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MODEL OCENY KRAJOWYCH STRATEGII PRZECIWKO COVID-19 OPARTY NA DEA

Streszczenie. W artykule przedstawiono wykorzystanie metody oceny obwiedni danych (DEA) jako elementu systemu wspomagania decyzji podczas pandemii COVID-19. Podkreślono brak mechanizmów informacji zwrotnej w celu oceny skuteczności środków zapobiegania pandemii i zasugerowano DEA jako narzędzie usprawniające podejmowanie decyzji. W artykule pokazano, w jaki sposób modele DEA mogą być wykorzystywane jako integralna część systemu kontroli, służąc jako rama decyzyjna, która wspiera wprowadzanie skutecznych środków w walce z pandemią. Rama składa się z trzech bloków: analiza danych, ocena Wydajności i jednostki decyzyjnej, gdzie DEA wspomaga zarówno ocenę wydajności, jak i podejmowanie decyzji.

DEA-BASED MODEL FOR ASSESSING NATIONAL STRATEGIES AGAINST COVID-19

Summary. This paper presents the use of Data Envelope Assessment (DEA) as part of a decision support system during the COVID-19 pandemic. It highlights the absence of feedback mechanisms to evaluate the effectiveness of pandemic measures and suggests DEA as a tool for improving decision-making. The main contribution of the paper is to demonstrate how DEA models can be used as an integral part of the control system, serving as a decision-making framework that supports the introduction of effective measures in the fight against a pandemic. The framework consists of three components: Data Analysis, Performance Evaluation, and Decision Unit, where DEA aids both performance assessment and decision-making.

1. Introduction

Although there is a rich set of methods and tools for evaluating the effectiveness of business and technology decisions, there is a noticeable lack of methods for evaluating the effectiveness of strategic decisions made during a crisis where there is no precedent to benchmark against. This was evident during the COVID-19 pandemic, where decisions to prevent the spread of the Cov-SARS-2 virus and mitigate the effects of the pandemic were made without a feedback mechanism to measure the effectiveness of the actions taken and to guide future decisions. Therefore, the objective of the research referred to in this paper was to explore the feasibility of using the DEA method, which is used in other domains, to perform such an evaluation. In addition, the study sought

