# AN INTEGRATED APPROACH FOR ENERGY EFFICIENCY ANALYSIS IN EUROPEAN UNION COUNTRIES

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## ABSTRACT

This paper evaluates the energy efficiency of EU countries over the period 2000–2010. At the first stage, Data Envelopment Analysis (DEA) is employed, combining multiple energy consumption data, economic outputs, structural indicators, and environmental factors. The efficiency estimates obtained from the analysis are evaluated in a second stage through a multiple criteria decision aiding methodology (MCDA). The proposed non-parametric approach combining DEA with MCDA enables the modeling of the problem in an integrated manner, providing not only energy efficiency estimates, but also supporting the analysis of the main contributing factors, as well as the development of a benchmarking model for energy efficiency evaluation in country level.

**Keywords**: Energy efficiency, Data envelopment analysis, Multiple criteria decision aiding

## 1. INTRODUCTION

In the 1970s and early 1980s, energy efficiency emerged as a major issue for sustainable economic growth. Even after the counter-oil shock of 1986 and the decline of oil prices, environmental concerns continued to rise, especially in the context of the growing debates on global warming and climate change, which gave energy efficiency improvement a new perspective. The latter, along with the world energy crisis of 1993, and in combination with the sharp increase in oil prices during the 2000s, have brought today energy efficiency into the policy agenda of many countries as a top priority issue.

Governments are increasingly aware of the urgent need to make better use of energy resources. The benefits of more efficient energy use are well known, including reduced investments in energy infrastructure, lower fossil fuel dependency, increased competitiveness, and improved consumer welfare. Efficiency gains also deliver environmental benefits by reducing greenhouse gas emissions and air pollution. It is therefore not surprising that tracking economy-wide energy efficiency trends is being undertaken in many countries on a regular basis (Ang et al., 2010).

Energy efficiency has now been recognized as an essential component of sustainable development policies, which seek to achieve a well-balanced trade-off between economic growth and competitiveness, energy security, and environmental sustainability. However, as McKibbin et al. (2011) point out, adoption rates for energy efficient technologies fall short of the levels that many believe are justified by the potential returns on such investments. Therefore, the re-evaluation of the connections between energy efficiency, growth, and economic performance is of major importance and has direct implications for the policies implemented at the country level. Researchers have developed appropriate indicators for monitoring economy-wide energy efficiency trends over time or comparing energy efficiency performances across countries/regions.

In this paper, the evaluation of energy efficiency is considered in a multidimensional context. The proposed approach is based on the consideration of data related to environmental pollution, country characteristics, information on the use of renewable sources, as well as energy consumption data. The framework adopted in this paper attempts to isolate the “underlying energy efficiency” for each country after controlling for economic output, environmental issues, as well as effects due to differences in the structure of the economy. Consequently, once the latter effects are adequately controlled for, the estimation of the underlying energy efficiency for each country is performed which shows i) the change of efficiency over the estimation period and ii) the differences in efficiency across the panel of countries aligned with Filippini and Hunt (2011). The analysis is based on data collected for European Union countries over the period 2000–2010.

On the methodological side, at the first stage we use data envelopment analysis (DEA) to measure the relative efficiency of the countries. DEA is a popular nonparametric efficiency analysis technique with many applications in energy management and environmental planning (see among

others, Boyd and Pang, 2000; Hu and Kao, 2007; Ramanathan, 2005; Zhou et al., 2007; Zhou et al., 2008a). At the second stage, the DEA efficiency classifications are used as inputs to a multicriteria decision making approach (MCDA), which is employed to build an operational model that combines energy efficiency, economic, and environmental indicators. The resulting multicriteria model evaluates all countries in a common setting and it can be easily used for benchmarking purposes.

The remainder of this paper has the following structure: Section 2 presents a literature review, followed in section 3 by the presentation of the main methodological tools employed in the analysis. Section 4 describes the data and variables used in the analysis, whereas section 5 presents and discusses the obtained results. Finally, section 6 concludes the paper and outlines some future research directions.

## 2. LITERATURE REVIEW

Energy efficiency is a difficult concept to define. It is often confused with energy conservation, but conservation simply means using less energy, whereas efficiency implies meeting a given demand with a lower use of resources (Gunn, 1997). The directive on energy end-use efficiency and energy services of the European Council and the Parliament defines energy efficiency as "a ratio between an output of performance, service, goods or energy, and an input of energy" (Directive 2006/32/EC; EU, 2006). An even trickier task than defining energy efficiency is measuring it. In order to measure energy efficiency changes over time at the economy-wide level, and to be able to make cross-country comparisons, a rich body of research has emerged. On one hand, various efficiency-related indicators have been developed, with the ratio of total national primary energy consumption to GDP (energy intensity) being among the most popular ones. On the other hand, most of the researchers focus on developing methods to accurately decompose the aggregate energy intensity into the true change in intensities at the disaggregated sectorial levels, and to understand the effects of structural changes in the economy.

Another line of research examines energy efficiency within a framework where energy is one of the many inputs of production, with the most widely used technique being data envelopment analysis (DEA). A recent literature survey by Zhou et al. (2008b) lists a total of 100 studies published from 1983 to 2006 using DEA in the area of energy and environmental analysis. According to the survey, 72 of these studies were published between 1999 and 2006, which shows a rapid increase in the number of studies using DEA. Zhou and Ang (2008) presented several DEA-type linear programming methods for measuring economy-wide energy efficiency performance using labor, capital stock and energy consumption as inputs, and GDP as the desirable output. DEA has also been widely used in energy efficiency studies at sector, sub-sector or firm level.

Bampatsou and Hadjiconstantinou (2004) use DEA to develop an efficiency index which combines economic activity, $CO_2$ emissions and energy consumption of the production process in 31

European countries for the year 2004. The study provides estimates about the margins of long term changes in the consumption levels of exhaustible energy resources. In a similar context, Ramanathan (2005) uses DEA to analyze the performance of 17 countries from the Middle East and North Africa in terms of four indicators of energy consumption and $CO_2$ emissions for the period 1992–1996. The authors conclude that oil-rich countries show no indication of following carbon-friendly policies for their economic development.

