# Agricultural Route Efficiencies, based on Data Envelopment Analysis (DEA)

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*Abstract: Agriculture is one of our most critical industries, since it provides food. The large size of the agricultural land implies that the treatment of the land must be performed efficiently by mechanization - ground, aircraft or drone (agricultural aircraft are used in this research). Land processing should be done in multiple routes to treat all plots due to the limited capacity of the aircraft. One set of routes needed for treatment of all plots on one agricultural land forms one processing plan. Suppose that we have several different processing plans generated intuitively or by using an exact or heuristics algorithm, the research question is which one to choose to efficiently treat the agricultural land divided into plots. We propose application of Data Envelopment Analysis (DEA) method for selecting efficient processing plans and selecting and scheduling the efficient routes within a plan, to ensure sustainability of the land treated. The first goal of this paper is to select a relatively efficient processing plan (from the predetermined set of plans) using the Data Envelopment Analysis (DEA) approach and to analyze relatively inefficient ones. The second goal of the application of DEA method is the selection of efficient routes within one efficient processing plan. Input and output variables are selected based on the analyzed problem's specific characteristics and the previously published research. As a result, relatively efficient plans and routes are selected, and relatively inefficient ones are further analyzed to improve their performance by changing the inputs and/or outputs.*

*Keywords: agricultural land processing; route planning; efficiency evaluation; Data envelopment analysis*

# 1 Introduction

Making agriculture more sustainable is a required aspect of every business activity related to that sector. The agriculture production consists of several conflicting resources [1] and the quality of the arable land decreases, and the human population increases; thus, many landscapes will be transformed into agricultural land.

The existing and future arable surface must be processed effectively and efficiently in order to be utilized and preserved for future use. Problems of evaluation and analysis of efficiency in the agriculture sector are often solved. Data Envelopment Analysis (DEA) is a commonly used technique for efficiency analysis [2]. DEA is suitable for the evaluation of agricultural production since it is a complex system with multiple inputs and outputs [3]. This research aims to select efficient routes and processing plans for agricultural land treatment using the DEA method. The motivation for this study arises after solving the vehicle routing problem in the treatment of agricultural land (agricultural land divided into plots) using agricultural aviation [4]. In order to solve the formulated problem, authors applied the exact or heuristics methods and the application of these method(s) resulted in processing plans. The processing plan represents a set of routes that an agricultural aircraft executes for treatment [4]. The greedy-based constructive heuristics developed by Andric Gusavac et al. [4] for solving large-scale problems can produce several production plans in multiple runs. The main issue is which of those plans is the most efficient regarding the multiple criteria. Furthermore, management could be faced with the problem of selecting and scheduling the land treatment routes within one processing plan. Therefore, to ensure the treated agricultural land's sustainability, we proposed the DEA method for selecting efficient processing plans and selecting and scheduling the efficient routes within a plan.

Main contribution of this paper is enabling the application of decision-making in the solving of the routing problem based on more than one criterion. Given that it is possible to obtain multiple set of routes (processing plans) for a certain dimension of the routing problem, the DEA method has proven to be extremely useful, because its application, based on several criteria, leads to the selection of efficient processing plans from a set of generated (exactly or by heuristics) plans. It is recognized that in a set of routes, efficient routes can also be identified, and ineffective ones can be analyzed to achieve their efficiency.

This paper is structured as follows: the DEA method is presented briefly in the second chapter, followed by the third chapter, where a detailed explanation of the problem is given. The proposed problem in this chapter is divided into two levels and solved consecutively. Concluding remarks and future research proposals are given in the last chapter of the paper.

# 2 Literature Review

The development of DEA method for evaluating efficiency made it possible to include, at the same time, multiple inputs, or multiple outputs into the analysis. The basic DEA model, defined in [2] was first used to measure the efficiency of non-profit sector. Today, DEA methods, either alone or in combination with other methods, is often applied to other areas, with diverse production inputs and outputs

[5][6]. Authors Andrić Gušavac and Savić [7] give a detailed review of the application of DEA method in agricultural land processing. Most of the papers presented in [7] examine technical efficiency and co-efficiency, and the lack of studies dealing with route efficiency in agriculture can be noticed.

