Computers and Chemical Engineering 90 (2016) 188–200

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Enhanced data envelopment analysis for sustainability assessment: A novel methodology and application to electricity technologies

Ángel Galán-Martín[a], Gonzalo Guillén-Gosálbez[a,b,*], Laurence Stamford[c], Adisa Azapagic[c]

[a] Departament d'Enginyeria Química, Universitat Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain
[b] Department of Chemical Engineering, Centre for Process Systems Engineering, Imperial College, South Kensington Campus, London SW7 2AZ, United Kingdom
[c] School of Chemical Engineering and Analytical Science, The University of Manchester, Mill, Sackville Street, Manchester M13 9PL, United Kingdom

ARTICLE INFO

Article history:
Received 19 November 2015
Received in revised form 25 March 2016
Accepted 16 April 2016
Available online 20 April 2016

Keywords:
Enhanced data envelopment analysis
Order of efficiency
Sustainability efficiency
Life cycle sustainability assessment
Sustainability targets
Electricity generation

ABSTRACT

Quantifying the level of sustainability attained by a system is a challenging task due to the need to consider a wide range of economic, environmental and social aspects simultaneously. This work explores the application of data envelopment analysis (DEA) to evaluate the sustainability 'efficiency' of a system. We propose an enhanced DEA methodology that uses the concept of 'order of efficiency' to compare and rank alternatives according to the extent to which they adhere to sustainability principles. The capabilities of the proposed approach are illustrated through a sustainability assessment of different technologies for electricity generation in United Kingdom. In addition to screening the alternatives based on sustainability principles, enhanced DEA provides improvement targets for the least sustainable alternatives that, if achieved, would make them more sustainable. The enhanced DEA shows clearly the ultimate distance to sustainability, helping industry and policy makers to improve the efficiency of technologies, products and policies.

1. Introduction

Sustainable development plays a key role in modern societies that seek "to meet the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987). Promoting sustainable development requires implementing concrete actions, projects, programs, plans and policies, which involve the simultaneous pursuit and satisfaction of economic, environmental, and social goals.

Setting sustainability goals and targets requires some knowledge and understanding of the current level of sustainability. This can be attained through sustainability assessments, by considering simultaneously all three 'pillars of sustainability'—economic, environmental and social (Azapagic and Perdan, 2000; Pope et al., 2004). A full characterization and evaluation of a system in these dimensions requires, therefore, the definition of a wide range of economic, environmental and social indicators, thereby leading to complex multi-criteria decision-making problems. A possible way to simplify the assessment is to define an aggregated sustainability metric by expressing preferences and assigning the weights of importance to the economic, environmental and social indicators (Gerdessen and Pascucci, 2013; Martins et al., 2007; Sikdar, 2003). However, while this approach is easy to implement, it is plagued with difficulties at both the philosophical and conceptual levels. This includes the fact that in many cases the value judgements underlying the expression of preferences are incompletely formed or do not exist so that their articulation prior to understanding the trade-offs between different sustainability criteria could be misleading and/or meaningless. This could impede the deliberative process among different stakeholders, which is central to decision making: the discursive mediation of conflicting interests and rival perspectives represents a process whereby the decision can be delivered in an ethically acceptable way (Azapagic and Perdan, 2005). In addition, valuable information on the performance of a system in a particular dimension might be lost during aggregation which could rule out some good alternatives before the trade-offs have been understood and explored by decision-makers.

One of the aims of sustainability assessment is to identify measures to be optimized in order to minimise or avoid adverse impacts

* Corresponding author at: Departament d'Enginyeria Química, Universitat Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain.
E-mail addresses: angel.galan@urv.cat (Á. Galán-Martín), g.guillen05@ic.ac.uk (G. Guillén-Gosálbez), laurence.stamford@manchester.ac.uk (L. Stamford), adisa.azapagic@manchester.ac.uk (A. Azapagic).

http://dx.doi.org/10.1016/j.compchemeng.2016.04.022
0098-1354/

(Gibson, 2001). Most sustainability assessment approaches establish a 'direction to target' (Pope et al., 2004), that is, whether or not a proposed measure in one direction represents a positive, neutral or negative contribution towards the sustainability target. This approach is limited in scope, as it provides no quantitative guidelines on how to improve the level of sustainability. 'Distance from target' approaches are more effective in practice because they measure the extent of progress towards (or away from) sustainability, making it possible to define quantitative targets that ensure a more sustainable development (Jaeger et al., 2011). Furthermore, quantitative methods can be coupled with mathematical programming techniques to automate the search for alternatives with improved environmental performance (Grossmann and Guillén-Gosálbez, 2010).

This paper proposes a novel approach based on data envelopment analysis (DEA) to quantify the level of sustainability attained by a system and identify targets for improvements. DEA is a non-parametric linear programming (LP) technique that measures the efficiency of a set of entities, termed decision-making units (DMUs), each transforming multiple inputs into multiple outputs (Charnes et al., 1978). In addition to calculating the efficiency scores, DEA provides specific guidelines, expressed as quantitative targets, which can be used to improve the efficiency level, in this context related to the level of sustainability.

There has been a substantial body of research on methodological developments and applications of DEA, but these efforts have primarily focused on the assessment of DMUs in areas of science and engineering outside environmental science (Liu et al., 2013, 2015). More recently, DEA was combined with life cycle assessment (LCA) to assess the environmental efficiency of different systems (Hoang and Alauddin, 2011; Iribarren et al., 2013; Lorenzo-Toja et al., 2014; Mohammadi et al., 2014; Vázquez-Rowe and Iribarren, 2014). These studies, however, covered only environmental and economic aspects but disregarded the social dimension of sustainability. Other authors have used DEA to assess the overall level of sustainability, but aggregated the multidimensional metrics into a single indicator (Chang et al., 2013; Khodakarami et al., 2014; Reig-Martínez et al., 2011; Tajbakhsh and Hassini, 2014), an approach that exhibits the limitations of the aggregation discussed earlier.

Despite its advantages, DEA shows two major limitations that are particularly critical when it is applied for sustainability assessment. First, it answers the question of whether a unit is efficient or not, but makes no distinction between the units deemed efficient (i.e., no ranking of efficient units is provided). Hence, since all the efficient units show the same efficiency score of 1, it is difficult to select a final alternative in the absence of a ranking scheme (Cook and Seiford, 2009). Secondly, efficiency scores are very sensitive to the number of inputs and outputs (i.e. the number of sustainability indicators in our context) as well as to the size of the sample (Bhagavath, 2006). For large sets of inputs and outputs with respect to the number of units, a case that arises very often in sustainability assessments, the lack of ranking leads to a poor discrimination in which many units can be regarded as efficient (Avkiran, 2002).

Improving the discriminatory power of standard DEA with no loss of information has become a major challenge that has attracted a significant research interest. Different approaches have been proposed to deal with the issue of ranking of DMUs in DEA (Adler et al., 2002; Hosseinzadeh Lotfi et al., 2013a). One important method for ranking the DMUs is based on the cross-efficiency technique (Washio and Yamada, 2013; Wu et al., 2012; Zerafat Angiz et al., 2013), whereby the units are self- and peer-evaluated. Some authors have also used super-efficiency methods (Chen et al., 2011, 2013; Li et al., 2007), based on the idea of excluding the unit under evaluation to analyse the remaining units. Other methodologies are based on finding optimal common weights to discriminate among the units, usually based on value judgements (Jahanshahloo et al., 2005; Wang et al., 2011, 2009). Other ways to rank the units are through benchmarking methods and statistical techniques (Chen and Deng, 2011; Lu and Lo, 2009). Some researchers have combined DEA with multiple-criteria decision-making methodologies in which additional preferential information is required (Hosseinzadeh Lotfi et al., 2013b; Jablonsky, 2011). However, despite the large number of approaches developed to further discriminate among the DEA units, no single methodology can be considered as a complete solution to the ranking problem.

To overcome the limitations of standard DEA, this work introduces an enhanced DEA methodology that is tailored sustainability assessments. This approach integrates standard DEA with the concept of order of efficiency (optimality), as originally proposed by Das (1999) and later used by Antipova et al. (2015) and Pozo et al. (2012). In essence, the idea is to apply standard DEA repeatedly for different combinations of metrics in each sustainability dimension separately so as to determine an overall sustainability efficiency. The capabilities of our methodology are illustrated through a sustainability assessment of electricity-generation technologies in the United Kingdom (UK), which are expected to play a major role in its future electricity mix (Stamford and Azapagic, 2014). The main advantages of the proposed approach are that: (i) it considers each sustainability dimension separately; (ii) it can handle a large number of economic, environmental and social indicators without compromising the discriminatory capabilities of the method; (iii) it provides a clear ranking of units based on their overall performance without the need to define explicit weights on the individual metrics; and (iv) it provides clear quantitative targets for the inefficient systems to become efficient.

The rest of the article is organised as follows. A motivating example is presented in Section 2, while in Section 3 we describe the standard and the enhanced DEA methodologies, revisiting in both cases the motivating example to illustrate the differences between the two approaches. A real case study that evaluates the sustainability of electricity technologies in the UK is introduced in Section 4 to demonstrate the capabilities of the proposed methodology. Finally, the conclusions of the work are drawn in Section 5.

2. Motivating example

This section introduces a simple example that motivates our methodological approach. Consider a set of units (e.g., technologies, products, processes, etc.), each characterised by multiple economic, environmental and social inputs, synonymous to sustainability decision criteria, and required to produce one unit of output (e.g., 1 kWh) As indicated in Table 1, seven technologies (A–G) are considered, each of which has three economic inputs (I-1, I-2 and I-3), three environmental (I-4, I-5 and I-6), and three social inputs (I-7, I-8 and I-9) to produce one unit of output (O-1). The table shows the values of each input, which are dimensionless for the purposes of this example, but otherwise would be expressed in appropriate units. Lower input levels imply better performance in all of the cases.

