Neural Comput & Applic (2017) 28:3683–3696
DOI 10.1007/s00521-016-2274-z

ORIGINAL ARTICLE

A hybrid goal programming and dynamic data envelopment analysis framework for sustainable supplier evaluation

Madjid Tavana[1,2] · Hadi Shabanpour[3] · Saeed Yousefi[4] · Reza Farzipoor Saen[4]

Received: 30 December 2015 / Accepted: 2 March 2016 / Published online: 17 March 2016

Abstract The evaluation of sustainable suppliers is one of the most complex tasks in sustainable supply chain management (SSCM). Classical data envelopment analysis (DEA) and dynamic DEA (DDEA) models are heavily dependent on historical data and do not forecast future efficiencies of decision-making units (DMUs). The primary objective of this paper is to present a new predictive paradigm for ranking sustainable suppliers in SSCM. The proposed model combines goal programming and DDEA in an integrated and seamless paradigm to determine the future efficiencies of DMUs (suppliers). It also shifts the decision maker's role from monitoring the past to planning the future. A case study is presented to demonstrate the applicability of the proposed model and exhibit the efficacy of the procedures and algorithms.

Keywords Dynamic data envelopment analysis · Goal programming · Sustainable supplier selection · Benchmarking · Decision-making units · Efficiency evaluation

✉ Madjid Tavana
tavana@lasalle.edu;
http://tavana.us

Hadi Shabanpour
hadi.shabanpour@gmail.com

Saeed Yousefi
saeedyousefi12@yahoo.com

Reza Farzipoor Saen
farzipour@yahoo.com

1 Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA 19141, USA

2 Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, 33098 Paderborn, Germany

3 Young Researchers and Elite Club, Karaj Branch, Islamic Azad University, Karaj, Iran

4 Department of Industrial Management, Faculty of Management and Accounting, Karaj Branch, Islamic Azad University, Karaj, Iran

1 Introduction

The success of many organizations depends on their ability to manage the flow of materials, information, and money. A supply chain is a network of organizational units connected with each other through the flow of materials, information, and money [62]. Many organizations choose to outsource their supply chain management (SCM) because overseeing SCM can be a demanding task [1]. In order to stay competitive in the global marketplace, organizations are under constant pressure to consider environmental and social criteria in addition to economic criteria. Dyllick and Hockerts [13] argued that sustainable SCM is the result of adding environmental and social responsibility factors into economic criteria. The ever-increasing demands for social responsibility have made sustainability a significant concern for organizations and for researchers [21]. A large number of researchers have shown that the success of SCM depends on the successful adoption of sustainability principles (e.g., [8, 23, 35]).

Selection of appropriate suppliers in SCM is a difficult task because it requires a wide range of multiple and often conflicting criteria [32, 51]. Conventional supplier selection criteria include price, quality, flexibility, and reputation [6]. However, modern supplier selection models have become more complicated because of the presence of sustainability criteria. A wide variety of methods from the technique for order of preference by similarity to ideal solution (TOPSIS) [32] to analytic network process (ANP) [37] have been proposed for supplier evaluation and selection.

Data envelopment analysis (DEA) is a technique for evaluating relative efficiency of decision-making units (DMUs) [11]. Various DEA models have been proposed to rank the DMUs during the past three decades. The concept of "ideal DMU" has been used to rank the DMUs in several DEA methods [22, 24, 30, 48, 52–54]. Yousefi et al. [61] developed an ideal DMU using the virtual network DEA approach for ranking both inefficient and efficient DMUs. To rank efficient DMUs, Andersen and Petersen [3] proposed the super-efficiency approach. Farzipoor Saen [17] used the super-efficiency technique for ranking suppliers in the presence of volume discount offers. The concept of "cross-efficiency" has also been used to rank efficiencies in DMUs [44].

One of the shortcomings of the conventional dynamic DEA (DDEA) models is their inability to properly calculate the future efficiencies of DMUs. This shortcoming resembles the proverb which says "to close the cage's door after jumping bird." The conventional DEA models evaluate DMUs merely in a specific period and neglect carry-over activities between consecutive periods. The carry-over activities play a significant role in measuring the efficiency of a DMU [49]. Färe and Grosskopf [14] have suggested using DDEA to overcome this carry-over shortcoming. Tone and Tsutsui [49] used carry-overs and developed a dynamic slacks-based measure (DSBM) model to evaluate DMUs in different periods. They introduced four types of carry-overs (links) including desirable, undesirable, discretionary, and nondiscretionary (fixed) links. In summary, conventional DDEA models cannot simultaneously evaluate the efficiency of DMUs in the past, present, and future periods.

Due to increasing global pressure on firms to incorporate sustainability principles into their business operations, several researchers have developed DEA models for evaluating the environmental efficiencies of DMUs [13, 28, 31, 46]. Another layer of complexity is added to this problem when DMUs produce undesirable (bad) outputs in addition to the desirable (good) outputs [47]. Emissions of carbon dioxide and air pollutions are common examples of undesirable outputs. Therefore, it is necessary to consider both desirable and undesirable outputs when evaluating the efficiencies of DMUs.

Previous DEA models in general and dynamic DEA methods in particular utilize historical data (past performance) to evaluate the efficiency of DMUs. The main objective of this paper is to demonstrate a transition from previous supervising methods of efficiency evaluation to a more futuristic planning perspective. We combine GP and dynamic DEA to simultaneously evaluate suppliers based on their past, present, and future performance. As a result, future efficiencies of suppliers are forecasted and a new ranking method is proposed. It is worth noting that a DMU in the conventional DEA literature is defined as an entity that consumes multiple inputs to produce multiple outputs. In this paper, each DMU is defined as a supplier.

Several hybrid DEA models have been proposed in the literature. Stewart [45] combined goal programming (GP) and DEA to determine benchmarks for inefficient DMUs based on subjective judgments of decision makers. However, he does not take into account historical data for the DMUs. To overcome this shortcoming, we combine GP and DDEA into an integrated and seamless framework. Accordingly, for the first time, sustainable suppliers are evaluated based on their past and future performance trends. To this end, we initially set managerial expectations into a set of operational input and output goals for the efficient and inefficient DMUs for the next period ($p + 1$). We then use the future goals and current values for the inputs and outputs and run the integrated GP and DDEA models to determine the adjusted goals (benchmarks) for each DMU (supplier). Note that the adjusted goals derived from the GP–DDEA model are considered as benchmarks for inefficient and efficient suppliers. On the other hand, the benchmark' values are used as the future data in the DDEA model. Subsequently, we use the DDEA model to evaluate the suppliers from the past periods to future periods, simultaneously. By so doing, not only we evaluate and rank sustainable suppliers, but also we change the focus of the model from previous monitoring to future planning. In summary, the practical advantages of the proposed GP–DDEA approach are as follows: (1) The decision maker's role is shifted from monitoring to future planning, and (2) by determining future supplier efficiencies, preventive actions can be taken so that decision makers can discontinue collaboration with suppliers who are expected to be inefficient.

The remainder of this paper is organized as follows. In Sect. 2, we present a review of supplier selection, DEA, and goal programming. In Sect. 3, we introduce the proposed hybrid model for supplier evaluation. In Sect. 4, we present a real-world case study to demonstrate the applicability of the proposed hybrid method and exhibit the efficacy of the procedures and algorithms. Finally, in Sect. 5, we present our conclusions and future research directions.