Lozano and Gutiérrez (2008) apply a number of non-parametric, linear programming (LP) models for measuring energy efficiency in 21 OECD countries from 1990 to 2004, using the environmental DEA technology concept. Lanfang and Jingwan (2009) propose a non-parametric method based on DEA to measure energy efficiency, taking into account undesirable factors such as water, gas, and solid wastes. In the same lines, Zhou et al. (2008c) present several DEA formulations for measuring economy-wide energy efficiency. In another study, Yu (2010) employs a panel data set of 16 OECD countries in order to estimate the relationship between overall energy efficiency and the behavior of households on energy consumption. Ceylan and Gunay (2010) analyze Turkey's economy-wide energy efficiency and its energy saving potential by means of cross-country comparison and benchmarking with the EU countries, for the period of 1995–2007, using a non-parametric frontier approach.

Table 1 presents a brief overview of some recent studies that use DEA in measuring energy efficiency at the country level.

Table 1: Studies that use DEA in measuring energy efficiency of countries

| **Author** | **Year** | **Country** | **Inputs** | **Outputs** |
|---|---|---|---|---|
| Hu and Wang (2006) | 1995–2002 | 29 regions in China | Labor, capital stock, energy Consumption, total sown area of farm crops | GDP |
| Hu and Kao (2007) | 1991–2000 | 17 APEC economies | Energy, labor, capital | GDP |
| Chien and Hu (2007) | 2001–2002 | 45 countries | Labor, capital stock, and energy consumption | GDP |
| Zhou and Ang (2008) | 1997–2001 | 21 OECD countries | Capital stock and labor force (non-energy inputs), coal, oil, gas and other energy as energy inputs | GDP, $CO_2$ emissions |
| Honma and Hu (2008) | 1993–2003 | Japan | Labor employment, private and public capital stocks, electric power for commercial and industrial use, electric power for residential use, gasoline, kerosene, heavy oil, light oil, city gas, butane gas, propane gas, coal, and coke | GDP |
| Lozano and Gutiérrez (2008) | 1990–2004 | USA | Population | GDP, primary energy consumption, Greenhouse Gas emissions |
| Ceylan and | 1995–2007 | Turkey | Capital, labor and total R&D | GDP, greenhouse |

| | | | | |
|---|---|---|---|---|
| Gunay (2010) | | | expenditure, oil, gas, solid fuels, nuclear energy and renewable energy consumption | gases |
| Shi et al. (2010) | 2000–2006 | 28 regions in China | Industrial investment in fixed assets, industrial energy consumption, industrial labor | Industrial added value and volume of industrial waste gas |
| Zhang et al. (2011) | 1980–2005 | 23 developing countries | Labor force, energy consumption, capital stock | GDP |
| Zhou et al. (2012) | 2001 | 21 OECD countries | Capital, labor, energy | GDP |

DEA has also become a popular tool for studying the efficiency at the firm and industry levels. For example, since the early 1990s, DEA has been used for studying the efficiency of electricity distribution utilities. Among the first publications in this area is the study on technical efficiency of the British electricity distribution industry (Weyman-Jones, 1991). Since then, many studies have appeared in the literature covering different business sectors from a single country as well as performing cross-country sectorial comparisons. Some recent examples of such studies using DEA for the measurement of efficiency in this field include Chien et al. (2003), Giannakis et al. (2005), Abbott (2006), and Hirschhausen et al. (2006).

Furthermore, DEA has gained popularity in environmental performance measurement. Färe and Grosskopf (2004) provide a formal index number of environmental performance using DEA techniques, taking into account three pollutants ($CO_2$, $SO_X$ and $NO_X$) as undesirable outputs. The proposed index suggests that there may be no clear-cut relationship between pollutants and per capita income. Zhou and Ang (2008a) apply environmental performance measures to study the carbon emission performance of eight world regions, in 2002, under different reference technologies. The results show that the environmental performance index of a certain country may change under different environmental DEA technologies because different models are adopted under different situations. As a result, the choice of a specific environmental DEA technology would play an important role in environmental performance measurement. What is more, the study shows that the undesirable outputs' orientation DEA model is particularly attractive because it provides a pure environmental performance measure. A more recent study demonstrates DEA's applicability to assess the environmental performance at the firm level, and more specifically for the major opto-electronic companies in Taiwan, using the Inefficiency Countervailed DEA (IC-DEA) method (Huang and Kao, 2012). Moreover, DEA has also been applied to study the productive efficiency of some specific energy sectors such as district heating plants (Agrell and Bogetoft, 2005; Lygnerud and Peltola-Ojala, 2010), oil and gas industries (Hawdon, 2003; Azadeh et al., 2007; Honma and Hu, 2008), coal industry (Fang et al., 2009; Yang and Pollitt, 2009).

In addition to DEA models, multicriteria decision making (MCDM) has also been extensively used for energy management and efficiency evaluation. MCDM is involved with decision problems under the presence of multiple (conflicting) decision criteria, which require the selection of the best alternatives, the ranking of the alternatives according to their overall performance, or their classification into predefined performance groups.

Diakoulaki et al. (1999) use a multicriteria methodology for the determination of the relative contribution of different factors in reaching a desired level of energy efficiency. Their analysis focuses on 13 EU countries and the USA in three points in time, namely 1983, 1988, and 1993, using data on economic growth, energy consumption and its breakdown into energy forms and sectors. The results show that richer countries achieve better energy intensity than the less developed ones. Appropriate pricing policies (mainly on electricity) and long-term structural changes of the energy system were the main effective means used for achieving efficient energy use in the late eighties and early nineties.

Neves et al. (2009) use the Soft Systems Methodology (SSM) and value focused thinking to elicit and structure objectives in MCDA models for evaluating energy efficiency initiatives, thus illustrating how these two methodologies may be used fruitfully. The study proves that SSM is a useful tool, which helps to clearly define the decision problem context and support the main actors involved, as well as to unveil the relevant objectives for each stakeholder. Moreover, Mavrotas and Trifillis (2006) use some basic principles from DEA to facilitate the evaluation of the environmental performance of 14 EU countries through a MCDM approach. Their analysis is based on energy intensity, emission intensity, acidifying gases intensity, as well as other indicators related to the composition of the countries' energy mix, the use of land, and recycling. The results show that countries which exhibit a wide range of performances across the criteria result in a wide range of scores in the cross-evaluation matrix, while countries with more accumulated scores in the criteria result in a more narrow multicriteria score range, thus being less sensitive to modifications in the relative importance of the evaluation criteria.

