A new hybrid method for the fair assignment of productivity targets to indirect corporate processes

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Abstract

Increasingly complex value chains and rising competition require firms to employ advanced planning mechanisms for efficient resource allocations aiming for an increase of their productivity level. Planning is frequently done by corporate entities based on performance analysis techniques such as the Data Envelopment Analysis (DEA). Within planning processes, total resource levels that should be allocated among processes are regularly defined ex-ante, giving rise to decision problems that go beyond basic efficiency analysis. We have developed a method allowing the allocation of an ex-ante defined resource level across various processes of an organization to ensure the achievement of overall productivity targets. We propose a mixed-integer/linear program (MILP) that incorporates a social welfare function, allowing decision makers to consider fairness aspects. The practicability of the method is demonstrated in a real-life case study of setting productivity targets to processes at a first-tier automotive supplier. The model-based allocation strategy is compared to alternative approaches, as well as the strategy applied by the organization in the past. The proposed approach is beneficial in two dimensions: Either fewer activities are required to reach the total productivity target, or a lower overall strain level among the activities in respect of their improvement efforts can be achieved.

Keywords

Data Envelopment Analysis; Fairness; Mixed-Integer/Linear Programming, Resource Allocation, Productivity Enhancement

1 Introduction

Decisions on resource level reductions are commonly made by top management. Typically, challenging market situations can require that all internal processes of an organization have to improve their productivity in the sense that they deliver the same level of output with less resources consumed. Advanced decision support methods are essential to facilitate the decision making process by top management. They allow precise statements regarding where and to which degree a resource level should be reduced to reach a pre-defined overall resource reduction target. Furthermore, fairness should be ensured among the decision alternatives regarding the efforts that each process faces to achieve required improvements. This study reports on a decision support approach fulfilling these requirements and addresses the overarching research question: *How should a pre-defined resource reduction level, aiming for an increase of productivity, among processes in an organization be allocated considering process resource efficiency and overall allocation fairness?*

Data Envelopment Analysis (DEA) has received significant attention for the purpose of allocating resources based on efficiency analyses (Korhonen & Syrjänen, 2004; Lozano & Villa, 2004; Lozano et al., 2004). To measure the efficiency among decision making units (DMU), which can be processes of an organization, it is commonly assumed that benchmarking figures are available. However, the burdens of generating valuable (external) benchmarking figures that allow precise productivity analysis are often very high and are probably not available at short notice. Therefore, it seems tempting to rely on internal organizational data for productivity analysis which might be available more widely (e.g. Seidenschwarz et al., 2009). The potential heterogeneity of DMUs in respect to the underlying distinct process technologies must be considered when a DEA analysis among the internal processes of a single organization is performed. One approach that addresses heterogeneity among DMUs in the context of resource allocation was introduced by Lozano (2014), and will be used as a basis for the approach developed in this study.

DEA is focused on determining efficient frontiers. If all processes would be improved to the level of the efficient frontier (e.g. reduction of input with constant output), the (theoretical) achievable input reduction (e.g. cost reduction) and therefore productivity increase might exceed what the decision maker actually wants to achieve. In other words, if the pre-defined resource reduction level is smaller than the maximum reduction level determined by DEA, the decision makers face the problem of determining resource reduction levels for each process. In such multiple-criteria decision situations, additional allocation premises are required, which should further allow the consideration of decisions maker preferences

(Korhonen & Syrjänen, 2004). Considering that the strain level of each process increases in tandem with its individual resource reduction level, we have developed a Mixed Integer Linear Programming (MILP) model for that purpose. It allows decision makers to control the level of fairness with regard to overall social welfare, based on a model introduced by Hooker and Williams (2012). We consider the strain level of a process by evaluating the required efforts of efficiency that a process needs to produce for performing the same tasks with fewer resources consumed (aiming for a higher level of productivity).

Based on the allocation premises of Hooker and Williams (2012), this study considers fairness with regards to equity among the DMUs, following the maximin principle defined by Rawls (1971) – maximizing the welfare of the worst of – until it takes too many resources from others, causing a switch to a utilitarian objective. The welfare of each activity is expressed through its individual strain level to reach cost reductions. To ensure the satisfaction of the fairness objective throughout the allocation process, a social welfare function is used, introduced by Williams and Cookson (2000) and extended by Hooker and Williams (2012). The benefit of formulating a social welfare function for the purpose of allocating resource level reductions is that the function can be subject to different constraints and be maximized, allowing always to determine the most desirable equity/efficiency trade-off for the decision maker. The developed decision-making method, relying only on internal information, is of particular interest for indirect processes (i.e. processes that are needed to keep the direct value generating process running), as the generation of reliable, external benchmarking figures for these processes is particularly difficult (Lee & Covell, 2008). Furthermore, as less improvement potential can currently be found in direct areas (Becker et al., 2007), a concentration of productivity improvement activities in indirect areas takes place in business practice.

The following section describes the requirements for allocating resources among the internal processes of an organization based on a review of DEA literature. With regard to the identified shortcomings of previous research, a new approach is proposed in Section 3. Section 4 applies the developed method to a real case study setting of a first-tier automotive supplier, analyzing indirect plant-related processes and evaluating the results in terms of alternative allocation proceedings. Lastly, Section 5 will provide an outlook on future research potential.

2 Literature Review

DEA is a mathematical approach for the evaluation of the relative efficiency of DMUs (Charnes, Cooper, & Rhodes, 1978). DEA is used for the measurement of the efficiency of a set of DMUs, in the sense that all DMUs transform the same type of resources (inputs) into the same type of products (outputs) using the same technology (Dyson et al., 2001). Accordingly, each DMU can consider all other DMUs as possible benchmarks to assess their relative efficiency.

It is commonly assumed that DMUs are homogenous. Nonetheless, when intending to apply DEA to detect inefficiencies among different processes of a single organization, potential sources of heterogeneity must be considered. Heterogeneity can occur for different reasons. It can be caused by different technologies used by the DMUs (Tiedemann et al., 2011; Sala-Garrido et al., 2011; Medal-Bartual et al., 2012; Wu et al., 2012; Wang et al., 2013), different applicable in- and outputs (Castelli et al., 2001; Saen et al., 2005; Cook et al., 2013), interdependencies between DMUs (Castelli et al., 2001), different sizes of DMUs (Sengupta, 2005; Samoilenko & Osei-Bryson, 2010), or even external factors (De Witte & Marques, 2010; Meza et al., 2011; Tao, 2013).

