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Resource Efficiency and Sustainable Electricity Production among European States: A Non-Homogenous Parallel Network Data Envelopment Analysis

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Abstract

This paper examines the sustainability and resource efficiency in electricity production of some European countries. As electricity is generated concurrently from different generation sources, performance assessment of electricity generation should incorporate the differences in the generation portfolios of states. A model is introduced to examine the performance of the electricity generation systems of different European countries while recognising the differences in their generation portfolios. Specifically, a parallel network optimisation model which deals with the non-homogeneity in the production portfolio of units under investigation is proposed. The aim is to allow cross-country benchmarking and overview of the capabilities of different countries in generation using different sources in line with the planned transition unto a single, smart European electricity grid. This study, therefore, provides insights into the overall production performance as well as the generation source-wise performance of each EU country compared to its peers.

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1 Introduction

Electricity generation globally comes from a variety of generation sources with varying environmental consequences and primary energy resource requirements. Generation sources may include renewable and non-renewable sources. As different countries may use different combinations of generation sources, cross-country performance benchmarking of sustainability of electricity production should incorporate such portfolio differences. However, existing literature either conducts performance assessment at the plant level usually in one country (Liu et al., 2010; Sueyoshi et al., 2010; Yang & Pollitt, 2009) or compare the total generation at the national level without providing performance assessment at the generation source-level (Li et al., 2016; Sueyoshi & Goto, 2013; Yang & Fukuyama, 2018).

Research at the plant level compares the operational efficiency of various generation plants of similar generation sources sometimes with process decomposition. Xie et al. (2012), for example, decomposed the Chinese power plant operation into generation and grid operations in the two-stage network DEA evaluation. Similarly, Bi et al. (2018) considered a two-stage problem with power generation and pollutant abatement as the sub-units under investigation. Other sub-process decompositions include financial objectives and sustainability objectives of the fossil power plants (Tajbakhsh & Hassini, 2018) and generation, transmission and distribution (Xie et al., 2018). Apart from the single-country evaluation prominent in these studies, these studies often fail to consider other generation sources in the same assessment. Hardly do such decomposition incorporate both renewable and non-renewable sources in the same performance assessment.

On the other hand, national-level assessment has tended to focus on the social, economic and environmental factors that constrain the production of energy (Vazhayil & Balasubramanian, 2013;

Zurano-Cervelló et al., 2018). These studies like Sueyoshi and Goto (2013) and Ewertowska et al. (2017) have treated the production system of the country as a 'black box' without providing an assessment of the performance at the individual source level as part of the performance assessment. The consequence is that the overall performance assessment does not consider the internal production mechanisms that resulted in the overall power generation.

In the European Union (EU), there is a focus on the transition towards a Sustainable Smart European Grid which may foster decentralised electricity generation and transmission in different countries (Crispim et al., 2014; IqtiyaniIlham et al., 2017). Additionally, the European Commission's TEN-E rules in line with the European Green Deal objective for becoming climate-neutral by 2050, require mandatory sustainability assessment, supporting decarbonising efforts, and a more integrated energy system (European Union, 2020) among other considerations that require a more integrated and comprehensive performance evaluation. Therefore, there is the need for evaluation approaches that consider country-specific considerations of electricity generation performance for each technology and the overall system while also allowing for cross-country performance evaluation. Comparing the performance of different plants producing electricity from a similar source does not allow for the determination of which countries are higher performers at that generation source. Also, the cross-country performance assessment that examines the total electricity generated and environmental outputs fail to provide an assessment of the sub-systems (different sources) that account for the overall generation performance.

To aid in decision support, the European Economic Area (EEA) produces annually an "Overview of electricity production and use in Europe" as a means of monitoring the performance of countries. This report monitors CO_2 emission intensity; Gross electricity production by fuel; the contribution of fuels to total electricity production; whether electricity production in Europe is becoming less carbon-intensive; whether electricity production in Europe is increasing; and whether power plants are becoming more efficient (EEA, 2019). The report provides descriptive summary of resource efficiency and emissions from the various generation sources without in-depth assessment and cross-country performance benchmarking in electricity generation and use. There is, therefore, the need for performance assessment to conduct cross-country assessment, that compares the performance of how resources are efficiently consumed for power generation at the technology level, as well as provides an assessment of the overall system while incorporating environmental outputs.

This paper, therefore, develops optimisation models that provide cross-country performance assessment in gross electricity production and emissions reduction and decomposes the overall performance to generation source-level performances. In this process, new optimisation models are developed to handle the non-homogeneity in the production processes. Additionally, models developed incorporate emissions as undesirable outputs in the performance assessment. The chapter is organised as follows: Section 2 provides an overview of the European electricity generation system from which models are formulated in section 3 and empirical analyses conducted in section 4. Finally in section 5 conclusions are drawn on the models developed, and the empirical assessment conducted.

2 Literature Review

2.1 The European electricity generation system

The EU has been a leader in promoting sustainable development in the international arena by way of campaigns, networks and regulations (Afgan & Carvalho, 2008; Gallego Carrera & Mack, 2010). While Europe has limited capacity in the supply of primary energy sources of fossil fuel, its capacity in terms of renewable energies is not yet fully development (Afgan & Carvalho, 2008). There is potential for hydro, solar geothermal and biomass to contribute to a large proportion of the total energy supply. Due to the increasingly integrated economies and energy sectors, the EU is the world second-largest energy consumer behind USA (Koroneos & Nanaki, 2007). It is not surprising that low-carbon energy sources (renewables and nuclear) currently dominate the electricity mix of EU countries (EEA, 2019). Figure 1 presents the 2017 generation mixes of the 28 European countries[1].

On average, 53 per cent of gross electricity production (GEP) in 2017 came from such low-carbon sources. EU countries have a wide range of renewable source integration in their production mixes. From 87 per cent renewable energy generation by Luxembourg to as low as 9 per cent for Cyprus. Together with Luxembourg, Lithuania, Austria, Latvia, Denmark, Croatia and Sweden have all managed over 50 per cent electricity generation from renewable sources. Other countries like Slovakia, Belgium and France with relatively low renewable generation source content had very large GEP from nuclear taking their total low-carbon generation source composition over the 50 per cent mark. Overall, 16 of these 28 countries had over 50 per cent of GEP from low-carbon sources. However, to achieve the EU's objective of reducing greenhouse gas emissions by 80-95 % by 2050, there will be a need for full decarbonisation of the electricity sector (EEA, 2019). From Figure 2 it is evident that gains in decarbonisation crossed the 50 per cent mark from 2012.

[1] UK was a member of the EU as at 2017

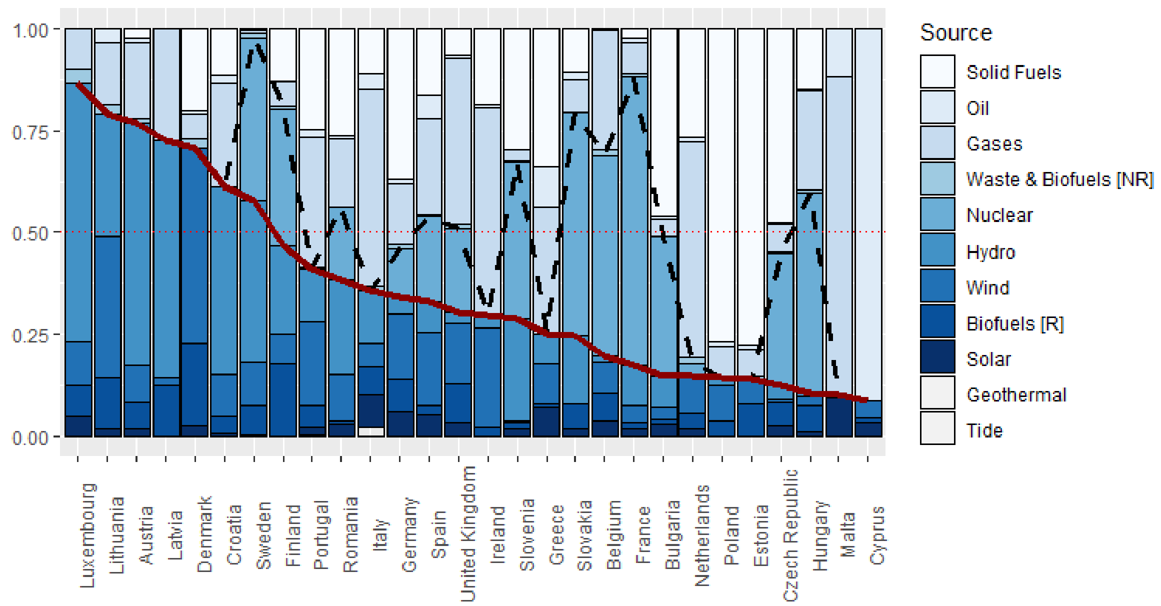

Figure 1. Electricity generation mixes of EU countries (2017)

The solid line shows the percentage of renewables in generation mix while the dashed-lines shows the percentage of low-carbon energy sources in the generation mix.