Besides the aforementioned studies related to energy efficiency and environmental performance at the country level, the review of Wang et al. (2009) verifies the increasing interest in using MCDM approaches in other related areas such as energy resource allocation, energy exploitation, energy policy setting, building energy management, transportation energy systems, etc. Moreover, the articles reviewed in the aforementioned study consider different energy supply systems, and focus on different types of analyses such as technological, economic, and sustainability evaluations.

Pohekar and Ramachandran (2004) review the literature from a sustainable energy planning perspective and also identify an increasing popularity and applicability of MCDM methods beyond 1990, which is indicative of a paradigm shift in energy planning approaches. Based on the authors' findings, MCDM methods are more popular in renewable energy planning, followed by energy resource allocation. In the same context of sustainable energy planning, Doukas et al. (2007) present a direct and flexible MCDM approach, using linguistic variables, to assist policy makers in formulating

sustainable technological energy priorities. McDowall and Eames (2007), use a multi-criteria mapping process to provide an integrated, transparent assessment of the environmental, social and economic sustainability of six possible future hydrogen energy systems for the UK, whereas Buchholz et al. (2009) evaluate the potential of MCDM to facilitate the design and implementation of sustainable bioenergy projects.

Furthermore, Zhou et al. (2006) attribute the increased popularity of MCDM, especially in decision-making for sustainable energy, to the multi-dimensional nature of the sustainability goal, and the complexity of the socio-economic and biophysical systems. For example, Qin et al. (2008) develop an MCDM-based expert system to tackle the interrelationships between climate change and the adaptation policies in Canada, and to facilitate the assessment of climate-change impacts on socio-economic and environmental sectors, as well as the formulation of relevant adaptation policies in terms of water resources management and other watersheds.

The above overview indicates that despite the rich literature on the use of DEA and MCDM for energy efficiency analysis and planning, there has been almost no attempt to combine in a unified context the information that the two approaches can provide. Thus, this study contributes to the literature by adopting an integrated DEA/MCDM approach. Furthermore, we use the most up-to-date data available for EU countries, from 2000 to 2010, which enables the identification of the impacts that the economic crisis has on the energy efficiency performance of the countries in the EU.

## 3. METHODOLOGY

### 3.1 Data Envelopment Analysis

DEA, originally proposed by Charnes et al. (1978), is a nonparametric frontier technique where efficiency of a particular entity is measured by its distance from the best practice frontier constructed by the best performing entities within the group. It is a well-established methodology for the evaluation of the relative efficiencies of a set of comparable entities (decision making units, DMUs) which transform multiple inputs (energy and non-energy inputs) into multiple outputs (desirable and undesirable). Relying on LP techniques and without having to introduce any subjective or economic prices (weights, costs, etc.), DEA provides a nonparametric estimate of the efficiency of each DMU in comparison to the best practice frontier constructed by the best performing DMUs (Zhou and Ang, 2008).

In particular, assume that there are data on $K$ inputs and $M$ outputs for $N$ DMUs. For the $i^{\text{th}}$ DMU these are represented by the vectors $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively. The $K \times N$ input matrix $\mathbf{X}$, and the $M \times N$ output matrix $\mathbf{Y}$, both represent the data for all DMUs. Then, the efficiency of the $i^{\text{th}}$ DMU is measured by the ratio:

$$\theta_i = \frac{\mathbf{u}_i \mathbf{y}_i}{\mathbf{v}_i \mathbf{x}_i} \in [0,1]$$

where $\mathbf{u}_i, \mathbf{v}_i \geq \mathbf{0}$ are weight vectors corresponding to the outputs and inputs for the $i^{\text{th}}$ DMU. DEA provides an assessment of the relative efficiency of a DMU compared to a set of other DMUs. Under constant returns to scale (CRS) and assuming an input orientation, the maximum efficiency for the $i^{\text{th}}$ DMU can be estimated through the LP formulation introduced by Charnes et al. (1978), which is expressed in dual form as follows (CCR model):

$$\begin{aligned} &\min && \theta_i^C \\ &\text{Subject to:} && \theta_i^C \mathbf{x}_i - \boldsymbol{\lambda}\mathbf{X} \geq \mathbf{0} \\ & && \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{y}_i \\ & && \boldsymbol{\lambda} \geq \mathbf{0},\ \theta_i^C \in \square \end{aligned}$$

With the solution of this LP problem, a country *i* is classified as efficient if $\theta_i^C = 1$ or inefficient if $\theta_i^C < 1$. Variable returns to scale (VRS) can be introduced by simply adding the convexity constraint $\lambda_1 + \cdots + \lambda_N = 1$ to the above model. This constraint ensures that a DMU is benchmarked only against other units of similar size. The resulting model is known as the BCC model (Banker et al., 1984).

The characteristics of DEA, and in particular: a) the lack of restrictive assumptions on the form of the production function that relates input(s) to output(s), and b) the possibility of using simultaneously multiple inputs and outputs, which can be specified by different units of measurement, provide the possibility of considering alternative approaches, based on different input and output combinations, thus enabling the in-depth examination of complicated issues (Bampatsou and Hadjiconstantinou, 2004). In addition to efficiency estimates, DEA also supports the identification of the sources of inefficiency, as well as the specification of performance targets.

## 3.2 Building an Operational Efficiency Evaluation Model through a Multicriteria Approach

The efficiency analysis results obtained with DEA provide useful indications on the relative performance of the countries. However, in the context of DEA, each country is evaluated with different weightings of the input and output variables, thus making it difficult to interpret the results in a common setting that would be applicable to all countries. Furthermore, DEA does not discriminate among efficient cases, as they all receive the same efficiency score. To address these issues, in this study we perform a second stage analysis aiming towards the development of a global evaluation model common to all countries. Such a model is particularly useful to decision and policy makers and it can be easily used for benchmarking purposes, without having to perform the DEA analysis every time one needs to evaluate the efficiency of a single country.

