Method Article

Multi-level DEA for the construction of multi-dimensional indices

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Abstract

Data Envelopment Analysis (DEA) is a non-parametric, mathematical programming method that is used to evaluate the performance of Decision Making Units. One variation of the method is focused on expanding the number of stages: inputs are transformed into intermediate measures and in turn those are transformed into outputs. DEA and its variations have been used to construct composite indicators. The purpose of the current paper is to propose a new variation of DEA that relies on a two-stage model for the construction of multi-dimensional indices. The proposed variation:

• Uses a two-stage DEA model for the calculation of each sub-indicator that will be integrated into the final index
• All the sub-indicators are integrated into the final index with the use of a Benefit-of-the-Doubt mathematical programming model.

As it was mentioned, the proposed method can be used for the construction of multi-dimensional indicators and in the current paper is used to calculate the sustainability of the EU-28 countries.

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**Specifications Table**

| Subject Area:          | Environmental Science |
|------------------------|-----------------------|
| More specific subject area: | Measurement of Sustainability |
| Method name:           | Data Envelopment Analysis |
| Name and reference of original method: | A. Charnes, W. Cooper and E. Rhodes, "Measuring the efficiency of decision-making units," European Journal of Operational Research, vol. 3, no. 4, pp. 429–444, 1978 |
|                        | Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management science, 30(9), 1078–1092. |
| Resource availability: | If applicable, include links to resources necessary to reproduce the method (e.g. data, software, hardware, reagent) |

**Method details**

**Background**

Data Envelopment Analysis (DEA) [1,2] belongs to the Multi-Criteria Decision Aid methods and is used to evaluate the Technical Efficiency of a group of Decision Making Units (DMUs). The term of technical efficiency is a measure of the DMUs’ performance relative to one another. In other words, efficiency is a measure of how well the DMU can transform inputs into outputs, without however considering how this transformation is achieved. Finally, DMUs can represent any type of entity (public or private organizations, departments, branches, countries etc.).

Thus, DEA offers a series of advantages in measuring the performance of DMUs:

- It is non-parametric and it is considered a mathematical programming technique
- It is not necessary to identify the relationship between inputs and outputs
- It requires less information than other parametric methods, since it can allow comparative assessment of units even when price information is not available
- It can provide insights into the reasons for which a unit is not efficient and propose measures for improvement [3,4].
- Inputs and outputs do not need to have common units of measurement.

The method was established by two seminal papers by Charnes, Cooper and Rhodes [5] and by Banker, Charnes and Cooper [6]. In [5] the DMUs are assumed to operate under Constant Returns to Scale (CRS) and the DEA models are approached with the method of Linear Programming models [1,7–9]. In DEA CRS, it is assumed that there are N DMUs that use n inputs to produce s outputs. We denote \( x_{ij} \) (i = 1...m, j = 1...N) the level of the \( i^{th} \) input of DMU \( j \), and \( y_{rj} \) (r = 1...s, j = 1...N) the level of the \( r^{th} \) output of DMUj.

Consequently, the calculation of the technical efficiency of the DMUs (for the input-oriented model) can be found by solving the following Linear Programming model:

\[
\min \Theta_0 - e \left( \sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+ \right)
\]

subject to constraints:

\[
\sum_{j=1}^{N} \lambda_j x_{ij} = \Theta_0 x_{ij} - S_i^-, \quad i = 1 \ldots m
\]

\[
\sum_{j=1}^{N} \lambda_j y_{rj} = y_{rj} + S_r^+, \quad r = 1 \ldots s
\]

\[
\lambda_j \geq 0, \quad j = 1 \ldots N, \quad S_r^+, S_i^- \geq 0
\]

The technical efficiency of the above problem is the value of \( \Theta_0 \) and it can take values between 0 (inefficient) and 1 (efficient). As for its interpretation, in the above, input-oriented model, it denotes...
the extent to which the DMU could reduce the level of its inputs without detriment to the levels of its outputs.

