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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.

Tone and Tsutsui (2010) investigated several classic methods for measuring efficiency changes over time, e.g., the window analysis and the Malmquist index. Then, these authors proposed a dynamic DEA model incorporating carry-over activities to measure period-specific efficiency based on the long-term optimization during the whole period. Tone and Tsutsui (2010) developed the dynamic DEA model proposed by Färe and Grosskopf using the slacks-based measure (SBM) framework, called dynamic SBM. The SBM model is non-radial and can deal with inputs/outputs individually, contrary to the radial approaches that assume proportional changes in inputs/outputs.

Chen (2009) proposed a production network including a collection of production processes performed by several interdependent groups of sub-DMUs within a DMU. Dynamic effects pertained to the situation where intermediate outputs consumed by one SDMU dynamically influenced its output level in the future. Chen (2009) argued that if these effects are not considered, we would obtain a biased measure of efficiency, because the measure could not faithfully reflect the underlying performance. Hence, the result would provide misleading information to the decision makers.

2.3. DEA in energy economics

DEA is becoming a common method among economists to measure the efficiency of both energy utilization and the environmental consequences derived from different production processes. For example, regarding the efficient use of resources, Sueyoshi and Goto (2015) discussed the use of DEA for environmental assessments in order to measure different types of efficiency among inputs, together with desirable and undesirable outputs. Similarly, Rashidi and Farzipoor Saen (2015) proposed a DEA model to calculate the eco-efficiency of DMUs and illustrated the correlation existing between energy consumption and undesirable outputs.

The use of frontier analysis to measure the energy efficiency performance of developing countries, with particular focus on China, constitutes an important increasing research trend. The efficiency performance of a country is generally measured in terms of energy-saving potential and CO_2 emissions. Research can be mainly classified by the type of frontier analysis employed by the authors. In particular, Li and Lin (2015) used the meta-frontier, and Wei et al. (2015), the non-parametric one. Ouyang and Sun (2015) adopted the stochastic frontier, Chen et al. (2015) the Bayesian stochastic one, and Lin and Du (2015) considered stochastic frontier dynamics.

Moreover, papers such as that of Jiang et al. (2015), who investigated the energy-saving potential associated with differences in firm ownership, i.e., domestically versus foreign-owned, link the use of DEA in energy economics to the international business literature. The potential extensions of this type of analysis allow to account for the relationship between energy utilization efficiency and economic growth. In this regard, Wang and Feng, (2015) analyzed the sources of production inefficiency and productivity growth in China. They decomposed production inefficiency into three components: input inefficiency, economic output inefficiency, and environmental inefficiency. Furthermore, by applying a method based on global DEA, they were able to analyze the key factors responsible for the change of environmental productivity during 2003–2011 from the point of view of technical progress, productive scale, and management level. We will return to this latter line of research when describing the potential extensions of the current model.

3. Proposed dynamic multi-stage DEA approach

Consider n ($j = 1,2,\ldots,n$) DMUs which consume m ($i = 1,2,\ldots,m$) types of inputs to produce k ($r = 1,2,\ldots,k$) types of outputs. The technical efficiency of the DMU under analysis, DMU_o, is calculated according to the CCR model as follows (Charnes et al., 1978):

$$Max\ z = \sum_{r=1}^{k} u_r y_{ro} \tag{1}$$

$$\sum_{i=1}^{m} v_{io} x_{io} = 1 \tag{2}$$

$$\sum_{r=1}^{k} u_r y_{rj} - \sum_{i=1}^{m} v_{ij} x_{ij} \le 0 \tag{3}$$

$$u_r \ge 0 \tag{4}$$

$$v_i \ge 0 \tag{5}$$

where v_i represents the input weights, u_r represents the output weights, and the subindex o accounts for the inputs and outputs of the DMU being analyzed. We use model (1)–(5) to maximize the efficiency of DMU_o and calculate the input and output coefficients for each DMU.

Some inputs may not be completely consumed in the current planning period and are transferred to the next planning periods, causing a dynamic process in which inputs are transferred between stages. In this study, a dynamic DMU has the following structure, as shown in Fig. 1.

Inputs are categorized into two groups, namely, X and X', which represent the first type and second type of inputs, respectively. Vector X consists of those inputs which have been used in the current planning period and are not transferred to the next stage. Vector X' consists of those inputs which are partially consumed in the current planning period whereby a certain percentage, i.e., % $(1 - \beta)$, is transferred to the next stage. This dynamic multi-stage structure is illustrated in Fig. 1, where the second type of inputs are assumed to be fertilizers.

Two different phases are considered to calculate the efficiency score of a dynamic multi-stage DMU. In the first phase, the efficiency of each dynamic multi-stage DMU is calculated in a multi-period planning horizon. In this phase, the output of period T is taken as the complete output of the DMU and the input of the first stage is taken as the complete input of the DMU. In the second phase, the efficiency of each dynamic multi-stage DMU is calculated in each stage of the planning horizon. In this phase, T models are developed, one for each planning period. Table 1 shows the indices, parameters, decision variables, and notations used in the modeling.

