DEA for the Assessment of Regions' Ability to Cope with Disasters

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Abstract Usually, DEA methods are used for the assessment of a region's disaster vulnerability. However, most of these methods work with precise values of all the characteristics of the regions. At the same time, in real life, quite often most of the data consists of expert estimates or approximate values. In this regard, we propose to use modified DEA methods, which will take into account inaccuracy of the data. We apply these methods to the evaluation of wildfire preventive measures in the Russian Federation regions.

Keywords Data envelopment analysis (DEA) · Efficiency assessment · Wildfire · Preventive measures

1 Introduction

Unfortunately, emergency situations, both natural and technological, are an integral part of the modern world. They constantly accompany people, threaten their lives, bring pain and suffering, damage and destroy material values, and cause huge, often irreparable, damage to the environment, society, and civilization.

The annual growth in the number of victims, by 8–9%, and material losses by 10% as a result of emergencies is a steady trend [7]. Global damage from natural disasters can amount up to about 160 billion dollars annually. In addition, the scale of anthropogenic activities in modern society and the complexity of technological processes increased, with the use of a significant amount of explosions, fire, radiation, and chemically hazardous substances. All these facts emphasize the importance of the problems associated with ensuring safety and preserving the economic potential and the environment in cases of emergency.

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Since it is important to predict and mitigate the consequences of disasters, the question arises how to execute this properly in certain conditions. Given that there are still no uniform rules, the only solution seems to be just a repetition of the most successful examples. For this reason, it is crucial to determine which cases are effective and which are not.

Consequently, it is necessary to apply some methods of efficiency assessment, compare the results for different examples, and choose the best alternative as a benchmark.

Since Huang et al. [8] claimed that quantitative assessment is very sensitive to the importance of various factors, it is decided to use linear programming approach for the efficiency assessment. This approach was proposed by Charnes and Cooper [3] and consists of using the linear fraction function of several features of the object as its efficiency. Later, this approach evolved into the widely used methodology known as data envelopment analysis [4]. Nowadays, it is used in different spheres and for different tasks: financial portfolio efficiency [15], for greenhouse gases control in electric power generation [12], manufacturing firm comparison [13], etc.

As mentioned above, data envelopment analysis (DEA) is based on the idea of efficiency assessment of different decision-making units (DMUs) by the fraction of DEA parameters. All objects are characterized by two vectors – inputs, such as resources spent, and outputs, which are basically interpreted as achieved results.

Considering multi-objective optimization (cost minimization and output maximization), Charnes et al. [4] proposed to calculate the efficiency of DMU as a fraction of weighted sum of outputs over the weighted sum of inputs. In addition, taking into account rationality and the meaning of the efficiency, there should be constraints, which guarantee that the efficiency of all objects lies in the interval $[0, 1]$.

As a result, the full form of the problem is written as

$$\max_{u_i, v_j} \frac{\sum_{i=1}^{M} u_i y_{ik}}{\sum_{j=1}^{N} v_j x_{jk}}$$

under the constraints $\forall i, j, k$

$$\begin{cases} \frac{\sum_{i=1}^{M} u_i y_{ik}}{\sum_{j=1}^{N} v_j x_{jk}} \leq 1 \\ u_i \geq 0 \\ v_j \geq 0 \end{cases}$$

Here, y_{ik} and x_{jk} are the outputs and inputs of the k-th DMU, while u_i, v_j are non-negative model coefficients, showing the importance of output and input parameters, respectively.

Solving this problem for each object in comparison, we get the optimal frontier, where the efficiency is equal to 1. For all DMUs lying below this frontier, the efficiency is evaluated using the distance from the benchmark frontier.

DEA has been applied for different disasters. For example, Li et al. [10] applied DEA to the flood disaster vulnerability assessment in the Dongting Lake region (China). Aleskerov and Demin [2] analyzed technological disasters in different regions of the Russian Federation. Meanwhile, Cheng and Chang [5] proposed to use it for the analysis of the effectiveness of earthquake risk reduction policy implementation, and Yu et al. [14] worked with the vulnerability of important economic Chinese regions to the typhoon disasters.

