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Green supplier selection problems with data scaling and production frontier estimations in a DEA model

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ABSTRACT

Considering ecological issues in supplier evaluation and management alongside business considerations is getting more recognition among firms. Data envelopment analysis (DEA) is one of those methods, which is frequently suggested by the literature to support management decisions. However, the data requirements of the method should be an important consideration. The literature often addresses the issue of desirable outputs and undesirable input as an important data related problem in case of the ecological use of DEA. This paper will present a new solution to manage these data problems along with connecting the evaluation of management criteria, environmental criteria and total cost aspects. The proposed environmental supplier selection problem is an extension of a former paper. The new model examines the effect of inventory related costs, such as EOQ costs of inventory holding or ordering costs on the selected supplier, extended with newly introduced scaled values of input and output indicators. The usage of scaled values is motivated by the problem of invariance to data alteration. In addition to the uncertainty of the data, the paper looks for a functional relationship between the input and output criterion values and the efficiency that can be assigned to them using DEA.

KEYWORDS

supplier selection, data envelopment analysis (DEA), data scaling, production frontiers

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1. INTRODUCTION

Suppliers are considered the key resource of an enterprise. Good supplier management and improved supplier performance contribute to the business success of organisations (Kannan – Tan, 2002; Tracey – Leng Tan 2001; Nair et al. 2015; Liu et al. 2017; Ahmed et al. 2022). Moreover, in today's globally competitive markets, increased need for flexibility and innovation lead to much higher complexity regarding management decisions. Therefore, there is a need for more transparent and systematic methods to support the evaluation of suppliers. However, in line with the growing importance of the purchasing function, the criteria system of supplier evaluation has become complex. While earlier the challenge was to compare short-term performance data against each other to define the best supplier, now large databases are handled together with expert judgements to ensure the availability of proper suppliers to reach low total costs, avoid risks and consider environmental effects.

The tasks of purchasers are very diverse from supplier pre-qualification, through supplier evaluation, to post-qualification (Roodhooft – Konings, 1997; Wu – Barnes 2011; Igarashi et al. 2013; Luzzini et al. 2014; Cole – Aitken 2019). One of the important problems of this is supplier selection. The choice of supplier in decision theory belongs to the topic of ranking. This implies that the decision-making units are sorted into a given set of considerations. This arrangement is available in a variety of methods, including TOPSIS, AHP, or data envelopment analysis (DEA), which is recommend in this paper. Each method has its own data requirements. This paper aims to focus on some data related issues of using DEA. It will address within one model the following:

- the problem of data scaling (the scaling or the range of criteria may be an influencing factor in the selection process) and data preference (whether lower or the higher values are preferred). This paper proposes to solve these two elementary practical problems by recalculating the starting data, which is also suggested in the literature (Lovell – Pastor 1995; Seiford – Zhu 2002).
- data uncertainty. Though many papers address data uncertainty, our paper has is based on a novel parametrized approach. The paper also looks for a functional relationship between the input and output criterion values and the efficiency that can be assigned to them using DEA. In the literature, this is called production frontier analysis. Sengupta (1987, 1992) and Tone and Sahoo (2003) examined the problem in detail.

The suggested model is a multilevel model which connects supplier evaluation with inventory control. The advantage of the proposed method is that it extends DEA in a TCO approach. The literature mostly does not include inventory costs in the DEA model among the criteria. This model interprets the inventory costs on the basis of the classic EOQ, i.e. it consists of two cost elements: inventory and order cost (Dobos – Vörösmarty 2021). The supplier is often unable to deliver the optimal batch size, so the purchasing manager should know the effectiveness of the proposed batch size. Since DEA determines efficiency, the parameterization can also provide answers to the results of the sensitivity analysis besides the uncertainty of the data (Xu et al. 2021).

The paper will be structured as follows: first it will provide a brief literature review presenting the challenges posed by the data required for supply management. In the next section, a DEA model will be developed based on an earlier method to investigate the effect of the data scaling problem in supply management. The scaling problem is extended with a transformation of different criteria to similar long intervals. This section ends with a numerical example. Then a production frontier analysis is supplied to express green criteria with other ones. Section 4 summarises the managerial implications of the paper. The concluding remarks are discussed in Sections 5.

2. LITERATURE REVIEW

In previous studies various methods have been proposed for supplier selection (Agarwal et al. 2011; Ho et al. 2010; Chai – Ngai 2020). However, as the purchasing function moved from a traditional transactional to a strategic approach, the task became getting more complex. In line with this the criteria system applied in supply management broadened.

Dickson's (1966) often cited study presented 23 supplier evaluation criteria. Later studies investigating the criteria identified that most of them were relevant for a long period: Weber et al. (1991) revealed that price/costs, delivery and quality were the most important and some later studies (e.g. Ho et al. 2010) proved that they are still the most relevant aspects. However, the way high (acceptable) quality, delivery and price/costs are achieved and measured has changed much and are often supplemented with the aspect of risk (Giunipero – Eltentawy 2004).

