EVALUATING THE EFFICIENCY OF LEAN MANAGEMENT PROJECTS USING DATA ENVELOPMENT ANALYSIS

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This paper describes approach to evaluate and compare efficiency of lean management projects, using a set of techniques known as Data Envelopment Analysis. DEA is a non-parametric linear programming method used to the efficiency evaluation of decision making units. Lean methods have been widely used as a tool for improving operational performance and also have been successfully implemented in many manufacturing and non-manufacturing organizations. This paper aims to develop a mathematical model to evaluate the efficiency of lean management projects. Paper provides the identification of important inputs and outputs for projects that are then analysed using DEA. Working with planned indicators values, this model helps to identify one or more projects that result in the maximum benefit to the organization. Using the real indicators values after implementation of a project, it can help to determine how the project was successful as compared with similar implemented projects.

KEYWORDS

data envelopment analysis, lean management project, project efficiency, project success, technical efficiency

1 INTRODUCTION

This article aims to present the DEA method as a convenient tool for evaluating and subsequently selecting projects or for arranging lean management projects by priority. In this article, the authors have focused on assessing the relative efficiency of 20 hypothetical lean management projects, namely projects to apply the Single Minute Exchange of Dies (SMED) method using a selected Data Envelopment Analysis (DEA) model. The methodology presented in this study aims to help managers identify efficient SMED projects and rank projects according to specified criteria, thus facilitating the subsequent selection of the project to be implemented. When applying the DEA method, it is assumed that projects identified as efficient will lead to the highest performance and, in turn, maximise utility for the organisation [Kumar 2007].

2 LITERATURE REVIEW

2.1 *Data Envelopment Analysis*

Many approaches and techniques have been proposed in connection with addressing project selection. Data Envelopment Analysis (DEA) is a method used to solve multi-criteria problems and, in recent years, it has been frequently used to assess the efficiency of production units. DEA is an important tool of economic management. Compared to statistical and other methods, it is a relatively new nonparametric method [Gupta 2014]. DEA is an optimisation method that is used to assess the technical efficiency, performance or productivity of production units based on the levels of inputs and outputs [Cook 2005]. While there are multiple analytical tools available for calculating technical efficiency, DEA is one of the simplest and most efficient ones [Sherman 2006]. DEA makes it possible to individually assess the efficiency of each production unit relative to the entire set of units. The objective of this method is to classify production units as efficient or inefficient and determine how an inefficient unit can reduce its inputs or increase its outputs in order to be considered efficient. DEA is convenient for determining the technical efficiency of units that are mutually comparable [Ramanathan 2003]. Such units use the same inputs and produce the same outputs, but there are certain differences in their performance. The units assessed are most often companies, organisational units, banks, hospitals, public administration organisations, territorial units etc. [Kumar 2007].

The basic objective of DEA is to compare the productivity of organisational units, here referred to as Decision Making Units (DMUs). The operations of each DMU require certain inputs and result in certain outputs. Inputs are quantities that are consumed in a particular operation, and outputs are the resulting products. In general, lower input values and higher output values are preferred. Unlike common efficiency-rate calculations, DEA uses mathematical programming that makes it possible to include a large number of inputs and outputs in the model [Kumar 2007].

The DEA model is used to calculate the relative technical efficiency score, which expresses a DMU's efficiency within the group of DMUs under study. Relative technical efficiency can be defined as the ratio between total weighted production and total weighted consumption of inputs. Based on efficiency rate, DMUs within the group are then classified as efficient or inefficient. Given the mechanism for choosing the weights of inputs and outputs, within the set of DMUs under study there is always at least one efficient DMU [Bogetoft 2011]. This kind of efficiency rate measures the DMU's distance from the efficiency frontier and expresses the proportional reduction of all inputs (for input-oriented models) or the proportional increase of all outputs (for output-oriented models) that is necessary in order to move the DMU onto the efficiency frontier [Ray 2004].

