4.4. Mix of electricity generation for the 27 studied countries. Source: IEA statistics, electronic version, 2012.

As already mentioned, countries tend to perform well in some damage categories and poor in others. This is because the environmental performance 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:

1) Considering the current electricity mixes, we would like to know which nations are environmentally efficient and which are inefficient.
2) 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.

4.4 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 each country. In essence, we follow here the combined method LCA + DEA, which was already applied to quantify the eco-efficiency of wind farms [373], among others aforementioned in subsection 2.3.1. In this case, CCR DEA input-oriented model 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.

4.4.1 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 nine technologies for electricity generation and two 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 4.4 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 [kWh^{-1}]	x_{1j}	4	7	8	4	2	5	6	5.5	6
Impact 2 [kWh^{-1}]	x_{2j}	3	3	1	2	4	2	4	2.5	2.5
Output [kWh]	y_{1j}	1	1	1	1	1	1	1	1	1

Fig. 4.5 displays the values of the two 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 in turn 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.

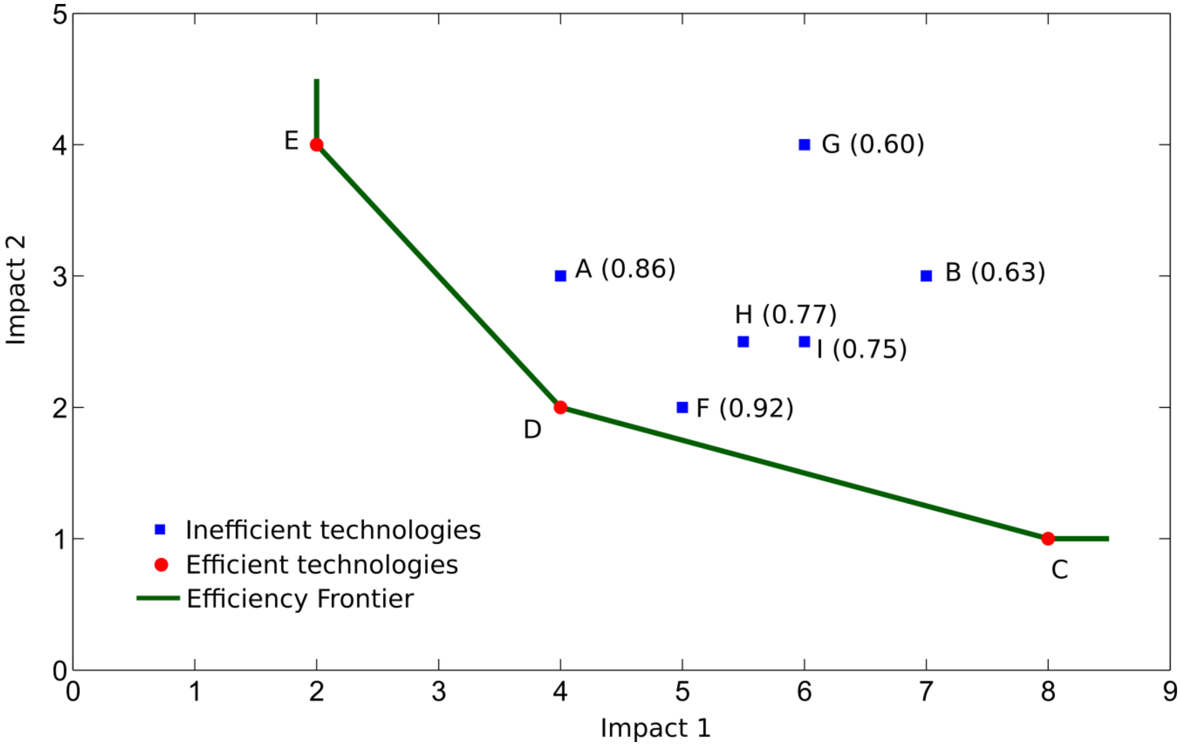


Fig.4.5. Interpretation of the DEA eco-efficiency measure for the alternatives in Table 4.4 as a radial distance to the frontier. The efficient value of each technology is shown into brackets (note that E, D and C have an efficiency score of 1).

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 $\underset{OA}{\rightarrow}$ be the line from the origin (0,0) to A, which crosses the frontier line at P (see Fig.4.6). 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 the 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 4.5. 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.

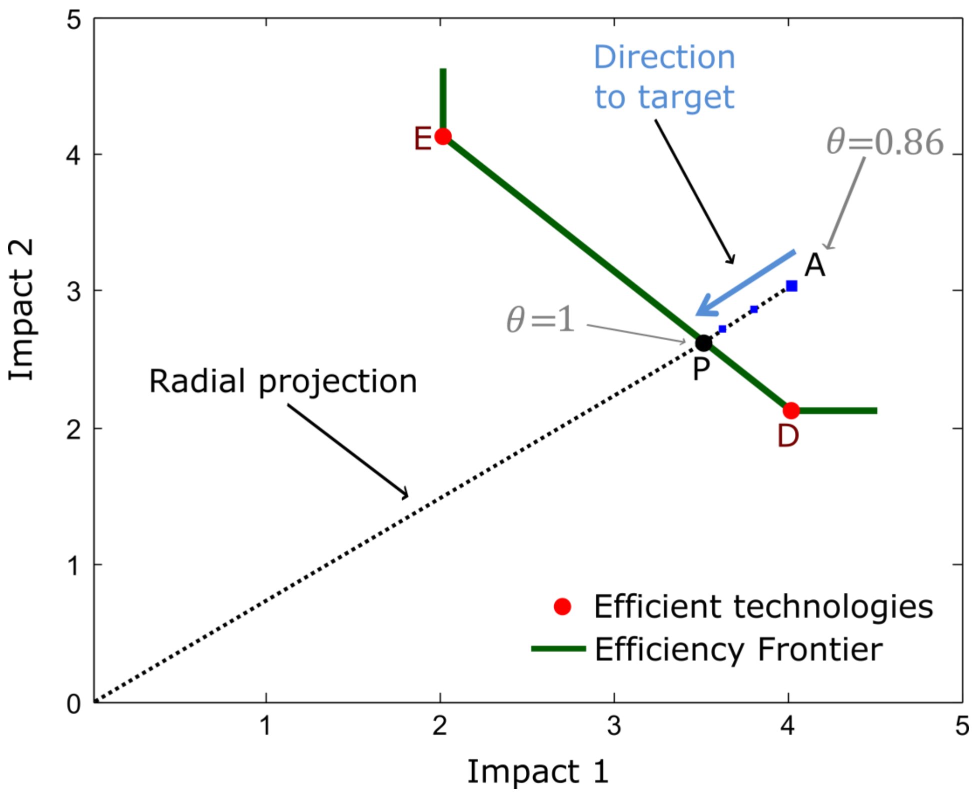


Fig. 4.6. Improvement of an inefficient point (technology) to make it efficient.

We extend the analysis in Figure 4.6 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, which 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 $\underset{OA}{\rightarrow}$ in Fig. 4.5 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.

4.4.1. Integrated use of LCA and DEA

Vazquez-Rowe *et al.*[67] developed a “five step LCA+DEA method” for the direct estimation of the environmental impact efficiency of DMUs and the simultaneous benchmarking of operational and environmental parameters (as described in subsection 4.3). We have adapted this approach by omitting some steps that are not required, as the environmental profiles are obtained in our case from LCIA data retrieved from an environmental database (*i.e.*, Ecoinvent 3.2) rather than calculated from mass and energy balances. Hence the following steps are applied in our case:

i. Data collection. Environmental LCIA data are 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 could 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 environmental impacts of the virtual DMUs and those corresponding to the current DMUs quantifies the environmental damage generated by inadequate operational practices. Clear guidelines are therefore proposed in this step for the inefficient units that could in turn be used to develop more efficient environmental regulations.

4.5 Case study

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 regarded as DMUs (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.

4.6 Numerical results and discussion

The results obtained by applying the input-oriented CCR DEA model are presented in the radar chart of Fig. 4.7. Results reveal that three 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).

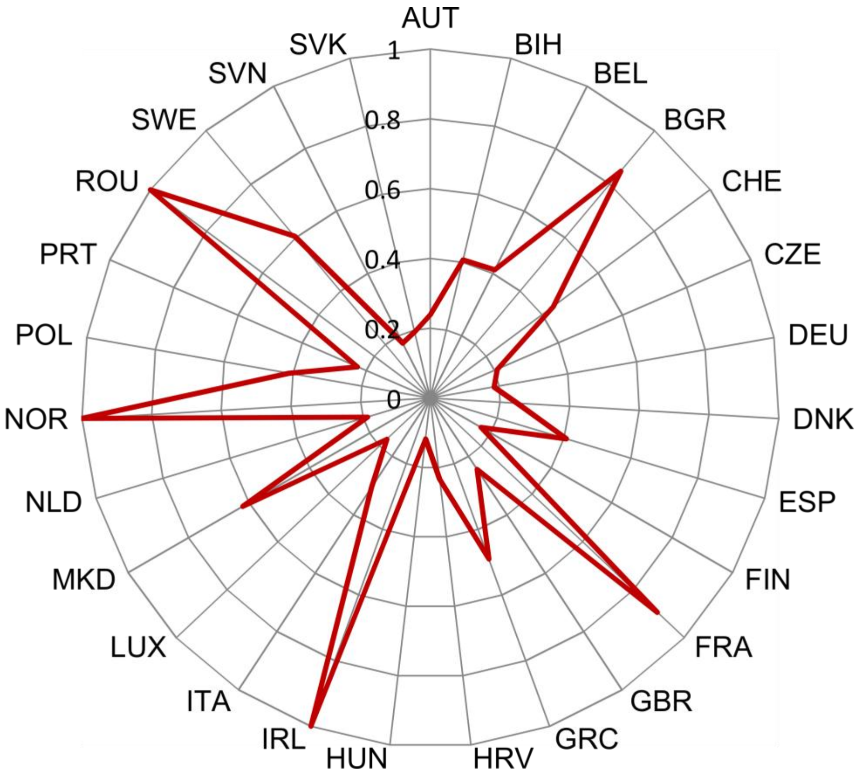


Fig. 4.7. Eco-efficiency of the electricity production mix of the 27 European top economies.

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 three efficient countries perform well in very few categories in which Norway fails to attain the best performance. This happens because they do not have some energy sources in their mixes (*i.e.*, nuclear, fossil fuels and 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. 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. Fig. 4.8 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.

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 their inputs (environmental impacts) drastically in order to resemble to Norway. This could 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).

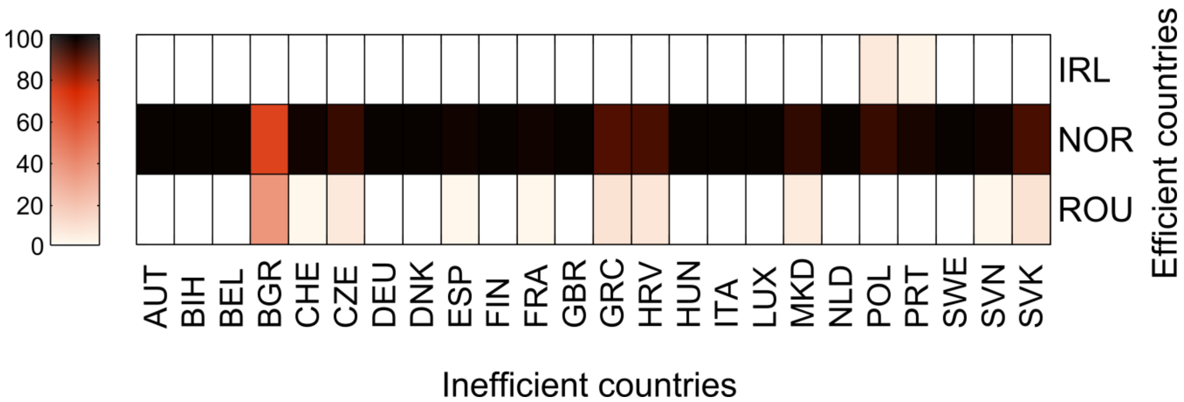


Fig. 4.8. Heat map of linear coefficients used for improving the inefficient countries considering the 27 European top economies.

As suggested by Atici and Podinovski[374], there are several ways of dealing with applications in which DMUs have different specializations or production profiles, as it 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 of these methods have the drawback of being based on value judgments. In this work we follow an alternative method that consists of removing the outliers from the analysis ([198],[197]). 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 than96.7% of its electricity using hydro power, it can be regarded as an outlier and therefore removed from the analysis in order to generate more meaningful results. For similar reasons, several energy efficiency approaches of European countries do not consider Norway into analysis [279]–[282].

The results obtained by applying the input-oriented CCR DEA model without considering Norway are presented in the radar chart of Fig. 4.9. Nineteen countries were found to be eco-efficient, while seven countries are inefficient. Ireland and Romania still appear as ecoefficient, as they do not have nuclear facilities (and therefore show very good performance in ionising radiation).

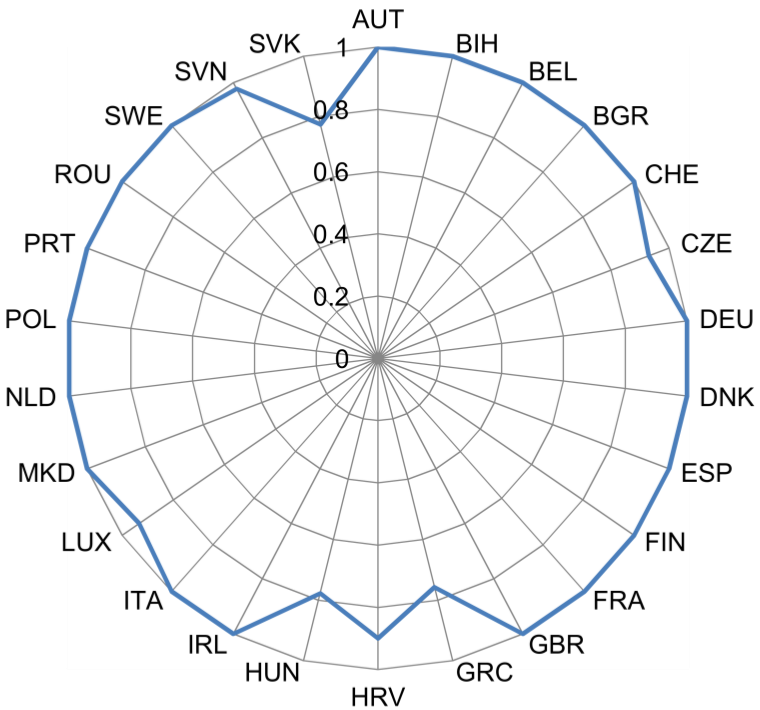


Fig. 4.9. Eco-efficiency of the electricity production mix of the 26 European top economies without considering Norway.

The inefficient countries are Czech Republic, Greece, Croatia, Hungary, Luxemburg, Slovenia and Slovakia. The efficiency value obtained shows 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.

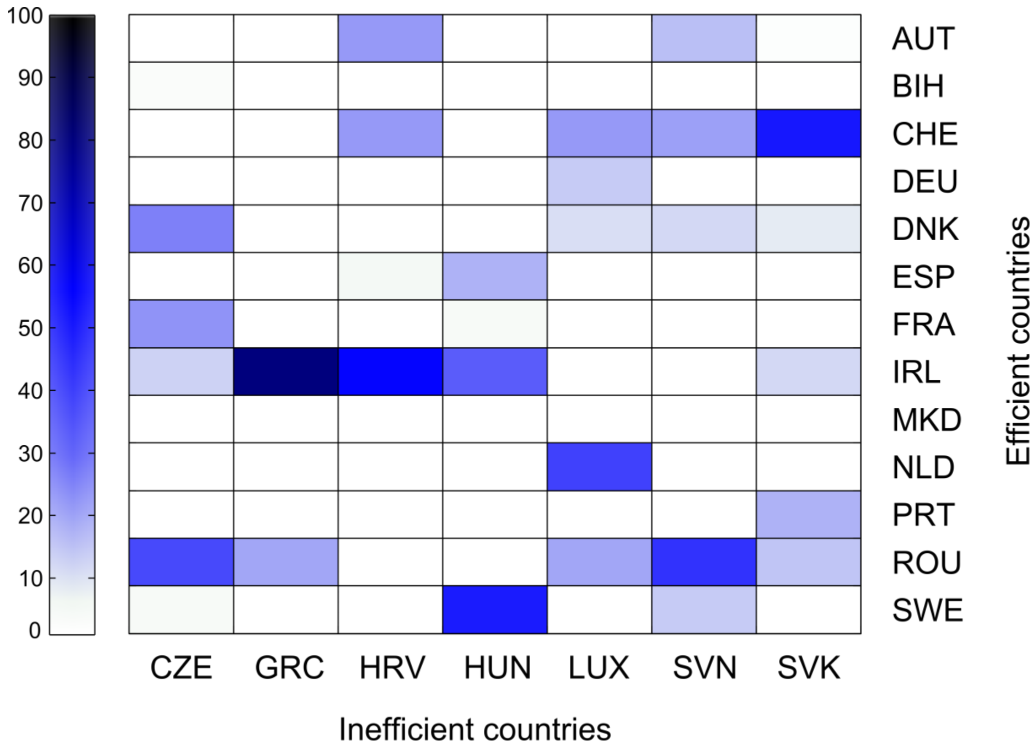


Fig. 4.10. Heat map of linear coefficients used for improving the inefficient countries considering the 26 European top economies (analysis without Norway).

We address next the issue of how to make the inefficient countries efficient taking as a basis the eco-efficient ones. Fig. 4.10 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. As an example on how to interpret the coefficients shown in Fig. 4.10, Luxemburg would become eco-efficient by making a linear combination of the countries in its efficiency reference set, which is composed of Switzerland, Germany, Denmark, Netherlands and Romania. The inputs and outputs of the efficiency reference set are multiplied with the coefficients shown in Fig. 4.10, and then added together to create a composition (*i.e.*, new electricity mix), which determines the hypothetical inputs that Luxemburg should have 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.

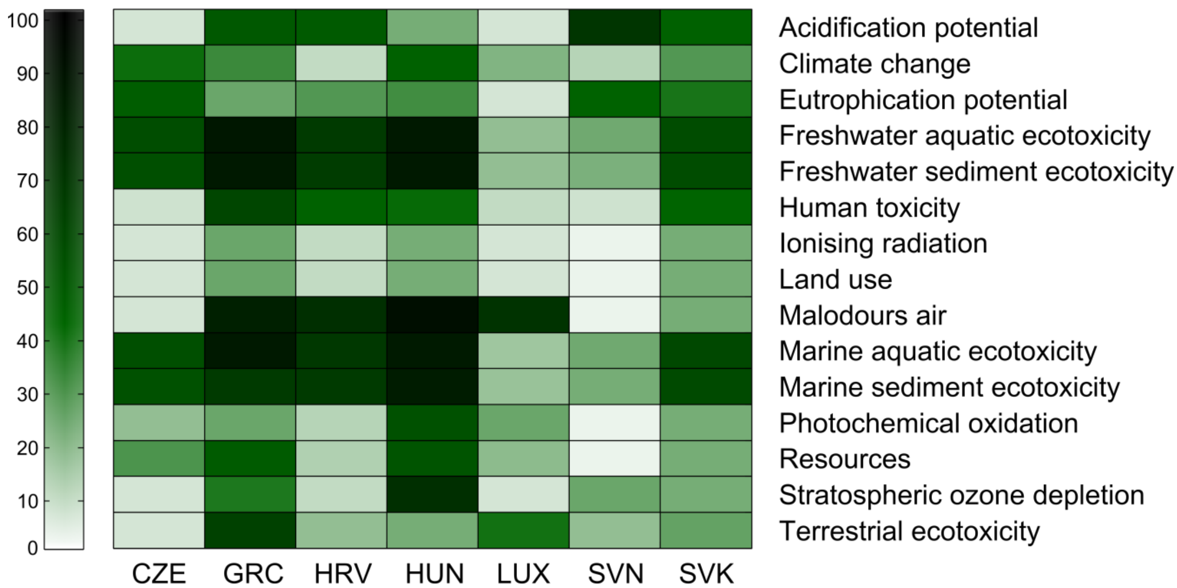


Fig. 4.11.Heat map of environmental impact reductions (%) for the inefficient countries.

Fig. 4.11 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 (percentage 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 can be attained by changing their electricity production mix. Fig. 4.12 shows a comparison between the current electricity production mix of the inefficient countries and the hypothetical mix that would make 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. As observed in Fig. 4.12, 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 concerning which targets need to be met in the future to ensure a better transition towards a cleaner energy system. In practice, these 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.

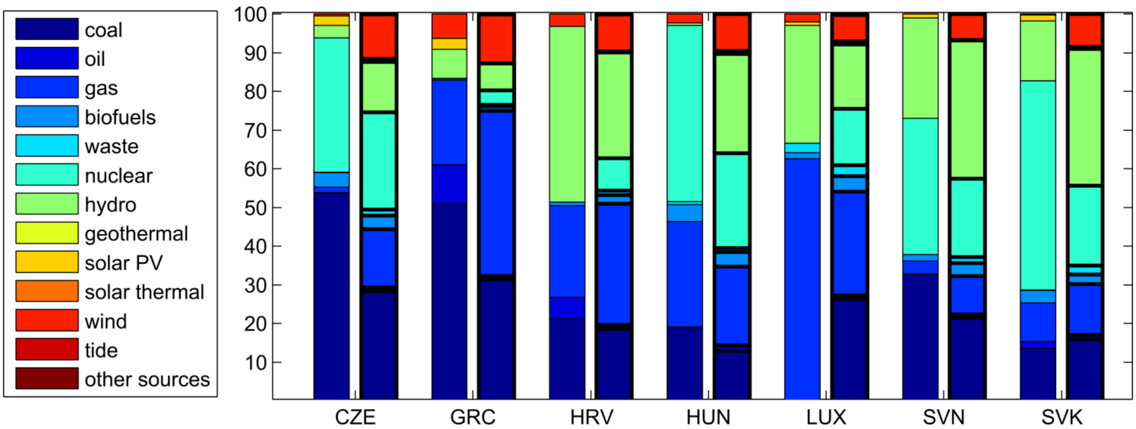


Fig. 4.12. Comparison between the current inefficient and the hypothetical efficient electricity production mix for each inefficient country.

4.7 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 approach 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 seven eco-inefficient countries out of 26. For these 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.

5. Combined use of life cycle assessment, data envelopment analysis and Monte Carlo simulation for quantifying environmental efficiencies under uncertainty

5.1 Introduction

The combined use of data envelopment analysis (DEA) and life cycle assessment (LCA) has recently emerged as a suitable technique for assessing the environmental efficiency of products. The standard approach DEA+LCA requires the input/output data to be perfectly known in advance. In practice, however, the environmental impact calculations are typically affected by a high degree of uncertainty stemming from lack of data and/or inaccurate measurements. LCA studies, in particular, require large amounts of data from disperse facilities embedded in the product's supply chain, which might be potentially owned by different stakeholders who might be reluctant to share this information (or even lack the necessary measurements). These uncertainties critically affect the outcome of LCA studies [2] and should be hence accounted for in the analysis to generated meaningful results.

This approach introduces a methodology that combines DEA, LCA and stochastic modelling to evaluate the environmental and eco-efficiency of products under uncertainty. The capabilities of this research are illustrated through its application to the assessment of several technologies for electricity generation.

5.2 Problem statement

The combined approach that integrates LCA and DEA proposed by Vázquez-Rowe *et al.*[67] joint with Monte Carlo simulation has been applied to evaluate the difference in efficiency and target values between deterministic and stochastic case for German electricity mix (Figure 5.1). We discuss in this chapter which countries are efficient in both cases and for those found to be inefficient, we obtain the quantitative environmental targets to make them efficient. The significant differences between the two case studies have been presented and appropriate improvements have been made.

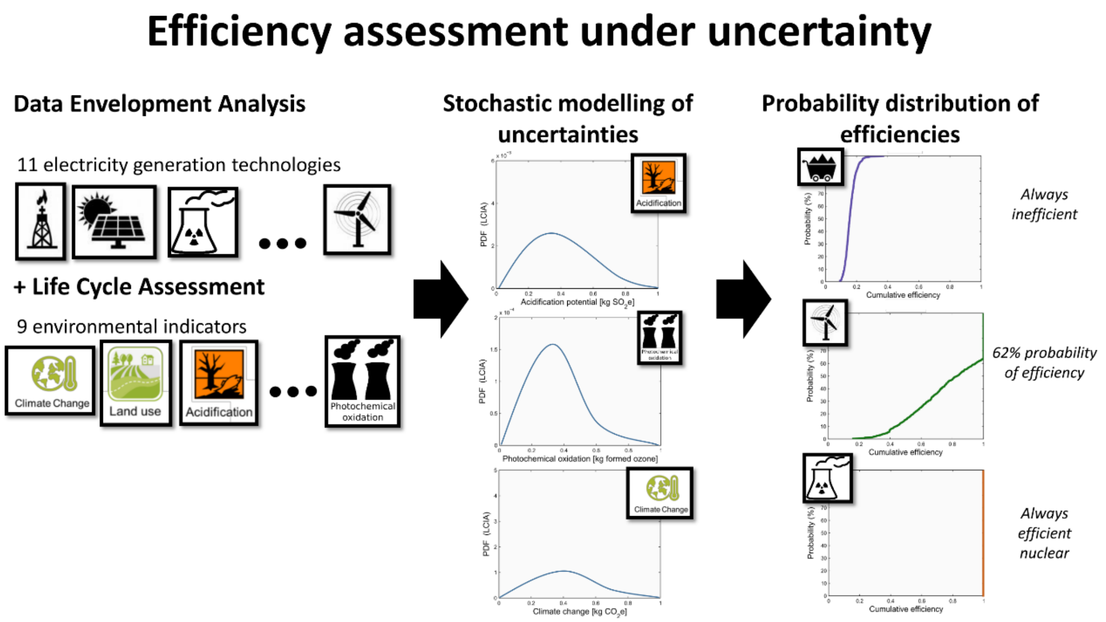


Fig.5.1. Graphical abstract of DEA under uncertainty study case.

To illustrate the need to include uncertainties in environmental efficiency assessment, we next introduce a motivating example that considers six technologies for electricity generation (*i.e.* wind 1, wind 2, wind 3, wind 4, nuclear 1 and nuclear 2, see details in Table 5.1). For this case the inputs are two environmental impacts (*i.e.* climate change and land use) and the output is one kWh (functional unit). Furthermore, we consider that these impacts can take on different values depending on the realization of the associated uncertainty. Therefore, in addition to the nominal case, we study three scenarios (labeled as scenarios 1, 2 and 3), where each of them corresponds to a sample of the uncertain parameters space entailing a set of specific parameters values. The nominal values for the impacts were retrieved from the environmental database EcoInvent v3.1 [358].

Table 5.1 Technologies considered in the motivating example.

