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USING A NON-PARAMETRIC TECHNIQUE TO EVALUATE THE EFFICIENCY OF A LOGISTICS COMPANY

Summary. Data Envelopment Analysis (DEA) is a relatively new method, a non-parametric technique used nowadays to evaluate the efficiency of the Decision-Making Units. Using this method, the Decision-Making Units can be compared between each other and the most effective ones can be found. Using the DEA method, the performance of a logistic company with twelve warehouses as DMUs is evaluated in this paper. "DEA Excel Solver" user program was used to solve the problem.

1. INTRODUCTION

Decision-making is a very important part of many tasks of logistics managers: for example, trying to decide which route to use for a particular shipment, which carriers to use and how much inventory to hold. Different people, depending on their role in the supply chain, will have various views when deciding what the optimal solution is [1]. One of the main goals of any organization is to achieve as much efficiency and profit as possible. According to Burdzik et al. [2], transport and logistics business systems are strongly correlated. The philosophy of efficient business is to achieve maximum results with minimum investments. Nowadays, most of the logistics processes are automated. Fedorko et al. (2018), in [18], emphasized that the automation of logistics processes was linked to the introduction of the latest technologies into a wide range of business operations. Automation of some of the logistics processes can make a logistic company more efficient and productive. Sabadka et al. (2019), in their research [19], stated that social changes led to an increase of customer individualism, resulting in increased expectations and demands. For this reason, to satisfy the customer demands, in all logistics phases, efficiency must be maintained at the highest possible level.

The Data Envelopment Analysis (DEA) is a non-parametric method for the measurement of the efficiency of a decision-making unit (DMU) like an organization or a Public Service, as stated by Ray in [11]. This method has advantages as well as disadvantages. One of the advantages of the DEA method is its frequency of use in the scientific literature and Arkay et al. (2012) emphasized in [12] that this method was one of the most important and well-known non-parametric techniques.

In [13], according to Farantos, one of the main advantages of DEA is the fact that the proportion of a small number of units in terms of the number of inputs and outputs may lead to unreliable results. The same author emphasized that compared with other efficiency measurement methods such as the labor-productivity measurement method, measuring the cost method and cost comparisons, the DEA method showed advantages that make them suitable for many researchers. In terms of disadvantages, he stated the fact that DEA is a deterministic method without the possibility of calculation of measurement errors and statistical noise.

Qian and Bing-Jiang [14] emphasized the fact that in practical problems, the evaluation of the efficiency of the DMUs should not only consider an „excellent“ side, but also the condition of being lower – “Inferiority”.

On the other hand, Yoshiyasu et al. [15] have proposed an inverted DEA method, which is used in the opposite way to the normal DEA method. This inverted DEA method evaluates the anti-efficiency of DMUs.

The major strategy of the manufacturing units according to Fedorko et al. [3] is the optimization of cost management planning. Business efficiency can be measured in all segments of the organization, ranging from workers, machines and devices to various production and other processes. There are various methods to compare the business units and their efficiency. When comparing the workers, one of the possible approaches is to measure their stress level related to the job [16]. On the other hand, the Data Envelopment Analysis (DEA) method is one of the characteristic methods for measuring the efficiency of the company's operations that are increasingly gaining importance in the operations of non-profit organizations. In the modern environment, a company is an executor of processes that transform inputs into the required outputs [4]. The most successful DEA methods have been implemented so far in the evaluation of the performance of bank branches, departments at universities, postal branches [5], schools, ports [6] and postal operators [17]. The DEA is one of the linear programming methods for the determination of the relative efficiency of the organization's business. More precisely, the DEA method shows how the output can be changed depending on the specified input parameters. In this way, by acting on the input, the desired target at the exit can be obtained from the system to achieve efficient system management. Cullinane and Wang used the DEA method in [7] for the determination of the relative efficiency of the 69 busiest European container terminals. They looked at three entrances: the length of the queue, the surface of the terminal, the number of cranes and the traffic of the container as the exit. Tongzon [8] considered the efficiency of four Australian and 12 container ports outside Australia for 1996 based on the total number of processed containers and the speed at which the ship was processed as it exits and the number of cranes, landing sites, trains, terminal areas and delay time as inputs. In this paper, the DEA method is used to evaluate the efficiency of the warehouses of a logistic company.