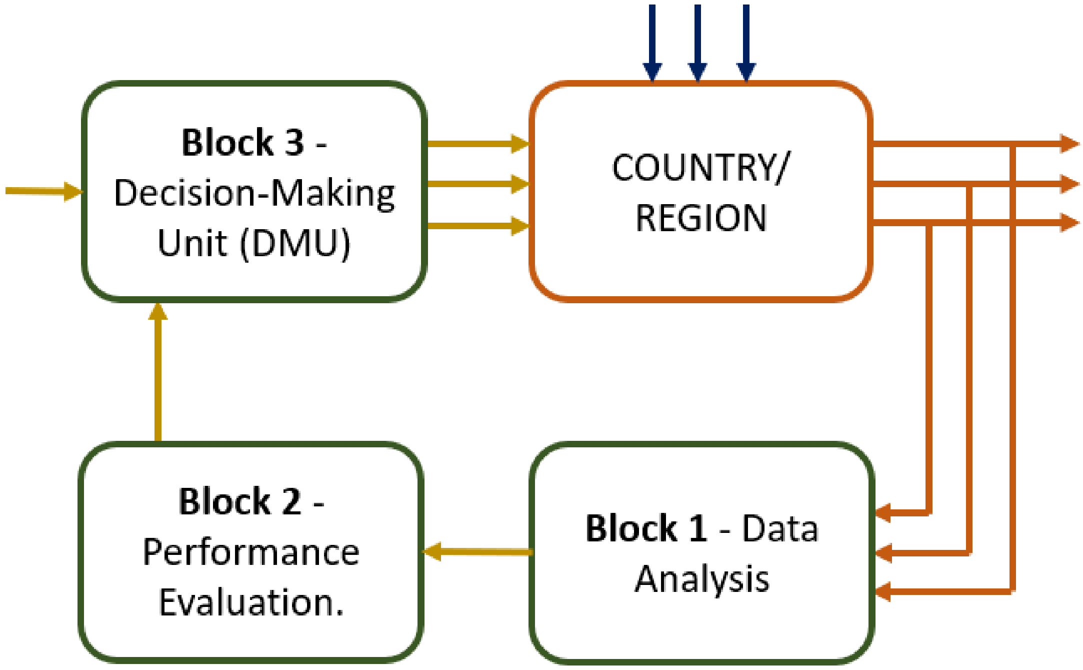

Fig. 1. Decision-making framework. Source: own elaboration.

to develop a framework of actions required to establish a regulatory framework that effectively supports decision-making using different tools and methods, such as DEA and multiple regression.

As of May 1, 2022, official reports from the World Health Organization indicate that the COVID-19 pandemic has resulted in 514 million cases of infection and 6,249,700 deaths [32]. The early stages of the pandemic highlighted the lack of preparedness of the international community, particularly the governing bodies of individual countries and regions, to respond effectively to the threat and the rapidly growing global crisis [1, 21].

Decision-makers are well-informed about the various strategies to combat the pandemic and have a wide range of tools at their disposal. These tools range in severity, with the mildest measures including mandates for social distancing, the use of personal protective equipment (such as masks, gloves, and face shields), and recommendations for increased hygiene practices [18]. However, if necessary, more restrictive measures that limit social freedom – such as remote work and study or complete lockdowns – can be implemented. Over time, pharmacological measures such as effective vaccines and drugs must be used in addition to these non-pharmaceutical countermeasures [28]. However, the challenge is to ensure the appropriate and efficient use of the tools to combat a pandemic throughout its various stages. As a result, there appears to be an urgent need for a decision-making framework to support effective action against a pandemic (see Figure 1).

The framework comprises the following components:

- **Block 1** – Data Analysis. Its primary function is to identify all the variables that affect the spread of the pandemic within specific countries/regions. This involves sorting out qualitative factors, collecting historical data for the identified variables, and initiating surveillance efforts for each country/region.

- **Block 2** – Performance Evaluation. This component is responsible for evaluating the performance of a country based on several variables, such as the number of fatalities, cases, population, and average age. Its primary objective is to determine the data analysis interval, i.e. the time that enables the system to respond to changes in control parameters. The component distinguishes between decision factors, which can be set by the country's government or regional management, and non-decision factors, over which they have no control. Finally, it presents a final ranking of the countries studied.
- **Block 3** – Decision-Making Unit (DMU) that oversees the control of certain factors influencing the course of the pandemic, particularly during the ongoing crisis. The DMU is responsible for making key decisions that can have a significant impact on the direction and severity of the pandemic. Within the DMU, several key components play a critical role in decision-making. These include (1) the analytical module, which subjects the effectiveness of various control measures within the planning period $t-1$ to the values of decision variables, such as school closures and mandatory mask wearing; (2) the optimization model, which finds the optimal level of decision variables (or patterns) in the planning period t to maximize their effectiveness in mitigating the spread of the pandemic in the next planning period $t+1$; (3) the regulatory and implementation part, which refers to the cooperation between the government and administrative units in a country to effectively implement the proposed changes. It is the responsibility of these units to ensure that the recommended measures are put into practice and closely monitored to achieve the desired results.

One of the critical components of the proposed approach is the performance evaluation component (i.e. the evaluator). It is responsible for providing feedback within the analyzed system and determining the effectiveness of policies implemented by individual countries and regions. To improve the efficiency evaluation process, highly effective methods such as those found in the Data Envelopment Analysis (DEA) group can be used. These models allow you to assess the efficiency of a group of objects across multiple factors, identify efficient patterns and technologies, estimate the impact of scale on object activity, and create rankings of efficient objects. This enhanced functionality of the Performance Evaluation component also covers the decision-making process for selecting control tools and methods.