Cases	Abbreviation	Technologies	Climate change [kg CO_2 – Eq]	Land use [m^2 times year (m^2a)]
A	Wind 1	wind, <1MW turbine, onshore	0.018245	0.002629
B	Wind 2	wind, >3MW turbine, onshore	0.033060	0.002403
C	Wind 3	wind, 1-3MW turbine, offshore	0.017106	0.000804
D	Wind 4	wind, 1-3MW turbine, onshore	0.019312	0.0011316
E	Nuclear 1	nuclear, boiling water reactor	0.015267	0.001131
F	Nuclear 2	nuclear, pressure water reactor	0.013490	0.0009585
		Uncertainty factor U_b	**1.05**	**1.5**

Figure 5.2 shows the performance attained by each technology in every scenario. The points in the figure represent technologies (i.e. DMUs), with solid markers indicating that the technology is efficient in the corresponding scenario and empty markers denoting the opposite (i.e. the technology is inefficient). The efficient frontier in each scenario is depicted with lines, where solid lines denote the strong frontier and discontinuous lines represent the weak frontier. Dotted lines provide the radial projections of one of the inefficient units (technology A) onto the efficiency frontier emerging in each scenario. Nominal values are represented in purple, while scenarios 1, 2 and 3 are illustrated in red,

green and yellow, respectively. As seen, in the nominal case (nominal values of the impacts), there are two technologies that emerge as efficient (*i.e.* C and F), since no single technology exists that improves any of them simultaneously in the two impacts. Conversely, for each of the inefficient technologies (*i.e.* A, B, D and E), it is always possible to identify another technology that improves such inefficient alternative simultaneously in both impacts. As an example, comparing A with F, the latter (which is efficient) improves the former (which is inefficient) in both impacts at the same time (i.e. 0.01824 of CO_2e for A compared to 0.01349 CO_2e for F in climate change; and 0.002629 for A compared to 0.0009585 for F in land occupation).

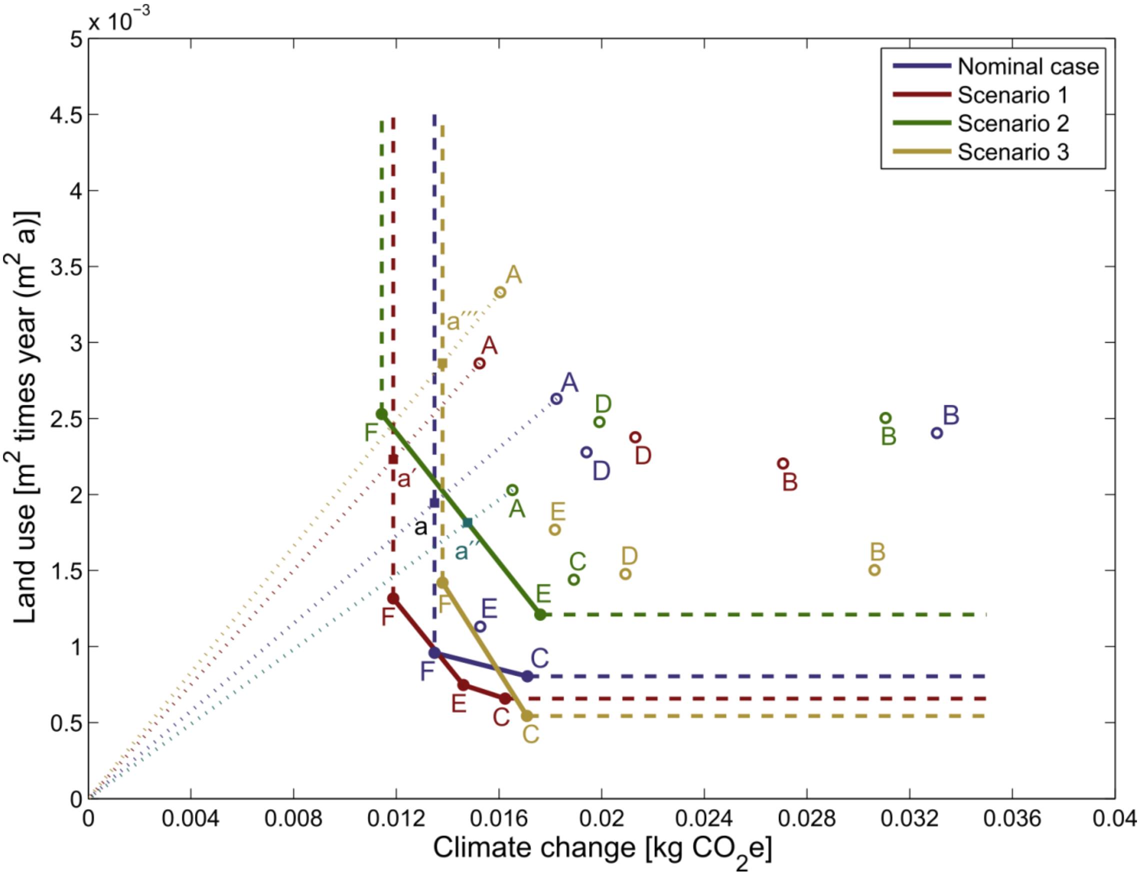


Fig.5.2. Efficient frontier and inefficient units for the nominal case and the three scenarios considering climate change and land use (as inputs) and the generation of 1kWh (as output).

A detailed analysis of the figure reveals that:

- Depending on the scenario, a DMU (*i.e.* technology) might be deemed efficient or inefficient. For example, technology C, which is efficient in the nominal case, becomes inefficient in scenario 2, while technology E that is inefficient in the nominal case becomes efficient in scenario 2. The efficient frontier is indeed formed by C and F in the nominal case and in scenario 3, but it is formed by C, E and F in scenario 1, and by E and F in scenario 2.
- Radial projections also vary from one scenario to another and so do the corresponding improvement targets. Technology A, which is inefficient in the nominal case, can be projected onto the nominal efficient frontier giving rise to point *a*, entailing a reduction target of 26% in both impacts. On the other hand, technology A in scenario 1 would lead to *a'*, with an associated reduction target of 22%.In scenario 2, however, A would be projected onto point *a''*, giving rise to a reduction target of 11% in both impacts. Finally, in scenario three, the projection of A is *a'''*, with reduction targets of 14%. Hence, it is clear that the projection of inefficient technologies onto the Pareto frontier varies for each technology and scenario.

These results arise the following questions: How should environmental efficiency be assessed under uncertainty? How can DMUs be ranked under uncertainty? How can we define robust targets for the inefficient units? In the following sections, we shall show how the approach proposed in this contribution clearly sheds light on these fundamental questions.

In this chapter, a novel approach is proposed to assess the environmental and eco-efficiency of a system under uncertainty which combines Monte Carlo simulation, LCA and DEA. The capabilities of this combined approach are illustrated through its application to the assessment of several electricity generation technologies considering uncertain environmental metrics.

This section is organized as follows. Firstly, we introduce an example to motivate the need to handle uncertainties in DEA. The approach proposed for environmental and eco-efficiency assessment under uncertainty, which integrates Monte Carlo simulation, LCA and DEA, is next presented. A case study is then introduced to illustrate how the methodology presented works in a practical example. The conclusions of the work are finally drawn in the last section of the chapter.

5.3 Methodology – DEA application

In this chapter, the input-oriented BCC DEA model (Eq. (3.26)-(3.30)) was used. This BBC model has been in our case appropriately extended to deal with multiple scenarios analysis.

5.3.1 Stochastic formulation with uncertain inputs/outputs

Considering t scenarios belonging to the set of scenarios S, each corresponding to a different materialization s of the uncertain parameters ($s=1,\ldots,t;\ s \in S$), for each such scenario, the quantification of efficiency of n DMUs is calculated (each with m inputs and p outputs). The following notation has been used:

- variable u_{rs} - weight associated with the r-th output in scenario s,
- variable v_{is} - weight given to the i-th input in scenario s,
- parameter x_{ijs} - amount of input i utilized by DMU_j in scenario s,
- parameter y_{rjs} - amount of output r produced by DMU_j in scenario s,

where $i = 1, \ldots, m;\ j = 1, \ldots, n; r = 1, \ldots, p; s = 1, \ldots, t$. Assuming that $x_{ijs} \geq 0, y_{rjs} \geq 0$ and for the test object with index j', the relative efficiency score in scenario s of DMU j' ($\theta_{j's}$) is given by the following LP model defined for every scenario:

$$(BBC_s) \quad \theta_{j's} = \max \sum_{r=1}^{p} u_r y_{rj's} - u_{j's} \qquad (5.1)$$

$$s.t \ \sum_{i=1}^{m} v_i x_{ij's} = 1 \qquad (5.2)$$

$$\sum_{r=1}^{p} u_r y_{rjs} - \sum_{i=1}^{m} v_i x_{ijs} - u_{j's} \leq 0 \ \forall j \qquad (5.3)$$

$$u_{rs} \geq 0 \ \forall r, v_{is} \geq 0 \ \forall i, u_{j's} \ unconstrained \qquad (5.4)$$

The dual form of linear program *(BBC$_s$)*, adapted to scenario case has been defined as follows:

$$\min \theta_{j's} \qquad (5.5)$$

Subject to

$$\sum_{j=1}^{n} \lambda_{js} y_{rjs} - y_{rj's} \geq 0 \quad \forall r \qquad (5.6)$$

$$\theta_{j's} x_{ij's} - \sum_{j=1}^{n} \lambda_j x_{ijs} \ \geq 0 \quad \forall i \qquad (5.7)$$

$$\sum_{j=1}^{n} \lambda_{js} = 1 \qquad (5.8)$$

$$\lambda_{js} \geq 0, \forall j, s, \ \theta_{j's} \ unconstrained \quad (5.9)$$

Decision variable λ_{js} represents the weight for DMU_j defined as peer of *j'* in scenario *s*. Note also that the aforementioned model assumes variable returns to scale (VRS), that is, that the DMUs do not operate at the same scale and that the output will not change at the same proportion as the inputs are changed (to ensure this, the summation of lambdas is forced to equal one).

5.3.2 Integrated use of LCA, DEA and Monte Carlo simulation

We next describe our overall approach for environmental and eco-efficiency assessment under uncertainty that makes use of the models defined above (Eq. (5.1) – (5.9)). Without loss of generality, we assume that LCA metrics, midpoint or endpoint, are employed to assess the environmental performance of the DMUs. LCA indicators for which lower values imply better performance can be defined as inputs, while the rest can be considered as "bad outputs" [284]. This approach, however, has the limitation that the metrics are not treated in the same manner (recall that DEA models can be input-oriented or output oriented). Hence, to avoid this asymmetric treatment of metrics, we suggest that all the LCA indicators are normalised so that lower values imply always better performance. This allows defining all of them as inputs. Note that normalization is an open issue in DEA. Scaling (multiplying with a factor, *i.e.*, using a common multiplier) does not alter the DEA outcome, whilst the same does not hold for translation (summing up a fixed number and multiplying with a parameter, *i.e.*, using a common coefficient). The general approach we present herein comprises the following five steps (Figure 5.3).

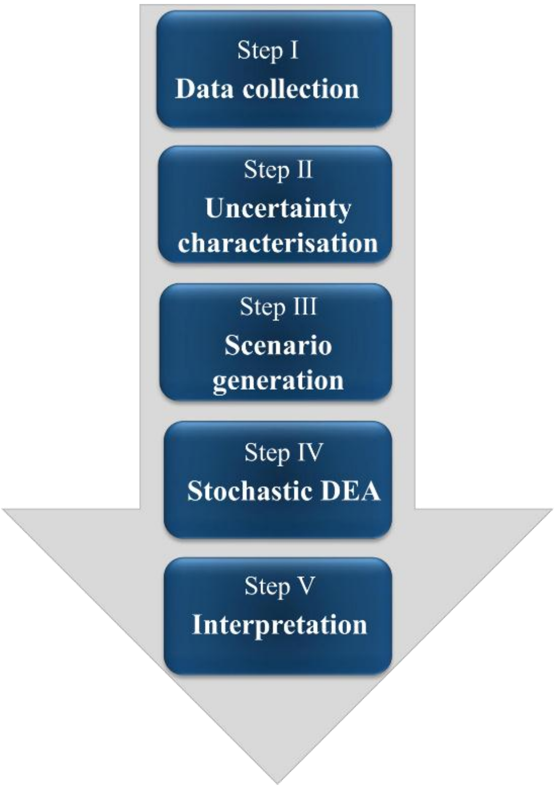


Fig.5.3. General scheme of the overall approach.

Step I: Data collection. Consider a set J of technologies (*i.e.* DMUs) assessed according to a set I of LCA metrics. The environmental impact associated with each technology is determined first following the general LCA methodology. Let $LCIA_{ij}$ be the impact of technology (DMU) j in damage category (input) i.

Step II: Uncertainty characterisation. We assume that the impact values are stochastic as a result of various uncertainty sources, including those affecting the life cycle inventory entries (LCI) that propagate through the damage assessment model as well as those present in the damage factors themselves.

In practice, uncertain impacts can be described through probability functions (either continuous or discrete). While uncertainties in damage factors are difficult to characterize, probability functions can be used to model stochastic LCI entries. These functions can be built using either historical data or qualitative information (*i.e.* the Pedigree matrix). There are several statistical methods to build distributions from historical data [375][376]. When such data on emissions, waste and feedstock requirements are missing, the Pedigree matrix [55] can still be used to model their underlying stochastic distributions. This approach assumes that each stochastic LCI variable follows a lognormal distribution whose parameters are established based on qualitative information on the data available, including reliability, completeness, temporal correlation, geographical correlation, further technological correlation and sample size. In this approach, LCI entries are assumed to follow lognormal distributions, that is, $LCI \sim \ln\mathrm{N}(\mu, \sigma)$, where μ and $\sigma$are the mean and standard deviation of the variable's natural logarithm. Specifically, the outcome of the Pedigree matrix provides the standard deviation of the distribution. Then, the mean parameter can be estimated from the standard deviation and the expected value, which is assumed to be equal to the nominal value of the LCI entry.

Step III: Scenario generation: Sampling methods (*e.g.*, Monte Carlo, Latin Hypercube, Sobol sequence, Halton sequence) are next used to generate potential outcomes for the stochastic inputs from the parameters of the underlying probability functions (modeled in step II). To this end, off-the-shelf software packages, such as Matlab or Crystal Ball [377], can be employed. After generating the values for the LCI entries, impact values in each scenario are calculated as follows:

$$x_{ijs} = LCIA_{ijs} = \sum_{b=1}^{q} LCI_{ijbs} dam_{ib} \, \forall i, j, s \quad (5.10)$$

where $LCIA_{ijs}$ is the value of LCA impact i for DMU j in scenario s (*e.g.*, global warming potential), LCI_{ijbs} is the life cycle entry of chemical b (*e.g.* CO_2 emissions) released during the manufacturing of DMU j in scenario s, and dam_{ib} is the damage factor that translates the amount of LCI entry b into impact i. Note that under the central limit theorem, impact values can be approximated by normal distributions when many stochastic LCI entries are involved in their calculation.

Step IV: Solving the stochastic DEA. The stochastic DEA (5.1) - (5.4) and its dual form (5.4) – (5.9) are solved iteratively for every scenario, obtaining efficiency scores and target values for each DMU j in each scenario.

Step V: Interpretation of results. Since calculations are repeated for different scenarios, thereby leading to a set of efficiency values and improvement targets, a key point is then how to use the DEA outcomes to assess the efficiency of a DMU under uncertainty. As will be discussed later, it is important to analyse the dispersion of efficiencies and targets so as to assess the robustness of the nominal DEA results. In essence, if the nominal and average values are very close to each other, then the insight remains unaltered with respect to the deterministic case. However, if the opposite situation occurs, it is recommended that the deterministic results are taken with caution and complemented properly with the information provided by the stochastic analysis.

5.3.3 *Revisited motivating example: Monte Carlo simulation and DEA in the context of our study*

For simplicity, we assume that the impacts (LCIA) in the motivating example (rather than the LCI entries themselves) follow lognormal distributions $\ln N(\mu, \sigma)$, where μ and

σ are the mean and standard deviation (defined via the Pedigree matrix) of the distribution. To complete the Pedigree matrix, we provide the lowest scores for all the categories (the corresponding uncertainty factor U_b for each category impact is presented in Table 5.1). Then, the standard deviation and the expected value of the distribution (assumed to be equal to the nominal value retrieved from Ecoinvent) are used to compute the mean parameter. A total of 500 scenarios are generated via Monte Carlo simulation from these distributions, in each of which the impacts take a different value.

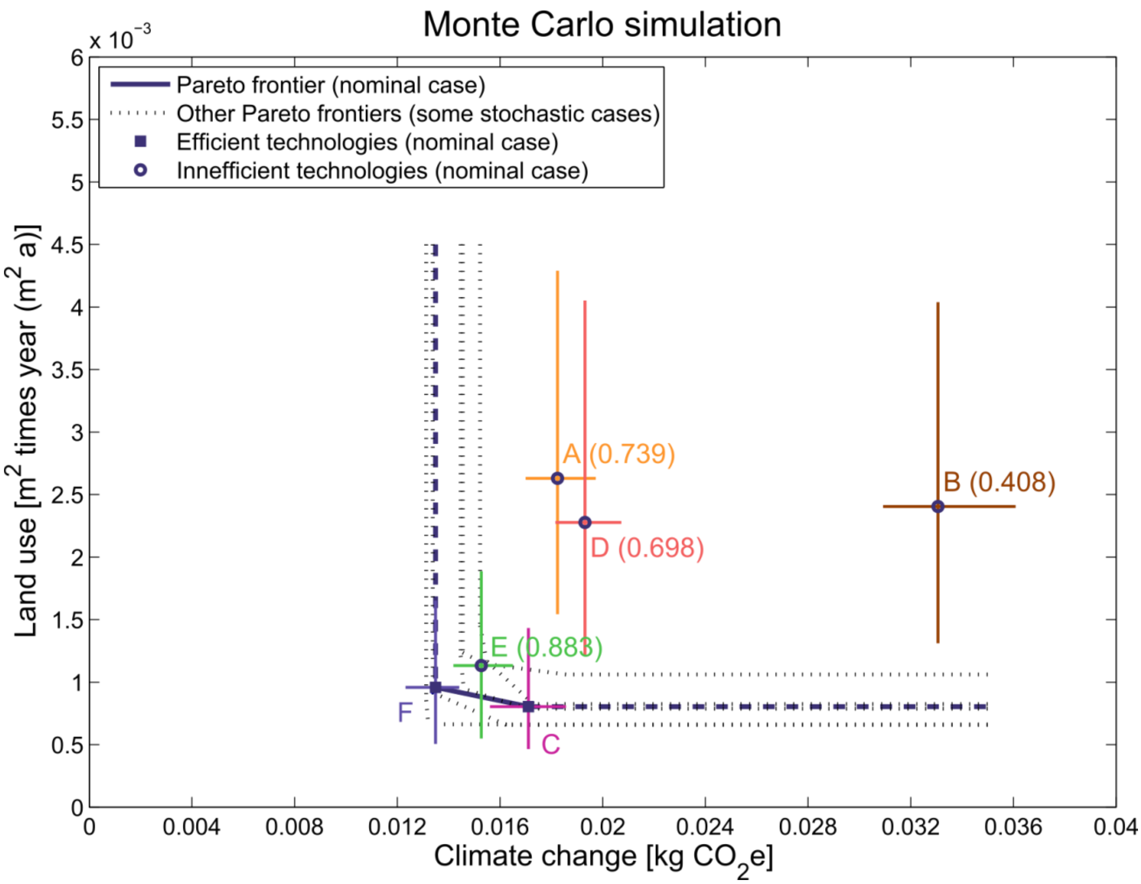


Fig.5.4. Efficient frontier and inefficient units for the motivating example under uncertainty. The efficiency value of each technology for the nominal case is shown in parenthesis (note that C and F have an efficiency score of one).

Figure 5.4 depicts the average impacts of the DMUs in a Cartesian plot with the corresponding 99% confidence interval for each impact value. Purple squares in the figure represent the efficient technologies for the nominal case (retrieved from Ecoinvent), while circumferences denote the inefficient ones (also in the nominal case). Dotted lines denote efficient frontiers corresponding to some of the 500 scenarios. Figure 5.5 shows the boxplot of efficiency values attained by each DMU, while Figure 5.6 depicts the cumulative probability curves of efficiency values associated with each alternative (which have been constructed using the data in Figure 5.4). In Figure 5.5, the bottom and top of each box represent the first (Q_1) and third (Q_3) quartiles, whereas the red lines inside the box depict the second quartile (the median). The black lines extended vertically from the boxes (whiskers) indicate variability outside the upper (Q_3+1.5IQR) and lower (Q_1-1.5IQR) quartiles, where IQR (inter quartile range) is the difference between the upper and lower quartiles. The values outside of the boxplot are outliers (represented with red 'plus' signs). The black squares depict the efficiency values of each technology for the nominal case, while the green circles represent the average efficiencies for each technology.

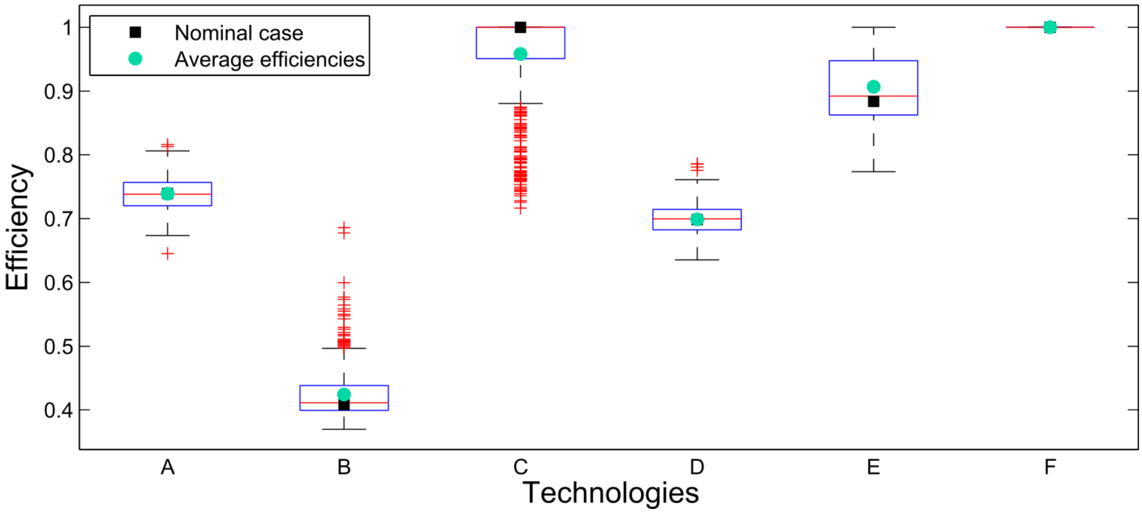


Fig.5.5. Box-and-whisker plot of efficiencies obtained from the stochastic results for the six technologies.

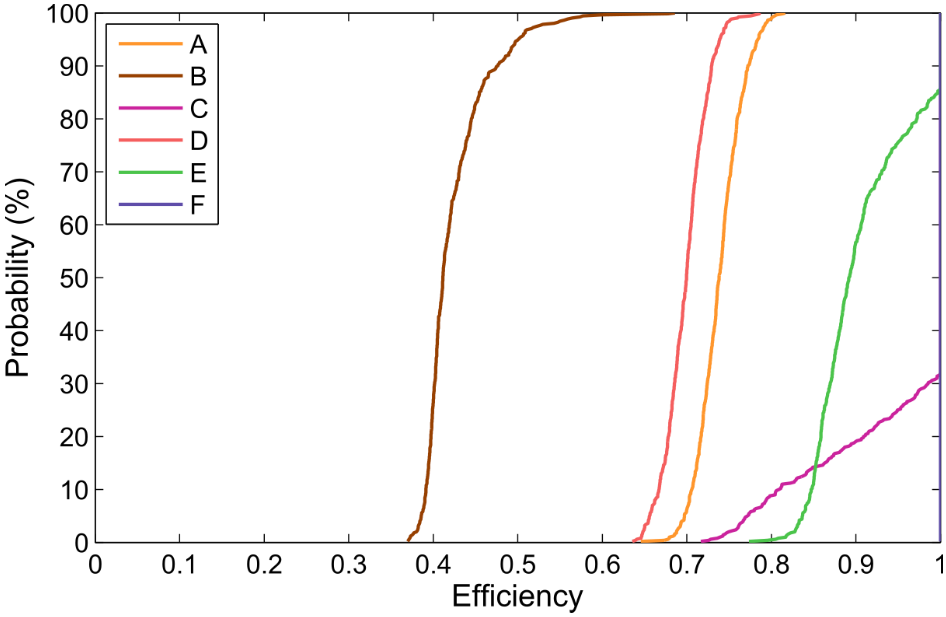


Fig.5.6. Cumulative probability curve for the efficiencies of the six technologies in the motivating example under uncertainty.

On the other hand, Figure 5.6 can be interpreted as follows: the probability that a given technology attains an efficiency value lower or equal than the x-coordinate in the horizontal axis is given by the y-coordinate shown in the corresponding cumulative curve. As an example, the probability of technology A obtaining an efficiency score below 0.7 is 6.2%. Hence, technologies A, B and D are inefficient in all of the scenarios (all show zero probabilities of efficiency values above 0.9).In contrast, technology F is always efficient regardless of the scenario selected (100% probability of efficiency values of one). Finally, C and E have 70% and 16%probabilities of achieving efficiency scores above 0.99, respectively.

We compare next the deterministic targets with the stochastic ones obtained from the Monte Carlo simulation (see Fig. 5.7). To this end, we use again boxplots. The inefficient technologies in the nominal case (A, B, D and E) show very high dispersion in their targets, while in the efficient ones (C and F) such dispersion is rather low (zero for F in all of the scenarios, as one could expect from Figure 5.6).

From the example above, it becomes clear that the results generated via DEA in the nominal case can differ quite significantly from the stochastic ones, to the point that a DMU can be deemed as efficient or inefficient depending on the scenario. This observation clearly motivates the need to apply stochastic simulation in the efficiency assessment. The next section provides a more complex example covering multiple LCA metrics, where a similar analysis is conducted.

