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A DATA ENVELOPMENT ANALYSIS APPROACH FOR EVALUATING EFFICIENCY OF THE EXTREME PROGRAMMING SYSTEM DEVELOPMENT METHODOLOGY

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ABSTRACT

Many organizations have deployed system development methodologies in order to improve information systems development. Various factors influencing the successful adoption of system development methodologies have been identified by numerous studies. However, a need was identified to evaluate the post-implementation efficiency of system development methodologies. The aim of this paper is to present theoretical and empirical background for an evaluation model to measure the efficiency of a software development methodology after implementation. A linear programming method called Data Envelopment Analysis was used to compare the application of the Extreme Programming system development methodology in different organizations. According to the results of the analysis, it was possible to classify organizations' use of Extreme Programming as efficient or inefficient. Recommendations could be made to increase efficiency of individual organizations that were classified as inefficient.

KEYWORDS

System Development Methodology, Data Envelopment Analysis, Extreme Programming, Information Systems.

1. INTRODUCTION

The use of a system development methodology (SDM) has been endorsed as being capable of rendering the development process to be more efficient, predictive and easier to control (Fitzgerald *et al.,* 2002). Also, it is argued to be a risk to assume that one can construct quality software without any kind of process to offer some guidance (Klopper *et al.,* 2007). Examples of other very influential sources of pressure in favour of the use of SDMs includes ISO-certifications and governments highly involved with IS development (Fitzgerald, 1996). However, the practical usefulness of SDMs is still a controversial issue (Fitzgerald, 1996; Nandhakumar and Avison, 1999).

Practitioners are faced with a wide variety of SDMs today, and yet more are produced every year (Jayaratna, 1994; Iivari *et al.,* 1999). Assuming that SDMs are used by organizations, one may still question whether SDMs are used efficiently and what they accomplish. The answers to these questions lie in research to evaluate SDMs (Wynekoop and Russo, 1995).

Various studies regarding the evaluation of SDMs exist in the literature. However, the problem is that several of these studies assume that SDMs are used and are efficient and the frameworks developed to evaluate and adopt SDMs are useful (Wynekoop and Russo, 1995). Furthermore, various researchers focused only on the adoption of SDMs and other information technology innovations (Moore and Benbasat, 1991; Iivari, 1996; Fitzgerald, 1998, Sultan and Chan, 2000; Riemenschneider *et al.,* 2002; Jeyaraj and Sabherwal, 2008).

A company's decision to adopt a SDM does not guarantee that all stakeholders will use the methodology, or that they will use it to its full potential. A need for the evaluation of post-implementation efficiency of a SDM was identified. This paper will contribute to the existing knowledge on SDM evaluation by providing a method to evaluate SDM efficiency after implementation and to identify areas needing improvement in individual companies. The use of Data Envelopment Analysis (DEA), a linear programming (LP) method developed by Charnes *et al.* (1978), is investigated in order to evaluate the efficiency of different companies using Extreme Programming (XP). With the aid of DEA the companies can be compared and their use of XP can be classified as efficient or inefficient.

The remainder of the paper is organized as follows. Section 2 defines a SDM and discusses the need to evaluate SDMs. Section 3 contains a brief definition and overview of the DEA method. Section 4 discusses the research design followed in this paper. Section 5 describes the evaluation of XP using DEA while section 6 presents the final conclusions.

2. SYSTEM DEVELOPMENT METHODOLOGIES

2.1 Definition

Defining a SDM is not easy. The term is not well defined either in the literature or by practitioners and there are no universally agreed definitions (Wynekoop and Russo 1997; Iivari *et al*., 2000; Avison and Fitzgeral, 2006). System development methodologies aim to make the IS development process as straightforward and as simple as possible (Walters *et al.,* 1994). It suggests certain procedures, methods, techniques, tools and documentation aids relevant to different phases of the information system development life-cycle (Nandhakumar and Avison, 1999).