Compared to the Dickson's (1966) criteria, sustainability criteria have emerged as new ones and have become increasingly important in recent decades (Kony 2019; Dutta et al. 2022). In addition to business considerations (price, quality, delivery), environmental and social responsibility aspects are increasingly indispensable in business relationships.

Formerly selection was a decision made after comparing bids. It was an important issue to handle the trade-offs and to measure the criteria against each other. Weber et al. (1991) reviewed the literature to reinvestigate Dickson's criteria, and to identify methodologies. They found that the vast majority of published methodologies were linear weighting models, mathematical models and a few probabilistic models. These at that time were suitable means to handle the identified criteria in a simple decision making process to choose the best supplier from among the bidders.

Since then the evaluation process has been transformed into a multistage process (Glock et al. 2017). It is still relevant to aim for achieving low cost, delivery and quality, but in this multistage process the evaluation became more systematic and thorough. Not only short-term measures count (e.g. price of the product, promised delivery date), but capabilities that allow long-term good performance are also considered (e.g. available capacity, technology level, financial stability) (Braglia – Petroni 2000; Sarkar – Mohapatra 2006; Kuo et al. 2010). This complex evaluation of suppliers indicates a development of methodology. As literature reviews on supplier evaluation revealed, Multi Attribute Decision Making (MADM) techniques (e.g. Analytic Hierarchy Process, AHP; Analytic Network Process, ANP; Technique for Order of Preference by Similarity to Ideal Solution, TOPSIS; Multi-Attribute Utility Theory, MAUT), mathematical programming models (Linear Programming, LP; Multiple Objective Linear Programming, MOLP; Mixed-integer Linear Programming, MILP and DEA, etc.) and artificial intelligence methods (case-based reasoning, neural network, decision tree, association rules, cluster analysis) were used (Setak et al. 2012) along with qualitative methods (Zimmer et al. 2016).

This paper will highlight DEA as one of the most frequently used techniques of supplier evaluation (Ho et al. 2010; Soheilirad et al. 2018; Sultana et al. 2016; Vörösmarty – Dobos 2021). DEA was first proposed by Charnes et al. (1978); it is a mathematical programming method for assessing the relative efficiency of homogenous decision making units (DMU). DEA has certain data requirements and a number of pitfalls have been identified. Dyson et al. (2001) describe four key assumptions with respect to the input/output set selected: it covers the full range of resources used, captures all activity levels and performance measures, the set of factors are common to all DMUs, and environmental variations has been assessed and captured if necessary. In addition, among the data requirements, homogeneity of data, the ratio of factors to DMUs, non-negative numbers and complete data have been highlighted (Dyson et al. 2001; Sarkis 2007; Kohl et al. 2019).

Papers presenting solutions for supplier evaluation with DEA highlight several issues in comparing criteria against each other. The most often addressed data handling problems are the following.

2.1. Cardinal and ordinal data

Traditionally, criteria were measured in their natural weights (e.g. price in euros, delivery in days). These are metrics, which reflect the ranking of the supplier, and it shows which supplier is better and by how much. In recent supplier evaluation systems ordinal data appears more frequently instead of cardinal data (Saen 2007; Azizi 2013; Toloo – Nalchigar 2011; Ebrahimi et al. 2021). In this case such data should be compared to each other, which does not reflect meaningful differences between the values.

2.2. Negative data

Positive numbers can measure traditional criteria. However, as new criteria about capabilities came into consideration, sometimes negative data (e.g. growth rate, or profit/loss) appears (Izadikhah – Saen 2016; Mohamad – Said 2012; Soltanifar – Sharafi 2022).

2.3. Imprecise data

Sometimes supplier evaluation faces the situation of imprecise data. It is often relevant in case of evaluating new suppliers. Uncertain information or imprecise data can be expressed in interval or fuzzy numbers (Chen et al. 2006; Wang et al. 2005; Karsak – Dursun 2014; Azadeh et al. 2017; Hatefi 2017; Dobos – Vörösmarty 2019b; Rashidi – Cullinane 2019; Wen et al. 2018).

2.4. Qualitative and quantitative data

Traditional offers mostly consisted of hard data, which could have been easily expressed in quantities (e.g. delivery in days). However, when capabilities are analysed, often soft data can only be used which are difficult to quantify (e.g. quality of equipment). Experts often evaluate this soft data. One of the problems is that it reflects subjective judgements (Shi et al. 2015). Consistency also needs to be ensured. Qualitative variables are often handled with other methods (He – Zhang 2018; Zeydan et al. 2011), which also helps to overcome the limitations of DEA. A critical drawback of DEA models is the use of different weights for effective DMUs. A further drawback in the decision process is that DMUs are usually divided as efficient and inefficient in DEA, while the decision losses of individual DMUs are not regarded. A third limitation of DEA is the number of DMUs. Cooper et al. (2007) recommended that the number of DMUs analyzed should be at least the maximum of the multiplication of numbers of input and output, or three times the sum of the number of input and number of output criteria.