Over the years, DEA has been used repeatedly in various studies to evaluate the efficiency of public health systems, hospitals, and other health services[17, 11, 3]. These studies used DEA to identify inefficiencies, restructure health care, and suggest changes for better management and cost savings.

The main contribution of this paper is to demonstrate how DEA models can be used as an integral part of the control system outlined at the beginning of this section. Specifically, in Block 2 of the framework, DEA can be used to assess the effectiveness of pandemic countermeasures implemented in different countries or regions. In addition, this paper will show that, due to the specific characteristics of DEA models, they can also be used in the analytical part of Block 3.

The paper is organized as follows: in Section 2., DEA models are discussed in the context of efficiency evaluation, their advantages and disadvantages, and models that seem best suited for the case study are indicated. In Sections 3. and 4. a sample analysis of efficiency for a group of countries is conducted, along with conclusions that can be drawn from the study itself. Finally in Section 5., an assessment of DEA models is made in the context of their application in the control system under examination.

2. Positioning of the paper – control and assessment in the medical sector

Research conducted in the 1990s demonstrated the usefulness of Data Envelopment Analysis (DEA) in measuring efficiency in the medical sector, using the UK's National Health Service as an example. DEA produced user-friendly and theoretically sound results that could measure relative efficiencies and suggest hospital improvements, making it a valuable explanatory and advisory tool for management monitoring and decision-making processes [16]. A recent study in Croatia using DEA on data from 12 units over two years confirmed its usefulness in assessing the efficiency of public health services and supporting management decision-making processes, identifying inefficient units, and setting targets based on efficient ones. The study concluded that DEA can be a useful tool in assessing and improving public health services [31].

The potential strategic role of DEA in the efficient and effective planning of scarce resources to fight the epidemic has been explored for several diseases, for example, to make international comparisons on the efficiency of implementation of HIV prevention programs, or to make comparisons between countries and identify best practices as a platform for improving tuberculosis prevention and control programs [24, 19, 29, 27]. S.P. Santos *et al.* in [26] discusses the challenges posed by the HIV/AIDS epidemic, particularly the issue of mother-to-child transmission. The paper explores the potential of using DEA to assess the effectiveness of HIV prevention programs in 52 low- and middle-income countries in preventing mother-to-child transmission of HIV. The study finds wide variation in the efficiency of service delivery across countries, with some countries more efficient than others in allocating resources to prevent transmission. The paper suggests that the results can help identify appropriate peer learning for each nation, as well as targets for performance improvement.

A DEA model was proposed by A.R.S.-R. Gaspar in [12] to analyze the performance of 33 low- and middle-income countries in tuberculosis prevention and control, which identified China, Bangladesh, Burundi, and Pakistan as effective countries. However, the study faced challenges due to data unavailability and missing values, and caution is advised in interpreting the results for certain countries. The study also identified benchmarks and best practices for non-effective countries to plan strategies to achieve specific goals.

In the early stages of the COVID-19 pandemic, this global threat challenged all countries to develop effective public health and administrative strategies to combat COVID-19 and sustain their economies. The first analytical tools used to compare the dynamics and character of COVID-19 in countries were the comparison of real data with well-known models of epidemic development using exponential contagion curves (e.g. SIR, SEIR, SIRD), as this is a prerequisite for devising effective strategies to prevent the spread of pandemics [18, 2]. Although COVID-19 containment efforts are evident in many well-governed nations, the prevalence of the virus continues to rise in countries with fair and poor governance. The outbreak, spread, and mitigation of the pandemic were under careful examination from its very beginning, as the preparation for a potential recurrent COVID-19 epidemic, e.g. [23, 7, 8].

