EVALUATION OF TRUCK DRIVERS' PERFORMANCE USING DATA ENVELOPMENT ANALYSIS

PETER ZBRANEK

Abstract: *High performance of employees is one of the key conditions for achieving a high performance of the whole organization. Therefore, it is necessary to use an appropriate system of its evaluation. Data Envelopment Analysis, a non-parametric method based on linear programming, combines several inputs and outputs of decision making units into a comprehensive indicator. Although this approach is frequently used to measure efficiency of a set of companies, individual employees could be evaluated in a similar way. In this paper, an input-oriented CCR DEA model with two inputs (working days, fuel), two desired outputs (mileage, number of successful attempts to use technical device in vehicle) and two undesired outputs (hours of idling, number of failed attempts to use technical device in vehicle) was used to rate performance of 219 truck drivers of a transport company. Using this method, 20 efficient and 199 inefficient employees were identified in this organization. An average employee of the company reached 89% of the best employee's performance. Furthermore, an input-oriented superefficiency DEA model was computed to rank performance of efficient employees. Finally, impact of age and years in service on calculated scores was investigated using Tobit regression analysis.*

Keywords: *Data Envelopment Analysis, undesired outputs, technical efficiency, superefficiency, employees' performance, truck drivers*

JEL Classification: *C44, M50*

1. INTRODUCTION

Evaluation of employees' performance is an important task for human resources management. Well-designed and properly used rating systems are therefore necessary for the efficient functioning of any organization ([24]. Several frequently used conventional approaches, however, suffer from a lack of quantitative tools, and thus have a tendency to be influenced by subjective factors which bring various challenges [8]. Therefore, there is a need for the development of new quantitative methods that will improve the evaluation process.

Data Envelopment Analysis is a non-parametric approach to measure the performance of decision-making units using linear programming tools. It is a method allowing a single comprehensive indicator of performance to be calculated for each decision-making unit based on the assessment of several inputs and outputs. This indicator, the technical efficiency score, provides an objective evaluation and the possibility of a consistent comparison of the relative performance of all decision-making units. The aim of the method is to identify decision-making units which produce the greatest amount of outputs while using the smallest amount of inputs. DEA also allows us to quantify how much the individual indicators should improve for the inefficient decision-making unit to achieve the best possible level.

Currently, it is one of the most successful methods of operational research with the most varied uses. It was originally developed to evaluate and compare production efficiency of the organizational units. The method has been successfully applied in assessing the performance of group of companies that use the same input for the same production output, for example shops, hospitals, bank branches, airports, agricultural holdings etc. Decision-making units which can be evaluated and compared by using this method, however, need not only to be businesses as a whole, but also individuals such as employees of a particular company. The most widespread area in this respect is a sport where DEA is quite often applied in assessing the productivity of players, for example in baseball [2], [12], [15], [18], [25], basketball [3], [7], [21], football [11], [14], [26], handball [10] and tennis [22].

Literature dedicated to the evaluation of employees' performance using DEA method is still scarce. Manoharan et al. [17] conducted a research on a sample of 18 production staff of a small Indian company producing car parts. The goal was to calculate efficiency of individual employees using DEA method and, on the basis of the results, suggest the training program which would eliminate any deficiencies and improve their performance. The study applied DEA model with variable returns to scale. In addition to the technical efficiency score, slack variables of individual employees and the reference set for each employee were also calculated. The authors argue that there is no well established pattern for the choice of model variables. However, inputs in general should involve sources used and outputs should reflect the level of outputs and services. Inputs, in this model, are knowledge of work, customer relations, workplace relationships and work habits. Quality and quantity of products produced by an employee were included as outputs.

Using the method of DEA, Osman et al. [20] carried out an evaluation of 32 nurses working in an intensive care at a hospital in Beirut in order to set the education plan and training for low performance nurses and a career development and remuneration for efficient nurses. The evaluation was made by their superior who, on the ordinal scale from 0 to 4, had evaluated 45 criteria. These were divided into 9 outputs and 6 inputs. Inputs were nonfinancial, for example education, knowledge of the work, teamwork, work habits and the like. Organization of the work, creativity, performance from several points of view and others were included in the outputs.