The best-known models are CCR and BCC. Designed by Charnes, Cooper and Rhodes in 1978, the CCR model is the historically first DEA model. The CCR model can be either input or output oriented, and it has been designed under constant returns to scale. The assumption of constant returns to scale is convenient in cases where all businesses operate at the optimal scale. As a result of imperfect competition, financial constraints etc. a business may not operate at the optimal scale. In 1984, Banker, Charnes and Cooper proposed an extension to the CCR model – the BCC model. Similarly to the CCR model, the BCC model derives from the role of mathematical programming. While the BCC model can also be either input or output oriented, unlike the CCR model it assumes variable returns to scale [Yao 2010]. With variable returns to scale, there are three distinct areas: an area of increasing returns to scale, an area of decreasing returns to scale, and an area of constant returns to scale. Assuming variable returns to scale, it no longer applies that – in order to maintain efficiency – an α-multiple of inputs must be matched with the same multiple of outputs. As a result of the assumption of variable returns to scale, a DMU will be classified as efficient even if the relative increase in outputs is lower or greater than the corresponding increase in inputs. In that case, the technical efficiency rate of the DMUs being assessed will be greater (or not lower) than under the assumption of constant returns to scale [Charnes 1994].

Input-oriented models try to find a virtual unit by minimising inputs while maintaining a given level of outputs. In this model, relative technical efficiency is expressed as the ratio between weighted outputs and weighted inputs, while meeting the condition that the efficiency rates of all other units are lower than or equal to one. A DMU with a relative technical efficiency ratio equal to one is efficient, a coefficient lower than one identifies the unit as inefficient [Jiang 2011].

Output-oriented models try to find a virtual unit by maximising outputs while maintaining the level of inputs. In this model, relative technical efficiency is expressed as the ratio between weighted outputs and weighted inputs, while meeting the condition that the efficiency rates of all other units are greater than or equal to one. A DMU with a relative technical efficiency ratio equal to one is efficient, a coefficient greater than one identifies the unit as inefficient [Jiang 2011].

If a DMU is classified as efficient in the CCR model, it is also efficient in the BCC model, but this does not apply the other way round [Cooper 2006]. Depending on the specific type of model and the relationship between the number of DMUs and the number of inputs and outputs, multiple units may be classified as efficient. Due to the possibility of further classification, super-efficiency models have been proposed in which the efficient units receive a super-efficiency rate greater than one (for input-oriented models) or lower than one (for output-oriented models). The best-known super-efficiency models are: the radial super-efficiency model developed by Andersen and Petersen, the directional distance function super efficiency model developed by Ray and the SMB super efficiency model developed by Tone [Zhang 2017].

The DEA method can be used to assess projects' relative efficiency and performance using a combination of multiple inputs and outputs that affect project performance [Yüksel 2012]. The method can be used to assess the efficiency of projects and then to prioritise them, to identify efficient and inefficient projects, to present reasons for inefficient projects, and to analyse factors that prevented projects from being efficient. Last but not least, the method can be used to assess the technical and allocation efficiency of the actual project teams. Specific applications of the DEA method in publications of authors focusing on the selected area are addressed in the next section of this article.