The GEP covers electricity generation from all types of power plants (main transformers) and private producers (auto-producers) using coal and lignite (solid fuels), oil, natural and derived gas (gases), non-renewable biomass and waste (waste & biofuels [NR]), nuclear and renewable sources comprising hydro, wind, renewable biofuels (Biofuels [R]), solar photovoltaics, geothermal, tide and other fuels (EEA, 2016; Eurostat, 2019). It must be noted that Directive 2001/77/EC which required an increased share of renewable sources in energy consumption by the year 2020 (EEA, 2017; Hadian & Madani, 2015; Kazagic et al., 2014) did not directly apply to the GEP since consumption is affected by distribution losses, trade among other factors (EEA, 2016).

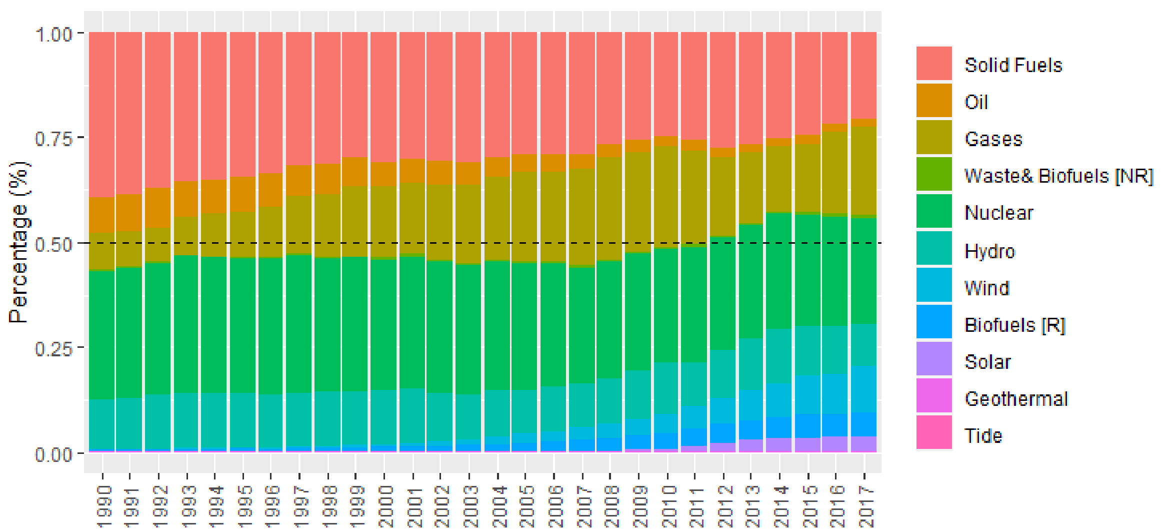

Figure 2. Combined gross generation mix of all 28 EU countries (1990-2017)

In the policy context, several directives, projections and guidelines exist to aid countries in the transformation towards reducing GhG emissions from the electricity sector. A binding target of 40 per cent GhG emission reductions until 2030 based on the 1990 levels have been set by the EU for the low-carbon energy transformation objective (Gerbaulet et al., 2019). Additionally, there is the objective for decarbonisation of at least 80 per cent of the 1990 levels by 2050 (European Commission, 2011). This is to be ensured through carbon capture and capacity investments in nuclear and renewable sources (Gerbaulet et al., 2019). Also, while Directive 2009/28/EC promotes the use of renewable sources, Directive 2009/29/EC focuses on improvement in GhG through trading schemes (EEA, 2019). Finally, COM[2010]-639 sets out strategies for competitive, sustainable and secure energy by setting new priority areas (European Commission, 2010). There is, therefore, efforts at capacity improvements, energy security and emissions reductions. Performance assessment models developed in subsequent sections reflect this policy environment.

2.2 Performance assessment of energy production

Performance assessment literature of sustainable energy production has been in two main strands – performance evaluation at the generation technology level (plant level) and performance comparison between different technologies (national level).

The first strand is studies that conduct performance evaluation on one type of energy generation technology usually incorporating undesirable outputs, such as emissions, in the production process. There is a large body of research in this area of DEA evaluation such as Yang and Pollitt (2009) who examined approaches for incorporating both undesirable outputs and uncontrollable variables into DEA in their performance evaluation of Chinese coal-fired power plants and Liu et al. (2010) who evaluated thermal power plants in Taiwan using radial DEA measurement. Sueyoshi and Goto (2012b) also conducted an environmental assessment of coal power plants in the U.S using radial DEA measurement under managerial and natural disposability, which followed an earlier study on performance analysis of the U.S coal-fired power plants (Sueyoshi et al., 2010). Sueyoshi and Goto (2012a) have also conducted a methodological comparison of radial and non-radial models in the evaluation of U.S. coal-fired power plants. On their part, Bi et al. (2014) conducted an energy efficiency evaluation of China's thermal power generation. Similarly, Liu et al. (2017) conducted a DEA cross efficiency evaluation of coal-fired power plants in China. There have been other studies like Sueyoshi and Goto (2012c) who focussed on the total power generation of the electricity system without the need to consider differences in the generation portfolio.

Recent research interest in this strand has focussed on decomposing the operations at the plant level to examine efficiency improvement potential in various sub-units of the plant. This has seen the application of various network DEA and hierarchical structure models. Starting from the earlier works of Cook et al. (1998) and Cook and Green (2005), recent studies include Xie et al. (2012) who decomposed the power plant operation into generation and grid operations in the two-stage network DEA evaluation and Bi et al. (2018) who considered a two-stage problem with power generation and pollutant abatement as the sub-units under investigation. Others include the two-stage evaluation of fossil fuel power plants by Tajbakhsh and Hassini (2018) with stages considering financial and sustainability objectives of the power plants. Xie et al. (2018) also conducted a dynamic network slacks-based evaluation of provincial power systems in China evaluating multiple operations of power plants – generation, transmission and distribution. Extensive reviews of studies in this strand of research have been conducted by Zhou et al. (2008), Sueyoshi et al. (2017) and Zhou et al. (2018).

These studies tend to focus on a type of production plant or examine the energy system as a composite without incorporating the differences in the production portfolios and hence focus on the power plant level, not the system-level. As such, policy recommendations are aimed at the plant level, not the national level which is relevant for sustainable energy policy. Due to the requirement for homogeneity in traditional DEA evaluation, studies are usually restricted to one type of generation technology ignoring the relevance of a system perspective. Countries produce power from different sources, therefore evaluation focussing on one or a few sources may lead to limited policy relevance. Additionally, it is important to consider the generation and use phases of the energy system for comprehensive decision support. All these studies in this strand focus on the generation phase of the energy system.

The second strand of DEA literature are studies that conduct performance comparison between different technologies. The focus here is usually some multi-criteria evaluation of several sources along some sustainability dimensions to identify sustainable and less sustainable technologies. These studies are quite limited in the literature. The focus of most of the studies in this strand have been on efficiency in energy production (Vazhayil & Balasubramanian, 2013; Zurano-Cervelló et al., 2018). Such studies mainly focus on the social, economic and environmental factors that constrain the production of energy. The system boundary for such research usually ends in the power production plants. Other studies like Sueyoshi and Goto (2013) and Ewertowska et al. (2017) focus on only the environmental dimension and treats the production process as a 'black-box' without considering the internal differences in the structure in the energy generation portfolio. As such, the system boundary of such environmental performance studies rather begins from the output of the power plant.

Many studies in this strand combine both renewable and non-renewable generation sources in their assessment. While this is appropriate since the energy supply of countries comes from both renewable and non-renewable sources, the requirement of homogeneity of decision-making units (DMUs) in DEA means studies either select units with the same portfolio structure (Sueyoshi & Goto, 2013) or focus on one country while comparing different technologies and assuming the production process across technologies are essentially the same (Rovere et al., 2010; Vazhayil & Balasubramanian, 2013). There are significant differences in the production structures of different countries and significant differences in the production processes of different generation sources. This must be reflected in such studies. Additionally, evaluation mostly focuses on a single country, however, energy policy and environmental impact go beyond one country. Therefore, there is a need for regional or global assessment.

Since the introduction of the traditional radial – CCR DEA model by Charnes et al. (1978) and radial BCC DEA model by Banker et al. (1984), there have been several advances in the methodology. There have been advances catering for nonhomogeneous DMUs (Cook et al., 2013), differences in production structures (Kao, 2014b) and treatment of bad outputs (Seiford & Zhu, 2002). Although the DEA literature is well advanced, its application in the second strand of sustainable energy production literature is still growing. There is the prevalence of mainly traditional models, which measure performance improvement targets on a radial basis, which suffer from an inability to detect non-proportional performance improvement targets. Non-radial approaches employed are limited to Directional Distance Function, which does not distinguish input improvements from output improvement. All of these studies have also been single objective problems mainly focussing on input minimisation.