Interesting paper concerning this area was also published by authors Shirouyehzad et al. [23] who measured the effectiveness of 55 employees of the company operating in the distribution industry. They used four motivational factors (wages, working conditions, workload, responsibility) as outputs. The outputs indirectly assessed performance through factors that have a demonstrable impact on it, namely work motivation, satisfaction, commitment to the organization and turnover. The authors used the DEA model with constant returns to scale and identified efficient and inefficient employees.

Zbranek [27], based on a similar principle, has carried out the first study of its kind in Slovakia, using the DEA model with constant returns to scale to assess the performance of 60 employees of a bakery business. The input variables represented three motivational factors (salary, working conditions and benefits). Three output variables (work motivation, job satisfaction and commitment to the organization) indirectly studied employees' performance. Based on the questionnaire survey, there were identified 12 efficient and 48 inefficient employees. The resulting recommendation of this paper was to build on this research and apply this method in companies which management has exact data on the inputs as well as outputs of individual employees. The implementation of this objective will be the subject of this article.

Rest of the text is organized as follows: In the second part we set out the objective of the paper and we describe the methods that will lead to its fulfillment. The third section contains the results, and the fourth section is devoted to discussions. The fifth section summarizes our research and the most important achievements.

2. SCIENTIFIC AIM, METHODOLOGY

2.1 SCIENTIFIC AIM

The aim of this paper is to evaluate employees' performance in the transport company using the Data Envelopment Analysis method. To achieve this, we will use input-oriented CCR DEA model which calculates the so-called radial measures of technical efficiency of all 219 evaluated truck drivers. This model will allow us to quantify the shortcomings of the individual inefficient employees and thus the possibility of their potential improvement. Furthermore, we will use the so-called Andersen-Petersen input-oriented DEA model to calculate super efficiency in order to rank the efficient staff. Finally, we will examine the impact of certain factors on the performance of drivers by using Tobit regression analysis.

2.2 METHODOLOGY

RADIAL INPUT-ORIENTED CCR DEA MODEL

The subject of the radial input-oriented DEA model is the calculation of the technical efficiency score that for the inefficient DMU points to the possibility of radial (equiproportional) reduction of the inputs in order to make given DMU efficient. DEA model with constant returns to scale was presented by Charnes, Cooper and Rhodes [13]. Its dual form can be expressed as follows:

Objective function:
$$min\ \theta_0 \tag{1}$$

Subject to:
$$\sum_{j=1}^{N} x_{ij}\lambda_j \le \theta_0 x_{i0}, i = 1, \dots, M$$
$$\sum_{j=1}^{N} y_{rj}\,\lambda_j \ge y_{r0}, r = 1, \dots, S$$
$$\lambda_j \ge 0, j = 1, \dots, N$$

where x_{ij} is i input of j employee, x_{i0} is i input of evaluated employee, y_{rj} is r output of j employee, y_{r0} is r input of evaluated employee, λ_j is intensity variable of j employee and ϑ_0 is the coefficient of reduction of inputs, the technical efficiency score of the evaluated employee.

The result of thus formulated linear programming task is technical efficiency score of evaluated employee ϑ_0, which is defined as the ability to achieve minimum inputs at a given level of outputs. This measurement indicates how many times level of inputs has to be proportionally reduced, maintaining the unchanged level of outputs, for employee to be technically efficient. If ϑ_0 equals one and a variable λ_j is equal one for rated employee and zero for all other employees, the employee is technically efficient. Otherwise, if the technical efficiency measurement ϑ_0 is less than 1, the employee is not technically efficient in comparison with others and must reduce inputs while level of outputs remains the same. If employee is rated inefficient, non-zero variables λ_j point to the elements of reference set. Convex combination of outputs and inputs of efficient employees' reference set with coefficients λ_j indicates so called target values, i.e. values of inputs and outputs of a virtual efficient reference employee on the frontier. Model assumes constant returns to scale, which means the proportional change in outputs due to the change of inputs. Therefore, if the inputs increase by 1%, outputs also increase by 1%.