Different approaches to addressing these sources of heterogeneity have been described in literature. One approach is to cluster DMUs into homogenous groups and examine multiple DEAs. This can be done by the comparison of the generated efficiency values with the help of statistical tests (Lee et al., 2009), the usage of efficiency values of each analysis as a basis for decision trees (Samoilenko & Osei-Bryson, 2008), the usage of a correction respectively connection factor to create comprehensive DEA results based on single analysis (Meza et al., 2011; Gomes et al., 2012; Cook et al., 2013), or neural networks (Samoilenko & Osei-Bryson, 2010). Furthermore, the ex-post clustering based on the results of multiple and recursive DEAs has been suggested (Sharma & Yu, 2009). Moreover, in order to address the aspect of different technologies, metafrontier analyses have recently gained attention (Tiedemann et al., 2011; Sala-Garrido, 2011; Medal-Bartual et al., 2012; Wang et al., 2013). In addition, using multidivisional DEAs to consider the efficiency of DMUs simultaneously but independently in one model have been demonstrated (Wu et al., 2012). Furthermore, smoothing techniques have been examined to reduce random variations causing heterogeneity, and are based on statistical tests and regression analysis (Sengupta, 2005). To ensure homogenous ex-ante data, the selection of only relevant benchmark partners has also been suggested (Adler et al., 2013). To address interdependencies between sub DMUs, the concept of network DEA has been introduced (e.g., Castelli et al., 2001). Finally, if input or output values are missing, AHP has been applied to generate such missing values (Saen et al., 2005).

There are some restrictions to applying the existing approach for the reduction of resource level among the processes of a single organization. While these restrictions can be addressed easily by adapting the model's constraints (see method development), the approach has its limitations if an ex-ante target setting of a total resource level is intended. In this case, an additional multiple criteria problem emerges, which is addressed by this study, and detailed in the following section.

3 Methodology

As a guidance throughout this section, the methodological approach, induced by a problem definition (see Section 1 and 2), is graphically summarized in Figure 1. The two main steps – DEA Analysis and Resource Allocation – have to be followed in order, besides the supporting activities of data collection and the definition of allocation premises. By doing so, an allocation decision can be made by the end.

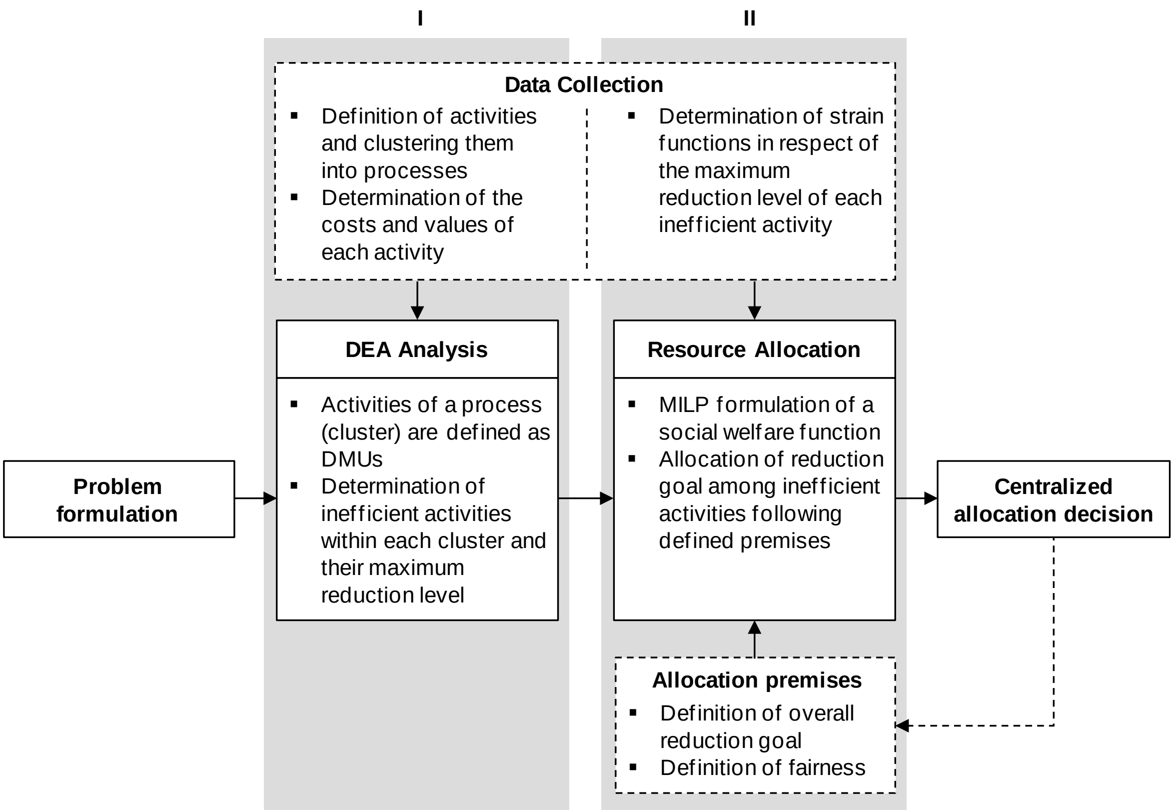


Figure 1: Methodology

Step I

The activities (a) of an organization are identified and clustered into homogenous processes (p). Within a process, activities can be considered homogenous and comparable with a DEA using the same technology. Each activity (a) has the same kind of inputs (I) and outputs (O) given by the amounts x_{ia} (inputs consumed) and y_{oa} (outputs generated). The processes can be heterogeneous with each other. A DEA model with variable returns to scale based on Lozano (2014) is proposed to identify the minimum input level ($\hat{x}_{ia}$) needed for each activity while being able to perform the same tasks (1). More precisely, the same output needs to be producible as formulated through the constraint (3), added to the approach of Lozano (2014) (e.g., Barnum et al., 2011).

The maximum cost reduction of each activity (R_a) – given by $R_a = c_{ia}\,(x_{ia} - \hat{x}_{ia})$ – is determined by the difference between the current input level (x_{ia}) and the minimum level calculated by the DEA. In the resource reduction in step II, only the inefficient activities (i.e. $x_{ia} > \hat{x}_{ia}$) are considered. This is done because the acceptance of the derived targets would otherwise be low in real case examples, and the efficient activities would not work in respect of their in- and output possibilities, set as a benchmark for the inefficient activities, as claimed by Asmild et al. (2009). It is noteworthy that, in this model, we do not consider the option of eliminating activities as suggested by Lozano (2014), as it is not feasible in the context of continuous improvement management, which aims for an improvement of the existing processes, not a reorganization of them.