2 Literature review

2.1 Supplier selection methods

Kumar et al. [29] have shown that DEA is an applicable and effective tool for supplier selection. Farzipoor Saen [19] suggested a DEA model for supplier selection in the presence of undesirable outputs and imprecise data. Noorizadeh et al. [36] introduced a model for supplier selection in the presence of dual-role factors, nondiscretionary inputs, and weight restrictions. Azadi and Farzipoor Saen [4] developed a new slacks-based measure model to help managers rank and select the most efficient suppliers in the presence of undesirable outputs and stochastic data. Azadi et al. [5] developed a chance-constrained DEA model for supplier selection in the presence of stochastic data and nondiscretionary factors. Weber et al. [55] proposed a multi-objective programming DEA model to evaluate suppliers. Zouggari and Benyoucef [62] classified, evaluated, and selected the most efficient suppliers by integrating the fuzzy analytic hierarchy process (AHP) with fuzzy TOPSIS techniques. Önüt et al. [37] used the fuzzy analytic network process (ANP) for supplier selection. Kahraman et al. [26] used fuzzy AHP and ANP to select the most efficient suppliers. Yahya and Kingsman [59] used AHP to introduce a systematic framework for ranking suppliers. Muralidharan et al. [34] developed an AHP-based model to help managers evaluate suppliers. Sarkis and Talluri [41] proposed organizational factors and strategic performance metrics to select the most efficient suppliers. Farzipoor Saen [18] proposed a DEA model for ranking suppliers in the presence of imprecise data, weight restrictions, and nondiscretionary factors.

2.2 Sustainable supplier selection

Sustainable supplier evaluation and selection combine environmental and social factors with economic factors [13]. In recent years, sustainability factors have played a pivotal role in suppliers' selection [56]. Ratan et al. [39] argue that sustainability principles compel companies to select the suppliers which develop the best products and services, preserve environmental resources, and look after manpower and communities. To select appropriate sustainable suppliers, Beamon [7] introduced ethical and social criteria as the prerequisites for sustainable SCM. Amindoust et al. [2] used a fuzzy inference system and proposed a ranking model for sustainable supplier selection. Wen et al. [56] introduced a model for sustainable supplier evaluation using intuitionistic fuzzy sets in a group decision-making model. Recently, Kumar et al. [29] proposed a unified green DEA model for selecting the most efficient suppliers using a comprehensive and environmentally friendly approach.

2.3 Undesirable outputs

Cooper et al. [12] have shown that DMUs with more desirable outputs and less undesirable outputs are recognized as efficient. Pittman [38], Färe et al. [15, 16], and Yaisawarng and Klein [60] were the first authors to take into account undesirable outputs in DEA. Seiford and Zhu [42] proposed a DEA model for dealing with both desirable and undesirable outputs to improve the performance of DMUs. Korhonen and Luptacik [27] considered undesirable outputs as inputs and measured eco-efficiency of 24 coal-fired power plants. Jahanshahloo et al. [25] considered undesirable inputs and outputs and proposed a new approach for efficiency evaluation.

2.4 Dynamic DEA and goal programming

The conventional DEA models evaluate efficiency of DMUs merely for a specific period of time. However, DDEA models evaluate DMUs in multiple periods [43]. A DDEA model was first developed by Sengupta [43]. Subsequently, Färe and Grosspkof [14] proposed a dynamic production frontier using an intermediate output which relates annual production processes. Tone and Tsutsui [49] used carry-over variables (links) and introduced a new dynamic slacks-based measure (DSBM) model for assessing DMUs in different time periods. They introduced four types of carry-overs (links) as desirable, undesirable, discretionary, and nondiscretionary (fixed) links. Moreover, Tone and Tsutsui [50] proposed a DDEA model with a network structure for merging network slacks-based measure (NSBM) and DSBM models. However, they did not propose any model for planning future efficiency of DMUs. The DDEA cannot calculate future efficiencies for DMUs. Therefore, the obtained benchmarks do not provide any recommendation for improving future efficiencies of DMUs.

GP is a multi-objective programming technique which uses the concept of minimizing deviations from goals in decision making [40]. Charnes, Cooper, and Ferguson were the first forerunners of GP [9]. GP was then extended by Charnes and Cooper [10]. The first operational usage of GP was designing and locating TV antennas which were used to launch the Apollo space capsule for landing the first men on moon in 1962. Determining the appropriate weights in GP can be a controversial issue [20]. AHP and other interactive methods have been proposed to dispel this controversy [57]. Stewart [45] incorporated GP into DEA using the Chebyshev function to introduce improvement benchmarks for inefficient and efficient DMUs. Stewart's goals were derived merely from the subjective judgments of decision makers and as such were set as benchmarks without considering historical data. The overall contribution of the model proposed in this study is fivefold: (1) An integrated GP and DDEA methods are proposed to evaluate future efficiency of DMUs (suppliers) for SSCM; (2) efficiency of the DMUs are evaluated in the past, present, and future periods, simultaneously; (3) suppliers are ranked given both the overall efficiency and forecasted trend of efficiency; (4) benchmarks for both efficient and inefficient suppliers are determined; and (5) a case study is presented to demonstrate the applicability of the proposed model and exhibit the efficacy of the procedures and algorithms.

3 Proposed method

3.1 Algorithm

The proposed algorithm involves five steps. In Step 1, we set the managerial goals for each supplier's inputs and outputs for the next $(p+1)$ period. In Step 2, we use the GP–DEA to evaluate goals and determine future benchmarks for all inefficient and efficient suppliers. In Step 3, we run DDEA and evaluate suppliers' efficiencies in multiple periods, simultaneously. Finally, in Step 4, we rank the suppliers based on both the efficiency trend and the overall efficiency scores. A graphical representation of the proposed framework is presented in Fig. 1.

3.2 Benchmarking by integrating goal programming and DEA

In this subsection, the DMU goals are used to establish benchmarks for each DMU. Here, expectations of decision makers are represented as goals in the form of inputs and outputs. Benchmarking is not limited to inefficient DMUs since if managers are not satisfied with the performance of efficient DMUs, they can adjust their goals (benchmarks). Moreover, the benchmarks should be realistic and stay inside the production possibility set (PPS). In the proposed model, the decision maker's role is shifted from supervision to future planning.

Let us define the following notations. Subscript j designates the DMUs $(j = 1,\ldots,m)$ which are evaluated during the past p periods $(p = 1,\ldots,P)$. Each period has n inputs $(i = 1,\ldots,n)$. The inputs and outputs are defined as follows in the proposed model:

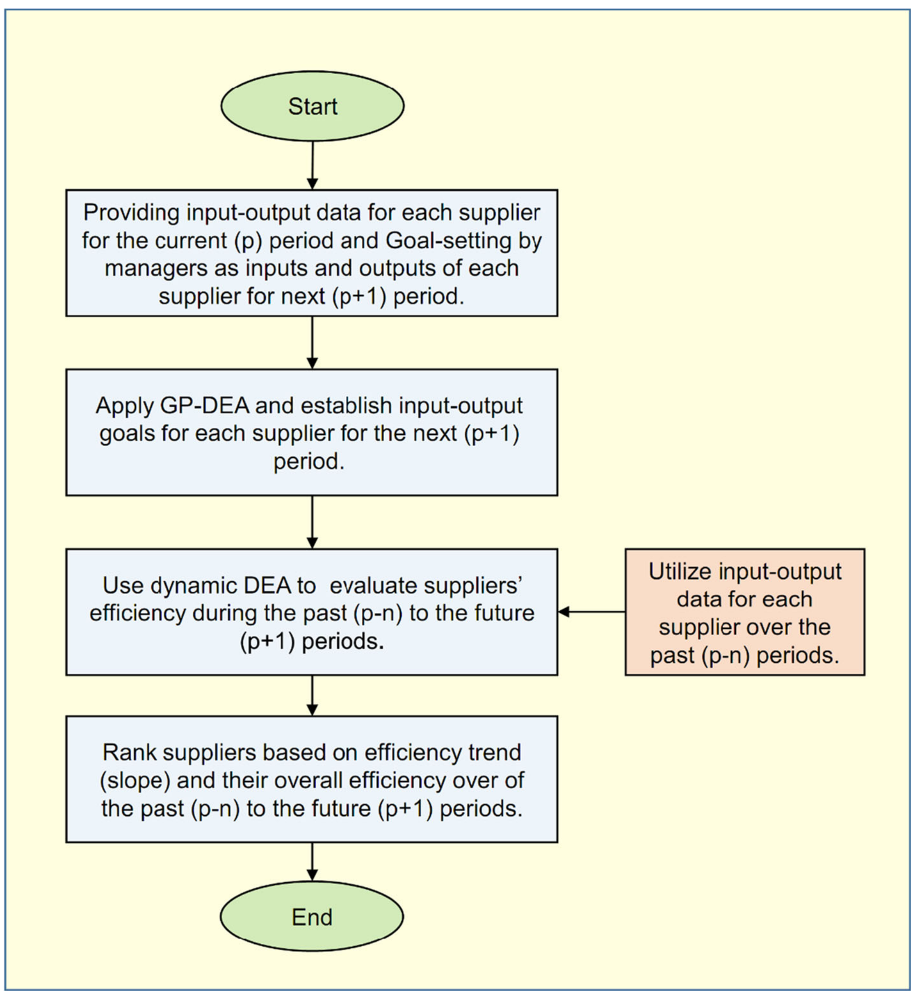

Fig. 1 Proposed framework

- x_{ij} $(i = 1, \ldots, n;\ j = 1, \ldots, m)$ as inputs,
- y_{rj}^{des} $(r = 1, \ldots, s;\ j = 1, \ldots, m)$ as desirable outputs for which their augmentations enhance the efficiency of DMUs.
- y_{rj}^{undes} $(r = 1, \ldots, s;\ j = 1, \ldots, m)$ as undesirable outputs for which their augmentations reduce the efficiency of DMUs.

At this juncture, the goals are defined as follows:

g_{ij} The goal related to ith input for the jth DMU
h_{ij} The goal related to rth output for the jth DMU

The benchmarks have three characteristics: (1) The benchmarks should be as close to the goals as possible; (2) the benchmarks should be located on the efficiency frontier of PPS; and (3) the combination of inputs and outputs of benchmarks should be close to the inputs and outputs of the dth DMU so that they can be realized in the next period. Note that the subscript d in the following expressions refers to the DMU under evaluation. Here, the three characteristics are elaborated as follows:

1. *The benchmarks should be as close to the goals as possible.* Ideally, we are looking for:

$$\begin{aligned} &x_{id}^{*} \geq g_{id}, \quad i = 1, \ldots, n \\ &y_{rd}^{*\text{des}} \geq h_{rd}, \quad r = 1, \ldots, s \text{ and desirable} \\ &y_{rd}^{*\text{undes}} \leq h_{rd}, \quad r = 1, \ldots, s \text{ and undesirable} \end{aligned} \tag{1}$$

Since goals may not be achievable, we use deviational variables for all the goals. δ_{ij}^{I} and δ_{rj}^{O} are, respectively, defined as deviational variables of the input goals and output goals. We wish to minimize the deviational variables.

In the conventional GP, the deviational variables are assumed nonnegative. However, in this paper, we adopt the Wierzbicki [58] reference point in which a "scalarizing function" of the deviational variables is minimized. This approach is more advantageous than the previous GP approaches because even if the "reference point" is in the interior of the PPS, the resulting GP solution will still display a projection on the efficient frontier [58]. Therefore, we have:

$$\begin{aligned} &x_{id}^{*} - \delta_{id}^{I} \leq g_{id}, \quad i = 1, \ldots, n \\ &y_{rd}^{*\text{undes}} - \delta_{rd}^{O} \leq h_{rd}, \quad r = 1, \ldots, s \text{ and undesirable} \\ &y_{rd}^{*\text{des}} + \delta_{rd}^{O} \geq h_{rd}, \quad r = 1, \ldots, s \text{ and desirable} \end{aligned} \tag{2}$$

In the traditional GP methods, the deviational variables are nonnegative. In this paper, using the Wierzbicki [58] reference point and the generalized GP in the *scalarizing* function, the deviational variables are minimized [45]. We use the *Chebychev scalarizing* function as follows:

$$\text{MAX}\left\{ \underset{i=1}{\overset{n}{\text{MAX}}}\ w_{id}^{I}\delta_{id}^{I},\ \ \underset{r=1}{\overset{s}{\text{MAX}}}\ w_{rd}^{o}\ \delta_{rd}^{O} \right\} + \varepsilon\left\{ \sum_{i=1}^{n} w_{id}^{I}\ \delta_{id}^{I} + \sum_{r=1}^{s} w_{rd}^{o}\delta_{rd}^{O} \right\} \tag{3}$$

In the above definition, w_{iJ}^{I} and w_{rJ}^{o} are the weights of the deviational variables and ε is a non-Archimedean small positive number. Moreover, it is assumed that the Wierzbicki [58] reference point is associated with the goals.

2. *The benchmarks should be located on the efficiency frontier of PPS.* The Wierzbicki function is used to ensure that the results are efficient [45]. Basically, the benchmarks are derived from a linear combination of the DMUs. As a result, the solutions will be on the efficiency frontier of PPS.
3. *The combination of inputs and outputs of benchmarks should be close to inputs and outputs of the dth DMU so that they can be realized in the next period.* We need to determine actual deviations from the current position of the jth DMU. Current values of the inputs and outputs of the jth DMU can be appropriate criteria for the Wierzbicki reference point and for creating an acceptable and standard DEA benchmark. This means that, even if the reference point is inside the feasible region, solutions are still on the efficiency frontier. For example, the reference points can be equal to the actual inputs and outputs of the efficient DMU. Then, an efficient combination of the reference DMUs represents the closest point to the jth DMU on the efficient frontier. However, this benchmark may not be acceptable for managers.

In other words, using goals to determine a reference point introduces benchmarks that are not in line with present performance of the jth DMU. In fact, Eqs. (2) is similar for all DMUs with similar goals.

The optimal values of ϖ_j represent a point on the efficient frontier that is close to the goal. In other words, a specific reference point is introduced for determining the benchmarks for every DMU. Such a specific reference point signifies a realistic distance between the goals and the present performance of the jth DMU. The reference point can be defined as follows:

$$\begin{aligned} &ref = \text{reference point} \\ &X_{id}^{\text{ref}} = \beta(x_{id} - g_{id}) \\ &y_{rd}^{\text{ref, des}} = \beta(h_{rd} - y_{rd}) \\ &y_{rd}^{\text{ref, undes}} = \beta(y_{rd} - h_{rd}) \\ &0 \leq \beta \leq 1 \end{aligned} \tag{4}$$

After determining the reference point, several efficient benchmarks are created based on different β values. Note that, β values indicate the importance of goals (importance of inputs and outputs) which are determined based on decision makers' opinion. Since the goals may have similar importance, we can assign equal β values for inputs and outputs. If β is equal to 1, it implies a large difference between the goals and the values of inputs and outputs. If β is less than 1, it implies small differences. Next, we use Model (5) to introduce the best benchmarks:

$$\begin{aligned}
&\text{Min } \Delta + \epsilon\left\{\sum_{i=1}^{n} w_{id}^{I}\,\delta_{id}^{I} + \sum_{r=1}^{S} w_{rd}^{o}\,\delta_{rd}^{o}\right\}\\
&s.t.\\
&\sum_{j=1}^{m} \varpi_j X_{ij} - \delta_{id}^{I} \le \beta(x_{id} - g_{id}), \quad i = 1,\ldots,n\\
&\sum_{j=1}^{m} \varpi_j\, y_{rj}^{\text{des}} + \delta_{rd}^{o} \ge \beta(h_{rd} - y_{rd}), \quad r = 1,\ldots,s\\
&\sum_{j=1}^{m} \varpi_j\, y_{rj}^{\text{undes}} + \delta_{rd}^{o} \ge \beta(y_{rd} - h_{rd}), \quad r = 1,\ldots,s\\
&\Delta - w_{rd}^{I}\,\delta_{rd}^{I} \ge 0, \quad i = 1,\ldots,n\\
&\Delta - w_{rd}^{o}\,\delta_{rd}^{o} \ge 0, \quad r = 1,\ldots,s\\
&\varpi_j \ge 0, \quad j = 1,\ldots,n, \;\; \Delta,\;\; \delta_{id}^{I},\;\; \delta_{rd}^{o} \text{ free}
\end{aligned} \tag{5}$$