Similar to DEA-CRS, the model under Variable Returns to Scale (VRS) relaxes the assumption of returns to scale and is again solved with the help of Linear Programming. It is assumed that there are \( N \) DMUs that use \( n \) inputs to produce \( s \) outputs. We denote \( x_{ij} (i = 1...m, j = 1...N) \) the level of the \( i \)th input of DMU \( j \), and \( y_{rj} (r = 1...s, j = 1...N) \) the level of the \( r \)th output of DMU \( j \). Then the calculation for the technical efficiency for the input-oriented model (defined as pure technical efficiency) can be found by solving:

\[
\min \Theta_0 = e \left( \sum_{i=1}^{m} S_i^+ + \sum_{r=1}^{s} S_r^- \right)
\]  

subject to constraints:

\[
\sum_{j=1}^{N} \lambda_j x_{ij} = \Theta_0 x_{i0} - S_i^-, \ i = 1...m \tag{6}
\]

\[
\sum_{j=1}^{N} \lambda_j y_{rj} = y_{r0} + S_r^+, \ r = 1...s \tag{7}
\]

\[
\sum_{j=1}^{N} \lambda_j = 1 \tag{8}
\]

\[
\lambda_j \geq 0, \ j = 1...N, S_i^+, S_r^- \geq 0 \tag{9}
\]

Once again, the technical efficiency is the value of \( \Theta_0 \) and it can take values between 0 and 1.

As it was mentioned above, one of the advantages of the method is that there are no knowledge requirements about the relationship between inputs and outputs. Hence, the performance of DMUs can be calculated without having to resort to complex functions that would decrease the interpretational capabilities of the method and increase the computation complexity of the models.

Nonetheless, that particular advantage renders DEA as a “black box method”, since the analyst and the decision-maker have knowledge only about the inputs and outputs, but none about what happens among them. Furthermore, one of the inherent characteristics of the DEA method is that the number of DMUs under assessment must be no less than three times the total number of inputs and outputs [10], otherwise the results are not meaningful since the Linear Program will consider the DMUs as efficient. To solve these issues, the two-stage DEA variation has been proposed [11], which is a special category of the network-DEA models [12].

One of the two-stage DEA variations that has been used in the literature [13] is the one proposed by Kao and Hwang [14]. In this model, it is assumed that there are \( N \) DMUs that use \( n \) inputs to produce \( d \) intermediate outputs that in turn produce \( s \) outputs. We denote \( x_{ij} (i = 1...m, j = 1...N) \) the level of the \( i \)th input, \( z_{dj} (d = 1...D, j = 1...N) \) the level of the \( d \)th intermediate output and \( y_{rj} (r = 1...s, j = 1...N) \) the level of the \( r \)th output of DMU \( j \). Then the overall efficiency is solved by the following model:

\[
E_0 = \max \frac{\sum_{r=1}^{s} r_{ij} y_{rj}}{\sum_{i=1}^{m} \omega_i x_{ij}} \tag{10}
\]

Subject to constraints:

\[
\frac{\sum_{r=1}^{s} r_{ij} y_{rj}}{\sum_{i=1}^{m} \omega_i x_{ij}} \leq 1, \ j = 1...N \tag{11}
\]

\[
\frac{\sum_{d=1}^{D} \mu_{dj} z_{dj}}{\sum_{i=1}^{m} \omega_i x_{ij}} \leq 1, \ j = 1...N \tag{12}
\]
\begin{align}
\sum_{r=1}^{s} \gamma_r y_{rj} &\leq 1, \quad j = 1 \ldots N \tag{13} \\
\sum_{d=1}^{D} \mu_d z_{dj} &\leq 0
\end{align}

\gamma_r, \mu_d, \omega_i \geq 0 \tag{14}

Constraint (11) indicates that the calculated overall efficiency should less than (meaning an inefficient DMU) or equal to 1 (meaning an efficient DMU). Constraint (12) indicates that the efficiency of the first stage (where inputs produce intermediate outputs) should be less than or equal to 1, while constraint (13) indicates the same for the calculated efficiency of the second stage (where intermediate outputs produce outputs). Constraint (14) describes that the multipliers \(\gamma_r, \mu_d, \omega_i\) (of the outputs, intermediate outputs and inputs respectively) should be positive. The above model uses common multipliers for the two stages. This commonality indicates that there is a conflict between the first and the second stage, as in the first one the multipliers of the intermediate outputs should be maximized (intermediate outputs act as outputs) while in the second the same multipliers should be minimized (intermediate outputs act as inputs).