Sets

A_p	set of activities a belonging to process p
I	set of inputs indexed by i
O	set of outputs indexed by o
P	set of processes indexed by p

Parameters

c_{ia}	unit costs of input i for activity a
x_{ia}	amount of input i consumed by activity a
y_{oa}	amount of output o generated by activity a

Decision variables

λ_{ja}	multiplier variable on activity *j* corresponding to activity *a*
$\hat{x}_{ia}$	minimum amount of input *i* to be consumed by activity *a*

Objective function

$$min \sum_{p \in P} \sum_{a \in A_p} \sum_{i \in I} c_{ia} \, \hat{x}_{ia} \tag{1}$$

Constraints

$$\sum_{j \in A_p} \lambda_{ja} \, x_{ij} \le \hat{x}_{ia} \qquad \forall\, i \in I \;\; \forall\, p \in P \;\; \forall\, a \in A_p \tag{2}$$

$$\sum_{j \in A_p} \lambda_{ja} \, y_{oj} = y_{oa} \qquad \forall\, o \in O \;\; \forall\, p \in P \;\; \forall\, a \in A_p \tag{3}$$

$$\sum_{j \in A_p} \lambda_{ja} = 1 \qquad \forall\, p \in P \;\; \forall\, a \in A_p \tag{4}$$

$$\lambda_{ja} \ge 0 \qquad \forall\, p \in P \;\; \forall\, j \in A_p \;\; \forall\, a \in A_p \tag{5}$$

$$\hat{x}_{ia} \ge 0 \qquad \forall\, p \in P \;\; \forall\, j \in A_p \;\; \forall\, a \in A_p \tag{6}$$

Step II

The DEA model having highlighted inefficient activities, the second step defines which activity and how much it needs to improve given the reduction goal *G* defined by the decision maker. By improvement we refer to reducing cost (or generally ressources) while producing the same value and therefore increasing productivity. If solely a constraint aiming for the allocation of the desired reduction goal would be to be added to the model in step I, but if *G* would be smaller than the determined maximum overall reduction level ($G < \sum_{a \in A} R_a$), an infinite number of optimal solutions would be possible. This could lead to extreme allocation scenarios in which, for example, some activities could receive very demanding reduction targets, while others remain unaffected. Consequently, further allocation objectives are required to ensure a specific and precise allocation proceeding.

Therefore, we incorporate fairness in our approach, an objective that has received recent attention in the literature (e.g., Ogryczak et al., 2006; Bertsimas et al., 2012). To allow the consideration of fairness in respect of the strain of each activity that needs to improve, we base our approach on an allocation model developed by Hooker and Williams (2012). To the best of our knowledge, this approach is so far unique in allowing for individual strain respectively utility levels of each DMU. If other objectives should be considered to ensure an allocation in line with stakeholder expectations, for example the ability of each DMU to change its input-output mix, alternative multiple criteria methods might be of interest, e.g., Korhonen & Syrjänen, 2004.

The approach of Hooker and Williams (2012) is based on a social welfare function, which is maximized in a MILP formulation. The two allocation principles integrated in this model are the maximin principle and, in extreme situations, the utilitarian objective. This allows the consideration of equity and efficiency in the decision process. We have defined the utility level (u_a) of each activity in respect of its strain level (s_a) as: $u_a = 1 - s_a$ where $s_a \in [0,1]$. The switch between the maximin principle to the utilitarian objective occurs when the difference between the utilities is higher than Δ: $u_a - u_{min} \geq \Delta$ with u_{min} being the lowest utility among all utilities. The threshold parameter Δ must be defined by the decision maker within the allocation process, and is measured in the same units as the utilities of the decision elements. When Δ is chosen, it ensures that the same policy is applied in any allocation situation by maximizing the social welfare function.

As the aim of this study is to facilitate the reduction of resources among activities, we will focus on the strain on each activity in reaching the required resource reduction levels. The necessary strain functions of the activities, required to design the *n*-person model, have to indicate how the strain level of the activities change with an increasing reduction level, and indicate their specific strain in respect of the intended cost reductions (r_a; $0 \leq r_a \leq R_a$). The strain level maximum at $s_a = 1$ is reached when $r_a = R_a$. A set of intervals (D) to determine the piece-wise linearized functions is defined. The interval in which r_a is allocated is determined by the lower (lb_{ad}) and upper bounds (ub_{ad}) of the intervals and φ_{ad}. To border the linearized utility functions in each interval in respect of r_a, further auxiliary decision variables, k_{ad}^{-} and k_{ad}^{+} are introduced. Furthermore, we rely on two additional decision variables, originally defined by Hooker and Williams (2012), which are required to perform the resource allocation: v_a and δ_a.

The following optimization model consequently calculates the allocated resource reduction (r_a) among inefficient activities in order to achieve the overall reduction goal (G). The decision maker can decide, in order to ensure fairness, to place more focus on either equity or utility among the activities in the allocation process through the choice of Δ. In other words, the Δ determines how many inefficient activities have to contribute in order to reach the overall resource level, and to what extent. For the sake of illustration, an exemplary linearized utility and strain function is shown in Figure 2.

Parameters

b_{ad}	y-intercept of the utility function of activity a in interval d
D	number of intervals d
Δ	threshold for switching from efficiency approach to equity approach
G	reduction goal
lb_{ad}	lower bound of the d^{th} interval of activity a
M	large number
m_{ad}	slope of the utility function of activity a in interval d
n	number of activities
R_a	maximum possible cost reduction of activity a
ub_{ad}	upper bound of the d^{th} interval of activity a

Decision variables

r_a	cost reduction for activity a
u_a	utility level of activity a
w	lowest utility level amongst all activities
z	overall utility contribution amongst all activities

Auxiliary decision variables

$$k_{ad}^{-} = \begin{cases} 1 \text{ if } r_a \geq lb_{ad} \\ 0 \quad \text{otherwise} \end{cases}$$

$$k_{ad}^{+} = \begin{cases} 1 \text{ if } r_a \leq ub_{ad} \\ 0 \quad \text{otherwise} \end{cases}$$

$$\varphi_{ad} = \begin{cases} 1 \text{ if } lb_{ad} \leq r_a \leq ub_{ad} \\ 0 \quad \text{otherwise} \end{cases}$$

δ_a	binary variable indicating if activity a is making a utilitarian ($\delta_a = 1$) or a rawlsian ($\delta_a = 0$) contribution in the objective function
v_a	auxilliary decision variable to specify the objective function contribution of activity a

