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Techniques of Efficiency Measurement in Ecology Research of Forest Management Using Data Envelopment Analysis

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Abstract

The paper deals with non-traditional techniques of efficiency assessment applicable when comparing the environmental management organizations, where their efficiency is not only determined by financial profit but also by the ecological aspect of their business operations. By the application of 'Data Envelopment Analysis' (DEA) the efficiency level was determined for 13 mechanization working units in the forestry. The efficiency of working units was estimated taking into consideration their business results and quantities of hazardous waste produced during their operations. Projections were made of inefficient units against the efficiency frontier, and sources and levels of inefficiency were established. The results show that the DEA may be an extremely useful tool both at a strategic and operational level of decision making in forestry. The paper also shows the advantages and possibilities provided to the management by DEA application, as well as some limitations of this model.

Keywords: Keywords: data envelopment analysis, efficiency, forestry, forestry mechanization, environment, hazardous waste

INTRODUCTION

In Indonesia, forests and forest land cover 2.8 million of hectares or 54% of the total area 81 % of forests are owned by the state, and the remaining are privately owned. The annual production tasks of forest management (the annual allowable cut in state-owned forests is up to 4.9 million m3) are achieved by using of a large number of different types of machinery. According to the data for 2006, the state forestry of Indonesia used about 300 adapted farm tractors, 300 skidders and 30 forwarders [1].

From an ecological point of view, the use of mechanization in forest operations is considered one of the most important stresses on forest ecosystems. These stresses result in direct and indirect damage and disturbance of the features of the key components of forests: soil, water, vegetation, forest fauna, etc. Today, compliance with highly demanding ecological standards in performing forest operations is equally prescribed by the generally accepted international standards in the field of preservation of biodiversity and environmental protection, as well as by the strategic documents of the forestry of RC and by the principles of forest certification. The issues of ecological efficiency of mechanization in performing forest operations were studied by many authors [2] to [9], while the issues of ecological standards in maintaining numerous forestry mechanization have so far not been the subject of professional discussions or research. This was the reason for establishing the quantities of hazardous waste produced in maintaining forestry mechanization within the research of the ecological aspect of planning and performing forest operations. The methodology of DEA was used for the assessment of the efficiency of working units in the forestry taking into consideration their business results as well as the quantities of hazardous waste produced during their operation. By the application of DEA in the assessment of the ecological aspect of the maintenance of forestry mechanization, new techniques which were traditionally not used by forestry for the evaluation of the operational efficiency have been introduced in the research. In recent years, DEA has become largely accepted at the level of production analysis (e.g. comparison of organizational units). For example, DEA was used for the determination of business success of different public and private institutions including banking [10], telecommunication [11], trade [12], iron and steel industry [13], etc.

A comprehensive review of the theory and application of the DEA was given by Cooper at al. [14]. The aim of this paper is the application of DEA in the assessment of the ecological aspect of the management of organizational units in forestry, and in making environmentally responsible business decisions. The assessment of a business and environmental consideration in maintaining forest machinery is an example based on which the research was carried out, and at the same time the possibilities of the application of DEA were shown. By the development and application of the DEA and other models of multiple-criteria decision making, a very powerful support could be provided to the forestry management at a strategic and operational level of decision making.

FORESTRY MECHANIZATION AND WASTE DISPOSAL PROBLEM

In accordance with the Forest Act the Central Forest (CF) manage the state-owned forest. CF mostly rely on their own capacities for felling, processing, skidding, forwarding and wood transportation, as well as for the construction of forest roads. These capacities are organized in 13 mechanization working units (hereinafter MWUs) within CF. According to the data for 2002, CF carried out 57% of timber skidding/forwarding and 29% of wood transportation by their own capacities. The remaining services were carried out by third-party contractors outside CF.