This paper is organized as follows: Section 1 presents an introduction, where the DEA method and its usage are described by many authors in many different areas. Section 2 describes the mentioned method with the formulae in a general case that can be used to solve the problem, which is mentioned in the third Section. The description of the problem, application of the DEA method as well as the sensitivity analysis are presented in Section 3 of this paper. Section 4 concludes the paper and presents the obtained results as well as the recommendations for improvements.

2. DATA ENVELOPMENT ANALYSIS (DEA) METHOD

An organization whose effectiveness should be evaluated in the DEA terminology is called the Decision-Making Unit (DMU). The authors of the DEA, Charnes, Cooper, and Rhodes, proposed an approach to calculate the efficiency, which is a non-parametric technique, i.e. does not require a specific functional form, as opposed to statistical approaches such as regression analysis. They multiplied multiple inputs into one "virtual" input and multiple outputs were reduced to a "virtual" output using weight coefficients. The issue of weight allocation was solved by allowing each unit to determine its own weight to maximize efficiency (ratio of the weight of its outputs and inputs), with the restriction that these weights must have positive values and then the quotient of the virtual output and the virtual input of each unit may not be greater than 1. This problem was defined by the linear programming problem known as the CCR ratio model. In this model, the decision-making unit is inefficient if it is possible to reduce any input without increasing any of the other inputs and achieving the same output. Based on the data on input and output variables, Data Envelopment Analysis determines whether an effective decision-making unit is or is not relative, by comparing with another DMUs included in the analysis. The limit of economic efficiency is empirically obtained maximum output variables that each decision-making unit can achieve with the given input variable and acts as a tab for inefficient units. The name of the data envelopment analysis comes from the fact that the method analyses each decision-making unit and checks whether its input variables can be performed from the bottom (the given output variables can be achieved with a smaller number of input variables), taking into account the value of the input variables, and whether its output variables can be performed from the top input variables and it is possible to produce higher output variables based on the value of the output variables of the remaining units. If the unit is able to perform it, it is relatively inefficient and, if not, it participates in the formation of the efficiency limit that represents here the equivalent for the border production function [9]. The DEA model is formulated in the form of the following tasks, given in formula (1):

$$max = \left(\frac{\sum_k v_k \cdot Y_{km}}{\sum_i n_i \cdot X_{im}}\right) \tag{1}$$

$$\frac{\sum_k v_k Y_{ki}}{\sum_i u_i X_{ij}} \geq 1 \; ; v_{k,} \, u_i \; \geq 0$$

with the following meaning: maximize the efficiency of the *m-th* unit with the constraint that the efficiency of all units is no greater than 1. The linear version of the model is given in formula (2) as follows:

$$max\left(E_{ffj} = \sum_k v_k \, Y_{km}\right) \tag{2}$$

$$\sum_i u_i x_{im} = b$$

$$\sum_k v_k Y_{kj} - \sum_i u_i X_{ij} \leq 0, \textit{for each } j$$

$$v_k, u_i \geq 0 \; or \; \mathcal{E}$$

where $\boldsymbol{Y_{kj}}$ is the value of the *k-th* output of the *j-th* unit, $\boldsymbol{v_k}$ is the weight associated with the *k-th* output, $\boldsymbol{X_{ij}}$ is the value of the *i-th* input in the *j-th* unit, $\boldsymbol{u_i}$ is the weight of the *i-th* input, *b* is a constant, $\boldsymbol{E_{ffj}}$ is the efficiency of the *j-th* unit and $\mathcal{E}$ is a small value, which can be introduced to avoid any input or output being excluded in determining efficiency.

Solving the linear version of the model determines the efficiency of the target (*m-th*) units. The obtained weight values ($\boldsymbol{u}, \boldsymbol{v}$) are the best from the point of view of the *m-th* unit. The weights obtained for any two units can be different because they have different criteria functions. If an observed unit is effective, with its optimal values for weight coefficients, no other unit can achieve a higher value of output variables for the given input variables, whereas for the inefficient units, this is not the case. The data for the various input and output variables are usually a very wide range of values.