3.1. Phase 1: efficiency score for the dynamic multi-stage structure

As mentioned above, X' represents the type of input that is only partially consumed in the current planning period and a percentage of which is transferred to the next stage. In our example, manure, which remains in the soil, represents this kind of input. Model (6)–(11) is proposed to calculate the efficiency score of a DMU with this dynamic multi-stage structure.

$$Max \quad z = \frac{u_T y_{To}}{\sum_{i=1}^{2} v_{i1} x_{i1o} + v'_1 x'_{1o}} \tag{6}$$

$$\frac{u_t y_{tj}}{\sum_{i=1}^{2} v_{it} x_{itj} + v'_t \left[\sum_{s=1}^{t} (1-\beta)^{s-1} x'_{(t-s+1)j} \right]} \le 1, \quad \forall t, j \tag{7}$$

$$\frac{u_T y_{Tj}}{\sum_{i=1}^{2} v_{i1} x_{i1j} + v'_1 x'_{1j}} \le 1, \quad \forall j \tag{8}$$

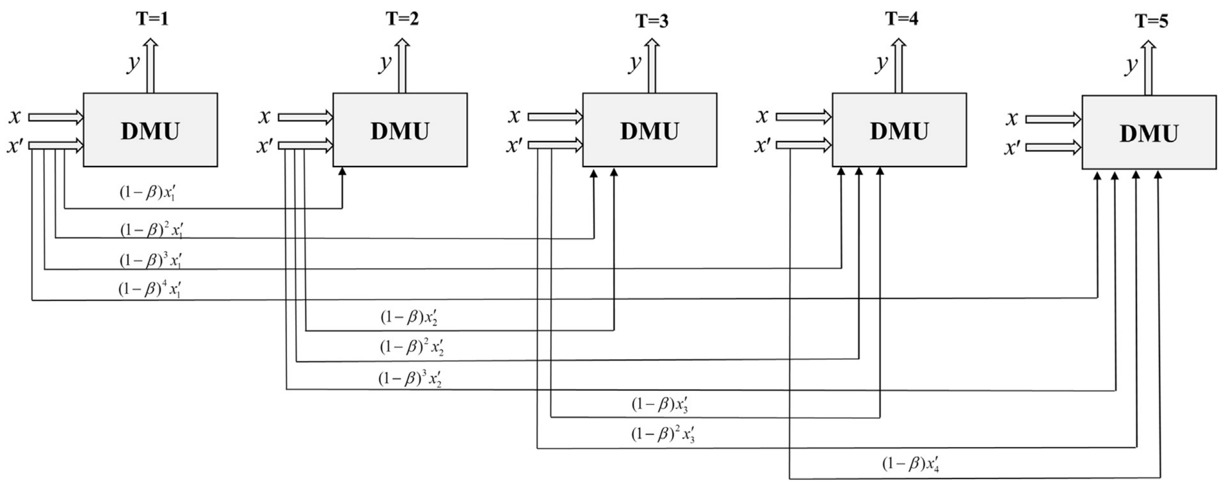

Fig. 1. A DMU in a time period of $t = 5$ with dynamic input.

$$u_t \geq 0\ , \qquad \forall t \tag{9}$$

$$v_{it} \geq 0\ , \qquad \forall i, t \tag{10}$$

$$v'_t \geq 0\ , \qquad \forall t \tag{11}$$

Objective function (6) measures the efficiency of the DMU through the whole planning horizon as shown in Fig. 1. The inputs of period $t = 1$ are assumed as complete inputs and the outputs of period $t = T$ are considered as final outputs. The inputs and outputs of all stages are described in Fig. 1. The set of constraints (7), which is written for all the planning horizon periods $t = 1,\ldots, T$ and all the DMUs, guarantees that for each DMU in each planning period, the efficiency score must be lower than or equal to one. In other words, these constraints are imposed to ensure that no DMU in none of the planning periods exceeds the maximum efficiency level, which has been set equal to one. Note that the term $\sum_{s=1}^{t}(1-\beta)^{s-1}x'_{(t-s+1)j}$ in constraint (7) reflects the dynamic cumulative nature of the inputs over the planning horizon. That is, partially consumed inputs accumulate through the different time periods at a predetermined $(1 - \beta)$ transfer rate. We will emphasize the importance of this term when discussing the numerical results of the model in Section 4.3. The set of constraints (8), which is written for all the DMUs $j = 1,\ldots,n$, guarantees that for each DMU in the whole planning horizon, the efficiency score must be lower than or equal to one. The set of constraints (9)–(11) defines the domain of the decision variables.