The model is fractional and to solve it there is the need to transform it into a linear using the Charnes-Cooper transformation [15]:

\begin{equation}
E_0 = \max \sum_{r=1}^{s} \gamma_r y_{r0}
\end{equation}

subject to constraints:

\begin{align}
\sum_{i=1}^{m} \omega_i x_{i0} &= 1 \tag{16} \\
\sum_{r=1}^{s} \gamma_r y_{rj} - \sum_{i=1}^{m} \omega_i x_{ij} &\leq 0, \quad j = 1 \ldots N \tag{17} \\
\sum_{d=1}^{D} \mu_d z_{dj} - \sum_{i=1}^{m} \omega_i x_{ij} &\leq 0, \quad j = 1 \ldots N \tag{18} \\
\sum_{r=1}^{s} \gamma_r y_{rj} - \sum_{d=1}^{D} \mu_d z_{dj} &\leq 0, \quad j = 1 \ldots N \tag{19} \\
\gamma_r, \omega_i, \mu_d &\geq 0 \tag{20}
\end{align}

The above model can produce results that may not be optimal. To solve the issue Kao and Hwang [14] proposed the maximization of one of if the \(E_0^1, E_0^2\) while maintaining the overall efficiency at \(E_0\). For example maximizing the individual efficiency \(E_0^2\):

\begin{equation}
E_0^2 = \max \sum_{r=1}^{s} \gamma_r y_{r0}
\end{equation}

subject to constraints:

\begin{align}
\sum_{d=1}^{D} \mu_d z_{d0} &= 1 \tag{22} \\
\sum_{r=1}^{s} \gamma_r y_{r0} - E_0 \sum_{i=1}^{m} \omega_i x_{i0} &\leq 0 \tag{23} \\
\sum_{r=1}^{s} \gamma_r y_{rj} - \sum_{i=1}^{m} \omega_i x_{ij} &\leq 0 \tag{24}
\end{align}
\[
\sum_{d=1}^{D} \mu_d z_{dj} - \sum_{i=1}^{m} \omega_i x_{ij} \leq 0
\]  
(25)

\[
\sum_{r=1}^{s} \gamma_r y_{rj} - \sum_{d=1}^{D} \mu_d z_{dj} \leq 0
\]  
(26)

\[
\gamma_r, \omega_i, \mu_d \geq 0
\]  
(27)

Consequently, the other efficiency will be calculated by:

\[
E_0^2 = E_0/E_0^1
\]  
(28)

Finally, Data Envelopment Analysis has been used as a method for constructing composite indicators. The variation for that issue is called Benefit-of-the-Doubt (BoD), and the model is used to calculate the optimal weights of the sub-indicators that will form the final index [16]. The BoD is a Linear Programming model:

\[
\max \sum_{r=1}^{s} w_{rj} y_{ri}
\]  
(29)

s.t. \[
\sum_{r=1}^{s} w_{rj} y_{rj} \leq 1 \quad (N \text{ constraints, one for each DMU } j = 1 \ldots N)
\]  
(30)

\[
w_{rj} \geq 0, \quad (s \text{ constraints one for each sub-indicator})
\]  
(31)

All of the above DEA variations have been used for the measurement of sustainability of countries and regions. Zhou et al. [17] performed an extensive literature review on the issue and the authors identified several gaps including: an underrepresentation of the social dimension in the construction of sustainability indices, the use of many different combinations of inputs and outputs that is limiting the creation of a standardized sustainability index and an overrepresentation of Chinese regions in related studies. Furthermore, Tsaples and Papathanasiou [18] identified that the methodological limitation of DEA regarding the number of inputs and outputs that was present in the classic DEA variations is still present in all the different approaches to calculate sustainability (whether with the two-stage models or the BoD approach). Thus, there is the need for the analyst to make a trade-off between the number of inputs and outputs that are necessary and the inclusion of as many sub-indicators as possible in the construction of a sustainability index. The result of that trade-off was, as mentioned before, the general lacking of the social dimension of sustainability in related studies.

Consequently, the purpose of the current paper is to propose a Data Envelopment Analysis variation that mitigates the above limitation and test it in the construction of a sustainability index of European countries.

Methods

The proposed method is presented in Fig. 1 below.