Papers related to the problems of evaluation and comparative analysis of agricultural efficiency are commonly dealing with the efficiency assessment of bus transportation [8-11] and air routes performance [12]. The DEA method has been used since the early 1990s to compare outcomes in public transport areas [8]. In their research, the authors Singh et al. [8] assess the efficiency of the bus routes to determine efficient and inefficient routes using the DEA method. Performance evaluation of electric trolley bus routes is researched in [13]. Authors in [14] aim to show and test a developed model for determining the optimal transport route among alternatives, where the solution is a green route obtained by using DEA method.

For the DEA method to be well applied, it is necessary to perform a good selection of the Decision-Making Unit (DMU) and input and output criteria (performance indicators). Literature review where input and output variables for the evaluation of the DMU in the analyzed published papers are shown in Table 1.

Table 1

Review of the application of DEA in the evaluation of route efficiency

| References | Inputs | Outputs |
|---|---|---|
| [13] | Fleet size. Man-hours, Electricity | Number of vehicle-km<br>Trips |
| [14] | Transport costs, External costs<br>Transport time | Given distance of transport route |
| [8] | Bus route length | Population along the bus route,<br>Social priority points |
| [10] | Phase 1 inputs:<br>Route length, Number of stops, Bus overlapping, Route directness, Metro overlapping<br><br>Phase 2 inputs:<br>Peak operation speed, Off-peak operation speed | Intermediate outputs:<br>Residential coverage, Bus connectivity, Employment coverage, Metro connectivity<br><br>Phase 2 outputs:<br>Annual average daily ridership |
| [11] | Fuel cost per bus per day,<br>Labor cost per bus per day,<br>Operating expenses | Profit and Average passengers per bus per day, Emission metric |
| [9] | Route distance, Number of buses,<br>Fuel consumption | Unlinked passenger trips |
| | Distance, Travel time, Service, Frequency, Deviation from shortest distance, Stops per km | Unlinked passenger trips |

Most published research of routes performance for airlines consider companies as DMUs and not routes; therefore, in these cases insight into the various operation route problems may be lost. Not many published papers deal with air routes efficiency, this topic is analyzed in paper by authors Shao and Sun [12]. For this research, it is important to outline the analysis of routes in air transport, so the input and output variables used in the analysis in this paper dealing with airline routes are presented in Table 2.

Table 2

Selected input and output variables for air transport

| References | Inputs | Outputs |
|---|---|---|
| [12] | Input of allocation stage:<br>Number of flights<br>Inter-phase measures:<br>Available seats, Available tonnage | Passenger transport function output:<br>Passenger throughput<br>Freight transport function output:<br>Mail and cargo throughput |

Route length is most often used as input factor in public urban transport in the literature [8-10], as well as fuel costs [9] [11] [15] [16].

# 3 Materials and Methods

DEA [2] was first introduced for measuring the relative efficiency of non-profit organizations. These organizations are called Decision-Making Units (DMUs) and whose performance depends on multiple inputs and outputs. Application areas of the DEA method are later expanded to a wide range of areas.

DEA determines the efficiency rate of each DMU$_k$ ($k$=1,...,$m$).It is important to notice that the efficiency of each decision-making unit (DMU) is measured in relation to the other decision units so the obtained efficiency measure is relative. Every unit produces s outputs, while consuming n inputs, where the values of inputs $x_{jk}$, ($j$=1,...,$n$) and outputs $y_{rk}$ ($r$=1,...,$s$) for each DMU$_k$ are given. An output-oriented DEA model is used in this research to determine the relative efficiency of each processing plan and each route, assuming constant returns-to-scale (CRS) [17]:

$$\min h_k = \sum_{j=1}^{n} v_j x_{jk} \tag{1}$$

*subject to:*

$$\sum_{r=1}^{s} u_r y_{rk} = 1 \tag{2}$$

$$\sum_{j=1}^{n} v_j x_{jp} - \sum_{r=1}^{s} u_r y_{rp} \geq 0,\ p = 1,...,k,...,m \tag{3}$$

$$v_j \geq \varepsilon,\ j = 1,...,n \tag{4}$$

$$u_r \geq \varepsilon,\ r = 1,...,s \tag{5}$$

where: $v_j,\ j = 1,...,n$, weights assigned to $j^{\text{th}}$ input; $u_r,\ r = 1,...,s$, weights assigned to $r^{\text{th}}$ output and $h_k$ is relative efficiency score of DMU$_k$.