The goal of the analysis is to assess the level of sustainability attained by each technology in Table 1, that is, we aim to address the following points:

- Which technologies are 'more efficient' in terms of sustainability (i.e. perform better considering sustainability principles)?
- For the ones found to be inefficient, how could we improve their level of sustainability?

Table 1
Motivating example: Seven technologies with nine inputs to produce one unit of output.

Technology	Economic inputs			Environmental inputs			Social inputs			Output
	I-1	I-2	I-3	I-4	I-5	I-6	I-7	I-8	I-9	O-1
A	4.0	5.0	2.9	1.0	2.5	3.0	4.2	2.1	1.3	1.0
B	2.5	1.0	3.7	2.0	5.0	2.0	3.1	3.4	4.0	1.0
C	2.0	1.3	1.0	4.5	4.3	1.0	1.3	5.0	2.7	1.0
D	4.5	7.0	8.0	2.0	7.0	8.0	0.5	7.0	7.0	1.0
E	3.0	3.0	1.8	2.5	1.5	5.0	3.0	1.8	3.3	1.0
F	6.5	2.0	2.1	1.3	2.0	4.0	0.8	3.2	2.4	1.0
G	3.0	3.5	1.1	4.0	3.1	3.0	2.0	2.7	1.9	1.0

DEA was not originally devised to assess the level of sustainability, so an enhanced version is required for this purpose. Both standard and enhanced DEA are discussed in the next section.

3. Methodology

The fundamentals of standard DEA are presented first before describing the improvements introduced in this work to tailor the method for sustainability assessment.

3.1. Data envelopment analysis

As mentioned earlier, DEA is a non-parametric LP technique that quantifies the relative efficiency of a set of comparable DMUs taking into account several inputs and outputs simultaneously (Charnes et al., 1978). DEA analyses each DMU individually by solving an LP model to identify those with the best performance, i.e., the ones deemed efficient, which form the "efficient frontier". DEA also measures in turn the level of efficiency of the non-frontier units (inefficient units), identifies sources of inefficiency, and provides specific guidelines on what changes are required to turn inefficient units into efficient.

The original input-oriented DEA model, known in the literature as the Charnes, Cooper and Rhodes (CCR) model, first proposed by these authors (Charnes et al., 1978) based on Farrell's work (Farrell, 1957), is a nonlinear program that measures the efficiency of a unit as the ratio of the weighted sum of their outputs and inputs. The goal of this model is to find the optimal weights that maximise the efficiency of a set of DMUs (i.e. for each such DMU, the best weights are found that maximise the outputs/inputs ratio).

Let us consider a set of $|J|$ DMUs j ($j = 1,\ldots,|J|$), each using $|I|$ inputs x_{ij} ($i = 1,\ldots,|I|$) to produce $|R|$ outputs y_{rj} ($r = 1,\ldots,|R|$). The CCR model defined for each DMU j, is stated as follows:

$$\text{Max}\theta_j = \sum_{r\in R} u_r y_{rj} \Big/ \sum_{i\in I} v_i x_{ij} \tag{1}$$

$$s.t. \sum_{r\in R} u_r y_{rj} - \sum_{i\in I} v_i x_{ij} \le 0 \qquad \forall j \in J \tag{2}$$

$$u_r, v_i \ge 0 \qquad \forall r \in R, i \in I \tag{3}$$

where θ_j is the technical efficiency of the DMU_j and u_r and v_i are free variables denoting the weights (multipliers) given to each output r and input i, respectively. Due to the flexibility in the weights, if a DMU_j satisfies $\theta_j = 1$, it is deemed efficient, and it is considered inefficient when $\theta_j < 1$. The latter implies that the DMU under evaluation is always inferior to other alternatives, even for the most favourable choice of weights (it is possible to reduce any of its inputs without reducing any output).

The previous CCR model is input-oriented, that is, an inefficient unit is turned into efficient through a proportional reduction of inputs and keeping the output constant. Moreover, the CCR model considers constant returns to scale (CRS), as it assumes that DMUs operate at the same scale and their outputs change proportionally when changes in the inputs are applied. The original input-oriented CCR DEA model (Charnes et al., 1978), which is nonlinear and non-convex, can be reformulated into the following LP model Eqs. (4–7), where the denominator is set to one and the numerator is maximised:

$$\text{Max}\theta_{j'} = \sum_{r\in R} u_r y_{rj'} \tag{4}$$

$$\text{s.t.} \sum_{i\in I} v_i x_{ij'} \tag{5}$$

$$\sum_{r\in R} u_r y_{rj} - \sum_{i\in I} v_i x_{ij} \le 0 \quad \forall j \in J \tag{6}$$

$$u_r, v_i \ge 0 \qquad \forall r \in R, i \in I \tag{7}$$

where the subscript j' denotes the specific DMU being assessed.

For this primal LP problem it is possible to formulate a partner problem (dual), which provides the same information as the primal (i.e., efficiency scores) and calculates in turn targets for the inefficient DMUs so as to become efficient. The LP dual model is formulated by assigning one dual variable to each constraint in the primal model (Cooper et al., 2004) as follows:

$$Z = \min \theta_o - \varepsilon \left(\sum_{r\in R} S_r^+ + \sum_{i\in I} S_i^- \right) \tag{8}$$

$$s.t. \sum_{j\in J} \lambda_j x_{ij} + S_i^- = \theta_o x_{io} \forall i \in I \tag{9}$$

$$\sum_{j\in J} \lambda_j y_{rj} - S_r^+ = y_{ro} \quad \forall r \in R \tag{10}$$

$$\lambda_j, S_i^-, S_r^+ \ge 0 \quad \forall j \in J, i \in I, r \in R \tag{11}$$

where ε is a non-Archimedean infinitesimal value designed to enforce strict positivity on variables. θ_o is unconstrained and measures the efficiency of the DMU_o under consideration and, therefore, it is less than or equal to 1 ($\theta_o \le 1$). S_r^+ and S_i^- are slack variables denoting the extra amount by which an input (or output) should be reduced (or increased) to be efficient. Note that the values of the slacks are all zero (S_r^+ and $S_i^- = 0$) in the efficient units ($\theta_0 = 1$), and strictly positive in the inefficient ones ($\theta_o < 1$). λ_j is a variable that represents the weight assigned to each efficient DMU (belonging to the reference set of an inefficient unit) to form a composite efficient unit that could be used as a benchmark to improve the inefficient unit. This composite unit is obtained by projecting radially the inefficient unit on the efficient frontier, which is the piece-wise linear function connecting all the efficient DMUs (those with an efficiency score of 1). To illustrate this, we use below a simplified motivating example described in Section 2.

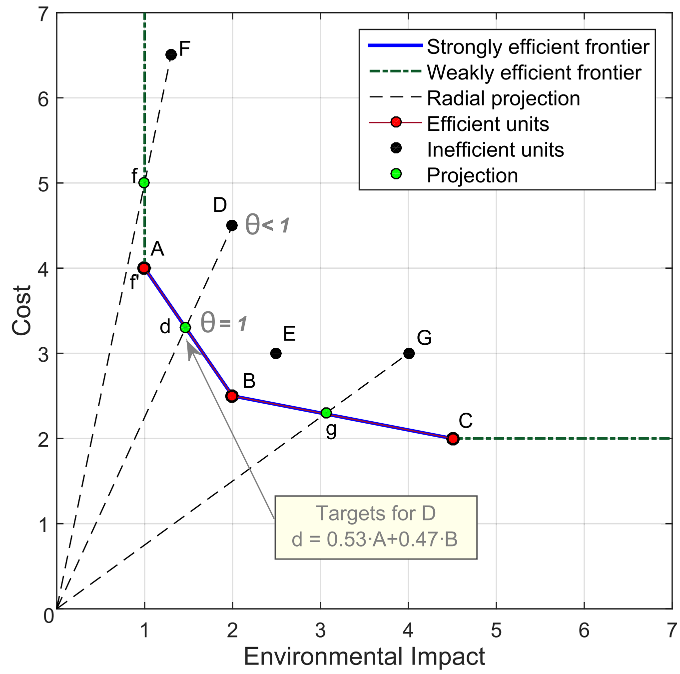

Fig. 1. Graphical representation of DEA results for the simplified motivating example. The figure shows the two inputs considered in the analysis, cost and environmental impact (note that the output is constant for all of the decision-making units).

3.1.1. An illustrative example for standard DEA

For simplicity, the analysis in the simplified example is restricted to one environmental input (I-1) (environmental impact), one economic input (I-4) (cost), and one output (O-1), as shown in Table 1. Fig. 1 provides a graphical representation of the DEA results. The efficient technologies, denoted by the red circles, determine the efficient frontier, which is the convex envelope depicted in blue colour. Inefficient systems are represented by black circles, while their radial projections on the frontier are depicted by green circles.

As can be observed in Fig. 1, technologies A, B and C have lower input values for the same output and are thus identified as efficient (i.e. their efficiency equals 1). The line connecting them determines the piece-wise linear efficient frontier. On the other hand, D, E, F and G are deemed inefficient because their efficiency score θ_j is lower than 1 (they produce the same level of output with higher inputs, that is, they are more expensive and cause greater environmental impact). DEA also quantifies the magnitude of inefficiency by referring to the efficient frontier. For instance, the efficiency of technology D is obtained from the ratio between two segments, the one that goes from zero to the intersecting point between the efficient frontier and the radial projection of D; and the one that connects zero and D (i.e., the ratio between $\overline{0d}$ and $\overline{0D}$ is equal to 0.73 for this case). The efficiency score represents the extent to which all the inputs should be proportionally reduced to reach the frontier; therefore, D should reduce its inputs to 73.33% of its current level in order to be efficient. Point d (which represents the hypothetical efficient unit for D) is generated by a linear combination of A and B, which is the reference set (peer group), using linear weights equal to 0.53 and 0.47 respectively, which are provided by the DEA model.