This second stage of the analysis is implemented using a multicriteria classification technique. In particular, the efficiency classifications as defined from the results of DEA are used to build the multicriteria evaluation model. The countries are classified as efficient or inefficient according to their DEA efficiency scores and a multicriteria model is then constructed, which combines *n* criteria, so that the model's classifications are as close as possible to DEA's efficiency classification. The UTADIS multicriteria method is used for this purpose (Doumpos and Zopounidis, 2002). The UTADIS method leads to the development of an additive value function of the following form:

$$V(\mathbf{x}_i) = \sum_{j=1}^{n} w_j v_j(x_{ij}) \in [0,1]$$

where $w_j$ is a non-negative trade-off constant for evaluation criterion $j$, and $v_j(x_j)$ is the corresponding marginal value function normalized between 0 and 1. The marginal value functions provide a decomposition of the aggregate result (global value) in terms of individual assessments at the criteria level. According to its global value, a country *i* is classified as efficient if and only if $V(\mathbf{x}_i) > t$, where $t$ is a cut-off point that distinguishes the efficient countries from the inefficient ones. The estimation of the additive value function and the optimal cut-off point is performed through LP techniques. Detailed description of the mathematical programming formulation used in the UTADIS method can be found in the works of Zopounidis and Doumpos (1999) and Doumpos and Zopounidis (2002).

## 4. DATA AND VARIABLES

For the empirical analysis, we use a panel data set for 26 EU countries[1] over the period 2000–2010. All data have been obtained from Eurostat, except for labor force data which were collected from the World Bank. In addition, the choice of a proper set of indicators and evaluation criteria is clearly an important issue. The multidimensional character of energy efficient and its multiple aspects (e.g., environmental, socio-economic, and technical) make it very difficult to specify a comprehensive set of relevant measurement indicators universally applicable under all contexts. In this study, on the basis of data availability and the existing literature, the input and output variables presented in Table 2 are selected. In the analysis we consider two different settings for the input variables and two different settings for the output variables, thus leading to four DEA models (henceforth denoted as M1, M2, M3, M4).

Table 2: Input and output variables

| Type | Variable | Unit | M1 | M2 | M3 | M4 |
|---|---|---|---|---|---|---|

[1] Malta is excluded due to unavailability of some data.

| | | | | | | |
|---|---|---|---|---|---|---|
| Outputs | Greenhouse gas emissions | Thousands of tonnes (CO2 equivalent) | ✓ | ✓ | ✓ | ✓ |
| | Gross domestic product | Millions of euros | ✓ | ✓ | | |
| | Industry, value added | Millions of euros | | | ✓ | ✓ |
| | Services, value added | Millions of euros | | | ✓ | ✓ |
| Inputs | Total energy consumption | Thousand tonnes of oil equivalent | ✓ | | ✓ | |
| | Fossil fuels energy consumption | Thousand tonnes of oil equivalent | | ✓ | | ✓ |
| | Other fuels energy consumption | Thousand tonnes of oil equivalent | | ✓ | | ✓ |
| | Labor force | Economically active population | ✓ | ✓ | ✓ | ✓ |
| | Domestic material consumption | Thousands of tonnes | ✓ | ✓ | ✓ | ✓ |

The first setting for the output variables considers greenhouse gas emissions (GHG) and gross domestic product (GDP), whereas in the second setting GDP is replaced by the value added from the industry and the services sectors, thus providing a more detailed insight in the economic output of each country. Several indicators, such as the gross domestic product (GDP) and greenhouse gas emissions, are widely used to monitor or track a country/region's performance in energy efficiency (Zhou and Ang, 2008; Zhou et al., 2012; see also studies in Table 1). The importance of energy on greenhouse gases (GHG) emissions is reflected by the fact that 65% of emissions in the World are currently attributed to the use and production of energy (Marrero, 2010). According to Marreno (2010), the elasticity between aggregate energy consumption and emissions is significantly greater than zero, but also below unity, indicating that a 20% reduction in energy consumption would not be sufficient to achieve the 20% emissions reduction goal. Therefore, an additional boost in efficiency or a shift in the energy mix toward less polluting energies would be required to achieve the emissions goal, which is the ultimate objective. What is more, Lozano and Gutiérrez (2008) show that the reasonable GDP growth rates are compatible with significant reductions (from current levels) in GHG emission levels, while higher levels of GDP could be attained if GHG consumption were reduced instead of increased.

Normally, the industry sector is more energy intensive than the service sector. Therefore, a structural shift from high-energy-consumption secondary industry to low-energy-consumption tertiary industry may lead to an improvement in the overall energy efficiency; solely due to structural changes in the economic activity of a country. Yu (2010), using the variations of the share of value-added from both the industry and the services sector, in terms of GDP, shows that the service share has a significant positive impact on energy efficiency. On the other hand, he also shows that the industry share has insignificant small positive effect (less than 0.25 percent) on the dependent variable, and as a result, may not affect energy efficiency in the country level prominently. Wei et al. (2009) and Zhao et al. (2010) examine the energy efficiency in China and find that it is negatively associated with the secondary industry share in GDP, and that the simultaneous improvement of energy efficiency in energy-intensive sectors is mainly due to industrial policies. Furthermore, Zhao et al. (2010) find that

low energy prices have directly contributed to high industrial energy consumption, and indirectly to the heavy industrial structure. Arcelus and Arocena (2000) compare the multifactor productivity levels and the changes across countries, and across time, using a nonparametric model. The evidence obtained from a sample of 14 OECD countries indicates a high degree of catching-up among the various countries for the total industry, manufacturing, and services sectors. Hu and Kao (2007) claim that a newly industrialized economy will have lower total-factor energy efficiency than agriculture-dominant and service-dominant economies. Hence, the industrial structure of an economy is a crucial factor for energy efficiency, and thus the energy-saving ratio; an industry-dominant economy can improve its energy efficiency and save energy more efficiently and effectively via shifting the economy structure toward services. Therefore, it is really important to examine the influence of the value added by the industry and the services sectors in GDP.