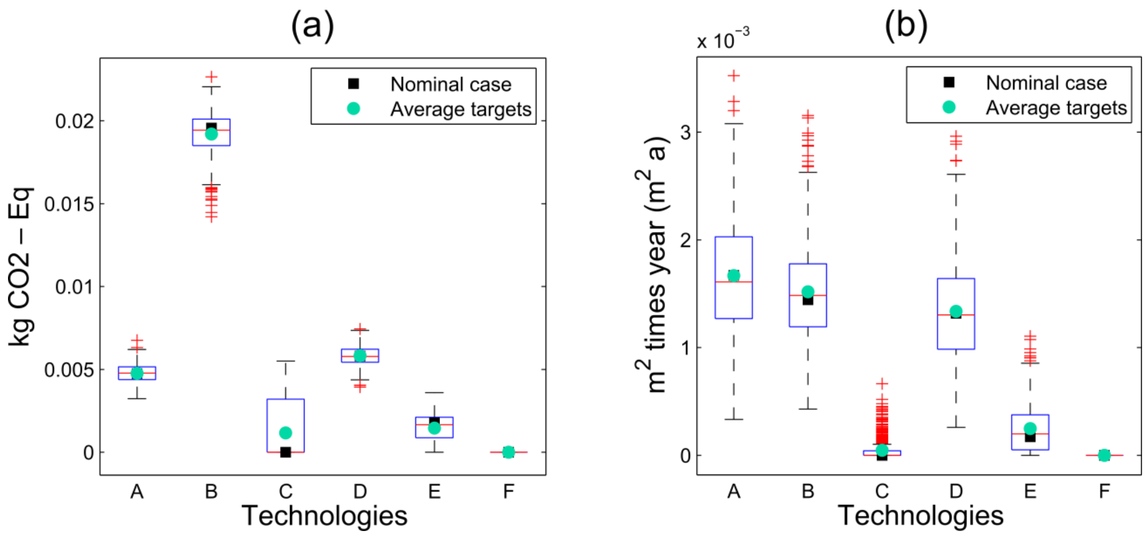


Fig.5.7. Improvement targets for the nominal and the stochastic case of the motivating example. Black squares represent the nominal case, while green circles depict the average DEA targets in the 500 scenarios. Subplot (a) depicts results for climate change whereas subplot (b) displays those for land use.

5.4 Case study

The capabilities of our approach are further illustrated through its application to several technologies for electricity generation. Our study covers 11 technologies (see Table 5.2) for energy production (functional unit: one kWh) assessed in terms of nine environmental impacts (see Table 5.3). We omit here the economic performance of each such technology, as the real costs of electricity generation are usually highly masked due to external regulations. The nominal LCIA data were retrieved from the environmental database EcoInvent v3.1 [372].

The calculations were carried out for the nominal scenario (case 1) and for low and high uncertainty levels (cases 2 and 3, respectively). The nominal scenario considers the deterministic LCA values retrieved from the environmental database. The uncertain cases are defined as follows. We assume that the LCA metrics follow lognormal distributions. The standard deviation of these lognormal distributions is established based on the Pedigree matrix. In case 2, the Pedigree factors are given the lowest scores, while in case 3 they are given the highest. In each impact, we consider the basic Pedigree factor of the main emission affecting that impact (*i.e.* for global warming, we consider kg CO_2e, with a factor U_b equal to 1.05). The considered uncertainty factors U_b for each impact score are given in Table 5.3. Further details on how the scenarios were generated are provided in the section 5.3.1.3.

Table 5.2 Technologies considered for electricity production.

Cases	Abbreviation	Technologies
1	geothermal	Geothermal
2	wind 1	Wind, <1MW turbine, onshore
3	wind 2	Wind, >3MW turbine, onshore
4	wind 3	Wind, 1-3MW turbine, offshore
5	wind 4	Wind, 1-3MW turbine, onshore
6	hard coal	Hard coal
7	lignite	Lignite
8	natural gas	Natural gas, at conventional power plant
9	nuclear 1	Nuclear, boiling water reactor
10	nuclear 2	Nuclear, pressure water reactor
11	oil	Oil

Table 5.3 Set of impact values considered in the study (impacts sorted in alphabetical order) in the nominal scenario.

		Technologies											Uncertainty factor U_b
Impact	**Unit**	**geothermal**	**wind 1**	**wind 2**	**wind 3**	**wind 4**	**hard coal**	**lignite**	**natural gas**	**nuclear 1**	**nuclear 2**	**oil**	
Acidification potential	kg SO_2e	$5.20\cdot10^{-4}$	$1.05\cdot10^{-4}$	$2.81\cdot10^{-4}$	$9.52\cdot10^{-5}$	$1.12\cdot10^{-4}$	$1.20\cdot10^{-3}$	$1.27\cdot10^{-3}$	$8.82\cdot10^{-4}$	$9.52\cdot10^{-5}$	$8.4\cdot10^{-5}$	$4.09\cdot10^{-3}$	**1.05**
Climate change	kg CO_2e	$7.79\cdot10^{-2}$	$1.82\cdot10^{-2}$	$3.31\cdot10^{-2}$	$1.71\cdot10^{-2}$	$1.93\cdot10^{-2}$	$1.10\cdot10^{0}$	$1.23\cdot10^{0}$	$5.84\cdot10^{-1}$	$1.53\cdot10^{-2}$	$1.35\cdot10^{-2}$	$1.15\cdot10^{0}$	**1.05**
Eutrophication potential	kg NO_xe	$6.92\cdot10^{-4}$	$5.70\cdot10^{-5}$	$1.28\cdot10^{-4}$	$5.40\cdot10^{-5}$	$6.95\cdot10^{-5}$	$8.66\cdot10^{-4}$	$1.11\cdot10^{-3}$	$5.71\cdot10^{-4}$	$5.95\cdot10^{-5}$	$5.32\cdot10^{-5}$	$1.52\cdot10^{-3}$	**1.50**
Freshwater aquatic eco-toxicity	kg 1.4-DCBe	$3.22\cdot10^{-2}$	$1.35\cdot10^{-1}$	$4.08\cdot10^{-1}$	$6.48\cdot10^{-2}$	$1.22\cdot10^{-1}$	$1.15\cdot10^{-1}$	$1.56\cdot10^{0}$	$2.36\cdot10^{-2}$	$2.21\cdot10^{-2}$	$1.99\cdot10^{-2}$	$3.25\cdot10^{-2}$	**2.00**
Land use	m^2 times year (m^2a)	$2.25\cdot10^{-3}$	$2.63\cdot10^{-3}$	$2.40\cdot10^{-3}$	$8.04\cdot10^{-4}$	$2.28\cdot10^{-3}$	$2.36\cdot10^{-2}$	$6.36\cdot10^{-3}$	$1.65\cdot10^{-3}$	$1.13\cdot10^{-3}$	$9.59\cdot10^{-4}$	$4.35\cdot10^{-3}$	**1.50**
Marine aquatic eco-toxicity	kg 1.4-DCBe	$1.11\cdot10^{-1}$	$4.37\cdot10^{-1}$	$1.31\cdot10^{0}$	$2.13\cdot10^{-1}$	$3.94\cdot10^{-1}$	$4.04\cdot10^{-1}$	$5.43\cdot10^{0}$	$1.12\cdot10^{-1}$	$8.50\cdot10^{-2}$	$7.68\cdot10^{-2}$	$3.13\cdot10^{-1}$	**2.00**
Photochemical oxidation	kg formed ozone	$2.59\cdot10^{-5}$	$5.23\cdot10^{-6}$	$8.98\cdot10^{-6}$	$4.11\cdot10^{-6}$	$5.22\cdot10^{-6}$	$6.09\cdot10^{-5}$	$2.03\cdot10^{-5}$	$5.89\cdot10^{-5}$	$2.03\cdot10^{-6}$	$1.81\cdot10^{-6}$	$9.73\cdot10^{-5}$	**1.50**
Stratospheric ozone depletion	kg CFC-11e	$4.28\cdot10^{-8}$	$1.38\cdot10^{-9}$	$2.69\cdot10^{-9}$	$1.15\cdot10^{-9}$	$1.64\cdot10^{-9}$	$3.02\cdot10^{-9}$	$7.73\cdot10^{-9}$	$1.76\cdot10^{-7}$	$1.53\cdot10^{-9}$	$1.09\cdot10^{-9}$	$1.79\cdot10^{-7}$	**1.50**
Terrestrial eco-toxicity	kg 1.4-DCBe	$2.21\cdot10^{-4}$	$1.91\cdot10^{-5}$	$2.99\cdot10^{-5}$	$1.39\cdot10^{-5}$	$1.90\cdot10^{-5}$	$1.50\cdot10^{-4}$	$1.35\cdot10^{-4}$	$2.01\cdot10^{-5}$	$1.96\cdot10^{-5}$	$1.75\cdot10^{-5}$	$2.90\cdot10^{-4}$	**2.00**

We generated two sets of 500 scenarios in each case via Monte Carlo sampling. Fig. 5.8 shows the dispersion of impacts for one technology (*i.e.* hard coal) in the different cases (for different uncertainty levels). As observed, it might be very hard to identify the best technology in a straightforward manner given the large number of scenarios encompassing different impact values.

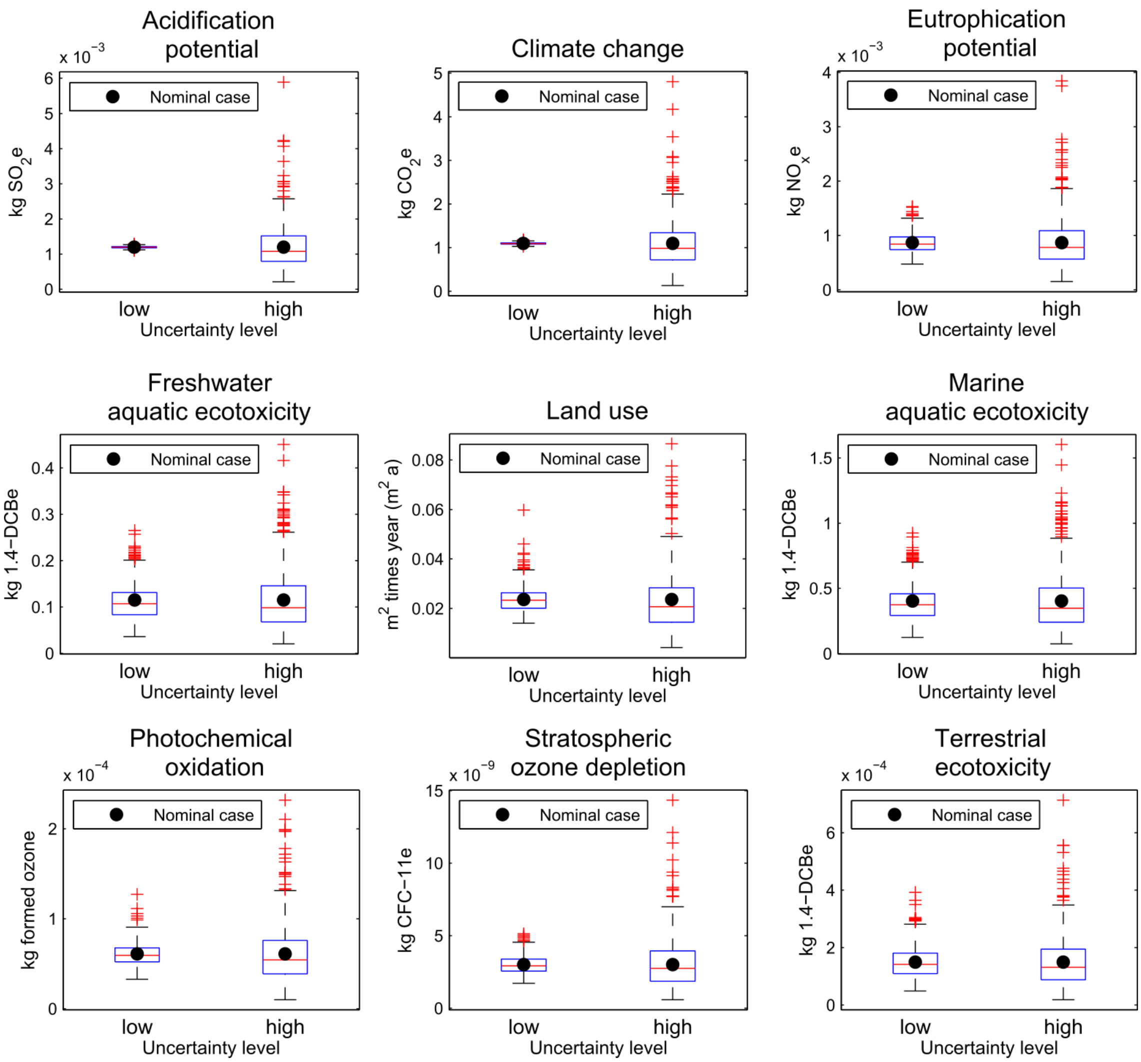


Fig.5.8. Distribution of impacts for hard coal considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details). The

boxplot bars represent the uncertain cases, while black points depict the nominal value impacts for hard coal. Data for the other technologies can be found in the next subsection.

3.4.1 Figures of the dispersion of all technologies considered

This subsection shows the boxplots for all technologies (geothermal, wind 1, wind 2, wind 3, wind 4, lignite, natural gas, nuclear 1, nuclear 2 and oil) considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details). The boxplot bars represent the uncertain cases, while black points depict the nominal value impacts for the technologies considered.

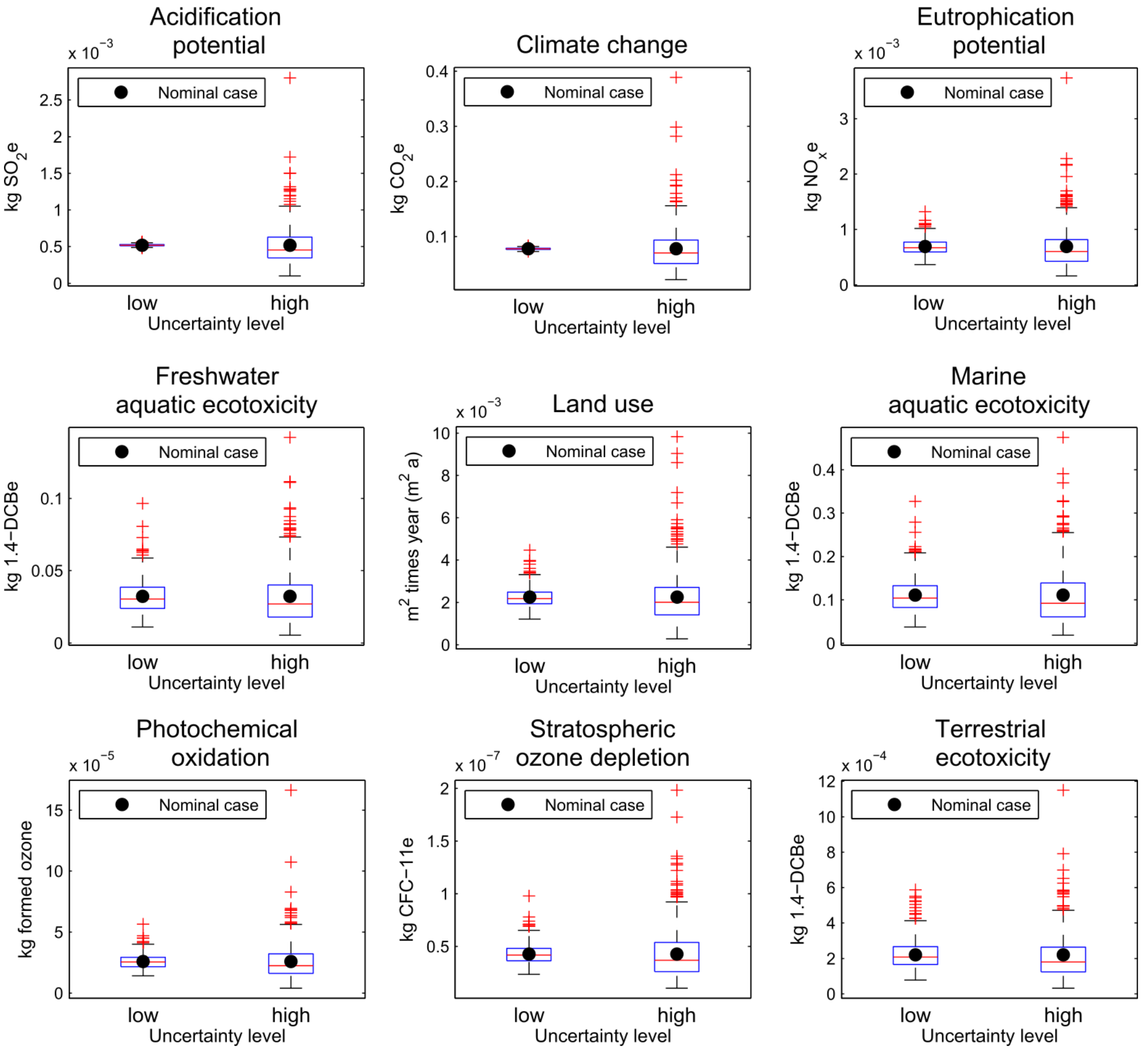


Fig.5.9. Boxplots for geothermal considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

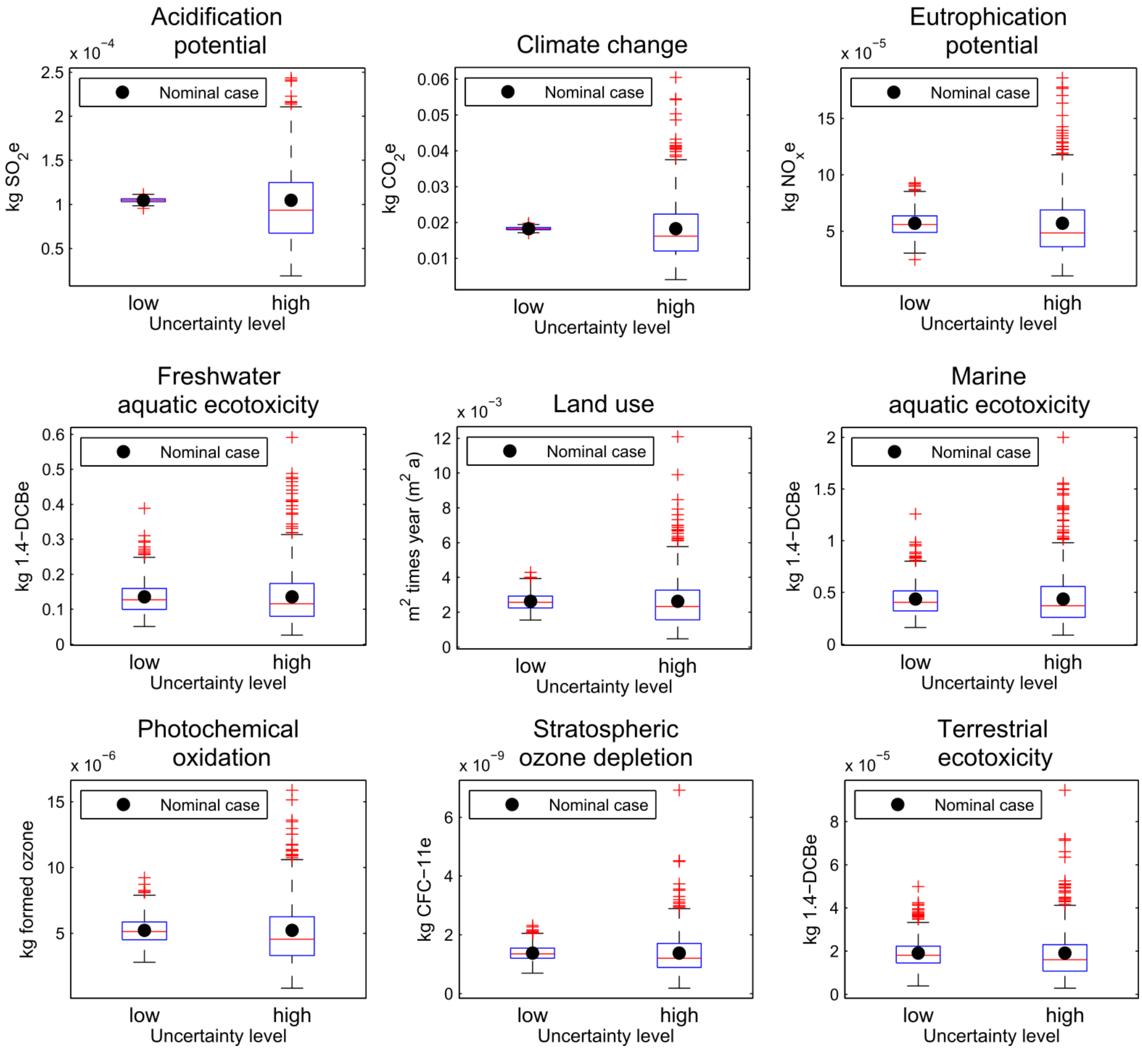


Fig.5.10. Boxplots for wind 1 considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

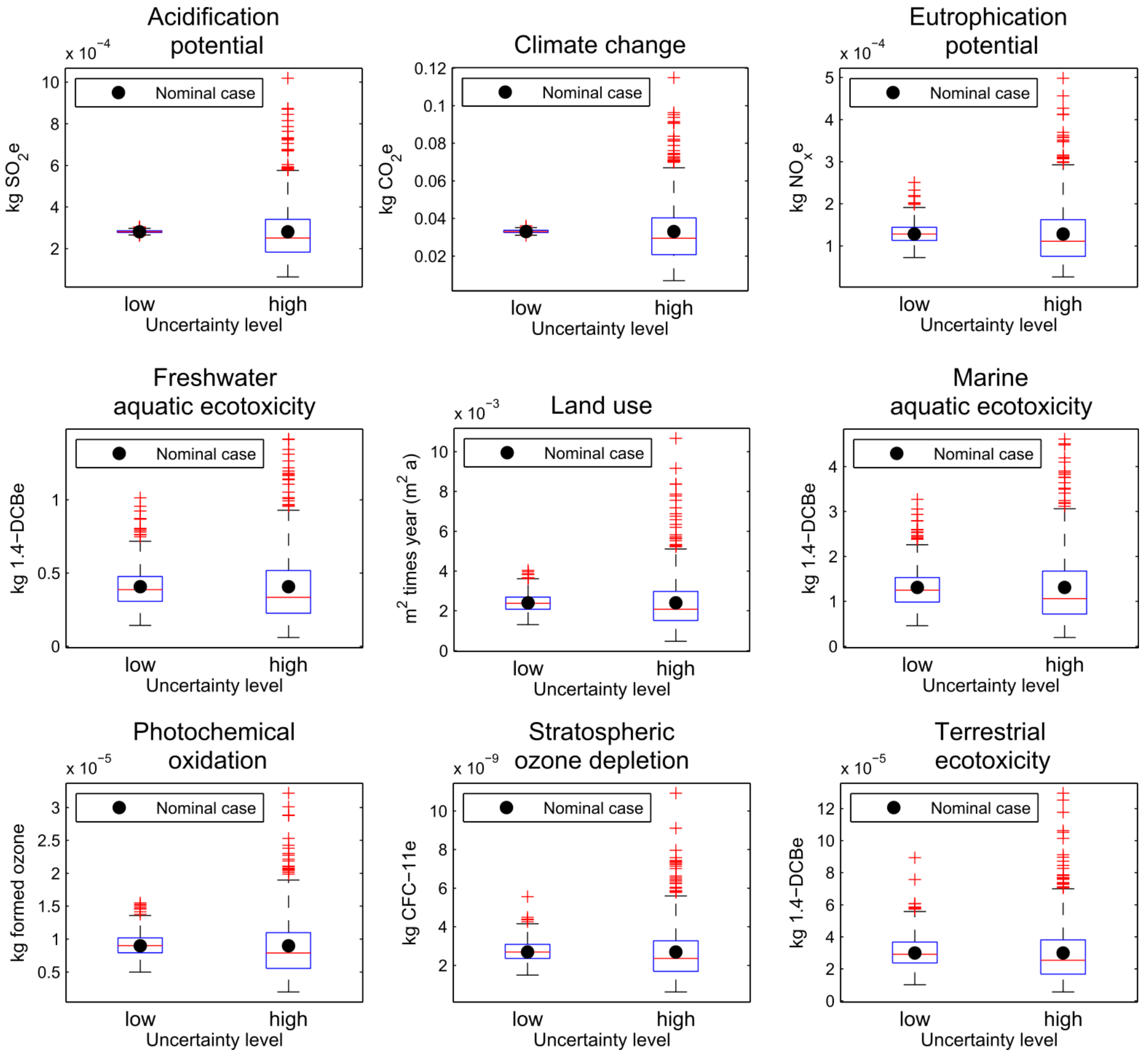


Fig.5.11. Boxplots for wind 2 considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

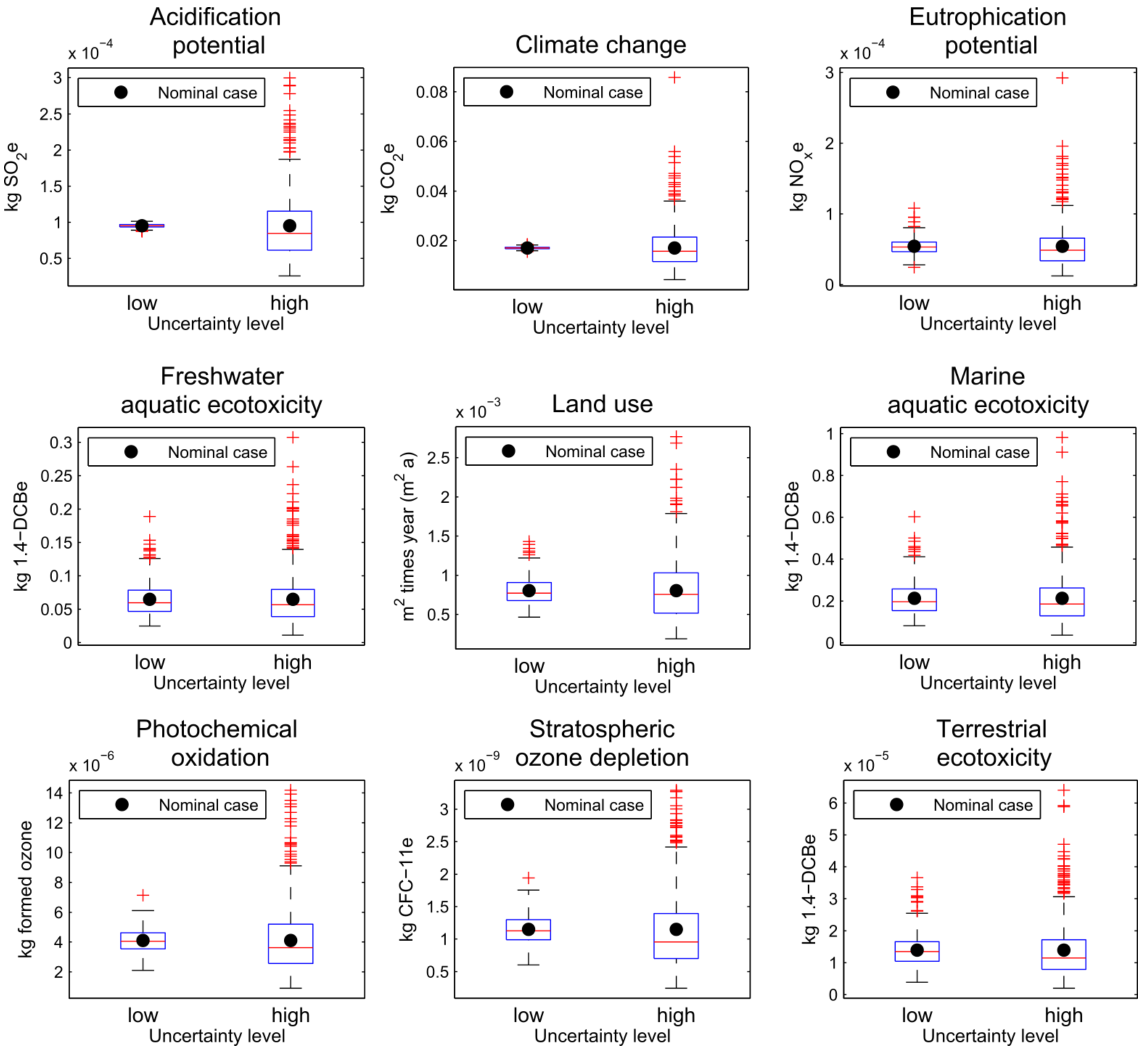


Fig.5.12. Boxplots for wind 3 considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