The maintenance of the mechanization of all MWUs is carried out in their own repair shops. Circumstances of a special significance for the relationship forestry mechanization–environment arose as of January 1, 2004 when the Waste Act

[15] came into force prescribing the obligation of due disposal of hazardous and other waste, so that all MWUs of CF had to perform their disposal of all types of waste in compliance with the law. Hazardous waste is particularly harmful for human health and the environment. In the meaning of the subject Act, hazardous waste is any waste containing any of the following characteristics: explosiveness, reactivity, inflammability, irritability, harmfulness, toxicity, infectivity, cancerogenity, mutagenity, teratogenity, exotoxicity, as well as characteristics of oxidation, corrosion and emission of poisonous gases as a result of a chemical reaction or biodegradation. Utility, industry, container, construction, electric and electronic waste and waste vehicles shall be classified as hazardous waste if they have any of the characteristics of hazardous waste. It is estimated [16] that in the RC approximately 200,000 tons of hazardous waste or 45 kg per capita is produced annually.

The law prescribes a considerable number and range of obligations related to management, handling and disposal of hazardous waste. Compliance with these regulations is directly controlled by competent state and inspection authorities. Adverse ecological effects of irresponsible and inappropriate disposal of hazardous waste are almost immeasurable.

There is much proof of serious contamination of water, soil and air by automotive waste disposed of without control. The vehicles (trucks, tractors, forwarders, bulldozers, etc.) and machine devices used in forestry contain a series of hazardous substances: motor and hydraulic oils, antifreeze, cooling fluids, battery, catalyzer, air-condition gas, oil filters, heavy metals, etc., which cause serious damage to the environment and jeopardise human health if disposed irresponsibly. The components of a vehicle body (chassis, superstructure, understructure, etc.) also represent hazardous waste in case they still contain some of the above risk substances or electronic assemblies. Motor oils and oil filters have to be disposed of as hazardous substances. It is well known that one liter of motor oil may contaminate one million liters of drinking water. Motor oils may contain different additives that are especially dangerous for the environment. The tires are the type of waste that needs special care. It takes 100 years and more for a discarded tire to decomposed. Waste tires occupy a large space in temporary waste tire dumps. By organizing separate collection of waste tires, their value can be completely recovered by recycling. To this end the disposal of waste tires in developed countries is strictly forbidden.

Waste, old vehicles and machine assemblies are not utility waste and consequently, they are not the responsibility of utility services. Different solutions are proposed for solving this problem, of which the most environmentally acceptable seems to be the delivery of old vehicles and their parts to specialized firms dealing with disassembly of vehicles and resale of parts. There are also plants for recycling unusable car wrecks. Batteries may contain heavy metals which cause direct damage to the environment and human health. Heavy metals increase the risk of cancer ogenic diseases. Antifreeze is used in large quantities and it is very often forgotten that its discharging in the sewer system or natural water flows causes serious contamination.

METHODOLOGY

To the end of establishing approximate quantities of hazardous waste in MWUs operating within CF, and in order to determine the awareness of general issues related to waste disposal, a Hazardous Waste Disposal Questionnaire was completed in MWUs. All 13 MWUs in CF were covered by the questionnaire. In defining the types of data to be covered by the questionnaire, the experts were consulted. The collection of data was carried out in late 2004. Data processing involved distribution of data, mathematical calculation of the relationship between relevant indicators and graphic visualization of results. The evaluation of efficiency by DEA involved the definition of inputs and outputs for the observed MWUs, their statistical processing and verification, and scaling so as to get the form suitable for analysis. According to the selected criteria the efficiency level of the observed forestry organizational units was determined.