One of the most comprehensive definitions, and the one used in this paper, is that of Huisman and Iivari (2006), who defined a SDM as a collective term which constitutes the following:

- *A systems development approach* is the philosophical view on which a SDM is build which includes the set of goals, guiding principles and beliefs, fundamental concepts, and principles of the systems development process that drive interpretations and actions. For example, XP is based on an agile approach.
- *A systems development process model* represents the sequence of states through which a system evolves. Incremental development is an example of a process model used by XP.
- *A Systems development method* is a systematic approach to conduct at least one phase of system development and consists of a set of guidelines, activities, techniques and tools.
- *A Systems development technique* is the specific procedures or steps for conducting a portion of a phase of software production. Amongst techniques used by XP are prototyping and paired programming.

In this paper the focus will be on the XP system development methodology. XP is based on an agile approach developed to fulfill a need for a faster, simpler and cheaper way to design software. XP breaks development into small chunks and relies on daily face-to-face communication and lots of testing. Projects are deployed in increments with a constant evaluation to accomplish the desired outcomes.

Avison and Fitzgerald (2006) have defined nowadays as an era where there is a reappraisal of the use of SDMs. This era of reassessment emphasized the need and importance for a valid and reliable method of evaluation, especially after a SDM was adopted. Different companies using XP was chosen to be evaluated for this paper, as XP is a popular SDM in use today.

2.2 A Need for Post-Implementation Evaluation of SDMs

Thousands of SDMs are in existence today, and yet more are produced every year (Jayaratna, 1994; Iivari *et al.*, 1999). The number of SDMs are not necessarily the problem, evaluating them are. A study by Siau and Rossi (1998) suggest four reasons for evaluating methods:

“Firstly, for researchers to better understand methods in order to improve and classify them. Secondly, practitioners want to use comparison as a practical tool for selecting methods. Thirdly, method developers want to know the strengths and weaknesses of the various methods. Fourthly, since no one method is suitable for all situations, we need to know when to use a particular method and when not to use a specific method.”

Studying the efficiency of SDMs is of theoretical and practical importance as it may affect both the development process and the product in development. In the current *era of methodology reassessment* it is essential to be acquainted with the efficiency of an SDM. It is even more important to be capable of identifying areas for improvement of SDM-use in order to accomplish better results with the SDM.

Various studies regarding the evaluation of SDMs exists. The problem is that several of these studies assume that (Wynekoop, 1995): SDMs are used and are efficient; and The frameworks that have been developed to evaluate and select SDMs are useful.

Another problem identified is that too many SDM evaluation methods focus only on technical aspects while both, technical (such as *use* and *training*) and social aspects (such as *voluntariness* and *support*) should be taken into consideration (Fitzgerald, 1996; Truex, 2000). Furthermore, various researchers focused only on the adoption of SDMs and other information technology innovations (Moore and Benbasat 1991; Iivari, 1996; Fitzgerald, 1998; Sultan and L. Chan, 2000; Riemenschneider *et al*., 2002; Jeyaraj and Sabherwal, 2008). Various theories have been developed for technology adoption such as Theory of reasoned action (TRA), Diffusion of innovations model (DOI), Technology acceptance model (TAM), etc. (Jeyaraj and Sabherwal, 2008). Avison and Fitzgerald (2006) also identified frameworks for SDM comparisons, such as Bjorn-Anderson's Framework, NIMSAD, Davis's Framework, and Avison and Taylor's Framework. Although each of these frameworks have their respective strengths and weaknesses, a major concern is that they all provide subjective unspecific criteria (Klopper *et al.*, 2007) Also, it is frameworks to compare different SDMs and to aid in the decision making process before adoption.

A need for the evaluation of post-implementation efficiency of a SDM was identified. This paper will contribute to the existing knowledge on SDM evaluation by providing a method to evaluate SDM efficiency after implementation and to help identifying areas for improvement. The use of data envelopment analysis, a linear programming method developed by Charnes *et al.* (1978), is investigated in order to evaluate the efficiency of different companies using the same SDM, namely XP.