Models used in the decision support systems (DSS) may also include models for scheduling work shifts in hospitals during periods of increased staffing needs during a coronavirus pandemic (e.g. [13]) and models for controlling vaccine supply by taking into account the size of population groups with different vaccination priorities (e.g., [25]). DMU can also be supported by emerging models that compare the effectiveness of introduced strategies in different countries, e.g., based on models from the DEA group [6, 4, 33] However, these issues are beyond the scope of this paper.

3. Material and Methods

Assessing the effectiveness of managerial decisions takes on various forms that can be categorized into three main groups, depending on the approach utilized. (1) The first group is indicative, which involves developing relationships between different quantities (such as indicators like debt, liquidity, and profitability). (2) The second group is parametric, which utilizes econometric methods and introduces a production function to evaluate efficiency. The Stochastic Frontier Approach (SFA), Thick Frontier Approach (TFA), and Distribution Free Approach (DFA) are examples of this group. (3) The third group is non-parametric and makes use of linear programming. Unlike parametric methods, non-parametric methods do not analyze the relationship between inputs and outputs. Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) method are examples of this group [14].

Selecting the most suitable method to evaluate efficiency while considering multiple criteria has been a significant scientific challenge for a long time. The parametric approach utilizes the production function, a well-known concept in microeconomics theory that establishes the relationship between inputs and outputs. The parameters of this function are determined using classical econometric estimation tools. On the other hand, the non-parametric approach to efficiency analysis involves constructing models that do not require knowledge of the relationships between inputs and outputs, and even less the arrangement of parameters determining these relationships [20, 14, 15].

Starting from typical efficiency evaluation analyses, for example, coefficients such as unit cost, unit profit, etc., we can represent efficiency in terms of a generalized quotient: a/b, where a stands for outputs and b for inputs. This ratio is typically used to measure partial efficiency, i.e., related to one type of input and one outcome. Of course, considering only partial efficiency in the evaluation can lead to several errors resulting from focusing on only one aspect of the activity. Therefore, it is necessary to strive to determine the total efficiency" of the evaluated unit, taking into account all inputs and outputs. However, when we want to move from partial efficiency to total efficiency, we encounter problems related to the selection of a representative group of inputs and results, and then the assignment of appropriate weights to them that allow us to determine the a/b ratio.

Data Envelopment Analysis (DEA) models do not require arbitrary weights to be assigned to individual inputs and outputs. In addition, the use of linear programming allows objects described by a relatively large number of parameters to be evaluated. This solves the common problem of having to specify only a few parameters; a larger number would make the calculations too complicated. Efficiency, which we can determine from an analysis using the DEA method, is the effectiveness (efficiency) of converting inputs into outputs. Of two objects (in our case, countries or regions) that differ in at least one input or output, the more efficient is the one that (1) produces greater results with no more inputs than the other, or (2) with fewer inputs than the other, does not produce fewer results [15]. Finally, the DEA method allows for a relative assessment of efficiency and the classification of countries into efficient and inefficient ones, as well as the identification of patterns among the inefficient ones [9].

The analysis consists of two parts. One is related to the admissible set of countries (regions), understood as a matrix consisting of vectors of empirical inputs and outputs associated with the evaluated countries. The other is related to the efficiency measurement, which in DEA models can take the following forms: (1) radial – proportional adjustment of inputs or outputs – classical models, and (2) non-radial – disproportional adjustment of inputs or outputs – Russell efficiency measurement [15] as well as based on input-output gaps and hyperbolic efficiency measurements, involving simultaneous decreasing inputs and increasing outputs, etc. [30, 15, 9, 10].

4. DEA-based model for assessment of national strategies against COVID-19

The main problem in assessing the effectiveness of the virus strategy is establishing a common baseline for all the countries analyzed. The main problem is the lack of consistent reporting systems across countries. Another issue that arises is the choice of the period for analysis, specifically the point in time from which to analyze a country's actions: (1) since the announcement of an epidemic in a country, (2) since the first information about the virus, (3) since a certain threshold number of patients in a given country.