3 Methods and modelling

3.1 General models

For *n* DMUs ($n = 1, \ldots, j$), there is the input vector $X \in \Re_+^m$ which can be used to produce the output set $P(X)$ comprising the set of desirable outputs $Y^D \in \Re_+^s$ and undesirable outputs $Y^U \in \Re_+^l$. This set is closed and bounded with inputs freely disposable. The weak disposability of the undesirable outputs means that if there exists $(Y^D, Y^U) \in P(X)$ and $0 \le \theta \le 1$ then it should mean that $(\theta Y^D, \theta Y^U) \in P(X)$ (Färe et al., 1989). Consequently, there is proportional abatement between the desirable and undesirable outputs such that reduction in undesirable output will come at the expense of desirable outputs. However, desirable outputs can be freely disposable. There is also implied a null-joint condition that no undesirable output can be produced if no desirable output is produced - $(Y^D, Y^U) \in P(X)$, if $Y^D = 0$ then $Y^U = 0$. This means that direct emissions from fuel combustion are modelled rather than lifecycle emissions. If lifecycle emissions are rather modelled, then it should be possible to produce positive units of emissions even when no electricity has been generated. However, we focus on modelling the direct emissions in this study. The production possibility set can be defined as:

$$P = \left\{ \left(X, Y^D, Y^U\right) \middle| X \ge \sum_{j=1}^{n} \lambda_j X_j, Y^D \le \sum_{j=1}^{n} \lambda_j Y_j^D, Y^U = \sum_{j=1}^{n} \lambda_j Y_j^U, \lambda_j \ge 0 \right\} \tag{1}$$

Following the traditional CCR efficiency model, the input-oriented DEA model with strongly disposable desirable inputs and outputs but weakly disposable undesirable outputs (2) and its dual (3) can be formulated as in:

$$\begin{aligned} E_0 = \quad & \min \phi \\ & \text{s.t.} \sum_{j=1}^{n} \lambda_j X_{ij} \le \phi X_{io} && i = 1, 2, \ldots, m \\ & \sum_{j=1}^{n} \lambda_j Y_{rj}^D \ge Y_{ro}^D && r = 1, 2, \ldots, s \\ & \sum_{j=1}^{n} \lambda_j Y_{kj}^U = Y_{ko}^U && k = 1, 2, \ldots, l \\ & \lambda_j \ge 0, \; j = 1, 2, \ldots, n \end{aligned} \tag{2}$$

$$
\begin{aligned}
E_0 = \max\ & \sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U} \\
\text{s.t.}\ & \sum_{i=1}^{m} v_i X_{io} = 1 \\
& \left(\sum_{r=1}^{s} u_r Y_{rj}^{D} + \sum_{k=1}^{l} c_k Y_{kj}^{U} \right) - \sum_{i=1}^{m} v_i X_{ij} \le 0 \qquad j = 1, 2, \ldots, n \\
& u_r, v_i \ge 0,\ c_k \text{ urs},\ r = 1, \ldots, s,\ \ k = 1, \ldots, l,\ \ i = 1, \ldots, m
\end{aligned} \tag{3}
$$

The models presented in (2) and (3) are based on the traditional 'black-box' DEA without sub-system integration. The model in (4) is based on Kao's (2009) relational model and incorporates the weakly disposable undesirable outputs. Given that the overall system can be decomposed into q sub-processes (p = 1,…, q). Each sub-process p has $X_i^{(p)}, i \in I^{(p)}$ inputs which are used in producing $Y_r^{D(p)}, r \in O^{D(p)}$ desirable outputs and $Y_k^{U(p)}, k \in O^{U(p)}$ undesirable outputs. It should be noted that the total system inputs and outputs are a sum of those of all the sub-processes. $\sum_{p=1}^{q} X_{ij}^{(p)} = X_{ij}, i = 1, \ldots, m$, $\sum_{p=1}^{q} Y_{rj}^{D(p)} = Y_{rj}^{D}, r = 1, \ldots, s$ and $\sum_{p=1}^{q} Y_{kj}^{U(p)} = Y_{kj}^{U}$, $k = 1, \ldots, l$. The general parallel network model to estimate the overall and sub-system efficiencies of the network presented in Figure 3 is formulated as:

$$
\begin{aligned}
E_0 = \max\ & \sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U} \\
\text{s.t.}\ & \sum_{i=1}^{m} v_i X_{io} = 1 \\
& \left(\sum_{r=1}^{s} u_r Y_{rj}^{D} + \sum_{k=1}^{l} c_k Y_{kj}^{U} \right) - \sum_{i=1}^{m} v_i X_{ij} \le 0 \qquad j = 1, 2, \ldots, n \\
& \left(\sum_{r \in O^{D(p)}} u_r Y_{rj}^{D(p)} + \sum_{k \in O^{U(p)}} c_k Y_{kj}^{U(p)} \right) - \sum_{i \in I^{(p)}} v_i X_{ij}^{(p)} \le 0 \qquad p = 1, \ldots, q,\ \ j = 1, 2, \ldots, n \\
& u_r, v_i \ge 0, c_k \text{ urs},\ r = 1, \ldots, s,\ k = 1, \ldots, l,\ i = 1, \ldots, m
\end{aligned} \tag{4}
$$

This model attaches the same input and output multipliers to the same type of inputs and outputs irrespective of the production system since the market price of the factor is expected to remain the same irrespective of the sub-process (Kao, 2012). From the optimal solution $\left(u_r^*,\ c_k^* \text{ and } v_i^*\right)$, the efficiencies for the system and sub-processes for each DMU can be computed as:

$$E_o = \frac{\sum_{r=1}^{s} u_r^* Y_{ro}^D + \sum_{k=1}^{l} c_k^* Y_{ko}^U}{\sum_{i=1}^{m} v_i^* X_{io}} = \sum_{r=1}^{s} u_r^* Y_{ro}^D + \sum_{k=1}^{l} c_k^* Y_{ko}^U$$

$$E_o^{(p)} = \frac{\sum_{r \in O^{D(p)}} u_r^* Y_{ro}^{D(p)} + \sum_{k \in O^{U(p)}} c_k^* Y_{ko}^{U(p)}}{\sum_{i \in I^{(p)}} v_i^* X_{io}^{(p)}}, \qquad p = 1, \ldots, q \tag{5}$$

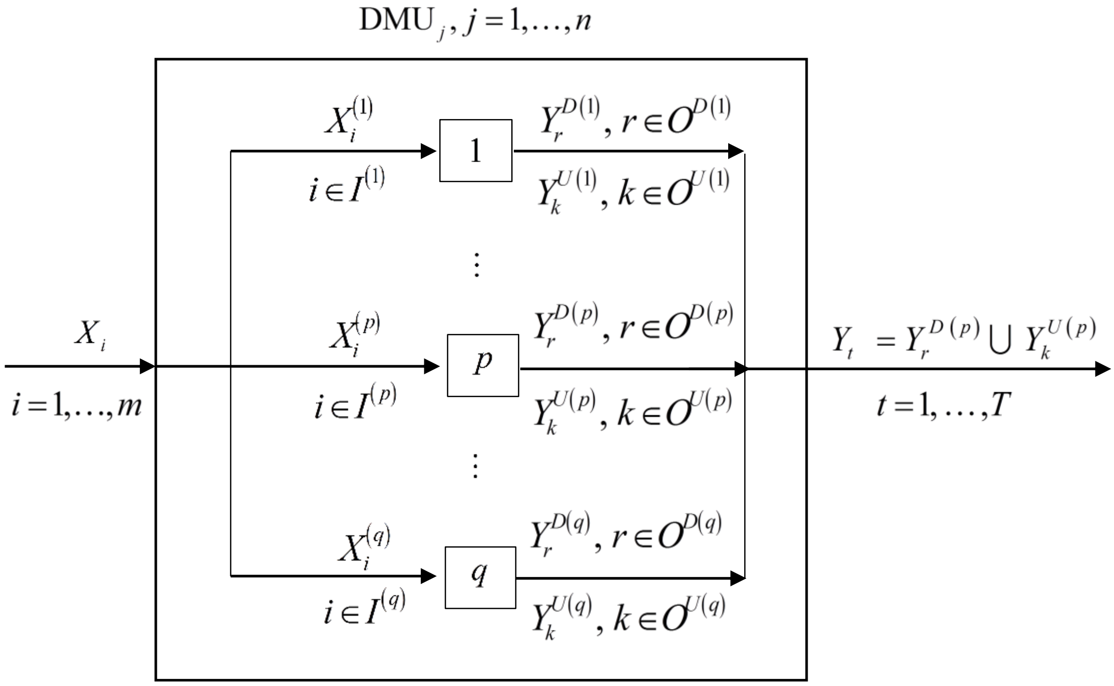

Figure 3. Schematic network structure

Where sub-processes are weighted by the proportion of inputs dedicated to the sub-process to the overall inputs in the system, Kao (2012, 2014a) show that the system efficiency is a weighted sum of the sub-process efficiencies. That is if the importance of a sub-process is defined by the proportion of resources dedicated to the sub-process to the overall system resources, $w^{(p)} = \sum_{i \in I^{(p)}} v_i X_{io}^{(p)} \Big/ \sum_{i=1}^{m} v_i X_{io}$, where $\sum_{p=1}^{q} \sum_{i \in I^{(p)}} v_i X_{io}^{(p)} = \sum_{i=1}^{m} v_i X_{io}$ then the weighted average of all sub-process efficiencies becomes:

$$\sum_{p=1}^{q} w^{(p)} E_o^{(p)} = \sum_{p=1}^{q} \left[\left(\frac{\sum_{i \in I^{(p)}} v_i X_{io}^{(p)}}{\sum_{i=1}^{m} v_i X_{io}} \right) \left(\frac{\sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U}}{\sum_{i \in I^{(p)}} v_i X_{io}^{(p)}} \right) \right]$$

$$= \frac{\sum_{r=1}^{s} u_r Y_{ro}^{D} + \sum_{k=1}^{l} c_k Y_{ko}^{U}}{\sum_{i=1}^{m} v_i X_{io}} \qquad (6)$$

3.2 Empirical modelling

3.2.1 Inputs and outputs

Although the source of energy may be different, sources are homogenous in terms of the electricity produced. The by-product of the power generated is GhG emission that is generated from fuel combustion in the production of non-renewable sources (excluding nuclear). Since this undesirable by-product is in a joint production with the desirable power generated, GhG emission is modelled as a weakly disposable output while GEP is modelled as freely disposable output. Output generation is subject to capacity restrictions, primary energy consumption and labour conditions. Since an increase in these factors will reasonably increase the desirable outputs, these factors are modelled as freely disposable desirable inputs. The general structure of the system and variables is presented in Figure 4.