3.3 Dynamic DEA

Let us now consider J *DMUs* $(j = 1,\ldots,m)$ under evaluation during p periods $(p = 1,\ldots,P)$. We consider n inputs in each period $(i = 1,\ldots,n)$. There are two kinds of inputs and outputs in each period: type 1 and type 2. The external inputs entering each period are called type 1. Moreover, the inputs that are outputs of previous $(p-1)$ periods are called type 2. In addition, some outputs enter into the next periods as inputs. In this case, decision maker minimizes the goals from the input aspect and also maximizes the goals from the output aspect. Accordingly, the outputs that leave the process and do not enter to the next $(p + 1)$ periods are referred to as type 2. Furthermore, the outputs that do not leave the process and enters into the next $(p + 1)$ periods are called type 1. Figure 2 presents the typical structure of the periods and the relevant inputs and outputs of a DMU.

As mentioned earlier, we define inputs which are represented by X_{ijp}^{α} $(i = 1,\ldots,n;\;\; j = 1,\ldots,m;\;\; p = 1,\ldots,P;\;\; \alpha = 1,2)$ where α represents the type of the input. In other words, if we have external input, α will be 1. Moreover, if the input comes from the previous period, α will be 2. We also define desirable and undesirable outputs as follows:

Desirable outputs are represented by $y_{rjp}^{\alpha,\text{des}}(r = 1,\ldots,s;\;\; j = 1,\ldots,m;\;\; p = 1,\ldots,P;\;\; \alpha = 1,\; 2)$, and undesirable outputs are represented by $y_{rjp}^{\alpha,\,\text{undes}}$ $(r = 1,\ldots,s;\;\; j = 1,\ldots,m;\;\; p = 1,\ldots,P;\;\; \alpha = 1,2)$.

The α for the desirable/undesirable outputs that enter into the next periods is represented by 1, while the α for the desirable/undesirable outputs that do not enter into the next periods is represented by 2. We consider following multipliers for each of the above factors:

λ_{rjp}^{1}	Multiplier of $y_{ijp}^{1,\,\text{des}}$ which exits from the pth period and does not enter into the next period
v_{rjp}^{2}	Multiplier of $y_{rjp}^{2,\text{des}}$ which exits from the pth period and enters into the next period
ξ_{rjp}^{1}	Multiplier of $y_{ijp}^{1,\text{undes}}$ which exits from the pth period as the final period and does not enter into the next period
τ_{rjp}^{2}	Multiplier of $y_{ijp}^{2,\text{undes}}$ which exits from the pth period as the final period and does not enter into the next period
ς_{ijp}^{1}	Multiplier of x_{ijp}^{1} which enters into the pth period as an external input
φ_{ijp}^{2}	Multiplier of x_{ijp}^{2} which enters into the pth period from $p-1$ period

The $y_{ijp}^{\alpha,\,\text{des}}$ is the factor that enhances the efficiency of the DMUs. Hence, we wish to maximize $y_{ijp}^{\alpha,\,\text{des}}$ in each period. Therefore, we have:

$$\sum_{r=1}^{s,\text{des}} \lambda_{rjp}^{1} y_{rjp}^{1} + \sum_{r=1}^{s,\text{des}} v_{rjp}^{2} y_{rjp}^{2} \tag{6}$$

The factors x_{ijp}^{α} and $y_{ijp}^{\alpha,\,\text{undes}}$ reduce the efficiency of the DMUs. Hence, we wish to minimize x_{ijp}^{α} and $y_{ijp}^{\alpha,\text{undes}}$ in each period. Therefore, we have:

$$\sum_{r=1}^{s,\text{undes}} \xi_{rjp}^{1} y_{rjp}^{1} + \sum_{i=1}^{n} \varsigma_{ijp}^{1} x_{ijp}^{1} + \sum_{r=1}^{s,\text{undes}} \tau_{ijp}^{2} y_{rjp}^{2} + \sum_{i=1}^{n} \varphi_{ijp}^{2} x_{ijp}^{2} \tag{7}$$

Note that Eq. (7) is the denominator in Eq. (8) in which undesirable factors are considered as input. Hence, the relevant efficiency is obtained by using Eq. (8). Consequently, the efficiency of the pth period is defined as follows:

$$\phi_p = \frac{\sum_{p=1}^{P}\left(\sum_{r=1}^{s,\text{des}} \lambda_{rjp}^{1} y_{rjp}^{1} + \sum_{r=1}^{s,\text{des}} v_{rjp}^{2} y_{rjp}^{2}\right)}{\sum_{r=1}^{s,\text{undes}} \xi_{rjp}^{1} y_{rjp}^{1} + \sum_{i=1}^{n} \varsigma_{ijp}^{1} x_{ijp}^{1} + \sum_{r=1}^{s,\text{undes}} \tau_{rjp}^{2} y_{rjp}^{2} + \sum_{i=1}^{n} \varphi_{ijp}^{2} x_{ijp}^{2}} \tag{8}$$

It should be noted that the first period has only type 1 inputs so that there are no outputs to enter into the first period. Thus, we define the efficiency of the first period as follows:

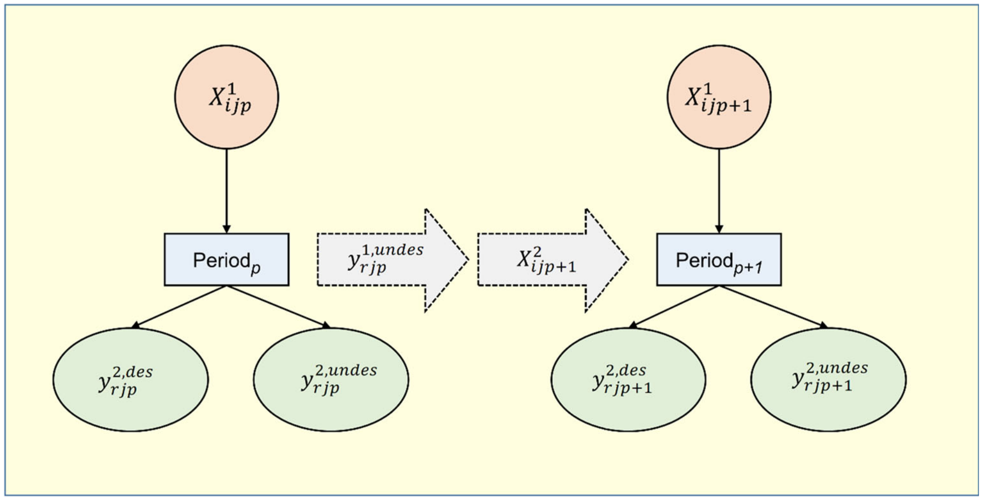

Fig. 2 Typical inputs and outputs structure for a DMU

$$\phi_1 = \frac{\sum_{r=1}^{s,\,\text{des}} \lambda^1_{rjp} y^1_{ijp} + \sum_{r=1}^{s,\text{des}} v^2_{rjp} y^2_{ijp}}{\sum_{r=1}^{s,\text{undes}} \xi^1_{rdp} y^1_{ijp} + \sum_{i=1}^{n} \varsigma^1_{idp} x^1_{ijp}} \tag{9}$$