3. DATA ENVELOPMENT ANALYSIS

3.1 Definition

A fairly large amount of research has been devoted to the development of efficiency measures as organizations want to increase efficiency (Cook and Seiford, 2009). These measures indicate whether a production unit, also known as a decision making unit (DMU), is operating efficiently or productively.

Data Envelopment Analysis is a linear programming (LP) method developed by Charnes, *et al.* (1978) and is used for evaluating the relative efficiency or productivity of a homogeneous group of operating decision making units, such as branches of the same bank, universities, hospitals, electric utilities, etc. DEA is a technique that converts multiple input and output measures into a single comprehensive measure of efficiency (for each DMU) which lies between zero (meaning the DMU is totally inefficient) and one (meaning the DMU is technically efficient). It measures efficiency of a DMU by determining which of the DMUs make efficient use of their input and which do not. A DMU is rated efficient if and only if the performances of other DMUs do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs. This is done by estimating the production function, which relates the inputs consumed to the outputs produced. The DEA model is summarized as follows (Vassiloglou and Giokas, 1990):

$$\boldsymbol{Maximise} \quad \boldsymbol{E_o} = \left(\sum_{i=1}^{k} \boldsymbol{u_i \psi_{io}}\right) \Bigg/ \left(\sum_{j=1}^{m} \boldsymbol{v_j x_{jo}}\right)$$

$$\boldsymbol{subject\ to}\quad \left(\sum_{i=1}^{k} u_i \psi_{ir}\right) \Big/ \left(\sum_{j=1}^{m} v_j x_{jr}\right) \leq 1 \quad r = 1, \dots, n$$

$$u_i, v_j > \varepsilon \qquad i=1,\dots,k \qquad j=1,\dots,m$$

where
o = the index of the unit being assessed from the set of $r = 1,\dots,n$ units
k = the number of outputs at the units
m = the number of inputs at the units
ψ_{ir} = observed output i at unit r
x_{jr} = observed input j at unit r
ε = small positive number
u_i = weight assigned to output i
v_j = weight assigned to input j

The above analysis is performed for the different units producing an efficiency rating for each of the n units. The required solution is the set of (u_i, v_j) values that maximise the efficiency ratio E_o of the unit being rated without resulting in an input-output ratio exceeding one (100% efficiency). Consequently, if a relative efficiency rating of 100% is not attained under this set of weights, it cannot be attained under any other set (for the same sample of units). This fractional programming problem is replaced with a LP equivalent through a series of transformations, which are set out in detail in Charnes *et al.* (1978).

Without DEA, analysis of complex organizations producing multiple outputs is often limited to examining ratios of outputs to inputs (Charnes *et al.*, 1994). Often only ambiguous conclusions can be reached from these ratios. DEA serves as an alternative to these unsatisfactory methods. DEA is a procedure to perform a frontier analysis of inputs and outputs rather than examining central tendencies so as to fit a regression plane through the center of the observations (Seiford and Thrall, 1990). It can be seen as an extension of ratio analysis since it enables us to consider the use of multiple inputs to produce multiple outputs (Reichmann, 2004). Another advantage is that the inputs and outputs do not need to have the same unit of measurement, nor any functional relationship to each other (Sowlati *et al*., 2005). Mathematical details of DEA do not form part of this paper. For a discussion of the basic DEA formulations, enhancements and more, see Charnes *et al*. (1994) and Seiford and Thrall (1990).

3.2 Graphical Example

In DEA a point on the efficiency frontier is termed efficient while any point not on the efficiency frontier is termed inefficient. The efficiency score of an inefficient DMU is based on its comparison with a virtual DMU (reference point) which does lie on the frontier. The general way to obtain a virtual DMU is by a radial projection from the origin which passes through the point being assessed and then intersects the efficiency frontier. Such a reference point represents a linear combination of other efficient DMUs which is called the reference set.