In order to perform mutual comparison of all relatively efficient units, a modified DEA model can be used. This model, proposed by Andersen and Petersen [18] enables the ranking of relatively efficient units, i.e., assessment of super-efficiency. Modification of the primary model implies that, from the set of constraints given by relation (3) in model (1-5), those constraints that correspond to DMU$_k$ are omitted. The form of these constrains is now:

$$\sum_{j=1}^{n} v_j x_{jp} - \sum_{r=1}^{s} u_r y_{rp} \geq 0,\ p = 1,...,m, p \neq k \tag{6}$$

These modified output-oriented DEA models enable the ranking of the efficient units similarly as inefficient based on an efficiency index greater or equal to 1.

The formulated model is solved using DEA Solver software [19] and at the end, analysis and results interpretation is performed.

# 4 Processing Plan and Route Efficiency Analysis using DEA Method

Let us suppose we have one agricultural land divided into plots and that one agricultural operation of chemical treatment must be processed on all the plots. Multiple routes have to be generated because an agricultural aircraft cannot treat all the plots in only one route due to the predefined capacity. The set of routes needed for all plots treatment forms one processing plan. The different processing plans can be generated intuitively or by using an exact or heuristics algorithm for solving the vehicle routing problem. For example, a specific cost minimization vehicle routing problem for aircraft processing of land agricultural land divided into plots is formulated by [4]. The performance measures for each plan can be calculated based on the obtained solution. In the real-world application, the decision-maker needs to determine the order of routes performing and make their schedule. This problem is, by definition, classified as a combinatorial problem that is difficult to solve. It became even more difficult in the presence of several input and output performance indicators. Furthermore, we already mentioned that special heuristics proposed in [4] could produce multiple processing plans by varying parameters in multiple runs. Those plans differ from the multiple criteria perspectives, such as performance indicators of total route length or total capacity usage. Thus, the necessity for criteria balancing and plans comparison arose.

Therefore, two research questions arise. The first research question: considering the possibility to generate multiple processing plans for one agricultural land, which processing plans from the observing set are relatively efficient based on multiple input and output criteria? The second research question: what is the relative efficiency of routes from one processing plan covering all plots? The answers to those questions are found by using the DEA method. Based on the previously stated, the efficiency evaluation by the DEA method is carried out through two steps, preceded by the preparation of the data and followed by the application of the obtained solution. The procedure of addressing the afore stated problem is presented in Figure 1.

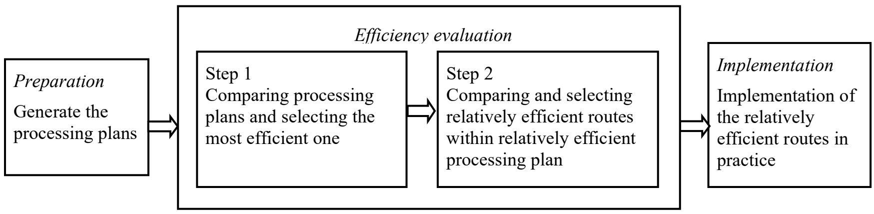


Figure 1
Procedure of processing plans and routes efficiency evolution in agriculture

For the first phase, the preparation of the data, the results (processing plans obtained by exact or heuristics methods) from the study conducted in [4] are used. These processing plans represent a set of routes that an agricultural aircraft executes for treatment. This phase is not in the focus of this paper; thus, a more detailed explanation of this step can be seen in [4].

Efficiency evaluation is conducted through two steps (Figure 1) When the processing plans are prepared, the first step in the application of the DEA method is to compare multiple plans that address the same problem and determine relatively efficient plans. In research presented in this paper, we used processing plans obtained in [4]. The full ranking of the relatively efficient plans can also be determined by applying the super-efficiency DEA model. In this way, the most efficient plan can be selected from a set of several solutions (relatively efficient processing plans), and it can be applied in practice in the last implementation phase. Relatively inefficient processing plans can be analyzed to perceive the necessary changes to values of inputs and/or outputs that need to be made for these plans to become relatively efficient as well. The next step is to compare the routes within one efficient plan using the DEA method (note: the DEA method can be applied for route selection to any processing plan from step 1). It is now possible to select relatively efficient routes that are part of a single plan, thus selecting the routes to be performed first in practice. After that, relatively inefficient routes can be analyzed to single out inputs and/or outputs of these routes whose values could be changed, and the relative inefficient routes could become relatively efficient.