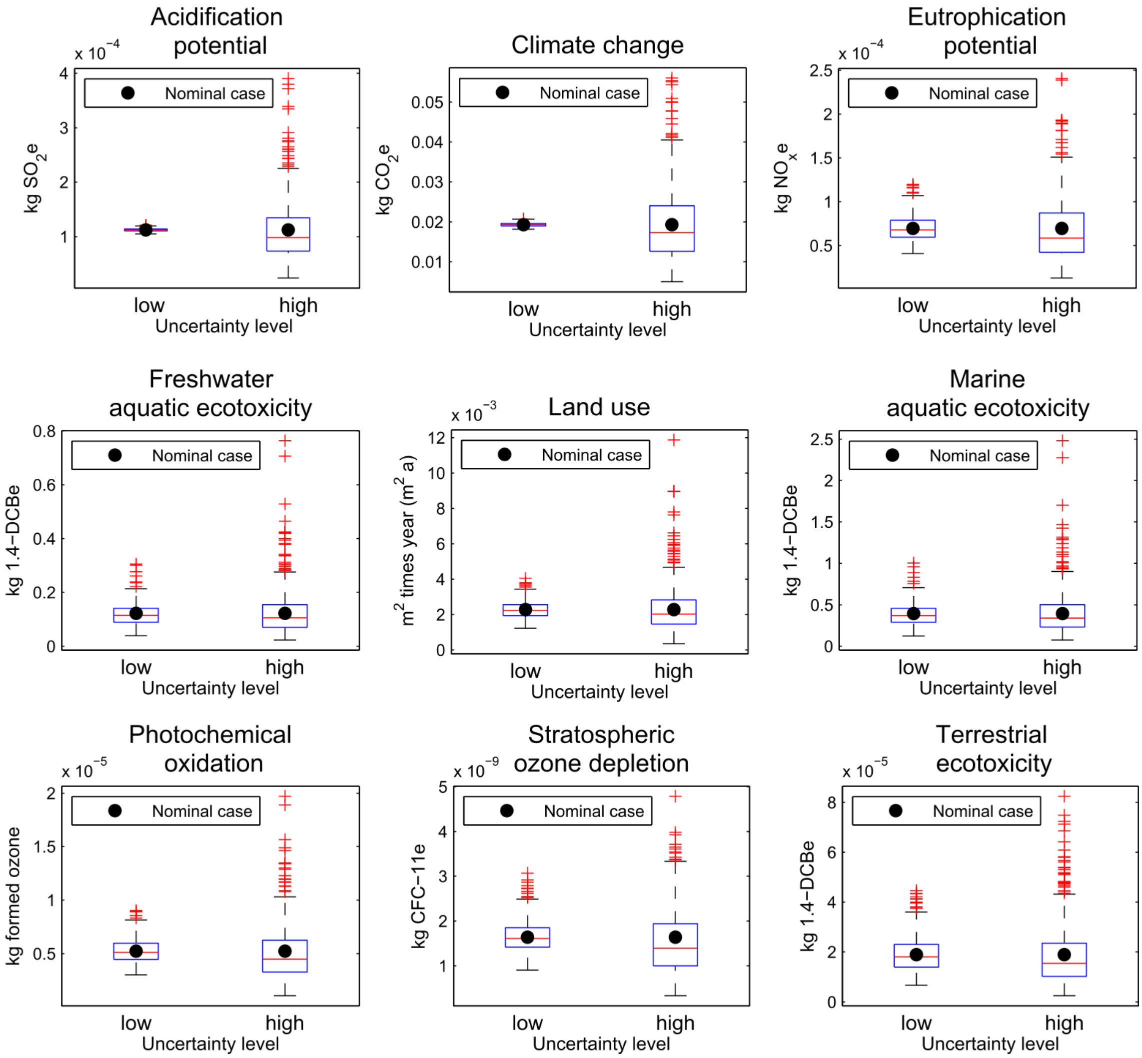


Fig.5.13. Boxplots for wind 4 considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

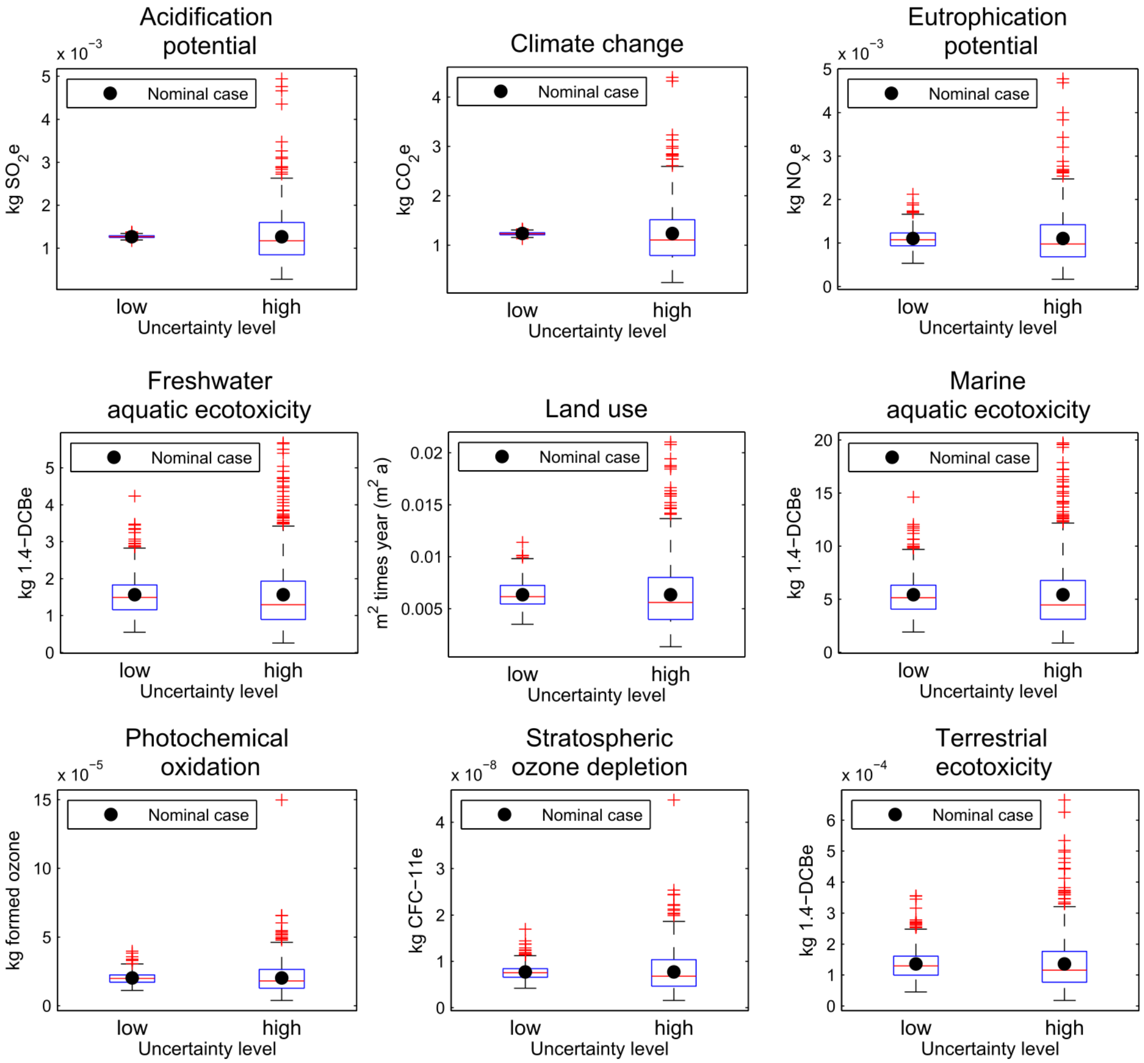


Fig.5.14. Boxplots for lignite considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

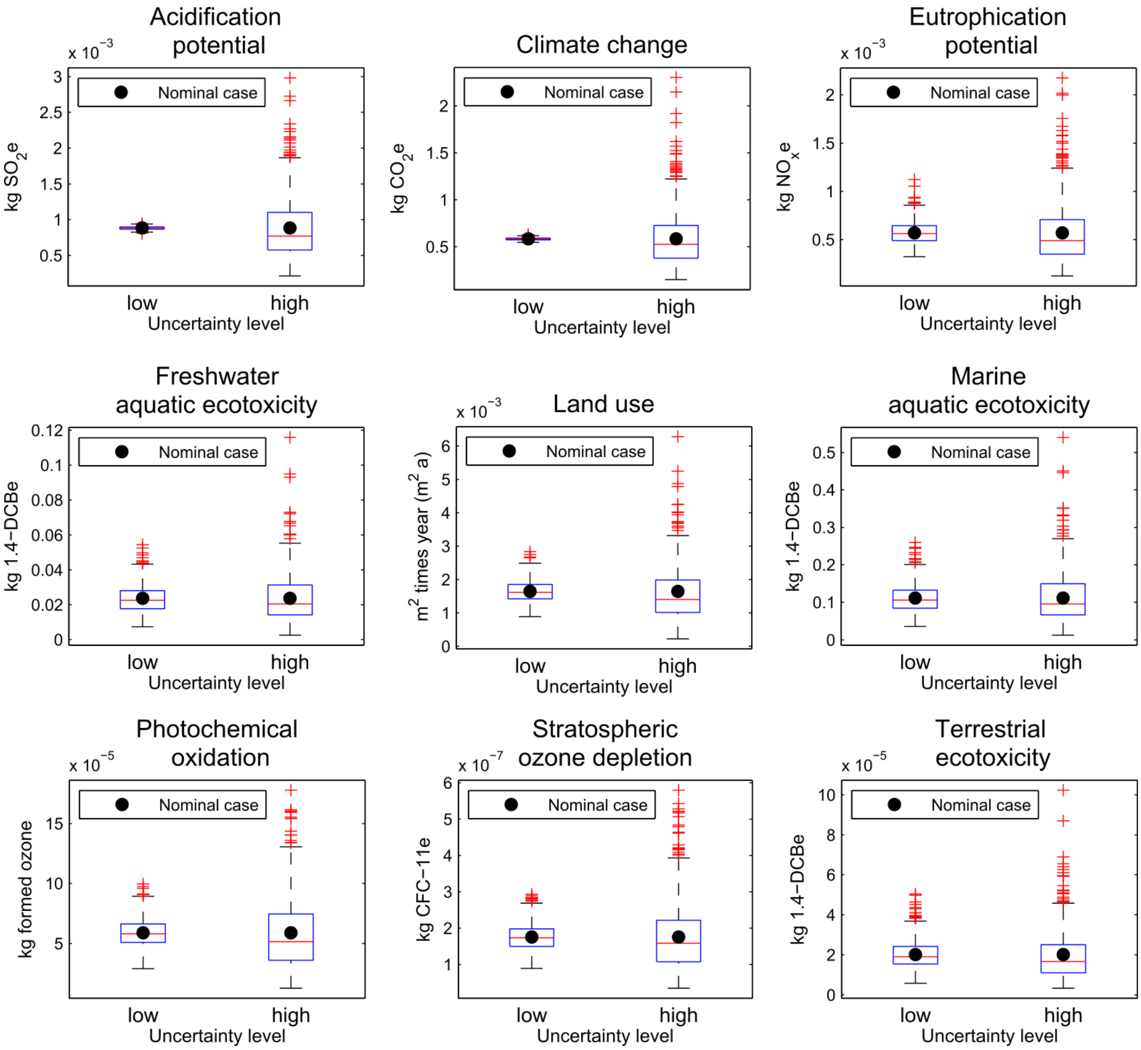


Fig.5.15. Boxplots for natural gas considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

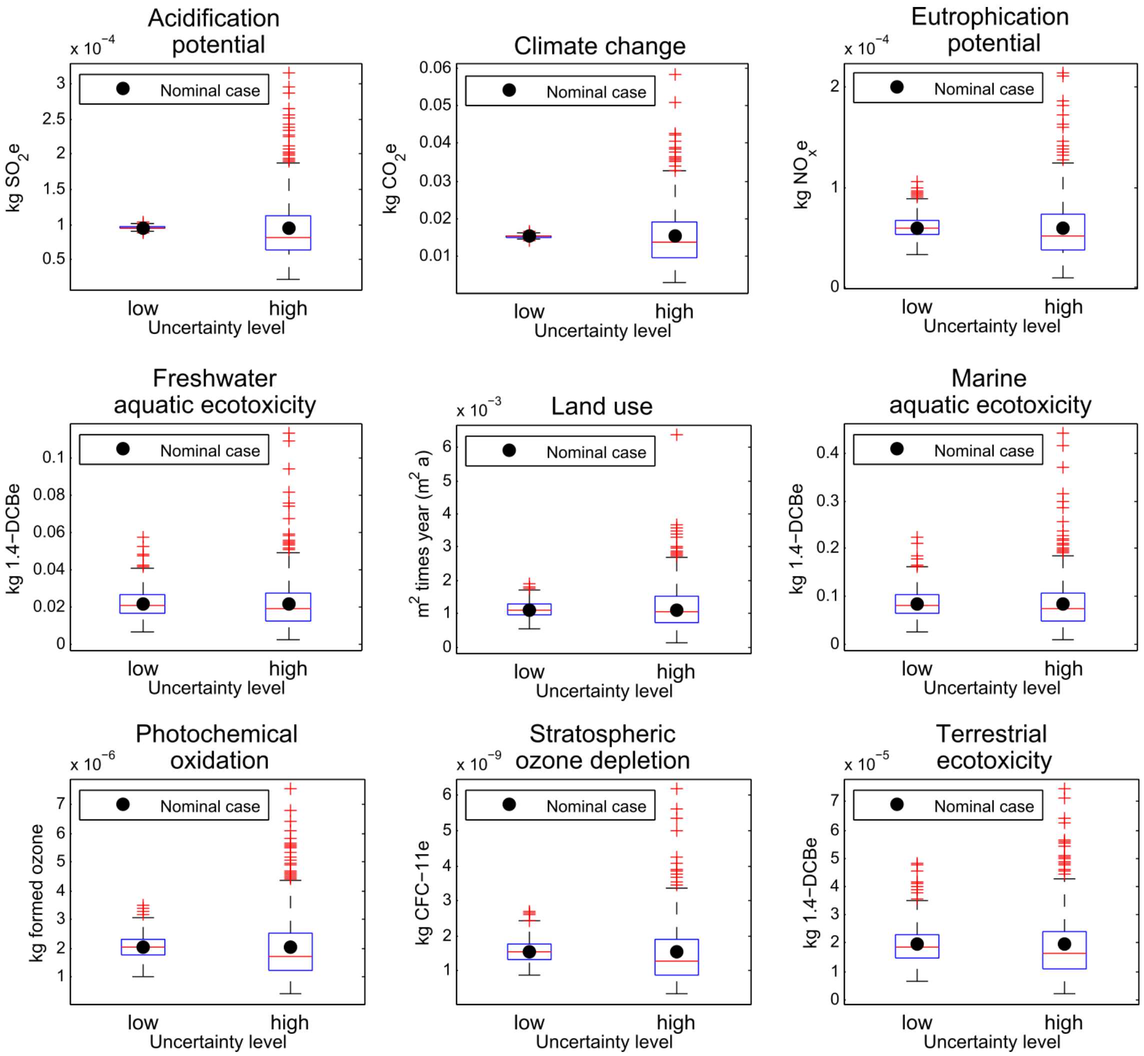


Fig.5.16. Boxplots for nuclear 1 considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

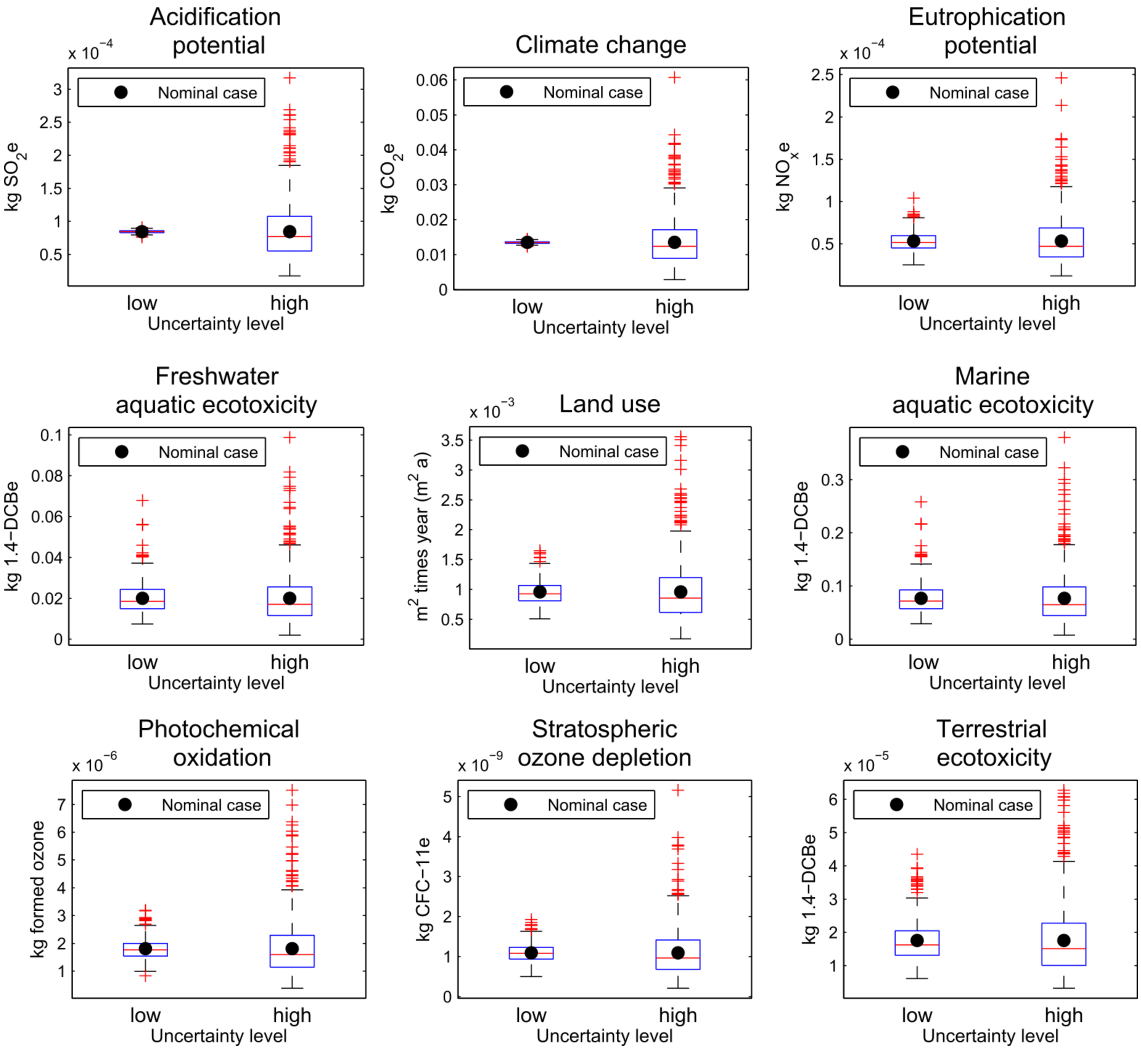


Fig.5.17. Boxplots for nuclear 2 considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

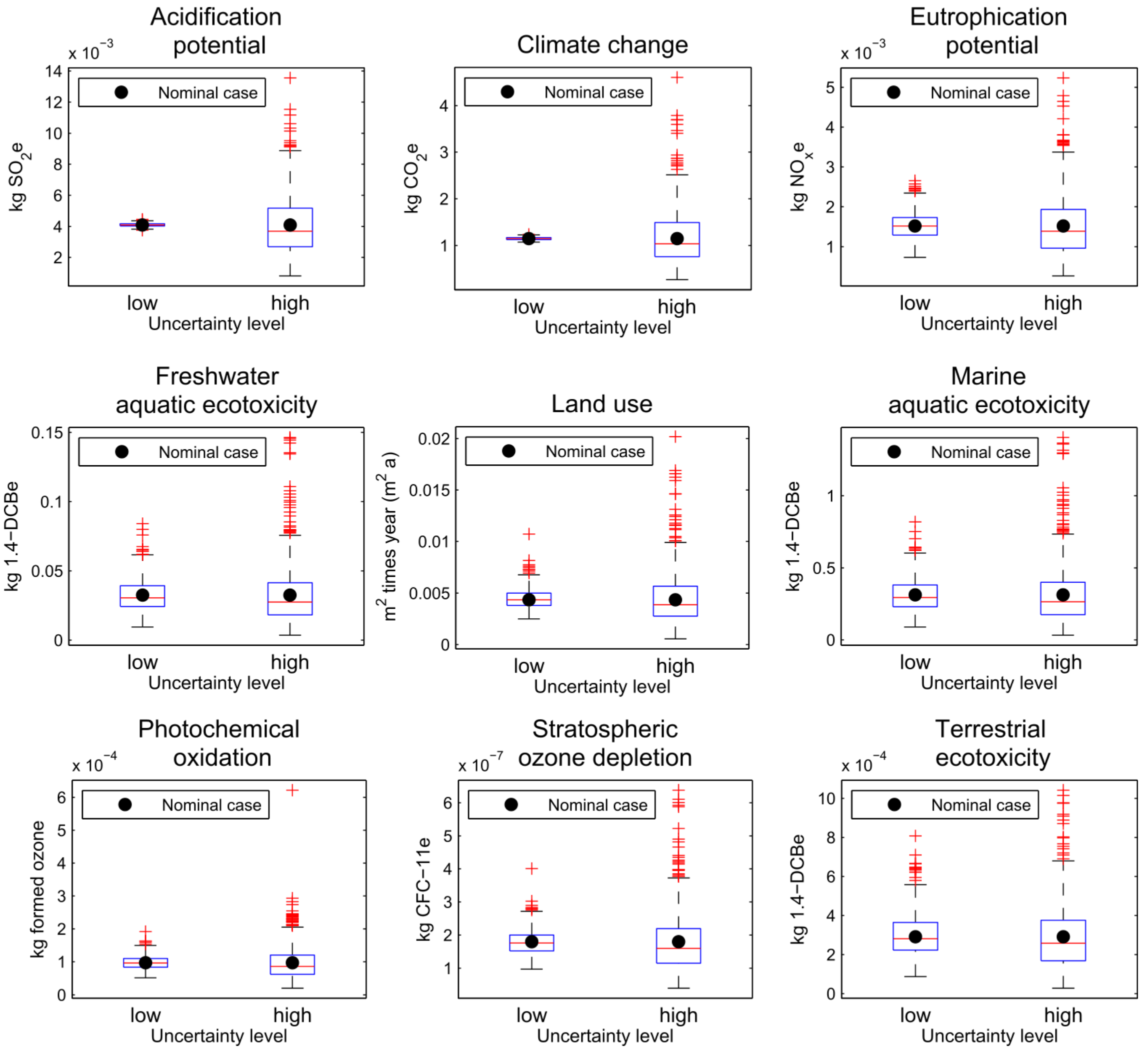


Fig.5.18. Boxplots for oil considering low and high uncertainty levels calculated according to the Pedigree matrix (see section 3.5.1.2 for more details).

5.5 Numerical results and discussion

In the ensuing sections we describe in detail the results of the environmental efficiency assessment under uncertainty for every case.

Case I: Deterministic approach.

We start by solving the deterministic DEA considering nominal impact values. Recall that each technology is modelled as a DMU whose environmental efficiency is assessed via DEA. As output, we consider one kWh of electricity, while nine environmental LCA impacts are defined as undesirable inputs.

Table 5.4 Efficiency values of the studied technologies for the nominal case.

Technology	Efficiency value
geothermal	0.694
wind 1	0.932
wind 2	0.493
wind 3	1
wind 4	0.811
hard coal	0.363
lignite	0.144
natural gas	0.869
nuclear 1	0.904
nuclear 2	1
oil	0.614

The results obtained by applying the input-oriented BCC DEA model in the nominal scenario are displayed in Table 5.4. Two technologies are found efficient in the nominal case. These are nuclear 2 (*i.e.*, production of high voltage electricity at a grid-connected nuclear pressure water reactor) and wind 3 (*i.e.*, production of high voltage electricity at offshore grid-connected wind power plants with 2 MW wind turbine). On the other hand, nine technologies are inefficient (efficiency lower than one), showing some of them very low efficiencies scores (like lignite, with an efficiency of 0.144, and hard coal, with an efficiency of 0.363).

Cases 2 and 3: Stochastic results

We next solve the stochastic DEA considering the two sets of scenarios defined above (low and high uncertainty levels). Figure 5.19 summarises the results in boxplots. As observed, in both the low (case 2) and high (case 3) uncertainty level cases the average efficiency is sometimes above the nominal one *(i.e.* wind 2, hard coal or lignite) and sometimes below (*i.e.* geothermal, wind 1, wind 3, natural gas or oil). It is worth to mention that in case 2, nuclear 2 has an efficiency score of one in all of the scenarios (the same behavior as in the nominal case).The dispersion of efficiencies varies from one technology to another and clearly increases gradually as we first move from the nominal case to the low and then high uncertainty level cases. The biggest mismatch between the nominal and average efficiencies is observed in nuclear 1 (0.904 in the nominal case versus 0.956 and 0.976, on average, in the stochastic cases with low and high uncertainty levels, respectively), oil (0.614 in the nominal case versus 0.529 and 0.544 in stochastic ones), wind 1 (0.932 in the nominal case versus 0.810 and 0.890 in the stochastic ones) and wind 2 (0.493 in the nominal case versus 0.510 and 0.565 in the stochastic cases).