DATA PROCESSING BY DEA

DEA has lately become the main technique in the analyses of productivity and efficiency used in comparing organizations [17], companies/enterprises [18] and regions and countries [19]. It was also applied for determining business efficiency in banking [20], agriculture [21], wood industry [22], school system [23], etc. In forestry DEA was first applied by Rhodes [24]. However, the number of efficiency measurements in forest literature based on non-parametric methods, such as DEA, is still limited. DEA developed by Charnes et al. [25], is a well-known non-parametric method for the assessment of relative efficiency of comparable entities/decision making units (DMU) with different level of inputs and outputs [14]. By linear programming, DEA models determine empiric efficiency frontier (frontier of production possibilities) based on data of used inputs and achieved outputs of all decision making units. Efficiency level is calculated for each production unit, and consequently, efficient and inefficient units may be differentiated. The best practice units, those that determine the efficiency frontier, are rated '1', while the degree of technical inefficiency of other decision making units is calculated based on the difference of their input-output ratio with respect to the efficiency frontier [26]. The analysis is focused on finding the 'best' virtual unit for each actual unit. If the virtual unit is better than the original one, either by achieving higher outputs with the same inputs or by achieving the same outputs with lower inputs than the actual unit, then it is inefficient. The basic assumption is that if a certain unit may produce y outputs with x inputs, the other units should be able to do the same if they work efficiently. While a typical statistical approach (regression analysis) is based on average values, DEA is based on extreme observations, and it compares each production unit only with the best unit. Efficiency is determined relatively with respect to other decision making units in the observed group. In this paper, the basic CCR and BCC models were applied. DEA Solver software was used for solving the problem.

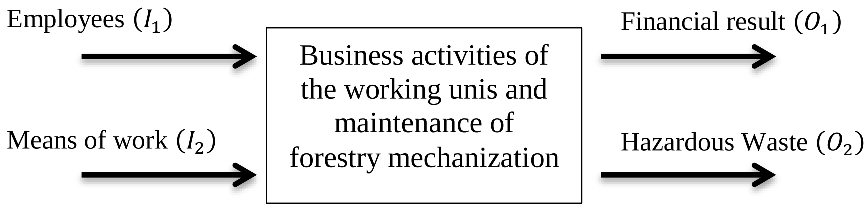

Figure 1: The Inputs, outputs and decision unit for DEA

RESULT

Volume and Content of Hazardous Waste

Generally, forestry does not generate large quantities of waste. Consequently, there is no special reference to forestry in the Waste Regulations of RC, which defines business activities that generate waste. However, some parts of forestry activities are included in some of the 20 main groups of defined business activities. This is also confirmed by the established quantities of waste (Table 1) that, roughly calculated, amount to less than 500 tons on an annual basis, which is a share lower than 0.25% of the total annual quantity of hazardous waste in RC. 420 kg of tires are disposed annually per one machine, as well as 375 kg of solid waste and 109 liters of motor and hydraulic oils. Conspicuous differences can be explained by different structure (e.g. some MWUs also maintain a considerable number of personal vehicles for the needs of the general forestry services), type and/or technical status (year of operating life, good working order, etc.) of mechanization in individual MWUs. A part of these differences is also caused by the way of keeping records on quantities, as it is sometimes based on the calendar year, and sometimes on the delivery cycle of individual types of waste to authorized collectors.

Table 1: Overview of MWUs with basic data

MWUs	Employees	Means of Work	Waste tires	Solid waste	Waste oil
	N	N		Ton	
X_1	106	58	11	3	0.5
X_2	95	48	5	15	4
X_3	88	42	18	10	5
X_4	60	34	5	15	2.5
X_5	95	29	27	2	3
X_6	58	28	23	10	5
X_7	42	22	7	2	2
X_8	35	21	6	10	2
X_9	51	21	9	16.5	4.5
X_{10}	62	20	15.5	2	3
x_{11}	38	19	12.5	16	2
X_{12}	46	15	8	6	3.5
x_{13}	27	10	7	30	3
Total	803	367	154.0	137.5	40.0

Efficiency Evaluation of Mechanization Working Units

In order to determine MWU efficiency by the application of DEA models, it is necessary to define inputs and outputs, to be used as the variables for the analysis. Two variables are selected for both inputs and outputs. The number of employees and the number of means of work are entered into the model as inputs. The total number of employees involves all production workers, administrative staff, technicians and professional management in working units.