For Step 1 in the proposed procedure of DEA application, the selected DMUs are processing plans, and in step 2, proposed DMUs are individual routes. The selection of input and output variables for the evaluation of the DMUs in each step is based on specifics of the problem itself and literature review where inputs and outputs in the analyzed published papers are shown in Table 1.

## 4.1. Selection of Relatively Efficient Processing plans

### 4.1.1 Input and Output Selection and Data Generation

In order to compare processing plans (processing plans are selected as DMUs) and select the relatively efficient ones for the application of DEA method, inputs proposed [7] are: (1) Total available capacity of all aircraft (in liters) - input 1; (2) Total cost of treatment of all plots (in monetary units) - input 2.

The aircraft (fuel tank) capacity is important because it determines the total length of flight. Total cost of treatment of all plots is the sum of total cost of aircraft flying throughout all the routes (for each route: from the airfield to the first plot in a route, flying between all plots in the routes, from the last plot in a route to the airfield and the cost of treatment of each plot).

Output variables that are proposed in this paper are:

(1) Total used capacity of all aircraft (in liters) - output 1
(2) Percentage share of effective flight in the total distance travelled [%] - output 2.

The total used capacity of all aircraft is calculated as the sum of individual capacities of all engaged aircraft, and the percentage share of effective flight in the total distance travelled is calculated as the sum of effective flight in each route in the processing plan. Effective flight is the flight of an aircraft that adds value, meaning that this part of the flight is only the part when the aircraft is flying over the plot and executing treatment. Input and output variables are selected based on the characteristics of the analyzed problem and based on the previous published research [9].

A total of 19 processing plans are generated by heuristics presented in the paper by Andric Gusavac et al. [4]. Each run of heuristics solves the instance with 100 plots and a maximum of 21 available aircraft. The number of plots to be treated is selected as a constant input parameter, and the parameter that varies is the number of aircraft used for plots treatment. As a result, obtained processing plans are considered as DMUs and their efficiency is evaluated in Step 1 (Figure 1).

Descriptive statistics for input data for the numerical example solved by the DEA method is shown in Table 3. Input 1 is obtained as the sum of the capacity of each available aircraft. The total cost of treating all plots represents the costs of treating all routes within the processing plan. The total used capacity of all aircraft is the sum of the capacity of each engaged aircraft, and the percentage share of effective flight in the total distance travelled is the sum of effective flight in each route plan. Effective flight is the flight over the plots when the aircraft is processing the plots and does not include the inter plot flight and flight between the airfield and the plots.

Table 3

Descriptive statistics for processing plans

| | **Input 1** | **Input 2** | **Output 1** | **Output 2** |
|---|---|---|---|---|
| Average | 6273.68 | 17171.20 | 4065.79 | 57.57 |
| Max | 8100.00 | 18357.00 | 4750.00 | 60.02 |
| Min | 4300.00 | 16461.10 | 3600.00 | 53.82 |
| St Dev | 1115.01 | 438.81 | 319.15 | 1.41 |
| Correlation | | | | |
| *Input 1* | 1 | 0.3636 | 0.06144 | -0.3652 |
| *Input 2* | | 1 | 0.87089 | -0.9994 |
| *Output 1* | | | 1 | -0.8753 |
| *Output 2* | | | | 1 |

### 4.1.2 Results Discussion

Software tool DEA-Solver-LV 8.0 [19] is used for solving the described example and the obtained values – the relative efficiency of processing plans is presented in Figure 2.

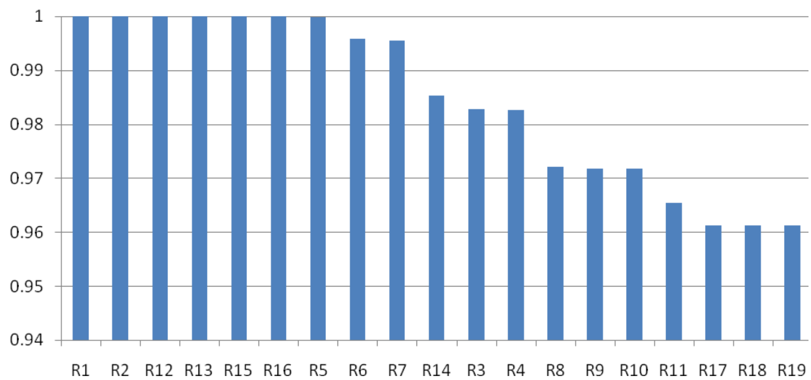


Figure 2

Relative efficiency of processing plans

Based on the obtained relative efficiency of the processing plans, it is possible to identify which inputs and/or outputs of relatively inefficient processing plans need to be reduced and/or increased for these plans to become relatively efficient. These possible changes for inputs and outputs are given in Table 4.