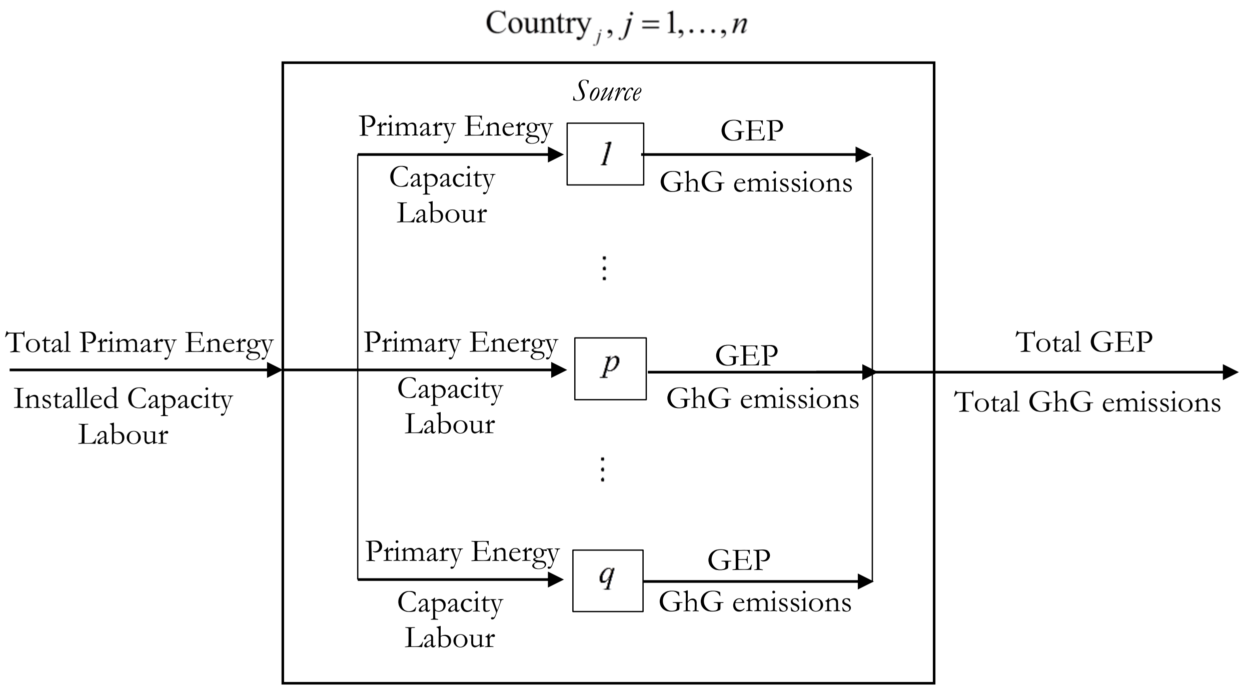

Figure 4. General structure of electricity generation system

3.2.2 Data and data sources

The sustainability and resource efficiency of the electricity generation systems of EU countries are assessed in this study. Data for assessment is sourced from the EU's Energy datasheets which are based on energy balance statistics from the Eurostat database. Eurostat's energy balance dataset provides uniform data across countries that allow for studying domestic energy and conducting an impact assessment of energy policy (Eurostat, 2019). Data analysed in this study cover the 10 years from 2008 to 2017. As earlier indicated, three inputs and two outputs are used in the assessment model. These include:

a. *Installed capacity* (X_1): Megawatts (MW) of installed electricity capacity.
b. *Transformation inputs* (X_2): Millions of tons of oil equivalent (Mtoe) of primary energy resources.
c. *Labour* (X_3): Thousands of persons aged from 15 to 64 years employed in electricity, gas and air conditioning supply.
d. *Gross electricity production* (Y_1): Terawatt hour (TWh) of gross electricity generated.
e. *Greenhouse gas emissions* (Y_2): Million tons of CO_2 (Mio ton CO_2) of greenhouse gas emissions.

In the European case, there are 28 member countries[2] whose electricity production has been categorised into 11 generation sources. These sources comprise 6 renewable sources (hydro, wind, renewable biomass, solar, geothermal and tidal energy), nuclear and 4 non-renewable sources (solid fuels, oil, gases, and non-renewable biofuels and waste). There is an additional category, called as 'other', which includes electricity produced from pumping in hydro stations and other fuels not accounted for elsewhere such as industrial wastes not classed as renewable (EEA, 2016). However, although there exists installed capacity for such a source in some countries, gross electricity production from the 'other' category for most countries is zero. Consequently, this source is eliminated from the assessment.

3.2.3 System description

The evaluation framework for this study is depicted in Figure 5. Starting with the GEP, each energy source has separate production quantities in the dataset. However, for the GhG the dataset reports a composite value for all combustible fuel sources. Consequently, this undesirable output is modelled in a shared-flow problem with allocations to solid fuels, oil, gases and waste and other biofuel sub-processes. For the inputs, each input has some level of sharing between the sub-processes. Installed capacity for renewable sources (except renewable biomass) and nuclear are known and dedicated to the sub-processes without the need for sharing. However, only the composite installed capacity for combustible fuels is reported. Consequently, this must be apportioned between solid fuels, oil, gases, renewable biomass and waste and non-renewable biofuels.

[2] 28 member countries in the study period (2008 to 2017)