Similarly, all inefficient DMUs can be projected onto the efficiency frontier, but in doing so we may sometimes obtain weakly-efficient composite units, as it happens with unit f (efficient unit for F), which shows a slack in the cost given by the distance $\overline{fA}$. In other words, unit F should reduce its inputs at least by 23.08% (efficiency equals to 76.92%) to be weakly-efficient. However, f would remain inferior since technology A has the same environmental impact but lower cost. Therefore, technology F presents a slack or excess of 1 unit in the cost, which implies an input value of 61.5% of its current level to be strongly efficient. That is, a reduction of 23.08% (from 6.5 to 5.0) in the cost for F is not enough to become strongly efficient. For that, the unit needs to decrease the cost by a further 38.5% (from 6.5 to 4.0), thereby reaching point f' with the same inputs and output than technology A.

Note that the criteria to be considered in DEA (i.e., the economic, environmental and social indicators) might be treated as inputs or outputs depending on whether they should be minimised or maximised, respectively (i.e., depending on whether lower or higher values imply better performance, respectively). Furthermore, it is possible to define all the indicators as inputs (whose value should be minimised) by carrying out a proper data transformation. Note also that if this transformation implies only scaling the input values, then it does not affect the results since the radial DEA models are unit invariant, that is, the efficiency scores are independent of the measurement units of the inputs and outputs. Further information on this topic can be found in Edelstein and Paradi (2013) and Tone (2001), among others.

3.1.2. Standard DEA for sustainability assessment applied to the motiviting example

To answer the questions posed in the motivating example, we propose to assess the efficiency in each sustainability dimension separately (i.e. economic, environmental and social) and then aggregate the results into an overall sustainability efficiency. Therefore, a unit will have a sustainability efficiency of 1 if it is efficient simultaneously in all three dimensions of sustainability.

Let θ_j^d be the efficiency of DMU j for the sustainability dimension d, that is, the efficiency calculated by DEA when only the inputs belonging to this dimension are considered. We define an overall sustainability efficiency, denoted by θ_j^{sust} and calculated by Eq. (12), as the average of the efficiencies in each sustainability dimension (reflecting a balanced integration of the three dimensions of sustainable development in which all of them are considered equally important):

$$\theta_j^{sust} = \frac{\sum_{d \in D} \theta_j^d}{|D|} \forall j \in J \tag{12}$$

Note that the efficiency scores (θ_j^d and θ_j^{sust}) fall within the range 0–1. As explained before, a DMU j is considered efficient in a specific sustainability dimension if its efficiency score equals 1 ($\theta_j^d = 1$). The higher the dimension's efficiency score, the higher the level of efficiency for that sustainability dimension. Similarly, a DMU j is considered efficient from the sustainability point of view if its overall sustainability efficiency score equals 1 ($\theta_j^{sust} = 1$), that is, if it is efficient for all three sustainability dimensions. The higher the sustainability efficiency scores, the higher the level of sustainability.

We now revisit the motivating example by applying standard DEA. The results are presented in Fig. 2 which shows the efficiency scores for each sustainability dimension and the overall sustainability efficiency for each technology. Each axis in the radar chart corresponds to a technology and the outermost ring represents an efficiency score of 1. The dashed orange, green and blue lines represent the economic, environmental and social efficiency, respectively, while the purple line represents the overall sustainability efficiency. Moreover, Fig. 2 displays the efficiency for each technology calculated considering simultaneously all of the inputs given in Table 1 (black dotted line) without classifying them according to the sustainability dimension they refer to.

As can be seen in Fig. 2, when considering all inputs simultaneously regardless of the dimension they belong to (black dotted line), all the technologies are deemed efficient (efficiency scores equal 1), thereby leading to a very poor discrimination and loss of information. This is because each technology performs well in at least one indicator, a situation that typically arises in sustainability studies. For example, an analysis of the input data shows that D is deemed efficient despite performing well for a single social indicator (I-7) and very poorly for the remaining economic and environmental metrics. Thus, the outcome of standard DEA in this case provides little insight into which technologies are more sustainable across the three sustainability dimensions.

By considering each sustainability dimension separately (i.e., applying DEA to each sustainability dimension at a time and then aggregating the results into the overall sustainability efficiency score), we can generate more insightful results. In this case, no single technology is found sustainable overall, since none is efficient simultaneously in all three dimensions. The technology with the highest overall sustainability efficiency is C (sustainability efficiency score of 0.95), followed by G (0.93), while D is the least sustainable (0.65). As observed in the efficiencies attained in each dimension, the discrimination can still be poor even after applying standard DEA to each of them separately. This is because some dimensions require the evaluation of many metrics, and because of this several technologies performing well only in a very small number of them can be deemed efficient within a specific dimension. For instance, technology B and C are both found economically efficient and it is not possible with standard DEA to discriminate between them. The same happens in the environmental and social dimensions, in which several technologies are found efficient, leaving open the question of which one is globally better still. Therefore, there is a need for enhancing standard DEA to overcome these limitations; this is discussed next.

3.2. Enhanced data envelopment analysis: order of efficiency

This section introduces an enhanced DEA method tailored for sustainability assessment that integrates the concept of 'order of efficiency'. The fundamentals of enhanced DEA are presented first, followed by revisiting the motivating example to demonstrate the capabilities of the approach.

In essence, our method ranks DMUs according to how they perform globally, without the need to define explicit weights for the inputs and outputs. This has at least two advantages: it removes the subjectivity associated with the weighting of decision criteria and eases the burden on decision-makers by avoiding the need for elicitation of preferences. This is achieved by integrating into standard DEA the concept of 'order of efficiency', originally introduced to rank Pareto optimal solutions from a set of many (Das, 1999). A solution is said to be efficient of order k if it is not dominated by any other solution in any of the possible k-elements subsets of objectives. This approach is well suited for cases with a large number of criteria (objectives) (Das, 1999), in which a large number of points might be regarded as Pareto optimal, even if they perform well in only one criterion out of a large number of objectives and poorly in the rest. The order of efficiency determines preferences among optimal solutions by ranking them according to their order of efficiency, whereby lower orders imply higher degrees of efficiency (Das, 1999) and, therefore, higher preferences for those solutions.

On the basis of the original concept, here we adopt the order of efficiency in the context of DEA, so that a DMU is identified as efficient of order k, if and only if, it is found efficient in any of the possible k-elements subsets of inputs. Following this proposed enhanced DEA approach, the calculations of standard DEA are repeated iteratively for all possible combinations of inputs/outputs and then aggregated into an overall efficiency metric (note that in this work, without loss of generality, we only consider combinations of inputs since it is possible to define all the indicators as inputs through a proper data transformation and a single output of 1 for all the DMUs). The enhanced DEA based methodology is summarised in Fig. 3 and explained in more detail below.

Let J be the set of DMUs to be analysed by DEA ($j = 1,\ldots,|J|$) according to a set T of sustainability criteria or indicators. Considering the set D of sustainability dimensions (i.e., economic, environmental and social), the first step requires categorizing the indicators within the sustainability dimension d they belong to, such that each dimension comprises $|I_d|$ sustainability criteria or indicators. These are defined as inputs whose values need to be minimised to produce a unit of output (fixing the output to 1 and transforming the inputs accordingly). In the second step (Fig. 3), within each sustainability dimension d, each and every of the possible combination t of inputs are identified, each containing k inputs out of $|I_d|$, with the total number of combinations given by $\binom{|I_d|}{k}$. In the third step, the DEA model is solved to determine the efficiency score for every DMU j in each combination of inputs t_k (denoted by θ_{jkt}^d).

Then, in step 4, the efficiency of order k (denoted by θ_{jk}^d) can be determined for each DMU j using Eq. (13) as the average efficiency in all possible combinations t containing elements of size k belonging to dimension d (note that each and every of the possible subset of inputs needs to be considered).

$$\theta_{jk}^{d} = \frac{\sum_{t \in T_{kd}} \theta_{jkt}^{d}}{\binom{|I_d|}{k}} \forall d \in D, j \in J, k \in K_d \tag{13}$$

A DMU j is said to be efficient of order k in a specific sustainability dimension d, if and only if, the efficiency for any subset of inputs t of cardinality k is equal to 1, that is, $\theta_{jkt}^d = 1$ for all $t \in T_k$, where T_k is the set of possible combinations of $|I|$ inputs of size k. Note that if a DMU is efficient of order k, it is also efficient of order $k' > k$. Note also that the utopia point (if attainable) is efficient of order 1, that is, it is

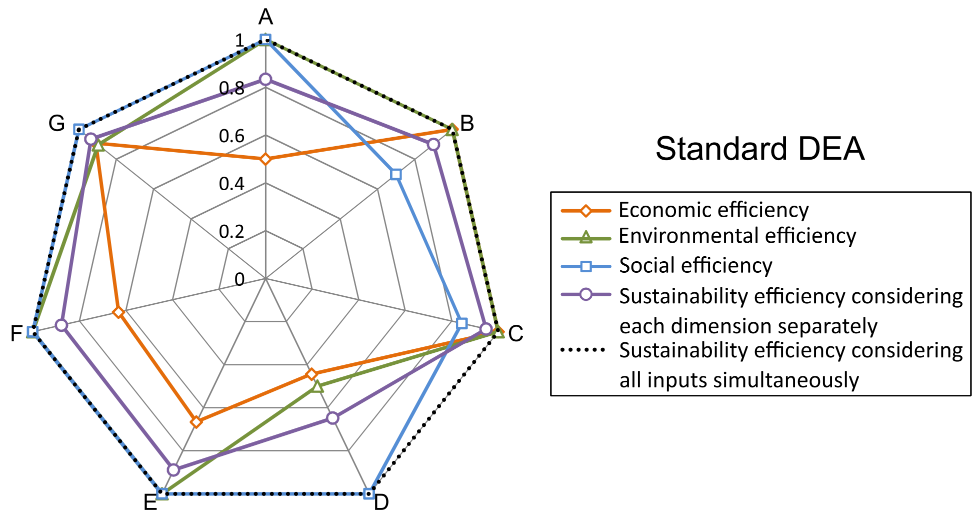

Fig. 2. Standard DEA results for the motivating example.

