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

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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

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(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?