Note that the last period has the outputs which formerly were called the type 2 outputs. Thus, the efficiency of final period is calculated as follows:

$$\phi_P = \frac{\sum_{r=1}^{s,\text{des}} v^2_{rjp} y^2_{rjp}}{\sum_{r=1}^{s,\text{undes}} \xi^1_{rdp} y^1_{rjp} + \sum_{i=1}^{n} \varsigma^1_{idp} x^1_{ijp} + \sum_{r=1}^{s,\text{undes}} \tau^2_{rjp} y^2_{rjp} + \sum_{i=1}^{n} \varphi^2_{ijp} x^2_{ijp}} \tag{10}$$

At this juncture, given the proposed input-oriented approach, we wish to optimize the overall efficiency (ϕ) of the network with respect to the constraints that ϕ_p should not exceed 1. Using Charnes and Cooper transformation technique, these fractional models are transformed into linear models. We have:

$$\begin{aligned}
&\max \sum_{p=1}^{P} \left(\sum_{r=1}^{s,\text{des}} \lambda^1_{rjp} y^1_{rjp} + \sum_{r=1}^{s,\text{des}} v^2_{rjp} y^2_{rjp} \right) \\
&s.t. \\
&\sum_{r=1}^{s,\text{undes}} \xi^1_{rdp} y^1_{rdp} + \sum_{i=1}^{n} \varsigma^1_{idp} x^1_{idp} + \sum_{r=1}^{s,\text{undes}} \tau^2_{rjp} y^2_{rjp} + \sum_{i=1}^{n} \varphi^2_{ijp} x^2_{ijp} = 1 \\
&\sum_{r=1}^{s,\text{des}} \lambda^1_{rjp} y^1_{rjp} + \sum_{r=1}^{s,\text{des}} v^2_{rjp} y^2_{rjp} \le \sum_{r=1}^{s,\text{undes}} \xi^1_{rjp} y^1_{rdp} + \sum_{i=1}^{n} \varsigma^1_{ijp} x^1_{idp} \\
&\sum_{r=1}^{s,\text{undes}} \xi^1_{rjp} y^1_{rjp} + \sum_{i=1}^{n} \varsigma^1_{ijp} x^1_{ijp} + \sum_{r=1}^{s,\text{undes}} \tau^2_{rjp} y^2_{rjp} + \sum_{i=1}^{n} \varphi^2_{ijp} x^2_{ijp} \ge \sum_{r=1}^{s,\text{des}} v^2_{rjp} y^2_{rjp} \\
&\lambda^1_{rjp},\ v^2_{rjp},\ \xi^1_{rjp},\ \tau^2_{rjp},\ \varsigma^1_{ijp},\ \varphi^2_{ijp},\ \xi^1_{rdp},\ \varsigma^1_{idp} \ge \varepsilon \\
&\varepsilon > 0, \text{(non-Archimedean)}
\end{aligned} \tag{11}$$

Here, ε is a non-Archimedean small positive value. Finally, we calculate the overall efficiency of each period as follows:

$$\Phi_j = \frac{\sum_{p=1}^{P} \phi_p}{P} \tag{12}$$

The above formula represents the average efficiency of the suppliers (DMUs) for each period.

4 Case study

The model proposed in this study was used at Semicon Technologies,[1] a large manufacturer of semiconductor equipment, memory chips, microprocessors, and microcontrollers located in Jersey City. Semicon must select the most sustainable suppliers of silicon wafers. The company is evaluating 20 suppliers (DMUs) who have supplied silicon wafers from 2013 to 2015. In this study, we use GP–DEA to establish the benchmarks for suppliers in year 2016. DDEA is then used to evaluate the suppliers. In each period, every supplier has three inputs and three outputs including two desirable outputs and one undesirable output. The inputs and outputs of suppliers are defined as follows:

- *Inputs:* Eco-design cost as an environmental criterion which enters into the pth period from the former period and cost of labor health and work safety as social criteria which enter into the process as external inputs.
- *Undesirable output:* Investments in eco-design products which is an undesirable output because investments originate from the previous period that are spent in eco-design of products.
- *Desirable outputs:* Profit and quality of the products manufactured by the suppliers.

We used the 9-point Likert scale presented in Table 1 to convert qualitative factors into quantitative values [33]. Using the 9-point Likert scale, the qualitative assessment of

[1] Some of the names and data presented in this study are changed to protect the anonymity of the company.

Table 1 Likert scale for suppliers' product quality

Value	Quality
1	Very weak quality
3	Weak quality
5	Medium quality
7	Good quality
9	High quality
2-4-6-8	Intermediate factors

product quality for each supplier is converted into its respective quantitative scores presented in Table 1.

The data set and the current values of inputs, desirable outputs, and undesirable output related to 2015 are presented in Table 2. Table 3 shows the management goals set for the 20 suppliers for 2016. Note that the suppliers' product quality was classified based on the data in Table 1. In addition, the managers considered different values for the goals reflecting the varying capabilities of the suppliers.

Using the managerial goals presented in Table 3, we determine the benchmarks for the 20 suppliers in 2016 based on Model (5) and assuming $\alpha = 1$. The benchmark results are presented in Table 4.

We then used the DDEA model proposed in this study and evaluated 20 suppliers in four periods. Figure 3 displays the relationships between inputs and outputs within multiple periods. For the sake of brevity we have shown the values for just two periods.

Table 2 Suppliers' 2015 inputs and outputs

DMUs	Inputs		Undesirable output	Desirable outputs	
	Eco-design cost	Cost of labor health and work safety	Investments in eco-design products	Quality of products	End of period profit
1	1350	95	850	7	48,500
2	1850	90	1950	7	53,100
3	2200	85	2100	6	49,200
4	2050	85	2400	5	39,000
5	2750	45	2600	9	38,500
6	2950	80	2200	8	42,800
7	1700	35	2850	9	28,500
8	2850	45	2500	9	35,000
9	1900	65	2450	8	39,500
10	2550	70	1800	4	50,600
11	1600	65	1750	5	37,200
12	2400	40	2900	9	29,000
13	2600	85	2300	8	44,900
14	2900	35	3000	9	30,200
15	2300	95	2500	7	49,700
16	2100	85	2350	9	47,800
17	1950	90	2450	8	39,400
18	1900	80	2650	5	41,300
19	2750	95	1850	7	49,500
20	2650	85	1750	9	51,100

Table 5 displays the inputs and desirable and undesirable outputs of the 20 suppliers for 2013, 2014, and 2015.

Next, we use Model (11) and calculate the efficiency of each supplier using the DDEA model. Table 6 presents the efficiency score of each supplier in 2013, 2014, 2015, and 2016. Expression (12) is used to calculate the overall efficiencies shown in the last column of Table 6. This overall efficiency displays the average efficiency of each supplier during the 4 years of analysis. As shown in Table 6, Supplier 7 has the highest overall efficiency score compared to the other suppliers.

In the conventional DEA models, if an inefficient DMU achieves the benchmark efficiency, it may still be considered as an inefficient DMU in next period since an efficient DMU in 1 year may improve its efficiency the following year. In order to overcome this shortcoming, we introduce the best sustainable supplier in 2016 as a benchmark for the rest of the suppliers in 2015. As a result, supplier 9 is introduced as a benchmark in 2016. This realistic benchmark ensures that if current inefficient/efficient suppliers achieve their goal (benchmark), they will be efficient in 2016.

One of the main contributions of this paper is that the rank suppliers are given both the overall efficiency and forecasted trend of efficiency of the suppliers. Some suppliers might have high relative efficiency score now, but their efficiency trend might be constant or even decreasing. In order to take into consideration the efficiency trend of suppliers, we consider it as a new criterion for evaluating suppliers. For example, in Table 6, the overall efficiency of the Suppliers 8 and 1 are 0.841 and 0.724, respectively. However, the efficiency trend of Supplier 8 is decreasing during 4 periods, while the efficiency trend of Supplier 1 is increasing. Note that if a supplier is efficient in all the periods, then the efficiency trend of such a supplier will be zero.