A simple graphical example by Anderson (1996) may illustrate these concepts easily. Assume that there are three baseball players (DMUs) A, B and C, with batting statistics as given in Table 1. The statistics shows the number of singles and home runs (outputs) each player produced with 100 at-bats (input).

Table 1. Player batting statistics

Player	At-bats	Singles	Home runs
A	100	40	0
B	100	20	5
C	100	10	20

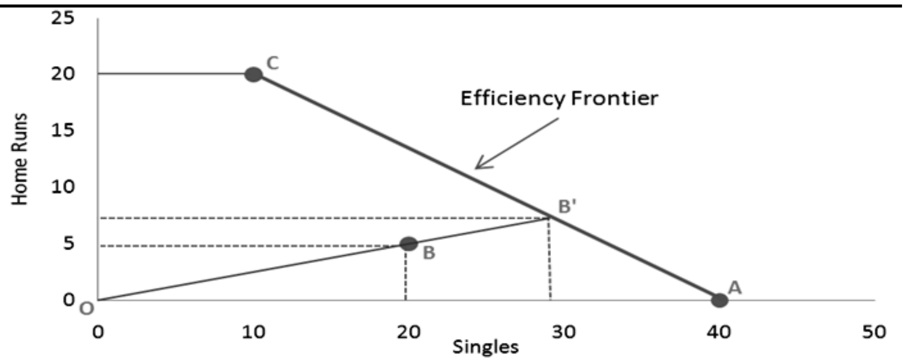

Figure 1. Graphical example of DEA (Anderson, 1996)

The points A and C, in Figure 1, represents efficient DMUs in terms of the outputs as represented on the x- and y-axis. The line segment connecting A and C shows the possibility of virtual DMUs that can be formed from the two units and is called the efficiency frontier. The efficient frontier defines the maximum combinations of outputs that can be produced for a given set of inputs. The segment connecting C with the y-axis is defined because of disposability of output and ensures that the projection will always encounter the frontier.

Unit B is inefficient, because it is below the efficiency frontier. Its efficiency score can be calculated by comparing it to the virtual unit B' formed from efficient units A and C (its reference set). The virtual unit B' is approximately 64% of unit A and 36% of unit C. (These measures can easily be calculated by measuring the lines AB', CB' and AC. The percentage of player C is then AB'/AC and the percentage of player A is CB'/AC). The efficiency of unit B is calculated by finding the fraction of inputs that B' would need to produce the same outputs as B. Hence, the efficiency of unit B is calculated as the ratio OB/OB' which is approximately 0.68 or 68%

4. RESEARCH DESIGN

4.1 The Input / Output Set

The positivistic research paradigm together with a quantitative research approach were followed. As depicted in Table 2, the choice of input and output variables for DEA modeling was done according to previous research regarding SDM use and evaluation. An input orientated DEA model was used which means that the LP was configured in such a way that inputs are optimized while attaining the same, or better, levels of output. Five input variables and two output variables were chosen. The input variables are *use, voluntariness, support, training,* and *cost* and the output variables are *impact* and *satisfaction.* These variables were chosen because they are quantifiable and can be consistently measured and collected. The number of variables was kept to a minimum as using too many may influence a DEA model negatively (Dyson *et al.,* 2001).

Controllable input variables have been chosen which enables management to make valid recommendations after a DEA evaluation. For instance *voluntariness* and *management support* are factors which management can control. It is quite difficult to make recommendations on a variable such as *organization culture*. It is most likely that top management will discard a recommendation such as: "To improve SDM efficiency, the organizational culture needs to be changed."

Also, too many SDM evaluation methods focus only on technical aspects while both, technical (such as *use* and *training*) and social aspects (such as *voluntariness* and *support*) should be taken into consideration (Hardgrave *et al.*, 2003; Vavpotic and M. Bajec 2009).