2.5. Undesirable output

To implement DEA, the input and output criteria must be defined. Criteria where smaller values are considered better are inputs, and the criteria where larger is better should be considered as outputs to increase the efficiency (Amindoust et al. 2013). However, in the presence of undesirable outputs, DMUs with more good (desirable) outputs and less bad (undesirable) outputs (e.g. waste, rejected products) relative to lower inputs should be recognized as efficient. However, as sustainability considerations appear among supplier evaluation criteria, undesirable outputs need to be handled in DEA framework more frequently (Azadi et al. 2017; Mahdiloo et al. 2015; Saen 2010).

2.6. Total costs of ownership (TCO) data

In traditional supplier selection, price was one among the criteria, in a more strategic approach to purchasing, the costs of managing a relationship with a supplier are considered. The challenge here is to grasp the important cost elements. Visani et al. (2016) used applied activity-based costing (ABC) to define a supplier performance index for each supplier. Ramanathan (2007) and Mohamady Garfamy (2006) used four groups of costs to address the most important costs of the relationship. Dobos and Vörösmarty (2019a) used an EOQ model to describe the most important logistic costs. Their paper highlighted that it is not possible to handle non-linear functions in DEA.

2.7. Data scaling

The natural measure of supplier selection criteria differs. For example, delivery lead time may be measured in hours or in days. This scaling difference may alter the result of the evaluation process (see the data alteration problem in Cook and Seiford 2009). Another problem is how to compare lead-times given in days and product quality measured using the defect rate.

This review revealed that methodology development addressed several problems of the data. Many of them are properly solved by methodologies as it was indicated before. However, there are two problems which are less often addressed.

First, a series of DEA methods use *imprecise, or uncertain type of information*. DEA models for stochastic and fuzzy data are available to treat them (e.g., Alikhani et al. 2019; Park et al. 2018; Rashidi – Cullinane 2019; Wen et al. 2018). A potential drawback is that they require knowledge and software that is less likely to be available to purchasing managers in SMEs or even for many larger companies. From a practical point of view, it would be important to have a methodology that can be solved with a software easily accessible and known to use, e.g. Microsoft Excel.

Second, the distorting effect of *different measuring scales* to the result of evaluation is seldom addressed. Some of the above-mentioned data handling issues and their solutions manage this problem: for example, TCO logic converts the criteria to cost, or for comparing expert opinions the same scale may be used to evaluate each criterion. The problem of scaling is well known in the literature, but only a limited number of contributions has focused on this issue. This is a complex problem, as scaling is often associated with the problem of imprecise data and is important to investigate it as it may have an effect on the result of the evaluation.

In the next section, this problem will be handled in a two-level solution. In the first level, a solution will be offered for the data alteration problem with the introduction of a similar scaling of an evaluation criterion in a similar range. In the second level, the imprecise data will be investigated by parametrizing the criteria. In addition to the uncertainty of the data, the paper looks for a functional relationship between the input and output criterion values and the efficiency that can be assigned to them using DEA. In the literature, this is called production frontier analysis. Sengupta (1987, 1992) examined the statistical side of this problem in detail, while Tone and Sahoo (2003) studied the linear algebraic side of the production function within the framework of the DEA. Daraio et al. (2019) collected and presented software solutions available for production frontier analysis. We use the statistical method proposed by Sengupta (1987, 1992), as after estimation, it is possible to express one or all of the green output criteria using the other input and/or output criterion values and the DEA efficiency.

3. A DEA MODEL WITH UTILITIES FOR GREEN SUPPLIER SELECTION UNDER LOT SIZING

In this section a DEA model to support supplier evaluation will be developed. The model will address the weaknesses of the current literature. The data will be analysed with parametrical linear programming. The parametrizing is presented through the inventory costs. With the parametrical linear programming, the data accurateness was tested and the results can be interpreted as sensitivity analyses in a DEA model. The consequences of data alteration can be revealed by comparing the results of the former evaluation and the offered novel method with utility values.

3.1. The extension of the green DEA method with inventory costs

Dobos and Vörösmarty (2019a) constructed a DEA model with EOQ-type inventory costs. Inventory related costs were involved in DEA-type supplier selection problems with raw data. In this case, the suppliers' ability to supply an ordered quantity is examined in an inventory cost saving way. It is assumed that the firm knows the setup and inventory holding costs of its suppliers, i.e., $(S_j;\ h_j)$, $j = 0, 1, 2, \ldots, p$ are known. The inventory costs for a known lot size can be calculated as (1)

$$x_j(q) = \frac{S_j \cdot D}{q} + \frac{h_j \cdot q}{2}, \qquad (1)$$

where parameter D is the yearly demand of the firm, and q is a given lot size (Dobos – Vörösmarty 2021).