The remaining input relates to the total number of machines at the disposal of a working unit (tractors, forwarders, trucks, construction machinery, etc.). Outputs are represented by the quantity of hazardous waste generated in the maintenance of mechanization and by the value of monetary gain/loss incurred by MWUs in the year concerned. Hazardous waste includes the quantities of waste tires, solid waste and waste oils.

The value of monetary gain/loss expresses the financial result of business activities of individual working units. The assessment of efficiency involved all 13 MWUs operating within CF. In the basic DEA models, the number of working units (i.e. decision making units that are compared) has to be at least 2 to 5 times larger than the total number of variables of inputs and outputs. Therefore, the total number of inputs and outputs is restricted to the above four indicators. Figure 1 shows the relationship between inputs and outputs, which are the input for the application of DEA models. According to Farrell [27], relative technical efficiency is the capability of a production unit to achieve maximum outputs for a given set of inputs and technology (output orientation) or, in the other case, to achieve maximum possible reductions in the quantities of inputs maintaining the same output levels (input orientation). In this research the output orientation is more acceptable. It seems wiser to achieve better financial results with the same inputs along with the reduction of the quantities of hazardous waste. Data scaling of quantities of hazardous waste as undesirable outputs will be explained in the following chapter. The assessment of efficiency of MWUs was carried out using the basic CCR and BCC models, which are also the most frequently applied DEA models. The selection of the model depends on the characteristics of data and business activity to be analyzed. If the increase of inputs results in the proportional increase of outputs, then the business activity is characterized by constant returns to scale and CCR model may be used. If the business activity is characterized by variable returns to scale, then BCC model may be used. If there is no a priori idea of the return properties, it is then recommendable to make an analysis with both models and to compare the results. If the results show no large differences, then the volume effect is not relevant and CCR model may be used. If differences are considerable, they may be attributed to the return effect with respect to the range of activities and the BCC model is more suitable for describing the analyzed business activity. 3.2.1 Data Scaling and Initial Results When the model was considered for the first time, input and output data were used in their original, unchanged values. Hence, the impact of structural characteristics of MWUs on the quantity of hazardous waste and financial business results were taken as the basic starting points for the analysis. Table 2 shows input and output rates, as they were originally collected (columns 2 to 5). The first column presents the compared MWUs. The second and third columns show the number of employees and machines of individual MWUs. The fourth and fifth columns show the financial result and quantities of waste, respectively, as the result of work and business activities of MWUs. Negative values of monetary indicators express the financial loss of business activities of MWUs in the year concerned Ecologically more unfavorable results are expressed by higher quantities of hazardous waste as undesirable outputs.

Table 2: Data set of result for input and input factor regarding different working units

DMU	Input		Outputs			
			Unscaled Data		Scaled Data	
	Employees (N)	Means of Work (N)	Financial Result	Waste (ton)	Financial Result (+3500)	Waste, ton (1/t x 10)
1	2	3	4	5	6	7
X_1	106	58	-3359	11	141	0.909
X_2	95	48	561	5	4061	2.000
X_3	88	42	-53	18	3447	0.556
X_4	60	34	-1109	5	2391	2.000
X_5	95	29	-124	27	3376	0.370
X_6	58	28	4409	23	7909	0.435
X_7	42	22	1841	7	5341	1.429
X_8	35	21	-1546	6	1954	1.667
X_9	51	21	-1202	9	2298	1.111
X_{10}	62	20	-3355	15.5	145	0.645
x_{11}	38	19	622	12.5	4122	0.800
X_{12}	46	15	2631	8	6131	1.250
x_{13}	27	10	336	7	3836	1.429

Table 3: Statistics of the scaled data for inputs and outputs involved in DEA Model