Model (6)–(11) is a fractional mathematical programming problem and it is not possible to find its global optimum solution. Therefore, the following linearization procedure is implemented. First, we define the variable $p = \left(\sum_{i=1}^{2} v_{i1}x_{i1o} + v'_1x'_{1o}\right)^{-1}$, which is replaced in the initial model (6)–(11). Then, after some basic algebra, constraint (7) is transformed into $u_t y_{tj} - \sum_{i=1}^{2} v_{it}x_{itj} - v'_t\left[\sum_{s=1}^{t}(1-\beta)^{s-1}x'_{(t-s+1)j}\right] \leq 0, \quad \forall t, j$, and both sides of this inequality are multiplied by p. Finally, the variable exchanges $u'_t = p \times u_t,\ \forall t, v'_{it} = p \times v_{it},\ \forall t,\ \forall i$, and $v_i'' = p \times v'_i,\ \forall i$, are defined and implemented. Given constraint (13), and in order to simplify the notation and presentation, the following linear programming problem defined by Eqs. (12)–(18) is obtained.

$$Max \quad z = u_T y_{To} \tag{12}$$

$$\sum_{i=1}^{2} v_{i1}x_{i1o} + v'_1x'_{1o} = 1 \tag{13}$$

$$u_t y_{tj} - \sum_{i=1}^{2} v_{it}x_{itj} - v'_t\left[\sum_{s=1}^{t}(1-\beta)^{s-1}x'_{(t-s+1)j}\right] \leq 0, \quad \forall t, j \tag{14}$$

$$u_T y_{Tj} - \sum_{i=1}^{2} v_{i1}x_{i1j} - v'_1x'_{1j} \leq 0, \ \ \forall j \tag{15}$$

$$u_t \geq 0\ , \qquad \forall t \tag{16}$$

$$v_{it} \geq 0\ , \qquad \forall i, t \tag{17}$$

$$v'_t \geq 0\ , \qquad \forall t \tag{18}$$

Solving model (12)–(18) will result in the relative efficiency scores of the DMUs with a dynamic multi-stage structure.

Theorem 1. Model (12)–(18) is always feasible. The objective function of model (12)–(18) is bounded. The upper bound of the objective function of model (12)–(18) is equal to one.

Proof. The extended form of model (12)–(18) is defined as follows:

$$Max \quad z = u_T y_{To} \tag{19}$$

$$\sum_{i=1}^{2} v_{i1}x_{i1o} + v'_1x'_{1o} = 1 \tag{20}$$

$$u_1 y_{1j} - \sum_{i=1}^{2} v_{i1}x_{i1j} - v'_1x'_{1j} \leq 0, \quad \forall j \tag{21}$$

$$u_2 y_{2j} - \sum_{i=1}^{2} v_{i2}x_{i2j} - v'_2\left((1-\beta)x'_{1j} + x'_{2j}\right) \leq 0, \quad \forall j \tag{22}$$

Table 1
Symbols used in the models.

t	Planning period index, $t = 1,2,\ldots, T$
i	Input number index, $i = 1,2,\ldots, m$
r	Output number index, $r = 1,2,\ldots, s$
j	DMU index, $j = 1,2,\ldots, n$
X_{itj}	The i^{th} first-type input of DMU j in the t^{th} stage
X_{tj}'	The second-type input of DMU j in the t^{th} stage
u_t	Output vector weight in t^{th} stage
v_{it}	Weight of the i^{th} first type input in the t^{th} stage
v_t'	Weight of the second-type input in the t^{th} stage
y_{tj}	Output of DMU j in the t^{th} stage
$(1 - \beta)$	Part of the second-type input transferred to the next stage

$$u_3 y_{3j} - \sum_{i=1}^{2} v_{i3} x_{i3j} - v'_3\left((1-\beta)^2 x'_{1j} + (1-\beta)x'_{2j} + x'_{3j}\right) \le 0, \quad \forall j \tag{23}$$

$$u_4 y_{4j} - \sum_{i=1}^{2} v_{i4} x_{i4j} - v'_4\left((1-\beta)^3 x'_{1j} + (1-\beta)^2 x'_{2j} + (1-\beta)x'_{3j} + x'_{4j}\right) \le 0, \quad \forall j \tag{24}$$

$$u_5 y_{5j} - \sum_{i=1}^{2} v_{i5} x_{i5j} - v'_5\left((1-\beta)^4 x'_{1j} + (1-\beta)^3 x'_{2j} + (1-\beta)^2 x'_{3j} + (1-\beta)x'_{4j} + x'_{5j}\right) \le 0, \quad \forall j \tag{25}$$

$$u_5 y_{5j} - \sum_{i=1}^{2} v_{i1} x_{i1j} - v'_1 x'_{1j} \le 0, \quad \forall j \tag{26}$$

$$u_t \ge 0, \quad t = 1, \ldots, 5 \tag{27}$$

$$v_{it} \ge 0, \quad \forall i;\ t = 1, \ldots, 5 \tag{28}$$

$$v'_t \ge 0, \quad t = 1, \ldots, 5 \tag{29}$$

Defining the proper dual decision variables (i.e., λ_j^t, λ_j, θ), the dual of model (12)–(18) is derived as model (30)–(36).