ANDERSEN-PETERSEN'S SUPEREFFICIENCY DEA MODEL

Model proposed by Andersen and Petersen [1] serves as a tool for distinguishing efficient decision-making units and their ranking. The specific feature of this model is that during the calculation of technical efficiency, the inputs and outputs of the evaluated DMU are excluded from the convex combinations of inputs/outputs of other DMUs. Mathematical notation of the input-oriented super DEA model is as follows:

Objective function:
$$min\ \theta_0 \tag{2}$$

Subject to:
$$\sum_{\substack{j=1 \\ j\neq 0}}^{N} x_{ij}\lambda_j \le \theta_0 x_{i0}, i = 1, \dots, M$$
$$\sum_{\substack{j=1 \\ j\neq 0}}^{N} y_{rj}\,\lambda_j \ge y_{r0}, r = 1, \dots, S$$
$$\lambda_j \ge 0, j = 1, \dots, N$$
$$\sum_{j=1}^{N} \lambda_j = 1$$

The application of this model allows efficient employees to achieve the technical efficiency score $\vartheta_0 > 1$, while the TE measurement of inefficient employees stays the same. Therefore, $\vartheta_0 < 1$ is still valid for these DMU. While the use of classical CCR DEA model has the same TE score for all efficient employees (ϑ_0 = 1), Andersen-Petersen's model shows different TE measurements for efficient employees. This allows their alignment from the best to the worst.

2.3 DATA AND VARIABLES

Empirical research was carried out by using data on truck drivers working for the transport company. Before applying the DEA models, it was necessary to adjust the data to meet the conditions required for the application of this approach.

The first refers to the number of decision-making units which, as stated by Bowlin [5], should be at least three times the number of input and output variables. The condition was met after including 4 input and 2 output variables and 219 assessed employees in the model.

Another condition for the successful application of DEA are positive values of all variables included in the model. Since the data used had included zero values, we have followed the procedure recommended by Bolwin [5] and replaced them by a number lower than the other values in the data set (for example, 0.01).

Another important step is to select appropriate input and output variables. A simple rule is that a variable is selected as an input if its lower value in the given outputs represents a better result, and as an output if its higher value is considered a better result in the given inputs. In addition, DEA allows to work with undesired outputs, where the higher rate is considered less preferred. One of the possible ways to include such variables into the model is their inclusion among the inputs, as is the case of this paper. Variables that we chose for our research are as follows:

Inputs:

- ***working days***: number of days worked by the employee in the period
- ***fuel***: the number of liters of fuel consumed by the employee in the period

Undesired outputs (treated as inputs):

- ***technology KO***: the number of failed attempts of the employee to use technological device in the vehicle during the period
- ***idling***: hours of employee's idling in the period

Desired outputs:

- ***mileage***: the number of kilometers driven by the employee in the period
- ***technology OK***: the number of successful attempts of the employee to use technological device in the vehicle during the period

After the quantification of the technical efficiency score of the individual employees, we have analyzed the impact of external factors, such as age and number of years worked in the company, on the calculated values of this indicator. Since age and number of years worked in the company are quantitative variables, it is possible to apply the regression analysis. As the technical efficiency score, which is the dependent variable, has a nature of a censored variable, we have applied Tobit regression instead of the classical linear regression model.

3. FINDINGS

Our research monitored the performance of 221 truck drivers working in the transport company for a period of three months. Two drivers had been excluded from the evaluation due to the incorrect data, so only 219 drivers underwent the DEA analysis. Table 1 presents descriptive statistics of four input variables (working days, fuel, technology KO, idling) and two output variables (mileage, technology OK).