	Inputs		Outputs	
	Employees (I_1)	Mean of Works (I_2)	Financial Result (O_1)	Waste (O_2)
Mean	62.77	28.23	3473.23	1.12
Std. Deviation	24.987	13.314	2115.47	0.539
Maximum	106	58	7909	2
Minimum	27	10	141	0.370
Total	803	367	45152	14.600

DEA requires non-negative data for outputs and exclusively positive data for inputs. It is also based on the assumption that the input values improve if their rate decreases, i.e. that the output values improve if their rate increases. It is, therefore, necessary to scale the initial data for two reasons. The first reason is related to eliminating negative values in the observed data. The second reason is to ensure that the entered data involve the characteristic that lower values are preferred with inputs and higher values are preferred with outputs. Both reasons are related to outputs. Input values are positive and they already have this 'lower-value-is-better' characteristic. Data scaling was carried out by the increasing financial results of all MWUs for the same rate in order to obtain a positive value even for the worst results. This was achieved by summing the value of gains/losses of individual MWUs and an arbitrarily large number (3500 in this case). Quantitative data of hazardous waste as undesirable outputs were scaled by taking the inverse of their actual values. In this way higher values became more desirable (meaning in fact lower quantities of hazardous waste), and equal relations were retained as between original data. The last two columns (Table 2) show the data adapted to analysis by DEA method. Possibilities and ways of data scaling for the needs of DEA analysis were described in details by Sarkis and Weinrach [28]. Table 3 presents the statistics of the scaled data for inputs and outputs. Mean values, standard deviation, maximum value, minimum value and total value based on scaled data are shown for each variable.

DEA Model Result

The results of the determination of MWU efficiency by the basic DEA models are presented in Table 4. These results show that the average CCR efficiency achieved in 2004 was 0.608. This means that the average (assumed) MWU, if it wishes to conduct business at the efficiency frontier, has to produce 64.5% more outputs1 with the used input level, i.e. achieve proportionally lower quantity of waste and higher profit. According to BCC model, the efficiency was 0.792 on average, meaning that an average MWU, if it wishes to be efficient, must produce 26.3% more outputs2 (increase of profit i.e. decrease of waste) with the same inputs. Two MWUs are relatively efficient according to CCR model (15.4%), and 7 MWUs (53.8%) according to BCC model. Furthermore, it can be seen that with relatively low mean values, approximately 60% and 80%, respectively depending on the used model (CCR or BCC), the lowest level of relative efficiency ranges between 0.162 (CCR) and 0.387 (BCC). Firstly, this implies that the observed MWUs can decrease the inputs by 39.2% (20.8%), without changing the output levels. And secondly, that there are considerable differences in business and in ecological effects of mechanization maintenance between the analyzed MWUs. Several MWUs are at or near the efficiency frontier, and still approximately 50% of MWUs express inefficiency higher than 40 and 20%, respectively.

Table 4: Result of CCR and BCC models

	CCR model	BCC Model
Number of MWUs	13	13
Efficient MWUs, N	2	7
Efficient MWUs, %	15.4%	53.8%
Relative efficiency, E	0.608	0.792
Maximum	1.000	1.000
Minimum	0.162	0.387
MWUs with efficiency Lower than E, N	6	6

If efficiency is divided by decision making units, a direct comparison may be carried out between individual MWUs. According to CCR model (Fig. 2) X_{12} and X_{13}MWUs were efficient. The efficiency of only one MWU (X_4) is around the average value (E = 0.867), while the remaining MWUs can be divided into two groups, of which one is considerably below the efficiency level, and the other is considerably above the average value with the efficiency of approximately 90%.

