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Allocation of emission permits in large data sets: a robust multi-criteria approach

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ABSTRACT

This paper addressed the issue of the allocation of emission permits (AEP) in large data sets, with the goal of providing government strategies to practically operate the AEP in a group of organizations, and realize economic, social and environmental goals at the same time. We propose a robust multi-criteria AEP approach, together with its tractable algorithm, by extending the classical theory of data envelopment analysis (DEA) for large data sets. Reasonable AEP mechanisms adjusted to the large data set can be derived from this approach. The main advantages of this approach are as follows. First, this approach shows real-world tractability of large data sets, as it takes the characteristics of large data sets into full consideration. Second, the proposed AEP mechanism can help centralized decision makers to achieve the lowest total group-level emission while keeping group-level outputs invariant, and the mechanism is proved to be sustainable theoretically. Third, besides obtaining an optimal allocation plan for emission permits, the proposed approach can be used to calculate the optimal emission standard and optimal total amount of permits to be allocated. The proposed approach was used in an empirical study of SO_2 emission permits allocation among 202 prefecture-level cities in mainland China. The results further demonstrated theoretical and practical values of our method. One valuable policy suggestion resulted from the empirical analysis is presented as well.

1. Introduction

In recent years, the development of science and technology has led to significant increase in the amount of worldwide data in various areas (Tien, 2013). Such big amounts of data can serve a powerful promotion for innovations, competition and productivity (James et al., 2011). Therefore, the forthcoming big data era will provide new opportunities for the development of management science and operation research (Letouzé, 2012). The big data can also help people secure a sustainable future (Griggs et al., 2013), so we should incorporate big data to model and test numerous different scenarios for sustainably transforming the consumption of resources and emission management as well (Gijzen, 2013). Since allocation of emission permits (AEP) plays an important role in both business and environmental management (Eshel, 2005), it is significant to study AEP under big data. The AEP is the process of allocating emission permits to organizations via suitable mechanisms to achieve economic, social and environmental goals simultaneously (Sun et al., 2014). An emission permit is an authorization for organizations to emit certain amount of specific pollutant (Song et al., 2015a,b). Besides obvious advantages for pollution control and environment management (Du et al., 2014; Ono, 2002), emission permits are shown to have significant impact on firm's operations (Li and Gu, 2012; Li, 2013). Because of the first key factor making big data differ from others is that big data has a much larger volume as compared to traditional data sets (McAfee et al., 2012), this paper primarily addresses the issue of AEP in large data sets.

The significance of research on the AEP in large data sets can be supported by the following reasons. First, there are few studies on the AEP that take large data sets into consideration. Since large data sets cannot be easily handled using current methods and tools, to develop suitable AEP mechanisms adjusted to large data sets is an

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urgent problem of environment management in the big data era. Second, the initial allocation of emission permits is the most essential question in the design of a reasonable AEP mechanism, which is still debated in the literature (Zhao et al., 2010). Third, as Sun et al. (2014) point out, few multi-criteria AEP mechanisms have been developed in the literature. The AEP, like other sustainability issues, has a complex and dynamic environment with multiple indices and various stakeholders (Wang et al., 2013). It is a formidable task to simply aggregate these indices, taking different stakeholders' preferences into account, to derive a composite indicator for allocating emission permits in such a situation (Ji et al., 2015). Fourth, most of the articles related to the AEP did not consider the importance of government influence, while, in fact, the government is counted as one of the most powerful stakeholders in the AEP (Schmidheiny and Stigson, 2000). Fifth, at the industry level, unreasonable allocation schemes may drive the whole industry to waste of resources, for such schemes may allocate massive permits to firms with the worst environmental performance (Borenstein, 1988). Finally, allocation schemes for permits have a clear impact on plant-level production efficiency and decisions of enterprises (Tanaka and Chen, 2012). For these reasons, the AEP in large data sets is one of the most intractable and vital issues in management science (Park et al., 2012), and remains a key challenge for the further research.