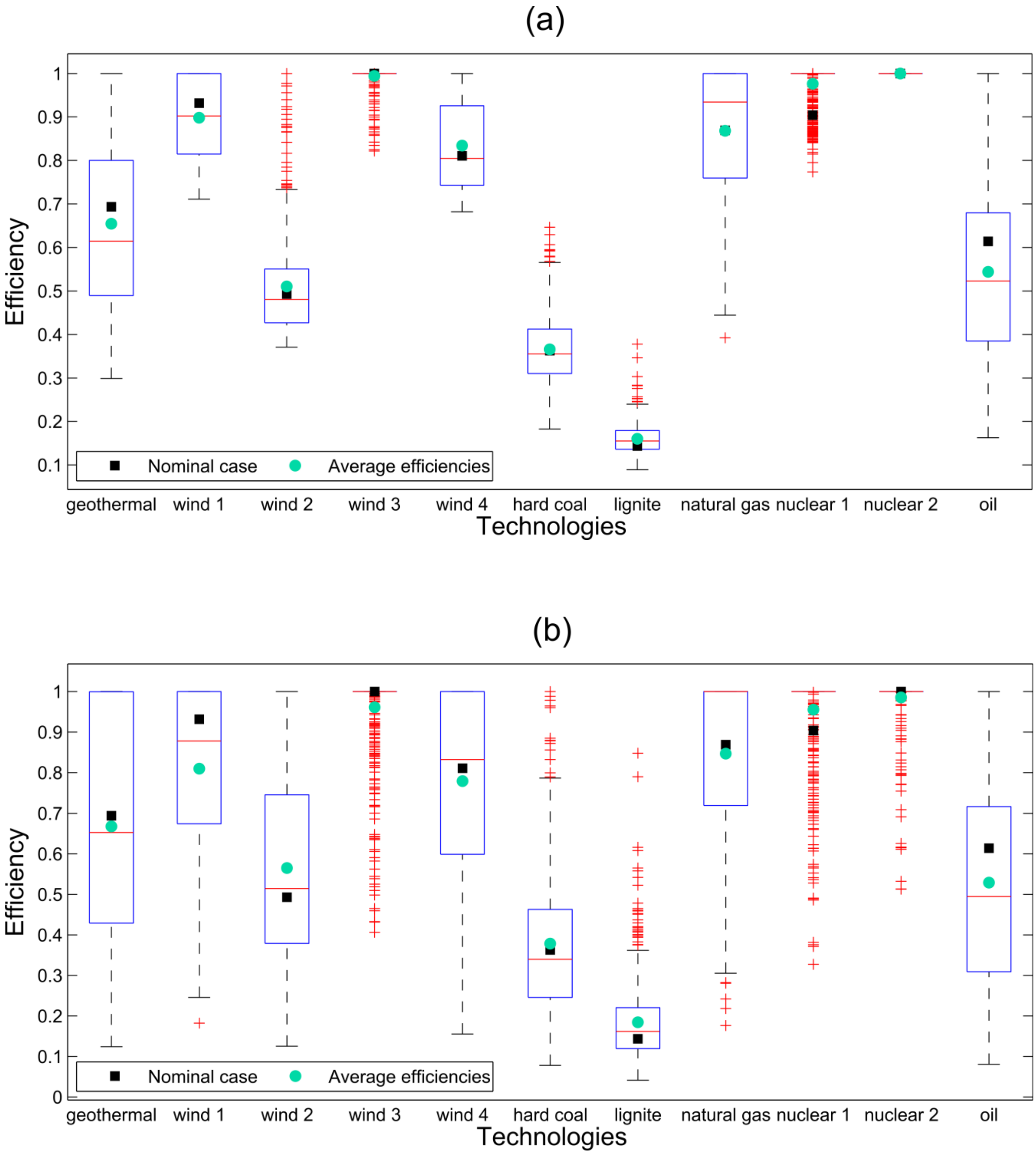


Fig.5.19. Distribution of efficiencies for every technology in each case: (a) low uncertainty level; (b) high uncertainty level. The black squares represent the efficiencies for the nominal impact values, while green points depict the average efficiencies of each technology in all the scenarios.

Table 5.5 shows the rankings of technologies in terms of efficiency values (either nominal values or average ones) obtained in the deterministic and stochastic cases. The ranking has been established by sorting the efficiency values in a descendant order (note that super-efficiency models could have been used to further discriminate between the efficient technologies in the nominal case, but this was not done for simplicity). As seen, the ranking for a low uncertainty level (case 2) is the same as the nominal one for all technologies except for the third-ranked (nuclear 1) and fourth-ranked (wind 1) ones. For a high uncertainty level (case 3), there are two places where the orders are reversed (technologies nuclear 1, natural gas and wind 1, in third, fourth and fifth positions, and technologies wind 2 and oil in eighth and ninth positions).

Table 5.5. Efficiency of the technologies ranked in a descendant order. We highlight the differences in ranking orders between the deterministic and the stochastic cases in bold and underlined. The value of the efficiency in cases 2 and 3 is the average of the efficiency over the 500 scenarios generated.

Deterministic case (case 1)			Low uncertainty level (case 2)		High uncertainty level (case 3)	
1	nuclear 2	1	1 nuclear 2	1	1 nuclear 2	0.986
2	wind 3	1	2 wind 3	0.994	2 wind 3	0.962
3	wind 1	0.932	**<u>3 (↑1) nuclear 1</u>**	<u>0.976</u>	**<u>3 (↑1) nuclear 1</u>**	<u>0.956</u>
4	nuclear 1	0.904	**<u>4 (↓1) wind 1</u>**	<u>0.898</u>	**<u>4 (↑1) natural gas</u>**	<u>0.847</u>
5	natural gas	0.869	5 natural gas	0.868	**<u>5 (↓2)wind 1</u>**	<u>0.810</u>
6	wind 4	0.811	6 wind 4	0.834	6 wind 4	0.779
7	geothermal	0.694	7 geothermal	0.655	7 geothermal	0.667
8	oil	0.614	8 oil	0.544	**<u>8 (↑1) wind 2</u>**	<u>0.565</u>
9	wind 2	0.493	9 wind 2	0.510	**<u>9 (↓1) oil</u>**	<u>0.529</u>
10	hard coal	0.363	10 hard coal	0.366	10 hard coal	0.378
11	lignite	0.144	11 lignite	0.160	11 lignite	0.184

Figure 5.20 shows the efficiency distribution for cases 2 and 3. As an example, in the low level of uncertainty case, natural gas has a 46% probability of attaining efficiency values below 0.90. This implies that the efficiency for this technology is lower than 0.90 in 230 out of the 500 scenarios. As observed, the technologies deemed efficient in the nominal case (nuclear 2 and wind 3) are inefficient in some scenarios (*i.e.* technology wind 3 shows 93% and 81% probabilities of efficiency values above 0.99 in cases 2 and case 3, respectively; whereas nuclear 2 deemed efficient in all of the scenarios in case 2, has a 92% probability of attaining an efficiency score above 0.99 in case 3).

In addition, the probability of being efficient (say an efficiency above 0.99) increases as we move from the nominal case to the low and high uncertainty level cases for those technologies with low efficiency scores (*i.e.* technology wind 2 has a probability of less than 1% of being efficient in case 2, and 9% in case 3).

As shown, lignite is the only technology that never becomes efficient in any scenario (*i.e.* it shows a zero probability of efficiency values above 0.90). On the other hand, hard coal is inefficient in the nominal case and in all the scenarios of case 2, but has a 2% probability of attaining an efficiency score above 0.99 in case 3.

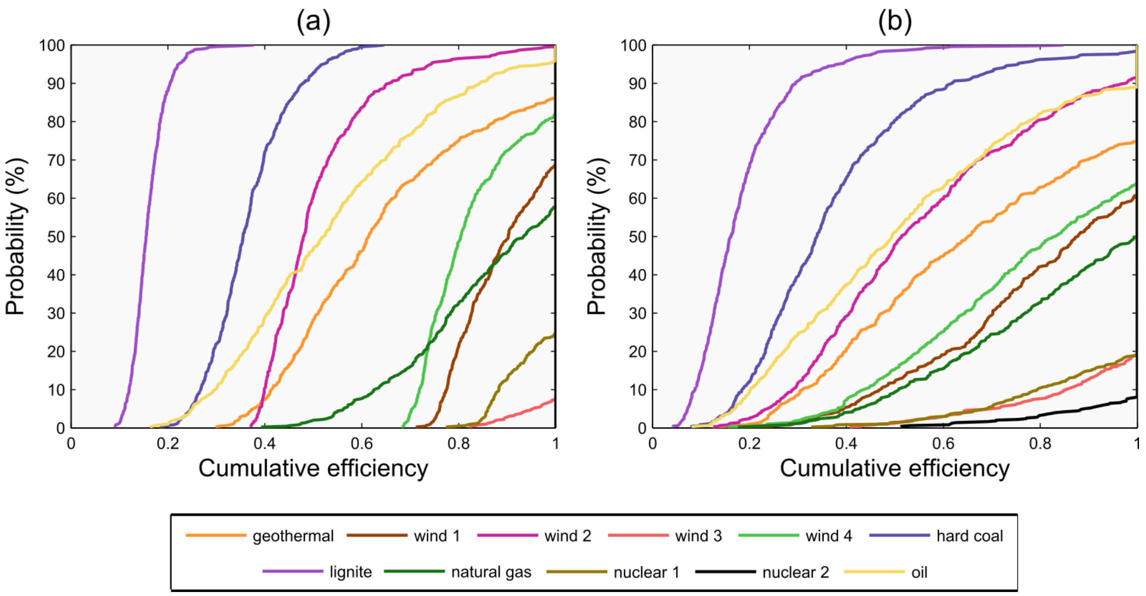
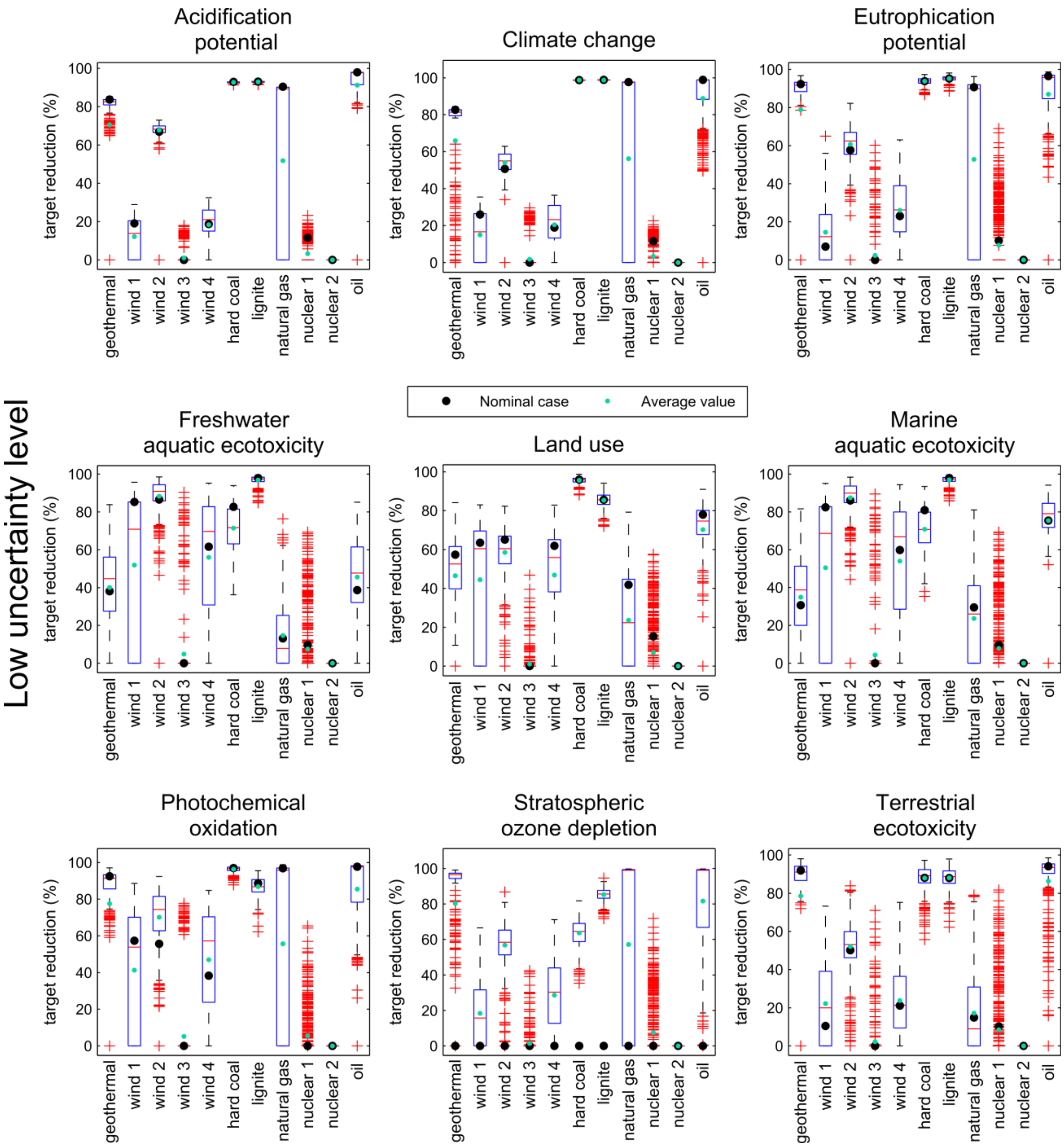


Fig.5.20. Cumulative probability distribution of efficiencies for each technology for the stochastic cases: (a) low uncertainty levels (case 2); (b) high uncertainty levels (case 3).



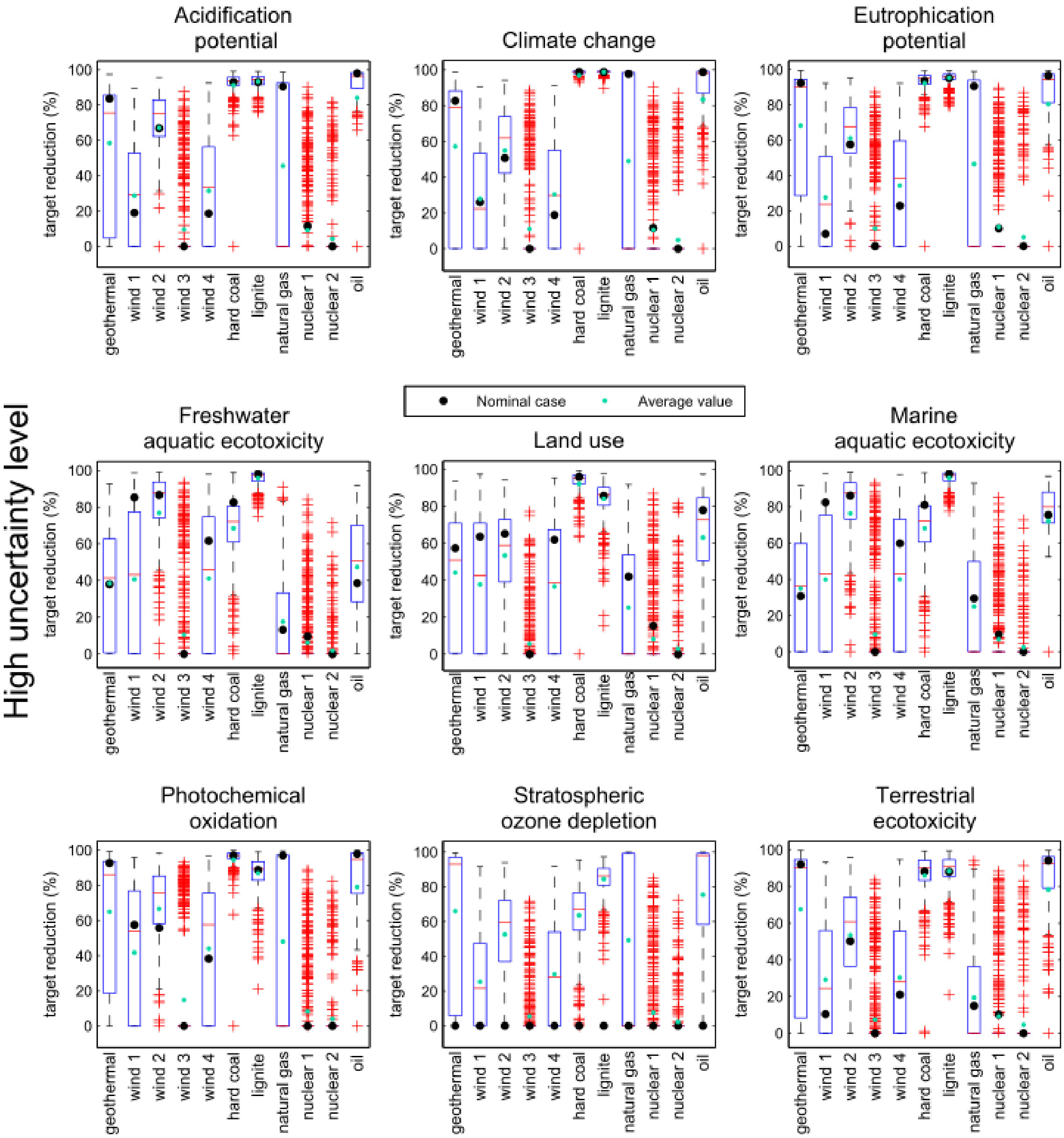


Fig.5.21. Improvement targets (expressed as percentage with respect to the nominal case) for the stochastic (with low and high uncertainty levels) and the deterministic cases. Note that black points represent the nominal case, while green points represent the average targets for each impact across all the 500 scenarios.

The dual models are solved next for the nominal and stochastic cases in order to obtain the improvement targets (i.e. percentage reduction needed with respect to the nominal case so as to become efficient, see Figure 5.21). As observed, nuclear 2 and wind 3 deemed efficient in the nominal case, show very low percentages of target reduction in the stochastic cases. Particularly, nuclear 2 is deemed efficient in all of the scenarios in the case with a low uncertainty level, showing zero targets regardless of the scenario considered. On the other hand, technologies with low efficiency scores (*i.e.* lignite or hard coal) show high percentage reductions in the deterministic and stochastic cases.

As seen, in both the low and high uncertainty level cases the average target values are sometimes above the nominal ones (*e.g.* wind 2,wind 3 or wind 4 except the freshwater and marine aquatic toxicity and land use damage categories) and sometimes below (*e.g.* geothermal or oil in climate change, acidification and eutrophication damage categories). The dispersion of targets varies also from one technology to another and clearly grows gradually as we first move from the nominal case to the low and then high uncertainty level cases. The highest differences between average and nominal targets are observed in natural gas, geothermal, wind 1 and oil technologies. For instance, the difference of targets for natural gas ranges between 38% and 48% in almost all of the impacts, except for water and terrestrial ecotoxicity damage categories. Geothermal is the second technology with the highest differences between deterministic and stochastic cases (differences ranging from 13% to 27% between the nominal and average targets depending on the category being analysed), followed by wind 1,with differences in the range 1% to 25% (except in water damage categories, where this difference falls in the range 31% to 44%).

Targets provide valuable information regarding the main weaknesses of the technologies and can therefore be used to identify potential areas of improvement. Note, however, that in our case some of them may be unattainable '*per se*', as there is little room for improvement in several energy generation technologies. Hence, improvement targets should be considered with caution. This might not be the case when assessing the environmental efficiency of other systems. Particularly, if the DMUs being assessed were facilities using the same technology but operating differently (and with uncertainties in their LCI measurements) then the targets computed using the proposed Monte Carlo DEA+LCA approach would be more meaningful.

Note that there is a maximum target value for every impact and technology such that if the technology accomplishes it, then it will be guaranteed to remain efficient in all of the scenarios. As seen in Figure 10, these maximum target values can differ significantly from the nominal one. As an example, the average target in the impact land use for the technology geothermal is 0.0012, while the maximum target that would guarantee its efficiency across all the scenarios is 0.00376 (for low uncertainty level case). These results confirm the convenience of including uncertainties when applying DEA to the environmental efficiency assessment of products and technologies.

5.6 Conclusions

This chapter introduced an approach that combines LCA, DEA and stochastic modelling for the benchmarking of systems according to multiple environmental criteria and considering the associated uncertainties. The approach presented was applied to the assessment of several technologies for electricity generation.

We found that the deterministic results (*i.e.* efficiencies and target values for the nominal case) can differ significantly from the stochastic ones, which affects the ranking of alternatives. This observation can be exploited to discriminate between alternatives that are deemed efficient in the deterministic case. More precisely, several alternatives may show the same efficiency level in the deterministic case, but it is very unlikely that the same will happen in the stochastic one.

The traditional deterministic DEA approach dichotomously categorizes the DMUs as efficient and inefficient (this division is definite and clear). On the other hand, the stochastic DEA provides no sharp categorization. Some DMUs may not always be efficient, yet they are deemed efficient with a certain probability.

Finally, it should be kept in mind that the case study results strongly depend on the data used in the analysis. Our framework focuses on the combined use of DEA and LCA where uncertainties are described via the Pedigree matrix. However, it could easily handle other environmental impact assessment methods and stochastic modelling approaches, where uncertainties are described via historical data and scenarios are generated by means of Latin Hypercube, Sobolor Halton algorithms, for instance. Furthermore, our methodology could also be employed to assess other types of efficiencies in cases where uncertainties on the data (*i.e.* inputs/outputs) are expected to have a significant impact on the outcome of the assessment. What emerges as a clear conclusion is that uncertainties can impact drastically the outcome of the DEA analysis as applied to the assessment of the environmental efficiency of a system and should be therefore considered in any study of this nature.

PART III: Conclusions

6. Conclusions and future work

6.1 General conclusions

The objective of this thesis has been to apply and analysis mathematical programming techniques and approaches for sustainability assessment. Specifically, input models and mathematical formulations have been developed to tackle the environmental efficiency in deterministic and uncertain conditions. Hence, two case studies has been addressed and solved by mathematical programming frameworks devised in this thesis.

The first part of this thesis (Part I) is the welcoming part to the sustainability development. In this section, the importance of the appropriate analysis and definition of sustainable development is highlighted due to the quick economic and technology growth during the last decade. Chapter 1 introduces the basic concepts of eco-efficiency concept towards Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA) including the uncertain aspects. The main objectives of this thesis toward the Life Cycle Assessment and Data Envelopment Analysis are described at the end of this chapter followed by the thesis outline as a guide of this work and an illustrative example of proposed methodology.

According to thesis outline, the brief historical overview of sustainability development is presented in Chapter 2, followed by the framework of LCA and DEA applications. From these areas, this thesis has been focused on the environmental energy efficiency, the impact assessment and the consideration of different sources/levels of uncertainty. The theory, concepts, methodology and tools used to solve the efficiency problems has been presented in Chapter 3.

In Part II, the eco-efficiency energy systems analysis is described toward two approach cases. In Chapter 4, an environmental eco-efficiency analysis of electricity mix of 27 European economies based on the integrated use of DEA and LCAtechnique is proposed. This approach identified environmentally efficient and inefficient countries considering as undesirable inputs several environmental impacts associated with the production of 1 kWh (regarded as output). The method provided as well the quantitative targets for the inefficient countries that (if attained) would make them efficient. Note that only the environmental performance of the electricity generation mixes of the top European countries, which display similar levels of development, have been taken into account while the economic, social, technological and political aspects have been left out of the analysis. The lack of quantitative indicators for describing the performance of a technology in these dimensions (except the economic case), were the reason for only the environmental aspect of the analysis.

This doctoral thesis has applied life cycle assessment and data envelopment analysis into sustainability assessment, paying special attention to the minimization of the environmental impact and the inclusion of uncertainty issues in the analysis. The following conclusions have been made:

- Our results provide valuable insights for governments and policy makers that aim to satisfy the electricity demand while minimizing the associated environmental impact (Chapter 4). However, when making decisions for the future electricity mix other considerations of economic and social nature should be considered. For example, the specific character of electricity mix of Norway has been classified this country as an outlier. After removing Norway from the analysis, the following seven countries out of 26 have been found eco-inefficient: Czech Republic, Greece, Croatia, Hungary, Luxemburg, Slovenia and Slovakia and the reduction values of their impact (compared to the current level) should be: 6.94%, 24.31%, 9.97%, 22.23%, 6.73%, 2.27% and 22.57%, respectively.

- For the aforementioned inefficient countries, the changes in their electricity mixes have been determined in order to make them efficient. The main proposed changes implied reductions of different magnitude in the share of fossil fuels, which cause significant environmental impacts.
- The consideration of uncertainty is crucial to allow the suitable generation of practical and good quality management for decision makers. Numerical results (see Chapter 5) show that the efficiency scores in the nominal and the stochastic cases can differ significantly, and the same applies to the target values established for the inefficient units. Moreover, the differences in efficiency values affect the ranking of alternatives. These results support the need to incorporate uncertainties into the LCA+DEA framework in order to provide further insight into the problem and assess the robustness of the results obtained.
- The deterministic DEA analysis show the clear division between efficient and inefficient DMUs, while in the stochastic DEA such a sharp categorization is not provided. On the contrary, the DMUs are presented with certain probability level.

6.2 Future work

Some issues requiring further investigation have been already revealed in the course of this work. Moreover, some of the potential research lines are suggested in this section.

We already mentioned that economic, social, technological and political aspects have been left out of the analysis (chapter 4), mainly because there are very few 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). Hence, future work can be extended by incorporating some social and economic metrics in the analysis.

On the other hand, the case study results strongly depend on the data used in the analysis. Our framework (chapter 5) uses the combined use of DEA and LCA where uncertainties are described via the Pedigree matrix, but could be easily extended to include other environmental impact methods and tools for stochastic modelling. The consideration of uncertainty for outcome of the DEA (impacts) is crucial when the meaningful results are sought, thus any future studies should also include sensitivity analysis.

7. Bibliography

[1] Brundtland, "Report of the World Commission on Environment and Development : Our Common Future Acronyms and Note on Terminology Chairman's Foreword," 1987.

[2] A. Claudia Pahl-Wostl, Sonja Schmidt and A. J. J. E. Rizzoli, "Complexity and Integrated Resources Management Transactions of the 2nd Biennial Meeting of the International Environmental Modelling and Software Society," 2004.

[3] T. C. Lindsey, "Sustainable principles: Common values for achieving sustainability," *J. Clean. Prod.*, vol. 19, no. 5, pp. 561–565, 2011.

[4] D. . Meadows, D. Meadows, J. Randers, and W. Behrens, *The Limits to Growth*, vol. 205. 1972.

[5] A. Forrester, M. Moos, J. Andrey, L. C. Johnson, and P. Bozuwa, "Council of Science Editors Task Force on Science Journals , Poverty , and Human Development," vol. 2, no. 1, 2006.

[6] World Comission, "Report of the World Commission on Environment and Development: Our Common Future," *Sustain. Dev.*, vol. 154, pp. 1–374, 1987.

[7] M. K. Tolbaa, "Sustainable water development: Opportunities and constraints," *Water Int.*, vol. 13, no. 4, 1988.

[8] Y. Kajikawa, "Research core and framework of sustainability science," *Sustain. Sci.*, vol. 3, no. 2, pp. 215–239, 2008.

[9] S. Lele and R. B. Norgaard, "Sustainability and the scientist's burden," *Conserv. Biol.*, vol. 10, no. 2, pp. 354-365, 1996.

[10] R. Shearman, "The meaning and ethics of sustainability," *Environ. Manage.*, vol. 14, no. 1, pp. 1-8, 1990.

[11] Y. Kajikawa, J. Ohno, Y. Takeda, K. Matsushima, and H. Komiyama, "Creating an academic landscape of sustainability science: An analysis of the citation

network," *Sustain. Sci.*, vol. 2, no. 2, pp. 221–231, 2007.

[12] A. Hannon and E. G. Callaghan, "Definitions and organizational practice of sustainability in the for-profit sector of Nova Scotia," *J. Clean. Prod.*, vol. 19, no. 8, pp. 877–884, 2011.