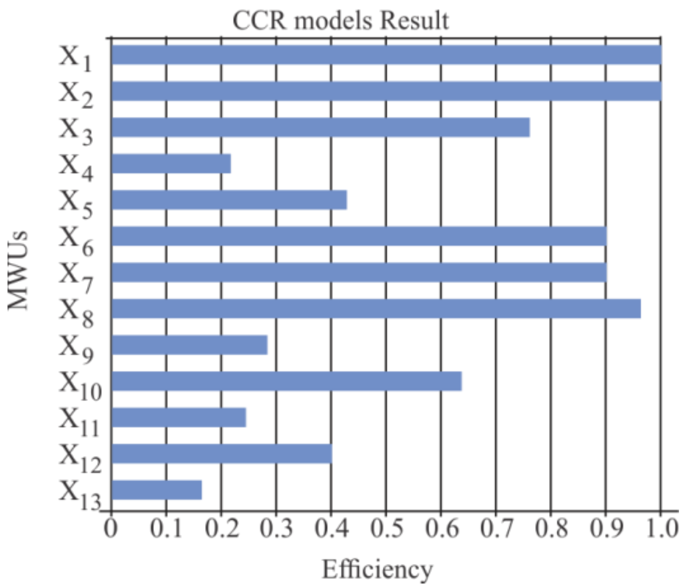

Figure 2: Efficiency of MWUs according to CCR model

Ranking according to BCC model is not as conspicuous (Fig. 3). Indeed, by the application of BCC model, a considerably higher number of observed decision making units becomes efficient, which implies that the model cannot properly identify efficient and inefficient units with the selected inputs and outputs. The problem arises from the number of efficient decision making units (those with the result 1.000).

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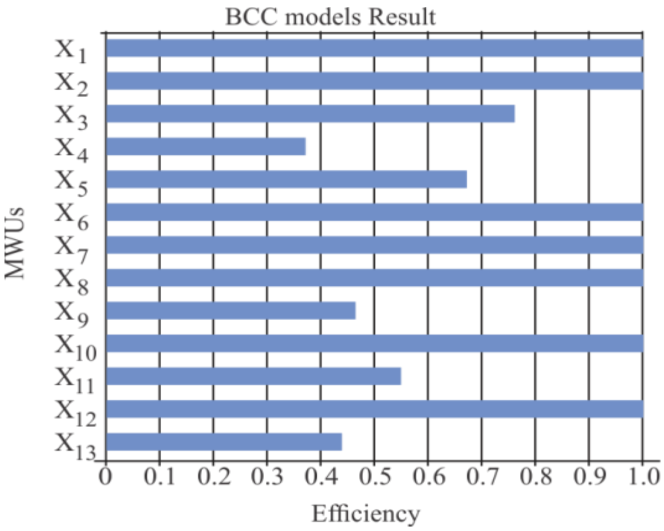

Figure 2: Efficiency of MWUs according to BCC model

In this case, along with the decision making units that are efficient according to CCR model, five more MWUs were assessed as relatively efficient. In total seven MWUs were rated '1'. However, such results, too, may be useful if additional models of decision making are applied, and if the results of DEA analysis are used as the first filter of inefficient decision making units. By the choice of output orientation, the projection path is determined of inefficient decision making units on efficiency frontier. By comparison between empiric and projected values, it is possible to identify the sources of inefficiency as well as their rate. The lower the percentage of the projected input values in empiric values (negative shares), the more important source of inefficiency this input is on the average. The higher the percentage of the projected output values in the empiric output values, the more significant source of inefficiency is this output (Table 5). The results with 0.00% mean that there is no difference between the projected and empiric input and/or output values, i.e. by themselves they are not a source of inefficiency. From Table 5 it can be concluded that the first output O1 (financial gain/loss) has a slightly higher impact on MWU inefficiency than the second output O2 (waste). On average, in the observed period MWUs should have achieved 263.01% more than the achieved quantity of output O1 and 255.93 % more than the achieved quantity of the second output O2, with an inversely expressed value. Similarly, they should have used 98.52% of the used quantities of input I1 and 81.32% of the used quantity of input I2. They would then be CCR efficient. Higher impact of outputs than of inputs on inefficiency, is preset by the choice of the model orientation. The most conspicuous differences between the projected and empiric values of outputs have been recorded with MWUs with the highest quantities of waste and negative financial results of business activities. For obtaining BCC efficiency, it is necessary to realize on average 175.32% more than the achieved quantity of output O1 and 43.39% more than the achieved quantity of output O2. On average, 86.04% of the used quantity of input I1 should have been used and 89.64% of the used quantity of input I2.