2.2 *Using Data Envelopment Analysis in project assessment*

In studying possible approaches to project assessment, the authors focused on researching publications in which the DEA method was used for project assessment purposes. Projects were considered to be decision making units. Until recently, DEA had been used mainly to study projects within specific functional areas. In a case study to evaluate the performance of engineering design projects, the DEA method was applied in order to compare projects within the engineering department of Belgian Armed Forces [Farris 2006]. The authors constructed a performance index that takes into account project duration as an output and also the key input variables that affect the duration (effort, project staffing, priority, number of officers, and technical complexity). The application of the DEA method proved to be convenient in the assessment and subsequent ranking of Lucent Technologies' telecommunications R&D projects [Linton 2007]. A more comprehensive approach was adopted by [Eilat 2008] in assessing R&D projects at different stages of their life cycle. A model was used that combined the concepts of the DEA and the balanced scorecard (BSC) methods. This approach is then applied to a case study of an industrial research laboratory that selects from dozens of R&D projects every year. A combination of DEA and BSC is also used in the article by [Sadeghani 2013]. The authors state that even though BSC and DEA are two different approaches, they complement each other and their combination is therefore useful. DEA is able to overcome the limitations of the BSC method and provides managers with additional useful information. On the other hand, BSC provides convenient inputs and outputs for the DEA model. The DEA method can be used for project quality assessment that is characterised by multiple variables and variable returns to scale [Zhang 2006]. Specifically, a DEA CCR model was designed, including expansion models for calculating a quality score that serves as the basis for assessment. The authors present a case study in which they apply the DEA method to assess 10 selected ITECHS projects and 20 projects from the SourceForge.net portal within two groups of data using five input/output metrics. The results show that this approach is efficient in assessing project quality and makes it possible to obtain accurate estimates of future improvements. The authors of the article [Xu 2011] have provided a different perspective on project performance assessment. They develop two performance assessment processes based on expected and actual performance objectives, while drawing a distinction between two aspects of performance: effectiveness and efficiency. While effectiveness assessment is done through a multi-criteria optimisation model, efficiency assessment is based on the DEA model. The authors conclude that the DEA model provides the relative assessment of project performance and identifies possible ways to improve inefficient projects. The results of this study can provide managers with insights in assessing project performance. The authors of [Shirouyehzad 2011] have also developed an approach that can help managers efficiently evaluate the performance of each project relative to the best project. The authors use the BCC model, which is applied to 12 DMUs having one input and two outputs. According to the authors, the proposed methodology – as mentioned in that study – may help managers to quantify project efficiency. The DEA method can be used as part of an integrated methodology for the evaluation and priority ranking of new product development projects [Hung 2009]. Its authors use fuzzy hierarchical analysis to determine the weights of assessment criteria and the DEA method to analyse efficiency, in order to identify NPD projects with market potential and high added value. The authors of the article [Yang 2010] assess 63 software projects at a major Canadian bank. The chosen DEA model was developed to measure software project efficiency, with a focus on factors that affect software productivity. Here, the dummy variable was used as the input and two production ratios operating with the cost, duration and size of the project were used as the outputs. In the publication [Yang 2015] the DEA method is used to assess the operational efficiency of more than a thousand healthcare projects implemented at the National Institutes of Health in New York. The authors place the main emphasis on the study of environmental variables that significantly affect project performance.

Since the authors of this article focused on lean management and improvement projects, they have studied scientific articles in which the authors used the DEA method in connection with tools supporting process improvement such as Total Productive Maintenance (TPM) or Six Sigma. In [Wang 2006], the DEA method is applied in checking TPM implementation performance. The objective was to assess the relative efficiency of 53 plants based on three inputs and four outputs. A CCR input-optimisation model working with constant returns to scale was used, which was subsequently assessed using Frontier Analyst. In addition, the authors of the [Jeon 2011] study also use DEA to measure the efficiency of TPM implementation, but with regard to the overall process of TPM implementation in a three-stage model. Finally, the authors of the article [Turanoglu Bekar 2016] propose a new framework for assessing the performance of the TPM method using a fuzzy-DEA model.