Similarly to the outputs, two settings are also used for modeling the inputs. In particular, the first setting has three inputs involving total energy consumption, labor force (treated as a non-discretionary input) and materials consumption. In the second setting, total energy consumption is replaced by fossil fuels consumption and the consumption of other energy sources (renewables and nuclear), thus providing a more refined view of the energy mix that each country employs. The majority of studies that measure energy efficiency using the DEA framework, choose inputs such as energy consumption, capital and labor (see studies in Table 1). Ramanathan (2005) uses also the fossil fuels energy consumption as a minimization indicator, in the sense that countries with lower values in this indicator are more preferred. Mandal (2010), use as inputs data related to capital, energy, labor and raw materials, and claim that the environmental regulation has the potential of positively affecting energy use. Moreover, Hu and Wang (2006) observe high correlation between the inputs (labor, capital stock, energy consumption, and total sown area of farm crops) and the single output (real GDP). In the same lines, Hu and Kao (2007) show that labor employment, capital stock and energy consumption, do actually correlate to GDP performance. The authors also find that energy efficiency can be over-estimated or under-estimated if energy consumption is taken as a single input with a certain portion of GDP output produced not only by energy input, but also by labor and capital. Hence, employing a multiple-inputs framework is important in order to correctly evaluate energy efficiency (Hu and Wang, 2006).

Figure 1 presents the evolution of the selected variables over the period of the analysis. As can be seen, all the variables present an upward trend until 2006–2007, and then a downward trend. Only the consumption of other fuels continues to exhibit an upward trend following 2007, mainly due to the increased use of renewable sources.

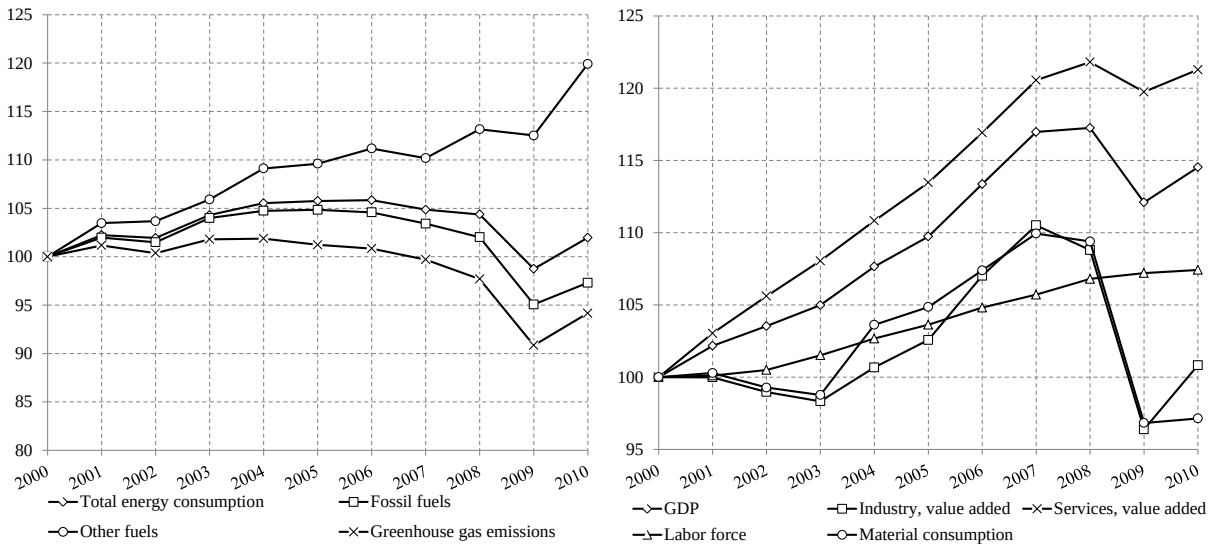


Figure 1: Evolution of the selected variables over the period 2000–2010

While the selected input and output variables are meaningful in the context of DEA, they are not useful in a multicriteria setting, as they do not allow for direct comparisons among the countries. Thus, in the second stage of the analysis, a set of 10 evaluation criteria are employed in order to build the final multicriteria evaluation model. Similarly to the modeling approach employed in DEA, the selected criteria (Table 3) combine energy efficiency indicators, economic growth and competitiveness indicators, environmental indicators, as well as two original indicators related to the primary energy source and the focus of the economy in each country. The primary energy source indicator is used to take into consideration the energy focus of a country in a particular year, indicating whether renewables, nuclear, natural gas, solid fuels, or petroleum consumption was the main energy source for the country. Economy focus is modeled as a binary indicator, designating whether the value added by the industrial sector of a country (as a percentage of GDP), at a given year, is above or below the overall average of all countries. The introduction of this indicator in the analysis enables the consideration of the differences between the various countries in terms of their level of industrial development (as industry is generally more energy intensive than services).

Table 3: Evaluation criteria for building the second stage multicriteria model.

| | |
|---|---|
| Energy intensity | Current account balance / GDP |
| Gross fixed capital formation / GDP | Unemployment rate |
| Environmental taxes / GDP | Greenhouse gas emissions / GDP |
| Resource productivity (GDP / Domestic material consumption) | Primary energy source indicator |
| GDP growth | Economy focus indicator |

## 5. RESULTS

### 5.1 DEA Results

Figure 2 illustrates the average constant returns-to-scale (CCR) and variable returns-to-scale (BCC) efficiency scores of the four models, over the whole period of the analysis. The ratios between the CCR and BCC efficiency scores are in all cases above 0.9, thus indicating that the scale effect is only marginal, which implies that the inefficiencies are mostly due to the policies implemented at the country level. Generally, there are high correlations between the results of the four models, with the correlation coefficient ranging between 0.94 (between models M2 and M3) and 0.97 (between models M1 and M3). Of course, the models with more inputs and outputs lead to higher efficiency estimates, but this is fairly common in DEA (i.e., the efficiency scores in DEA generally increase with the number of inputs and outputs).

