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A dynamic multi-stage data envelopment analysis model with application to energy consumption in the cotton industry

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ABSTRACT

Data envelopment analysis (DEA) is a non-parametric method for evaluating the relative efficiency of homogenous decision making units (DMUs) with multiple inputs and outputs. In this paper, we present a dynamic multi-stage DEA (DMS-DEA) approach to evaluate the efficiency of cotton production energy consumption. In the proposed model, the farms which consume resources (i.e., fertilizers, seeds, and pesticides) to produce cotton are assumed to be the DMUs. Inputs not consumed during a planning period are carried over to the next period in the planning horizon. Initially, a DMS-DEA model is used to determine the overall efficiency of the DMUs with dynamic inputs. Next, the efficiency score of each DMU is calculated for each time period in the planning horizon. We demonstrate the applicability of the proposed method and exhibit the efficacy of the procedures and algorithms with a real-life case study of energy consumption in the cotton industry.

1. Introduction

Data envelopment analysis (DEA) is a non-parametric method based on linear programming for measuring the relative efficiency of homogeneous decision making units (DMUs) with multiple inputs and multiple outputs. DEA has been applied in different sectors such as manufacturing, transportation, and various service industries such as insurance, banking, and education. Energy systems have been a particularly important area for the application of DEA models. In recent years, energy consumption in the production of agricultural crops such as barberry, hay, rose, maze, beet, and strawberry has attracted the attention of DEA researchers. Researchers have shown that a small reduction in agricultural energy consumption may yield huge benefits in terms of energy savings. In the past decades, DEA has been used extensively for measuring efficiency in the production of agricultural crops.

DEA is a powerful method for evaluating the efficiency or performance of a group of DMUs in specific application domains such as banking, healthcare, and agriculture, among others (Liu et al., 2013). Golany and Roll (1989) point out that these industries adopt DEA for a variety of reasons, including identifying sources of inefficiency, ranking the DMUs, or developing a quantitative basis for reallocating resources.

In recent years, the efficiency of production in agriculture has attracted a lot of attention. DEA has increasingly been used to investigate various problems in farming and the agricultural sector. However, most of these studies have been conducted on products which are used in the food industry and apply classical DEA models, which generally ignore many real-world conditions such as the multiplicity of process stages and the dynamic nature of criteria.

Finally, the existing dynamic DEA models, including time windows models and the Malmquist productivity index, usually neglect carry-over activities between two consecutive terms and only focus on the

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local optimization of single time periods, thus treating each time period separately. However, in the actual business world, long-term planning and investment are both subjects of great concern. In order to cope with this long-term point of view, a dynamic DEA model must incorporate carry-over activities and enable us to measure period-specific efficiency based on the optimization of the whole period of time being considered.

In this paper, we propose a dynamic multi-stage DEA (DMS-DEA) model to resolve the aforementioned gaps in classic DEA models. Our approach allows us to compare the efficiency score achieved by a DMU in the entire planning horizon with the dynamic evolution exhibited through each of the assumed time periods. Moreover, we will use our model to illustrate the differences between the scores of the DMUs when different time intervals are used to measure their efficiency. These comparisons add a strategic component to the model, linking the paper to the international business literature and allowing for extensions into the strategic domain.

The remainder of this paper is organized as follows. In Section 2, we review the applications of DEA in agriculture as well as dynamic DEA models. In Section 3, we describe in detail the DMS-DEA model proposed in this study. In Section 4, we present a case study to demonstrate the applicability of the proposed model and exhibit the efficacy of the multi-stage procedures. In Section 5, we present our conclusions and suggest future research directions.

2. Literature review

DEA is a widely used mathematical programming technique that was originally developed by Charnes et al. (1978) and was extended by Banker et al. (1984) to include variable returns to scale. DEA generalizes the Farrell (1957) single-input single-output technical efficiency measure to the multiple-input multiple-output case in order to evaluate the relative efficiency of peer units with respect to multiple performance measures (Charnes et al., 1994; Cooper et al., 1999). The units under evaluation in DEA are DMUs. A DMU is considered efficient when no other DMU can produce more outputs using an equal or lesser amount of inputs. DEA generalizes the standard efficiency measurement from a single-input single-output ratio to a multiple-input multiple-output ratio by using a ratio of the weighted sum of outputs to the weighted sum of inputs (Cooper et al., 2006). Unlike parametric methods, which require a detailed knowledge of the process, DEA is non-parametric and does not require an explicit functional form relating inputs and outputs (see Cooper et al., 2006 and Cook and Seiford, 2009 for an appraisal of the theoretical foundations and developments in DEA). Numerous applications in recent years have been accompanied by new extensions and developments in expanding the concept and methodology of DEA (see Seiford, 1997, and Emrouznejad et al., 2008, for an extensive bibliography of DEA).