The authors of the article [Kumar 2007] used the DEA method to select Six Sigma projects. They identified important inputs and outputs associated with the introduction of Six Sigma projects. They gave a hypothetical example and analysed a dataset of 20 fictitious projects using a DEA tool. In the same year, several other authors also described potential applications of the DEA method for selecting Six Sigma projects. According to [Mawby 2007], the main objective of the DEA approach to selecting the Six Sigma project portfolio is to determine the priorities for each project more objectively than would be the case if most other methods were used. Assessing the performance of Six Sigma projects is an important issue for companies that apply Six Sigma projects [Yüksel 2012]. Yüksel uses an input-oriented DEA model to assess the performance of Six Sigma projects. The case study included only 5 projects and the author identified two inputs (hours worked and costs per project) and three outputs (financial gains, increase in sigma level, and increase in customer satisfaction). The authors of the article [Meza 2013] aim to assess the performance of individual Lean Six Sigma projects and develop recommendations for strategies to improve operational efficiency using the DEA method. An important part consisted in a survey that provided a basis for identifying the critical factors for project success, which were subsequently used as inputs of the DEA model. A different approach can be found in [Alinezhad 2013], where the DEA method was applied to interval data in order to select high-priority Six Sigma projects with maximum financial benefits to the organization. In order to obtain a full ranking of projects, a dummy project with maximum of inputs and minimum of outputs was used. The authors of the article [Yousefi 2014] used Linear Discriminant Analysis to verify that the DEA model proposed by them was suitable for selecting Six Sigma projects, and presented a case study from the electricity distribution industry. The most important step in reducing the risk of Six Sigma projects' failure is to successfully select those with the most benefits and fewest risks. According to the authors of the article [Arafah 2015], there are many different formulations of the DEA model that can influence both the selection process and the final choice of the project. The success of a Six Sigma initiative is then affected by successful project selection at the beginning. These authors apply nine different DEA formulations to several case studies and conclude that different DEA formulations result in the selection of different projects. Finally, the authors of the article [Bazrkar 2017] focus – in their study – on identifying priorities and selecting the best Lean Six Sigma project using the cross-efficiency model within the DEA method.

Process improvement is associated, among other things, with reducing process duration or, if relevant, the duration of sub-activities. The following section briefly describes the SMED tool, which is used to reduce the machine set-up time.

2.3 Single Minute Exchange of Die

Single Minute Exchange of Die (SMED) or quick changeover is one of the lean production methods used to reduce set up times. Quick changeover makes it possible to significantly reduce the machine set-up time during changeover from one type of manufactured product to another, eliminates wastefulness that is associated with changeover, and ensures flexible production [Shingo 1985].

The objective of this method is to reduce set-up times (the time needed to exchange tools and preparations, i.e. the time between the completion of the last high-quality piece from a given production batch to the production of the first high-quality piece of the next production batch) [Ferguson 2013].

This method was developed by Japanese industrial engineer Shigeo Shingo, who applied it to help several companies to significantly reduce machine set-up times. His pioneering work resulted in an average set-up time reduction of 94% (e.g. from 90 minutes to less than five minutes). The increasing diversity of products led to an increase in the number of changeovers from one type of manufactured product to another. Each transition required a new set-up and, in turn, led to losses of valuable production time as a result of increased idle time. Having spent many years working to solve this problem, Shigeo Shingo came up with a method that would reduce the entire set-up time to single-digit figures, thus saving useful production time that would otherwise be lost during machine set-up [Mukherjee 2006].

Set-up operations are divided into internal set-up operations, which are only performed when the machine is switched off, and external set-up operations, which can be performed even when the machine is running. The basic solution for successful SMED implementation is to reduce both set-up times and to transfer elements from internal operations to external operations, thus reducing production equipment downtime [Wang 2011]. After transferring internal operations to external ones, the required internal set-up time can be reduced by 30 % to 50 % [Shingo 1985].

The SMED method makes it possible to significantly reduce changeover times. Quick changeover makes it possible to do changeovers more frequently and reduce the size of economically viable production batches. This leads to a reduction in inventory and, consequently, to better quality control and waste reduction. The SMED method makes it possible to reduce the production lead time and deliver products to the customer in a timely manner. Other effects of SMED implementation include increased productivity, elimination of setup errors, improved quality, and increased safety [Wang 2011].

3 METHODOLOGY

This study was implemented in a fictitious company operating in the automotive industry. 20 hypothetical SMED projects were selected for Data Envelopment Analysis. It involves the introduction of the SMED tool on some of the 20 pressing/welding machines and the company is deciding which of them should be selected for implementation. However, the company's budget does not allow the implementation of all projects; the company wants to implement only those projects that are found to be efficient according to the presented DEA method and, at the same time, that represent the highest potential and value added.