$$Min \quad \theta \tag{30}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{n} \lambda_j^t \times x_{itj} + \sum_{j=1}^{n} \lambda_j \times x_{i1j} \le \theta \times x_{i1o}, \quad \forall i \tag{31}$$

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j^1 \times x'_{1j} + \sum_{j=1}^{n} \lambda_j^2\left((1-\beta)x'_{1j} + x'_{2j}\right) \\
&+ \sum_{j=1}^{n} \lambda_j^3\left((1-\beta)^2 x'_{1j} + (1-\beta)x'_{2j} + x'_{3j}\right) \\
&+ \sum_{j=1}^{n} \lambda_j^4\left((1-\beta)^3 x'_{1j} + (1-\beta)^2 x'_{2j} + (1-\beta)x'_{3j} + x'_{4j}\right) \\
&+ \sum_{j=1}^{n} \lambda_j^5\left((1-\beta)^4 x'_{1j} + (1-\beta)^3 x'_{2j} + (1-\beta)^2 x'_{3j} + (1-\beta)x'_{4j} + x'_{5j}\right) \\
&+ \sum_{j=1}^{n} \lambda_j \times x'_{1j} \le \theta \times x'_{1o}
\end{aligned} \tag{32}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{n} \lambda_j^t \times y_{tj} + \sum_{j=1}^{n} \lambda_j \times y_{Tj} \ge y_{To} \tag{33}$$

$$\lambda_j^t \ge 0, \quad \forall j, t \tag{34}$$

$$\lambda_j \ge 0, \quad \forall j \tag{35}$$

$$\theta \text{ free in sign} \tag{36}$$

$$\begin{aligned}
&\theta = 1 \\
&\lambda_j^t = 0, \forall t, j \\
&\lambda_j = 0, \forall j; j \ne o
\end{aligned} \tag{37}$$

It is clear that solution (37) is always feasible for model (30)–(36). The feasibility of this solution is independent of the values for the inputs and outputs for all the stages. Thus, model (30)–(36) has at least one feasible solution such as (37). Hence, model (30)–(36) is always feasible. It should be concluded that the dual of model (30)–(36) (i.e., model (19)–(29)) is always feasible.

We should note that the optimum value of the objective function in model (30)–(36), known as θ^*, will be lower than or equal to one. This is due to the value of the feasible solution (37) of the objective function being equal to one ($\theta = 1$). In other words, we have $\theta^* \le \theta = 1$. Hence, $\theta^* \le 1$. By virtue of the duality theorem in linear programming, the objective functions of the primal and dual programs are equal in optimality. Therefore, $\theta^* = z^* \le 1$. This completes the proof.

3.2. Phase 2: efficiency score for each time period

In this phase, the efficiency of n DMUs in each of the t time periods of the planning horizon is calculated separately. In this phase, the efficiency scores of all the DMUs are determined in a specific time period. The parametric model (38)–(42) for the entire planning horizon is proposed as follows:

$$Max \quad z_t = \frac{u_t y_{to}}{\sum_{i=1}^{2} v_{it} x_{ito} + v'_t\left[\sum_{s=1}^{t}(1-\beta)^{s-1} x'_{(t-s+1)o}\right]} \tag{38}$$

$$\frac{u_t y_{tj}}{\sum_{i=1}^{2} v_{it} x_{itj} + v'_t\left[\sum_{s=1}^{t}(1-\beta)^{s-1} x'_{(t-s+1)j}\right]} \le 1, \quad \forall j \tag{39}$$

$$u_t \ge 0 \tag{40}$$

$$v_{it} \ge 0, \quad \forall i \tag{41}$$

$$v'_t \ge 0 \tag{42}$$

Model (38)–(42) is a parametric fractional mathematical programming problem. In this regard, $t = 1, 2, 3, \ldots, T$ is a parameter for model (38)–(42). For instance, in order to calculate the relative efficiency of the DMUs in the third year of planning, model (38)–(42) must be solved for each DMU by setting $t = 3$. Similarly, to the set of constraints (7) in phase 1, the corresponding constraints defined in (39) guarantee that the maximum efficiency score achieved by a given DMU in a predetermined period of time, which accounts for the cumulative nature of the inputs over the planning horizon, is less than or equal to one.

Model (38)–(42) is a fractional mathematical programming problem for which a global optimum is not easily achieved. As we did in the case of model (6)–(11), a standard linearization procedure is implemented as follows. First, we define the variable $q = \left(\sum_{i=1}^{2} v_{it} x_{ito} + v'_t\left[\sum_{s=1}^{t}(1-\beta)^{s-1} x'_{(t-s+1)o}\right]\right)^{-1}$ and replace it in model

Table 2
Input and output of the provinces.