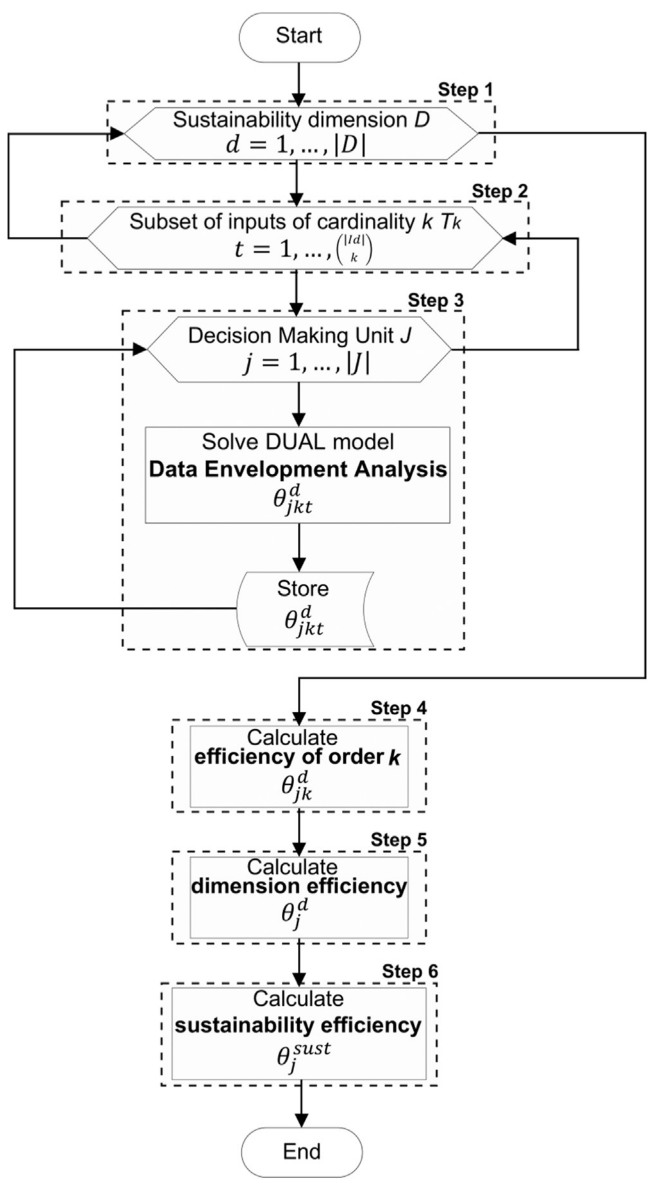

Fig. 3. Algorithm of the proposed enhanced DEA methodology to assess the sustainability efficiency in the economic, environmental and social dimensions.

the best in every input individually. Therefore, as mentioned earlier, lower orders of efficiency reflect a better overall performance, since that implies a more balanced performance in all inputs.

To compute the efficiency of order k, we run the DEA calculations for each and every possible combination of inputs. This approach is equivalent to imposing bounds on the weights (multipliers) in the DEA model, so that inputs i' not included in a specific subset are given a fixed weight equal to 0 ($v_{i'} = 0$), while the weights for the other included inputs are considered as free variables. The advantage of our approach is that there is no need to define explicit weights for inputs/outputs. Instead, we solve the DEA models for every combination of inputs.

Furthermore, we define an overall efficiency score in each dimension (i.e., dimension efficiency denoted by θ_j^d) for each DMU j as the average of all of the efficiency scores obtained for all of the orders of efficiency. That is, in the fifth step in Fig. 3, the dimension efficiency is determined as the average of all of the efficiency scores computed by DEA for all of the possible combinations of inputs within each sustainability dimension d, as given in Eq. (14):

$$\theta_j^d = \frac{\sum_{k \in K_d} \sum_{t \in T_{kd}} \theta_{jkt}^d}{\sum_{k \in K_d} \begin{pmatrix} |I_d| \\ k \end{pmatrix}} \forall d \in D, j \in J \tag{14}$$

where d represents the sustainability dimension (i.e., economic, environmental and social) to which the efficiency refers, I_d is the set of inputs (i.e., sustainability criteria or metrics) that quantify different aspects of that dimension, T_{kd} is the set of combinations of order k of these inputs covered by dimension d, and K_d is the set of allowable orders in dimension d (note that $|K_\mathrm{d}| = |I_d|$).

The dimension efficiency (θ_j^d) takes values between 0 and 1, where a score of 1 means that the DMU j under consideration is efficient in the sustainability dimension d, that is, efficient in all of the possible subsets of inputs—a situation that will take place only if DMU j is the best in all of the inputs simultaneously. In this context, DMUs with greater efficiency scores are considered more efficient within a sustainability dimension.

Finally, with the values of the dimension efficiencies in hand, we can determine in step 6 the overall sustainability efficiency θ_j^{sust} using Eq. (12). The overall sustainability efficiency allows ranking of all the DMUs in terms of their sustainability performance, since greater sustainability efficiency scores reflect better level of sustainability for a given DMU. It should be noted, however, that we refer to sustainability in the context of efficiency so that the solutions found efficient may not necessarily be fully sustainable according to the original Brundtland definition of sustainability (WCED, 1987).

One of the advantages of the DEA model is that it can be implemented in standard software packages and solved very efficiently using LP methods, which can potentially encourage a widespread adoption of the methodology proposed herein. In this work, without loss of generality, we employ the input-oriented CCR DEA model, which considers CRS. However, the methodology could be extended to output-orientation and be formulated using the BCC DEA model (named after Banker, Chames and Cooper (1984)), which considers variable returns to scale by adding an additional convexity constraint on λ_j ($\sum_j \lambda_j$=1). The choice between the two models depends on the application being addressed; for further discussion on this topic, see Lozano et al. (2009). Note, however, that when all the indicators are treated as inputs (by fixing the output to 1), the selection of either a CCR or BCC model may become irrelevant since all units produce the same output levels.

The inefficiency assessment for every combination of inputs provides a large number of improvement targets that are difficult to interpret. Hence, we propose to establish improvement targets for every unit deemed inefficient in each individual dimension, considering all of the inputs in that dimension simultaneously (i.e. higher order of efficiency), rather than all of the possible combinations of inputs. More precisely, let us denote by E the reference set of efficient DMUs j for an inefficient DMU j'. For each DMU j' found inefficient in a specific dimension d' considering all the inputs within that dimension (i.e., k equals to $|I|$), the corresponding targets that its inputs i ($x_{ij'}$) should achieve to make the unit efficient are given in Eq. (15). Note that x_{ij} is a parameter representing the input values of the DMUs in the reference set, while variables $\theta_{j'}$, λ_j and S_i^- are computed by solving the dual DEA model Eqs. (8–11). Hence, the target value for input i in dimension d' that DMU j' should attain is computed as follows:

$$target\_input_{d'j'i} = \sum_{j \in E} \lambda_j x_{ij} = \theta_{j'} x_{ij'} - S_i^- \qquad \forall i \in I, d' \in D, j' \in J \quad (15)$$

where λ_j are the linear combination coefficients that multiply the members of the peer group of j', $\theta_{j'}$ is the efficiency score of the inefficient unit j' and S_i^- is a slack variable denoting the extra amount by which the input i should be reduced to be strongly efficient.

3.2.1. An illustrative example for enhanced DEA

To illustrate the enhanced DEA methodology that integrates the concept of order of efficiency, the example in Table 1 is revisited next considering only the economic inputs (i.e., I-1, I-2 and I-3). Fig. 4 illustrates graphically the concept of efficiency of order k (in this case, efficiency of order 3, as three inputs are considered), where technologies A–G are represented by coloured lines. The vertical axis shows the efficiency score for each technology when three inputs are considered, while the other axes display the value of each input for each technology.

As can be seen in Fig. 4, technologies B and C are found to be efficient of order 3 as their efficiency score is equal to 1, while the other technologies are inefficient of order 3 (i.e., efficiency scores are below 1). For the latter, an inefficiency assessment can be performed to set targets for reaching the efficiency frontier, as explained in Section 3.2.

The efficiency calculations are repeated next for each possible subset of inputs (one subset of order 3, three subsets of order 2 and three subsets of order 1). Fig. 5 summarises the results for each order of efficiency (i.e., orders 3, 2 and 1), with Fig. 5a showing the results for the original order of efficiency (order 3), Fig. 5b and c give the efficiency scores for each subset of inputs of order 2 and

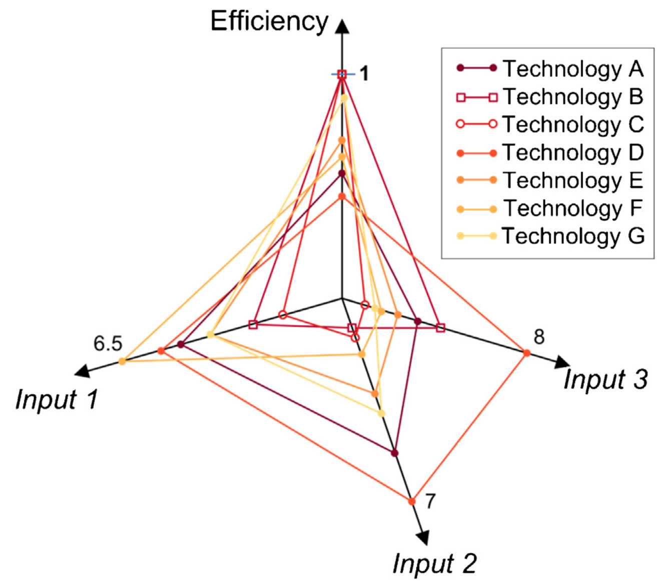

Fig. 4. Illustrative example of efficiency of order 3. The vertical axis shows the efficiency score of every technology considering the 3 inputs simultaneously, while the remaining axes show the amount of inputs consumed by every technology.