[13] A. Bodini, "Building a systemic environmental monitoring and indicators for sustainability: What has the ecological network approach to offer?," *Ecol. Indic.*, vol. 15, no. 1, pp. 140–148, 2012.

[14] J. Sachs and A. Warner, "Natural Resource Abundance and Economic Growth," *National Bureau of Economic Research*, p. 5398, 1995.

[15] F. A. Vollenbroek, "Sustainable development and the challenge of innovation," *J. Clean. Prod.*, vol. 10, no. 3, pp. 215–223, 2002.

[16] S. M. Lélé, "Sustainable development: A critical review," *World Dev.*, vol. 19, no. 6, pp. 607–621, 1991.

[17] T. Dyllick and K. Hockerts, "Beyond the business case for corporate sustainability," *Bus. Strateg. Environ.*, vol. 11, no. 2, pp. 130-141, 2002.

[18] P. Saling, A. Kicherer, B. Dittrich-Krämer, R. Wittlinger, W. Zombik, I. Schmidt, W. Schrott, and S. Schmidt, "Eco-efficiency analysis by BASF: The method," *Int. J. Life Cycle Assess.*, vol. 7, no. 4, pp. 203-218, 2002.

[19] GRI, "Sustainability Reporting Guidelines," pp. 1–104, 2002.

[20] Global Reporting Initiative, "G3 Sustainability Reporting Guidelines," *G3 Guid.*, p. G3 Guideline, 2011.

[21] D. Krajnc and P. Glavič, "How to compare companies on relevant dimensions of sustainability," *Ecol. Econ.*, vol. 55, no. 4, pp. 551-563, 2005.

[22] M. Narodoslawsky and C. Krotscheck, "Integrated ecological optimization of processes with the sustainable process index," *Waste Manag.*, vol. 20, no. 8, pp. 599-603, 2000.

[23] M. Narodoslawsky and C. Krotscheck, "The sustainable process index (SPI): evaluating processes according to environmental compatibility," *J. Hazard.*

Mater., vol. 41, no. 2–3, pp. 383-397, 1995.

[24] C. Krotscheck and M. Narodoslawsky, "The Sustainable Process Index. A new dimension in ecological evaluation," *Ecol. Eng.*, vol. 6, no. 4, pp. 241-258, 1996.

[25] A. Azapagic and S. Perdan, "Indicators of sustainable development for industry: a general framework," *Trans IChemE*, vol. 78, no. July, pp. 243–261, 2000.

[26] A. Azapagic, "Developing a framework for sustainable development indicators for the mining and minerals industry," *J. Clean. Prod.*, vol. 12, no. 6, pp. 639–662, 2004.

[27] N. H. Afgan and M. G. Carvalho, "Sustainability assessment of hydrogen energy systems," *International Journal of Hydrogen Energy*, vol. 29, no. 13. pp. 1327–1342, 2004.

[28] C. Böhringer and P. E. P. Jochem, "Measuring the immeasurable - A survey of sustainability indices," *Ecol. Econ.*, vol. 63, no. 1, pp. 1–8, 2007.

[29] R. K. Singh, H. R. Murty, S. K. Gupta, and A. K. Dikshit, "An overview of sustainability assessment methodologies," *Ecol. Indic.*, vol. 9, no. 2, pp. 189–212, 2009.

[30] C. Lo Prete, B. F. Hobbs, C. S. Norman, S. Cano-Andrade, A. Fuentes, M. R. von Spakovsky, and L. Mili, "Sustainability and reliability assessment of microgrids in a regional electricity market," *Energy*, vol. 41, no. 1, pp. 192–202, 2012.

[31] V. Ibáñez-Forés, M. D. Bovea, and V. Pérez-Belis, "A holistic review of applied methodologies for assessing and selecting the optimal technological alternative from a sustainability perspective," *J. Clean. Prod.*, vol. 70, pp. 259–281, 2014.

[32] N. H. Afgan and M. Darwish, "Multi-criteria sustainability assessment of water desalination and energy systems - Kuwait case," *Desalin. Water Treat.*, vol. 25, no. 1–3, pp. 241-250, 2011.

[33] S. E. Shmelev and B. Rodríguez-Labajos, "Dynamic multidimensional assessment of sustainability at the macro level: The case of Austria," *Ecol. Econ.*, vol. 68, no. 10, pp. 2560–2573, 2009.

[34] L. Adrianto, Y. Matsuda, and Y. Sakuma, "Assessing local sustainability of fisheries system: A multi-criteria participatory approach with the case of Yoron Island, Kagoshima prefecture, Japan," *Mar. Policy*, vol. 29, no. 1, pp. 9–23, 2005.

[35] A. Torres-Delgado and J. Saarinen, "Using indicators to assess sustainable tourism development: a review," *Tour. Geogr.*, vol. 16, no. 1, pp. 31-47, 2014.

[36] V. Hiltunen, J. Kangas, and J. Pykäläinen, "Voting methods in strategic forest planning - Experiences from Metsähallitus," *For. Policy Econ.*, vol. 10, no. 3, pp. 117–127, 2008.

[37] G. Liu, "Development of a general sustainability indicator for renewable energy systems: A review," *Renew. Sustain. Energy Rev.*, vol. 31, pp. 611-621, 2014.

[38] J. Schwarz, B. Beloff, and E. Beaver, "Use sustainability metrics to guide decision-making," *Chemical Engineering Progress*, vol. 98, no. 7, pp. 58-63, 2002.

[39] A. A. Martins, T. M. Mata, C. A. V Costa, and S. K. Sikdar, "Framework for sustainability metrics," *Ind. Eng. Chem. Res.*, vol. 46, no. 10, pp. 2962–2973, 2007.

[40] G. Huppes and M. Ishikawa, "A Framework for Quantified Eco-efficiency Analysis," *J. Ind. Ecol.*, vol. 9, no. 4, pp. 25–41, Oct. 2005.

[41] S. K. Sikdar, "Sustainable development and sustainability metrics," *AIChE J.*, vol. 49, no. 8, pp. 1928-1932, 2003.

[42] G. A. Norris, "Social impacts in product life cycles: Towards life cycle attribute assessment," *Int. J. Life Cycle Assess.*, vol. 11, no. SPEC. ISS., pp. 97-104, 2006.

[43] I. Schmidt, M. Meurer, P. Saling, A. Kicherer, W. Reuter, and C.-O. Gensch, "SEEbalance®: Managing sustainability of products and processes with the socio-eco-efficiency analysis by BASF," *Greener Manag. Int.*, no. 45, p. 79, 2004.

[44] D. Hunkeler, "Societal LCA methodology and case study," *Int. J. Life Cycle Assess.*, vol. 11, no. 6, pp. 371-382, 2006.

[45] S. Schmidheiny, "Changing course - a global business perspective for

development and environment," vol. 1, 1992.

[46] O. Michelsen, A. M. Fet, and A. Dahlsrud, "Eco-efficiency in extended supply chains: a case study of furniture production.," *J. Environ. Manage.*, vol. 79, no. 3, pp. 290–297, May 2006.

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

[48] C. Jasch, "Environmental performance evaluation and indicators," *J. Clean. Prod.*, vol. 8, no. 1, pp. 79-88, 2000.

[49] T. Kuosmanen and M. Kortelainen, "Measuring Eco-efficiency of Production with Data Envelopment Analysis," *J. Ind. Ecol.*, vol. 9, no. 4, pp. 59–72, Oct. 2005.

[50] H. Dyckhoff and K. Allen, "Measuring ecological efficiency with data envelopment analysis (DEA)," *Eur. J. Oper. Res.*, vol. 132, no. 2, pp. 312–325, Jul. 2001.

[51] ISO, "ISO 14044 Environmental management—life cycle assessment—requirements and guidelines," 2006.

[52] ISO, "ISO 14040 Environmental management—life cycle assessment—principles and framework," 2006.

[53] A. Zamagni, P. Buttol, P. P.L., B. R., and M. P., "Critical review of the current research needs and limitations related to ISO-LCA practice," *Deliv. D7 Work Packag. 5 CALCAS Proj.*, no. 37075, p. 106, 2008.

[54] M. Huijbregts, "Application of uncertainty and variability in LCA," *Int. J. Life Cycle Assess.*, vol. 3, no. 5, pp. 273–280, 1998.

[55] B. P. Weidema and M. S. Wesnæs, "Data quality management for life cycle inventories—an example of using data quality indicators," *J. Clean. Prod.*, vol. 4, no. 3–4, pp. 167–174, Jan. 1996.

[56] G. Finnveden, M. Z. Hauschild, T. Ekvall, J. Guinée, R. Heijungs, S. Hellweg, A. Koehler, D. Pennington, and S. Suh, "Recent developments in Life Cycle Assessment," *J. Environ. Manage.*, vol. 91, no. 1, pp. 1-21, 2009.

[57] S.-C. Lo, H. Ma, and S.-L. Lo, "Quantifying and reducing uncertainty in life cycle assessment using the Bayesian Monte Carlo method," *Sci. Total Environ.*, vol. 340, no. 1–3, pp. 23–33, 2005.

[58] R. R. Tan, "Using fuzzy numbers to propagate uncertainty in matrix-based LCI," *Int. J. Life Cycle Assess.*, vol. 13, no. 7, pp. 585–592, 2008.

[59] J. William Owens, "LCA impact assessment categories technical feasibility and accuracy," *Int. J. Life Cycle Assess.*, vol. 1, no. 3, pp. 151-158, 1996.

[60] W. D. Cook and L. M. Seiford, "Data envelopment analysis (DEA) - Thirty years on," *Eur. J. Oper. Res.*, vol. 192, no. 1, pp. 1-17, 2009.

[61] M. Farrell, "The measurement of productive efficiency," *J. R. Stat. Soc. Ser. A, 120*, pp. 253–281, 1957.

[62] A. Charnes, W. W. Cooper, and E. Rhodes, "Measuring the efficiency of decision making units," *Eur. J. Oper. Res.*, vol. 2, no. 6, pp. 429–444, Nov. 1978.

[63] S. Hongye, "Generalized Additive Models of DEA and Generalized Non-Dominated Solution in Multi-objective Programming," in *2010 International Conference on Computational Intelligence and Security*, pp. 596–600, 2010.

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

[65] S. Lozano, D. Iribarren, M. T. Moreira, and G. Feijoo, "Environmental impact efficiency in mussel cultivation," *Resour. Conserv. Recycl.*, vol. 54, no. 12, pp. 1269-1277, 2010.

[66] S. Lozano, D. Iribarren, M. T. Moreira, and G. Feijoo, "The link between operational efficiency and environmental impacts. A joint application of Life Cycle Assessment and Data Envelopment Analysis," *Sci. Total Environ.*, vol. 407, no. 5,pp. 1744-1754, 2009.

[67] D. Iribarren, I. Vázquez-Rowe, M. T. Moreira, and G. Feijoo, "Further potentials in the joint implementation of life cycle assessment and data envelopment

analysis.," *Sci. Total Environ.*, vol. 408, no. 22, pp. 5265–72, Oct. 2010.

[68] I. Vázquez-Rowe, D. Iribarren, M. T. Moreira, and G. Feijoo, "Combined application of life cycle assessment and data envelopment analysis as a methodological approach for the assessment of fisheries," *Int. J. Life Cycle Assess.*, vol. 15, no. 3, pp. 272–283, Feb. 2010.

[69] M. Farrell, "The measurement of productive efficiency," *J. R. Stat. Soc. Ser. A, 120*, pp. 253–281, 1957.

[70] J. D. Linton, R. Klassen, and V. Jayaraman, "Sustainable supply chains: An introduction," *J. Oper. Manag.*, vol. 25, no. 6, pp. 1075-1082, 2007.

[71] G. Hart, "The tragedy of commons," *Science (80-.).*, vol. 162, pp. 1245–1248, 1968.

[72] J. H. Spangenberg, "A European methodology for sustainable development strategy reviews," *Environ. Policy Gov.*, vol. 20, no. 2, pp. 123-134, 2010.

[73] C. R. Carter and D. S. Rogers, "A framework of sustainable supply chain management: Moving toward new theory," *Int. J. Phys. Distrib. Logist. Manag.*, vol. 38, no. 5, pp. 360-387, 2008.

[74] A. Mascarenhas, P. Coelho, E. Subtil, and T. B. Ramos, "The role of common local indicators in regional sustainability assessment," *Ecol. Indic.*, vol. 10, no. 3, pp. 646-656, 2010.

[75] A. Polido, E. João, and T. B. Ramos, "Strategic Environmental Assessment practices in European small islands: Insights from Azores and Orkney islands," *Environ. Impact Assess. Rev.*, vol. 57, pp. 18-30, 2016.

[76] P. Coelho, A. Mascarenhas, P. Vaz, A. Dores, and T. B. Ramos, "A framework for regional sustainability assessment: Developing indicators for a Portuguese region," *Sustain. Dev.*, vol. 18, no. 4, pp. 211–219, 2010.

[77] A. R. Domingues, S. Moreno Pires, S. Caeiro, and T. B. Ramos, "Defining criteria and indicators for a sustainability label of local public services," *Ecol. Indic.*, vol. 57, pp. 452-464, 2015.

[78] N. Alghamdi, A. den Heijer, and H. de Jonge, "Assessment tools' indicators for sustainability in universities: an analytical overview," *Int. J. Sustain. High. Educ.*, vol. 18, no. 1, pp. 84-115, 2017.

[79] T. Ramos and S. M. Pires, "Sustainability assessment: The role of indicators," Sustainability Assessment Tools in Higher Education Institutions. pp. 81-99. 2013.

[80] Ž. Tunčikiene and R. Korsakiene, "Sustainable development of public institutions: The model of functional review," *J. Secur. Sustain. Issues*, vol. 4, no. 2, pp.187-195, 2014.

[81] R. Shortall, B. Davidsdottir, and G. Axelsson, "Geothermal energy for sustainable development: A review of sustainability impacts and assessment frameworks," *Renew. Sustain. Energy Rev.*, vol. 44, pp. 391-406, 2015.

[82] S. Chu and A. Majumdar, "Opportunities and challenges for a sustainable energy future.," *Nature*, vol. 488, no. 7411, pp. 294–303, 2012.

[83] C. Bhowmik, S. Bhowmik, A. Ray, and K. M. Pandey, "Optimal green energy planning for sustainable development: A review," *Renew. Sustain. Energy Rev.*, 2015.

[84] R. Ramanathan and J. K. Parikh, "Transport sector in India: An analysis in the context of sustainable development," *Transp. Policy*, vol. 6, no. 1, pp. 35–45, 1999.

[85] J. A. Garza-Reyes, B. Villarreal, V. Kumar, and P. Molina Ruiz, "Lean and green in the transport and logistics sector – a case study of simultaneous deployment," *Prod. Plan. Control*, vol. 27, no. 15, pp. 1221-1232, 2016.

[86] O. Ortiz, F. Castells, and G. Sonnemann, "Sustainability in the construction industry: A review of recent developments based on LCA," *Constr. Build. Mater.*, vol. 23, no. 1, pp. 28-39, 2009.

[87] D. Tilman, K. G. Cassman, P. A. Matson, R. Naylor, and S. Polasky, "Agricultural sustainability and intensive production practices," *Nature*, vol. 418, no. 6898, pp. 671-677, 2002.

[88] S. Seuring and M. Müller, "From a literature review to a conceptual framework for sustainable supply chain management," *J. Clean. Prod.*, vol. 16, no. 15, pp. 169-1710, 2008.

[89] M. A. Curran, "Life Cycle Assessment: A review of the methodology and its application to sustainability," *Curr. Opin. Chem. Eng.*, vol. 2, no. 3, pp. 273–277, 2013.

[90] A.-M. Baumann, H. , Tillman, *The Hitchhiker's guide to LCA*, Studentlit. Lund, 2004.

[91] J. B. Guinée, R. Heijungs, G. Huppes, A. Zamagni, P. Masoni, R. Buonamici, T. Ekvall, and T. Rydberg, "Life cycle assessment: Past, present, and future," *Environ. Sci. Technol.*, vol. 45, no. 1, pp. 90-96, 2011.

[92] J. A. Fava and A. Page, "Application of product life-cycle assessment to product stewardship and pollution prevention programs," *Water Sci. Technol.*, vol. 26, no. 1–2, pp. 275-287, 1992.

[93] G. Huppes, *LCA yesterday, today and tomorrow*, Leiden Uni. Leiden: Centre of environmental science, pp. 29-49, 1996.

[94] H. A. U. de Haes and G. Huppes, "Life cycle assessment and its applications," *J. Clean. Prod.*, vol. 1, no. 3–4, 1993.

[95] SETAC, "Guidelines for life-cycle assessment. A code or practice.," in *SETAC Workshop*, 1993.

[96] R. Heijungs, J. B. Guinee, G. Huppes, R. M. Lankreijer, D. H. Udo, a. W. Sleeswijk, a. M. M. Ansems, P. G. Eggels, R. Duit, and H. P. Goede, *Environmental Life Cycle Assessment of Products - Vol1: Guide*, no. October. 1992.

[97] M. Goedkoop and R. Spriensma, "The Eco-indicator 99 - A damage oriented method for Life Cycle Impact Assessment," *Assessment*, p. 144, 2001.

[98] "UN Environment Programme Life Cycle Initiative website." [Online]. Available: http://lcinitiative.unep.fr/. [Accessed: 29-Mar-2010].

[99] Commission of the European Communities and COM, “Integrated Product Policy - Building on Environmental Life- Cycle Thinking.” 302 final, Brussels, Belgium, 2003.

[100] C. Commission of the European Communities, “Taking sustainable use of resources forward: A Thematic Strategy on the prevention and recycling of waste.,” *2005*. [Online]. Available: http://eur-lex.europa.eu/LexUriServ/. [Accessed: 15-Mar-2010].

[101] C. Commission of the European Communities, “Thematic strategy on the sustainable use of natural resources.” 670 final, Brussels, Belgium, 2005.

[102] M. Pehnt, “Dynamic life cycle assessment (LCA) of renewable energy technologies,” *Renew. Energy*, vol. 31, no. 1, pp. 55–71, 2006.

[103] A. Levasseur, P. Lesage, M. Margni, L. Deschěnes, and R. Samson, “Considering time in LCA: Dynamic LCA and its application to global warming impact assessments,” *Environ. Sci. Technol.*, vol. 44, no. 8, pp. 3169-3174, 2010.

[104] Sonnemann, G., Castells, F., Schuhmacher, M., & Hauschild, M. “Integrated life-cycle and risk assessment for industrial processes,” *The International Journal of Life Cycle Assessment*, vol. 9, no. 3, pp. 206-207, 2004.

[105] S. Suh, M. Lenzen, G. J. Treloar, H. Hondo, A. Horvath, G. Huppes, O. Jolliet, U. Klann, W. Krewitt, Y. Moriguchi, J. Munksgaard, and G. Norris, “System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches,” *Environ. Sci. Technol.*, vol. 38, no. 3, pp. 657–664, 2004.

[106] T. E. Swarr, D. Hunkeler, W. Klöpffer, H. L. Pesonen, A. Ciroth, A. C. Brent, and R. Pagan, “Environmental life-cycle costing: A code of practice,” *Int. J. Life Cycle Assess.*, vol. 16, no. 5, pp. 389–391, 2011.

[107] Y. S. Sherif and W. J. Kolarik, “Life cycle costing: Concept and practice,” *Omega*, vol. 9, no. 3, pp. 287-296, 1981.

[108] B. Federal and P. Planning, *GUIDELINES FOR SOCIAL LIFE CYCLE*. 2009.

[109] J. Guinée, “Handbook on life cycle assessment - Operational guide to the ISO

standards," *TheInternational Journal of Life Cycle Assessment*, vol. 6, no. 5, p. 255, 2001.

[110] CALCAS, "Co-ordination Action for innovation in Life-Cycle Analysis for Sustainability Website." .

[111] R. G. and S. M. Frischknecht R., Jungbluth N., Althaus H.-J., Doka G., Dones R., Heck T., Hellweg S., Hischier R., Nemecek T., "The ecoinvent database: Overview and methodological framework," *International Journal of Life Cycle Assessment* vol. 10, no. 8, pp.3-9, 2005. .

[112] M. A. Curran, M. Mann, and G. Norris, "The international workshop on electricity data for life cycle inventories," *J. Clean. Prod.*, vol. 13, no. 8, pp. 853–862, 2005.

[113] F. Berkhout and R. Howes, "The adoption of life-cycle approaches by industry: Patterns and impacts," *Resour. Conserv. Recycl.*, vol. 20, no. 2, pp. 71-94, 1997.

[114] S. Lim and K. T. Lee, "Parallel production of biodiesel and bioethanol in palm-oil-based biorefineries: Life cycle assessment on the energy and greenhouse gases emissions," *Biofuels, Bioprod. Biorefining*, vol. 5, no. 2, pp. 132-150, 2011.

[115] D. K. S. Ng and R. T. L. Ng, "Applications of process system engineering in palm-based biomass processing industry," *Curr. Opin. Chem. Eng.*, vol. 2, no. 4, pp. 448-454, 2013.

[116] A. Singh and S. I. Olsen, "A critical review of biochemical conversion, sustainability and life cycle assessment of algal biofuels," *Appl. Energy*, vol. 88, no. 10, pp. 3548-3555, 2011.

[117] M. L. G. Renó, E. E. S. Lora, J. C. E. Palacio, O. J. Venturini, J. Buchgeister, and O. Almazan, "A LCA (life cycle assessment) of the methanol production from sugarcane bagasse," *Energy*, vol. 36, no. 6, pp. 3716-3726, 2011.

[118] M. L. G. Renó, O. A. D. Olmo, J. C. E. Palacio, E. E. S. Lora, and O. J. Venturini, "Sugarcane biorefineries: Case studies applied to the Brazilian sugar-alcohol industry," *Energy Convers. Manag.*, vol. 86, pp. 981-991, 2014.

[119] L. Lardon, A. Hélias, B. Sialve, J.-P. Steyer, and O. Bernard, "Life-cycle

assessment of biodiesel production from microalgae," *Environ. Sci. Technol.*, vol. 43, no. 17, pp. 6475-6481, 2009.

[120] H. Baumann, "LCA use in Swedish industry," *Int. J. Life Cycle Assess.*, vol. 1, no. 3, 1996.

[121] S. T. Chubbs and B. A. Steiner, "Life Cycle Assessment in the Steel Industry," *Environmental Progress*, vol. 17, no. 2, pp. 92-95, 1998.

[122] S. B. Young and W. H. Vanderburg, "Life cycle assessment (LCA) and industrial materials," in *Proc Int Symp Res Conserv Environ Technol Metall Ind*, pp. 217-227, 1994.

[123] S. S. Muthu, "LCA of cotton shopping bags". *Handbook of life cycle assessment (LCA) of textiles and clothing*., pp. 283-299, 2015.

[124] B. K. Henry, S. J. Russell, S. F. Ledgard, S. Gollnow, S. G. Wiedemann, B. Nebel, D. Maslen, and P. Swan, "LCA of wool textiles and clothing".*Handbook of life cycle assessment (LCA) of textiles and clothing*, pp. 217-254, 2015.

[125] L. Jacquemin, P. Y. Pontalier, and C. Sablayrolles, "Life cycle assessment (LCA) applied to the process industry: A review," *Int. J. Life Cycle Assess.*, vol. 17, no. 8, pp. 1028–1041, 2012.

[126] V. M. Taborianski and R. T. A. Prado, "Comparative evaluation of the contribution of residential water heating systems to the variation of greenhouse gases stock in the atmosphere," *Build. Environ.*, vol. 39, no. 6, pp. 645-652, 2004.

[127] J. A. Fava, "Will the next 10 years be as productive in advancing life cycle approaches as the last 15 years?," *Int. J. Life Cycle Assess.*, vol. 11, pp. 6-8, 2006.

[128] O. Ortiz, F. Castells, and G. Sonnemann, "Sustainability in the construction industry: A review of recent developments based on LCA," *Constr. Build. Mater.*, vol. 23, no. 1, pp. 28–39, 2009.

[129] M. M. Khasreen, P. F. G. Banfill, and G. F. Menzies, "Life-cycle assessment and the environmental impact of buildings: A review," *Sustainability*, vol. 1, no. 3, pp. 674-701, 2009.

[130] A. Sharma, A. Saxena, M. Sethi, V. Shree, and Varun, "Life cycle assessment of buildings: A review," *Renew. Sustain. Energy Rev.*, vol. 15, no. 1, pp. 871–875, 2011.

[131] L. F. Cabeza, L. Rinc??n, V. Vilari??o, G. P??rez, and A. Castell, "Life cycle assessment (LCA) and life cycle energy analysis (LCEA) of buildings and the building sector: A review," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 394–416, 2014.

[132] H. Gregory and P. Bruno, "Life Cycle Assessment applied to urban settlements," *SB10 Mad*, pp. 1–11, 2010.

[133] P. Roy, D. Nei, T. Orikasa, Q. Xu, H. Okadome, N. Nakamura, and T. Shiina, "A review of life cycle assessment (LCA) on some food products," *J. Food Eng.*, vol. 90, no. 1, pp. 1–10, 2009.

[134] J. Braschkat, A. Patyk, M. Quirin, and G. A. Reinhardt, "Life cycle assessment of bread production - a comparison of eight different scenarios," in *Proceedings of the Fourth International Conference on Life Cycle Assessment in the Agri-Food Sector*, Bygholm, Denmark, 2003.

[135] M. V. Holderbeke, N. Sanjuan, T. Geerken, and D. D. Vooght, "The history of bread production: using LCA in the past.," in *Proceedings of the Fourth International Conference on Life Cycle Assessment in the Agri-Food Sector*, Bygholm, Denmark, 2003.

[136] L. Rosing and A. M. Nielsen, "When a hole matters – the story of the hole in a bread fro French hotdog.," in *Proceedings of the Fourth International Conference on Life Cycle Assessment in the Agri-Food Sector*, Bygholm, Denmark, 2003.

[137] A. Hospido, M. T. Moreira, and G. Feijoo, "Environmental analysis of beer production," *Int. J. Agric. Resour. Gov. Ecol.*, vol. 4, no. 2, pp. 152-162, 2005.

[138] C. Koroneos, G. Roumbas, Z. Gabari, E. Papagiannidou, and N. Moussiopoulos, "Life cycle assessment of beer production in Greece," *J. Clean. Prod.*, vol. 13, no. 4, pp. 433-439, 2005.

[139] K. Andersson, T. Ohlsson, and P. Olsson, "Screening life cycle assessment (LCA) of tomato ketchup: A case study," *J. Clean. Prod.*, vol. 6, no. 3–4, pp. 277-288, 1998.

[140] K. Andersson and T. Ohlsson, "Including environmental aspects in production development: A case study of tomato ketchup," *LWT - Food Sci. Technol.*, vol. 32, no. 3, pp. 134-141, 1999.

[141] A. Antón, J. I. Montero, P. Muñoz, and F. Castells, "LCA and tomato production in Mediterranean greenhouses," *Int. J. Agric. Resour. Gov. Ecol.*, vol. 4, no. 2, pp. 102-112, 2005.

[142] M. Breiling, H. Tatsuo, and R. Matsuhashi, "Contribution of rice production to Japanese greenhouse gas emissions applying life cycle assessment as a methodology." Laboratory for Land Resource Sciences, Department of Biological and Environmental Engineering, Graduate School for Agriculture and Life Sciences, The University of Tokyo 32, 1999.