Criteria	Name	Description	Measurement unit
Inputs	Fertilizer	Amount of fertilizer used in a hectare in 1 year	Ton/hectare
	Pesticide	Amount of pesticide used in a hectare in 1 year	Lit $\times 10^3$/hectare
	Seed	Amount of seed used in a hectare in 1 year	Ton/hectare
Outputs	Produced cotton	Amount of cotton produced in a hectare in 1 year	Ton/hectare

Table 3
Data for input and output of the provinces.

Province	Output				Input											
	Cotton				Fertilizer				Pesticides				Seed			
	Std. Dev.	Ave.	Max	Min	Std. Dev.	Ave.	Max	Min	Std. Dev.	Ave.	Max	Min	Std. Dev.	Ave.	Max	Min
Ardebil	7075.2	14815.5	26080	7336.5	43	26	99	0	524	614	1361	32.1	33.4	59	95	24
Esfehan	4268.9	16122.4	20052.6	9317.6	185.5	479.5	767.4	327	631.4	1532	2386	917	22.1	47	81	25
Tehran	1511.8	6668.7	8096.3	4488.9	328.2	503	871.6	3	318	274.8	714	24.1	45.4	53	99	4.8
Khorasan	9320.5	113244	124983	100503	185	291.1	478.2	73	208	733.8	901.2	376	36	28	88	3.2
Semnan	1477.2	12733.5	15188.9	11374.5	375.2	434.9	976.1	7.2	862.7	1119	2146	168	34.8	37	86	1.7
Fars	4087.0	30243.5	35411.5	24855.5	18.6	18.4	49	0	689.1	1064	1807	201	29.1	63	85	13
Qom	1474.0	8478.9	10007.8	6490.3	333.2	356.4	811.8	0	483.8	1079	1500	367	27.5	49	89	13
Golestan	16465	32545	60700.1	18699.8	133.7	177.3	366.3	17	455.1	1563	1927	914	33.9	54	89	9.5
Markazi	2040.3	4962.5	6922.2	2545.1	419	187.4	937	0	790.1	1568	2763	563	21.8	55	80	22
Yazd	827.8	1590.8	2816.5	621.1	7476	3902	17266	147	346.6	370.5	928	0	38.4	43	96	4.8
Kerman	1513.1	5542	7356.1	3912.1	172	2341	2892	1123	808.6	607.7	2008	0	32.2	32	80	1.7

(38)-(42). Then, constraint (39) is transformed into $u_t y_{tj} - \sum_{i=1}^{2} v_{it} x_{itj} - v'_t \left[\sum_{s=1}^{t} (1-\beta)^{s-1} x'_{(t-s+1)j}\right] \leq 0, \quad \forall j$, and both sides of this inequality are multiplied by the variable q. Finally, the variable exchanges $u'_t = q \times u_t, \forall\, t, v'_{it} = q \times v_{it}, \forall\, t, \forall\, i$, and $v''_i = q \times v_i, \forall\, i$, are defined and implemented. Given constraint (44), the resulting linear form associated with model (38)–(42) is given by (43)–(48).

$$Max \quad z_t = u_t y_{to} \tag{43}$$

$$\sum_{i=1}^{2} v_{it} x_{ito} + v'_t \left[\sum_{s=1}^{t} (1-\beta)^{s-1} x'_{(t-s+1)o}\right] = 1 \tag{44}$$

$$u_t y_{tj} - \sum_{i=1}^{2} v_{it} x_{itj} - v'_t \left[\sum_{s=1}^{t} (1-\beta)^{s-1} x'_{(t-s+1)j}\right] \leq 0, \quad \forall j \tag{45}$$

$$u_t \geq 0\ , \qquad \forall t \tag{46}$$

$$v_{it} \geq 0\ , \qquad \forall i, t \tag{47}$$

$$v'_t \geq 0\ , \qquad \forall t \tag{48}$$

Theorem 2. Model (43)–(48) is always feasible for the entire planning horizon. The objective function of model (43)–(48) for the entire planning horizon is bounded. The upper bound of the objective function of model (43)–(48) for the entire planning horizon is equal to one.

Proof. Considering Theorem 1, the proof is straightforward and the details are not presented for the sake of brevity.

4. Case study and results

The proposed models have been applied in a real case study consisting of 11 cotton producers in Iran. A cotton producer in this study is assumed to be a DMU which consumes some inputs in order to produce some outputs. This study is conducted on the basis of data collected during 5 years in several Iran provinces including: Ardabil, Isfahan, Tehran, Khorasan Razavi, Semnan, Fars, Qom, Golestan, Markazi, Yazd, and Kerman. Three main input factors involved in cotton production including fertilizer, seed, and pesticide are considered for evaluation in this study. The inputs and outputs considered in this study are presented in Table 2.