The management indicators are now vector $(x_i;\ x_i(q))$, and the green indicators y_i. As it can be seen, the management indicators are parametrized with lot size q.

Let us introduce a new weight for the inventory costs v_{n+1}. The new weight vector is extended with the weight of the inventory costs $(v;\ v_{n+1})$ for all suppliers. The new model has the following form

$$u \cdot y_0 \rightarrow max \tag{2}$$

s.t.

$$v \cdot x_{0} \cdot + v_{n+1} \cdot x_0(q) = 1, \tag{3}$$

$$u \cdot y_j - \left(v \cdot x_{j} \cdot + v_{n+1} \cdot x_j(q)\right) \leq 0;\; j = 0, 1, 2, \ldots, p. \tag{4}$$

$$u \geq 0, (v;\; v_{n+1}) \geq 0. \tag{5}$$

The parametric problem (2)–(5) is a linear programming one. A numerical solution of this model is available in Dobos and Vörösmarty (2019a).

The basic problem in DEA models is the range of criteria. The criteria are often transformed on a similar normalised measure, i.e. the criteria have the same interval length. We offer the following linear normalisation functions. The offered normalisation functions of criteria have a range between 1 and 20. The choice of scale range is, of course, always subjective. The choice of 20 was for clarity. For managerial data, i.e. for the input, we have used the function

$$X_{ij} = \frac{19}{x_j^{max} - x_j^{min}} \cdot x_{ij} - 19 \cdot \frac{x_j^{max}}{x_j^{max} - x_j^{min}} - 1,$$

where value x_j^{min} is the worst value of criterion j, and value x_j^{max} is the best value of this criterion. For the output, i.e. green data, we have applied

$$Y_{ij} = \frac{19}{y_j^{max} - y_j^{min}} \cdot y_{ij} - 19 \cdot \frac{y_j^{max}}{y_j^{max} - y_j^{min}} + 20,$$

where value y_j^{max} is the best value of criterion j, and value y_j^{min} is the worst value of this criterion. The transformation used is an affine transformation, as analysed by Färe and Grosskopf (2013).

The transformed model has the following form (2')–(5')

$$u \cdot Y_0 \rightarrow max \tag{2'}$$

s.t.

$$v \cdot X_{0} \cdot + v_{n+1} \cdot X_0(q) = 1, \tag{3'}$$

$$u \cdot Y_j - \left(v \cdot X_{j} \cdot + v_{n+1} \cdot X_j(q)\right) \leq 0;\; j = 0, 1, 2, \ldots, p. \tag{4'}$$

$$u \geq 0, (v;\; v_{n+1}) \geq 0. \tag{5'}$$

The model (2')–(5') is analysed as a parametrised linear programming problem numerically. The results are then compared in dependence of the lot sizes.

3.2. Numerical example for the green supplier selection method extended with lot sizing

A numerical example is shown below. The assumption is that the firm has information about all the criteria, i.e. the management criteria of its suppliers, such as lead-time, quality of the products, offered price, and the EOQ-related costs of vendors in dependence on the lot sizes. The green criteria of the analysis are the reusability level of the supplied products and the CO_2

emission level during their production. Data in Table 1 are constructed for illustration purposes. The criteria reflect management considerations on the one hand and incorporate environmental aspects into the assessment on the other. Among the suppliers, there is no supplier that is the best in all criteria.

The basic data of the example is represented in Table 1 in the case of a lot size $q = 50$, interest rate $k = 0.1$, and demand $D = 100$ in a year. The example fulfils the general rule for the number of decision-making units (suppliers), to obtain proper results. The number of vendors is equal to 18, where $p = \max\{m \cdot n;\ 3 \cdot (m + n)\}$, and p is the number of vendors, m is the number of outputs, and n the number of inputs (Cooper et al. 2007).

Table 1 presents a parametrisation of vendors in the lot size. A number of data tables are constructed in dependence of the lot sizes. The EOQ related cost parameters are shown in Table 2. The bold numbers in the tables indicate the best, preferred values in the following.

Table 1. Data for numerical example ($q = 50$)

Supplier	Management criteria				Environmental criteria	
	Lead-time (Day, LT)	Quality (%, QU)	Price ($, PR)	EOQ ($, EOQ)	Reusability (%, RU)	CO2 emission (g, CO2)
1	2	80	2	45	70	30
2	**1**	70	3	87.5	50	**10**
3	3	90	5	132.5	60	15
4	1.5	85	**1**	42.5	40	20
5	2.5	75	2.5	146.25	65	35
6	2	**95**	4	130	**90**	25
7	3	80	1.5	103.75	75	15
8	1.5	85	3.5	188.75	85	20
9	**1**	70	3.5	68.75	55	**10**
10	2.5	75	4	90	45	**10**
11	3.5	90	2.5	126.25	80	25
12	2	65	1.5	103.75	50	20
13	3	85	3	167.5	75	15
14	1.5	70	4.5	151.25	85	20
15	**1**	65	2	125	75	15
16	2	70	5	152.5	80	**10**
17	**1**	90	**1**	82.5	85	15
18	3	85	2.5	126.25	75	20

Source: authors.