3. DESCRIPTION OF THE PROBLEM AND APPLICATION OF THE DEA METHOD

There is an existing large company with many warehouses. According to its size, equipment, the volume of the products and turnover outcomes per year, the authors of this paper selected twelve of them, which are similar. These twelve warehouses represent the decision-making units (DMUs). In all warehouses, the picking process is done manually. With this order, workers are picking goods and set up pallets. After that, goods are wrapped in a special foil, also manually, the full pallet is carried to the front of the warehouse and the next action involves checking by the checkers. Management of the company from year to year closely monitors the picking process. Efficiency in these warehouses is not at the same level. Some warehouses have higher efficiency than others. In the rest of this paper, the DEA method will be applied to find the most efficient unit.

3.1. Application of the data envelopment analysis method for solving the problem

Four main stages can be identified in the implementation of the efficiency study using the DEA method [1, 10]:

1. Defining and selecting the decision-making units whose relative efficiency should be determined.
2. Determination of the input and output variables that are relevant and suitable for assessing the relative efficiency of the selected decision-making units.
3. Choosing an adequate DEA model.
4. Dealing with the DEA model, analysis and interpretation of results.

In this paper, the problem of warehouse efficiency is solved to improve efficiency. The DEA method was used to determine the efficiency of each warehouse, depending on the given inputs and outputs. In the DEA model, two-input and one-output variables are considered. The variables, taken as the inputs are the number of picking workers (pickers), as well as the average time duration of the picking process. Regarding the output variable, it is the total annual income. Data on the number of warehouse workers, average picking time and total desired annual revenues were obtained from the company's management. It is important to emphasize that a logistic company with some warehouses operates efficiently and achieves the desired profit annually. Applying the DEA methodology, it will be determined as to what needs to be changed in the input variables and for how many percentages in terms of the initial state to operate efficiently in all warehouses. The values of the variables (input and output data) are shown in table 1.

Table 1

Values of the variables in the DEA model

Decision-making units (DMU)	Input variables		Output variable
	Number of pickers	Average time of picking [min]	Annual income [millions of euros]
Warehouse 1	11	8	1.5
Warehouse 2	10	10	1.8
Warehouse 3	12	7	1.4
Warehouse 4	9	12	1.1
Warehouse 5	14	9	1.6
Warehouse 6	8	8	1.1
Warehouse 7	9	7	1.6
Warehouse 8	10	9	1
Warehouse 9	11	9	1.3
Warehouse 10	13	9	1.7
Warehouse 11	6	8	1.2
Warehouse 12	9	7	1.5

The formulation of the linear programming task in terms of the first decision-making unit (warehouse 1) is as follows:

$Max\ 1.5v1$

$11u1 + 8u2 = 1$

$11u1 + 8u2 - 1.5v1 \geq 0;$

$10u1 + 10u2 - 1.8v1 \geq 0;$

$12u1 + 7u2 - 1.4v1 \geq 0;$

$9u1 + 12u2 - 1.1v1 \geq 0;$

$14u1 + 9u2 - 1.6v1 \geq 0;$

$8u1 + 8u2 - 1.1v1 \geq 0;$

$9u1 + 7u2 - 1.6v1 \geq 0;$

$10u1 + 9u2 - v1 \geq 0;$

$11u1 + 9u2 - 1.3v1 \geq 0;$

$13u1 + 9u2 - 1.7v1 \geq 0;$
$6u1 + 8u2 - 1.2v1 \geq 0;$
$9u1 + 7u2 - 1.5v1 \geq 0;$
$u1 \geq 0.001; u2 \geq 0.001;\ v1 \geq 0.001$

where $u1$ and $u2$ are the coefficient weights of the input variables, and $v1$ is the coefficient weight of the output variable. In the same way, equation systems are set up for other decision-making units (warehouse 2 - warehouse 12) and the values of their relative efficiencies are shown in table 2.