Below, the definition of the set of DMUs is followed first by the identification of possible input and output variables and then by the construction of an input-oriented CCR-I model. After that, the model is applied to data to give an example of its use for relative efficiency assessment and subsequently the selection of one or more SMED projects for implementation.

3.1 Definition of Inputs and Outputs parameters

Project selection criteria can be divided into three categories: bottom-line criteria (customer impact, impact on business strategy, impact on core competencies, financial impact); feasibility criteria (required resources, available expertise, implementation complexity, probability of success), and organisational impact criteria (educational benefits, benefits for learning and growth, cross-functional benefits) [Misra 2008].

Below, attention is given to defining potential inputs and outputs. The measures to be minimised are considered as inputs (I), while the measures to be maximised are considered as outputs (O).

The following inputs can be used: (I1) project costs (training and upgrading-training), (I2) project preparation time, (I3) cost of modifications and changes at the workplace (e.g. construction work), (I4) cost of resources helping reduce time required for changeover to another type of product (quick-release jigs, consumables, lubricants, detergents).

Furthermore, the following outputs can be tracked in assessing SMED projects: (O1) reduction in external set-up time, (O2) reduction in internal set-up time (time spent searching, waiting, walking, setting-up), (O3) reduction in set-up errors, (O4) reduction in production lead time, (O5) reduction in unnecessary movements, (O6) increase in work safety, (O7) increase in machine utilisation rate, (O8) increased productivity, (O9) reduction in inventory of spare parts and accessories. Another important indicator that can be tracked is (O10) changeover time, i.e. the time that is needed during changeover from manufacturing one product to another product. This indicator is the sum of the times of the following four activities: preparation time, tool change time, set-up time, and inspection time. Indicator (O11) First Time Through (FTT) makes it possible to track production process quality. It can be calculated as the ratio of the number of good parts to the total number of parts. Another important indicator is (O12) OEE, which takes into account three sub-indicators – (Availability of equipment, Performance of equipment and Quality of production on the equipment.

It is known that too many inputs and outputs as compared with the number of DMUs may adversely affect the discriminatory power of the selected DEA model [Zizka 2017]. There are various rules, one of the best-known rules states that the number of DMUs should be at least twice or even three times the number of inputs and outputs [Raab 2002]. In this paper, 3 input and 3 output variables have been specified, while there are 20 DMUs. Since most inputs and outputs have a probabilistic nature, their expected values have been used. The inputs and outputs used are expressed in different units of measurement.

Based on completed correlation and regression analysis, the following inputs have been used for measuring technical efficiency: (I1) project costs (CZK), (I2) project preparation time (days), and (I4) cost of resources helping reduce time required for changeover to another type of product (CZK). The following outputs have been chosen: (O7) increase in machine utilisation rate (%), (O10) reduction in changeover time (minutes), and (O11) FTT (%).

Tab. 1 and 2 show the inputs and outputs that were used for all 20 hypothetical SMED projects.

Project	I1 (CZK)	I2 (days)	I4 (CZK)
Project 1	18,876	64	18,450
Project 2	14,157	81	15,450
Project 3	21,054	51	7,800
Project 4	14,520	50	29,850
Project 5	35,816	82	2,300
Project 6	21,054	65	9,850
Project 7	18,876	78	16,980
Project 8	19,360	50	8,750
Project 9	19,360	56	14,500
Project 10	14,157	78	18,950
Project 11	35,816	65	7,560
Project 12	28,072	57	1,900
Project 13	28,072	51	12,650
Project 14	26,862	82	5,500
Project 15	18,876	82	17,500
Project 16	14,520	56	17,980
Project 17	21,054	57	6,450
Project 18	14,520	64	22,580
Project 19	35,816	79	13,550
Project 20	26,862	79	10,250