Table 2. EOQ costs parameters

Supplier	Ordering ($)	Inventory holding ($)	EOQ ($)
1	20	0.2	45
2	40	0.3	87.5
3	60	0.5	132.5
4	20	0.1	42.5
5	70	0.25	146.25
6	60	0.4	130
7	50	0.15	103.75
8	90	0.35	188.75
9	30	0.35	68.75
10	40	0.4	90
11	60	0.25	126.25
12	50	0.15	103.75
13	80	0.3	167.5
14	70	0.45	151.25
15	60	0.2	125
16	70	0.5	152.5
17	40	0.1	82.5
18	60	0.25	126.25

Source: authors.

The EOQ costs for suppliers 1, to 3, etc. are calculated as follows:

$$x_1(50) = 20 \bullet \frac{100}{50} + 2 \bullet \frac{50}{2} = 90,$$

$$x_2(50) = 40 \bullet \frac{100}{50} + 3 \bullet \frac{50}{2} = 155,$$

$$x_3(50) = 60 \bullet \frac{100}{50} + 5 \bullet \frac{50}{2} = 245,$$

etc.

The optimal lot sizes of these vendors are 89.44, 154.92, and 244.95 units. Transforming the data of Table 1 in this form means that a better result of a criterion is has a higher value than that of a worse one. If a better criterion has a higher value, than the evaluation of that criterion is unchanged (this is the case for e.g., reusability, lead-time and price). If the better criterion receives a lower value, then two methods are available to build: a negative sign is chosen before either the given data, or the inverse of the data. In the analysis, the first solution is chosen to handle this problem. The new, transformed data is presented in Table 3.

The optimal efficiency indicators for the vendors are represented in Table 4, in dependence on the lot sizes.

In the numerical example, two sets of criteria were formulated: management (traditional purchasing criteria extended with EOQ related costs) and green criteria. The results show that the 17th and first suppliers are efficient in a wide range of lot sizes if the chosen lot size of the buyer is smaller than 150. If the lot size is not smaller than 150, then the best supplier is the 17th one. If the basic information is studied, it is obvious that the 17th supplier has the best lead time, quality, and price. It shows that this supplier is Pareto optimal in a decision theory context.

The weights vectors of this numerical example suggest that the weights of lead-time, price, and CO_2 emissions should be neglected in the evaluation of the suppliers. The EOQ aspect

Table 3. The transformed data with utility values for $q = 50$

		Management criteria			Environmental criteria	
Supplier	Lead time (LT)	Quality (QU)	Price (PR)	EOQ (EOQ)	Reusability (RU)	CO2 emission (CO2)
1	−8.6	−10.5	−5.75	−1.325	12.4	4.8
2	−1	−16.833	−10.5	−6.846	4.8	20
3	−16.2	−4.167	−20	−12.692	8.6	16.2
4	−4.8	−7.333	−1	−1	1	12.4
5	−12.4	−13.667	−8.125	−14.479	10.5	1
6	−8.6	−1	−15.25	−12.368	20	8.6
7	−16.2	−10.5	−3.375	−8.957	14.3	16.2
8	−4.8	−7.333	−12.875	−20	18.1	12.4
9	−1	−16.833	−12.875	−4.410	6.7	20
10	−12.4	−13.667	−15.25	−7.171	2.9	20
11	−20	−4.1667	−8.125	−11.880	16.2	8.6
12	−8.6	−20	−3.375	−8.957	4.8	12.4
13	−16.2	−7.333	−10.5	−17.239	14.3	16.2
14	−4.8	−16.833	−17.625	−15.128	18.1	12.4
15	−1	−20	−5.75	−11.718	14.3	16.2
16	−8.6	−16.833	−20	−15.291	16.2	20
17	−1	−4.167	−1	−6.197	18.1	16.2
18	−16.2	−7.333	−8.125	−11.880	14.3	12.4

Source: authors.

Table 4. Parametrical solution of the DEA model for the supplier 1 with utility values (DEA and cross efficiencies)