Table 2

Relative efficiencies for all decision-making units (warehouses)

Decision-making unit (DMU)	Efficiency
(DMU 1) Warehouse 1	0.8202
(DMU 2) Warehouse 2	0.9642
(DMU 3) Warehouse 3	0.8747
(DMU 4) Warehouse 4	0.6111
(DMU 5) Warehouse 5	0.7775
(DMU 6) Warehouse 6	0.7366
(DMU 7) Warehouse 7	1
(DMU 8) Warehouse 8	0.5474
(DMU 9) Warehouse 9	0.6587
(DMU 10) Warehouse 10	0.8614
(DMU 11) Warehouse 11	1
(DMU 12) Warehouse 12	0.9375

It may be noted that the seventh and eleventh warehouses operate efficiently in terms of the pickers, average time of picking and annual income. With the efficiency of an equal unit of this decision-making unit, they represent the limit of efficiency. The efficiency of the remaining units is less than one and this indicates the need to increase or reduce the value of the input variables to become effective for the given output.

3.2. "DEA excel solver" for the sensitivity analysis

The main objective of the sensitivity analysis is to determine the causes of the sensitivity as well as how the performance of all inefficient units could be improved [1]. The decision-making units with an efficiency less than 1 can be improved by better utilization of the input values and obtaining higher quality outputs. For each inefficient unit, it is necessary to determine a reference set that makes at least one of all efficient decision-making units and dual values associated with the units in that set. Table 3 presents a report obtained using the "DEA Excel Solver" user program into which the values from Table 1 are imported.

The reference set for DMU 1 is {VII} and the value of the dual variable associated with them {0.9375}. The reference set for DMU IV is (XI) and the dual variable value is {0.9166}. Using a dual variables reference set, a complex decision-making unit is formulated. When the input (output) vector of the decision-making unit from the reference set and the ideal price as weight coefficients are multiplied, the average input vector (output) for a given unit is obtained. The sensitivity report is given with "DEA Excel Solver". As an example, DMU 8 will be used. The report from the sensitivity analysis is presented in Fig. 1.

The average input vector of the composite unit is obtained of DMU {VII} and DMU {XI} as shown in the above report. This is calculated as follows:

$$0.4744 \cdot \begin{bmatrix} \mathbf{9} \\ \mathbf{7} \end{bmatrix} + 0.2007 \cdot \begin{bmatrix} \mathbf{6} \\ \mathbf{8} \end{bmatrix} = \begin{bmatrix} \mathbf{5.47} \\ \mathbf{4.92} \end{bmatrix}$$

The average output vector of a composite unit is calculated as follows:
$0.4744 \cdot [\mathbf{1.6}] + 0.2007 \cdot [\mathbf{1.2}] = [\mathbf{1}]$

If we compare these vectors with the inputs (outputs) of the DMU VIII in Table 1, it can be noticed that the composite unit achieves the same output for lower values of the input values. Input 1 (the number of pickers) as well as input 2 (the average time of picking) should be reduced by 45.3% to make the observed decision-making unit effective. Table 4 below shows the results of the "DEA Excel Solver" with newly imported inputs.

Table 3

Efficiency of the user program "DEA excel solver" report

Decision Making Unit		**Input-oriented model**	**Sum λ**	**Reference assemble and dual variable**			
Serial number	**Name**	**Efficiency**					
1	I	0.8202	1.8750	0.9375	VII	0.9375	VII
2	II	0.9642	1.2856	0.6428	VII	0.6428	XI
3	III	0.8747	1.75	0.8750	VII	0.8750	VII
4	IV	0.6111	1.8332	0.9166	XI	0.9166	XI
5	V	0.7775	2	1	VII	1	VII
6	VI	0.7366	0.7856	0.3928	VII	0.3928	XI
7	VII	1	1.0000	1.0000	VII		
8	VIII	0.5474	0.6751	0.4744	VII	0.2007	XI
9	IX	0.6587	0.8344	0.7466	VII	0.0878	XI
10	X	0.8614	2.125	1.0625	VII	1.0625	VII
11	XI	1	1.0000	1.0000	XI		
12	XII	0.9375	1.875	0.9375	VII	0.9375	VII

Table 4

Newly imported input values for the desired output

	Input variables		**Output variable**
Decision making units (DMU)	**Number pickers**	**Average Time of picking [min]**	**Annual income [millions of euros]**
Warehouse 1	8.43	6.56	1.5
Warehouse 2	9.64	9.64	1.8
Warehouse 3	7.87	6.12	1.4
Warehouse 4	5.50	7.33	1.1
Warehouse 5	9	7	1.6
Warehouse 6	5.89	5.89	1.1
Warehouse 7	9	7	1.6
Warehouse 8	5.47	4.92	1
Warehouse 9	7.24	5.92	1.3
Warehouse 10	9.56	7.43	1.7
Warehouse 11	6	8	1.2
Warehouse 12	8.44	6.56	1.5