Given the main purpose of the work, i.e. to use DEA as an efficiency measurement system (Block 2) during an ongoing pandemic state, it was decided to base the construction of the model on data from the first 60 days after the occurrence of 100 cases in a country. This approach seems sufficient from the point of view of the purpose of the work, and the model developed in this way will also apply to other periods.

The next step in the assessment is the preliminary identification of parameters describing the strategy of action of each country under analysis, which should include a sufficient number of factors so that the space created by them reflects reality. At this point, the main problem becomes the aforementioned lack of access to standardized data. Therefore, the set of parameters analyzed is a compromise between the number of countries studied and the access to data on them.

From the identified parameters, a group of available factors with a significant impact on efficiency is selected:

- Healthcare spending in 2018 per capita;
- Number of tests at 60 days per 100,000 population;
- Number of available hospital beds per 1,000 inhabitants;
- Population density in number of people per km2;
- Median age;

- Percentage of people over 65;
- Infection growth rate, defined as the average 30-day increase in cases per 1 day;
- Number of infections after 60 days per 1 million inhabitants;
- Growth rate of deaths, defined as a 30-day average increase in cases per 1 day;
- Number of deaths after 60 days/1 million population.

It is important to note that not all of these factors are within the control of those who manage a country's pandemic preparedness. For example, a country's government directly influences the number of tests carried out or the preparation of health services, while factors such as average age and population density are beyond its decision-making capacity in the short term. Therefore, the selected group of parameters was divided into dispositional inputs - those whose level is set, for example, by the government of a country or region; non-dispositional inputs - those that do not depend on decisions made; and outcomes. Table 1 shows the breakdown of the parameters selected for analysis.

Table 1

Selected parameters for analysis

Expenses	**Disposable Inputs**	**Non-disposable Outputs**
Healthcare spending in 2018 per capita	Population density, or the number of people per km2	Infection growth rate, i.e. 30-day average of 1-day case growth
Number of tests at 60 days per 100,000 population	Median age	Number of infections after 60 days per 1 million population
Number of available hospital beds per 1,000 inhabitants	Percentage of population over 65	Growth rate of fatal cases, i.e. 30-day average of 1-day case growth Number of deaths after 60 days/1 million population.

To determine the efficiency of pandemic operations, a model based on a non-radial assessment of inefficiency with the assumption of fixed scale effects was chosen. The choice of this approach stems from the fact that most of the basic models have a common flaw related to identifying the number of fully efficient facilities too much. Often, almost half of the studied objects are fully efficient, which usually far exceeds the needs of the analysis conducted. One of the solutions to this problem is the model presented below, based on the measurement of non-radial super-efficiency. The main advantages of this model in the case discussed are: (1) The ability to rank both inefficient and efficient DMUs; (2) The assessment of efficiency from the perspective of the utilization of individual disposable inputs [34]. These capabilities will be discussed in detail in the next section.

The objective function (1) represents the minimization of the average of the level multipliers of individual disposable input. Condition (2) ensures that the non-decision inputs of the common technology of a set of objects are less than or equal to the non-decision inputs of the j-th object. Condition (3), on the other hand, ensures that the decision inputs of the common technology of a set of objects are less than or equal to the smallest possible part of the decision inputs incurred by the j-th object. Condition (4) ensures that the desired results of the common technology of a set of objects are greater than or equal to the desired results of the j-th object belonging to the set of objects under examination $\{1, \ldots, K\}$.

$$E_j = min \frac{\sum_{q=1}^{Q} \theta_{jq}}{Q} \tag{1}$$

subject to

$$\sum_{k=1, k \neq j}^{K} x_{nk} \lambda_{kj} \leq x_{nj}, \quad n = 1, 2, ..., N, \tag{2}$$

$$\sum_{k=1, k \neq j}^{K} e_{qk} \lambda_{kj} \leq \theta_{jq} e_{qj}, \quad q = 1, 2, ..., Q, \tag{3}$$

$$\sum_{k=1, k \neq j}^{K} g_{rk} \lambda_{kj} \geq g_{rj}, \quad r = 1, 2, ..., R, \tag{4}$$