No. of supplier/ Lot size	25	50	75	100	125	150	175	200	225	250	275	300
1	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.837	0.685	0.576	0.495	0.433	0.385
2	0.157	0.156	0.153	0.149	0.144	0.137	0.121	0.106	0.094	0.084	0.076	0.073
3	0.280	0.259	0.230	0.197	0.164	0.134	0.115	0.101	0.089	0.080	0.072	0.066
4	0.109	0.113	0.122	0.138	0.168	0.238	0.244	0.217	0.194	0.175	0.160	0.147
5	0.232	0.229	0.225	0.219	0.212	0.202	0.190	0.179	0.169	0.160	0.151	0.144
6	0.726	0.675	0.602	0.519	0.436	0.358	0.311	0.278	0.249	0.226	0.206	0.190
7	0.474	0.474	0.476	0.477	0.480	0.483	0.469	0.453	0.436	0.421	0.406	0.393
8	0.352	0.342	0.324	0.302	0.275	0.246	0.227	0.212	0.198	0.186	0.175	0.165
9	0.272	0.266	0.257	0.244	0.228	0.210	0.177	0.149	0.127	0.111	0.098	0.088
10	0.105	0.101	0.094	0.087	0.078	0.068	0.058	0.050	0.043	0.038	0.034	0.031
11	0.535	0.517	0.490	0.454	0.412	0.367	0.336	0.313	0.291	0.272	0.255	0.240
12	0.122	0.124	0.128	0.134	0.143	0.158	0.158	0.152	0.146	0.141	0.136	0.132
13	0.316	0.307	0.293	0.275	0.253	0.229	0.219	0.198	0.186	0.175	0.165	0.156
14	0.372	0.361	0.344	0.322	0.295	0.266	0.236	0.212	0.191	0.173	0.159	0.146
15	0.316	0.318	0.321	0.327	0.334	0.345	0.334	0.317	0.301	0.287	0.273	0.261
16	0.332	0.321	0.303	0.280	0.254	0.225	0.198	0.176	0.157	0.142	0.129	0.119
17	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
18	0.429	0.419	0.403	0.380	0.353	0.322	0.297	0.276	0.257	0.240	0.225	0.212

Source: authors.

received a higher weight than other criteria. In this evaluation situation, the logistic subsystem, i.e. logistical costs of the supplier, should receive a strong weight to influence the selection decision.

3.3. Comparison of results with raw data and utility values

Dobos and Vörösmarty (2019b) used transformed raw data. The question is now whether the model with utility values gives similar results of efficiency indicators or whether it provides different results. The efficiency indicators in dependence of the lot sizes of the model without utility values are presented in Table 5.

As it was seen, the 17th supplier is an efficient supplier in both cases, independent of the data transformations and values of lot sizes. So it can be concluded that this supplier can be chosen as

Table 5. Parametrical solution of the DEA model for supplier 1 without utility values (DEA and cross efficiencies)

No. of supplier/lot size	25	50	75	100	125	150	175	200	225	250	275	300
1	**1.000**	0.961	0.736	0.724	0.720	0.718	0.716	0.715	0.714	0.714	0.714	0.713
2	0.524	0.398	0.322	0.441	0.440	0.439	0.438	0.438	0.437	0.437	0.437	0.437
3	0.363	0.303	0.240	0.619	0.618	0.617	0.617	0.617	0.617	0.616	0.616	0.616
4	0.687	0.760	0.666	0.451	0.449	0.448	0.447	0.447	0.447	0.446	0.446	0.446
5	0.400	0.397	0.371	0.609	0.610	0.611	0.612	0.612	0.612	0.612	0.612	0.613
6	0.612	0.505	0.418	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
7	0.575	0.674	0.652	0.774	0.774	0.774	0.775	0.775	0.775	0.775	0.775	0.775
8	0.452	0.393	0.362	0.857	0.861	0.864	0.866	0.867	0.868	0.869	0.869	0.869
9	0.676	0.461	0.343	0.482	0.479	0.477	0.476	0.476	0.475	0.475	0.475	0.475
10	0.374	0.309	0.236	0.412	0.410	0.409	0.409	0.408	0.408	0.408	0.407	0.407
11	0.503	0.541	0.492	0.887	0.889	0.890	0.891	0.891	0.891	0.891	0.892	0.892
12	0.426	0.449	0.435	0.425	0.424	0.424	0.424	0.424	0.424	0.424	0.424	0.424
13	0.398	0.394	0.366	0.771	0.774	0.776	0.777	0.778	0.779	0.779	0.780	0.780
14	0.532	0.416	0.347	0.714	0.714	0.713	0.713	0.713	0.713	0.713	0.713	0.713
15	0.607	0.545	0.517	0.627	0.627	0.627	0.627	0.627	0.627	0.627	0.627	0.627
16	0.473	0.373	0.304	0.665	0.664	0.663	0.663	0.663	0.663	0.663	0.663	0.662
17	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
18	0.492	0.508	0.461	0.791	0.792	0.792	0.793	0.793	0.793	0.793	0.793	0.793

Source: authors.

a potential supplier independent of the measure system. Without utility values, the sixth supplier is an efficient supplier for lot sizes between 100 and 300, however, with utility values this supplier is no longer an efficient one. Without utility values, the first supplier is efficient only in case of a lot size of 25. In the new DEA model, i.e. with utility values, the first supplier is an efficient one if the lot sizes lie between 25 and 150.