Future studies should consider other variables such as *usefulness, ease of use, relative advantage, maturity, experience, trialability,* etc. These variables, and more, were already proven by various researchers to have a significant implication on the efficiency of SDMs (Moore and Benbasat, 1991; Chau, 1996; Iivari 1996; Khalifa and Verner, 2000; Sultan and Chan, 2000; Huisman and Iivari, 2002; Riemenschneider *et al.*, 2002; Hardgrave *et al.*, 2003; Huisman and Iivari, 2006; Vavpotic and Bajek, 2009).

Table 2. Input and output variables

Variable	**Description**
Inputs	
Use	SDM-use was identified by various researchers as an important issue in IS research. (Wynekoop and Russo, 1995; Huisman and Iivari, 2003). Use can be divided into two categories namely horizontal use, which relates to the SDM use across the entire organization and vertical use, which relates to the extent an SDM and its underlying methods and tools were used in the different phases of the development life cycle.
Voluntariness	Voluntariness is the extent to which SDM users see the adoption of a certain SDM and its underlying approach, methods and tools as voluntary or mandatory (Moore and Benbasat, 1991). It has been proven by various researchers to be a significant factor, with a direct effect on the intention to use SDMs (Hardgrave *et al.,* 2003). Research by Iivari (1996) has shown that unless management prescribes the use of CASE tools or other methods, software developers often do not use it.
Support	The degree to which top management, IS management and developers supports the use of a SDM on projects. According to a study by Huisman and Iivari (2002) there is a significant positive relationship between management support and the individual deployment of a SDM. If a SDM is not regarded as useful by developers, its prospects for successful deployment may not be very promising (Riemenschneider *et al.*, 2002).
Training	Training provides the development team with a better understanding of the SDM to be used. It may reduce uncertainty and increase amenability (Fitzgerald, 1997). Training was also found to have a positive effect on the perceived ease of use of a SDM (Riemenschneider and Hardgrave, 2001).
Cost	Cost can be divided into aspects such as purchase cost, training cost, embedding/implementing cost and costs regarding applications and tools to aid the development team in efficient use of the SDM (Avison and Fitzgerald, 2006).
Outputs	

Variable	Description
Impact	Impact of a SDM can be divided into two focus areas (Huisman and Iivari, 2006) namely: (1) its impact on the quality of the product (developed system) and (2) its impact on the quality and productivity of the systems development process. These criteria also formed part of the measures used by Wynekoop and Russo (1997) for measuring the efficiency of SDMs.
Satisfaction	Satisfaction of a SDM is the overall satisfaction regarding to a blend of variables such as use, usefulness, ease of use, cost, impact, etc. Satisfaction plays a big role in acceptance of a SDM (McChesney and Glass, 1992).

The input and output variables as portrayed in Table 1 were gathered from a targeted population using a survey in the form of a web-based questionnaire. The questionnaire consisted of 11 questions and primarily used a 5-point Likert scale together with a few open ended questions. Companies using XP were targeted and a total of 37 companies indicated that they use XP which will be evaluated with DEA in the subsequent section.

4.2 Transformation of Input Variables

The DEA model used for this analysis will always attempt to reduce the amount of inputs to produce the same amount of outputs. In other words it is a minimization of inputs. Using 'cost' as an input makes perfectly sense, because the aim is to reduce costs while still producing the same outputs. A problem arises when using a variable such as 'support' as an input. Reducing support will not lead to the same or better outputs; in fact it may cause a reduction in the output efficiency. Hence, to maintain or increase the level of output, some variables must be reduced while others must be increased within the same DEA application. Therefore, the variables that need to be maximized, must first be transformed in order to be used in an input orientated DEA model. After the transformations the variables may be minimized. After performing DEA, as depicted in Figure 2, the results of the analysis must be transformed back to their original state in order to make sense. By omitting the necessary transformations, the DEA results will have major discrepancies and have no value for any decision maker.