The mathematical formulation of the above is as follows:

There are k sub-indicators (k = 1…K) that the overall final Index consists of. For each sub-indicator, there are N DMUs that use n inputs to produce d intermediate outputs that in turn produce s outputs. We denote \( x_{ij}^k \) (i = 1…m, j = 1…N) the level of the \( t \)th input, \( z_{dj}^k \) (d = 1…D, j = 1…N) the level of the \( d \)th intermediate output and \( y_{rj}^k \) (r = 1…s, j = 1…N) the level of the \( r \)th output of DMU j of sub-indicator k. Then the overall efficiency/each sub-indicator is:

\[
E_0^k = \max \sum_{r=1}^{s} y_{rj}^k y_{r0}^k
\]  
(32)

Subject to constraints:
Fig. 1. Graphical representation of the proposed method. Each sub-indicator that is entailed in sustainability is measured with the two-level DEA variation that is proposed in Eqs. (32)–(37) below. For example, in the left part of Figure, Sub-indicator 1 is calculated with specific inputs, intermediate outputs and outputs for the specific sub-indicator. Once all sub-indicators have been calculated, they are used as inputs to the Benefit-of-the-Doubt model, described by the Eqs. (38)–(41) below (shown in the right part of Figure). Hence, the benefit-of-the-doubt model produces the final sustainability index.

Thus, the model is solved as many times as the number of sub-indicators $k$ that the final index consists of. Furthermore, for each sub-indicator, the efficiencies of each stage are calculated with the help of Eqs. (21)–(28). Once all the sub-indicators have been calculated, they are integrated into the
The final composite index with the help of the Benefit-of-the-Doubt model:

\[ SI = \max \sum_{k=1}^{K} w_k E_{k0}^k \]  

subject to constraints:

\[ \sum_{k=1}^{K} w_k E_{0k} \leq 1 \]  \hspace{1cm} (39)

\[ w_k \geq a, \quad k = 1 \ldots K \]  \hspace{1cm} (40)

\[ \sum_{k=1}^{K} w_k = 1 \]  \hspace{1cm} (41)

Constraint (39) indicates that the constructed indicator SI will be less than or equal to 1. Constrain (40) ensures that all sub-indicators will participate in the construction of the overall composite index with the parameter a defined by the analyst. Constrain (41) indicates that the sum of the calculated weights will be equal to 1. In the next section the proposed method is used to construct a sustainability index for European countries.

**Case study**

Sustainability is a term that is used to measured sustainable development [19] and it is a structure that incorporates an economic, environmental and social dimension [20]. In the current paper, the following inputs, intermediates and outputs are used for each dimension:

- **Economic**
  - Inputs: Gross fixed capital at current prices (PPS), Total Labour force (x1000 persons)
  - Intermediate measures: GDP per capita in PPS-Index (EU28 = 100)
  - Outputs: Median equivalised net income [Purchasing power standard (PPS)], Final consumption expenditure of households [Current prices, million euro]

- **Environmental**
  - Inputs: Population, Gross electricity production [Thousand tonnes of oil equivalent (TOE)]
  - Intermediate measures: Final energy consumption (Terajoule)
  - Outputs: Terrestrial protected area (km2), Share of renewable energy in gross final energy consumption (%), Greenhouse gas emissions (in CO₂ equivalent)

- **Social**
  - Inputs: Gross fixed capital at current prices (PPS), GDP per capita in PPS-Index (EU28 = 100)
  - Intermediate measures: Total expenditure (Euro per inhabitant)
  - Outputs: Patent applications to the European patent office (EPO) by priority year, Overall life satisfaction, Satisfaction with living environment, Percentage of females in total labor population

All the data were obtained by Eurostat [21] and concern the EU-28 countries for the year 2018. Finally, a remark on the nature of outputs in DEA. In general, the outputs in DEA should be maximized, however, in the construction of the environmental sub-indicator there is the output of Greenhouse gas emissions in CO₂ equivalent, which should be minimized. To solve the issue, a linear monotonic transformation is performed [22]. The results from best to worst are illustrated in Table 1 below:

The table is ranked according to the value of the sustainability index. For example, Malta has the highest sustainability index compared to the other countries with a value of 0.778. The individual sub-indicators that are entailed in sustainability have a value of 1 for the economic sub-indicator, 0.223 for the environmental sub-indicator and 0.296 for the social sub-indicator. These results indicate that Malta has a high sustainability index due to its great economic performance (compared to the
Table 1
Economic, environmental, social sub-indicators and final sustainability index for the EU-28 countries. Table 1 contains a Country column where the country whose sustainability indicator is calculated and compared with the other countries. The second column contains the value of that sustainability index, while the last three columns indicate the value of the individual sub-indicators that are entailed in the final sustainability index.

| Country       | Sustainability index | Economic sub-indicator | Environmental sub-indicator | Social sub-indicator |
|---------------|----------------------|------------------------|-----------------------------|----------------------|
| Malta         | 0.778                | 1                      | 0.223                       | 0.296                |
| Latvia        | 0.544                | 0.122                  | 0.697                       | 0.249                |
| Estonia       | 0.536                | 0.186                  | 0.681                       | 0.214                |
| Germany       | 0.524                | 0.004                  | 0.038                       | 0.739                |
| Cyprus        | 0.509                | 0.615                  | 0.316                       | 0.205                |
| Lithuania     | 0.459                | 0.095                  | 0.589                       | 0.214                |
| Luxemburg     | 0.458                | 0.584                  | 0.255                       | 0.0719               |
| Finland       | 0.381                | 0.067                  | 0.495                       | 0.157                |
| Croatia       | 0.358                | 0.07                   | 0.457                       | 0.186                |
| France        | 0.343                | 0.006                  | 0.061                       | 0.475                |
| Slovenia      | 0.338                | 0.168                  | 0.405                       | 0.198                |
| Sweden        | 0.300                | 0.032                  | 0.38                        | 0.198                |
| Bulgaria      | 0.244                | 0.036                  | 0.296                       | 0.213                |
| United Kingdom| 0.235                | 0.003                  | 0.02                        | 0.331                |
| Italy         | 0.206                | 0.007                  | 0.056                       | 0.281                |
| Romania       | 0.17                 | 0.008                  | 0.191                       | 0.2                  |
| Spain         | 0.162                | 0.008                  | 0.171                       | 0.194                |
| Poland        | 0.159                | 0.008                  | 0.093                       | 0.206                |
| Greece        | 0.157                | 0.035                  | 0.188                       | 0.131                |
| Netherlands   | 0.146                | 0.021                  | 0.023                       | 0.2                  |
| Slovakia      | 0.146                | 0.039                  | 0.169                       | 0.145                |
| Hungary       | 0.144                | 0.022                  | 0.16                        | 0.167                |
| Austria       | 0.139                | 0.039                  | 0.153                       | 0.157                |
| Denmark       | 0.132                | 0.064                  | 0.145                       | 0.142                |
| Portugal      | 0.13                 | 0.033                  | 0.136                       | 0.149                |
| Czech Republic| 0.123                | 0.023                  | 0.077                       | 0.155                |
| Ireland       | 0.119                | 0.072                  | 0.132                       | 0.107                |
| Belgium       | 0.115                | 0.032                  | 0.032                       | 0.151                |

Other countries). However, the economic prosperity is not accompanied by the same environmental or social performance. As a result, policy makers in Malta might consider placing greater importance in the environment and the social processes of the country, should they wish to achieve sustainable development.

Furthermore, the rest of the countries can be roughly separate into 2 groups: those countries like Latvia, Germany and Slovenia that have a sustainability index between 0.55 and 0.3. The last group that performs the worst includes countries like Greece, Netherlands and Belgium.

Conclusions

The purpose of the current paper was to propose a variation of Data Envelopment Analysis that can be used for the construction of multi-dimensional indices. The proposed method relies on the combination of a two-stage DEA model [13] for the evaluation of each dimension/sub-indicator and a BoD model [16] for the final construction of the sustainability index. Finally, the model is tested to evaluate the sustainability of EU-28 countries.

The proposed method does not come without its limitations. Firstly, as it was mentioned in the case study, the sustainability index is derived from a specific set of inputs, outputs and intermediate measures. However, since there is no unified definition of sustainability, different datasets can be used which would alter the results. Moreover, sustainability need not only be constructed by combining three sub-indicators; more could be included. Finally, different data sources could be used. All these limitations are future avenues of research for the enrichment of the proposed method.
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.mex.2020.101169.

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