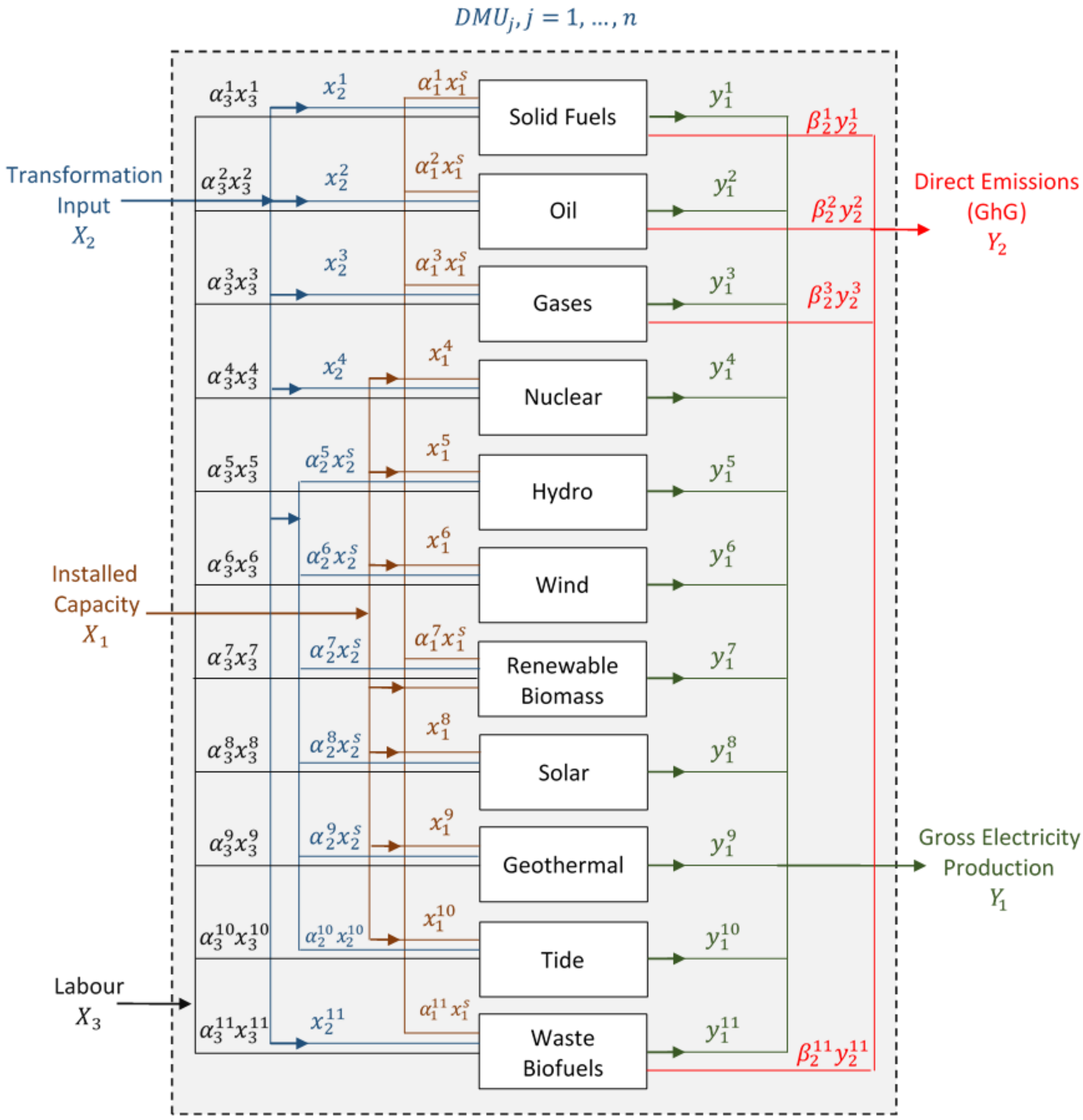

Figure 5. Evaluation framework of the production system

Transformation input for non-renewable energy sources is known and dedicated, however, for renewable sources, the transformation input must be optimally allocated between these sources to maximise efficiency. Finally, the labour variable is a composite score for the entire industry. As such, the exact number of people employed in each sub-process is unknown. This variable must, therefore, be allocated across all sub-processes.

3.2.4 Model formulation

System descriptions in the previous sub-sections show that the system is characterised by a parallel network of 11 sources with shared-flows in both inputs and some output variables. Additionally, the existence of an undesirable output which is in a joint production with the desirable output shows that the empirical model must capture weak disposability. This is formulated as follows:

$$
\begin{aligned}
& E_0 = \max \ u_1 Y_{1o} + u_2 Y_{2o} \\
& \quad \text{subject to:} \\
& \qquad v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o} = 1 \\
& \qquad u_1 Y_{1j} + u_2 Y_{2j} - \left(v_1 X_{1j} + v_2 X_{2j} + v_3 X_{3j} \right) \le 0 \\
& \qquad \left(u_1 Y_{1j}^{(1)} + u_2 \beta_2^{(1)} Y_{2j} \right) - \left(v_1 \alpha_1^{(1)} X_{1j}^{s} + v_2 X_{2j}^{(1)} + v_3 \alpha_3^{(1)} X_{3j} \right) \le 0 \\
& \qquad \left(u_1 Y_{1j}^{(2)} + u_2 \beta_2^{(2)} Y_{2j} \right) - \left(v_1 \alpha_1^{(2)} X_{1j}^{s} + v_2 X_{2j}^{(2)} + v_3 \alpha_3^{(2)} X_{3j} \right) \le 0 \\
& \qquad \left(u_1 Y_{1j}^{(3)} + u_2 \beta_2^{(3)} Y_{2j} \right) - \left(v_1 \alpha_1^{(3)} X_{1j}^{s} + v_2 X_{2j}^{(3)} + v_3 \alpha_3^{(3)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(4)} - \left(v_1 X_{1j}^{(4)} + v_2 X_{2j}^{(4)} + v_3 \alpha_3^{(4)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(5)} - \left(v_1 X_{1j}^{(5)} + v_2 \alpha_2^{(5)} X_{2j}^{s} + v_3 \alpha_3^{(5)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(6)} - \left(v_1 X_{1j}^{(6)} + v_2 \alpha_2^{(6)} X_{2j}^{s} + v_3 \alpha_3^{(6)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(7)} - \left(v_1 \alpha_1^{(7)} X_{1j}^{s} + v_2 \alpha_2^{(7)} X_{2j}^{s} + v_3 \alpha_3^{(7)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(8)} - \left(v_1 X_{1j}^{(8)} + v_2 \alpha_2^{(8)} X_{2j}^{s} + v_3 \alpha_3^{(8)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(9)} - \left(v_1 X_{1j}^{(9)} + v_2 \alpha_2^{(9)} X_{2j}^{s} + v_3 \alpha_3^{(9)} X_{3j} \right) \le 0 \\
& \qquad u_1 Y_{1j}^{(10)} - \left(v_1 X_{1j}^{(10)} + v_2 \alpha_2^{(10)} X_{2j}^{s} + v_3 \alpha_3^{(10)} X_{3j} \right) \le 0 \\
& \qquad \left(u_1 Y_{1j}^{(11)} + u_2 \beta_2^{(11)} Y_{2j} \right) - \left(v_1 \alpha_1^{(11)} X_{1j}^{s} + v_2 X_{2j}^{(11)} + v_3 \alpha_3^{(11)} X_{3j} \right) \le 0 \\
& \qquad \beta_2^{(1)} + \beta_2^{(2)} + \beta_2^{(3)} + \beta_2^{(11)} = 1 \\
& \qquad \alpha_1^{(1)} + \alpha_1^{(2)} + \alpha_1^{(3)} + \alpha_1^{(7)} + \alpha_1^{(11)} = 1 \\
& \qquad \alpha_2^{(5)} + \alpha_2^{(6)} + \alpha_1^{(7)} + \alpha_2^{(8)} + \alpha_2^{(9)} + \alpha_2^{(10)} = 1 \\
& \qquad \alpha_3^{(1)} + \alpha_3^{(2)} + \alpha_3^{(3)} + \alpha_3^{(4)} + \alpha_3^{(5)} + \alpha_3^{(6)} + \alpha_3^{(7)} + \alpha_3^{(8)} + \alpha_3^{(9)} + \alpha_3^{(10)} + \alpha_3^{(11)} = 1 \\
& \qquad a_i^{(p)} \le \alpha_i^{(p)} \le b_i^{(p)} \\
& \qquad a_r^{(p)} \le \beta_r^{(p)} \le b_r^{(p)} \\
& \qquad u_1, v_i \ge \varepsilon, u_2 \ \text{urs}, \ r = 1,\ldots,s, \quad i = 1,\ldots,m, \quad j = 1,2,\ldots,n
\end{aligned}
\tag{7}
$$

Since the model in (7) is nonlinear, it must be transformed into an LP problem. Both the shared inputs and outputs must be apportioned across the relevant sub-processes. While the sharing proportions for the inputs are determined in the efficiency model, that of the output (GhG) is externally determined. For the jth country ($j = 1, 2, \ldots, n$), the emissions output variable of the pth technology ($p = 1, 2, \ldots, q$) for time t ($t = 1, 2, \ldots T$) is determined by the contribution of the technology to the production mix and the Global Warming Potential (GWP) attributable to the technology as follows:

$$
\mathrm{GhG}_{pjt} = \left(R_{pjt}\mathrm{GWP}_{pj} \Big/ \sum_{p=1}^{q} R_{pjt}\mathrm{GWP}_{pj} \right) \times \mathrm{GhG}_{jt} \tag{8}
$$

Where R_{pjt} represents the contribution of the generation source to the total non-renewable and non-nuclear generation at time *t*. Consequently, the sum of the contributions across all the sources is unity, $\sum_{p=1}^{q} R_{pjt} = 1$. GWP_{pj} is the emissions factor represented by the 100-year GWP for source *p* and country *j*. The term in the brackets is, therefore, a generation mix adjusted proportion which satisfies the null-joint condition. Therefore, if a country has no electricity generated from a particular source, then no GhG is assigned to the source, given that $\mathrm{GhG}_{pj} = \beta_2^{(p)} Y_{2j}$. Such decomposition is done in literature in the absence of sub-process emissions information (Kumar Mandal & Madheswaran, 2010). The 100-year GWP is sourced from the Ecoinvent database (version 3) by Wernet et al. (2016).