Objective function

$$max\ z \tag{7}$$

Constraints

$$z \leq (n - 1)\,\Delta + \sum_{p \in P} \sum_{a \in A_p} v_a \tag{8}$$

$$u_a - \Delta \leq v_a \leq u_a - \Delta\,\delta_a \qquad \forall\, p \in P\ \ \forall\, a \in A_p \tag{9}$$

$$w \leq v_a \leq w + M\,\delta_a \qquad \forall\, p \in P\ \ \forall\, a \in A_p \tag{10}$$

$$u_a - m_{ad}\, r_a \leq b_{ad} + M\left(1 - \varphi_{ad}\right) \qquad \forall\, p \in P\ \ \forall\, a \in A_p\ \ d = 1, \ldots, D \tag{11}$$

$$lb_{ad}\, k^{-}_{ad} \leq r_a \qquad \forall\, p \in P\ \ \forall\, a \in A_p\ \ d = 1, \ldots, D \tag{12}$$

$$r_a \leq ub_{ad}\, k^{+}_{ad} + \left(1 - k^{+}_{ad}\right) M \qquad \forall\, p \in P\ \ \forall\, a \in A_p\ \ d = 1, \ldots, D \tag{13}$$

$$k^{-}_{ad} + k^{+}_{ad} = 1 + \varphi_{ad} \qquad \forall\, p \in P\ \ \forall\, a \in A_p\ \ d = 1, \ldots, D \tag{14}$$

$$\sum_{d=1}^{D} \varphi_{ad} = 1 \qquad \forall\, p \in P\ \ \forall\, a \in A_p \tag{15}$$

$$\sum_{p \in P} \sum_{a \in A_p} r_a \geq G \tag{16}$$

$$0 \leq r_a \leq R_a \qquad \forall\, p \in P\ \ \forall\, a \in A_p \tag{17}$$

$$u_a \geq 0 \qquad \forall\, p \in P\ \ \forall\, a \in A_p \tag{18}$$

$$\delta_a \in \{0,1\} \qquad \forall\, p \in P\ \ \forall\, a \in A_p \tag{19}$$

The objective function (7) maximizes social welfare. Constraints (8)–(10) ensure that the premises underlying the objective function (following a maximin principle and, in extreme situations, a utilitarian objective) are fulfilled. δ_a is 0 and v_a is u_{min} if $u_a - u_{min} < \Delta$ and 1 respectively $u_a - \Delta$ otherwise. Constraints (11)–(15) connect the utility via the strain of activities *a* and the corresponding reduction target r_a, respectively. This is done via a linearization of the utility regarding the strain functions. Constraint (16) ensures that the overall target *G* is met, while constraint (17) ensures that r_a does not exceed R_a. Finally, constraints (18) and (19) define the domain of the remaining decision variables.

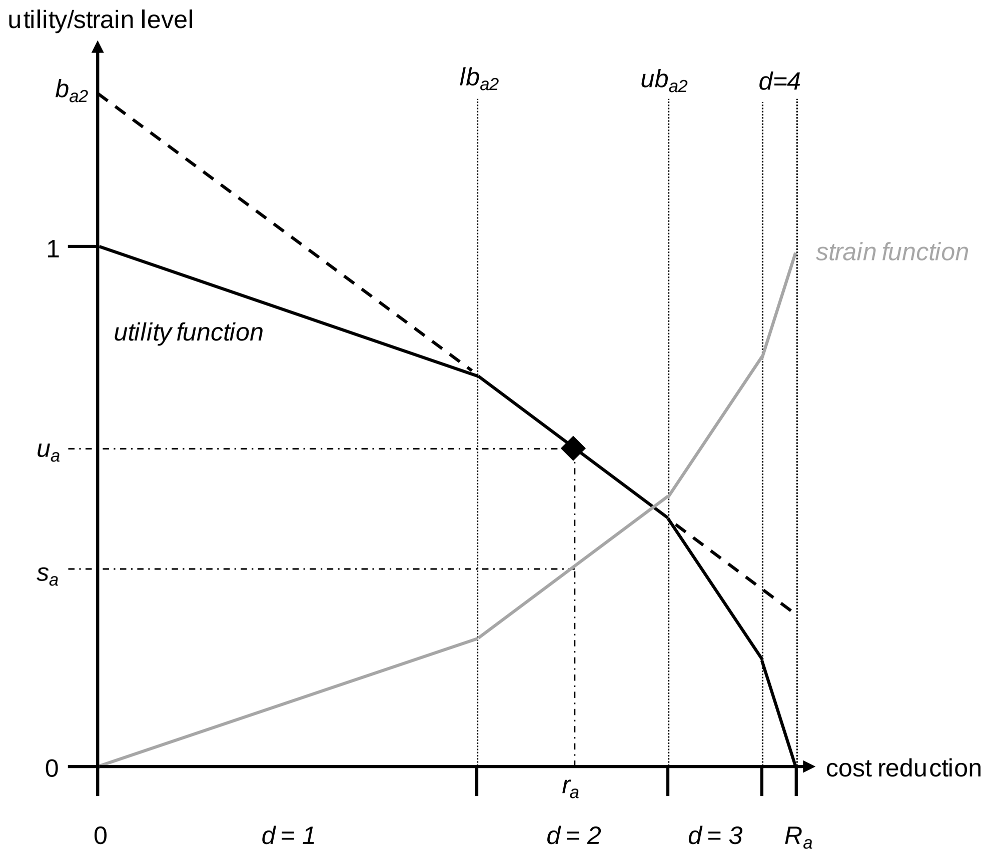


Figure 2: Illustration of a linearized utility and a strain function

To facilitate the implementation of the developed approach in real-life situations, we describe how best to collect the necessary data in the following section.

Data collection

First, the activities need to be identified and mapped. In order to determine the importance of each activity Analytic Network Process (ANP) is used to account for interdependencies between activities. In order to collect the cost incurred from each activity, activity-based costing (ABC) is adopted. The complete description on how to search the required input values for the DEA, (i.e. costs), as well as outputs values, is described in Ihrig et al. (2017).

One essential element of Hooker and Williams' (2012) approach is the definition of a utility function. To determine the utility functions, several approaches are conceivable (Farquhar, 1984), although there is still no gold standard for doing so (Heldmann et al., 2009). In our case study, the extraction of the utility function with the help of a strain function by expert evaluations and piece-wise linearization, roughly based on the approach described by Goodwin and Wright (2004), has demonstrated its practicality.

4 Case Study

To demonstrate the practicality of the developed method, we apply it in a real case setting. The case study organization is a first-tier automotive supplier plant that is confronted by demanding cost pressures. Top management asserted that cost reductions across their indirect processes are crucial in order to stay competitive. In the following, the same process data are used as in Ihrig et al. (2017).

4.1 Step I

First, the direct core processes of the plant and all indirect activities *a* (DMUs for DEA) that increase the internal, and indirectly the external customer value, are identified. The activities range across logistics, maintenance, and quality management functions. The activities are clustered into homogenous processes *p* (clusters for DEA) and the interdependencies have been identified.

The 83 identified activities are analyzed using ABC to determine their cost (c_{ia}, inputs in DEA). The ANP, which takes into account interdependencies, is applied to determine their values in ensuring the direct processes of the organization's running (y_{oa} – output in DEA). The values of the activities are assessed according to the criteria of quality and delivery in a group decision process (see Appendix 2, Table 5). Given this data, the maximum cost reduction of each activity can be calculated. Both optimization models have been implemented and solved using CPLEX.

31 of 83 activities were found inefficient. Their total reduction potential is 15.94 million EUR, which is 28% of the total cost (56.56 million EUR) incurred by all activities in one fiscal business year (see Appendix 2, Table 6).