[143] F. Brentrup, J. Küsters, H. Kuhlmann, and J. Lammel, "Application of the Life Cycle Assessment methodology to agricultural production: An example of sugar beet production with different forms of nitrogen fertilisers," *Eur. J. Agron.*, vol. 14, no. 3, pp. 221-233, 2001.

[144] R. Bennett, R. Phipps, A. Strange, and P. Grey, "Environmental and human health impacts of growing genetically modified herbicide-tolerant sugar beet: A life-cycle assessment," *Plant Biotechnol. J.*, vol. 2, no. 4, pp. 273-278, 2004.

[145] M. K. Chauhan, Varun, S. Chaudhary, S. Kumar, and Samar, "Life cycle assessment of sugar industry: A review," *Renew. Sustain. Energy Rev.*, vol. 15, no. 7, pp. 3445-3453, 2011.

[146] B. Mattsson and E. Wallen, "Environmental life cycle assessment (LCA) of organic potatoes.," in *Proceedings of the 26th International Horticultural Congress, ISHS, Acta Horticulturae 691.*, 2003.

[147] M.-J. Yan, J. Humphreys, and N. M. Holden, "An evaluation of life cycle

assessment of European milk production.," *J. Environ. Manage.*, vol. 92, no. 3, pp. 372–379, 2011.

[148] A. Hospido, M. T. Moreira, and G. Feijoo, "Simplified life cycle assessment of galician milk production," *Int. Dairy J.*, vol. 13, no. 10, pp. 783,796, 2003.

[149] C. Cederberg and M. Stadig, "System Expansion and Allocation in Life Cycle Assessment of Milk and Beef Production," *Int. J. Life Cycle Assess.*, vol. 8, no. 6, pp. 350-356, 2003.

[150] C. Cederberg and B. Mattsson, "Life cycle assessment of milk production - a comparison of conventional and organic farming," *J. Clean. Prod.*, vol. 8, no. 1, pp. 49-60, 2000.

[151] I. J. M. De Boer, "Environmental impact assessment of conventional and organic milk production," *Livest. Prod. Sci.*, vol. 80, no. 1–2, pp. 69-77, 2003.

[152] M. de Vries and I. J. M. de Boer, "Comparing environmental impacts for livestock products: A review of life cycle assessments," *Livest. Sci.*, vol. 128, no. 1–3, pp. 1–11, 2010.

[153] K. Hyde, A. Smith, M. Smith, and S. Henningsson, "Challenge of waste minimization in the food and drink industry: A demonstration project in East Anglia, UK," *J. Clean. Prod.*, vol. 9, no. 1, pp. 57-64, 2001.

[154] S. Henningsson, K. Hyde, A. Smith, and M. Campbell, "The value of resource efficiency in the food industry: A waste minimisation project in East Anglia, UK," *J. Clean. Prod.*, vol. 12, no. 5, pp. 505-512, 2004.

[155] P. Muñoz, A. Anton, J. I. Montero, and F. Castells, "Using LCA for the improvement of waste management in greenhouse tomato production," in *Proceedings of the Fourth International Conference on Life Cycle Assessment in the Agri-Food Sector*, 2004.

[156] Y. Hirai, M. Murata, S. Sakai, and H. Takatsuki, "Life cycle assessment for foodwaste recycling and management.," in *Proceedings of the Fourth International Conference on EcoBalance*.

[157] H. A. Udo de Haes and R. Heijungs, “Life-cycle assessment for energy analysis and management,” *Appl. Energy*, vol. 84, no. 7–8, pp. 817–827, 2007.

[158] S. Suh, M. Lenzen, G. J. Treloar, H. Hondo, A. Horvath, G. Huppes, O. Jolliet, U. Klann, W. Krewitt, Y. Moriguchi, J. Munksgaard, and G. Norris, “System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches,” *Environ. Sci. Technol.*, vol. 38, no. 3, pp. 657-664, 2004.

[159] R. L. Cornelissen and G. G. Hirs, “The value of the exergetic life cycle assessment besides the LCA,” *Energy Convers. Manag.*, vol. 43, no. 9–12, pp. 1417-1424, 2002.

[160] M. Wang, H. Lee, and J. Molburg, “Allocation of Energy Use in Petroleum Refineries to Petroleum Products: Implications for Life-Cycle Energy Use and Emission Inventory of Petroleum Transportation Fuels,” *Int. J. Life Cycle Assess.*, vol. 9, no. 1, pp. 34-44, 2004.

[161] I. K. Bhat and R. Prakash, “LCA of renewable energy for electricity generation systems—A review,” *Renew. Sustain. Energy Rev.*, vol. 13, no. 5, pp. 1067–1073, Jun. 2009.

[162] N. Jungbluth, C. Bauer, R. Dones, and R. Frischknecht, “Life cycle assessment for emerging technologies: Case studies for photovoltaic and wind power,” *Int. J. Life Cycle Assess.*, vol. 10, no. 1, pp. 24-34, 2005.

[163] L. Schleisner, “Life cycle assessment of a wind farm and related externalities,” *Renew. Energy*, vol. 20, no. 3, pp. 279-288, 2000.

[164] B. N. Haack, “Net energy analysis of small wind energy conversion systems,” *Appl. Energy*, vol. 9, no. 3, pp. 193-200, 1981.

[165] H. Schaefer and G. Hagedorn, “Hidden energy and correlated environmental characteristics of P.V. power generation,” *Renew. Energy*, vol. 2, no. 2, pp. 159-166, 1992.

[166] R. Prakash and N. K. Bansal, “Energy analysis of solar photovoltaic module production in India,” *Energy Sources*, vol. 17, no. 6, pp. 605-613, 1995.

[167] E. A. Alsema, "Energy pay-back time and CO2 emissions of PV systems," *Prog. Photovoltaics Res. Appl.*, vol. 8, no. 1, pp. 17-25, 2000.

[168] Y. Tripanagnostopoulos, M. Souliotis, R. Battisti, and A. Corrado, "Energy, cost and LCA results of PV and hybrid PV/T solar systems," *Prog. Photovoltaics Res. Appl.*, vol. 13, no. 3, pp. 235-250, 2005.

[169] E. Carnevale, L. Lombardi, and L. Zanchi, "Life cycle assessment of solar energy systems: Comparison of photovoltaic and water thermal heater at domestic scale," *Energy*, vol. 77, pp. 434-446, 2014.

[170] K. Tahara, T. Kojima, and A. Inaba, "Evaluation of CO2 payback time of power plants by LCA," *Energy Convers. Manag.*, vol. 38, no. SUPPL. 1, pp. S615-S620, 1997.

[171] M. Lenzen, "Greenhouse gas analysis of solar-thermal electricity generation," *Sol. Energy*, vol. 65, no. 6, pp. 353-368, 1999.

[172] M. Carpentieri, A. Corti, and L. Lombardi, "Life cycle assessment (LCA) of an integrated biomass gasification combined cycle (IBGCC) with CO2 removal," *Energy Convers. Manag.*, vol. 46, no. 11–12, pp. 1790-1808, 2005.

[173] A. Corti and L. Lombardi, "Biomass integrated gasification combined cycle with reduced CO2 emissions: Performance analysis and life cycle assessment (LCA)," *Energy*, vol. 29, no. 12–15 SPEC, pp. 2109-2124, 2004.

[174] D. Hartmann and M. Kaltschmitt, "Electricity generation from solid biomass via co-combustion with coal. Energy and emission balances from a German case study," *Biomass and Bioenergy*, vol. 16, no. 6, pp. 397-406, 1999.

[175] A. Kadiyala, R. Kommalapati, and Z. Huque, "Evaluation of the life cycle greenhouse gas emissions from hydroelectricity generation systems," *Sustain.*, vol. 8, no. 6, pp. 539, 2016.

[176] P. H. Gleick, "Environmental consequences of hydroelectric development: The role of facility size and type," *Energy*, vol. 17, no. 8, pp. 735-747, 1992.

[177] L. Gagnon and J. F. Van de Vate, "Greenhouse gas emissions from hydropower:

The state of research in 1996," *Energy Policy*, vol. 25, no. 1, pp. 7-13, 1997.

[178] F. Cherubini and A. H. Strømman, "Life cycle assessment of bioenergy systems: State of the art and future challenges," *Bioresour. Technol.*, vol. 102, no. 2, pp. 437–451, 2011.

[179] R. Turconi, A. Boldrin, and T. Astrup, "Life cycle assessment (LCA) of electricity generation technologies: Overview, comparability and limitations," *Renew. Sustain. Energy Rev.*, vol. 28, pp. 555-565, 2013.

[180] J. R. May and D. J. Brennan, "Life cycle assessment of Australian fossil energy options," *Process Saf. Environ. Prot. Trans. Inst. Chem. Eng. Part B*, vol. 81, no. 5, pp. 317-330, 2003.

[181] N. A. Odeh and T. T. Cockerill, "Life cycle analysis of UK coal fired power plants," *Energy Convers. Manag.*, vol. 49, no. 2, pp. 212-220, 2008.

[182] J. R. May and D. J. Brennan, "Erratum: Life Cycle Assessment of Australian Fossil Energy Options (Process Safety and Environmental Protection (September 2003) 81:B5 (317-330))," *Process Saf. Environ. Prot.*, vol. 82, no. 1, 2004.

[183] L. Gagnon, C. Bélanger, and Y. Uchiyama, "Life-cycle assessment of electricity generation options: The status of research in year 2001," *Energy Policy*, vol. 30, no. 14, pp. 1267-1278, 2002.

[184] H. Hondo, "Life cycle GHG emission analysis of power generation systems: Japanese case," *Energy*, vol. 30, no. 11–12 SPEC, pp. 2042-2056, 2005.

[185] N. Nomura, A. Inaba, Y. Tonooka, and M. Akai, "Life-cycle emission of oxidic gases from power-generation systems," *Appl. Energy*, vol. 68, no. 2, pp. 215-227, 2001.

[186] M. Lenzen, "Life cycle energy and greenhouse gas emissions of nuclear energy: A review," *Energy Convers. Manag.*, vol. 49, no. 8, pp. 2178-2199, 2008.

[187] B. K. Sovacool, "Valuing the greenhouse gas emissions from nuclear power: A critical survey," *Energy Policy*, vol. 36, no. 8, pp. 2950-2963, 2008.

[188] H. L. Raadal, L. Gagnon, I. S. Modahl, and O. J. Hanssen, "Life cycle greenhouse

gas (GHG) emissions from the generation of wind and hydro power," *Renew. Sustain. Energy Rev.*, vol. 15, no. 7, pp. 3417-3422, 2011.

[189] F. I. Khan, K. Hawboldt, and M. T. Iqbal, "Life Cycle Analysis of wind-fuel cell integrated system," *Renew. Energy*, vol. 30, no. 2, pp. 157-177, 2005.

[190] S. Krauter and R. Rüther, "Considerations for the calculation of greenhouse gas reduction by photovoltaic solar energy," *Renew. Energy*, vol. 29, no. 3, pp. 345-355, 2004.

[191] H. Mälkki and K. Alanne, "An overview of life cycle assessment (LCA) and research-based teaching in renewable and sustainable energy education," *Renew. Sustain. Energy Rev.*, vol. 69, pp. 218-231, 2017.

[192] R. D. Banker, A. Charnes, and W. W. Cooper, "Some models for estimating technical and scale inefficiencies in data envelopment analysis.," *Manage. Sci.*, vol. 30, no. 9, pp. 1078-1092, 1984.

[193] A. Emrouznejad, B. R. Parker, and G. Tavares, "Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA," *Socioecon. Plann. Sci.*, vol. 42, no. 3, pp. 151-157, 2008.

[194] S. Kaffash and M. Marra, "Data envelopment analysis in financial services: a citations network analysis of banks, insurance companies and money market funds," *Ann. Oper. Res.*, pp. 1-38, 2016.

[195] M. D. Fethi and F. Pasiouras, "Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey," *Eur. J. Oper. Res.*, vol. 204, no. 2, pp. 189-198, 2010.

[196] F. M. Othman, N. A. Mohd-Zamil, S. Z. A. Rasid, A. Vakilbashi, and M. Mokhber, "Data envelopment analysis: A tool of measuring efficiency in banking sector," *Int. J. Econ. Financ. Issues*, vol. 6, no. 3, 2016.

[197] E. Thanassoulis, "Data envelopment analysis and its use in banking," *Interfaces (Providence).*, vol. 29, no. 3, pp. 1–13, 1999.

[198] B. Golany and J. E. Storbeck, "A data envelopment analysis of the operational

efficiency of bank branches," *Interfaces (Providence).*, vol. 29, no. 3, pp. 14–26, 1999.

[199] J. Johnes, "Data envelopment analysis and its application to the measurement of efficiency in higher education," *Econ. Educ. Rev.*, vol. 25, no. 3, pp. 273–288, 2006.

[200] Y. C. Ng and S. K. Li, "Measuring the research performance of Chinese higher education institutions: An application of data envelopment analysis," *Educ. Econ.*, vol. 8, no. 2, pp. 139-156, 2000.

[201] M. A. J. Ramírez and P. A. C. Martínez, "An efficiency comparison between higher education institutions using the Data Envelopment Analysis model," in *23rd International Conference for Production Research, ICPR 2015*.

[202] Z. Alwadood, N. M. Noor, and M. F. Kamarudin, "Performance measure of academic departments using data envelopment analysis," in *ISBEIA 2011 - 2011 IEEE Symposium on Business, Engineering and Industrial Applications*, 2011.

[203] J. Santos and I. Themido, "An application of recent developments of Data Envelopment Analysis to the evaluation of secondary schools in Portugal," *Int. J. Serv. Technol. Manag.*, vol. 2, no. 1–2, pp. 142-160, 2001.

[204] E. Thanassoulis, K. De Witte, J. Johnes, G. Johnes, G. Karagiannis, and C. S. Portela, "Applications of data envelopment analysis in education, " In *Data Envelopment Analysis*, vol. 238. pp. 367-438, 2016.

[205] H. F. A. Gomez, S. A. T. Arias, W. C. Castro, R. Nunez-l, F. Robalino, J. Mauricio, V. Munoz, T. Alvarado-Barros, and J. Mocha-Bonilla, "Grading vs. scientific publications: Data envelopment analysis as a method of teacher assessment," in *Proceedings of 2016 International Conference on Interactive Mobile Communication Technologies and Learning, IMCL 2016*, 2016.

[206] J. Sarkis and S. Talluri, "Using data envelopment analysis for ecoefficiency evaluation, " *Handbook of Sustainable Development Planning: Studies in Modelling and Decision Support*. p. 141, 2013

[207] A. Sözen, İ. Alp, and A. Özdemir, "Assessment of operational and environmental performance of the thermal power plants in Turkey by using data envelopment analysis," *Energy Policy*, vol. 38, no. 10, pp. 6194–6203, Oct. 2010.

[208] K. Sarıca and I. Or, "Efficiency assessment of Turkish power plants using data envelopment analysis," *Energy*, vol. 32, no. 8, pp. 1484–1499, Aug. 2007.

[209] C. H. Liu, S. J. Lin, and C. Lewis, "Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis," *Energy Policy*, vol. 38, no. 2, pp. 1049–1058, Feb. 2010.

[210] V. Fasone and S. Zapata-Aguirre, "Measuring business performance in the airport context: a critical review of literature," *Int. J. Product. Perform. Manag.*, vol. 65, no. 8, pp. 1137-1158, 2016.

[211] E. Thanassoulis, "DEA and its use in the regulation of water companies," *Eur. J. Oper. Res.*, vol. 127, no. 1, pp. 1-13, 2000.

[212] M. J. Mahmoudi, B. Fathi, H. Sajadifar, and A. Shahsavari, "Measuring efficiency of water and wastewater company: A DEA approach," *Res. J. Appl. Sci. Eng. Technol.*, vol. 4, no. 12, pp. 1642-1648, 2012.

[213] M. Molinos-Senante, G. Donoso, and R. Sala-Garrido, "Assessing the efficiency of Chilean water and sewerage companies accounting for uncertainty," *Environ. Sci. Policy*, vol. 61, pp. 116-123, 2016.

[214] M. Molinos-Senante, R. Sala-Garrido, and M. Lafuente, "The role of environmental variables on the efficiency of water and sewerage companies: a case study of Chile," *Environ. Sci. Pollut. Res.*, vol. 22, no. 13, pp. 10242-10253, 2015.

[215] G. Romano and A. Guerrini, "Measuring and comparing the efficiency of water utility companies: A data envelopment analysis approach," *Util. Policy*, vol. 19, no. 3, pp. 202-209, 2011.

[216] R. C. Marques, "Comparing private and public performance of Portuguese water services," *Water Policy*, vol. 10, no. 1, pp. 25-42, 2008.

[217] E. Thanassoulis, “Use of data envelopment analysis in the regulation of UK water utilities: Water distribution,” *Eur. J. Oper. Res.*, vol. 126, no. 2, pp. 436-453, 2000.

[218] M. Molinos-Senante, A. Maziotis, M. Mocholí-Arce, and R. Sala-Garrido, “Accounting for service quality to customers in the efficiency of water companies: Evidence from England and Wales,” *Water Policy*, vol. 18, no. 2, pp. 513-532, 2016.

[219] J. Byrnes, L. Crase, B. Dollery, and R. Villano, “The relative economic efficiency of urban water utilities in regional New South Wales and Victoria,” *Resour. Energy Econ.*, vol. 32, no. 3, pp. 439–455, 2010.

[220] G. Güngör-Demirci, J. Lee, and J. Keck, “Performance Assessment of a Water Utility in California,” in *World Environmental and Water Resources Congress 2016: Watershed Management, Irrigation and Drainage, and Water Resources Planning and Management - Papers from Sessions of the Proceedings of the 2016 World Environmental and Water Resources Congress*, 2016.

[221] F. Dexter and L. O’Neill, “Data envelopment analysis to determine by how much hospitals can increase elective inpatient surgical workload for each specialty,” *Anesth. Analg.*, vol. 99, no. 5, pp. 1492-1500, 2004.

[222] S. Gautam, L. Hicks, T. Johnson, and B. Mishra, “Measuring the Performance of Critical Access Hospitals in Missouri Using Data Envelopment Analysis,” *J. Rural Heal.*, vol. 29, no. 2, pp. 150-158, 2013.

[223] M. Guerra, A. A. De Souza, and D. R. Moreira, “Performance analysis: A study using data envelopment analysis in 26 Brazilian Hospitals,” *J. Health Care Finance*, vol. 38, no. 4, p. 19, 2012.

[224] S. Wang, Q. Ma, and Z. Guan, “Measuring hospital efficiency in China using grey relational analysis and data envelopment analysis,” in *Proceedings of 2007 IEEE International Conference on Grey Systems and Intelligent Services, GSIS 2007*, 2007.

[225] T. Fixler, J. C. Paradi, and X. Yang, “A data envelopment analysis approach for measuring the efficiency of Canadian acute care hospitals,” *Heal. Serv. Manag. Res.*, vol. 27, no. 3–4, pp. 57-69, 2014.

[226] C. Jehu-Appiah, S. Sekidde, M. Adjuik, J. Akazili, S. D. Almeida, F. Nyonator, R. Baltussen, E. Z. Asbu, and J. M. Kirigia, “Ownership and technical efficiency of hospitals: Evidence from Ghana using data envelopment analysis,” *Cost Eff. Resour. Alloc.*, vol. 12, no. 1, p. 9, 2014.

[227] J. M. Kirigia, A. Emrouznejad, and L. G. Sambo, “Measurement of technical efficiency of public hospitals in Kenya: Using data envelopment analysis,” *J. Med. Syst.*, vol. 26, no. 1, pp. 39-45, 2002.

[228] M. A. Fernández and R. Becerra, “An Analysis of Spanish Hotel Efficiency,” *Cornell Hosp. Q.*, vol. 56, no. 3, pp. 248-257, 2015.

[229] Y. Chyan and W.-M. Lu, “Performance benchmarking for Taiwan’s international tourist hotels,” *INFOR*, vol. 44, no. 3, pp. 229-245, 2006.

[230] N. Tumer, “Measuring hotel performance using data envelopment analysis,” *Anatolia*, vol. 21, no. 2, pp. 271-287, 2010.

[231] F.-C. Wolff, “Lift ticket prices and quality in French ski resorts: Insights from a non-parametric analysis,” *Eur. J. Oper. Res.*, vol. 237, no. 3, pp. 1155-1164, 2014.

[232] J. P. Tian, W. Liu, N. Zang, and L. J. Chen, “Review of eco-industrial park development in China,” *Shengtai Xuebao/ Acta Ecol. Sin.*, vol. 36, no. 22, 2016.

[233] M. Izadikhah and R. Farzipoor Saen, “A new data envelopment analysis method for ranking decision making units: An application in industrial parks,” *Expert Syst.*, vol. 32, no. 5, pp. 596-608, 2015.

[234] Y.-D. Liu, “Profitability measurement of UK theme parks: An aggregate approach,” *Int. J. Tour. Res.*, vol. 10, no. 3, pp. 283-288, 2008.

[235] V. Bosetti and G. Locatelli, “A data envelopment analysis approach to the assessment of natural parks’ economic efficiency and sustainability. The case of Italian national parks,” *Sustain. Dev.*, vol. 14, no. 4, pp. 277-286, 2006.

[236] A. Tajbakhsh and E. Hassini, "A data envelopment analysis approach to evaluate sustainability in supply chain networks," *J. Clean. Prod.*, vol. 105,pp. 74-85, 2015.

[237] W. P. Wong, J. Jaruphongsa, and L. H. Lee, "Supply chain performance measurement system: A Monte Carlo DEA-based approach," *Int. J. Ind. Syst. Eng.*, vol. 3, no. 2, pp. 162-188, 2008.

[238] W. P. Wong and K. Y. Wong, "A review on benchmarking of supply chain performance measures," *Benchmarking*, vol. 15, no. 1, pp. 25-51, 2008.

[239] R. Färe, S. Grosskopf, and J. Logan, "The relative efficiency of Illinois electric utilities," *Resour. Energy*, vol. 5, no. 4, pp. 349-367, 1983.

[240] K. Mukherjee, "Energy use efficiency in U.S. manufacturing: A nonparametric analysis," *Energy Econ.*, vol. 30, no. 1, pp. 76–96, 2008.

[241] S. Honma and J. L. Hu, "Total-factor energy efficiency of regions in Japan," *Energy Policy*, vol. 36, no. 2, pp. 821–833, 2008.

[242] A. Hailu and T. S. Veeman, "Non-parametric productivity analysis with undesirable outputs: An application to the Canadian pulp and paper industry," *Am. J. Agric. Econ.*, vol. 83, no. 3, pp. 605-616, 2001.

[243] J. L. Hu and C. H. Kao, "Efficient energy-saving targets for APEC economies," *Energy Policy*, vol. 35, no. 1, pp. 373–382, 2007.

[244] P. Zhou, B. W. Ang, and K. L. Poh, "A survey of data envelopment analysis in energy and environmental studies," *Eur. J. Oper. Res.*, vol. 189, no. 1, pp. 1-18, 2008.

[245] A. Mardani, E. K. Zavadskas, D. Streimikiene, A. Jusoh, and M. Khoshnoudi, "A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency," *Renew. Sustain. Energy Rev.*, 2015.

[246] B. Zhang, J. Bi, Z. Fan, Z. Yuan, and J. Ge, "Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach," *Ecol. Econ.*, vol. 68, no. 1–2, pp. 306-316, 2008.

[247] A.-H. Wu, Y.-Y. Cao, and B. Liu, "Energy efficiency evaluation for regions in China: An application of DEA and Malmquist indices," *Energy Effic.*, vol. 7, no. 3, pp. 429-439, 2014.

[248] J. Chen, M. Song, and L. Xu, "Evaluation of environmental efficiency in China using data envelopment analysis," *Ecol. Indic.*, vol. 52, pp. 577-583, 2015.

[249] M. Li and Q. Wang, "International environmental efficiency differences and their determinants," *Energy*, vol. 78, pp. 411-420, 2014.

[250] M. Goto, A. Otsuka, and T. Sueyoshi, "DEA (Data Envelopment Analysis) assessment of operational and environmental efficiencies on Japanese regional industries," *Energy*, vol. 66, pp. 535-549, 2014.

[251] A. Ç. Köne and T. Büke, "A comparison for Turkish provinces' performance of urban air pollution," *Renew. Sustain. Energy Rev.*, vol. 16, no. 2, pp. 1300-1310, 2012.

[252] S. Suzuki, P. Nijkamp, and P. Rietveld, "A target-oriented data envelopment analysis for energy-environment efficiency improvement in Japan," *Energy Effic.*, vol. 8, no. 3, pp. 433-446, 2015.

[253] J.-L. Hu and S.-C. Wang, "Total-factor energy efficiency of regions in China," *Energy Policy*, vol. 34, no. 17, pp. 3206-3217, 2006.

[254] D. Q. Zhou, F. Y. Meng, Y. Bai, and S. Q. Cai, "Energy efficiency and congestion assessment with energy mix effect: The case of APEC countries," *J. Clean. Prod.*, vol. 142, pp. 819-828, 2017.

[255] F. De Castro Camioto, D. A. Do Nascimento Rebelatto, and R. T. Rocha, "Energy efficiency analysis of BRICS countries: A study using Data Envelopment Analysis | Análise da eficiência energética nos países do BRICS: Um estudo envolvendo a Análise por Envoltória de Dados," *Corros. Eng. Sci. Technol.*, vol. 23, no. 1, pp. 192-203, 2016.

[256] M. Camarero, J. Castillo, A. J. Picazo-Tadeo, and C. Tamarit, "Eco-Efficiency and Convergence in OECD Countries," *Environ. Resour. Econ.*, vol. 55, no. 1, pp. 87-

106, 2013.

[257] S. Mallikarjun and H. F. Lewis, "Energy technology allocation for distributed energy resources: A strategic technology-policy framework," *Energy*, vol. 72, pp. 783-799, 2014.

[258] X.-P. Zhang, X.-M. Cheng, J.-H. Yuan, and X.-J. Gao, "Total-factor energy efficiency in developing countries," *Energy Policy*, vol. 39, no. 2, pp. 644-650, 2011.

[259] J. Li, X. Geng, and J. Li, "A comparison of electricity generation system sustainability among G20 countries," *Sustainability*, vol. 8, no. 12, p. 1276, 2016.

[260] S. Blancard and E. Martin, "Energy efficiency measurement in agriculture with imprecise energy content information," *Energy Policy*, vol. 66, pp. 198-208, 2014.

[261] J. Morfeldt and S. Silveira, "Capturing energy efficiency in European iron and steel production—comparing specific energy consumption and Malmquist productivity index," *Energy Effic.*, vol. 7, no. 6, pp. 955-972, 2014.

[262] Y.-M. Wei, H. Liao, and Y. Fan, "An empirical analysis of energy efficiency in China's iron and steel sector," *Energy*, vol. 32, no. 12, pp. 2262-2270, 2007.