Table 5: Data on relative shares projected to empiric value of inputs and outputs

MWUs	CCR Model				BCC Model			
	I_1	I_2	O_1	O_2	I_1	I_2	O_1	O_2
X_1	0.00	-32.31	999.90	516.93	-43.40	-41.38	999.90	120.00
X_2	0.00	-26.70	232.36	151.32	0.00	0.00	0.00	0.00
X_3	0.00	-22.40	262.71	738.10	-44.49	-56.93	90.12	90.12
X_4	0.00	-34.64	256.52	58.73	0.00	0.00	0.00	0.00
X_5	-6.39	0.00	251.10	552.50	-44.36	-22.66	111.70	111.70
X_6	0.00	-23.28	4.19	605.82	0.00	0.00	0.00	0.00
X_7	0.00	-29.29	11.72	55.56	0.00	0.00	0.00	0.00
X_8	0.00	-38.27	154.48	11.11	0.00	0.00	0.00	0.00
X_9	0.00	-10.05	215.31	142.86	-15.01	0.00	49.45	49.45
X_{10}	-12.90	0.00	999.90	342.86	-34.27	0.00	999.90	158.33
x_{11}	0.00	-25.93	30.98	151.32	0.00	-13.75	28.12	34.49
X_{12}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
x_{13}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Together	-1.48	-18.68	263.01	255.93	-13.96	-10.36	175.32	43.39

It should be noted that the projected values may be realized as some MWU covered by the analysis achieved them successfully.

DISCUSSION AND CONCLUSION

This paper provides an insight into additional techniques of efficiency assessment applicable in comparing organizations dealing with environmental management, where their success is not only determined based on financial profits but also on the ecological aspect of business operations. The possibility of an application of DEA is presented from the standpoint of multi-criteria evaluation of environmental and financial efficiency of forestry organizational units. In the example shown in this paper and based on the actual data and use of DEA, we have assessed the ecological aspect of mechanization maintenance and the result of business activities of the working units operating within „Hrvatske šume“ ltd. Zagreb. Based on the obtained results of CCR and BCC models, the projections were determined of inefficient MWUs on the efficiency frontier as well as sources and rates of inefficiency. It has been established that the average efficiency is 0.608 (CCR) and 0.792 (BCC), respectively. Two MWUs are relatively efficient according to CCR model (15.4%) and 7 MWUs (53.8%) according BCC model. Gains achieved or financial losses incurred by individual working units proved to be a slightly more significant source of inefficiency. It is, however, considered that special significance and attention should be paid to maintenance and hazardous waste as the second output compared. The role of maintenance in Quality Management is described in [29].

The determined quantities of hazardous waste and the relation to the environment as the element of business strategy imply that there is no systematic care for the environmental protection at the level of the parent company, and that there is no comprehensive concept of waste management in the majority of MWUs.

Apart from being a relatively new methodology in forestry, the choice of DEA method for the assessment of business efficiency is justified by its suitability for assessing the efficiency of a large number of decision making units. Further to the determination of the most successful decision making units, this procedure also provides valuable insights into the management. Using the best decision-making units as benchmarks, the inefficient can see what changes need to be made in their resources so as to improve their business. It should be emphasized that the projected values are achievable, as they have been achieved by some decision making units covered by the analysis. Efficiency is determined relatively, by comparison of each production unit only with the best one in the group concerned. In this way, by the use of DEA, it is possible to objectively determine the highest possible levels in conducting business for each segment and in total, and also to identify the resources whose use not sufficiently efficient. Furthermore, by such research it is possible to identify the points of possible improvement in conducting business activities, as well as sources of business inefficiency. DEA method can identify the goals, but not give the answer to the question how to achieve these goals. Manager knowledge and experience is required to get the answer to this question.