Table 4
Projection for input and output parameters for processing plans

| DMU | Input 1 | | Input 2 | | Output 1 | | Output 2 | |
|---|---|---|---|---|---|---|---|---|
| | Parameter | Projection | Parameter | Projection | Parameter | Projection | Parameter | Projection |
| R1 | 4300 | 4300.0 | 17203.9 | 17203.9 | 4300 | 4300.0 | 57.43 | 57.4 |
| R2 | 4650 | 4650.0 | 16461.1 | 16461.1 | 3600 | 3600.0 | 60.02 | 60.0 |
| R3 | 4900 | 4900.0 | 16950.3 | 16950.3 | 3900 | 3967.8 | 58.29 | 59.3 |
| R4 | 5100 | 5100.0 | 16950.3 | 16950.3 | 3900 | 3969.3 | 58.29 | 59.3 |
| R5 | 5250 | 5250.0 | 17133.1 | 17133.1 | 4250 | 4250.5 | 57.67 | 57.7 |
| R6 | 5500 | 5500.0 | 17118.3 | 17118.3 | 4200 | 4217.4 | 57.72 | 57.9 |
| R7 | 5700 | 5700.0 | 17118.3 | 17118.3 | 4200 | 4218.9 | 57.72 | 58.0 |
| R8 | 5850 | 5850.0 | 17156.8 | 17156.8 | 4000 | 4114.4 | 57.59 | 59.2 |
| R9 | 6100 | 6077.6 | 17156.8 | 17156.8 | 4000 | 4116.1 | 57.59 | 59.3 |
| R10 | 6300 | 6077.6 | 17156.8 | 17156.8 | 4000 | 4116.1 | 57.59 | 59.3 |
| R11 | 6450 | 5227.9 | 16919.5 | 16919.5 | 3700 | 3832.8 | 58.39 | 60.5 |
| R12 | 6700 | 6700.0 | 17156.4 | 17156.4 | 4300 | 4300.0 | 57.59 | 57.6 |
| R13 | 6900 | 6700.0 | 17156.4 | 17156.4 | 4300 | 4300.0 | 57.59 | 57.6 |
| R14 | 7050 | 5506.6 | 16858.1 | 16858.1 | 3850 | 3906.9 | 58.61 | 59.5 |
| R15 | 7300 | 7300.0 | 18357.0 | 18357.0 | 4750 | 4750.0 | 53.82 | 53.8 |
| R16 | 7500 | 7500.0 | 18357.0 | 18357.0 | 4750 | 4750.0 | 53.82 | 53.8 |
| R17 | 7650 | 5415.0 | 17014.3 | 17014.3 | 3750 | 3900.9 | 58.07 | 60.4 |
| R18 | 7900 | 5415.0 | 17014.3 | 17014.3 | 3750 | 3900.9 | 58.07 | 60.4 |
| R19 | 8100 | 5415.0 | 17014.3 | 17014.3 | 3750 | 3900.9 | 58.07 | 60.4 |

It is interesting to notice that only input 1 needs to be reduced so the relatively inefficient processing plans become relatively efficient. The reduction is from 0.37-3.53% for the processing plans R9, R10 and R13, and greater reduction needs to be done for processing plans R11, R14 and R17-R19, where the reduction is from 18.9-33.1%.

For the six relatively efficient DMUs (R1, R2, R12, R13, R15 and R16) no changes for the parameters' values are needed and the difference between the real and the projection value is zero. In order to make relatively inefficient DMUs efficient, it is possible to influence the real values of these parameters (output 1 and 2) and change them to the values given in Table 4 (increase to the projection values). These changes for outputs 1 and 2 are at maximum 4.0%.

Input 2 (total treatment cost of all plots within one treatment plan) does not need to be changed to make the treatment plan relatively efficient, and input 1 (available capacity of all aircraft) can only be reduced for eight relatively inefficient plans (out of 13) for these plans to become relatively efficient. Outputs have a much greater impact, as expected, given that an output-oriented DEA model is applied.