Fertilizer and seed are considered as an input which is transferred from each planning year to the next. That is, some parts of fertilizer and seed used in a given year are consumed in the same year and other parts remain in the environment for the following year. Thus, in a T-year planning period, a certain amount of seed and fertilizer is used each year and the remaining is transferred to the following years of planning. This transference is based upon a coefficient β representing a fraction or a percentage, which in our case is equal to 0.9 for 1 year. This means that 0.9 of such inputs are used in the base year and 0.1 of such inputs are transferred into the following year. This process takes place in all the years of the planning horizon. Table 3 describes the data for the inputs and outputs during the 5 years of the planning horizon.

For the sake of brevity, we have supplied the descriptive statistics (i.e., average, minimum, maximum, and standard deviation) of inputs and outputs in Table 3. For example, the province of Tehran used 503 tons of fertilizers, 274.8 kilo-liters of pesticides, and 53 tons of seeds to produce 6668.7 tons of cotton on average during the 5 years considered.

4.1. Phase 1 results

In this phase, each province is studied through a 5-year period and an efficiency score is calculated for each DMU during the planning horizon. That is, the efficiency of each province is calculated for the whole planning horizon, determining which among the 11 provinces are efficient and which are inefficient. Table 4 shows the efficiency score of each province and their ranks in this 5-year period.

The provinces of Kerman and Golestan are found to be efficient DMUs with efficiency scores equal to one, while the other provinces are labeled as inefficient DMUs. Yazd and Ardebil are recognized as the weakest DMUs with efficiency scores equal to 0.007 and 0.04, respectively.

4.2. Phase 2 results

In this phase, efficiency is calculated for each planning period separately. Thus, five efficiency scores are calculated for each DMU during

Table 4
Efficiency scores during the 5-year period.

Province	Kerman	Yazd	Markazi	Golestan	Qom	Fars	Semnan	Khorasan	Tehran	Esfehan	Ardebil
Efficiency	1	0.0071	0.0545	1	0.1310	0.2466	0.2002	0.7176	0.0509	0.1660	0.0482
Ranking	1	10	7	1	6	3	4	2	8	5	9

Table 5
Efficiency scores in each planning period.

Province	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	Average	Ranking
Ardebil	0.0914	0.7157	0.0928	0.1373	0.0730	0.2220	5
Esfehan	0.1476	0.1535	0.1746	0.1606	0.0927	0.1458	9
Tehran	0.0153	0.6669	0.0705	0.0619	0.0801	0.1789	7
Khorasan	0.4880	1	1	1	1	0.8976	1
Semnan	0.1047	0.3286	0.1322	0.1051	0.1184	0.1578	8
Fars	0.1887	1	0.2864	0.2616	0.2473	0.3968	4
Qom	0.0780	0.0395	0.0871	0.0600	0.0832	0.0696	10
Golestan	1	0.7523	0.2819	0.2358	0.1860	0.4912	2
Markazi	0.0277	0.7333	0.02589	0.05620	0.0689	0.1824	6
Yazd	0.0180	0.0637	0.0136	0.0102	0.0062	0.0223	11
Kerman	1	1	0.0575	0.0362	0.0409	0.4269	3

the planning horizon. The average of the efficiency scores for each province in the 5-year period is presented in Table 5. The provinces are ranked in the last column based upon the average efficiency scores.

Note that the results differ from those presented in Table 4. In this case, the provinces of Khorasan and Golestan occupy the first and second position in the rank, respectively, while Qom and Yazd are relegated to the last two positions. Moreover, a comparison of the average efficiency scores of each province during this 5-year period is presented in Fig. 2.

Clearly, Khorasan had the largest average efficiency score during the planning horizon.

In general, the efficiency scores presented in Tables 4 and 5 can be interpreted as follows. The Phase 1 scores in Table 4 show the overall efficiency of the DMUs through the whole planning horizon. These scores provide a long-term efficiency perspective. The Phase 2 scores in Table 5 reflect the efficiency of each DMU in each period of the planning horizon. These scores illustrate the short-term efficiency of each DMU *as well as its evolution through time*. A thorough comparison of both types of scores would help managers to find out at which exact planning period a DMU starts to lose or gain efficiency.

Moreover, as can be directly inferred from both tables, the long-term and short-term efficiencies may substantially differ for a given DMU. Thus, the strategic decision of which DMU to select in terms of efficiency depends on the type of score being considered. For example, the choice between establishing short-term or long-term relations with different DMUs (or firms) is directly determined by the expected evolution of their efficiency scores. The capacity of managers and decision makers to compare both types of scores is crucial to avoid a suboptimal choice. We discuss the main implications derived from these differences in efficiency scores in greater detail through the next section.

Note, finally, that the cumulative dynamic character of our model endows it with an advantage over the heuristic methods, such as the scatter search algorithm, that can be used to compare the behavior of the DMUs in each period with respect to the whole planning horizon being considered.