[263] R. Pahlavan, S. Rafiee, and M. Omid, "Assessing the technical efficiency in potato production in Iran," *Int. J. Green Energy*, vol. 9, no. 3, pp. 229-242, 2012.

[264] B. Khoshnevisan, S. Rafiee, M. Omid, and H. Mousazadeh, "Applying data envelopment analysis approach to improve energy efficiency and reduce GHG (greenhouse gas) emission of wheat production," *Energy*, vol. 58, pp. 588-593, 2013.

[265] J. Raczka, "Explaining the performance of heat plants in Poland," *Energy Economics*, vol. 23, no. 4, pp. 355-370, 2001.

[266] J. Munksgaard, L.-L. Pade, and P. Fristrup, "Efficiency gains in Danish district heating. Is there anything to learn from benchmarking?," *Energy Policy*, vol. 33, no. 15, pp. 1986-1997, 2005.

[267] D. Hawdon, "Efficiency, performance and regulation of the international gas

industry-a bootstrap DEA approach," *Energy Policy*, vol. 31, no. 11, pp. 1167-1178, 2003.

[268] H. A. Kashani, "Regulation and efficiency: An empirical analysis of the United Kingdom continental shelf petroleum industry," *Energy Policy*, vol. 33, no. 7, pp. 915-925, 2005.

[269] S. Munisamy and B. Arabi, "Eco-efficiency change in power plants: Using a slacks-based measure for the meta-frontier Malmquist-Luenberger productivity index," *J. Clean. Prod.*, vol. 105, pp. 218-232, 2015.

[270] R. G. Thompson, E. Lee, and R. M. Thrall, "DEA/AR-efficiency of U.S. independent oil/gas producers over time," *Comput. Oper. Res.*, vol. 19, no. 5, pp. 377-391, 1992.

[271] M. Kulshreshtha and J. K. Parikh, "Study of efficiency and productivity growth in opencast and underground coal mining in India: A DEA analysis," *Energy Econ.*, vol. 24, no. 5, pp. 439-453, 2002.

[272] T. Chien and J.-L. Hu, "Renewable energy and macroeconomic efficiency of OECD and non-OECD economies," *Energy Policy*, vol. 35, no. 7, pp. 3606-3615, 2007.

[273] C. Woo, Y. Chung, D. Chun, H. Seo, and S. Hong, "The static and dynamic environmental efficiency of renewable energy: A Malmquist index analysis of OECD countries," *Renew. Sustain. Energy Rev.*, vol. 47, pp. 367-376, 2015.

[274] H. Wang, "A generalized MCDA-DEA (multi-criterion decision analysis-data envelopment analysis) approach to construct slacks-based composite indicator," *Energy*, vol. 80, pp. 114-122, 2015.

[275] V.-N. Hoang and D. S. P. Rao, "Measuring and decomposing sustainable efficiency in agricultural production: A cumulative exergy balance approach," *Ecol. Econ.*, vol. 69, no. 9, pp. 1765-1776, 2010.

[276] G. Egilmez, M. Kucukvar, and O. Tatari, "Sustainability assessment of U.S. manufacturing sectors: An economic input output-based frontier approach," *J.*

Clean. Prod., vol. 53, pp. 91-102, 2013.

[277] E. Houshyar, H. Azadi, M. Almassi, M. J. Sheikh Davoodi, and F. Witlox, "Sustainable and efficient energy consumption of corn production in Southwest Iran: Combination of multi-fuzzy and DEA modeling," *Energy*, vol. 44, no. 1, pp. 672-681, 2012.

[278] F. D. C. Camioto, E. B. Mariano, and D. A. D. N. Rebelatto, "Efficiency in Brazil's industrial sectors in terms of energy and sustainable development," *Environ. Sci. Policy*, vol. 37, pp. 50-60, 2014.

[279] C. Bampatsou, S. Papadopoulos, and E. Zervas, "Technical efficiency of economic systems of EU-15 countries based on energy consumption," *Energy Policy*, vol. 55, pp. 426-434, 2013.

[280] M. Robaina-Alves, V. Moutinho, and P. MacEdo, "A new frontier approach to model the eco-efficiency in European countries," *J. Clean. Prod.*, vol. 103, pp. 562-573, 2015.

[281] M.-C. Chang, "Energy intensity, target level of energy intensity, and room for improvement in energy intensity: An application to the study of regions in the EU," *Energy Policy*, vol. 67, pp. 648-655, 2014.

[282] R.-Z. Pang, Z.-Q. Deng, and J.-L. Hu, "Clean energy use and total-factor efficiencies: An international comparison," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 1158-1171, 2015.

[283] I. Vázquez-Rowe and D. Iribarren, "Review of Life-Cycle Approaches Coupled with Data Envelopment Analysis: Launching the CFP + DEA Method for Energy Policy Making," *Sci. World J.*, vol. 2015, pp. 1–10, 2015.

[284] D. Iribarren, A. Hospido, M. T. Moreira, and G. Feijoo, "Benchmarking environmental and operational parameters through eco-efficiency criteria for dairy farms.," *Sci. Total Environ.*, vol. 409, no. 10, pp. 1786–98, Apr. 2011.

[285] I. Vázquez-Rowe, P. Villanueva-Rey, D. Iribarren, M. Teresa Moreira, and G. Feijoo, "Joint life cycle assessment and data envelopment analysis of grape

production for vinification in the Rías Baixas appellation (NW Spain)," *J. Clean. Prod.*, vol. 27, pp. 92–102, May 2012.

[286] A. Mohammadi, S. Rafiee, A. Jafari, T. Dalgaard, M. T. Knudsen, A. Keyhani, S. H. Mousavi-Avval, and J. E. Hermansen, "Potential greenhouse gas emission reductions in soybean farming: a combined use of Life Cycle Assessment and Data Envelopment Analysis," *J. Clean. Prod.*, vol. 54, pp. 89–100, Sep. 2013.

[287] A. Mohammadi, S. Rafiee, A. Jafari, A. Keyhani, T. Dalgaard, M. T. Knudsen, T. L. T. Nguyen, R. Borek, and J. E. Hermansen, "Joint Life Cycle Assessment and Data Envelopment Analysis for the benchmarking of environmental impacts in rice paddy production," *J. Clean. Prod.*, vol. 106, pp. 521-532, 2015.

[288] A. D. Soteriades, P. Faverdin, S. Moreau, T. Charroin, M. Blanchard, and A. W. Stott, "An approach to holistically assess (dairy) farm eco-efficiency by combining Life Cycle Analysis with Data Envelopment Analysis models and methodologies," *Animal*, vol. 10, no. 11, pp. 1-12, 2016.

[289] I. Vázquez-Rowe, D. Iribarren, A. Hospido, M. T. Moreira, and G. Feijoo, "Computation of operational and environmental benchmarks within selected galician fishing fleets," *J. Ind. Ecol.*, vol. 15, no. 5, pp. 776-795, 2011.

[290] Á. Avadí, I. Vázquez-Rowe, and P. Fréon, "Eco-efficiency assessment of the Peruvian anchoveta steel and wooden fleets using the LCA+DEA framework," *J. Clean. Prod.*, vol. 70, pp. 118–131, May 2014.

[291] Y. Lorenzo-Toja, I. Vázquez-Rowe, S. Chenel, D. Marín-Navarro, M. T. Moreira, and G. Feijoo, "Eco-efficiency analysis of Spanish WWTPs using the LCA+DEA method," *Water Res.*, vol. 68, pp. 651-666, 2015.

[292] D. Iribarren and I. Vázquez-rowe, "Is Labor a Suitable Input in LCA + DEA Studies? Insights on the Combined Use of Economic, Environmental and Social Parameters," *Soc. Sci.*, vol. 2, no. 3, pp. 114–130, 2013.

[293] D. Iribarren, M. Martín-Gamboa, T. O'Mahony, and J. Dufour, "Screening of socio-economic indicators for sustainability assessment: a combined life cycle

assessment and data envelopment analysis approach," *Int. J. Life Cycle Assess.*, vol. 21, no. 2, pp. 202-214, 2016.

[294] Á. Galán-Martín, G. Guillén-Gosálbez, L. Stamford, and A. Azapagic, "Enhanced data envelopment analysis for sustainability assessment: A novel methodology and application to electricity technologies," *Comput. Chem. Eng.*, vol. 90, pp. 188-200, 2016.

[295] N. Sanjuan, J. Ribal, G. Clemente, and M. L. Fenollosa, "Measuring and Improving Eco-efficiency Using Data Envelopment Analysis: A Case Study of Mahón-Menorca Cheese," *J. Ind. Ecol.*, vol. 15, no. 4, pp. 614–628, 2011.

[296] P. Jan, D. Dux, M. Lips, M. Alig, and M. Dumondel, "On the link between economic and environmental performance of Swiss dairy farms of the alpine area," *Int. J. Life Cycle Assess.*, vol. 17, no. 6, pp. 706–719, 2012.

[297] Y. Barba-Gutiérrez, B. Adenso-Díaz, and S. Lozano, "Eco-Efficiency of Electric and Electronic Appliances: A Data Envelopment Analysis (DEA)," *Environ. Model. Assess.*, vol. 14, no. 4, pp. 439–447, Jan. 2008.

[298] S. Lozano, B. Adenso-Díaz, and Y. Barba-Gutiérrez, "Russell non-radial eco-efficiency measure and scale elasticity of a sample of electric/electronic products," *J. Franklin Inst.*, vol. 348, no. 7, pp. 1605–1614, 2011.

[299] O. Tatari and M. Kucukvar, "Eco-efficiency of construction materials: Data envelopment analysis," *J. Constr. Eng. Manag.*, vol. 138, no. 6, pp. 733-741, 2012.

[300] C. Kao and S. T. Liu, "Fuzzy efficiency measures in data envelopment analysis," *Fuzzy Sets Syst.*, vol. 113, no. 3, pp. 427–437, 2000.

[301] J. K. Sengupta, "A fuzzy systems approach in data envelopment analysis," *Comput. Math. with Appl.*, vol. 24, no. 8–9, pp. 259–266, Oct. 1992.

[302] M. Zerafat Angiz L., A. Emrouznejad, and A. Mustafa, "Fuzzy assessment of performance of a decision making units using DEA: A non-radial approach," *Expert Syst. Appl.*, vol. 37, no. 7, pp. 5153-5157, 2010.

[303] D. Aigner, C. A. K. Lovell, and P. Schmidt, “Formulation and estimation of stochastic frontier production function models,” *J. Econom.*, vol. 6, no. 1, pp. 21–37, Jul. 1977.

[304] C. J. O’Donnell, R. G. Chambers, and J. Quiggin, “Efficiency analysis in the presence of uncertainty,” *J. Product. Anal.*, vol. 33, no. 1, pp. 1-17, 2010.

[305] W. W. Cooper, K. S. Park, and G. Yu, “Idea and AR-IDEA: models for dealing with imprecise data in DEA,” *Manage. Sci.*, vol. 45, no. 4, pp. 597–607, 1999.

[306] M. Azadi, R. F. Saen, and M. Tavana, “Supplier selection using chance-constrained data envelopment analysis with non-discretionary factors and stochastic data,” *Int. J. Ind. Syst. Eng.*, vol. 10, no. 2, p. 167, 2012.

[307] J. K. Sengupta, “Data envelopment analysis for efficiency measurement in the stochastic case,” *Comput. Oper. Res.*, vol. 14, no. 2, pp. 117–129, Jan. 1987.

[308] L. Simar and P. W. Wilson, “Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models,” *Manage. Sci.*, vol. 44, no. 1, pp. 49–61, 1998.

[309] S. E. Atkinson and P. W. Wilson, “Comparing mean efficiency and productivity scores from small samples: A bootstrap methodology,” *J. Product. Anal.*, vol. 6, no. 2, pp. 137–152, Jul. 1995.

[310] S. J. Sadjadi and H. Omrani, “Data envelopment analysis with uncertain data: An application for Iranian electricity distribution companies,” *Energy Policy*, vol. 36, no. 11, pp. 4247-4254, 2008.

[311] C. Kao and S.-T. Liu, “Stochastic data envelopment analysis in measuring the efficiency of Taiwan commercial banks,” *Eur. J. Oper. Res.*, vol. 196, no. 1, pp. 312–322, 2009.

[312] R. G. Dyson and E. a Shale, “Data envelopment analysis, operational research and uncertainty,” *J. Oper. Res. Soc.*, vol. 61, no. 1, pp. 25–34, 2010.

[313] G. Egilmez, S. Gumus, M. Kucukvar, and O. Tatari, “A fuzzy data envelopment analysis framework for dealing with uncertainty impacts of input-output life cycle

assessment models on eco-efficiency assessment," *J. Clean. Prod.*, vol. 129, pp. 622-636, 2015.

[314] A. Azadeh, Y. Rahimi, M. Zarrin, A. Ghaderi, and N. Shabanpour, "A decision-making methodology for vendor selection problem with uncertain inputs," *Transp. Lett.*, pp. 1-18, 2016.

[315] S. Bray, L. Caggiani, and M. Ottomanelli, "Measuring transport systems efficiency under uncertainty by fuzzy sets theory based data envelopment analysis: Theoretical and practical comparison with traditional DEA model," in *Transportation Research Procedia*, vol. 5, pp. 186-200, 2015.

[316] M. Abbasi and M. A. Kaviani, "Operational efficiency-based ranking framework using uncertain DEA methods: An application to the cement industry in Iran," *Manag. Decis.*, vol. 54, no. 4, pp. 902-928, 2016.

[317] P. Wanke, C. P. Barros, and A. Emrouznejad, "Assessing productive efficiency of banks using integrated Fuzzy-DEA and bootstrapping: A case of Mozambican banks," *Eur. J. Oper. Res.*, vol. 249, no. 1, pp. 378-389, 2016.

[318] M. Shwartz, J. F. Burgess, and J. Zhu, "A DEA based composite measure of quality and its associated data uncertainty interval for health care provider profiling and pay-for-performance," *Eur. J. Oper. Res.*, vol. 253, no. 2, pp. 489-502, 2016.

[319] M. Dotoli, N. Epicoco, M. Falagario, and F. Sciancalepore, "A stochastic cross-efficiency data envelopment analysis approach for supplier selection under uncertainty," *Int. Trans. Oper. Res.*, vol. 23, no. 4, 2016.

[320] M. Dotoli, N. Epicoco, M. Falagario, and F. Sciancalepore, "Supplier evaluation and selection under uncertainty via an integrated model using cross-efficiency Data Envelopment Analysis and Monte Carlo simulation," in *19th IEEE International Conference on Emerging Technologies and Factory Automation, ETFA 2014*, 2014.

[321] N. Costantino, M. Dotoli, M. Falagario, and F. Sciancalepore, "A model using

Data Envelopment Analysis for the cross evaluation of suppliers under uncertainty," in *KMIS 2011 - Proceedings of the International Conference on Knowledge Management and Information Sharing*, 2011.

[322] M. Torres-Jiménez, C. R. García-Alonso, L. Salvador-Carulla, and V. Fernández-Rodríguez, "Evaluation of system efficiency using the Monte Carlo DEA: The case of small health areas," *Eur. J. Oper. Res.*, vol. 242, no. 2, pp. 525-535, 2015.

[323] D. E. Bell, H. Raiffa, and A. Tversky, *Decision making: Descriptive, normative, and perspective interactions*. Cambridge University Press, 1988.

[324] I. E. Grossmann, J. A. Caballero, and H. Yeomans, "Advances in mathematical programming for the synthesis of process systems," *Lat. Am. Appl. Res.*, vol. 30, no. 4, pp. 263-284, 2000.

[325] G. B. Dantzig, "Linear Programming," *Operations Research*, vol. 50, no. 1. pp. 42–47, 2002.

[326] A. Charnes and W. W. Cooper, *Management Models and Industrial Applications of Linear Programming*. vol. 1, New York: Wiley, 1961.

[327] W. Leontief, "Domestic Production and Foreign Trade; The American Capital Position Re-Examined," in *Proceedings of the American Philosophical Society, vol. 97, no. 4*, 1953, pp. 332–349.

[328] G. Tintner, "Game theory, linear programming and input-output analysis," *Zeitschrift für Natl.*, vol. 17, no. 1, pp. 1-38, 1957.

[329] T. C. Koopmans, "An analysis of production as an efficient combination of activities." Cowles Commission for Research in Econimics Monograpf no. 13. Wiley, New York., 1951.

[330] R. W. Shephard, "Cost and Production Funtions," *Princeton University Press*, Princeton, 1953.

[331] J. . Boles, "Efficiency Squared-Efficient Computation of Efficiency Indexes," in *Thirty-ninth Ann. Meeting, Western Farm Econ. Assoc.*, 1966.

[332] R. G. Bressler, "The Measurement of Productive Efficiency," in *Thirty-ninth Ann.*

Meeting, Western Farm Econ. Assoc., vol. 39, pp. 129-136, 1966.

[333] W. D. Seitz, “Efficiency Measures for Steam-Electric Generation Plants,” in *Thirty-ninth Ann. Meeting, Western Farm Econ. Assoc.*, vol. 39, pp. 143-151, 1966.

[334] B. L. Sitorus, “Productive Efficiency and Redundant Factors of Production in Traditional Agriculture of Underdeveloped Countries,” in *Thirty-ninth Ann. Meeting, Western Farm Econ. Assoc.*, vol. 39, pp. 153-158, 1966.

[335] C. P. Timmer, “Using a probabilistic frontier production function to measure technical efficiency,” *J. Polit. Econ.*, pp. 776–794, 1971.

[336] S. N. Afriat, “Efficiency estimation of production functions,” *Int. Econ. Rev. (Philadelphia).*, vol. 13, no. 3, pp. 568–98, 1972.

[337] W. E. Diewert and C. Parkan, “Linear Programming Tests of Regularity Conditions for Production Functions,” in *Quantitative Studies on Production and Prices*, K. N. and R. W. S. W. Eichhorn, R. Henn, Ed. Vienna:Physica Verlag., 1983, pp. 131–158.

[338] L. Simar and P. W. Wilson, “Statistical Inference in Nonparametric Frontier Models: Recent Developments and Perspectives. ”, *The Measurement of Productive Efficiency (H. Fried, CAK Lovell and SS Schmidt Eds)*, Oxford University Press, Inc,pp. 421-521, 2008.

[339] L. Simar and P. W. Wilson, “Testing restrictions in nonparametric efficiency models,” *Commun. Stat. Part B Simul. Comput.*, vol. 30, no. 1, pp. 159-184, 2001.

[340] W. W. Cooper, L. M. Seifors, and K. Tone, *Introduction to Data Envelopment Analysis and its Uses: with DEA-solver software and references.*. Springer Science& Business Media, 2006.

[341] W. W. Cooper, L. M. Seiford, and K. Tone, *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Boston, MA: Springer US, 2007.

[342] T. W. Jonsbråten, R. J.-B. Wets, and D. L. Woodruff, “A class of stochastic

programs with decision dependent random elements," *Ann. Oper. Res.*, vol. 82, pp. 83-106, 1998.

[343] Z. Li and M. G. Ierapetritou, "Process scheduling under uncertainty using multiparametric programming," *AIChE J.*, vol. 53, no. 12, pp. 3183-3203, 2007.

[344] N. V. Sahinidis, "Optimization under uncertainty: State-of-the-art and opportunities," *Comput. Chem. Eng.*, vol. 28, no. 6–7, pp. 971-983, 2004.

[345] J. J. Krüger, "A Monte Carlo study of old and new frontier methods for efficiency measurement," *Eur. J. Oper. Res.*, vol. 222, no. 1, pp. 137-148, 2012.

[346] R. D. Banker, A. Charnes, W. W. Cooper, and A. Maindiratta, "A comparison of DEA and translog estimates of production functions using simulated data from a known technology.," in *Applications of Modern Production Theory: Efficiency and Productivity.*, A. Dogramaci and R. Färe, Eds. Kluwer, Boston (Mass.), 1987, pp. 33–58.

[347] R. D. Banker, V. M. Gadh, and W. L. Gorr, "A Monte Carlo comparison of two production frontier estimation methods: Corrected ordinary least squares and data envelopment analysis," *Eur. J. Oper. Res.*, vol. 67, no. 3, pp. 332-343, 1993.

[348] R. D. Banker, H. Chang, and W. W. Cooper, "Simulation studies of efficiency, returns to scale and misspecification with nonlinear functions in DEA," *Ann. Oper. Res.*, vol. 66, no. 4, pp. 231-253, 1996.

[349] R. Heijungs and R. Frischknecht, "Representing Statistical Distributions for Uncertain Parameters in LCA Relationships between mathematical forms , their representation in EcoSpold ," *Int. J. Life Cycle Assess.*, vol. 10, no. 4, pp. 248–254, 2005.

[350] B. P. Weidema, "Multi-user test of the data quality matrix for product life cycle inventory data," *Int. J. Life Cycle Assess.*, vol. 3, no. 5, pp. 259–265, 1998.

[351] Weidema, Bo Pedersen, et al., "Overview and methodology: Data quality guideline for the ecoinvent database version 3," *Swiss Centre for Life Cycle Inventories*, vol. 3, no. 1, 2013.

[352] R. Fourer, D. M. Gay, and B. W. Kernighan, "AMPL: A Mathematical Programming Language," *Manage. Sci.*, vol. 36, pp. 519–554, 1990.

[353] J., Bisschop, M., Roelofs, "AIMMS User ' s Guide - Web Services www.aimms.com.", 2006 (accessed April 2017).

[354] IBM, *IBM ILOG CPLEX Optimization Studio OPL Language User's Manual*. 2015.

[355] R. E. Rosenthal, "GAMS — A User 's Guide," *GAMS Doc. 24.6.*, no. January, pp. 1–316, 2016.

[356] E. Castillo, A. J. Conejo, P. Pedregal, R. Garcia, and N. Alguacil, "Building and Solving Mathematical Programming Models in Engineering and Science," vol. 4, p. 568, 2001.

[357] D. Chattopadhyay, "Application of general algebraic modeling system to power system optimization," *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 15–22, 1999.

[358] G. Wernet, C. Bauer, B. Steubing, J. Reinhard, and B. Moreno-Ruiz, E. Weidema, "The ecoinvent database version 3 (part I): overview and methodology.," *The International Journal of Life Cycle Assessment, [online] 21(9)*, 2016. [Online]. Available: http://link.springer.com/10.1007/s11367-016-1087-8. [Accessed: 30-Nov-2015].

[359] "SPINE@CPM database. Competence Center in Environmental Assessment of Product and Material Systems (CPM)." Chalmers University of Technology, Goteborg, 2007.

[360] JEMAI, "Japan Environmental Management Association for Industry (JEMAI). JEMAI database.," 2007. Available: http://www.jemai.or.jp/english/index.cfm (accessed April 2017).

[361] NREL, "National Renewable Energy Laboratory (NREL). US Life Cycle Inventory Database. NREL, Golden, CO.," 2004. Available: http://www.nrel.gov/lci/ (accessed April 2017).

[362] UBA, "Umweltbundesamt (German Environmental Protection Agency). PROBAS

Database.," 2007. Available: http://www.probas.umweltbundesamt.de/php/index.php (accessed April 2017).

[363] RMIT, "Centre for Design, RMIT University. Australian LCI Database," 2007. Available: http://www.auslci.com/ (accessed April 2017).

[364] European Commission, "European Commission, Directorate General Joint Research Centre (JRC), European Reference Life Cycle Database (ELCD).," *2007*. .

[365] "GABI 4.3," *PE International: Stuttgart, Germany*, 2007. Available: www.gabi-%0Asoftware.com (accessed April 2017).

[366] "ELCD," 2006. [Online]. Available: http://eplca.jrc.ec.europa.eu/ELCD3/.

[367] European Parliament and Council of the European Union, *Decision No 406/2009/EC of the European Parliament and of the Council of 23 April 2009 on the effort of Member States to reduce their greenhouse gas emissions to meet the Community's greenhouse gas emission reduction commitments up to 2020*. 2009, pp. 136–148.

[368] R. Frischknecht, A. Braunschweig, P. Hofstetter, and P. Suter, "Human health damages due to ionising radiation in life cycle impact assessment," *Environ. Impact Assess. Rev.*, vol. 20, no. 2, pp. 159–189, Apr. 2000.

[369] "Internatiol Energy Agency (IEA)." Available: http://www.planete-energies.com/en/medias/infographics/global-energy-mix-1990-2035 (accessed April 2017).

[370] Y. Zhang, J. McKechnie, D. Cormier, R. Lyng, W. Mabee, A. Ogino, and H. L. Maclean, "Life cycle emissions and cost of producing electricity from coal, natural gas, and wood pellets in Ontario, Canada.," *Environ. Sci. Technol.*, vol. 44, no. 1, pp. 538–44, Jan. 2010.

[371] L. Van Oers, "CML-IA–Database Containing Characterization Factors for Life Cycle Impact Assessment (Centre of Environmental Science (CML)),"download unter http://www. leidenuniv. nl/interfac/-cml/ssp/index. html, Leiden, 2004

(accessed April 2017).

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

[373] D. Iribarren, M. Martín-Gamboa, and J. Dufour, "Environmental benchmarking of wind farms according to their operational performance," *Energy*, vol. 61, pp. 589–597, 2013.

[374] K. B. Atici and V. V. Podinovski, "Using data envelopment analysis for the assessment of technical efficiency of units with different specialisations: An application to agriculture," *Omega*, vol. 54, pp. 72–83, Jul. 2015.

[375] J. A. Murtha, "Incorporating historical data in Monte Carlo simulation," in *Proceedings - Petroleum Computer Conference*, vol. 6, no. 02, pp. 11-17, 1993.

[376] S. Jeon and B. Hong, "Monte Carlo simulation-based traffic speed forecasting using historical big data," *Futur. Gener. Comput. Syst.*, vol. 65, pp. 182-195, 2015.

[377] S. Sciencedirect, C. Ball, A. Cb, M. S. Poland, E. B. V All, and I. Numerical, "Science of the Total Environment Stochastic approach to municipal solid waste land fi ll life based on the contaminant transit time modeling using the Monte Carlo (MC) simulation Bogus ł aw Bieda □," vol. 442, pp. 489–496, 2013.

8. Appendices

8.1 Publications

Ewertowska, A., Galán-Martín, A., Guillén-Gosálbez, G., Gavaldà, 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. doi:10.1016/j.jclepro.2015.11.100. http://www.sciencedirect.com/science/article/pii/S0959652615018326

Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis. Ewertowska, A., Galán-Martín, A., Guillén-Gosálbez, G., Gavaldà, J., Jiménez, L.AIChE 2015, 2015 AIChE Annual Meeting. https://aiche.confex.com/aiche/2015/webprogram/Paper432557.html

Ewertowska, A., Gavaldà, J., Jiménez, L., Guillén-Gosálbez, G. Combined use of life cycle assessment, data envelopment analysis and Monte Carlo simulation for quantifying environmental efficiencies under uncertainty. (**Submitted** to Journal of Cleaner Production, March 2017)

Torres, A., Ewertowska, A., Pozo, C., Gavaldà, J., Jiménez, L., Guillén-Gosálbez, G. Eco-efficiency of insulation materials: the combined use of life cycle assement, data envelopment analysis and Energy Plus (***Manuscript in progress***).