## 4.2. Ranking of the Relatively Efficient Processing Plans based on Super-Efficiency

As can be seen in Figure 2, six of 19 processing plans have an efficiency index equal to 1. This is the result of a flexible choice of weighting factors in the DEA method that favored aircraft capacity utilization as an output parameter. Using a DEA model for super-efficiency assessment (given in Section 2), the analysis was re-done to rank efficient DMUs (Figure 4).

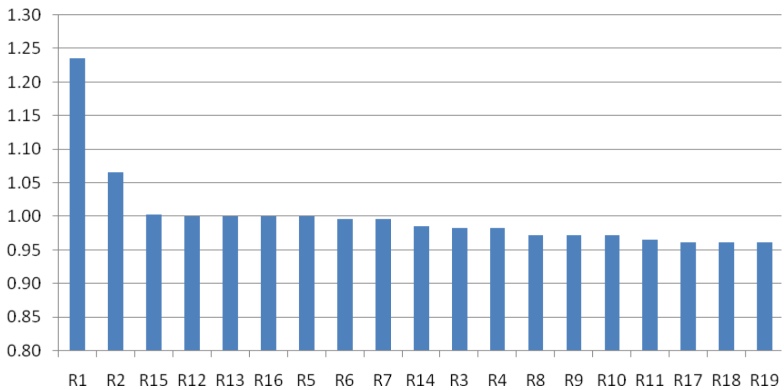


Figure 4
Super efficiency of processing plans

Figure 4 shows that two plans R1 and R2 have a super-efficiency index higher than 1 and processing plan R1 stands out in relation to other plans. The first-ranked plan R1 was singled out as the best solution, considering that real and relevant data were used for experiments in the analysis and the data from this processing plan will be used in further analysis to select relatively efficient routes within one processing plan.

## 4.3. Selection of Relatively Efficient Routes within One Processing Plan

### 4.3.1 Input and Output Selection and Data Generation

Now, when one super-efficient processing plan is selected, it is necessary to compare the routes within that one plan and to select relatively efficient routes. For the next phase of DEA application, the first ranking processing plan R1 is chosen–

it is an example, with 100 plots and 21 available aircraft. For detailed explanation of the processing plan structure see [4].

When a set of routes which need to be performed in order to finish a treatment of the land is determined, DEA is applied, and relatively efficient routes are selected. In order to process the whole agricultural land with chemical treatment, it is necessary to perform all the routes within one processing plan. The question that arises here is which routes should be performed first. The answer could be found in routes efficiency evaluation.

In the approach proposed here for the evaluation of route efficiency within one processing plan, the classical output-oriented CCR DEA model is used, and the proposed input and output variables for the application of the DEA method are given below:

- Input variables: Input 1 - Aircraft capacity (in liters)
  Input 2 - Total cost of plot treatment in the route (in monetary units)

- Output variables: Output 1 - Total treated surface area of all plots in the Route [acre]
  Output 2 - Percentage share of effective flight in the Total distance travelled [%]

Aircraft capacity represents the total available capacity of the aircraft fuel tank. It comprises the total distance of one aircraft flight. Total cost of treatment in the route comprises of the total cost of flying the aircraft from and to the airport, the cost of the realized flight between all plots in the route, and the cost of flying over each plot in the route during its treatment.

Table 5

Descriptive statistics for routes within processing plan

| | **Input 1** | **Input 2** | **Output 1** | **Output 2** |
|---|---|---|---|---|
| Average | 204.76 | 819.23 | 47.05 | 56.12 |
| Max | 250.00 | 1400.20 | 95.00 | 70.30 |
| Min | 150.00 | 307.30 | 16.00 | 43.05 |
| St Dev | 40.55 | 289.41 | 20.83 | 6.94 |
| Correlation | | | | |
| *Input 1* | 1 | -0.3348 | -0.4401 | -0.5001 |
| *Input 2* | | 1 | 0.96809 | 0.53487 |
| *Output 1* | | | 1 | 0.71107 |
| *Output 2* | | | | 1 |

The total treated surface area of plots in the route represents the total sum of the surface area of all plots in the considered route. In order to treat all plots in one route, the aircraft must fly from the airport to the first plot in the route, fly between each plot in the route and fly from the last plot in the route to the airport. Only the part of the flight related to plot treatment in the route is effective flight and this is the reason that Percentage share of effective flight in the total distance travelled is chosen as output 2. Descriptive statistics (maximum and minimum values, average values and standard deviation) and correlation analysis are shown in Table 5. The example was solved for an instance of the following dimensions: 21 aircraft and 100 plots. The obtained solution - the processing plan includes 21 routes that cover (treat) all the plots.