1, respectively, and Fig. 5d shows the overall economic efficiency score (orange dotted line) for each technology, determined by Eq. (14).

As can be observed in Fig. 5a, technologies B and C are identified as efficient of order 3. Technology C is in turn efficient of order 2, since it is efficient for any combination of two inputs (Fig. 5b). That is, when input 3 is removed and we consider only {input1, input 2}, technologies B and C are efficient. The same happens when input 1 is removed from the analysis, to consider only {input1, input 2}. On the contrary, when input 2 is removed, giving rise to the space {input1, input 2}, C remains efficient, while B is found inefficient. Hence, B is efficient of order 3, but not of order 2. Furthermore, C is inefficient of order 1 (Fig. 5c), since it shows the best performance in inputs 1 and 3 but not in input 2. Thus, this analysis reveals that technologies A, D, E–G are inefficient of orders 3 to 1, technology B is efficient of order 3, and technology C is efficient of order 2 (and, therefore, of order 3 as well). In addittion, in terms of the overall economic efficiency (Fig. 5d), C is the most economically efficient (score of 0.97) and D the least (0.35).

Therefore, as this simplified example demonstrates, the combined use of DEA and the concept of order of efficiency enables a further discrimination of alternatives. For example, B and C were indistinguishable for the original three inputs considered because they both showed an efficiency of 1. However, after estimating the order of efficiency they could be ranked easily according to the overall economic efficiency scores, which for B is 0.87 and for C 0.97.

3.2.2. Enhanced DEA for sustainability assessment applied to the motivating example

We now revisit the motivating example by applying the enhanced DEA approach. Fig. 6 displays the efficiency in each sustainability dimension along with the overall sustainability efficiency for each technology. Technology A is the best in the environmental and social dimensions (with the efficiency of 0.88 and 0.87, respectively), while technology C is the best for the economic aspect (0.97). After aggregating all the efficiency values, technology C emerges as the most sustainable option, with the highest sustainability efficiency score of 0.78; technology D is the least sustainable, scoring only 0.5.

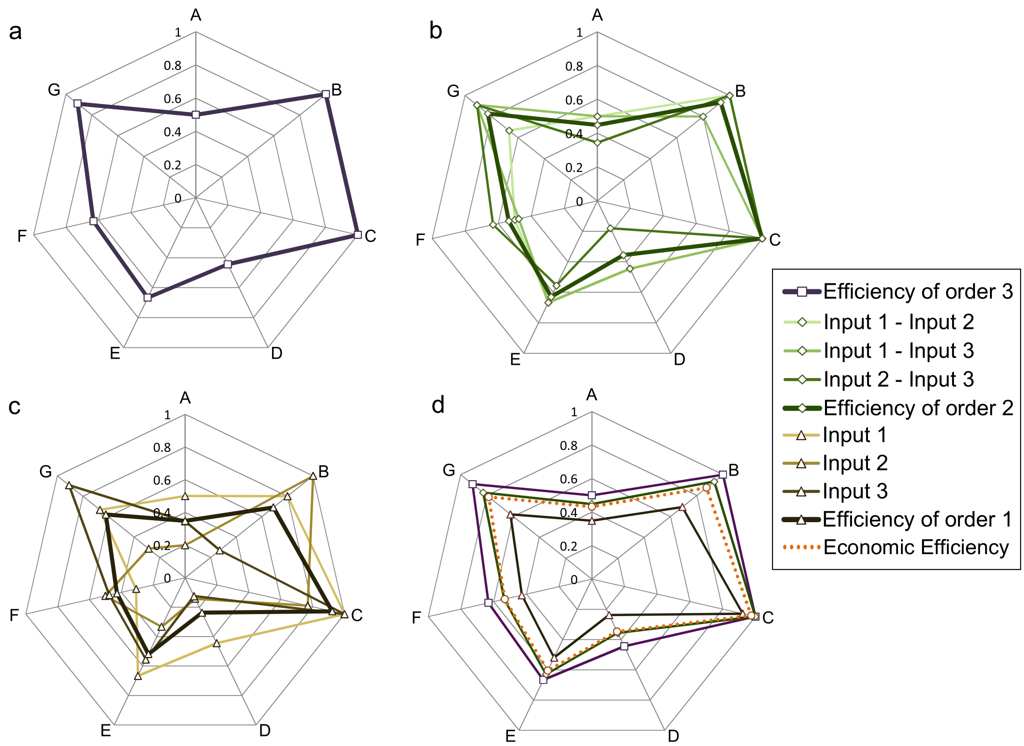

Fig. 5. Graphic representation of efficiency of order of k (for a given set of economic inputs) and economic efficiency (when all the subsets of economic inputs are considered simultaneously).

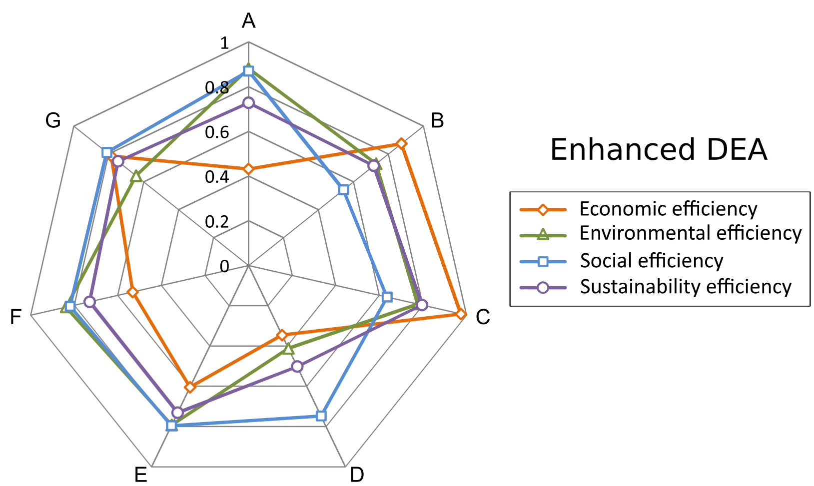

Fig. 6. Enhanced DEA results for the motivating example.

Comparing the results of enhanced DEA (Fig. 6) with those obtained with standard DEA (Fig. 2), it is clear that the former improves the discriminatory capabilities between the technologies, since no single technology now has the same efficiency score as any of the others, thereby enabling their ranking according to the efficiency in each dimension and the overall sustainability efficiency.

4. Application of the enhanced DEA method to a real case study

The capabilities of the proposed methodology are illustrated next through its application to a real case study that assesses several electricity-generation technologies expected to play a major role in a future UK electricity mix. The data are sourced from Stamford and Azapagic (2014). Each of these technologies is defined as a DMU that uses a given amount of economic, environmental and social inputs to produce 1 kWh of electricity as an output. The specific technologies studied are: nuclear (pressurised water reactor, PWR), gas (combined cycle gas turbine, CCGT), coal with and without carbon capture and storage (CCS), wind (offshore), solar photovoltaics (PV) and biomass (wood and *Miscanthus* pellets). Stamford and Azapagic (2014) assessed 36 inputs (sustainability criteria) for these technologies following a life cycle approach. To simplify the analysis, we consider 18 inputs here: three economic, nine environmental and six social life cycle sustainability indicators (Table 2). For further details on these metrics, see Stamford and Azapagic (2014).

Note that we treat all sustainability indicators as inputs while holding the output equal to 1 kWh. For all sustainability indicators, lower values mean better performance, except the direct employment for which a higher value is preferred. The values of

Table 2
Sustainability indicators considered as inputs in the enhanced DEA methodology.

Sustainability dimension	Sustainability indicators[a]	Units[b]
Economic	Capital cost	£ kWh^{-1}
	Operation and maintenance cost	£ kWh^{-1}
	Fuel cost	£ kWh^{-1}
Environmental	Freshwater eco-toxicity	kg DCB-eq kWh^{-1}
	Marine eco-toxicity	kg DCB-eq kWh^{-1}
	Global warming	kg CO_2-eq kWh^{-1}
	Ozone depletion	kg CFC-11-eq kWh^{-1}
	Acidification	kg SO_2-eq kWh^{-1}
	Eutrophication	kg PO43-eq kWh^{-1}
	Photochemical smog	kg C_2H_4-eq kWh^{-1}
	Land occupation	m^2year kWh^{-1}
	Land eco-toxicity	kg DCB-eq kWh^{-1}
Social	Direct employment	person-years kWh^{-1}
	Worker injuries	injuries kWh^{-1}
	Human toxicity potential	kg DCB-eq kWh^{-1}
	Radiation: total	DALY kWh^{-1}
	Depletion of elements	kg Sb-eq kWh^{-1}
	Depletion of fossil fuels	MJ kWh^{-1}

[a] For all the indicators except direct employment, the lower the value, the higher the level of sustainability.
[b] DCB: dichlorobenzene. DALY: disability-adjusted lost years.

the inputs were normalised to a common interval [0, 1] so that 0 corresponds to the minimum and 1 to the maximum value (opposite for the direct employment indicator). Zero values in the inputs were avoided by adding a small epsilon value to them.

The DEA dual model Eqs. (8–11) combined with the order of efficiency concept (see the algorithm in Fig. 3) were both implemented in the General Algebraic Modelling System (GAMS) version 24.4.1, solving the LP formulations with the solver CPLEX 12.6.1.0 on an AMD A8-5500 APU with Raedon 3.20 GHz and 8.0 GB RAM. The efficiency of each technology was optimized in each of the 581 possible subset of inputs (7 in the economic dimension, 511 in the environmental dimension and 63 in the social dimension), giving rise to a total of 4648 runs. The CPU time was below one second for all of the instances.