4.3. Discussion of the results

One of the main contributions of the current model is its capacity to compare the efficiency scores received for the entire planning horizon with those obtained in each one of its periods. The former scores provide a summary of the general efficiency of a DMU when comparing its initial resources with the output it is able to produce in the last period. Note, however, that this score could be misleading, particularly if considered from a strategic perspective. That is, a DMU may achieve a relatively high efficiency level through the entire planning horizon when considering the final output produced given its initial resources. This result is optimal in efficiency terms if the DMU is considered *from a long-term planning perspective*.

However, it can be claimed that the evolution of the efficiency level through the different planning periods provides a much more realistic approach to describing the behavior of the DMU. In other words, the efficiency level, whether it is increasing or decreasing, constitutes highly valuable information as we approach the final period. For example, when analyzing different DMUs in the international business literature, i.e., when deciding whether to merge with a foreign firm or acquire it, the quality indicators observed are essential. These indicators play a considerable strategic role. Considering these indicators explicitly would expand the scope of the dynamic DEA literature in areas such as international business or industrial organization, by providing a strategic approach to measuring the efficiency evolution of the DMUs.

Indeed, by observing the evolution of the efficiency scores, we may reach a conclusion which is significantly different from that obtained by analyzing the entire planning horizon. Consider the first four ranked DMUs based on the entire planning horizon, as described in Table 4. These positions are occupied by the provinces of Golestan and Kerman, followed by Khorasan, and finally, Fars. However, when observing the evolution of the efficiency scores obtained by each DMU through each of the planning periods, we see how Khorasan exhibits a significantly stronger improvement than the other three and it is therefore ranked first, followed by Golestan, Kerman, and Fars. Fig. 3 illustrates this dynamic behavior.

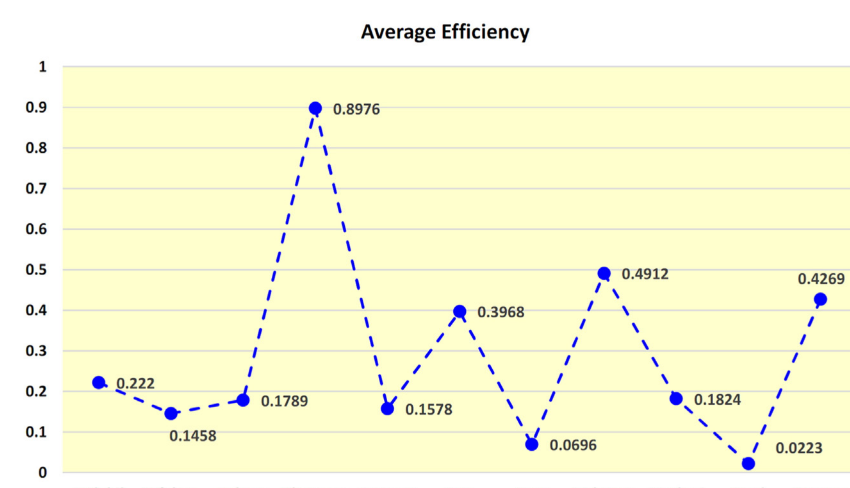

Fig. 2. Average efficiency scores during the 5-year planning period.

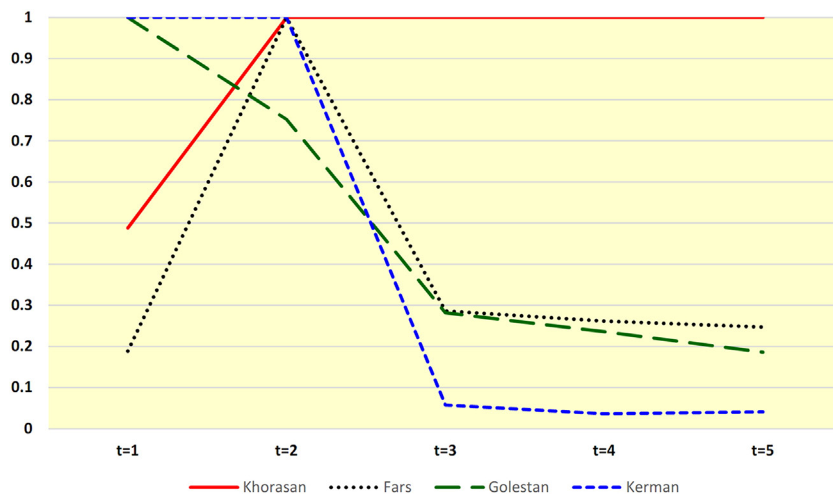

Fig. 3. Evolution of efficiency scores through the planning period for the provinces selected.

This distinction between dynamic approaches is essential since, when the entire planning horizon was considered, Khorasan was ranked in third position after a tie between Golestan and Kerman in the first one. The evolution of the efficiency scores obtained through each of the individual periods tells a different story, with the average of Khorasan being clearly above that of Golestan and Kerman and the efficiency of the latter ones decaying rapidly after the second period.