$$\lambda_{kj} \geq 0, \quad k = 1, 2, ..., K \tag{5}$$

where:
E_j – the rating confection for the j-th object under examination;
K – the number of elements in the set of objects under study;
N – the number of elements in the set of non-disposable inputs;
Q – the number of elements in the set of disposable inputs;
R – the number of elements in the set of results obtained for the object;
x_{nj} – non-disposable inputs n of object j;
e_{qj} – disposable inputs q of object j;
g_{rj} – results r obtained on object j;
λ_{kj} – the decision variable, i.e. the weight of object k from the point of view of the object j under examination;
θ_{jq} – the input level multiplier in object j;

5. Results and discussion

Because of the non-radial super-efficiency model chosen, the efficiency measure used to evaluate objects in such models is the aforementioned Russell efficiency (E). It can come in two forms: strong Russell efficiency (Es) and weak Russell efficiency (Ew). Weak efficiency allows for substitution of decision inputs, which means that for example a country that is super-efficiency at using one input ($\theta_{j1} > 1$) but inefficient at another ($\theta_{j2} < 1$) may end up being fully efficient ($Ew = 1$) in the sense of Russell's weak efficiency. Strong Russell efficiency ($Es = 1$), on the other hand, means that a country must use all decision inputs efficiently ($\theta_{j1} \geq 1, \theta_{j2} \geq 1$). The Russel's strong and weak efficiency indices are shown in the last two columns of Table 2.

It should be noted that some countries owe their high ranking to unreliable values of some parameters. The calculations are based on publicly available data from reports

Table 2

Analysis results

No.	Country	θ_1 ranking index for: Number of tests after 60 days per 1000 mixes.	θ_2 ranking index for: Number of available hospital beds per 100,000 inhabitants	θ_3 ranking index for: Health care spending in 2018 per capita	Russel efficiency Strong (Es)	Russel efficiency Weak (Ew)
1	Greece	1.00	1.00	1.00	1.00	1.00
2	New Zealand	1.00	1.00	0.98	0.99	1.00
3	Australia	0.78	0.90	1.00	0.89	1.00
4	Latvia	0.63	1.00	1.00	0.88	1.00
5	Slovakia	0.49	1.00	1.00	0.83	1.00
6	South Korea	0.40	1.00	1.00	0.80	1.00
7	Slovenia	0.83	0.43	0.97	0.74	0.74
8	Hungary	0.47	0.79	0.67	0.64	0.64
9	Estonia	0.66	0.44	0.53	0.54	0.54
10	Lithuania	0.58	0.57	0.31	0.49	0.49
11	Poland	0.41	0.64	0.40	0.48	0.48
12	Finland	0.46	0.15	0.37	0.33	0.33
13	Czechia	0.25	0.26	0.17	0.23	0.23
14	Norway	0.14	0.10	0.27	0.17	0.17
15	Luxembourg	0.29	0.08	0.12	0.16	0.16
16	Sweden	0.26	0.05	0.15	0.16	0.16
17	Canada	0.16	0.10	0.21	0.15	0.15
18	Denmark	0.19	0.10	0.15	0.15	0.15
19	United Kingdom	0.16	0.05	0.06	0.09	0.09
20	France	0.09	0.06	0.12	0.09	0.09
21	Portugal	0.11	0.08	0.03	0.07	0.07
22	Austria	0.09	0.07	0.06	0.07	0.07
23	Italy	0.11	0.05	0.03	0.07	0.07
24	Germany	0.07	0.06	0.06	0.06	0.06
25	United States	0.12	0.02	0.04	0.06	0.06
26	Ireland	0.08	0.04	0.06	0.06	0.06
27	Spain	0.08	0.04	0.02	0.05	0.05
28	Switzerland	0.08	0.02	0.03	0.04	0.04
29	Belgium	0.05	0.03	0.02	0.03	0.03