3.4. Estimations of production frontiers for some lot sizes

After comparing the efficiency values calculated using the raw and utility values, we turn to how the effect of environmental aspects on efficiency can be functionally determined. The least squares method, well known from descriptive statistics, is used to perform the tests. As data obtained from non-statistical studies are available in our case, we cannot give more importance to the indicators known from the statistics, but rather the values show fitness.

In these studies, we look for functional relationships, which can be interpreted as production functions. In the general study, we look for a function where efficiency depends on the input x and output criteria y, i.e., the goal is to find an efficiency function $\varepsilon(x, y) = f(x, y)$ relationship that best fits our data. To test the relationships, we consider three functions $f(x, y)$:

1. linear: $\varepsilon(x, y) = a_0 + a \cdot x + b \cdot y$,
2. hyperboloid: $\varepsilon^2(x, y) = a_0 + a \cdot x^T \cdot \langle x \rangle + b \cdot y^T \cdot \langle y \rangle + b$, and
3. Cobb-Douglas (C-D): $\varepsilon(x, y) = \alpha_0 \cdot \prod_{i=1}^{m} x_i^{\alpha_i} \cdot \prod_{j=1}^{n} x_j^{\beta_j}$, type functions.

Since in our previous analysis we calculated the DEA efficiency only for the first DMU, while for the other DMUs we determined only the cross-efficiencies, and on the other hand we examined the former efficiencies depending on the lot sizes, we have to determine the DEA efficiencies for each DMU and put this to lot size. So that the reader is not burdened with unnecessary details, we illustrate the results through the lot sizes of $q = 25$ and $q = 150$. DEA efficiencies for two lot sizes are shown in Table 6.

Table 6. DEA efficiencies ε (x, y) for the two lot sizes 25 and 150 (percents)

Supplier	$q = 25$	$q = 150$
1	100.0	100.0
2	100.0	26.5
3	86.3	79.4
4	100.0	100.0
5	23.2	20.2
6	100.0	100.0
7	56.1	51.5
8	48.2	48.2
9	100.0	100.0
10	65.3	46.1
11	63.5	63.5
12	31.9	31.0
13	51.8	51.8
14	40.6	26.6
15	94.3	94.3
16	41.6	30.8
17	100.0	100.0
18	43.6	41.8

Source: authors.

For the two batch sizes, we estimated three possible production functions each. Next, we call the type of function with the largest coefficient of determination, i.e. R^2, the most appropriate production function for our given data. In the analysis, we disregard the significance level of the estimated parameters because the shape of the functions is important to us and not the level of acceptance. Table 7 presents the possible functions along with their estimated coefficients.

For both lot sizes, the Cobb-Douglas type production function gave the highest coefficient of determination. At a lot size of 25, the highest square of R^2 is 0.866, which is extremely high. For a lot size of 150, this value was 0.681, which is considered medium but still adequate. ANOVA analysis was found to be significant for all six studies. The results are shown in Table 8.

Table 7. Estimation of the DEA efficiencies in dependence of criteria values for the two lot sizes

Models	Lot sizes	Equations
Linear model	$q = 25$	$\varepsilon^{lin,25} = 125.317 - 2.068 \cdot LT - 2.403 \cdot QU + 0.723 \cdot PR - 3.573 \cdot EOQ + 0.500 \cdot RU + 0.917 \cdot CO2$
	$q = 150$	$\varepsilon^{lin,150} = 120.479 - 1.587 \cdot LT - 2.665 \cdot QU + 2.313 \cdot PR - 4.999 \cdot EOQ + 1.363 \cdot RU + 0.290 \cdot CO2$
Quadratic model	$q = 25$	$(\varepsilon^{qua,25})^2 = 11,173.674 - 16.506 \cdot LT^2 - 13.879 \cdot QU^2 + 0.700 \cdot PR^2 - 21.995 \cdot EOQ^2 + 2.378 \cdot RU^2 + 3.945 \cdot CO2^2$
	$q = 150$	$(\varepsilon^{qua,150})^2 = 10,419.443 - 14.406 \cdot LT^2 - 13.479 \cdot QU^2 + 14.441 \cdot PR^2 - 27.998 \cdot EOQ^2 + 7.700 \cdot RU^2 - 2.706 \cdot CO2^2$
Cobb-Douglas model	$q = 25$	$\varepsilon^{C-D,25} = 157.591 \cdot LT^{-0.192} \cdot QU^{-0.321} \cdot PR^{0.119} \cdot EOQ^{-0.366} \cdot RU^{0.049} \cdot CO2^{0.225}$
	$q = 150$	$\varepsilon^{C-D,150} = 149.605 \cdot LT^{-0.096} \cdot QU^{-0.365} \cdot PR^{0.238} \cdot EOQ^{-0.728} \cdot RU^{0.257} \cdot CO2^{0.222}$

Source: authors.