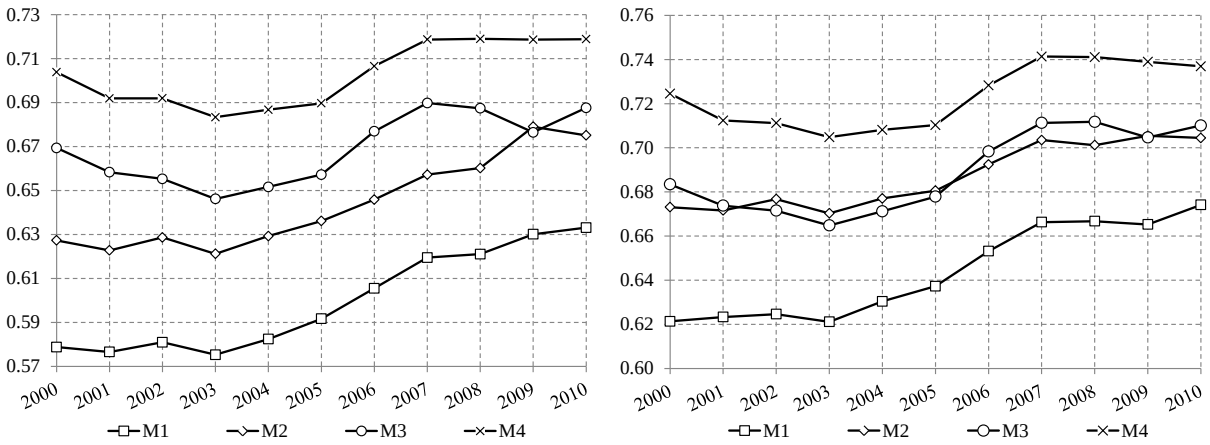


Figure 2: Average efficiency scores for the four models (CCR left, BCC right)

When examining the efficiency trends over time, one can observe some minor, yet noticeable differences between the four models. In particular, under both constant (CCR efficiency) and variable (BCC efficiency) returns to scale, the period 2000–2003 is characterized by stable efficiency scores according to models M1 and M2, whereas models M3 and M4 indicate a slightly decreasing trend. In the subsequent period up to 2007 steady improvement is observed under all models (the improvement is larger in the case of models M1 and M2). Finally, during 2008–2010 models M1 and M2 indicate further (minor) improvement, whereas under models M3 and M4 the efficiency scores are almost stable.

These differences among the pairs of models {M1, M2} and {M3, M4}, as far as the observed efficiency trends are concerned, indicate that the decomposition of the GDP output in models M3 and M4 does affect the results. Indeed, if GDP is taken as a single output of economic activity (models M1, M2), the efficiency trend is clearly positive (at least after 2003). But if the structure of the

economies is explicitly taken into consideration (i.e., separation of GDP into the value added by industry and services in models M3 and M4), then the efficiency improvements decrease. In that regard, models M1 and M2 act more like multidimensional proxies of energy intensity, whereas models M3 and M4 provide a better representation of the dynamics and trends in the actual energy efficiency of the countries. On the basis of these findings, the subsequent analysis focuses on model M4, which provides the most comprehensive consideration of the economic outputs of the countries and their energy mix.

Table 4 presents the countries' global CCR efficiency scores averaged over all ten years of the analysis, as well as the percentage changes over again the whole period of the analysis, and during the period of the recent economic crisis (2008–2010). Luxembourg, Ireland, Netherlands, United Kingdom, and Cyprus achieved the highest efficiency scores (overall), whereas Hungary, the Czech Republic, Poland, Bulgaria, and Romania have the lowest scores. Results confirm that countries with more service-oriented economies are more energy-efficient compared to more industrial-oriented economies. Nevertheless, most of the low performing countries (except for Romania) achieved considerable improvements over the period of the analysis, including the period 2008–2010.

Table 4: Overall CCR efficiency scores (averaged over 2000–2010) and percentage changes (model M4)

| | Average | 2000–10 | 2008–10 | | Average | 2000–10 | 2008–10 |
|---|---|---|---|---|---|---|---|
| LU | 1.000 | 0.0 | 0.0 | SI | 0.759 | –1.3 | –4.2 |
| IE | 0.993 | –4.2 | –4.2 | BE | 0.759 | –9.6 | –6.9 |
| NL | 0.988 | 0.0 | 1.2 | ES | 0.658 | 7.1 | 6.1 |
| UK | 0.980 | 0.6 | 0.0 | GR | 0.595 | 25.2 | 2.0 |
| CY | 0.968 | –3.0 | 2.5 | LT | 0.576 | –3.9 | 10.9 |
| DK | 0.960 | 2.7 | 2.2 | PT | 0.549 | 5.6 | 10.6 |
| SE | 0.960 | 9.2 | 0.0 | EE | 0.537 | –23.7 | 0.1 |
| DE | 0.928 | 5.2 | –5.0 | SK | 0.349 | 24.1 | –5.8 |
| AT | 0.908 | 1.0 | –0.4 | HU | 0.341 | 18.6 | 4.9 |
| LV | 0.900 | –12.6 | 1.9 | CZ | 0.332 | 32.5 | 3.5 |
| IT | 0.894 | –2.6 | –8.3 | PL | 0.312 | 21.0 | 5.2 |
| FR | 0.846 | 20.9 | 7.7 | BG | 0.203 | 28.6 | 16.2 |
| FI | 0.781 | –2.1 | –11.1 | RO | 0.195 | –0.5 | –2.6 |

Table 5 summarizes the estimated input and output improvements (averaged by year) that inefficient countries should seek to achieve in order to improve their efficiency status (under the BCC model). The results are reported for all outputs and inputs, except for labor force, which is treated as

non-discretionary (uncontrolled) input. Given the rapid growth of the services sector (see Figure 1), it is of no surprise that the corresponding variable is the one where most of the improvement efforts should focus. The consumption of renewables and nuclear energy (other fuels) is also an area where improvement should be sought after, followed by greenhouse gas emissions, and the consumption of materials.