submitted by individual countries during the first phase of the pandemic. At that time, as well as in later years, the basic problem was not the consistency of the published parameter (e.g., "deaths due to COVID-19"), but the way and procedure of its measurement/reading in individual countries (e.g., whether COVID-19 is the cause of death in the case of comorbidities). This problem is a separate issue and is not the subject of this work, but the authors are aware of it and are aware that the control system described in the introduction has no possibility of functioning correctly without standardization of measurement procedures. However, from the point of view of the purpose of the work, which is to present DEA models as tools for measuring the efficiency of individual countries, the approximation obtained seems satisfactory to the authors.

According to the results presented in Table 2, only one country can boast a strong Russel efficiency, that is Greece, so all other countries are included in the ranking of inefficient solutions. The best of the remaining countries is New Zealand, while the worst is Belgium. For example, the lack of full efficiency for New Zealand as shown in Table 2 ($\hat{\theta}_1 = 1$, $\hat{\theta}_2 = 1$, $\hat{\theta}_3 = 0.98$) is because the optimal input-output vector would produce the same results as New Zealand with 2% less health spending. On the other hand, New Zealand and 4 other countries are weakly efficient in the Russel sense. In the so-called weak Russel efficiency, there is the aforementioned substitution of sub-indices, which means that a country can be considered efficient if only one input gives a relatively high-efficiency index.

Slovakia ($\hat{\theta}_1 = 0.49$,$\hat{\theta}_2 = 1$, $\hat{\theta}_3 = 1$) is another example that explains the individual elements in Table 2. Slovakia's weak Russell efficiency is 1. In contrast, its strong Russell efficiency is 0.83. The country has used the number of beds and health expenditure efficiently in the first 60 days after diagnosis of 100 COVID-19 cases, while the number of tests performed is inefficient($\hat{\theta}_1 = 0.49$). Other countries could achieve similar results by reducing the commitment to this issue by 51%. In addition, by analyzing the detailed results of the model, and in particular the level of the decision variable λ_{kj}, we can conclude the benchmark countries suggested by the model. For the analyzed Slovakia, λ_{kj} has a value different from zero for the vectors of Lithuania and New Zealand, which means that the vectors of these countries are benchmarks for Slovakia.

As we can see, the final choice between weak and strong efficiency depends on the decision inputs adopted and the objects analyzed. In the case discussed in this work, both approaches have their pros and cons. Weak efficiency allows for substitution, which is important in the case under study since a country can use healthcare financing inefficiently, but make up for it by testing its population efficiently. On the other hand, with strong efficiency, we have a pool of fully efficient countries and thus do not receive information that some inputs are not being used fully efficiently.

6. Conclusions

As we can see from the example above, DEA allows us to rank the analyzed countries from the point of view of many factors affecting the efficiency of their operations. In addition, for inefficient objects, we get information about patterns of behavior. Moreover, the use of such models does not require the involvement of experts to update the ranking, and calculations can be performed automatically after any change in the state of the object or at a predetermined frequency. From the point of view of applying DEA models to a pandemic decision support system, the discussed features speak in favor of these models. On the other hand, a perceived problem at this stage in applying DEA for such purposes is the relative nature of the calculated efficiency. The ranking shown represents the efficiency relative to the other analyzed objects in time unit t. The next ranking will evaluate the same objects, but in terms of factors in the next time interval $t+1$, and present a new ranking. The problem that arises here is the question: did a particular object rank higher because it did something better in period $t+1$? or did all other objects do something worse in the same period? The solution to this problem seems to be the index proposed by S. Malmquist [22], which has been further developed over the years by [5, 10], among others. The Malmquist index represents the increase in the total productivity of the assessed unit, as it reflects the progress or regression of productivity with the progress or regression of the common technology of a set of facilities between two periods [9]. The use of the Malmquist index is not feasible at this stage of the research, as it requires consistent data disaggregated by intervention period, which is the goal of further research by the authors of this paper.

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