To linearize the remainder of model (7), we first set $k_i^{(p)} = v_i \alpha_i^{(p)}$. Since $\sum_{p=1}^{q} \alpha_i^{(p)} = 1$, therefore, $v_i \sum_{p=1}^{q} \alpha_i^{(p)} = v_i = \sum_{p=1}^{q} k_i^{(p)}$. Using the Charnes and Cooper (1973) transformation, we set $t = 1/\left(v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o}\right)$ and define $\mu_r = t u_r$, $\nu_i = t v_i$ and $\gamma_i^{(p)} = t k_i^{(p)}$. The nonlinear programming problem above can, therefore, be reduced to the problem:

$$
\begin{aligned}
E_0 = \max\ & \mu_1 Y_{1o} + \mu_2 Y_{2o} \\
\text{s.t.}\ & \nu_1 X_{1o} + \nu_2 X_{2o} + \nu_3 X_{3o} = 1 \\
& \mu_1 Y_{1j} + \mu_2 Y_{2j} - \nu_1 X_{1j} - \nu_2 X_{2j} - \nu_3 X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(1)} + \mu_2 Y_{2j}^{(1)} - \gamma_1^{(1)} X_{1j}^{s} - \nu_2 X_{2j}^{(1)} - \gamma_3^{(1)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(2)} + \mu_2 Y_{2j}^{(2)} - \gamma_1^{(2)} X_{1j}^{s} - \nu_2 X_{2j}^{(2)} - \gamma_3^{(2)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(3)} + \mu_2 Y_{2j}^{(3)} - \gamma_1^{(3)} X_{1j}^{s} - \nu_2 X_{2j}^{(3)} - \gamma_3^{(3)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(4)} - \nu_1 X_{1j}^{(4)} - \nu_2 X_{2j}^{(4)} - \gamma_3^{(4)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(5)} - \nu_1 X_{1j}^{(5)} - \gamma_2^{(5)} X_{2j}^{s} - \gamma_3^{(5)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(6)} - \nu_1 X_{1j}^{(6)} - \gamma_2^{(6)} X_{2j}^{s} - \gamma_3^{(6)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(7)} - \gamma_1^{(7)} X_{1j}^{s} - \gamma_2^{(7)} X_{2j}^{s} - \gamma_3^{(7)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(8)} - \nu_1 X_{1j}^{(8)} - \gamma_2^{(8)} X_{2j}^{s} - \gamma_3^{(8)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(9)} - \nu_1 X_{1j}^{(9)} - \gamma_2^{(9)} X_{2j}^{s} - \gamma_3^{(9)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(10)} - \nu_1 X_{1j}^{(10)} - \gamma_2^{(10)} X_{2j}^{s} - \gamma_3^{(10)} X_{3j} \le 0 \\
& \mu_1 Y_{1j}^{(11)} + \mu_2 Y_{2j}^{(11)} - \gamma_1^{(11)} X_{1j}^{s} - \nu_2 X_{2j}^{(11)} - \gamma_3^{(11)} X_{3j} \le 0 \\
& \gamma_1^{(1)} + \gamma_1^{(2)} + \gamma_1^{(3)} + \gamma_1^{(7)} + \gamma_1^{(11)} = \nu_1 \\
& \gamma_2^{(5)} + \gamma_2^{(6)} + \gamma_2^{(7)} + \gamma_2^{(8)} + \gamma_2^{(9)} + \gamma_2^{(10)} = \nu_2 \\
& \gamma_3^{(1)} + \gamma_3^{(2)} + \gamma_3^{(3)} + \gamma_3^{(4)} + \gamma_3^{(5)} + \gamma_3^{(6)} + \gamma_3^{(7)} + \gamma_3^{(8)} + \gamma_3^{(9)} + \gamma_3^{(10)} + \gamma_3^{(11)} = \nu_3 \\
& \nu_i a_i^{(p)} \le \gamma_i^{(p)} \le \nu_i b_i^{(p)} \\
& \mu_1, \nu_i, \gamma_i^{(p)} \ge \varepsilon, \mu_2 \text{ urs},\ r = 1, \dots, s, \quad i = 1, \dots, m, \quad p = 1, \dots, q, \\
& j = 1, 2, \dots, n
\end{aligned}
\tag{9}
$$

Note that for the second output, $(Y_{2j}^{(p)})$ is determined using (8). From the optimal solution $\left(\mu_r^*, v_i^*, \gamma_i^{*(p)}\right)$, the system and sub-process efficiencies can be determined as:

$$
\begin{aligned}
&E_0 = \frac{\mu_1^* Y_{1o} + \mu_2^* Y_{2o}}{v_1^* X_{1o} + v_2^* X_{2o} + v_3^* X_{3o}}, && E_0^{(6)} = \frac{\mu_1^* Y_{1o}^{(6)}}{v_1^* X_{1o}^{(6)} + \gamma_2^{*(6)} X_{2o}^{s} + \gamma_3^{*(6)} X_{3o}} \\
&E_0^{(1)} = \frac{\mu_1^* Y_{1o}^{(1)} + \mu_2^* Y_{2o}^{(1)}}{\gamma_1^{*(1)} X_{1o}^{s} + v_2^* X_{2o}^{(1)} + \gamma_3^{*(1)} X_{3o}}, && E_0^{(7)} = \frac{\mu_1^* Y_{1j}^{(7)}}{\gamma_1^{*(7)} X_{1o}^{s} + \gamma_2^{*(7)} X_{2o}^{s} + \gamma_3^{*(7)} X_{3o}} \\
&E_0^{(2)} = \frac{\mu_1^* Y_{1o}^{(2)} + \mu_2^* Y_{2o}^{(2)}}{\gamma_1^{*(2)} X_{1o}^{s} + v_2^* X_{2o}^{(2)} + \gamma_3^{*(2)} X_{3o}}, && E_0^{(8)} = \frac{\mu_1^* Y_{1o}^{(8)}}{v_1^* X_{1o}^{(8)} + \gamma_2^{*(8)} X_{2o}^{s} + \gamma_3^{*(8)} X_{3o}} \\
&E_0^{(3)} = \frac{\mu_1^* Y_{1o}^{(3)} + \mu_2^* Y_{2o}^{(3)}}{\gamma_1^{*(3)} X_{1o}^{s} + v_2^* X_{2o}^{(3)} + \gamma_3^{*(3)} X_{3o}}, && E_0^{(9)} = \frac{\mu_1^* Y_{1o}^{(9)}}{v_1^* X_{1o}^{(9)} + \gamma_2^{*(9)} X_{2o}^{s} + \gamma_3^{*(9)} X_{3o}} \\
&E_0^{(4)} = \frac{\mu_1^* Y_{1o}^{(4)}}{v_1^* X_{1o}^{(4)} + v_2^* X_{2o}^{(4)} + \gamma_3^{*(4)} X_{3o}}, && E_0^{(10)} = \frac{\mu_1^* Y_{1o}^{(10)}}{v_1^* X_{1o}^{(10)} + \gamma_2^{*(10)} X_{2o}^{s} + \gamma_3^{*(10)} X_{3o}} \\
&E_0^{(5)} = \frac{\mu_1^* Y_{1o}^{(5)}}{v_1^* X_{1o}^{(5)} + \gamma_2^{*(5)} X_{2o}^{s} + \gamma_3^{*(5)} X_{3o}}, && E_0^{(11)} = \frac{\mu_1^* Y_{1o}^{(11)} + \mu_2^* Y_{2o}^{(11)}}{\gamma_1^{*(11)} X_{1o}^{s} + v_2^* X_{2o}^{(11)} + \gamma_3^{*(11)} X_{3o}}
\end{aligned}
\tag{10}
$$

Note that the models formulated assume that all DMUs have the same set (or portfolio) of sub-processes (i.e. generation sources). However, in reality different countries may generate electricity using different combination of these 11 generation sources. Therefore, maintaining the model as formulated in the presence of shared variables may mean some DMUs may receive allocations to non-existent sub-processes. The consequence may be the possibility of getting efficiency scores for non-existing sub-processes. Also, the deprivation of shared inputs from actual sub-processes may result in overestimation of efficiency scores.

To cater for the sub-process non-homogeneity, we define L_n as the set of all the sub-processes of the system. For each DMU *j*, we also define L_j as the set of sub-processes, out of the L_n, that the specific DMU uses, such that $L_j \subseteq L_n$.

The first set of constraints for the split factors require that the sum of the split factors for existing sub-processes in the set L_j will be one.

$$
\begin{aligned}
&\alpha_1^{(1)} + \alpha_1^{(2)} + \alpha_1^{(3)} + \alpha_1^{(7)} + \alpha_1^{(11)} = 1 \\
&\alpha_2^{(5)} + \alpha_2^{(6)} + \alpha_1^{(7)} + \alpha_2^{(8)} + \alpha_2^{(9)} + \alpha_2^{(10)} = 1 \\
&\alpha_3^{(1)} + \alpha_3^{(2)} + \alpha_3^{(3)} + \alpha_3^{(4)} + \alpha_3^{(5)} + \alpha_3^{(6)} + \alpha_3^{(7)} + \alpha_3^{(8)} + \alpha_3^{(9)} + \alpha_3^{(10)} + \alpha_3^{(11)} = 1
\end{aligned}
\tag{11}
$$

If a sub-process *p* is not the member of L_j but a member of L_n, then split factor for that particular sub-process will be zero. This will ensure no allocation is made to non-existing sub-processes for a particular DMU. Therefore, all elements in the set-theoretic difference of L_n and L_j $(L_n \setminus L_j)$ are set to zero:

$$\alpha_i^{(p)} = 0, \qquad p \in L_n \setminus L_j \tag{12}$$

Finally, upper and lower bounds are set for the split factors for only the existing sub-processes so that at least some units of the shared variable will be allocated to all existing sub-processes.

$$a_i^{(p)} \leq \alpha_i^{(p)} \leq b_i^{(p)} \qquad p \in L_j \tag{13}$$

In the next section, the models developed are empirically applied to the European context.

4 Findings and discussions

This section is dedicated to the empirical assessment of the sustainability and resource efficiency in the electricity generation systems of the 28 EU countries examined.

4.1 Data and description

This study uses a total of five variables, comprising two outputs and three inputs, for empirical assessment. One of the outputs is an undesirable output modelled as weakly disposable and in joint production with the desirable output in some of the sub-processes. The summary statistics of the variables used are presented in Table 1.