Microsoft Excel 16.0 Sensitivity Report
Worksheet: [Sensitivity analysis - DMU 8.xlsx]Sheet1
Report Created: 12/28/2019 10:26:59 PM

Variable Cells

Cell	Name	Final Value	Reduced Cost	Objective Coefficient	Allowable Increase	Allowable Decrease
C28	v1	0.080291971	0	0	2.40740741	0.76388889
D28	v2	0.02189781	0	0	0.6875	2.16666667
E28	u1	0.547445255	0	1	1E+30	1

Constraints

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
C30	limitations	1	0.547445255	1	1E+30	0.99543333
C31	limitations	0.237226277	0	0	0.23722628	1E+30
C32	limitations	0.03649635	0	0	0.03649635	1E+30
C33	limitations	0.350364964	0	0	0.35036496	1E+30
C34	limitations	0.383211679	0	0	0.38321168	1E+30
C35	limitations	0.445255474	0	0	0.44525547	1E+30
C36	limitations	0.215328467	0	0	0.21532847	1E+30
C37	limitations	-7.7716E-16	-0.47445255	0	0.09954333	0.05747126
C38	limitations	0.452554745	0	0	0.45255474	1E+30
C39	limitations	0.368613139	0	0	0.36861314	1E+30
C40	limitations	0.310218978	0	0	0.31021898	1E+30
C41	limitations	-5.5511E-16	-0.20072993	0	0.305175	0.05586592
C42	limitations	0.054744526	0	0	0.05474453	1E+30
C43	limitations	0.080291971	0	0.0001	0.08019197	1E+30
C44	limitations	0.02189781	0	0.0001	0.02179781	1E+30
C45	limitations	0.547445255	0	0.0001	0.54734526	1E+30

Fig. 1. The sensitivity analysis report for DMU 8

4. CONCLUSION

It can be concluded that the DEA method is one of the most often used to calculate the efficiency of Decision-Making Units (DMUs). In this paper, the DEA method was used to evaluate the efficiency of the twelve warehouses marked as DMUs.

The authors of this paper came to the conclusion that not many of these operated efficiently. The most efficient DMUs are DMU 7 (warehouse 7) and DMU 11 (warehouse 11), with maximal efficiency equal to one. The others operate in an acceptable range, but little changes have had to be done to improve efficiency.

To achieve desirable outputs, the input variables had to be corrected. After the input variables are corrected, as shown in Table 4, all the DMUs will operate efficiently.

If the DMU1 and DMU2 are taken into consideration, in the beginning (Table1), it can be noticed that the number pickers was eleven and ten, while the average time of picking was eight and ten, respectively. After applying the DEA method, the following changes have noticed. In warehouse 1, the number of pickers should be reduced from 11 to 8.43, while the average picking time should be reduced from 8 to 6.56 minutes. After the correction, DMU1 will be able to operate with maximal efficiency. For DMU2, the number of picking workers should be decreased from 10 to 9.64 and the average picking time from 10 to 9.64 as well. After the correction, warehouse 2 will be able to operate efficiently.

As can be noticed, the number of pickers is 8.43 and 9.64. In reality, it is not possible to have 0.43 or 0.64 workers. In such a case, the recommendation of the authors of this paper is to employee the people under contract that will temporarily solve the problem in such situations, that is, maintain and fulfill the output parameters.

The main objective of the paper was to address the importance of the DEA method as an effective tool that can be used in logistics to evaluate the efficiencies of the logistics business units. Due to its flexibility in solving different types of problems, it shows good potential for use in logistics and supply chains. The advantage of this method is that it can precisely determine the inefficient decision-making unit as well as determine which input parameters should be improved to reach a suitable output.

The future recommendations and directions should be to apply the DEA method in combination with some other parametric or non-parametric techniques to evaluate the efficiency of some other logistics entities. The method is very efficient and other authors are encouraged to examine some of the inefficient logistics processes to increase efficiency and profitability.

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