Moreover, deciding which periods should be included in the analysis could also lead to different conclusions, which is an essential result from a strategic perspective. For example, Fig. 3 illustrates how, despite a much more inefficient first period, Fars performed better than Golestan and Kerman in periods 2–5 and its efficiency is currently higher than that of both these provinces.

The implications derived from this trend can be observed in Table 6. In this table, we calculate a new average and its corresponding ranking based on the efficiency scores obtained in periods 2–5. According to this new ranking, Khorasan remains as the most efficient province, while Fars moves to a second position, followed by Golestan and Kerman, respectively. It may be argued that this latter ranking describes the *dynamic evolution* of the efficiency of the provinces better than the previous one. This result illustrates the strategic component inherent in the choice of the time interval periods when presenting the results. The current DEA approach sheds a considerable amount of light on this problem.

As stated above, these results become essential in research areas such as international business and strategy, where the entry requests of multinational corporations or banks in foreign locations are based on their expected interactions with the local firms. The differences in the patterns of efficiency evolution illustrated in this paper are crucial in this regard. That is, the expected outcomes calculated by the multinational will depend on the type of efficiency score that the DMUs decide to emphasize, a decision that should, at the same time, be based on their potential interactions with the multinational firm.

At the same time, a potential extension of the current model to the field of energy economics could concentrate on the study of energy networks where, instead of time, the evaluation of efficiency is defined for different nodes within a network. In the literature review, we referred to the development of network DEA models that measure the efficiency of the different sub-processes composing a network. In particular, this branch of the DEA literature has concentrated on identifying the specific sources of (technological) productive efficiency within firms (Färe and Grosskopf, 2000; Lewis and Sexton, 2004) and their effect on the development level of countries (Prieto and Zofío, 2007).

Table 6
Average efficiency scores in selected planning periods.

Province	Average periods 1–5	Ranking	Average periods 2–5	Ranking
Khorasan	0.8976	1	1	1
Fars	0.3968	4	0.4488	2
Golestan	0.4912	2	0.3640	3
Kerman	0.4269	3	0.2836	4

The application of network DEA models to analyze the technological development of countries is particularly relevant, given the recent emphasis placed on the relation existing between economic growth and the quality of the national energy networks (Elliott et al., 2015; Stern, 2012). However, despite accounting for the interdependencies that result from the structure of a connected network, these models lack the dynamic cumulative structure introduced in the current one. Note that our model can be easily redefined to account for the (cumulative) interdependencies taking place within a network, a fundamental characteristic when analyzing energy networks.

The capacity of the model to measure the efficiency of the DMUs over different periods of time, as well as the individual pattern followed by each unit, is particularly important from a strategic perspective. For example, Nagayama and Horita (2014) illustrate how the structure of natural gas pipeline networks determines the strategic interactions among those countries involved in its trade. Adapting our model to describe payoff scenarios based on the potential efficiency patterns of the DMUs in cumulative network transmission structures could prove to be essential in determining the equilibria of the corresponding games.

5. Conclusions and future research directions

We have proposed a DMS-DEA model to assess the efficiency score of cotton-producing farms in Iran. This model has allowed us to illustrate the dynamic and multi-period nature of a DMU in which parts of its inputs are transferred from one period to future periods of planning. The efficiency of the DMUs was calculated using two different phases. In the first phase, the efficiency was calculated for a T-year period. In the second phase, the efficiency was calculated for each year separately throughout the planning horizon. The proposed approach was used to evaluate energy consumption in cotton-producing farms. Cotton is considered to be a strategic agricultural product both in Iran and the world. The results have illustrated the proper performance of the approach proposed using a dynamic multi-stage structure.

The contribution of this research is threefold: (1) we have developed a DMS-DEA model to calculate the efficiency of the DMUs both in a multi-year planning horizon and in each period of the planning horizon;

(2) we have analyzed the properties of the proposed DMS-DEA model through several theorems; and (3) we have applied the proposed DMS-DEA model to a real-world case study of cotton production in Iran.

The limitations of this research and future research directions are classified as follows: (1) We have used data for a 5-year period, but longer periods may result in more reliable indicators for the efficiency scores of the DMUs; (2) Fuzzy sets or random variables can be used to represent the uncertainty inherent in the data; (3) The model proposed in this research was developed based on constant returns to scale, but future research could extend the results under the assumption of variable returns to scale; (4) We have developed a multiplier form of the DEA model in a dynamic multi-period situation. However, the model could be extended using an envelopment form. The corresponding primal dual analysis may constitute a more useful tool for the projection of the inefficient DMUs toward the efficient frontier; (5) We have used the input-orientation perspective in order to develop our model, but the model could also be developed using an output-oriented approach; (6) The proposed approach can be customized for other sectors such as the military one, education, and various service industries; (7) Finally, we must emphasize once again the importance of carry-over activities in our model. This type of interaction between planning periods can also be used to measure the expected evolution of efficiency based on the cumulative properties of, for example, knowledge and technology.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.06.020.

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