Table 1. Descriptive statistics of inputs and outputs (2008-2017)

variables	n	mean	sd	min	max
Outputs:					
Gross electricity production (TWh)[a]	280	117.25	162.79	0.86	652.04
Greenhouse gas emissions (mio ton CO_2)[b]	280	41.4	65.95	0.24	336.72
Inputs:					
Installed capacity (MW)	280	33340	45756.16	571	215142
Transformation inputs (Mtoe)	280	23.92	34.35	0.16	137.94
Labour (Thousand)	280	57.06	76.84	0.8	374.5

[a] *Desirable output*
[b] *Undesirable output*

The summary statistics are based on the 10-year dataset for all 28 EU countries. As such the dataset is a balanced panel with 280 observations. On average gross electricity production for the 10 years stands at 117.25 TWh per country with high variation among countries. Malta, for example, had the lowest GEP in 2016 of about 0.86 TWh with power mainly generated from oil combustion power plants (0.72 TWh) and Solar (0.13 TWh). On the other spectrum is Germany with about 652 TWh in 2017 with reliance on solid fuel-based power plants. This variation among the EU countries is observed across all the variables with even higher variations, relative to the means, in emissions and transformation inputs.

Majority of the countries, 27 out of the 28 countries, had complete data for all variables for the entire study period. The only exception was Malta which had missing employment data in the electricity, gas, steam and air conditioning supply industrial sector from 2014 to 2017. However, as there was complete data from 2008 to 2014 and complete employment data across all industries for the entire study period, the average proportion of the industry data to the national level for 2008 to 2014 was used for estimating reasonable employment figures for the missing period.

Consequently, 1.072% (sd = 0.00102) of the national employment figures for 2014 to 2017 were used as estimates of the industry employment values for the missing periods.

4.2 Efficiency assessment

This section presents and discusses the results of the assessment of the sustainability and resource efficiency in electricity generation among the EU countries. Results presented in this section aim at providing an overview of the performance of individual countries in minimising resource use in generating electricity from different production sources and minimising emissions. First, the system efficiency scores, which looks at the overall industry level data across all generation sources, are presented. This is followed by a decomposition of the system efficiencies at the country-level.

4.3 System efficiency

System-level efficiency scores in the traditional 'black-box' DEA sense do not incorporate any information about the composition of generation sources. As such the country-level total inputs and total outputs are used in the efficiency assessment as shown in (3). There is, therefore, no need to split any inputs across sub-processes. However, such aggregation which ignores the internal sub-divisions have the tendency of overestimating the actual efficiency of the DMUs (Castelli et al., 2010; Cook et al., 2000; Tone & Tsutsui, 2009). This is shown in Figure 6 where the system efficiencies based on the black-box approach and the parallel network model are compared.

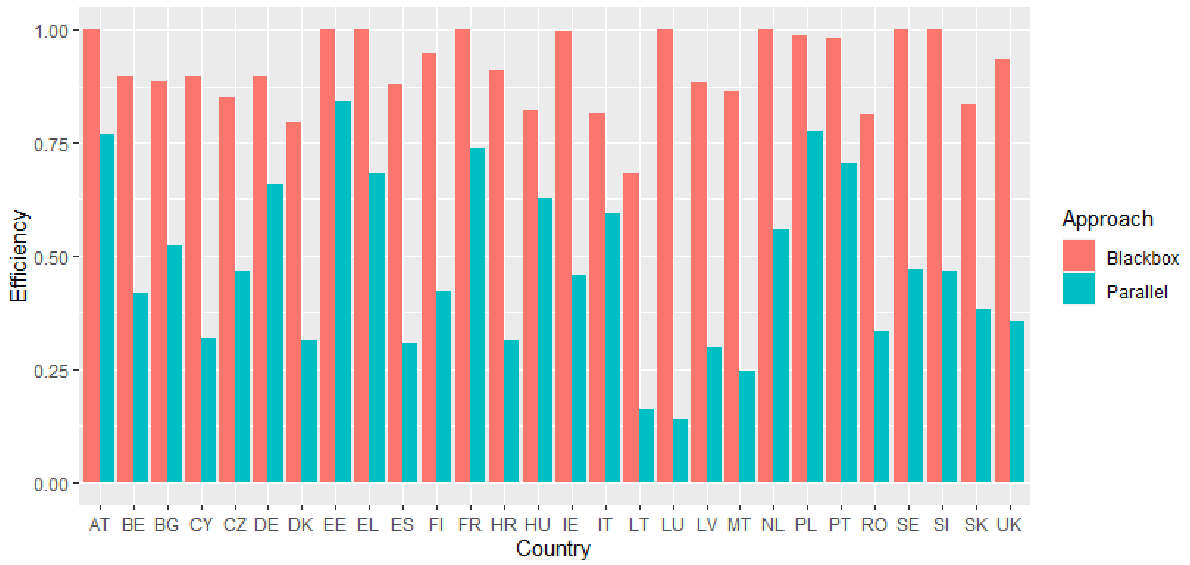

Figure 6. System efficiencies from 'black-box' DEA model and parallel network model (2017)

For each country, the black-box approach shows a higher efficiency score than the parallel network approach. As a result, the parallel network approach is more discriminatory than the black-box approach. Additionally, it allows for the decomposition of the system efficiency to provide additional information on which specific sub-processes require performance improvement (Kao & Hwang, 2008).

Since all countries were examined over 10 years from 2008 to 2017, a summary of the individual country performance is presented in Figure 7 and Figure 8. Figure 7 is a boxplot with jitters that is ordered according to the median overall system efficiencies in ascending order. As such, countries on the far right of the figure had relatively higher resource efficiency and sustainable electricity generation on average over the study period. As can be seen in the figure, over the 10 years, higher performers on average have included Estonia (EE), Poland (PL), Greece (EL) and Austria (AT). Other countries with average system-level efficiency higher than 50% include France (FR), Portugal (PT), Germany (DE), Italy (IT), Netherlands and others. Half of the EU countries have median system efficiency below 50% on average over the 10 years. Luxembourg (LU), Latvia (LV) and Lithuania (LT) are at the lower levels of sustainability in electricity generation. This is generally, similar to the 2017 distributions shown in Figure 6.

A review of the jitters in Figure 7 shows that the performance of most countries differs yearly. Hungary, for example, had an average efficiency of 0.4223. However, Hungary saw system efficiency as high as 0.6281 in 2017, which shows large improvement over the previous years' scores. To trace the yearly progress in resource efficiency and sustainable electricity generation, we present in Figure 8, a level plot of the individual country and EU-wide (average) system efficiencies over time. From the level plot, it is evident that countries like Austria, Estonia and Poland have maintained higher efficiency scores in the 0.7 to 1 range. Other countries like Latvia, Lithuania and Luxembourg have had scores in the lower end of the scale over the years. When scores of the 28 countries are averaged, it can be observed that resource efficiency and sustainable electricity generation in the EU have been within the 0.4 to 0.6 range with no clear pattern towards performance improvement.

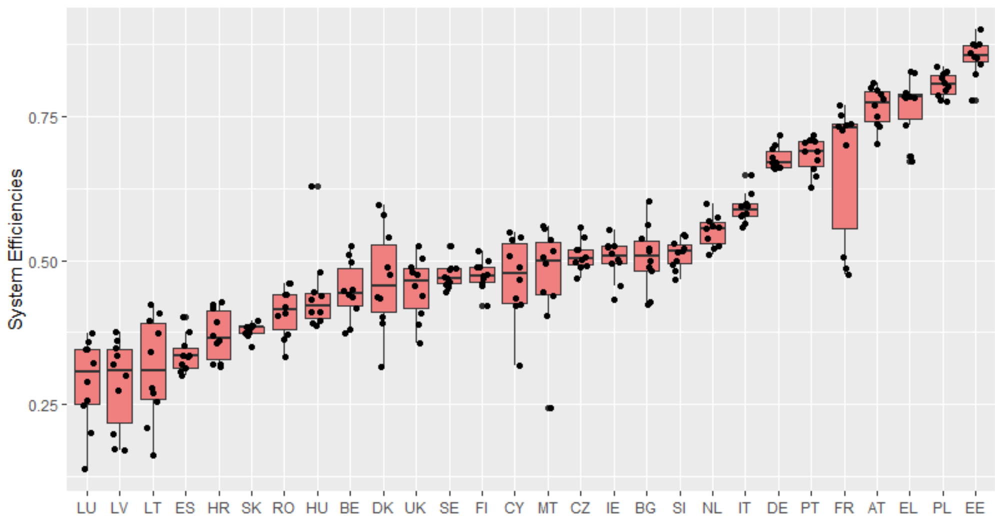

Figure 7. Boxplot with jitters of yearly system efficiencies across countries (2008-2017)