As we can see, the average company employee has worked almost 59 days the last three months during which he consumed 5 710,5 liters of fuel to run over 17 321 km. The employees used a technological device in the vehicle during loading and unloading of goods on average 41 times correctly and 15 times incorrectly. The average employee has more than 83 "empty" hours when his car went at idle. Applying input-oriented CCR DEA model (Model 1), we have calculated the technical efficiency score for each employee which is a comprehensive indicator of his performance. Its descriptive statistics are presented in Table 2.

Employees reaching a maximum value of the technical efficiency measurement equal to 1 are technically efficient. Drivers whose technical efficiency score reached a value less than 1 are not technically efficient and they should proportionally reduce their inputs to the level given by the calculated degree of the technical efficiency score. It was revealed that there are only 20 technically efficient drivers and 199 technically inefficient drivers. Average value of technical efficiency was 0.89 with a standard deviation of 0.06. This means that the average company employee's performance during the reporting period amounted to 89% of the best performance. If such an employee is to be technically efficient, he should proportionally reduce his inputs, including unwanted outputs, by 11%. The technical efficiency score of the worst employee reached 0.7 which means that this driver, at a given desired output, should proportionally reduce his inputs and unwanted outputs by up to 30% to become technically efficient.

Table 1 Input and output variables, descriptive statistics

	INPUTS				OUTPUTS	
	working days	**fuel**	**tech. KO**	**idling (hrs)**	**mileage**	**tech. OK**
Mean	58,99	5710,54	15,45	83,41	17321,03	41,11
St. Deviation	18,01	2086,75	13,08	40,61	6591,79	23,31
Maximum	86	11985,51	81	287,3	36959	161
Minimum	7	492,86	0	6,1	1443	0
Mode	73	-	9	-	22012	48
Median	63	5889,22	11	80,08	17743	41

Source: own calculations

Table 2 The technical efficiency score, descriptive statistics

	Mean	St. Dev.	Maximum	Minimum	Mode	Median
TE score	0,89	0,06	1	0,7	1	0,88

Source: own calculations

Table 3 Ranking of the employees according to the superefficiency measurement

#	Score	#	Score	#	Score	#	Score
1.	1,593	6.	1,214	11.	1,073	16.	1,013
2.	1,41	7.	1,204	12.	1,045	17.	1,012
3.	1,374	8.	1,138	13.	1,024	18.	1,007
4.	1,304	9.	1,094	14.	1,021	19.	1
5.	1,239	10.	1,078	15.	1,019	20.	1

Source: own calculations

When using Model 1, we were able to rank the inefficient employees from the best to the worst but we were not able to do that with the efficient ones. This deficiency was overcome by Andersen-Petersen model for calculating super efficiency (Model 2). Super efficiency values can no longer be interpreted as was the case with the degree of efficiency in the Model 1. Their importance lies only in the fact that they allow us to rank the efficient employees from the best to the worst. In the Table 3 we see 20 efficient (best performing) employees ranked on the basis of the calculated values of super efficiency from the best to the worst.

We have also studied the impact of some external factors on the calculated technical efficiency score of individual employees, i.e. their performance. These factors were gender, age and years of service in the company. Since over 99% of drivers were male and only 1% were female, the effect of gender on employee's performance could not be objectively judged. Therefore, we have analyzed only the impact of the other two factors.

Only 3% of the company employees are aged 18 to 25 years. 14% of drivers working for the company are aged 26 to 35 years. Most of the drivers, 35%, are in the age range of 36 to 45 years. The second largest group consists of drivers who are between 46 and 55 years, making 33% of the total. The company has 15% of drivers who are older than 55 years. Regarding the time spent by the drivers in the company, 20% of the employees work there for less than two years, 44% work there for 2-4 years, 22% works there for 4-6 years and 14% of the employees have worked in the company for more than 6 years. These results are summarized in Table 4.