The main disadvantage of the method lies in the fact that it is sensible to extreme observations and random errors. The basic assumption is that there are no random errors and that all deviations from the efficiency frontier represent inefficiency. The results obtained by 'Data Envelopment Analysis' are very sensitive to the type of input data and data scaling, if required. Along with the selection of the basic model, the determination of input data (determination of inputs and outputs) should be the only subjectivity element entered into DEA. This is the basic limitation in the application of DEA method as the decision-making tool. Analysts, researchers, decision makers should be aware of these limitations, as well as of the limitations of other models. A comparison of the characteristics of DEA and other multiple-criteria decision making models was given by Sarkis and Weinrach [28].

DEA solutions of relative efficiency are in the interest of researchers, executive officers and managers due to the following characteristics of the method:

(i). characterization of each decision making unit by one result of relative efficiency,
(ii). simultaneous processing of more outputs and inputs, where each input and output may be expressed in different measurement units,
(iii). improvements suggested by the model to inefficient decision making units are based on the results achieved by efficient decision making units,
(iv). no knowledge of an explicit connection between inputs and outputs is required.

In this way DEA becomes the new tool of the management for the analysis of relative efficiency of decision-making units in the public sector and enables a new approach to the organization and analysis of data, cost-effective analysis, frontier estimation and theory of learning from the most successful ones.

REFERENCES

[1] Achuthan, N.R., and Hardjawidjaja, A. (2001). “Project scheduling under time dependent costs a branch and bound algorithm”. Annals of Operations Research, 108, 55–74.

[2] Brooke, A., Kendrick, D., and Meeraus, A. (1988). “GAMS - A User’s Guide”. Redwood City: Scientific Press.

[3] Cao, Xiaolin. & Han, Bing. (2002). “Establishment and control of the objective system of construction project management”. Journal of Chongqing University (Natural Science Edition). No.7.

[4] Deckro, R.F., Herbert, J.E., Verdini, W.A., Grimsrud, P.E., and Venkateshwar, S. (1995). “Nonlinear time/ cost trade-off models in project management”. Computers and Industrial Engineering, 28(2), 219–229.

[5] Demeulemeester, E., De Reyck, B., Foubert, B., Herroelen, W., and Vanhoucke, M., (1998). “New

computational results on the discrete time/ cost trade-off problem in project networks”. Journal of the Operational Research Society, 49(11), 1153–1163.

[6] Drud, A.S. (1994). “CONOPT – A Large-Scale GRG Code”. ORSA Journal on Computing, 6(2), 207–216.

[7] Kapur, K.C. (1973). “An algorithm for project cost-duration analysis problems with quadratic and convex cost functions”. AIIE Transactions, 5(4), 314–322.

[8] Möhring, R.H., Schulz, A.S., Stork, F., and Uetz, M. (2001). “On project scheduling with irregular starting time costs”. Operations Research Letters, 28(4), 149–154.

[9] Turnquist, M.A., Nozick, L.K. (2004). “A nonlinear optimization model of time and resource allocation decisions in projects with uncertainty”. Engineering Management Journal, 16(1), 40–49.

[10] Vanhoucke, M., Demeulemeester, E., and Herroelen, W. (2002). “Discrete time/cost trade-offs in project scheduling with time-switch constraints”. Journal of the Operational Research Society, 53(7), 741–751.

[11] Yang, IT. (2005). “Chance-constrained time-cost trade-off analysis considering funding variability”. Journal of Construction Engineering and Management, 131(9), 1002–1012.