Table 5: Suggested average improvements in input and outputs (% changes)

| | Greenhouse gas emis. | Industry, value added | Services, value added | Fossil fuels | Other fuels | Domestic mat. cons. |
|---|---|---|---|---|---|---|
| 2000 | 6.2 | 4.1 | 37.2 | 2.3 | 9.6 | 3.1 |
| 2001 | 6.5 | 3.8 | 32.4 | 2.5 | 10.1 | 2.4 |
| 2002 | 6.2 | 2.7 | 28.0 | 2.5 | 9.6 | 2.9 |
| 2003 | 7.0 | 2.1 | 23.6 | 3.1 | 8.9 | 3.2 |
| 2004 | 7.0 | 2.1 | 21.4 | 3.4 | 8.3 | 3.7 |
| 2005 | 6.4 | 1.3 | 18.6 | 2.8 | 8.4 | 4.1 |
| 2006 | 5.5 | 0.8 | 18.8 | 2.4 | 7.3 | 4.9 |
| 2007 | 4.6 | 1.1 | 18.3 | 1.9 | 5.8 | 5.3 |
| 2008 | 4.5 | 1.6 | 17.4 | 1.7 | 6.6 | 6.4 |
| 2009 | 5.8 | 1.6 | 16.7 | 1.6 | 8.9 | 7.1 |
| 2010 | 5.0 | 0.8 | 18.1 | 1.9 | 7.9 | 7.6 |
| Average | 5.9 | 2.0 | 22.8 | 2.4 | 8.3 | 4.6 |

## 5.2 Second Stage Results

For the reasons explained in the previous subsection, the development of the multicriteria evaluation model in the second stage of the analysis is based on model M4. Given their CCR efficiencies under model M4, all countries are classified as efficient (efficiency score equal to 1) or inefficient (efficiency score lower than 1). The objective of the second stage analysis is to construct an operational multicriteria evaluation model for evaluating the energy efficiency of all countries in a multidimensional context. For this purpose the UTADIS multicriteria method is employed to fit a model that combines the selected set of criteria presented in section 4 (Table 3) in order to replicate the DEA-based efficiency classification of the countries, as accurately as possible. Overall, the sample includes 37 efficient country-year observations and 249 inefficient cases. Table 6 presents the means of the selected indicators for each group. All differences are statistically significant at the 5% level according to the nonparametric Mann-Whitney test (except for gross fixed capital formation / GDP and GDP growth).

Table 6: The mean of the selected indicators for efficient and inefficient countries.

| | Efficient | Inefficient |
|---|---|---|
| Energy intensity | 152.64 | 354.08 |
| Gross fixed capital formation / GDP | 3.39 | 3.12 |
| Environmental taxes / GDP | 2.98 | 2.67 |
| Resource productivity | 1.82 | 1.13 |
| GDP growth | 3.03 | 2.64 |
| Current account balance / GDP | 3.49 | –3.25 |
| Unemployment rate | 4.93 | 8.71 |
| Greenhouse gas emissions / GDP | 0.42 | 0.91 |
| Primary energy source indicator | 2.05 | 1.70 |
| Economy focus indicator | 0.70 | 0.44 |

Notes: The primary energy source indicator is modeled through a 3-point scale (1=solid fuels, 2=gas, petroleum, nuclear, 3=renewables), and economy focus is a binary indicator (0=industry focused, 1=services focused)

Table 7 presents the criteria tradeoffs in the multicriteria additive model fitted on the above data. These tradeoffs can be regarded as proxies of the relative importance of the criteria, whereas Figure 3 illustrates the marginal value functions for the four most important criteria, which indicate the decomposition of the global performance into partial scores at the criteria level. Moreover, the indicators' tradeoffs indicate that the energy intensity of the economy is the most important factor with a weight of 25.77%, followed by current account balance/GDP, resource productivity, and unemployment. Thus, the model puts emphasis on a mixture of factors combining energy intensity, the competitiveness of the countries (as measured by the current account balance/GDP ratio), as well as structural indicators related to the economic activity in a country, such as unemployment, and resource productivity. The remaining five factors contribute a total of 37.47% to the model.

Table 7: Criteria's tradeoffs (weights in %)

| Criteria | Weight | Criteria | Weight |
|---|---|---|---|
| Energy intensity | 25.77 | Environmental taxes / GDP | 7.83 |
| Current account balance / GDP | 13.28 | Primary energy source indicator | 7.18 |
| Unemployment rate | 11.85 | GDP growth | 6.44 |
| Resource productivity | 11.63 | Greenhouse Gas Emissions / GDP | 5.95 |
| Gross fixed capital formation / GDP | 7.97 | Economy focus indicator | 2.09 |