We used Tobit regression analysis for the technical efficiency score when examining the impact of the age of employees and the number of years worked in the company. In terms of age, the analysis has revealed its statistically significant negative impact on the technical efficiency score of the employees and hence their performance. The older the employees the lower is their performance. Conversely, years of service had statistically significant positive impact on the performance of drivers. The longer the employees are in the company, the higher is their performance. After years spent in the company, the employees may become more loyal and are willing to do for its sake more than employees who started only recently. Descriptive statistics are presented in Table 5 and Table 6.

4. DISCUSSIONS

Nowadays companies use several traditional systems for the evaluation of employees' performance.

Table 4 Gender, age structure and employees' years of service

Gender		Age		Length of service	
Male	99%	18-25	3%	0-2 years	20%
Female	1%	26-35	14%	2-4 years	44%
		36-45	35%	4-6 years	22%
		46-55	33%	6+ years	14%
		55+	15%		

Source: own calculations

Table 5 Age structure and technical efficiency score

Age	Mean	St. Dev.	Maximum	Minimum	Mode	Median
18-25	0,84	0,03	0,89	0,82	-	0,83
26-35	0,92	0,06	1	0,82	1	0,92
36-45	0,90	0,06	1	0,76	1	0,89
46-55	0,89	0,06	1	0,70	1	0,88
55+	0,86	0,06	0,98	0,75	-	0,86

Source: own calculations

Table 6 Years in service and technical efficiency score

Years in service	Mean	St. Dev.	Maximum	Minimum	Mode	Median
0-2 years	0,86	0,06	1	0,70	-	0,86
2-4 years	0,89	0,06	1	0,76	1	0,88
4-6 years	0,91	0,06	1	0,80	1	0,89
6+ years	0,90	0,05	1	0,77	1	0,89

Source: own calculations

This concerns, for example, the graphic rating scale, alternation ranking, paired comparison, forced distribution, critical incident appraisal, narrative forms, behaviorally anchored rating scales, management by objectives [8].

Several authors, for example Oberg [19] or Colby and Wallace [6], however, pointed out several shortcomings of existing traditional systems, which they believe are not relevant to organizational objectives, subject to personal bias and often influenced more heavily by personality than by performance. Other disad vantages of traditional approaches are, according to Dulewicz [9], classification of employees as inefficient without determination of the factors which need to be improved, the inability to quantify the shortages of the employees with poor performance, the inability to express what performance is expected from the employees. The qualitative evaluation leads to various errors [16], moreover, they are usually time consuming, include inefficient and exhausting processes, they are based on insufficient information, they depend on person's evaluation and are suitable only for small amounts of data. Evaluation systems with such deficiencies can lead to many undesired consequences. As Manoharan et al. [17] states, some of the limitations of traditional systems of employees' performance evaluation can be overcome using the traditional quantitative methods. Their disadvantage, however, is that input/output shares are taken into account individually. The calculated indicators are therefore not limited to only one input and/or output.

Data Envelopment Analysis method, that we have applied for employees' performance evaluation in this paper, overcomes the previously stated shortcomings of the traditional quantitative approaches because it allows to calculate a single comprehensive indicator of employees' performance, covering several inputs and outputs without the knowledge of their relative importance. Furthermore, DEA responds to employees' expectations about quantifying their shortcomings, overcoming the disadvantages of quality evaluation systems and is not dependent on the units of measurement. Since this is a non-parametric approach, DEA is not bound by the normal distribution of input and output variables [17].

On the other hand, there are also some disadvantages of the method. Results are sensitive to the selection of inputs and outputs, so their relative importance needs to be analyzed prior to the calculation. However, there is no way to test their appropriateness. The number of efficient DMUs on the frontier tends to increase with the number of inputs and output variables ([4]. Thuss, management of the company should well consider how much input and output variables will be included in the model, as well as what input or output variables they consider to be the most relevant in terms of employees' performance.