Regard heterogeneity of the examined processes, it should be pointed out that they all serve the same organizational internal customer (direct production process), allowing the evaluation of all activities in one ANP model using overall valid evaluation criteria. Furthermore, as the activities depend on each other, having an impact on the respective priority value of each activity in the ANP analysis, a non-centralized analysis of the allocation of the overall target *G* would probably lead to only a partially optimal solution.

4.2 Step II

A reduction target *G* is determined by the decision maker. In the case study, we examine possible total reductions from *G*=1 to 15 million EUR, with 1 million EUR interval steps. Each cost reduction level is examined in respect of Δ ranging from 0 to 1 in 0.01 steps. In total, we have run 1.515 possible allocation scenarios (101 different Δ, 15 cost reduction levels).

An expert focus group, including two senior accounting managers and one process expert, has been held in order to construct the strain functions of the activities. One representative activity of each of the eight clusters has been chosen for the discussion.

In Figure 3, the possible shapes of the strain curves discussed by the experts can be found as well as a brief explanation of their rationale. In course of the discussion, it has been decided by the experts that the function type 2 represents the most appropriate shape for all activities and should therefore be considered for the further data analysis. This is in line with the assumption that the utility function of a risk averse behavior (which we assume in such a decision situation) is best described by a monotonic increasing concave function (Murthy & Sarkar, 1998). Since in our setting the strain is the inverse of the utility and therefore rather a loss than a gain, as described on the y-axis, the choice of a convex strain function is supported (see discussion for criticism).

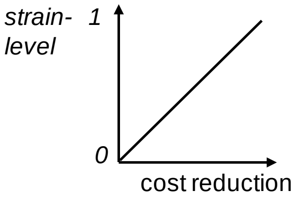
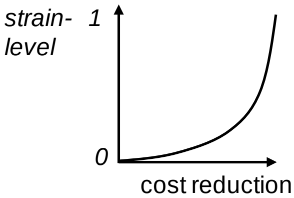
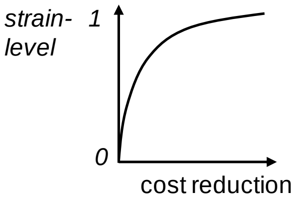
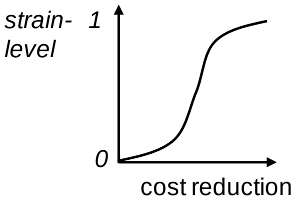
	Strain function	Explanation
1.		*“As the activity is driven by repetitive subtasks, the strain of reduction should increase linearly with the increase of the intended cost reductions.”*
2.		*“The first improvements should be achieved fairly easy, but approaching the maximum reduction, it will become very difficult.”*
3.		*“Any improvement will lead to major interruptions. If the first improvements are realized, further improvements should not cause that much more strain.”*
4.		*“The first improvements should be achieved fairly easy, but at some point major difficulties will emerge, that are hard to realize. If these difficulties are overcome, further improvements should not cause that much more strain.”*

Figure 3: Shapes of the strain curves and explanations

The experts have been asked to determine function parameters using a certainty equivalence approach as well as a mid-value splitting technique, what represents half the difficulty of reaching the maximum reduction level, respectively one quarter for the activities (see Appendix 1 for how the request was designed). The function shape extracted from this approach is shown in Table 1 in the intervals *d* according to R_a, revealing the maximum cost reduction determined by DEA (x-intercept).

d	m_{ad}	b_{ad}
1	$-\frac{0.25}{0.56\,R_a}$	1
2	$-\frac{0.25}{0.25\,R_a}$	1.3
3	$-\frac{0.25}{0.14\,R_a}$	1.94
4	$-\frac{0.25}{0.05\,R_a}$	5.33

Table 1: Linearized concave utility function of type 2

The decision maker has to determine Δ. Hooker and Williams (2012) do not discuss how this should be done in general, as allocation strategy that should be followed is to be decided by the decision maker. However, in respect of the case setting a range of Δ and some turning points can be determined, which are probably of high interest for the decision maker. The range from 0 to Δ, in which at least for one activity δ_a=1 is valid, making a utilitarian contribution to the objective function, is listed in Table 2. For this purpose, we define Δ_{rawl} to be the threshold at which any $\Delta \in [\Delta_{rawl},1]$ will lead to an allocation scenario in which all activities make a maximin contribution.

	Reduction goals *G* in million EUR														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Δ_{rawl}	0.04	0.06	0.09	0.10	0.14	0.17	0.20	0.23	0.25	0.31	0.37	0.43	0.47	0.59	0.70

Table 2: Δ_{rawl} for various reduction goals *G*

Furthermore, an interesting turning point has been identified, in which the number of activities that have to contribute in order to reach the overall reduction goal ($r_a > 0$) increases abruptly with larger Δ, and the number of those with δ_a=1 (meaning more activities contributing to the social welfare function by the maximin principle) drops sharply at the same time. For a reduction level *G* of 10 million EUR, for example, this turning point lies between a Δ of 0.23 and 0.24 (see Figure 4). Furthermore, the cumulated total strain level of all activities experiences the sharpest increase at this point (see Figure 5).

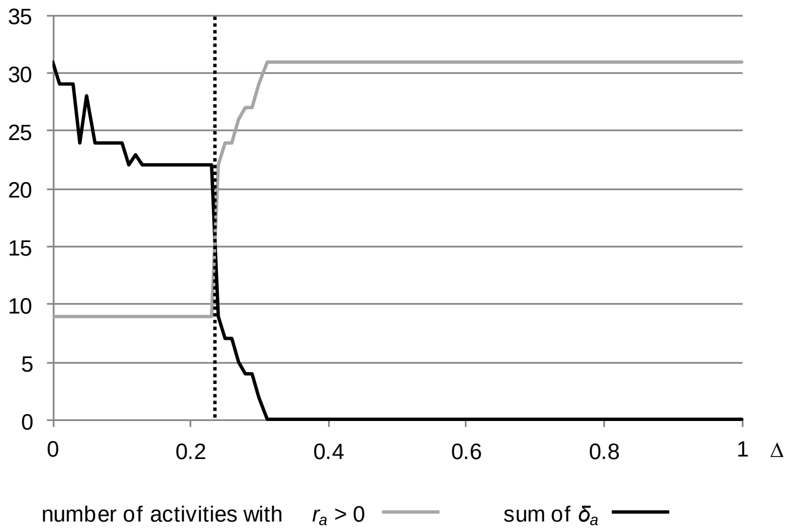


Figure 4: Turning point for a reduction level of 10 million EUR

With regard to a possible demand to reach other higher reduction goals over time, and the fact that Δ is probably chosen only once to ensure consistent policymaking, this turning point is of additional interest. If, for example, a reduction level of 11 million EUR is intended, this point also indicates when a switch from 10 to 11 million EUR would allow the decision maker to choose a level, so that the total strain level, as well as the number of activities that need to contribute in order to reach the total reduction goal, would be the same (see Figure 5).