Moreover, there are some modifications of DEA. For instance, de Almada Garcia et al. [6] used DEA for the assessment of the security level at a nuclear power plant. For this purpose, it was proposed to take into account the specification of some problems. For example, it was claimed that the severity of the failure mode is much more important than all other criteria (occurrence and detectability). Therefore, it is necessary to place some restrictions on the features' weight indices. This will allow the construction of a more realistic and more precise method, which will pay attention to the ratio of importance of different criteria, which must be respected in solving some problems.

However, for the application of all aforementioned versions of DEA, it is necessary to get precise assessments of all DMUs' features. Meanwhile some characteristics, such as a region's population or GDP, are estimated roughly, because small deviations in these parameters are not so important.

Furthermore, there are some characteristics which cannot be measured directly. For instance, in the case of a region's disaster preventive measures' efficiency comparison, such features as the potential number of killed or injured people, or total economic losses, are evaluated using some simulation models. Therefore, these parameters cannot be precise because of inaccuracy of the simulation process and are usually given as approximate values.

As a result, it is clear that for application in real life, it is better to use some specific DEA modifications which can work with approximate data.

2 Framework

In our research, we propose two methods which will solve the highlighted problem.

We discard all stochastic and probabilistic approaches based on fuzzy logic, which are mainly used in modern DEA modifications for rough data [9, 11]. Indeed, in some cases it might be too demanding to request stochastic or probabilistic evaluations of parameters. That is why we propose to use simple intervals for the parameter assessment instead of single value (pair $\left(y_{ik}^{-}, y_{ik}^{+}\right)$ instead of y_{ik}). But for the comparison of the objects, we need to clarify new methodology for the parameters' value comparison ($>_i$ – comparison according to the i-th output feature):

$$\text{object}_k >_i \text{object}_l \iff y_{ik}^{-} > y_{il}^{+}$$

In turn, if both inequalities $y_{ik}^{+} > y_{il}^{-}$ and $y_{il}^{+} > y_{ik}^{-}$ hold, which means that intervals $\left(y_{ik}^{-}, y_{ik}^{+}\right)$ and $\left(y_{il}^{-}, y_{il}^{+}\right)$ are intersecting, objects k and l are incomparable.

Using this type of data representation and parameters comparison, we can apply two IDEA (interval DEA) methods.

The first one is based on the idea that some DMUs might be near the efficiency frontier. But, in the case of basic DEA, they will not get 100% efficiency. We want to discard this drawback. Hence, we propose to assign 100% efficiency, not only to the objects on the best efficiency frontier but also to the DMUs, which are incomparable with them. As a result, the so-called best tube of 100% efficient objects is constructed (consequently, the method is called the "best tube" IDEA). Efficiency of all other DMUs is assessed by the basic DEA.

The second proposed IDEA method is based on the idea that any parameter (both input and output) might be the most important during the DMU comparison. Consequently, if one of the objects has the best value according to at least one feature, it should be considered as the best one. Technically, it means that the Pareto optimality principle should be used:

$$\text{object}_k > \text{object}_l \iff \begin{cases} y_k \geq y_l \\ x_k \leq x_l \end{cases} \iff \begin{cases} \forall i y_{ik}^{-} \geq y_{il}^{+} \\ \forall j x_{jk}^{+} \leq x_{jl}^{-} \end{cases}$$

This principle has some attractive properties [1] and can be efficiently applied for the comparison of the objects with interval assessments of the features.

According to the Pareto optimality principle, the set of the best objects is constructed from all objects which are not Pareto-dominated:

$$C_{\text{Pareto}}(X) = \{y \in X | \nexists x \in X : x > y\}$$

As a result, we propose the Pareto IDEA, according to which, in the first step, the procedure chooses all Pareto optimal DMUs and assigns 100% efficiency. Afterward, all other objects are evaluated by the basic DEA.