In order to solve this problem, we consider the weights of the efficiency trend and the overall efficiency. We provide the following formula for incorporating both the efficiency trends and the overall efficiencies:

$$\vartheta_i = \beta\theta_0^* + (1-\beta)R, \quad 0 \le \beta \le 1 \tag{13}$$

where ϑ_i is the ith score obtained by supplier. θ_0^* indicates the overall efficiency of DMU. β represents the importance of the overall efficiency (as determined by the decision maker). The more β, the more important is the overall efficiency of a DMU. The less β, the more important is the efficiency trend. R represents the efficiency slope of a DMU during multiple periods. A negative slope indicates an decreasing trend in the relative efficiency, and a positive

Table 3 Suppliers' 2016 input and output goals

DMUs	Inputs		Undesirable output	Desirable outputs	
	Eco-design cost	Cost of labor health and work safety	Investments in eco-design products	Quality of products	End of period profit
1	850	80	1500	9	38,500
2	1950	70	2500	7	40,000
3	2100	60	2600	7	38,500
4	2400	65	2700	9	40,500
5	2600	60	3000	9	39,500
6	2200	55	2900	8	40,000
7	2850	60	2600	7	38,500
8	2500	40	2900	9	39,500
9	2450	40	2700	9	42,500
10	1800	45	2450	9	41,000
11	1750	40	2250	7	39,500
12	2900	60	2800	7	38,500
13	2300	60	2900	8	39,000
14	3000	70	2650	9	40,500
15	2500	45	2950	8	39,000
16	2350	50	3100	9	38,500
17	2450	40	3200	9	40,500
18	2650	50	3000	7	32,500
19	1850	60	3250	9	37,500
20	1750	55	2950	9	39,500

Table 4 Suppliers' 2016 input and output benchmarks

DMUs	Inputs		Undesirable output	Desirable outputs	
	Eco-design cost	Cost of labor health and work safety	Investments in eco-design products	Quality of products	End of period profit
1	2863	42	2770	9	2546
2	2003	71	2430	7	4032
3	2547	42	2893	9	2983
4	2673	54	2781	9	3612
5	3456	69	3245	6	3559
6	2301	61	3165	8	4876
7	3671	75	3241	8	3762
8	2554	52	3341	9	3098
9	3091	48	3422	8	2930
10	2006	47	2278	9	3981
11	2963	59	2987	8	3670
12	2793	71	2892	8	3998
13	2637	52	3067	9	3012
14	2873	57	2897	8	4129
15	3178	63	2987	8	3598
16	3289	49	2987	9	3419
17	2766	59	3419	9	4023
18	3298	61	3296	8	3987
19	3388	69	3827	7	3891
20	3128	60	3001	8	4012

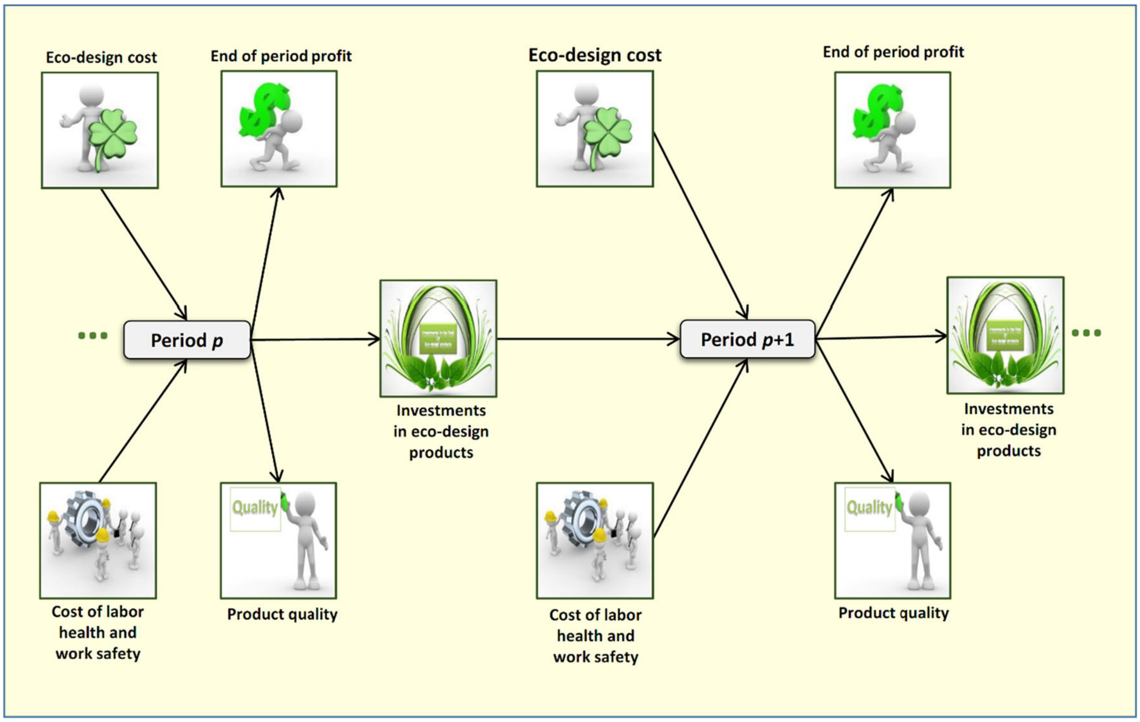

Fig. 3 Structure of the dynamic DEA model for four periods

slope displays an increasing trend in the relative efficiency. Table 7 shows the supplier rankings on both the overall efficiency and the efficiency slope for $\beta = 0.5$.

As shown here, Supplier 1 is the best sustainable supplier at Semicon. Despite the fact that Supplier 8 was the best sustainable supplier in terms of the overall efficiency, it became the worst supplier because of its decreasing trend of efficiency. Therefore, decision makers should not merely focus on the overall efficiency. They must also take into account the efficiency trend for each supplier. In summary, decision makers should not only purchase from suppliers with an acceptable overall efficiency but also with acceptable increasing efficiency trend.

5 Conclusion and future research directions

Sustainable supplier selection problem is a strategic problem in most manufacturing companies. We introduced a new evaluation and ranking approach for selecting the best sustainable suppliers. The contributions of this paper are threefold:

First, it develops a new focus on the issue of sustainability for suppler selection which is an increasingly important strategic problem for most manufacturing companies. We proposed an innovative DDEA model that forecasts future efficiencies of the DMUs, thus shifting the focus of the decision maker's role from monitoring the past to planning the future. This approach is very relevant for sustainability problems since the environmental and social impact of current decisions is generally difficult to forecast. Moreover, company goals and benchmarks for various environmental and social criteria can vary greatly from year to in the fast-paced competitive global landscape. The model provides a basis for other researchers to develop forecasting models for other sustainability problems.

Second, it derives a new DEA model which integrates GP with DDEA to determine the future efficiencies of the DMUs (suppliers). The proposed model addresses some of the shortcomings of previous DEA models. For example, conventional DDEA models cannot properly calculate the future efficiencies of DMUs and overall cannot evaluate the efficiencies of DMUs in the past, present, and future periods, simultaneously. The proposed model also addresses the shortcomings of several hybrid models that have been proposed in the literature. In particular, Stewart [45] combined GP and DEA to determine benchmarks for the inefficiencies of DMUs based on subjective judgments of decision makers. The proposed model, which integrates GP with DDEA, fills a gap of Stewart's [45] model which does not take into account historical data of the DMUs. The proposed model is the first one that evaluates sustainable suppliers based upon past and future performance trends.