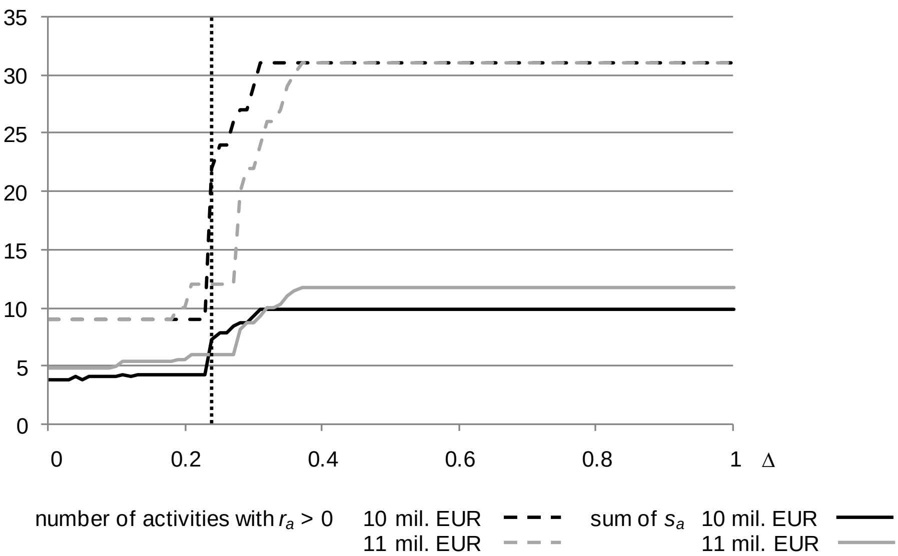


Figure 5: Turning point for a reduction level of 10 million EUR in comparison to a reduction level of 11 million EUR (own illustration)

However, it would not be possible to prevent at least one activity from experiencing a sharp increase in strain as *w* indicates, as shown in Table 3 (meaning that the utility level of the worst off will drop, indicating at the same time that its corresponding strain level increases; see Figure 7 and 8 in Appendix 2 for a detailed comparison of the change in distribution of the individual strain levels among the activities).

	Δ	
	0.23	0.24
w for reduction of 10 million EUR	0.524	0.666
w for reduction of 11 million EUR	0.502	0.502

Table 3: Comparison of *w* at turning point (own illustration)

Even though no general recommendation can be derived regarding how to choose Δ, the analysis shows that at least an interesting range (see table 3) could be identified, which is probably worthwhile for the decision makers to consider.

4.3 Comparison to alternative resource allocations

The advantage of the developed approach becomes obvious when the allocation results are compared with alternative methods for deciding a total productivity gain of 10 million EUR. When reliable information is not available, the Pareto principle is often used to allocate the required reductions among activities bearing the largest costs (e.g., Grosfeld-Nir et al., 2007). The Pareto-principle has been applied on a regular basis at the case study organization in several resource allocation situations. It has also been applied in previous budgeting processes for the examined indirect processes. In this research, we impose uniformly distributed cost reductions among the activities that contribute 80% of the total costs (37 of 83 activities) corresponding to their share of the total desired reduction level. In addition, the Target Setting for Indirect Processes (TSIP) method (Ihrig et al., 2017) can be considered as a valid alternative to decide on the activities that require cost reductions and is also currently applied by the case organization. The method, based on an adapted value control chart, also suggests imposing the reductions on 37 activities (not all the same as in the Pareto-principle). The resulting strain levels for both approaches (TSIP and Pareto) were determined with the assistance of the above-defined, convex-shaped strain function (Figure 3, type 2). For those activities that should receive reduction targets within the Pareto and TSIP proceeding, but which are performing their tasks efficiently according to the DEA (R_a=0), we considered the same function shape, assuming that their maximum reduction is equal to their total costs. By doing so, those activities are probably included in the analysis with strain values that are too low. In Table 4, the results of these two proceedings in comparison to our developed method are presented.

	Pareto	TSIP	New approach		
			Δ		
			0	0.23	>0.31
sum of strain level ($\sum s_a$)	7.11	6.01	3.81	4.29	9.85
highest strain	1.00	1.00	0.75	0.48	0.32
second highest strain	1.00	0.57	0.75	0.48	0.32
third highest strain	1.00	0.52	0.56	0.48	0.32
number of required reductions	37	37	9	9	31

Table 4: Comparison of the results of different allocation proceedings

Within the Pareto-principle, it is remarkable that the highest strains are all 1 (non-efficient activities according to DEA obtained targets larger or equal to R_a). Even though the sum of the strain values of all activities is not significantly high (keeping in mind the probability of strain value that are too low), it is doubtful that the imposed reductions can be reached. In comparison, the TSIP approach reaches a lower overall strain level, and the strains of the activities are, apart from one exception, lower than 0.6. One reason is that the TSIP approach is based on an efficiency analysis and considers the 'potential for improvement' of each activity, determined by an ANP analysis, within its allocation process (implicitly representing an alternative formulation of the production function of each process). Therefore, the probability of reaching the imposed productivity targets can be considered to be much higher. With regard to our developed method, it is remarkable that, if a low Δ is chosen, even lower strain values can be reached with considerably smaller numbers of activities that need to contribute. However, these activities experience relatively high strain levels. In summary, our developed approach is beneficial for two reasons. First, all allocated resource level reductions lie within the production possibility set of the respective activities; second, the satisfaction of a pre-defined fairness policy among the activities by the decision maker is ensured.

5 Conclusion

The allocation of resources and therefore productivity targets by a decision maker is a highly challenging task. Literature has not given detailed insight into how to do so if productivity targets are to be allocated among processes of a single organization, and in the absence of (external) benchmarking figures. The core idea of our method is to define processes and their corresponding costs as inputs, and their value as output within a DEA. Resources are allocated by means of an optimization model, incorporating a social welfare function that enables the decision maker to determine whether the focus should be on equity or utility. The advantage of the developed approach have become obvious when applied in a real case setting, and when compared to alternative allocation methods. It allows for the allocation of resource reductions and therefore productivity gains among significantly fewer processes, while still generating low strain levels and ensuring fairness.

However, considering the usage of DEA for efficiency analysis, one general aspect of DEA has to be reflected critically: the number of activities under each process might not be sufficient in all case settings (rule of thumb: the number of DMUs should be at least three times as high as the sum of all input and output factors Paradi & Zhu, 2013). Even though this could just be a matter of how to design the process structure appropriately in real case contexts, this aspect should not go unmentioned. Furthermore, it needs to be considered that, if an ANP is intended to determine the process values, the number of alternatives should not exceed a critical large number at the same time. Therefore, in the case study design, adaptations for the ANP analysis were necessary in cooperation with the case organization.