Table 1. Data used as inputs in DEA modelling

Project	O7 (%)	O10 (min)	O11 (%)
Project 1	5	25	7
Project 2	6	40	5
Project 3	9	25	9
Project 4	7	50	4
Project 5	2	20	15
Project 6	4	30	7
Project 7	9	45	8
Project 8	8	25	10
Project 9	13	35	9
Project 10	14	50	4
Project 11	14	15	11
Project 12	5	12	12
Project 13	6	15	13
Project 14	3	10	10
Project 15	12	30	9
Project 16	15	48	5
Project 17	11	15	10
Project 18	12	55	6
Project 19	4	30	12
Project 20	2	30	10

Table 2. Data used as outputs in DEA modelling

3.2 *Construction of the DEA model*

The paper assumes that projects have constant returns to scale and that inputs are easier to control than outputs. That is why an input-oriented CCR-I model operating on the assumption of constant returns to scale is used for selecting efficient DMUs. This means that organisations are able to linearly transform inputs into outputs without increasing or reducing efficiency.

Input Oriented CCR-I model

Suppose, that we have *n* DMUs where each DMU_j, $j = 1, 2, ..., n$, produces the same s outputs, Y_{rj} ($r = 1, 2, ..., s$), using the same *m* inputs, X_{ij} ($i = 1, 2, ..., m$). The efficiency of a specific DMU_q can be evaluated by the CCR model of DEA. Its dual form can be formulated as:

$$E_0 = \min .\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$
$$s.t.\sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- = \theta X_{i0}, i = 1,...,m,$$
$$\sum_{j=1}^{n} \lambda_j Y_{rj} - s_i^+ = Y_{r0}, r = 1,...,s, \qquad (1)$$
$$\lambda_j, s_i^-, s_i^+ \geq 0, j = 1,...,n, i = 1,...,m, r = 1,...,s.$$
$$\theta \textit{ unrestricted in sign.}$$

where λ_j, $j = 1, 2, ..., n$ are weights of all DMUs, s^-_i, $i = 1, 2, ..., m$ and s^+_r, $r = 1, 2, ..., s$ are slack/surplus variables, $\varepsilon > 0$ is non-Archimedean element defined to be smaller than any positive real number, θ is the efficiency score of the DMU_q that expresses the reduction rate of inputs in order this unit reaches the efficient frontier.

For the further classification of efficient projects, the CCR-I model was supplemented with Andersen and Petersen super-efficiency model. Therefore, it will be possible to create a ranking of all projects from efficient to inefficient. Its formulation is very close to the standard formulation of the CCR-I model. Only difference is that the weights of the DMU_q, i.e. λ_q, are set to zero:

$$\lambda_q = 0 \qquad (2)$$

This causes that the DMU_q is removed from the set of units and the efficient frontier changes its shape after this removal.

4 RESULTS

The next step is to calculate the relative technical efficiency of each project in order to identify efficient projects. The calculation was made in the DEA Solver for MS Excel 2010 environment.

The CCR-I model assumes that the company operates at the optimal scale, i.e. under conditions of constant returns to scale (CRS). The technical efficiency score determined using the CCR model is called overall technical efficiency (OTE). Project with OTE equal to 1 is efficient, whereas OTE lower than 1 indicates an inefficient project. Subsequently, the ranking of the projects was compiled based on the OTE values.

Tab. 3 shows that projects 3, 4, 5, 8, 9, 10, 11, 12, 13, 15, 16, 17 and 18 are efficient and, in turn, eligible for implementation in the process.

Project	CCR-I efficiency scores (OTE)	Efficiency ranking
Project 1	0.746795	8.
Project 2	0.960437	3.
Project 3	1.000000	1.
Project 4	1.000000	1.
Project 5	1.000000	1.
Project 6	0.948098	4.
Project 7	0.987953	2.
Project 8	1.000000	1.
Project 9	1.000000	1.
Project 10	1.000000	1.
Project 11	1.000000	1.
Project 12	1.000000	1.
Project 13	1.000000	1.
Project 14	0.810633	6.
Project 15	1.000000	1.
Project 16	1.000000	1.
Project 17	1.000000	1.
Project 18	1.000000	1.
Project 19	0.766052	7.
Project 20	0.881317	5.