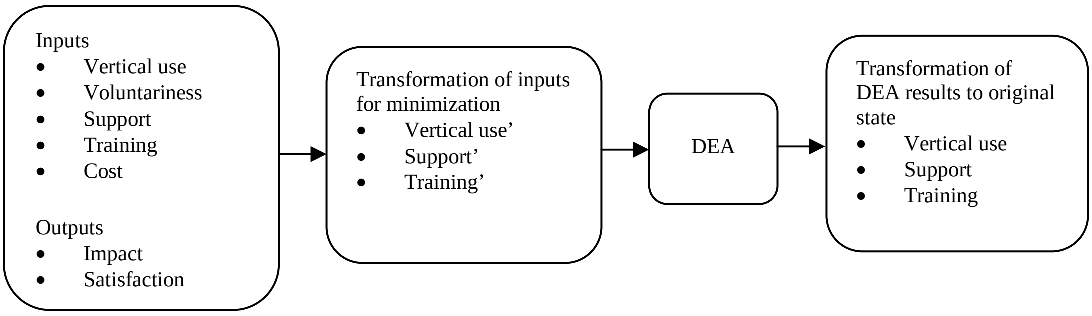

Figure 2. Process of transforming variables before and after a DEA application.

The transformations, needed for the variables, can easily be done by reverse coding the values. Since, the variables are on a one to five Likert-scale, a reverse code can easily be obtained by subtracting the variable's value from 6, for example: Support' = 6 - Support.

5. EVALUTING THE EFFICIENCY OF XP USING DEA

For the purpose of this paper, efficiency means output is produced at the least possible cost, or using the minimum amount of inputs. As already stated, DEA is only a measure of relative efficiency as it compares each unit only to the other units in the analysis. Therefore it is of utmost importance to have a representative sample otherwise the DEA results may be biased. A DMU, a company in this case, is efficient if it is able to produce the same amount of output as other DMUs in the analysis, but using fewer inputs. Efficiency of a company in this paper relates to the efficient use of XP.

This section presents a discussion on the DEA results for the 37 companies using the XP system development methodology. If the efficiency rating equals one, then the company being measured is at least as efficient as any other company in the analysis. If the value is less than one, it is relatively inefficient compared to other companies in the analysis. Table 3 contains the DEA results (efficiency for each company) of the DEA model described in section 3.1. Each row in Table 3 represents the solution to a LP. For each inefficient DMU, DEA has identified an efficiency reference set. This is the set of relative efficient DMUs to which the inefficient DMU has been most directly compared. DEA forms a virtual DMU consisting of the DMUs in the reference set. This virtual DMU acts as a benchmark to which the DMU under analysis is compared. For instance DMU_5 was compared with a virtual DMU, which is a weighted composite of DMUs 8, 10 and 23, and was rated as 60% efficient. The weight assigned to each DMU in the reference set is given in parenthesis in the 'Reference Set' column.

See section 3.2 for a discussion on how the DEA model selects a reference set for each inefficient DMU.

Table 3. DEA results for 37 companies using XP as a SDM

DMU	***Efficiency***	***Reference Set** – DMU(weight assigned to DMU)*				
1	0.70	10(0.244)	25(0.366)	26(0.203)	28(0.088)	
2	0.70	10(0.184)	14(0.109	25(0.472	31(0.04)	36(0.194)
3	0.73	10(0.06)	25(0.301	31(0.196	36(0.442)	
4	1.00					
5	0.60	8(0.29)	10(0.45)	23(0.193)		
6	0.75	10(0.254)	14(0.554)	25(0.033)	36(0.159)	
7	0.45	12(0.036)	25(0.334)	31(0.447)		
8	1.00					
9	1.00					
10	1.00					
11	0.61	14(0.576)	23(0.11)	28(0.093)	31(0.22)	
12	1.00					
13	0.55	9(0.066)	14(0.087) 31(0.244)	25(0.122)	26(0.213)	28(0.124)
14	1.00					
15	1.00					
16	0.52	10(0.13)	25(0.456)	26(0.022)	28(0.172)	
17	0.80	15(0.4)	28(0.057)	36(0.343)		
18	1.00					
19	0.66	15(0.659)				