2.1. Efficiency analysis in agriculture

Fare et al. (1985) was the first study to apply the technical efficiency approach to investigate agriculture economics. Chavas and Aliber (1993) conducted a nonparametric analysis of technical, allocative, scale, and scope efficiency of agriculture production. Coelli (1995) surveyed the recent developments in the estimation of frontier functions and the measurement of efficiency and discussed the potential applicability of these methods in the agricultural industry. The author discussed frontier production and the construction of technical, allocative, scale, and overall efficiency measures relative to these estimated frontiers. Sharma et al. (1997, 1999) used DEA and the stochastic frontier production function to study the productive efficiency of the swine industry. They showed that DEA is more robust than the parametric approach in measuring the productive efficiencies.

Abay et al. (2004) studied the efficiency of energy consumption in tobacco production in Turkey. The study, which was conducted on 300 farmers, showed that the technical efficiency in all areas was 0.456 and the Western and South-Western parts enjoyed the maximum efficiency in the consumption of the input. Reig-Martínez and Picazo-Tadeo (2004) used DEA to evaluate efficiency in personal gardens so as to identify efficient units of citrus production in Spain. Nasiri and Singh (2009) used the DEA method to measure energy consumption in rice farms. They also evaluated and analyzed the technical efficiency of farms with different sizes. Banaeian et al. (2010) used the DEA method to evaluate the efficiency of energy consumption in nut production. Mousavi-Aval et al. (2011) used DEA to study the energy consumed in apple production. They analyzed the operations of apple producers based on various inputs and showed that up to 11.3% of input energy can be saved. Mousavi-Aval et al. (2012) studied the efficiency of barberry farms with different sizes using DEA. Chauhan et al. (2006) used the DEA method to study the efficiency of rice farms in terms of energy consumption. They showed that 11.6% of input energy could be saved in these farms. Mohammadi et al. (2011) studied the efficiency of energy consumption and wasting of energy by Kiwi fruit producers using DEA. They showed that up to 12.2% of input energy could be saved. Ghasemi Mobtaker et al. (2012) conducted a study on the optimization of input energy for hay production. They presented a model for energy consumption efficiency in hay production using DEA. Pahlavan et al. (2012)) used the DEA method to distinguish efficient and non-efficient rose producers. They also showed the best operational methods for energy consumption.

2.2. Dynamic DEA models

Classic DEA models serve many purposes such as calculating efficiency scores for all the DMUs, estimating production functions, and projecting the inefficient DMUs toward the efficient frontier. However, these models are not able to assign the inefficiency to a particular process in real-life cases. Clearly, when the efficiency score of a given DMU is calculated using classic DEA models, it cannot be assigned to any of the internal processes ongoing in the DMU. That is, the classic DEA models ignore the internal processes and sub-processes in the DMU. Thus, efficiency and inefficiency are associated with a DMU, not to its internal sub-processes. However, in real-life problems, when a DMU has a complicated structure and internal processes are ongoing, decision makers would like to know about the efficiency of each sub-process. This issue has been addressed in the DEA literature using network DEA models.

Moreover, classic DEA models calculate the efficiency scores of the DMUs based on their past records of inputs and outputs. Thus, these models cannot be applied to the cases in which a DMU is assessed during a planning horizon with multiple periods. However, decision makers may follow the trend of a given DMU during multiple periods. In such situations, the inputs and outputs of a DMU may vary according to a pre-defined configuration during the planning horizon, which results in a dynamic process. Again, classic DEA models are not able to handle such cases, and these problems have been addressed by dynamic and multi-period DEA models.

Tone and Tsutsui (2014) proposed a dynamic DEA model involving a network structure in each period within the framework of a slacks-based measure approach. Their model evaluates (1) the overall efficiency over the entire period observed, (2) the dynamic change of period efficiency, and (3) the dynamic change of divisional efficiency. The model proposed by Tone and Tsutsui (2014) can be implemented in input-, output- or non-(both) oriented forms under the CRS or VRS assumptions on the production possibility set.

Wang et al. (2013) proposed a dynamic DEA framework considering energy and non-energy desirable and undesirable criteria. These authors used the method proposed to calculate China's regional total-factor energy and environmental efficiency. Their empirical results showed that the east area of China has the highest energy and environmental efficiency, while the efficiency of the west area is the lowest one.