5. CONCLUSION

The aim of this paper was to implement the evaluation of drivers' performance in the transport company by using the Data Envelopment Analysis method. By applying input-oriented CCR DEA model, we have identified from among 219 employees working for the company 20 efficient (best performing) and 199 inefficient drivers who need to improve their performance. Based on the calculated scores of technical efficiency of each inefficient driver, we were able to quantify their weaknesses and rank them according to their performance. We then applied the Andersen-Petersen model to calculate super efficiency that allowed us to clearly rank the performance of 20 efficient employees. Finally, by using Tobit regression analysis we came to the conclusion that employees´ performance is higher if they have worked in the company for several years, but conversely less in their old age.

Based on thus calculated rate of technical efficiency or super efficiency we can reward or promote the best performing employees, and choose a training plan or other arrangements for drivers with the worst performance. Development of employees' performance is also possible to track in the time by applying Malmquist productivity indices. Knowing the data from multiple time periods we can thus determine whether the individual drivers have improved, stagnated or deteriorated in their performance and thus set additional management measures. Such an approach, according to our knowledge of evaluation of employees' performance in the available literature, has not yet been applied. Therefore, it is an attractive opportunity for future work in this area.

REFERENCES

[1] ANDERSEN, P., PETERSEN, N. C. 1993. A procedure for ranking efficient units in data envelopment analysis. ***Management Science*,** 1993, Vol. 39, No. 10, pp. 1261-1264.

[2] ANDERSON, T. R., SHARP, G. P. 1997. A new measure of baseball batters using DEA. ***Annals of Operations Research*,** 1997, Vol. 73, pp. 141-155.

[3] BAI, F., LAM, K. F. 2009. ***Testing the effects of environmental variables on efficiency and generating multiple weight sets for cross-evaluation with DEA: An application to the National Basketball Association***. Kowloon : City University of Hong Kong, 2009.

[4] BERG, S. 2010. ***Water Utility Benchmarking: Measurement, Methodology, and Performance Incentives***. London : IWA Publishing, 2010. 172 p., ISBN: 9781843392729.

[5] BOWLIN, W. F. 1998. Measuring Performance: An Introduction to Data Envelopment Analysis (DEA). ***Journal of Cost Analysis*,** 1998, Vol. 15, No. 2, pp. 3-27.

[6] COLBY, J. D., WALLACE, R. L. 1975. Performance appraisal - help or hindrance to employee productivity. ***Personnel Administrator*,** 1975, Vol. 26, No. 2, pp. 37-49.

[7] COOPER, W. W., RUIZ, J. L., SIRVENT, I. 2009. Selecting non-zero weights to evaluate effectiveness of basketbal players with DEA. ***European Journal of Operational Research*,** 2009, Vol. 195, No. 2, pp. 563-574.

[8] DU, J. 2013. Staff performance appraisal based on data envelopment analysis (DEA). ***Journal of Chemical and Pharmaceutical Research*,** 2013, Vol. 5, No. 11, pp. 102-105.

[9] DULEWICZ, V. 1989. ***Assessment and selection in organisations: methods and practices for recruitment and appraisal***. New York: John Wiley & Sons, 1989.

[10] GUTIÉRREZ, Ó., RUIZ, J. L. 2013. Data Envelopment Analysis and Cross-Efficiency Evaluation in the Management of Sports Teams: The Assessment of Game Performance of Players in the Spanish Handball League. ***Journal of Sport Management*,** 2013, Vol. 27, pp. 217-229.

[11] HIROTSU, N., YOSHII, H., AOBA, Y., YOSHIMURA, M. 2012. Evaluation of J-League players using DEA. ***Football Science***, 2012, Vol. 9, pp. 1-13.

[12] HOWARD, L. W., MILLER, J. L. 1993. Fair Pay for Fair Play: Estimating Pay Equity in Professional Baseball with Data Envelopment Analysis. ***The Academy of Management Journal*,** 1993, Vol. 36, No. 4, pp. 882-894.