Fig. 7 outlines the steps followed to assess the sustainability of the electricity technologies based on the algorithm in Fig. 3. The first step requires categorizing the indicators as inputs or outputs within the sustainability dimension d they belong to—the indicators are modelled as economic, environmental or social inputs required to produce a certain amount of output. In the second step, each and every of the possible subsets of inputs t for each order of efficiency k are identified (t_k) within each category. In the third step, the DEA model is applied to determine the efficiency score of each electricity technology for each combination of inputs t_k (θ^d_{jkt}). Then, within each dimension d and for each DMU j, the efficiency of each order k (θ^d_{jk}) and the overall dimension efficiency are determined (θ^d_j) in steps 4 and 5, respectively. Finally, the overall sustainability efficiency score (θ^{sust}_j) for each DMU j is computed in step 6.

4.1. Efficiency of different sustainability dimensions

The results are summarised in Figs. 8–10 with each line corresponding to a different order of efficiency. The darkest line represents the overall efficiency in each sustainability dimension calculated by Eq. (14).

The economic efficiency assessment (Fig. 8) shows that all the technologies except for coal CCS are efficient of order 3. Among them, only gas electricity is efficient of order 2 (and also of order 3), but no technology is efficient of order 1. The biomass options show the highest overall economic efficiency (0.80), while coal CCS is the least economically efficient technology (with an overall economic efficiency score of 0.38). Note that the technology with the largest efficiency score might not have the lowest efficiency order. This is the case with biomass which has the highest economic efficiency score, while gas shows the best (lowest) efficiency order. This is because gas performs poorly for the fuel cost indicator, while biomass performs well in all of the economic indicators simultaneously. Nevertheless, biomass is economically the most sustainable option, for the economic indicators considered here.

The results of the environmental efficiency assessment in Fig. 9 suggest that coal, solar PV and biomass are environmentally inefficient. Offshore wind and coal CCS are efficient of order 9, gas of order 7 (and also of orders 8 and 9), while nuclear is efficient of order 5 (and also of orders 6 to 9). No single technology has an order of efficiency below 5. Nuclear has the best overall environmental efficiency score (0.94), followed by gas, wind and coal CCS (0.89, 0.87, and 0.66, respectively). On the other hand, biomass with wood pellets, solar PV, biomass with *Miscanthus* pellets and coal are the least environmentally efficient technologies, with the efficiency scores of 0.47, 0.35, 0.32, and 0.22, respectively. Note that, as opposed to the previous case, here the technology with the best overall environmental efficiency score (nuclear) also has the best (lowest) order of efficiency. Thus, based on the inputs (indicators) considered in this case study, nuclear electricity is environmentally the most sustainable option.

The social efficiency assessment in Fig. 10 indicates that all of the technologies, except coal and biomass with *Miscanthus* pellets, are socially efficient of order 6. Nuclear and wind are in turn socially efficient of order 5 while gas is socially efficient of order 2 (and, therefore, also of orders 3 to 6). Moreover, the overall social efficiency score of gas is the largest by far (0.9). Again, the technology with the best efficiency score (i.e. gas) has the best efficiency order. Hence, this technology is clearly the best from a social sustainability perspective.

4.2. Overall sustainability efficiency

Fig. 11 provides the overall sustainability efficiency scores along with the dimension efficiency score for each technology. Gas electricity has the highest overall sustainability efficiency score (0.86), followed by nuclear (0.78) and wind (0.76). Biomass with wood pellets, coal CCS, and biomass with *Miscanthus* pellets have the sustainability efficiency values of 0.64, 0.58 and 0.57, respectively. Finally, solar PV and coal show the worst scores of 0.54 and 0.45, respectively.

4.3. Inefficiency assessment

For each technology found inefficient (when all the inputs within each sustainability dimension are considered), the corresponding targets that its inputs should achieve to make the technology efficient were determined using Eq. (15). The improvement targets for each technology are summarised in Fig. 12. The figure shows the percentage reductions in the form of a heat map that should be attained in each current indicator value to make the technology efficient in a given dimension. Each cell is coloured according to the reduction value assigned to each input—the darker the shade, the higher the reduction needed. Note that in the case of the indicator *direct employment*, the target is a positive increment rather than a reduction.

In the economic dimension, coal CCS is the only inefficient technology. To become efficient, it should reduce its capital and fuel costs by 34%, and its operation and maintenance cost by 62%. These targets can be seen as either pure targets to reach the economic efficiency, or as the level of financial subsidies necessary to make the technology efficient.

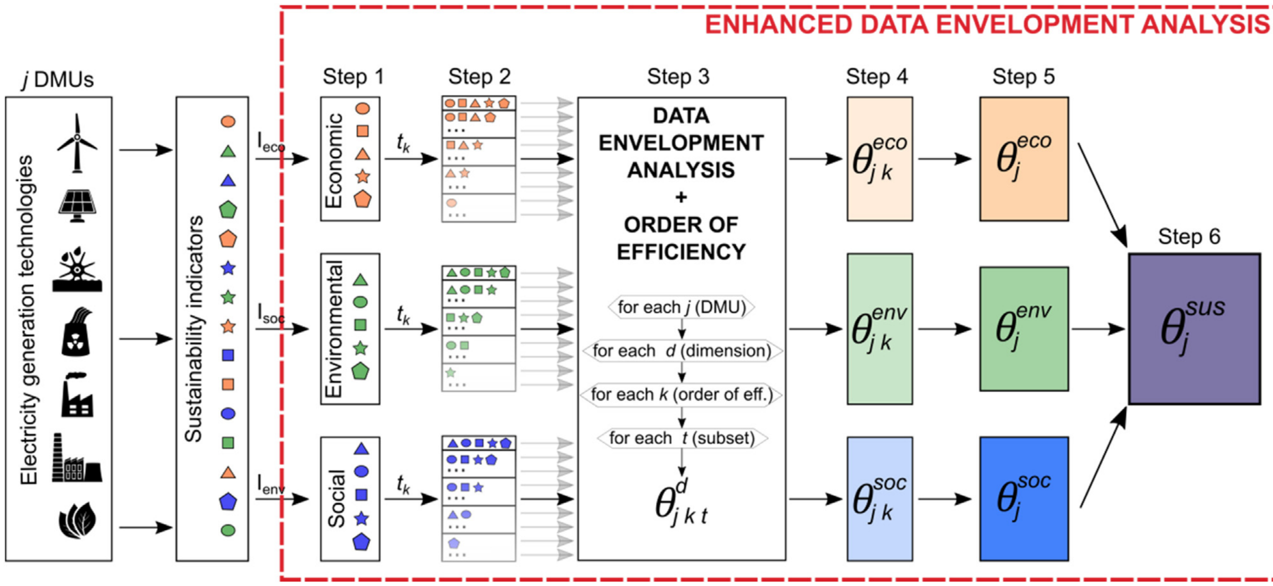

Fig. 7. Graphical summary of the enhanced DEA method applied to assess the sustainability of the electricity generation technologies.

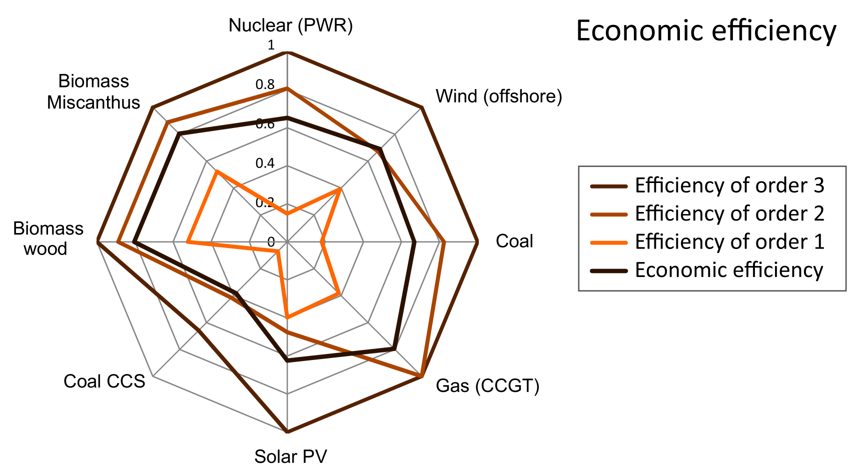

Fig. 8. Economic efficiency of electricity generation technologies.

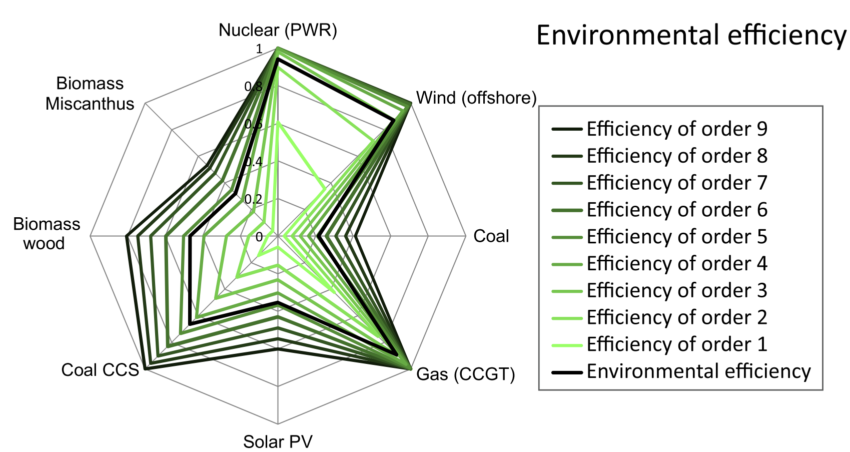

Fig. 9. Environmental efficiency of electricity technologies.