Furthermore, the associated efforts cannot be denied. Specifically, the determination of the process and activity values and their respective strain functions demand some effort. This was also the case in the examined real case study. Even though it was intended to keep the efforts at a reasonable level to determine the strain functions, it appeared that different experts evaluated the activities differently, making additional, in-depth discussions and simplifications necessary. Along with these simplifications a potential loss in accuracy and increase in subjectivity cannot be denied. In future research alternative strain function extractions might therefore be of interest. Some might consider SMART(ER) (Edwards & Barron, 1994) or UTA (Jacquet-Lagreze & Siskos, 1982) to be useful; two commonly discussed approaches in the literature to determine utility functions.

With regard to the unique possibilities of the developed method and the demand of managers for advanced decision methods, along with an increase in the dissemination of comprehensive process management approaches, we are hopeful that the research insights will gain wider attention in academia and in practice.

Appendix

1 Strain Function Extraction

The certainty equivalence approach that was used to extract the strain function was designed as the follows: the process experts of the case organization were requested to evaluate piece-wise what represents half of the difficulty level and that which represents one and three quarters, respectively, in order to reach the total reduction level of activity 3.5 ($x_{i3.5}$ = 492.437; $R_{3.5}$ = 338.480). The request was designed using spreadsheet software. Based on the evaluations, the piece-wise linearized utility function was derived in respect of R_a. and by inverting s_a The proceeding is exemplarily shown below, indicating the request for two intervals (one quarter and half the strain with regard to the maximum reduction level).

Do you perceive the reduction of 169'240 as half as difficult as the reduction of 338'480 ?	Yes	
	No, less difficult	x
	No, more difficult	

Do you perceive the reduction of 253'860 as half as difficult as the reduction of 338'480 ?	Yes	
	No, less difficult	x
	No, more difficult	

Do you perceive the reduction of 296'170 as half as difficult as the reduction of 338'480 ?	Yes	
	No, less difficult	
	No, more difficult	x

Do you perceive the reduction of 275'015 as half as difficult as the reduction of 338'480 ?	Yes	x
	No, less difficult	
	No, more difficult	

Do you perceive the reduction of 137'508 as half as difficult as the reduction of 275'015 ?	Yes	
	No, less difficult	x
	No, more difficult	

Do you perceive the reduction of 206'261 as half as difficult as the reduction of 275'015 ?	Yes	
	No, less difficult	
	No, more difficult	x

Do you perceive the reduction of 171'884 as half as difficult as the reduction of 275'015 ?	Yes	
	No, less difficult	x
	No, more difficult	

Do you perceive the reduction of 189'073 as half as difficult as the reduction of 275'015 ?	Yes	x
	No, less difficult	
	No, more difficult	

Figure 6: Exemplary certainty equivalence approach (own illustration)

2. Case Study Data Analysis

a - activity-	x_{ia} [EUR]	y_{oa} - quality-	y_{oa} - delivery-
1.1	8‘214	0.001	0.003
1.2	65‘712	0.011	0.004
1.3	123‘210	0.005	0.003
1.4	41‘070	0.002	0.003
1.5	8‘214	0.001	0.002
1.6	748‘198	0.008	0.005
1.7	24‘642	0.003	0.004
1.8	82‘140	0.003	0.003
1.9	8‘214	0.001	0.002
1.10	1‘235‘693	0.010	0.121
1.11	1‘000‘807	0.010	0.075
1.12	1‘820‘540	0.010	0.043
1.13	297‘875	0.010	0.034
2.1	61‘099	0.001	0.002
2.2	236‘314	0.001	0.002
2.3	365‘657	0.002	0.002
2.4	303‘555	0.002	0.002
2.5	237‘703	0.003	0.002
2.6	425‘447	0.015	0.002
2.7	651‘869	0.015	0.002
2.8	280‘732	0.012	0.011
3.1	195‘573	0.008	0.001
3.2	905‘638	0.008	0.002
3.3	452‘819	0.061	0.008

a - activity-	x_{ia} [EUR]	y_{oa} - quality-	y_{oa} - delivery-
5.1	148‘302	0.004	0.001
5.2	323‘483	0.009	0.007
5.3	328‘560	0.003	0.002
5.4	82‘140	0.003	0.002
5.5	287‘490	0.006	0.005
5.6	32‘856	0.004	0.003
5.7	410‘700	0.042	0.005
5.8	328‘560	0.096	0.027
5.9	82‘140	0.005	0.003
5.10	82‘140	0.009	0.003
5.11	134‘399	0.059	0.019
5.12	263‘236	0.013	0.018
5.13	228‘560	0.028	0.018
6.1	545‘443	0.002	0.006
6.2	2‘051‘585	0.002	0.010
6.3	444‘012	0.001	0.001
6.4	1‘442‘738	0.000	0.001
6.5	665‘093	0.001	0.004
6.6	2‘660‘371	0.001	0.008
6.7	590‘783	0.000	0.000
6.8	368‘879	0.000	0.000
6.9	484‘082	0.000	0.001
6.10	418‘576	0.000	0.001
6.11	3‘661‘751	0.003	0.015

3.4	204‘014	0.004	0.000
3.5	492‘437	0.010	0.005
3.6	2‘083‘747	0.010	0.010
3.7	392‘579	0.009	0.017
3.8	121‘971	0.011	0.007
3.9	242‘627	0.013	0.002
3.10	290‘279	0.010	0.002
4.1	1‘513‘443	0.017	0.021
4.2	62‘696	0.008	0.004
4.3	160‘240	0.010	0.015
4.4	312‘132	0.006	0.003
4.5	427‘128	0.007	0.006
4.6	6‘911‘206	0.091	0.026
4.7	2‘226‘686	0.034	0.058
4.8	2‘123‘634	0.008	0.024
4.9	1‘087‘685	0.033	0.009
4.10	1‘339‘668	0.033	0.033
4.11	664‘902	0.006	0.057

6.12	406‘533	0.003	0.015
7.1	998‘168	0.006	0.014
7.2	845‘905	0.006	0.014
7.3	284‘777	0.005	0.013
7.4	274‘834	0.004	0.012
7.5	154‘141	0.002	0.008
7.6	1‘518‘811	0.004	0.012
7.7	2‘575‘714	0.001	0.007
7.8	71‘344	0.005	0.012
7.9	71‘344	0.005	0.012
8.1	2‘223‘265	0.021	0.004
8.2	82‘140	0.019	0.005
8.3	82‘140	0.010	0.005
8.4	65‘712	0.005	0.001
8.5	32‘856	0.011	0.004
8.6	246‘420	0.012	0.005
8.7	328‘560	0.007	0.007