The existing literature has developed three main types of methods for initial allocation of emission permits: auctions, allocating permits based on historical emission data (grandfathering) and using current emission data as the AEP basis (output-based allocation) (Sun et al., 2014). The allocation of permits by auction is generally welcomed by the academic community (Liao et al., 2015), since auction has significance advantages in reducing costs and increasing social welfare (Xu and Huang, 2014, 2015). Additionally, recent development of multi-unit auction mechanism design done by Huang and Xu (2013) shows the great potential of applying auction mechanisms to allocate emission permits in a multi-criteria environment. Something slowing the paces of auction-based AEP schemes being successfully used in practice is that auction-based AEP schemes may lead to a monopolistic industry (Takeda et al., 2014). Moreover, auctions may lead to loud objections from the public, as they are usually associated with huge capital transfers between the private sector and government (Lozano et al., 2009). Regarding grandfathering, it has a positive impact on the reduction of firms' production costs, since it is free for emission permits (Böhringer and Lange, 2005). At the same time, grandfathering is a history-based AEP method, which can be unfriendly to firms just entered the industry (Åhman et al., 2007). The output-based allocation, which uses current data as the AEP basis, can partly overcome the disadvantages of grandfathering (Neuhoff et al., 2006). But unfortunately, the emission data orientation and dynamic allocation mechanisms of output-based allocation may lead companies to actually increase emissions to earn a higher level of permits (Fischer and Fox, 2007).

The aim of this work is to develop a reasonable mechanism for initial allocation of emission permits that has at least the following two characteristics. First, the AEP mechanism should fulfil all purposes of the government allocating permits to organizations. It is because that the government is the real controller of the whole AEP process, any AEP mechanism that fails to realize the will of government will no doubt be abandoned. In common sense, the fundamental requirement for any AEP is to reduce emissions as much as possible. Besides, the social welfare should not be damaged by the AEP, otherwise it will be rejected by the society. So the most desirable result of an AEP process should be creating more social welfare with less negative impacts, such as energy consumption and pollutant emission. Such a result is Pareto Optimal. Since relative efficient defined in the data envelopment analysis (DEA) has been theoretically proved to be equivalent to Pareto Optimality (Chen and Delmas, 2012), it implies that the DEA can potentially deal with the AEP problem. The DEA was originally proposed by Charnes et al. (1978), and has been widely applied in both theoretical and empirical environmental studies (Zhou et al., 2008; Song et al., 2012). Compared to other methods, the DEA presents great advantages in dealing with negative factors and the aggregation of multiple indices in complex environments (Chen, 2014; Song et al., 2015a,b). Therefore, we adopt and extend the classical DEA theory to build a Pareto Optimal AEP mechanism in this paper.

Second, the AEP mechanism should be tractable and enforceable for practical use in large data sets. Actually, the AEP is a very practical issue that originals from the real world. Considering that the volume of real-world data is becoming large and large, any AEP mechanism that cannot be successfully applied into practice with large data sets will no doubt make no sense. Recent empirical studies have already shown that DEA-based AEP mechanisms have better tractability compared to other methods (Feng et al., 2015; Miao et al., 2015; Zhang et al., 2015). To make the proposed AEP mechanism enforceable in large data sets, this research extends the classical DEA concepts and definitions, such as the DEA efficiency and DEA frontier, to their large-data-sets versions. The extensions make the DEA less data-sensitive in large data sets by affording a robust lower bound for productivity estimation. Additionally, this research integrates the determination of the standard emission amounts into the AEP mechanism. We use a control variable, representing the emission standard, in the proposed model to determine the emission standard before allocating permits. Such pollutant emission standards are evident in a variety of fields and industries, and an AEP process would be meaningless without usage of such pollutant emission standards. Therefore, taking such standards into account is necessary for designing enforceable AEP mechanisms in large data sets.

The rest of this paper is organized as follows. Section 2 provides a detailed methodology description accompanied with several fundamental concepts ahead. The proposed robust multi-criteria AEP approach, including detailed procedures of model construction and a tractable allocation algorithm, is presented in Section 3. In Section 4, the proposed AEP approach is applied in an empirical study of allocating SO_2 emission permits to 202 Chinese prefecture-level cities. Conclusions and further extensions are discussed in Section 5.

2. Methodology

2.1. Fundamental concepts

According to the conventional DEA framework, an observation is treated as DEA-efficient or Pareto-efficient if any of its inputs or outputs cannot be improved without damaging other indices when compared to other observations (Cooper et al., 2011a). Assume that every observation has m inputs and s outputs, then each observation can be seen as a point in the $(m+s)$-dimensional space if we treat its (input, output) vector as coordinates. Then the feasible production set is the area between the frontier spanned by all DEA-efficient observations' convex combinations and the input-axis.

If we further assume here are n observations in total, use O_j to represent the jth observation denote the ith input and rth output as x_{ij} and y_{rj} respectively. Then formula (1) and formula (2) are mathematical representations of the feasible production set under the assumption of constant returns to scale (CRS[1]) and variable returns to scale (VRS), respectively.

[1] CRS, VRS, CCR and BCC are basic concepts in DEA theory, thus we omit their definitions here. For details, Please see Cooper et al. (2011b).