As mentioned earlier, coal, solar PV and both biomass options are inefficient in the environmental dimension. The corresponding improvement targets are also shown in Fig. 12. Among them, coal has the largest improvement targets. One-third of the total UK electricity consumption is generated from coal (DECC, 2015, 2014) and coal is expected to remain in the future UK energy mix to some extent. Hence, minimising its environmental impact may contribute significantly to reducing the environmental footprint

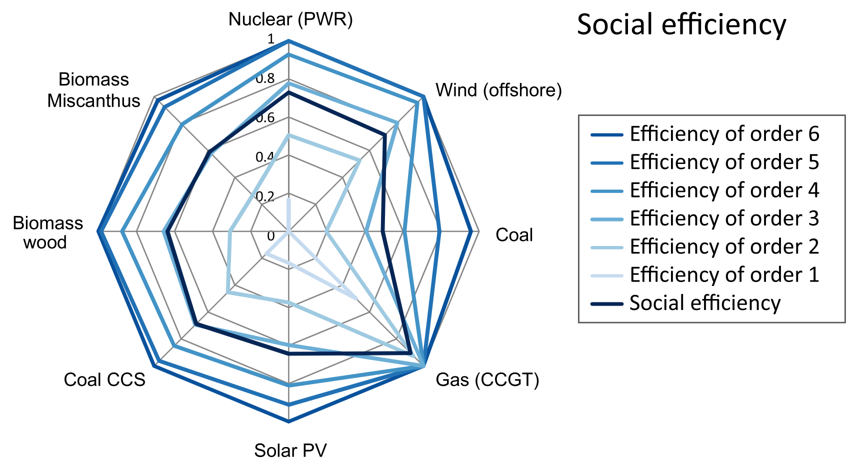

Fig. 10. Social efficiency of electricity generation technologies.

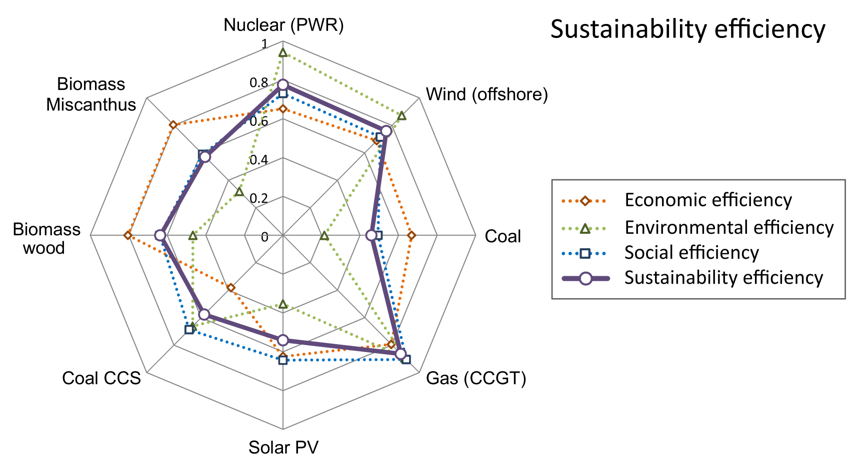

Fig. 11. Overall sustainability efficiency of the technologies for electricity generation.

of energy generation in the UK. For solar PV the environmental impacts that require largest reductions are land occupation (89%), marine ecotoxicity (90%), eutrophication (84%) and acidification (77%), which are mainly caused during the manufacture of the solar facilities. Regarding the biomass options, the most critical categories are land occupation (99%), acidification (97%), photochemical smog (95%) and eutrophication (93%). These impacts are primarily driven by biomass cultivation; therefore, the use of second-generation biomass, such as agricultural and forestry residues or waste, could help to achieve the reductions required.

Finally, for the social dimension, coal and biomass with *Miscanthus* pellets are found inefficient. The highest improvements are required for coal in the categories human toxicity potential, workers injuries and depletion of fossil fuels, which should be reduced by 89%, 77% and 62%, respectively. By comparison, the improvements needed for the biomass option are relatively small: radiation, human toxicity potential and worker injures should be reduced respectively by 36%, 23% and 19% to become socially efficient.

5. Conclusions

In this work, we have proposed an enhanced DEA methodology for the assessment of the level of sustainability attained by a system. Our approach improves the discriminatory capabilities of standard DEA by grouping the inputs into economic, environmental and social indicators and by integrating the concept of order of efficiency. The latter allows dealing with a large number of economic, environmental and social indicators simultaneously. The main advantages of enhanced DEA are: (i) it considers each sustainability dimension separately; (ii) it can handle a large number of economic, environmental and social criteria; (iii) it enables ranking of alternatives according to the extent to which they adhere to defined sustainability principles without the need to elicit preference weights for the criteria; and (iv) it provides clear quantitative targets for the inefficient systems to become efficient, i.e. sustainable.

The capabilities of the methodology have been illustrated by application to a real case study assessing the level of sustainability of different electricity generation technologies. Gas, nuclear and wind electricity have been found efficient in all three dimensions of sustainability simultaneously when all the indicators within each dimension were considered. Gas electricity has the highest overall sustainability efficiency (mainly because of its very good performance in the social dimension), followed by nuclear and wind. Gas is also the most economically and socially efficient (highest economic and social efficiency scores), while nuclear is the best in the environmental dimension.

The proposed methodology can facilitate transition towards a more sustainable society by identifying the most sustainable options. Furthermore, it helps to pinpoint in a systematic manner the main sources of inefficiency and set improvement targets. This information can be useful for industry as an aid for improving technologies and products and for policy makers when designing future

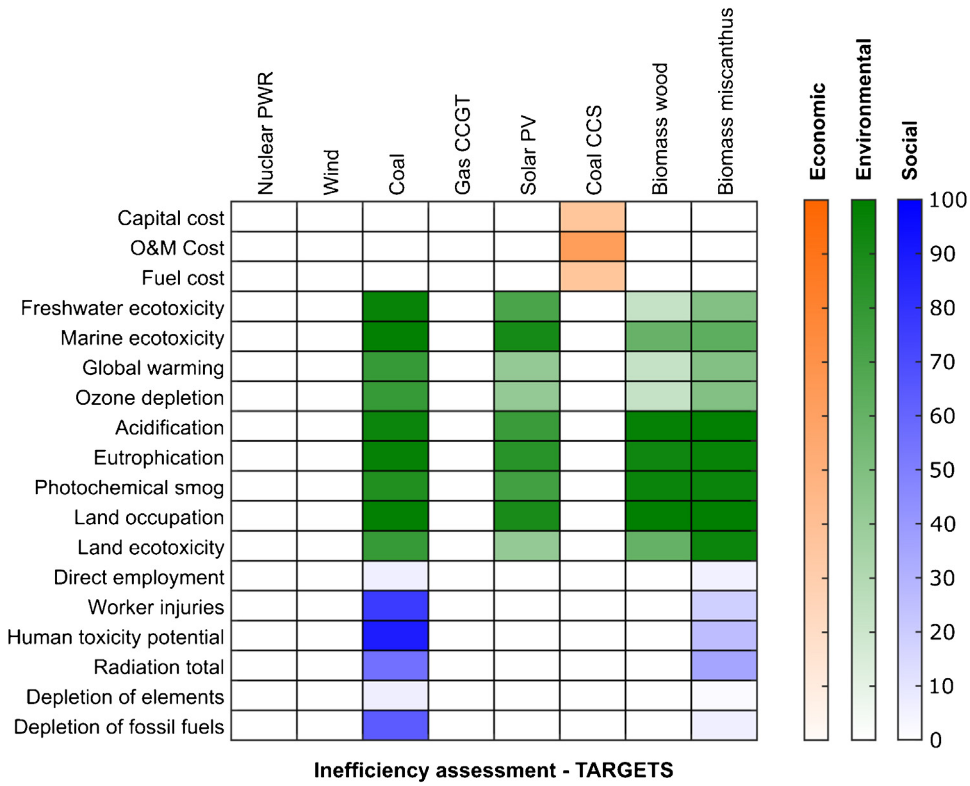

Fig. 12. Heat map of inputs reductions for the electricity generation technologies required to achieve the economic, environmental and social efficiency.

policies in accordance with the principles of sustainable development.

Acknowledgements

The authors wish to acknowledge the financial support for this research from the Spanish Ministry of Education and Science (Projects CTQ2012-37039-C02, DPI2012-37154-C02-02) and UK Engineering and Physical Sciences Research Council (EPSRC, Grant no. EP/K011820/1). We also would like to acknowledge financial support from the Pump-Priming Research Programme of The University of Manchester.

References

Adler, N., Friedman, L., Sinuany-Stern, Z., 2002. Review of ranking methods in the data envelopment analysis context. Eur. J. Oper. Res. 140, 249–265, http://dx.doi.org/10.1016/S0377-2217(02)00068-1.

Antipova, E., Pozo, C., Guillén-Gosálbez, G., Boer, D., Cabeza, L.F., Jiménez, L., 2015. On the use of filters to facilitate the post-optimal analysis of the Pareto solutions in multi-objective optimization. Comput. Chem. Eng. 74, 48–58, http://dx.doi.org/10.1016/j.compchemeng.2014.12.012.

Avkiran, N.K., 2002. Productivity Analysis in the Service Sector with Data Envelopment Analysis. In: Avkiran, N.K. (Ed.), 2nd edition. Camira, Qld.

Azapagic, A., Perdan, S., 2005. An integrated sustainability decision-support framework Part I: Problem structuring. Int. J. Sustain. Dev. World Ecol. 12 (2), 11–98.

Azapagic, A., Perdan, S., 2000. Indicators of sustainable development for industry: a general framework. Process Saf. Environ. Prot. 78, 243–261.

Bhagavath, V., 2006. Technical efficiency measurement by data envelopment analysis: An application in transportation. Alliance J. Bus. Res. 1, 60–72.

Chang, D.-S., Kuo, L.R., Chen, Y., 2013. Industrial changes in corporate sustainability performance—an empirical overview using data envelopment analysis. J. Clean. Prod. 56, 147–155, http://dx.doi.org/10.1016/j.jclepro.2011.09.015.