Table 3. Results of CCR-I model

In a situation where resources in the organisation are limited, it is desirable to be able to appropriately allocate them to the most beneficial projects, which may be the best of the efficient projects. As mentioned above, the conventional CCR-I model does not rank efficient projects in any way. Therefore, the super-efficiency model described in Section 3.2 will be used, which makes it possible to rank efficient projects according to their super-efficiency score values. In this concept efficient projects acquire a super-efficiency score greater than 1. The higher the value of the super-efficiency score, the better the project evaluation.

Project	CCR-I super-efficiency scores	Super-efficiency ranking
Project 1	0.746795	20.
Project 2	0.960437	15.
Project 3	1.060718	11.
Project 4	1.163636	7.
Project 5	1.376812	2.
Project 6	0.948098	16.
Project 7	0.987953	14.
Project 8	1.130704	8.
Project 9	1.082840	10.
Project 10	1.021522	12.
Project 11	1.109562	9.
Project 12	1.806999	1.
Project 13	1.218244	5.
Project 14	0.810633	18.
Project 15	1.007958	13.

Project 16	1.313843	3.
Project 17	1.261104	4.
Project 18	1.175472	6.
Project 19	0.766052	19.
Project 20	0.881317	17.

Table 4. Results of CCR-I super-efficiency model

Tab. 4 lists the projects in new and more precise order according to their super-efficiency score values. Because the efficient project 12 is the first one, it should have priority for implementation, and the implementation of other projects would depend on the availability of resources in the organisation. To shorten the set-up time, the priority is given to measures that do not require additional resources, but which offer significant potential for improvement.

In the company, for example, could be set an amount of CZK 400,000 as the maximum of available resources of project costs (staff training and upgrading-training) and the cost of resources helping reduce time required for changeover to another type of product. The sum of these costs for all 13 effective projects is CZK 453,967. Taking into account the maximum amount of the budget, it is obvious that implementation of two effective projects (namely project 15 and project 10) would be abandoned. Consequently, 11 efficient SMED projects would be selected and the sum of the monitored cost components would be CZK 384,484.

5 CONCLUSIONS

The present article deals with the use of the DEA method in addressing a major issue that concerns most manufacturing businesses, i.e. in assessment and selecting SMED projects.

First, cross-sectional resource search was conducted focusing on one of the methods of multi-criteria evaluation of variants, the DEA method. The use of DEA method in the assessment and selection of projects was theoretically examined. Due to the focus of this article on lean management and process improvement projects, the use of the DEA method was followed in connection with tools to support process improvement.

A hypothetical case study then deals with a selected tool to support process improvement, the SMED tool, which is used to reduce the machine set-up time. In the case study, the DEA method was implemented in a fictitious company operating in the automotive industry. The aim was to select from a set of 20 hypothetical SMED projects the effective projects that would be appropriate to be implemented, and to create their order from the most efficient to the least efficient.

The authors dealt with the identification of potential input and output variables of the DEA model that can be used to assess SMED projects. Of these, 3 inputs and 3 outputs were selected for the case study. An input-oriented CCR-I model operating on the assumption of constant returns to scale was used for selecting efficient projects. For the purpose of the further classification of efficient projects, the above-mentioned efficiency model was supplemented with Andersen and Petersen super-efficiency model. Applying both models to hypothetical data, 13 SMED projects were selected, which could be described as effective and recommended for implementation. All projects were then ranked from the most effective to the least effective project. This allows the selection of a few of the best-rated projects from the effective project group if the budget of the resources defined to cover project costs is limited.

There is no doubt that the company can achieve many benefits if SMED is properly implemented and standardized. But the first and essential step is to select the right project to be implemented. The authors of this article introduced the approach that can make this selection easier in practice.

Depending on the availability of data, there are several other ways to extend DEA application. In further research, we would like to apply the DEA method on real data in other companies. Besides the SMED tool, we consider to evaluate the effectiveness of another lean management tool.

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