Table 5: Case study raw data (own illustration)

a - activity-	R_a [EUR]	r_a [EUR]	s_a	δ_a	w
1.3	93‘122	-	0.00	1.00	0.52
1.4	22‘869	-	0.00	1.00	0.52
1.6	686‘370	541‘034	0.48	-	0.52
1.8	59‘286	-	0.00	1.00	0.52
1.11	259‘443	-	0.00	1.00	0.52
1.12	1‘428‘559	1‘126‘068	0.48	-	0.52
2.2	175‘215	-	0.00	1.00	0.52
2.3	263‘213	-	0.00	1.00	0.52
2.4	211‘448	-	0.00	1.00	0.52
2.5	122‘339	-	0.00	1.00	0.52
2.7	226‘422	-	0.00	1.00	0.52
3.2	712‘888	561‘938	0.48	-	0.52
3.5	338‘480	-	0.00	1.00	0.52
3.6	1‘867‘173	1‘471‘808	0.48	-	0.52
3.9	12‘345	-	0.00	1.00	0.52
3.10	85‘902	-	0.00	1.00	0.52
4.1	969‘606	764‘297	0.48	-	0.52
4.5	213‘825	-	0.00	1.00	0.52
4.8	1‘852‘104	1‘459‘929	0.48	-	0.52
5.2	241‘434	-	0.00	1.00	0.52
5.5	230‘119	-	0.00	1.00	0.52
5.9	40‘885	-	0.00	1.00	0.52
5.13	9‘648	-	0.00	1.00	0.52
6.1	119‘059	-	0.00	1.00	0.52
6.2	892‘053	703‘165	0.48	-	0.52
6.5	284‘987	-	0.00	1.00	0.52
6.9	65‘506	-	0.00	1.00	0.52
6.11	3‘255‘218	2‘565‘941	0.48	-	0.52
7.3	9‘943	-	0.00	1.00	0.52
7.6	1‘022‘285	805‘821	0.48	-	0.52
8.6	164‘280	-	0.00	1.00	0.52
	∑15.8 million EUR	∑10 million EUR			

Table 6: Analysis for Δ=0.23 and G=10 million EUR (own illustration)

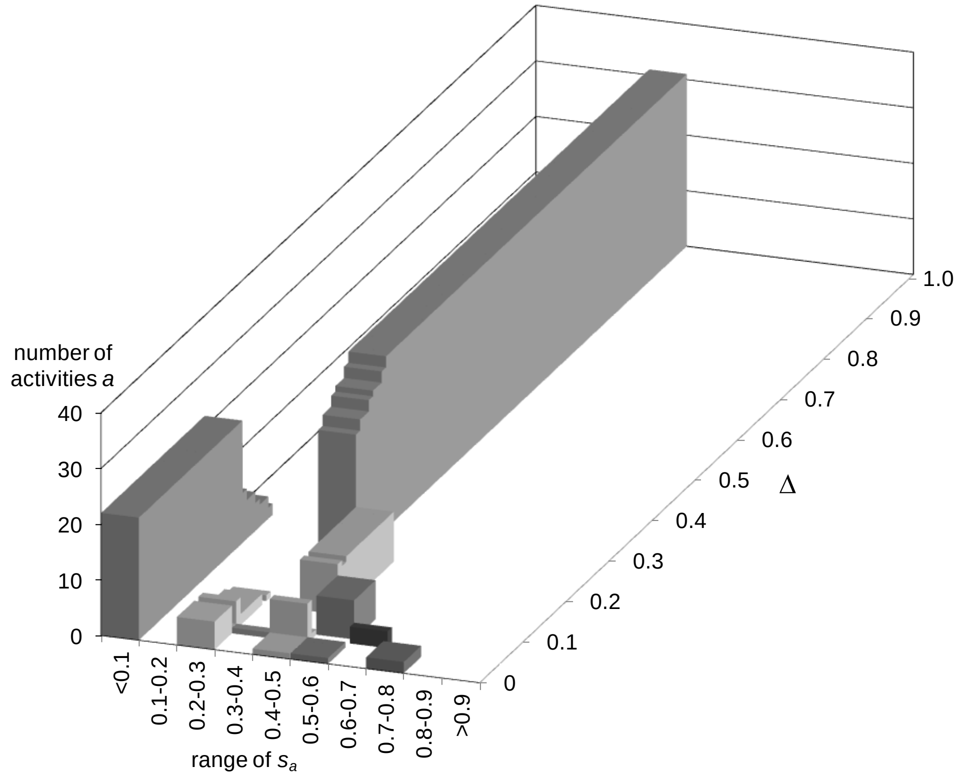


Figure 7: Distribution of s_a at 10 million EUR cost reduction (own illustration)

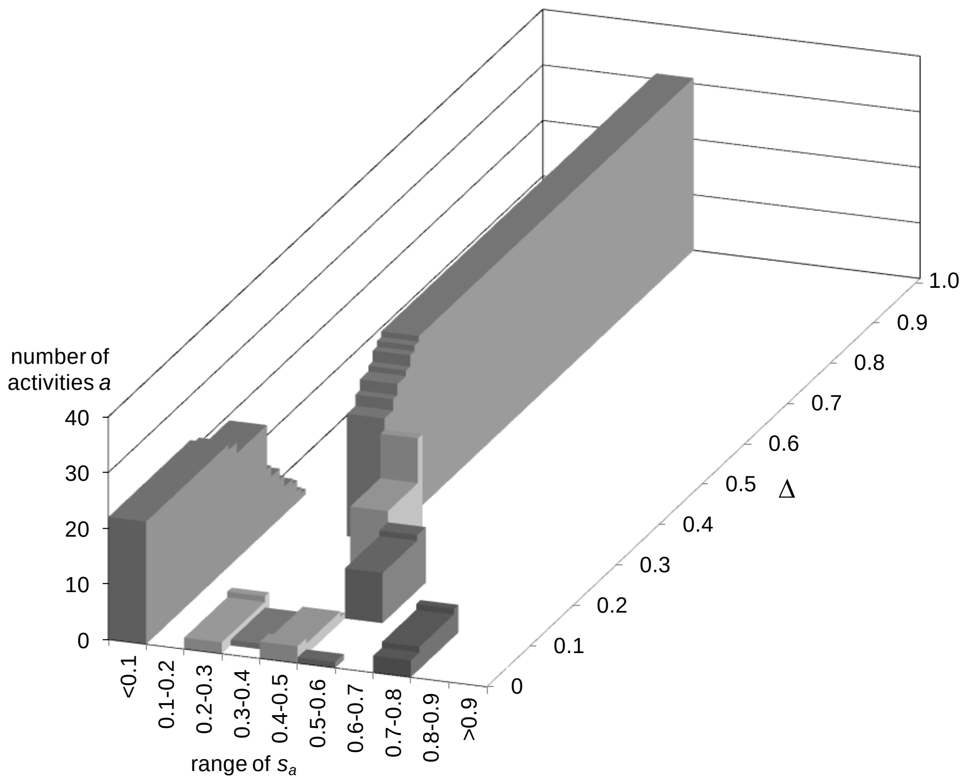


Figure 8: Distribution of s_a at 11 million EUR cost reduction (own illustration)

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