[13] CHARNES, A., COOPER, W. W., RHODES, E. 1978. Measuring the efficiency of decision making units. ***European Journal of Operational Research*,** 1978, Vol. 2, No. 6, pp. 429-444.

[14] KIM, T., Jiang, B. 2006. ***DEA based performance measurement and management of sports players using English Premier League data***. Soul: Soul National University, Korea, 2006.

[15] KIM, T., CHO, H. 2004. Performance evaluation and management of baseball players. ***Review of Business and Economics*,** 2004, Vol. 17, No. 6, pp. 2131-2348.

[16] LOCHER, A. H., TEEL, K. S. 1977. Performance appraisal: a survey of current practices. ***Personnel Journal***, 1977, Vol. 56, No. 5, pp. 245-257.

[17] MANOHARAN, T. R., MURALIDHARAN, C., DESHMUKH, S. G. 2009. Employee Performance Appraisal Using Data Envelopment Analysis: A Case Study. ***Research and Practice in Human Resource Management***, 2009, Vol. 17, No. 1, pp. 92-111.

[18] MAZUR, M. J. 1994. Evaluating the relative efficiency of baseball players. In CHARNES, A. et al.: ***Data Envelopment Analysis: Theory, methodology and application*,** Boston : Kluwer Academic Publisher, 1994, pp.369-391.

[19] OBERG, W. 1972. Make performance appraisal relevant. ***Harvard Business Review***, 1972, Vol. 50, No. 1, pp. 18-32.

[20] OSMAN, I. H., BERBARY, L. N., SIDANI, Y., AL-AYOUBI, B., EMROUZNEJAD, A. 2011. Data Envelopment Analysis Model for the Appraisal and Relative Performance Evaluation of Nurses at an Intensive Care Unit. ***Journal of Medical Systems***, 2011, Vol. 35, No. 5, pp. 1039-1062.

[21] RADOVANOVIČ, S., RADOJIČIČ, M., JEREMIČ, V., SAVIČ, G. 2013. A Novel Approach in Evaluating Efficiency of Basketball Players. ***Journal for Theory and Practice Management***, 2013, Vol. 67.

[22] RUIZ, J. L., PASTOR, D., PASTOR, J. T. 2013. Assessing professional tennis players using Data Envelopment Analysis (DEA). ***Journal of Sports Economics*,** 2013, Vol. 14, No. 3, pp. 276-302.

[23] SHIROUYEHZAD, H., LOTFI, F. H., ARYANEZHAD, M. B., DABESTANI, R. 2012. A Data Envelopment Analysis Approach For Measuring The Efficiency Of Employees: A Case Study. ***South African Journal of Industrial Engineering***, 2012, Vol. 23, No. 1, pp. 191-201.

[24] SLUSHER, E. A. 1975. A systems look at performance appraisal. ***Personnel Journal***, 1975, Vol. 54, No. 2, pp. 114-117.

[25] SUEYOSHI, T., OHNISHI, K., KINASE, Y. 1999. A benchmark approach for baseball evaluation. ***European Journal of Operational Research*,** 1999, Vol. 115, No. 3, pp. 429-448.

[26] TIEDEMANN, T., FRANCKSEN, T., LATACS-LOHMANN, U. 2011. Assessing the performance of German Bundesliga football players: a non-parametric metafrontier approach. ***Central European Journal of Operations Research*,** 2011, Vol. 19, No. 4, pp. 571-587.

[27] ZBRANEK, P. 2013. Data envelopment analysis as a tool for evaluation of employees performance. ***Review of Agricultural and Applied Economics*,** 2013, Vol. 16, No. 1, pp. 12-21.

Peter ZBRANEK, Ing.
Slovak University of Agriculture in Nitra, Faculty of Economics and Management
Department of Statistics and Operational Research
Tr. A. Hlinku 2, 949 76, Nitra, Slovakia
e-mail: zbranek.peter@gmail.com