3 Application of the Model

Next, we compare wildfire preventive measures in different regions of the Russian Federation. Any precautionary measures definitely demand financial funds, and this is the most important input parameter. However, information about direct expenditures on fire-preventive events is not available, so we use two different money flows as input parameters: environmental protection and investments in agriculture and forestry. The first money flow directly influences the security of the forests. Meanwhile, the second money flow improves the quality of forestry. As a result, the quality and the amount of produced wood increase, and wildfire security is one of the ways of saving the forest, which can then be sold in future.

In turn, we also need to parametrize the results of precautionary measures. In this part, we consider two main characteristics: the number of wildfires in the region and the area of forest land covered by fires.

In order to conduct our research more correctly, we compare only 46 Russian regions, which face the problem of wildfires (these regions have at least 10 wildfires per year). We apply three methodologies for these DMUs: basic DEA, best tube IDEA, and Pareto IDEA.

4 Results and Analysis

As a result of applying different methodologies, we got three efficiency assessments for each region. Consequently, there are three different rankings of the Russian regions, according to each DEA modification.

As expected, the results of all methods give us almost the same order, with slight distinctions (the best regions are in Table 1 and the worst regions are in Table 2). The main difference is the fact that interval DEA shows better results (higher efficiency), because it assigns 100% result to some "additional" objects in the comparison set, which are furthermore excluded from the subsequent efficiency evaluation process. As a result, the benchmark for all inefficient DMUs becomes worse and improves their efficiency.

Moving to particular results, it is necessary to point out seven regions, which get 100% efficiency according to all methods: Novgorod Oblast, Udmurtia, Penza Oblast, Ulyanovsk Oblast, Republic of Khakassia, Kamchatka Krai, and Magadan Oblast. Good results of these regions can be explained by different reasons. The first five are just regions with small territory (less than 0.4% of the area of the Russian Federation); therefore it is not complicated to monitor and resist wildfires. Magadan Oblast mainly consists of mountainous desert, so wildfire is also not a

Table 1 Regions with the best wildfire preventive measures

	Basic DEA	Best tube IDEA	Pareto IDEA
Novgorod Oblast	1	1	1
Udmurtia	1	1	1
Penza Oblast	1	1	1
Ulyanovsk Oblast	1	1	1
Republic of Khakassia	1	1	1
Kamchatka Krai	1	1	1
Magadan Oblast	1	1	1
Vladimir Oblast	0.93	1	1
Saratov Oblast	0.82	1	1
Kemerovo Oblast	0.57	1	1
Sakhalin Oblast	0.46	0.58	1

Table 2 Regions with the worst wildfire preventive measures

	Basic DEA	Best tube IDEA	Pareto IDEA
Krasnoyarsk Krai	0.00	0.00	0.01
Irkutsk Oblast	0.00	0.00	0.02
Sverdlovsk Oblast	0.00	0.01	0.03
Chelyabinsk Oblast	0.01	0.01	0.05
Republic of Bashkortostan	0.01	0.02	0.07

serious problem for this region. Kamchatka Krai is the only region which might be characterized as a real benchmark, because more than 14.5% of the Kamchatka Krai represents the specially protected area and, according to the results of the research, protection is provided by high qualified professionals.

However, the worst regions – Krasnoyarsk Krai, Irkutsk Oblast, and Sverdlovsk Oblast – should also be mentioned, and their low ranking can be explained by the fact that these regions are at the top of the region list according to area (Krasnoyarsk Krai constitutes about 14% of the Russian Federation area). But the fact is that in every summer in the Russian Federation, huge territories in Siberia suffer from wildfires.

5 Conclusion

We applied two new methods based on data envelopment analysis to the regions of the Russian Federation. Both of them help in solving the problem of uncertainties in the data by using interval assessments of the regional parameters. Obtained rankings of preventive measures in different regions are similar to the ranking obtained by the basic DEA.

It should be mentioned that these methods may be successfully applied to similar problems.

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