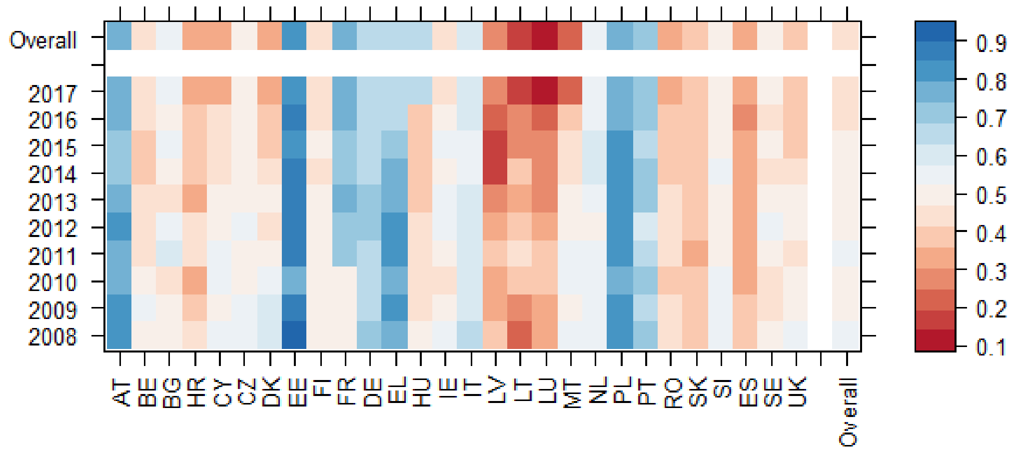

Figure 8. The level plot of yearly system efficiencies across countries (2008-2017)

4.4 Sub-process efficiency

To understand the source of the system efficiencies, it is important to decompose the system efficiencies. Decomposition is done from the optimal multipliers using the equations in (10). The decomposition of the 2017 system efficiencies is presented in Table 2. Each country's system efficiency is decomposed into the sub-system efficiencies. It is important to remember that the system efficiency is a weighted average of the sub-system efficiencies where the weights are the ratio of the resource consumption in a specific sub-process to the overall system-wide resource consumption (Kao, 2012, 2014a, 2014b).

From Table 2 Lithuania, for example, has a very low system efficiency of 0.1620. However, a closer look at the decomposition shows clearly that the country's sustainable production problem has nothing to do with its oil-fuelled power plants as it is a leader in this technology (1.0000). It also has a relative advantage in generating power from renewable biomass (0.4148). Its lower efficiency in generating power using hydroelectricity, solar, among others is the primary cause of the lower 2017 performance levels. The implication is that other countries use lower units of inputs to generate higher levels of clean electricity using these technologies than Lithuania does. For hydroelectricity as an example, Austria is the leader in sustainable and resource efficient production. Consequently, it is also possible to examine at the technology level which countries are higher performers.

Table 2. Decomposition of system efficiencies (2017)

Country	System	Decomposition										
		Solid Fuels	Oil	Gas	Nuclear	Hydro	Wind	Ren. Biomass	Solar	Geo thermal	Tide	Waste & NR Bio
AT	0.7684	0.4901	0.3769	0.7719	n.a.	0.9271	0.7019	0.4811	0.4145	0.0001	n.a.	0.6064
BE	0.4173	0.0030	0.0071	1.0000	0.7905	0.1172	0.2770	0.5439	0.1087	n.a.	n.a.	0.4370
BG	0.5217	0.9847	0.3243	0.2948	0.2481	0.1052	0.2566	0.2213	0.1615	n.a.	n.a.	n.a.
HR	0.3148	0.5843	0.2518	0.5054	n.a.	0.0372	0.2356	0.2461	0.0996	n.a.	n.a.	n.a.
CY	0.3175	n.a.	0.3302	n.a.	n.a.	n.a.	0.0001	0.0052	0.0374	n.a.	n.a.	n.a.
CZ	0.4685	0.7270	0.0397	0.3696	0.2406	0.1600	0.2256	0.2650	0.1263	n.a.	n.a.	0.1330
DK	0.3155	0.9934	0.4876	0.5195	n.a.	0.0009	0.2220	0.0007	0.0269	n.a.	n.a.	0.0182
EE	0.8415	1.0000	0.5034	0.5683	n.a.	0.0002	0.2456	0.8716	n.a.	n.a.	n.a.	0.3722
FI	0.4204	0.2414	0.0078	0.1327	0.8932	0.5390	0.2800	1.0000	0.0695	n.a.	n.a.	0.3241
FR	0.7371	0.5804	0.3941	0.7268	0.8336	0.6249	0.6826	0.2699	0.4144	0.0271	0.7727	0.4734
DE	0.6605	0.9265	0.2124	0.6027	0.5774	0.3115	0.7295	0.7051	0.3892	0.0252	n.a.	0.2882
EL	0.6805	0.7074	0.5867	1.0000	n.a.	0.0016	0.1890	0.0104	0.1369	n.a.	n.a.	n.a.
HU	0.6281	0.6474	0.0248	0.5563	0.8751	0.1464	0.8574	0.3888	0.3776	0.0055	n.a.	0.6556
IE	0.4561	0.5748	0.1489	0.5695	n.a.	0.0744	0.2104	0.0002	0.0014	n.a.	n.a.	0.2313
IT	0.5945	0.7261	0.3498	0.8639	n.a.	0.4098	0.5639	0.2847	0.5180	1.0000	n.a.	0.3766
LV	0.2994	0.0001	0.0029	0.8183	n.a.	0.2399	0.2271	0.4115	0.0213	n.a.	n.a.	n.a.
LT	0.1620	n.a.	1.0000	0.2226	n.a.	0.0064	0.2903	0.4148	0.0694	n.a.	n.a.	0.2253
LU	0.1375	n.a.	0.0003	0.2843	n.a.	0.1219	0.2339	0.6112	0.1010	n.a.	n.a.	0.3232
MT	0.2451	n.a.	0.2970	0.2483	n.a.	n.a.	0.000*	0.0018	0.0327	n.a.	n.a.	n.a.
NL	0.5589	0.3292	0.1847	1.0000	0.0278	0.0191	0.2777	0.0113	0.0811	n.a.	n.a.	0.0313
PL	0.7759	0.9165	0.2699	0.4867	n.a.	0.1436	0.3022	0.0145	0.0470	n.a.	n.a.	0.0799
PT	0.7060	0.9312	0.8704	0.8708	n.a.	0.3521	0.9268	0.3389	0.6338	0.2884	0.0001	0.4299
RO	0.3323	0.4508	0.1888	0.4578	0.2514	0.2648	0.2913	0.0202	0.1605	n.a.	n.a.	0.000*
SK	0.3841	0.2878	0.0644	0.2903	0.7877	0.2188	0.1712	0.5296	0.1144	n.a.	n.a.	0.0224
SI	0.4672	0.8017	0.0073	0.1875	0.6629	0.3671	0.1268	0.2461	0.1371	n.a.	n.a.	0.0252
ES	0.3078	0.3141	0.4275	0.6789	0.2761	0.1252	0.2537	0.0546	0.2437	n.a.	n.a.	0.0920
SE	0.4688	0.000*	0.0030	0.0220	0.8189	0.4716	0.3180	1.0000	0.1116	n.a.	n.a.	0.5876
UK	0.3566	0.1285	0.0180	0.8139	0.6049	0.2270	0.3009	0.8956	0.1076	n.a.	0.0175	0.2132
Geomean	0.4351	0.2080	0.0911	0.4454	0.4357	0.0888	0.1344	0.1079	0.1046	0.0205	0.0124	0.1215

n.a. the country does not produce electricity using this sub-process
** near-zero value*

5 Conclusions and Recommendations

In this study, DEA-based optimisation models that provide a cross-country performance assessment of electricity production in the presence of different country-specific portfolio of generation sources are developed. The novel approach proposed allow for a better allocation of split factors across sub-processes, therefore, correcting the potential overestimation of efficiencies as a result of artificially smaller inputs from allocation of inputs to non-existing sub-processes. Additionally, the potential for non-existing sub-processes to be assigned efficiency scores have been solved.

An empirical application of the models is conducted using data on the 28 EU countries as of the end of 2017. Previous studies have either conducted a country-wide assessment of sustainable and resource efficient electricity production without considering the sub-systems in the country or conducted sub-system assessment of one type of production technology in a single country or across countries. However, this empirical assessment incorporates multiple production technologies and multiple countries in one performance assessment framework. We observed that half of the EU countries have a median overall score lower than 50% on average for the 10-year study period. Higher performers in this phase included Estonia, Poland, Greece and Austria. In averaging the system scores across the countries, it was observed that resource efficiency and sustainable electricity generation in the EU have been within the 0.4 to 0.6 range, over the study period, without a clear pattern towards performance improvement. Country-specific decomposition of the overall efficiencies was also conducted and reported. The contribution of this paper is, therefore, the introduction of a model, which recognises differences in the generation portfolios of EU countries, to examine the performance of the electricity production systems of EU countries.

Some improvement can be made to the empirical assessments in future research. First, we made no distinction in the importance of gross electricity production from renewable and non-renewable sources. Additionally, the weights of the sub-processes were determined using resource consumption. Where available, external weighting of the importance of electricity generation sources can be incorporated in the practical assessment of the system sustainability and resource efficiency. Second, while the literature on assurance regions for multiplier restriction in DEA is well advanced, multiplier restriction in this paper was limited to a minimum and maximum bounds. In practical application, it is possible to more extensively define assurance regions to control the relative importance of optimal multipliers in a manner that is consistent with actual factor prices.

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