Table 5 Historical data

DMUs	2013					2014					2015				
	Inputs		Undesirable output	Desirable outputs		Inputs		Undesirable output	Desirable outputs		Inputs		Undesirable output	Desirable outputs	
	Eco-design expenses	Healthcare and safety expenses	Eco-design product investment	Quality	Year-end profits	Eco-design expenses	Healthcare and safety expenses	Eco-design expenses	Quality	Year-end profits	Eco-design expenses	Healthcare and safety expenses	Eco-design product investment	Quality	Year-end profits
1	1250	70	950	7	36,800	950	65	1350	7	44,500	1350	95	850	7	48,500
2	2600	35	2850	9	29,000	2850	85	1850	5	47,000	1850	90	1950	7	53,100
3	2100	50	2350	9	34,500	2350	65	2200	7	41,500	2200	85	2100	6	49,200
4	2000	40	1950	7	30,500	1950	70	2050	9	33,000	2050	85	2400	5	39,000
5	2150	85	2400	8	39,500	2400	70	2750	7	43,800	2750	45	2600	9	38,500
6	2350	60	1850	5	41,200	1850	45	2950	9	31,400	2950	80	2200	8	42,800
7	1550	55	1900	3	43,600	1900	55	1700	5	46,500	1700	35	2850	9	28,500
8	2650	40	2750	9	27,000	2750	45	2850	9	29,500	2850	45	2500	9	35,000
9	2900	45	3100	9	28,500	3100	70	1900	9	52,500	1900	65	2450	8	39,500
10	1800	60	1500	7	43,700	1500	50	2550	8	42,000	2550	70	1800	4	50,600
11	1950	55	1800	6	41,800	1800	55	1600	4	40,600	1600	65	1750	5	37,200
12	1850	75	2600	7	35,200	2600	70	2400	5	36,700	2400	40	2900	9	29,000
13	2100	50	2200	8	37,500	2200	75	2600	9	43,600	2600	85	2300	8	44,900
14	1950	80	1950	9	39,100	1950	40	2900	9	30,500	2900	35	3000	9	30,200
15	2200	75	2300	7	36,200	2300	90	2300	8	56,000	2300	95	2500	7	49,700
16	2100	85	1950	8	41,200	1950	65	2100	9	52,500	2100	85	2350	9	47,800
17	1950	80	1850	7	44,800	1850	75	1950	7	51,000	1950	90	2450	8	39,400
18	2700	40	2900	9	27,000	2900	80	1900	6	49,500	1900	80	2650	5	41,300
19	2150	95	2100	5	44,500	40	44,500	2750	9	31,000	2750	95	1850	7	49,500
20	2350	90	2150	9	47,800	55	47,800	2650	9	43,700	2650	85	1750	9	51,100

Table 6 Suppliers' efficiency scores using dynamic DEA model

DMUs	2013 ϕ_{2012}	2014 ϕ_{2013}	2015 ϕ_{2014}	2016 ϕ_{2015}	Overall efficiency
1	0.589	0.667	0.756	0.883	0.724
2	0.839	0.635	0.729	0.804	0.752
3	0.729	0.641	0.736	0.769	0.719
4	0.765	0.548	0.825	0.730	0.717
5	0.810	0.651	0.781	0.798	0.760
6	0.739	0.623	0.765	0.845	0.743
7	0.821	0.801	1	0.830	0.863
8	1	1	0.723	0.641	0.841
9	0.812	0.679	0.803	1	0.824
10	0.731	0.842	0.733	0.693	0.750
11	0.559	0.762	0.586	0.719	0.657
12	0.674	0.766	0.874	0.685	0.750
13	0.832	0.689	0.812	0.901	0.810
14	0.719	0.873	0.649	0.786	0.757
15	0.743	0.598	0.689	0.649	0.670
16	0.587	0.701	0.832	0.816	0.690
17	0.635	0.711	0.681	0.730	0.689
18	0.833	0.610	0.744	0.681	0.717
19	0.705	0.879	0.789	0.806	0.795
20	0.819	0.799	0.761	0.849	0.807

Table 7 Suppliers' ranking based on both overall efficiency and efficiency slope ($\boldsymbol{\beta} = 0.5$)

DMUs	R	$\boldsymbol{\theta}_0^*$	ϑ_i	Rank
1	0.9933	0.724	0.8586	1
2	−0.0141	0.752	0.3689	13
3	0.5075	0.719	0.6132	7
4	−0.186	0.717	0.2655	16
5	0.1649	0.760	0.4624	12
6	0.6466	0.743	0.6948	5
7	−0.3167	0.863	0.2731	15
8	−0.9366	0.841	−0.0478	20
9	0.6709	0.824	0.7474	3
10	−0.4484	0.750	0.1508	17
11	0.3957	0.657	0.5268	9
12	0.1970	0.750	0.4735	11
13	0.4824	0.810	0.6462	6
14	−0.0316	0.757	0.3627	14
15	−0.4014	0.670	0.1343	19
16	0.9259	0.690	0.8079	2
17	0.7940	0.689	0.7415	4
18	−0.4387	0.717	0.1391	18
19	0.3848	0.795	0.5899	8
20	0.1819	0.807	0.4944	10

We have carried out a comprehensive review of the literature to show that our model is both unique and innovative.

Third, the presentation of the case demonstrates the applicability of the model and the efficacy of the procedures and algorithms. The case shows that decision makers should not merely focus on the overall efficiency, but that they must also take into account the efficiency trend for each supplier. This provides a useful approach to determine the most efficient suppliers by taking into account acceptable overall efficiencies as well as acceptable increasing efficiency trends. The case justifies the usefulness and applicability of efficiency trend analysis.

There are several future research directions that can develop from this paper. The model can be applied to other DEA application areas such as manufacturing, banking, agriculture, and various public and nonprofit organizations such as hospitals and police forces. It would be interesting to determine the role that efficiency trend analysis could play in many of these applications. Another direction for future research would be to extend the model in the presence of fuzzy data. Fuzzy data are an excellent way to model uncertainties which can be an important aspect of any problem that deals with sustainability criteria. In short, the model introduces many new ideas to the theory and application of DEA analysis and thus provides many opportunities to explore different ways to extend existing DEA models.

Acknowledgments The authors would like to thank the anonymous reviewers and the editor for their insightful comments and suggestions.

References

1. Ageron B, Gunasekaran A, Spalanzani A (2012) Sustainable supply management: an empirical study. Int J Prod Econ 140(1):168–182
2. Amindoust A, Ahmed S, Saghafinia A, Bahreininejad A (2012) Sustainable supplier selection: a ranking model based on fuzzy inference system. Appl Soft Comput 12(6):1668–1677
3. Andersen P, Petersen NC (1993) A procedure for ranking efficient units in data envelopment analysis. Manag Sci 39(10): 1261–1264
4. Azadi M, Farzipoor Saen R (2012) Developing a new chance-constrained DEA model for suppliers selection in the presence of undesirable outputs. Int J Oper Res 13(11):44–66
5. Azadi M, Farzipoor Saen R, Tavana M (2012) Supplier selection using chance constrained data envelopment analysis with nondiscretionary factors and stochastic data. Int J Ind Syst Eng 13(2):167–196
6. Bai C, Sarkis J (2010) Integrating sustainability into supplier selection with grey system and rough set methodologies. Int J Prod Econ 124(1):252–264
7. Beamon BM (2005) Environmental and sustainability ethics in supply chain management. Sci Eng Ethics 11(2):221–234