### 4.3.2 Results Discussion

Software tool DEA-Solver-LV 8.0 [19] is used for solving the described example and the obtained values – relative efficiency of routes in one processing plan are presented in Figure 4.

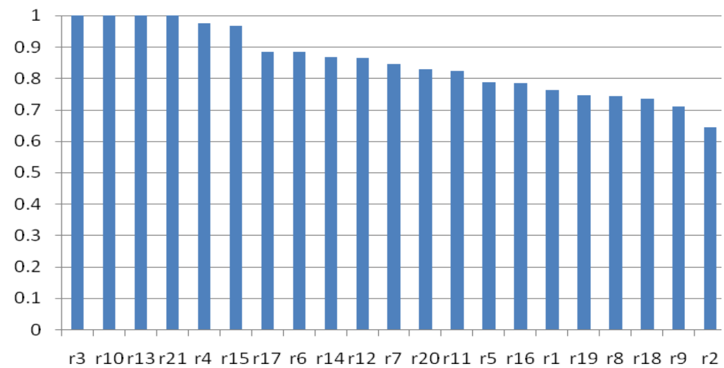


Figure 4

Relative efficiency of routes

Based on obtained results, four routes are relatively efficient and 17 are relatively inefficient. These results can be used for efficient scheduling, where the relatively efficient routes can be scheduled first in practice, and for the inefficient routes some further analysis can be done. It is possible to identify which inputs and/or outputs of relatively inefficient routes need to be reduced and/or increased as these routes could become relatively efficient. These possible changes i.e., projections are shown in detail in Table 6.

Table 6

Projection for input and output parameters for routes

| DMU | Input 1 | | Input 2 | | Output 1 | | Output 2 | |
|---|---|---|---|---|---|---|---|---|
| | Parameter | Projection | Parameter | Projection | Parameter | Projection | Parameter | Projection |
| R1 | 250 | 169.9 | 1054.3 | 1054.3 | 56 | 73.3 | 53.1 | 69.5 |
| R2 | 250 | 195.2 | 604.0 | 604 | 26 | 40.4 | 43.0 | 66.9 |
| R3 | 200 | 200.0 | 447.1 | 447.1 | 29 | 29.0 | 64.9 | 64.9 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| R4 | 150 | 150.0 | 1085.0 | 1085 | 71 | 74.0 | 65.4 | 66.7 |
| R5 | 250 | 184.6 | 815.0 | 815 | 44 | 55.8 | 53.9 | 68.4 |
| R6 | 200 | 200.0 | 346.1 | 346.1 | 17 | 19.6 | 49.1 | 55.6 |
| R7 | 150 | 150.0 | 1151.4 | 1151.4 | 66 | 79.2 | 57.3 | 67.8 |
| R8 | 250 | 189.0 | 733.2 | 733.2 | 37 | 49.8 | 50.5 | 67.9 |
| R9 | 200 | 197.2 | 552.6 | 552.6 | 26 | 36.6 | 47.0 | 66.3 |
| R10 | 150 | 150.0 | 692.2 | 692.2 | 43 | 43.0 | 62.1 | 62.1 |
| R11 | 250 | 193.2 | 649.7 | 649.7 | 36 | 43.7 | 55.4 | 67.3 |
| R12 | 200 | 171.3 | 1032.9 | 1032.9 | 62 | 71.7 | 60.0 | 69.4 |
| R13 | 200 | 200.0 | 307.3 | 307.3 | 16 | 16.0 | 52.1 | 52.1 |
| R14 | 250 | 186.7 | 775.9 | 775.9 | 46 | 52.9 | 59.3 | 68.2 |
| R15 | 150 | 150.0 | 1400.2 | 1351.3 | 92 | 95.0 | 65.7 | 70.3 |
| R16 | 250 | 170.6 | 1044.3 | 1044.3 | 57 | 72.5 | 54.6 | 69.5 |
| R17 | 200 | 186.5 | 779.8 | 779.8 | 47 | 53.2 | 60.3 | 68.2 |
| R18 | 150 | 150.0 | 830.1 | 830.1 | 39 | 53.9 | 47.0 | 63.8 |
| R19 | 250 | 184.2 | 822.2 | 822.2 | 42 | 56.3 | 51.0 | 68.4 |

For plans that are relatively efficient, the changes are zero. Projection data for routes' inputs and outputs can help when choosing which route can be realized first in practice and which inputs and outputs can be changed for those routes that are relatively inefficient to become relatively efficient. For routes with an efficiency index less than 1, one can increase the index affecting specific inputs and/or outputs. In this way these routes can become relatively efficient and as such be applied in practice in land treatment.