Table 8. Coefficient of Determination and ANOVA tests for the two lot sizes

	$q = 25$		$q = 150$	
	Coefficient of Determination (R^2)	Significance of ANOVA	Coefficient of Determination (R^2)	Significance of ANOVA
Linear model	0.772	0.005	0.631	0.048
Quadratic model	0.683	0.024	0.589	0.078
Cobb-Douglas model	0.866	0.000	0.681	0.024

Source: authors.

The result that neither linear nor hyperboloid regression yielded a more convincing result than the Cobb-Douglas type production function stems from the fact that for constant inputs the Cobb-Douglas production function is concave, while for constant outputs the inputs give a convex function. This also draws attention to the fact that DEA efficiencies as outcome variables can be successfully explained by Cobb-Douglas-type functions of input and output criteria.

Next it was examined how output criteria, i.e., one of the environmental criteria, say reuse (RU), can be expressed as a function of other input and output criteria and efficiency. We convert the production function for a batch size of 25. After the transformation, we get the following:

$$RU = 10^{-44.857} \bullet \varepsilon^{-20.408} \bullet LT^{3.918} \bullet QU^{6.551} \bullet PR^{-2.429} \bullet EOQ^{7.469} \bullet CO2^{-4.592}.$$

Equality shows that if we examine the iso-reuse curve, lead-time, quality, and inventory costs, we get a convex, increasing function, while DEA efficiency, price, and CO2 are concave monotonically decreasing functions. The same results are obtained when the batch size is 150.

4. MANAGERIAL IMPLICATIONS

The paper's managerial implications can be traced to three issues related to supplier evaluation criteria. A critical element of supplier evaluation is the choice of criteria (Dickson 1966; Weber et al. 1991). As the size of the company increases, it becomes important that the purchasing decision becomes more formalised. As part of this process, the criteria for the stakeholders in the sourcing decision need to be formulated and then the supplier performance ranked during the evaluation. For a more complex set of criteria, the ranking requires the use of a decision support methodology. This article has addressed the data requirements of the DEA methodology, highlighting the following managerial implications.

The first issue highlighted is that the application of the DEA method also raises the difficulty of how to interpret the input and output data. The available data depend on the direction of the optimum. We expect output data to be as good as possible. At the same time, there may be some output information for which it is better to get a lower value in our DEA tables. In our numerical example, we have defined the CO_2 emissions value as output variable where it is better to get lower value. This means that its value must be transformed. In the case of inputs, it is optimal if the value of the input variable is as small as possible. In our numerical example, however, in the case of quality, it is better to have a higher value, so we need to transform it to a scale where the smaller transformed value corresponds to the higher value in original data.

The other problem concerns the scale range of input and output variables. In many cases, variables are defined on different scales. In the numerical example, the maximum range of lead time was given in days between 1 and 3.5. At the same time, quality ranges between 65 and 90 percent. This may refer to the great difference in weights that can be overcome by transforming all variables, both inputs and outputs into the same scale, in our case between 1 and 20. This also translates to variables on the same scales.

The third advantage of the proposed method is of interpreting stochastic and fuzzy DEA methods for managers. Because these methods assume deep mathematical, IT and programming skills in DEA, it is almost a "research" challenge for managers with little time to solve such problems. We have recommended the application of parametric DEA because partial DEA models can be solved with commercial software, like Microsoft Solver. To do this, only one column of the DEA table must be modified with the values of the lot size. This sensitivity test can also answer the question of which vendors will be efficient at each value of the lot size, i.e. they can be selected for delivery.

Finally, production frontier estimation allows us to express output, green criteria as a function of management, input criteria. This econometric estimation represents the green criteria as a function.

5. CONCLUSION AND FURTHER RESEARCH

In this paper a new method is offered to handle the data processing problem of supplier selection and evaluation. The literature review highlighted the research gap: data scaling or alteration and imprecise data are seldom examined and solutions fail to connect the two problems. In the supplier selection and evaluation procedure, DEA models are applied to handle the two problems. Mathematically the problem is too difficult to solve with analytical methods. To avoid this difficulty, numerical examples were presented to gain insight into the functioning of such a system.

Data scaling problems are not addressed in literature properly, but as the numerical example of this paper presented, it has an effect on the result of the evaluation. Further simulation studies are required to deepen knowledge in this context.

Following the suggestion of Sengupta (1987, 1992), DEA efficiencies were estimated using input and output criteria. The best approximation was given by the Cobb-Douglas type production function. This function makes it possible to express green output criteria with input declines and DEA efficiency.

The solutions for the scaling problem are likely to be connected to imprecise data. The literature offers several techniques to solve data uncertainty problems such as fuzzy and interval methodology, but the parametrization of data can be a suitable procedure as well.

An additional research option is how to combine the solution presented in this article with DEA cross-efficiency. This makes it possible to use DEA cross-efficiency during selection.

Throughout our investigation, we aimed at proposing solutions that are easily available and can be applied with known software. Further research could investigate what attitudes other than the available software influence the openness of decision makers to use decision support methods in business decisions.

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