8. Carter CR, Jennings MM (2002) Logistics social responsibility: an integrative framework. J Bus Logist 23(1):145–180
9. Charnes A, Cooper WW, Ferguson RO (1955) Optimal estimation of executive compensation by linear programming. Manag Sci 1(2):138–151
10. Charnes A, Cooper WW (1961) Management models and industrial applications of linear programming. Wiley, New York
11. Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444
12. Cooper WW, Seiford LM, Tone K (2007) Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software, 2nd edn. Springer, New York
13. Dyllick T, Hockerts K (2002) Beyond the business case for corporate sustainability. Bus Strateg Environ 11(2):130–141
14. Färe R, Grosskopf S (1996) Productivity and intermediate products: a frontier approach. Econ Lett 50(1):65–70
15. Färe R, Grosskopf S, Lovell K, Pasurka C (1989) Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 71(1):90–98
16. Färe F, Grosskopf S, Tyteca D (1996) An activity analysis model of the environmental performance of firms—application to fossil-fuel-fired electric utilities. Ecol Econ 18(2):161–175
17. Farzipoor Saen R (2008) Using super-efficiency analysis for ranking suppliers in the presence of volume discount offers. Int J Phys Distrib Logist Manag 38(8):637–651
18. Farzipoor Saen R (2009) A decision model for ranking suppliers in the presence of cardinal and ordinal data, weight restrictions, and nondiscretionary factors. Ann Oper Res 172(1):177–192
19. Farzipoor Saen R (2010) Developing a new data envelopment analysis methodology for supplier selection in the presence of both undesirable outputs and imprecise data. Int J Adv Manuf Technol 51(9):1243–1250
20. Gass SI (1986) A process for determining priorities and weights for large scale linear goal programmes. J Oper Res Soc 37(8):779–785
21. Govindan K, Khodaverdi R, Jafarian A (2013) A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. J Clean Prod 47:345–354
22. Hatami-Marbini A, Saati S, Tavana M (2010) An ideal-seeking fuzzy data envelopment analysis framework. Appl Soft Comput 10(4):1062–1070
23. Hsu CW, Hu AH (2007) Green supply chain management in the electronic industry. Int J Environ Sci Technol 5(2):205–216
24. Jahanshahloo GR, Hosseinzadeh Lotfi F, Khanmohammadi M, Kazemimanesh M, Rezaie V (2010) Ranking of units by positive ideal DMU with common weights. Expert Syst Appl 37(12): 7483–7488
25. Jahanshahloo GR, Hosseinzadeh Lotfi F, Shoja N, Tohidi G, Razavyan S (2005) Undesirable inputs and outputs in DEA models. Appl Math Comput 169(2):917–925
26. Kahraman C, Cebeci U, Ulukan Z (2003) Multi-criteria supplier selection using fuzzy AHP. Logist Inf Manag Syst 16(6):382–394
27. Korhonen PJ, Luptacik M (2004) Eco-efficiency analysis of power plants: an extension of data envelopment analysis. Eur J Oper Res 154(2):437–446
28. Kumar S (2006) Environmentally sensitive productivity growth: a global analysis using Malmquist–Luenberger index. Ecol Econ 56(2):280–293
29. Kumar A, Jain V, Kumar SA (2014) A comprehensive environment friendly approach for supplier selection. Omega 42(1):109–123
30. Li L, Li M, Wu C (2013) Production efficiency evaluation of energy companies based on the improved super-efficiency data envelopment analysis considering undesirable outputs. Math Comput Model 58(5–6):1057–1067
31. Liang L, Wu D, Hua Z (2004) MES-DEA modeling for analyzing anti-industrial pollution efficiency and its application in Anhui province of China. Int J Glob Energy Issues 22(2–4):88–98
32. Liao CN, Kao HP (2011) An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. Expert Syst Appl 38(9):10803–10811
33. Likert R (1932) A technique for the measurement of attitudes. Arch Psychol 22(140):1–55
34. Muralidharan C, Anantharaman N, Deshmukh SG (2002) A multi-criteria group decision-making model for supplier rating. J Supply Chain Manag 38(4):22–33
35. Murphy PR, Poist RF (2003) Green perspectives and practices: a comparative logistics study. Supply Chain Manag Int J 8(2):122–131
36. Noorizadeh A, Mahdiloo M, Farzipoor Saen R (2011) Supplier selection in the presence of dual-role factors, nondiscretionary inputs, and weight restrictions. Int J Product Qual Manag 8(2):134–152
37. Önüt S, Kara SS, Işik E (2009) Long term supplier selection using a combined fuzzy MCDM approach: a case study for a telecommunication company. Expert Syst Appl 36(2):3887–3895
38. Pittman R (1983) Multilateral productivity comparisons with undesirable outputs. Econ J 93(372):883–891
39. Ratan SRA, Sekhari A, Rahman M (2010) Sustainable supply chain management: state-of-the-art. In: International conference on software, knowledge, information management and applications, Paro, Bhutan
40. Romero C (2004) A general structure of achievement function for a goal programming model. Eur J Oper Res 153(3):675–686
41. Sarkis J, Talluri S (2004) Evaluating and selecting e-commerce software and communication systems for a supply chain. Eur J Oper Res 159(2):318–329
42. Seiford LM, Zhu J (2002) Modeling undesirable factors in efficiency evaluation. Eur J Oper Res 142(1):16–20
43. Sengupta JK (1995) Dynamics of data envelopment analysis: theory of systems efficiency. Kluwer Academic Publishers, Dordrecht
44. Sexton TR, Silkman RH, Hogan AJ (1986) Data envelopment analysis: critique and extensions, vol 32, no 1. In: Silkman RH (ed) Measuring efficiency: an assessment of data envelopment analysis. Jossey-Bass, San Francisco, pp 73–105
45. Stewart TJ (2010) Goal directed benchmarking for organizational efficiency. Omega 38(6):534–539
46. Sueyoshi T, Goto M (2010) Should the US clean air act include CO2 emission control? Examination by data envelopment analysis. Energy Policy 38(10):5902–5911
47. Sueyoshi T, Goto M (2011) Methodological comparison between two unified (operational and environmental) efficiency measurements for environmental assessment. Eur J Oper Res 210(3):684–693
48. Sun J, Wu J, Guo D (2013) Performance ranking of units considering ideal and anti-ideal DMU with common weights. Appl Math Model 37(9):6301–6310
49. Tone K, Tsutsui M (2010) Dynamic DEA: a slacks-based measure approach. Omega 38(3–4):145–156
50. Tone K, Tsutsui M (2014) Dynamic DEA with network structure: a slacks-based measure approach. Omega 42(1):124–131
51. Tseng M-L, Chiang JH, Lan LW (2009) Selection of optimal supplier in supply chain management strategy with analytic network process and choquet integral. Comput Ind Eng 57(1):330–340
52. Wang Y-M, Chin K-S, Luo Y (2011) Cross-efficiency evaluation based on ideal and anti-ideal decision making units. Expert Syst Appl 38(8):10312–10319
53. Wang Y-M, Luo Y (2006) DEA efficiency assessment using ideal and anti-ideal decision making units. Appl Math Comput 173(2):902–915

54. Wang NS, Yi RH, Wang W (2008) Evaluating the performances of decision-making units based on interval efficiencies. J Comput Appl Math 216(2):328–343
55. Weber A, Current J, Desai A (2000) An optimization approach to determining the number of vendors to employ. Int J Supply Chain Manag 5(2):90–98
56. Wen L, Xu L, Wang R (2013) Sustainable supplier evaluation based on intuitionistic fuzzy sets group decision methods. J Inf Comput Sci 10(10):3209–3220
57. White BJ (1996) Developing products and their rhetoric from a single hierarchical model. Proc Annu Conf Soc Tech Commun 43:223–224
58. Wierzbicki AP (1999) Reference point approaches. In: Gal T, Stewart TJ, Hanne T (eds) Multicriteria decision making: advances in MCDM models, algorithms, theory, and applications, Chapter 9. Kluwer Academic Publishers, Boston
59. Yahya S, Kingsman B (1999) Vendor rating for an entrepreneur development programme: a case study using the analytic hierarchy process method. J Oper Res Soc 50(9):916–930
60. Yaisawarng S, Klein J (1994) The effects of sulfur dioxide controls on productivity change in the US electric power industry. Rev Econ Stat 76(3):447–460
61. Yousefi S, Shabanpour H, Farzipoor Saen R, Faramarzi GR (2014) Making an ideal decision making unit using virtual network data envelopment analysis approach. Int J Bus Perform Manag 15(4):316–328
62. Zouggari A, Benyoucef L (2012) Simulation based fuzzy TOPSIS approach for group multi-criteria supplier selection problem. Eng Appl Artif Intell 25(3):507–519