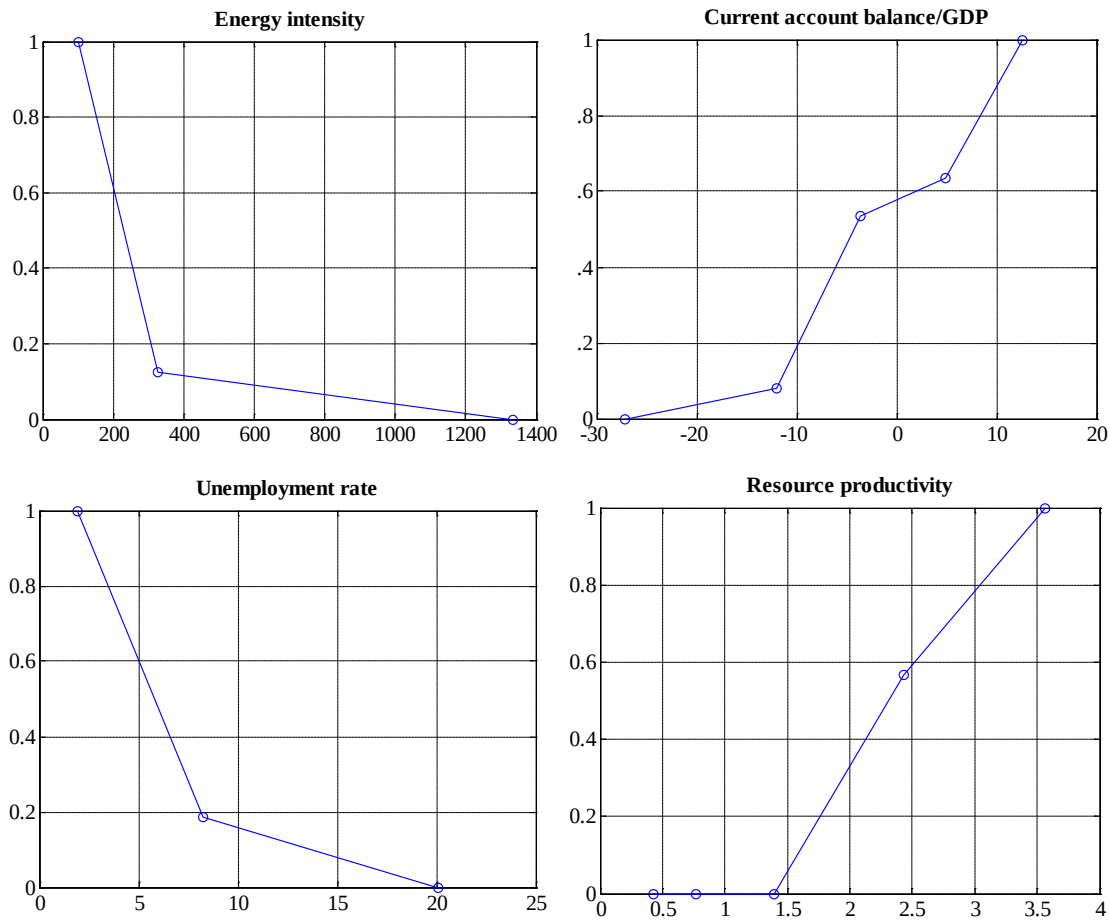


Figure 3: Marginal value functions for the criteria for the largest tradeoff constants

Figure 4 presents a comparison of the multicriteria evaluation results to the efficiency scores obtained under the DEA model M4 (CCR model). To facilitate the comparison, the annual averages are indexed using 2000 as the base year. Overall, the multicriteria results are more volatile compared to the CCR efficiency estimates obtained with DEA. This is of no surprise given that the multicriteria model takes into consideration a wider set of evaluation criteria of diverse nature. Nevertheless, there is a very strong overall correlation between the multicriteria results and the DEA efficiency scores, as the Pearson correlation[2] equals 0.821 and Kendall's tau[3] equals 0.682.

Furthermore, the discrepancies between the classification of the countries according to their CCR efficiencies and the classification induced by the multicriteria results are limited, as the accuracy rate is 86.5% for the DEA efficient countries and 93.4% for the DEA inefficient ones, with the overall

[2] Pearson's correlation coefficient between two variables is defined as the covariance of the two variables divided by the product of their standard deviations. It is a measure of the strength of linear dependence between two variables, ranging between [–1, 1].

[3] The Kendall's tau coefficient is a statistic used to measure the rank correlation between two measured quantities. Similarly to other correlation measures, Kendall's tau ranges in [–1, 1], with larger positive/negative values indicating a stronger (positive or negative) rank association of the two variables.

accuracy rate equaling 93%. Table 8 summarizes the differences in the DEA and the multicriteria classification results.

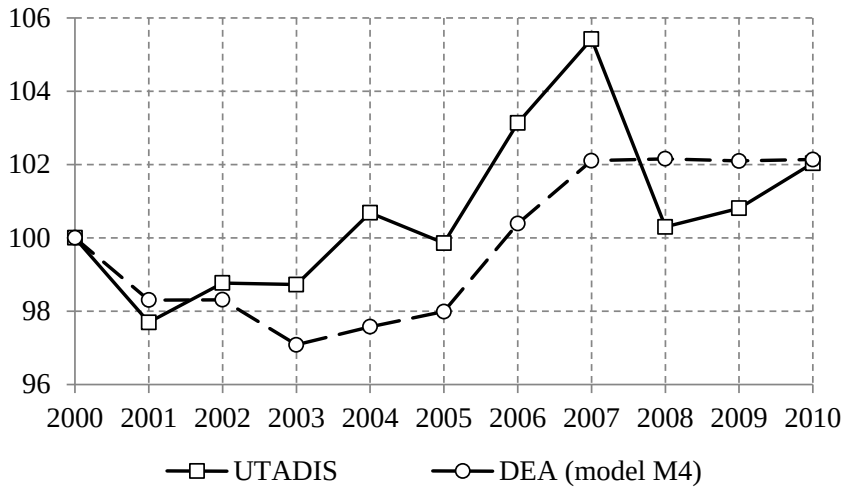


Figure 4: Comparison of the average multicriteria scores in each year to the DEA efficiency scores

Table 8: Discrepancies between the DEA efficiency classification and the multicriteria classification results

| DEA inefficient countries classified as efficient | DEA efficient countries classified as inefficient |
|---|---|
| Denmark (2000, 2006, 2007) | Cyprus (2000, 2001, 2004) |
| Luxembourg (2005) | Denmark (2010) |
| Netherlands (2001–2005, 2007, 2009) | Germany (2007) |
| Sweden (2008) | |
| United Kingdom (2003–2006) | |

## 6. CONCLUSIONS

In this study an integrated approach to energy efficiency evaluation is developed and implemented in the context of EU countries. The proposed approach considers energy efficiency in a multidimensional context, combining multiple energy consumption data, economic outputs, structural indicators, and environmental factors. DEA is employed under different modeling settings to perform a relative evaluation of the efficiency of the EU countries over the period 2000–2010. The results obtained with a more comprehensive consideration of economic outputs and energy consumption

provide a better indication of the true energy efficiency, compared to simpler models that consider only aggregate energy and GDP data.

Combining the results of DEA with a multicriteria classification technique enabled the construction of an operational model that provides analysts and policy makers with evaluations of the countries' energy efficiency in absolute terms, based on a common setting for all countries, without the need to perform DEA analysis again.

Overall, the results indicate that despite the considerable improvements achieved in terms of energy intensity, a more refined view of energy consumption and economic activity data indicates that there is still much to be done towards the improvement of the actual energy efficiency of EU countries. The economic crisis over the past few years had negative effects (on average).

Future research could consider a wide range of issues. Among others these may involve the consideration of more detailed data on structural factors, the analysis of specific energy-intensive business sectors, the enrichment of the dataset with countries outside the EU and a more extensive time period, as well as the evaluation of the actions and policies implemented to improve energy efficiency at the country level.

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