DEA method provides not only answers regarding the relative efficiency of DMUs, but answers regarding the possible value changes in the input data, which can be used for achieving relative efficiency of relative inefficient DMUs. These possible changes are given in DEA solver report named projection analysis and, in the route selection case, the smallest average change of input and output variables is for the total available capacity of the aircraft input parameter. If the value for this variable is decreased (on average) for 11.36%, then the relatively inefficient routes would become relatively efficient. However, the capacity of the aircraft cannot be reduced by a certain percentage, because the capacity is predetermined, but it is possible to use aircraft with lower capacity. As for other inputs and outputs, the average change for Input 2 is extremely small (about 0.2%), while the average change for outputs is almost 20%. It is possible that these larger average changes are a consequence of the larger distance between the plots, so that the aircraft, in fact, does not have enough fuel capacity to finish the treatment of larger number of plots in one route. The proposal for overcoming this problem is to group the plots of agricultural land into groups and the aircraft would then consume less fuel on a flight that is not effective, and which involves "idling", i.e., flight between plots to be treated. In this case, the maximum area of grouped plots should certainly be considered, so as not to get into a situation where the plane cannot process a new and larger (grouped) plot in one flight. Another proposal for future research is to analyze solutions when larger capacity aircraft are involved in solving a given problem.

The influence of different parameters related to various processing plans and routes within one plan is analyzed from the aspect of relative efficiency. It is interesting that the average changes in output 1 for routes that are not relatively efficient are almost 20%, and almost 20% is the change in output 2. These parameters indicate that the distances of plots are far from the airfield and that the aircraft spends a large part of the flight on a flight that is not effective. The proposal for overcoming this situation is the introduction of another airfield or moving the existing one closer to the plots that need to be treated.

## Conclusions

This paper examined a specific problem concerning the selection of relatively efficient processing plans and routes involved in Agriculture. The studied problem consists of application of DEA method on the predetermined set of processing plans and its application on the determined set of routes. The solution to the formulated problem is a relatively efficient processing plan and relatively efficient routes within the plan. The method used for the solution process is DEA method, and according to our knowledge and the analysis of the published research, DEA method has not yet been applied to the formulated problem. DEA is an effective and very useful tool for evaluating performance in a wide range of areas that can help management facilitate this process and focus on key Agriculture competencies, as it is shown in this paper, for the route efficiency problem.

The practical benefits of the research presented in this paper, comprises of selection and ranking of relatively efficient processing plans and selection and scheduling of relatively efficient routes. Relatively inefficient plans and routes can be further analyzed to determine the efficient projection of the input and output parameters.

The application of the proposed approach supports sustainable and responsible planning of the agricultural resources' usage. Reducing the emission of harmful gases that directly affect the reduction of the carbon footprint is achieved by applying the obtained solutions, which is of exceptional environmental importance.

Future research can be in evaluation of the efficiency of routes, where it is possible to apply modified DEA models, that would enable, for some of the inputs (e.g., aircraft capacity) to be exogenously fixed. Some inputs or outputs could be included in the efficiency analysis, e.g., the time of treatment of parcels. Introducing restrictions on the significance of certain inputs and outputs is also an interesting directions for future work.

Given the actuality of the application of Unmanned Aerial Vehicles (UAV) in Agriculture, it is very interesting to apply the proposed approach to the problems that are solved by the application of UAVs, in precision agriculture. In that case, the presented approach should be modified and applied in precise Agriculture to drone route efficiencies.

Negative impacts on the environment, such as the emission of harmful gases, can be included when applying the DEA methods, as one of the outputs that would be treated as an unwanted output. In this way, the negative impact of the treatment of agricultural land would be reduced and the efficiency of the processing plans and the routes themselves would be checked both from the point of view of the speed and efficiency of the land treatment (economic effect) and from the point of view of the impact on the environment (ecological effect).

The extensive literature review shows that the use of the DEA method, in agriculture has revealed, an increasing trend in the past decade, due to most developed papers having with practical implications. A big part of this paper presented a practical application, suggesting that the adoption of the DEA method, is widely used in agriculture.

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