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

Chen, J.-X., Deng, M., 2011. A cross-dependence based ranking system for efficient and inefficient units in DEA. Expert Syst. Appl. 38, 9648–9655, http://dx.doi.org/10.1016/j.eswa.2011.01.165.

Chen, J.-X., Deng, M., Gingras, S., 2011. A modified super-efficiency measure based on simultaneous input–output projection in data envelopment analysis. Comput. Oper. Res. 38, 496–504, http://dx.doi.org/10.1016/j.cor.2010.07.008.

Chen, Y., Du, J., Huo, J., 2013. Super-efficiency based on a modified directional distance function. Omega 41, 621–625, http://dx.doi.org/10.1016/j.omega.2012.06.006.

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

Cooper, W.W., Seiford, L.M., Zhu, J., 2004. Data Envelopment Analysis: History, Models and Interpretations. Kluwer Academic Publishers, Boston.

DECC, 2014. Digest of United Kingdom Energy Statistics. Department of Energy & Climate Change, London.

DECC, 2014. Energy Statistics: UK Energy Statistics: Provisional Data. Departament of Energy & Climate Change, London https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/40699/Press_Notice_Feb_2015.pdf.

Das, I., 1999. A preference ordering among various Pareto optimal alternatives. Struct. Optim. 18, 30–35.

Edelstein, B., Paradi, J.C., 2013. Ensuring units invariant slack selection in radial data envelopment analysis models, and incorporating slacks into an overall efficiency score. Omega 41, 31–40, http://dx.doi.org/10.1016/j.omega.2011.09.008.

Farrell, M.J., 1957. The measurement of productive efficiency. J. R. Stat. Soc. Ser. A, 253–281.

Gerdessen, J.C., Pascucci, S., 2013. Data Envelopment Analysis of sustainability indicators of European agricultural systems at regional level. Agric. Syst. 118, 78–90, http://dx.doi.org/10.1016/j.agsy.2013.03.004.

Gibson, R.B., 2001. Specification of sustainability-based environmental assessment decision criteria and implications for determining significance in environmental assessment. Canadian Environmental Assessment Agency Research and Development Program, Ottawa, Available at http://www.acee.gc.ca/015/001/009/index_e.htm.

Grossmann, I.E., Guillén-Gosálbez, G., 2010. Scope for the application of mathematical programming techniques in the synthesis and planning of sustainable processes. Comput. Chem. Eng. 34, 1365–1376, http://dx.doi.org/10.1016/j.compchemeng.2009.11.012.

Hoang, V.-N., Alauddin, M., 2011. Input-Orientated Data Envelopment Analysis Framework for Measuring and Decomposing Economic, Environmental and Ecological Efficiency: An Application to OECD Agriculture. Environ. Resour. Econ. 51, 431–452, http://dx.doi.org/10.1007/s10640-011-9506-6.

Hosseinzadeh Lotfi, F., Jahanshahloo, G.R., Khodabakhshi, M., Rostamy-Malkhlifeh, M., Moghaddas, Z., Vaez-Ghasemi, M., 2013a. A review of ranking models in data envelopment analysis. J. Appl. Math. 2013, 1–20, http://dx.doi.org/10.1155/2013/492421.

Hosseinzadeh Lotfi, F., Rostamy-Malkhalifeh, M., Aghayi, N., Ghelej Beigi, Z., Gholami, K., 2013b. An improved method for ranking alternatives in multiple criteria decision analysis. Appl. Math. Model. 37, 25–33, http://dx.doi.org/10.1016/j.apm.2011.09.074.

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

Jablonsky, J., 2011. Multicriteria approaches for ranking of efficient units in DEA models. Cent. Eur. J. Oper. Res. 20, 435–449, http://dx.doi.org/10.1007/s10100-011-0223-6.

Jaeger, C.J., Tàbara, D.J., Jaeger, J., 2011. European research on sustainable development. Transformative Science Approaches for Sustainability, vol. 1. Springer, Berlin (Germany), pp. 1.

Jahanshahloo, G.R., Memariani, A., Lotfi, F.H., Rezai, H.Z., 2005. A note on some of DEA models and finding efficiency and complete ranking using common set of weights. Appl. Math. Comput. 166, 265–281, http://dx.doi.org/10.1016/j.amc.2004.04.088.

Khodakarami, M., Shabani, A., Farzipoor Saen, R., 2014. A new look at measuring sustainability of industrial parks: a two-stage data envelopment analysis approach. Clean Technol. Environ. Policy 16, 1577–1596, http://dx.doi.org/10.1007/s10098-014-0733-8.

Li, S., Jahanshahloo, G.R., Khodabakhshi, M., 2007. A super-efficiency model for ranking efficient units in data envelopment analysis. Appl. Math. Comput. 184, 638–648, http://dx.doi.org/10.1016/j.amc.2006.06.063.

Liu, J.S., Lu, L.Y.Y., Lu, W.-M., Lin, B.J.Y., 2013. A survey of DEA applications. Omega 41, 893–902, http://dx.doi.org/10.1016/j.omega.2012.11.004.

Liu, J.S., Lu, L.Y.Y., Lu, W.-M., 2015. Research fronts in data envelopment analysis. Omega 58, 33–45, http://dx.doi.org/10.1016/j.omega.2015.04.004.

Lorenzo-Toja, Y., Vázquez-Rowe, I., Chenel, S., Marín-Navarro, D., Moreira, M.T., Feijoo, G., 2014. Eco-efficiency analysis of Spanish WWTPs using the LCA + sDEA method. Water Res. 68, 637–650, http://dx.doi.org/10.1016/j.watres.2014.10.040.

Lozano, S., Iribarren, D., Moreira, M.T., Feijoo, G., 2009. The link between operational efficiency and environmental impacts. A joint application of life cycle assessment and data envelopment analysis. Sci. Total Environ. 407, 1744–1754, http://dx.doi.org/10.1016/j.scitotenv.2008.10.062.

Lu, W.-M., Lo, S.-F., 2009. An interactive benchmark model ranking performers—application to financial holding companies. Math. Comput. Model. 49, 172–179, http://dx.doi.org/10.1016/j.mcm.2008.06.008.

Martins, A.A., Mata, T.M., Costa, C.A.V., Sikdar, S.K., 2007. Framework for sustainability metrics. Ind. Eng. Chem. Res. 46, 2962–2973, http://dx.doi.org/10.1021/ie060692l.

Mohammadi, A., Rafiee, S., Jafari, A., Keyhani, A., Dalgaard, T., Knudsen, M.T., Nguyen, T.L.T., Borek, R., Hermansen, J.E., 2014. Joint life cycle assessment and data envelopment analysis for the benchmarking of environmental impacts in rice paddy production. J. Clean. Prod., http://dx.doi.org/10.1016/j.jclepro.2014.05.008.

Pope, J., Annandale, D., Morrison-Saunders, A., 2004. Conceptualising sustainability assessment. Environ. Impact Assess. Rev. 24, 595–616, http://dx.doi.org/10.1016/j.eiar.2004.03.001.

Pozo, C., Guillén-Gosálbez, G., Sorribas, A., Jiménez, L., 2012. Identifying the preferred subset of enzymatic profiles in nonlinear kinetic metabolic models via multiobjective global optimization and Pareto filters. PLoS One 7, e43487, http://dx.doi.org/10.1371/journal.pone.0043487.

Reig-Martínez, E., Gómez-Limón, J.A., Picazo-Tadeo, A.J., 2011. Ranking farms with a composite indicator of sustainability. Agric. Econ. 42, 561–575, http://dx.doi.org/10.1111/j.1574-0862.2011.00536.x.

Sikdar, S.K., 2003. Sustainable development and sustainability metrics. AIChE J. 49, 1928–1932, http://dx.doi.org/10.1002/aic.690490802.

Stamford, L., Azapagic, A., 2014. Life cycle sustainability assessment of UK electricity scenarios to 2070. Energy Sustain. Dev. 23, 194–211, http://dx.doi.org/10.1016/j.esd.2014.09.008.

Tajbakhsh, A., Hassini, E., 2014. A data envelopment analysis approach to evaluate sustainability in supply chain networks. J. Clean. Prod., http://dx.doi.org/10.1016/j.jclepro.2014.07.054.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Oper. Res. 130, 498–509, http://dx.doi.org/10.1016/S0377-2217(99)00407-5.

Vázquez-Rowe, I., Iribarren, D., 2014. Review of life-cycle approaches coupled with data envelopment analysis: launching the CFP + DEA method for energy policy making. Sci. World J. 2015 (2015), 10.

WCED, 1987. Our Common Future—The Brundtland Report. World Commission on Environment and Development, Geneva.

Wang, Y.-M., Luo, Y., Liang, L., 2009. Ranking decision making units by imposing a minimum weight restriction in the data envelopment analysis. J. Comput. Appl. Math. 223, 469–484, http://dx.doi.org/10.1016/j.cam.2008.01.022.

Wang, Y.-M., Luo, Y., Lan, Y.-X., 2011. Common weights for fully ranking decision making units by regression analysis. Expert Syst. Appl. 38, 9122–9128, http://dx.doi.org/10.1016/j.eswa.2011.01.004.

Washio, S., Yamada, S., 2013. Evaluation method based on ranking in data envelopment analysis. Expert Syst. Appl. 40, 257–262, http://dx.doi.org/10.1016/j.eswa.2012.07.015.

Wu, J., Sun, J., Liang, L., 2012. Cross efficiency evaluation method based on weight-balanced data envelopment analysis model. Comput. Ind. Eng. 63, 513–519, http://dx.doi.org/10.1016/j.cie.2012.04.017.

Zerafat Angiz, M., Mustafa, A., Kamali, M.J., 2013. Cross-ranking of decision making units in data envelopment analysis. Appl. Math. Model. 37, 398–405, http://dx.doi.org/10.1016/j.apm.2012.02.038.