DMU	*Efficiency*	***Reference Set*** *– DMU(weight assigned to DMU)*				
20	0.67	10(0.319)	14(0.223)	23(0.408)	31(0.05)	
21	1.00					
22	0.52	10(0.372)	14(0.058)	23(0.277)	25(0.093)	
23	1.00	23(1)				
24	0.75	10(0.008)	12(0.05)	25(0.356)	31(0.317)	36(0.279)
25	1.00	25(1)				
26	1.00	26(1)				
27	0.62	10(0.081)	14(0.187)	23(0.076)	25(0.183)	31(0.274)
28	1.00					
29	0.80	31(1)				
30	0.61	9(0.329)	10(0.152)	23(0.373)	25(0.021)	31(0.024)
31	1.00					
32	1.00					
33	0.95	8(0.71)	36(0.237)			
34	0.86	10(0.252)	14(0.003)	25(0.274)	31(0.222)	36(0.249)
35	0.73	8(0.109)	10(0.419)	23(0.293)		
36	1.00					
37	1.00					

According to the results as depicted in Table 3, 17 companies out of the 37 were identified as efficient which represents 46% of the total number of companies. Levels of inefficiency ranged from 95% to 45% which indicates that they were anything between 5% and 55% less efficient than the efficient companies they were compared with. Being used 13 times, DMU_{10} was the most prominent efficient peer.

Table 4 contains the results of the average efficient versus the average inefficient companies. Note that the variables that have to be maximized in order to be optimal are indicated with a (+) and variables needing minimization are indicated with a (-). The choice between maximization or minimization of the variables is based on Table 2 and a literature survey reported in De Jager (2010). As expected inefficient DMUs have lower *vertical use*, *support*, and *training*, while *voluntariness* and *cost* are higher. Likely, the inefficient DMUs' outputs, namely *impact* and *satisfaction* are lower. Due to DEA's optimization the variables of the average efficient company is somewhat better than those of the average inefficient company, especially *voluntariness*.

Table 4. Average efficient vs. average inefficient company

Variable	*Efficient (n=17)*	*Inefficient (n=20)*	*Shortage/Excess*	*% Diff*
Inputs				
Vertical use *(+)*	4.30	3.43	-0.87	-20.23%
Voluntariness *(-)*	1.76	2.55	0.79	44.50%
Support *(+)*	4.24	3.68	-0.55	-13.03%
Training *(+)*	3.62	2.89	-0.73	-20.18%
Cost *(-)*	2.04	2.45	0.41	19.86%
Outputs				
Impact *(+)*	4.52	3.97	-0.55	-12.20%
Satisfaction *(+)*	4.76	4.10	-0.66	-13.95%

By only analyzing the results in Table 4, one can already make a few recommendations on how to improve a company's efficiency. In other words how to make efficient use of XP. Compared to the average efficient company, it is clear that *voluntariness* carries a relatively large weight for a good *impact* and *satisfaction* rating. These values only represent averages and the question still remains, what can an individual company do to improve the *impact* and *satisfaction*? Or, what would the effect be on *impact* and *satisfaction* if a company increases their SDM *support* for example? The answers to these questions have much more managerial value.

Instead of just identifying inefficient DMUs and their reference sets, additional insight about the degree of inefficiency can be provided by DEA (Metzger, 1994). The true managerial value of DEA comes to its strength when results are analyzed individually. For illustrative purposes DMU_7 was chosen for a more in-depth analysis. Any other DMU may be analyzed in the same manner.

Table 5. DMU_7 compared with its efficiency reference set

DMU_7: 45%					***Reference Set***		
Variables	**Original**	**Target**	**Shortage / Excess**	**% Diff**	**Dmu_{12}** (0.036)	**Dmu_{25}**(0.334)	**Dmu_{31}**(0.447)
Inputs							
Vertical use	1.500	3.975	-2.475	-62.26%	5.000	3.833	3.167
Voluntariness	4.000	1.409	2.591	183.98%	5.000	1.000	2.000
Support	2.000	4.469	-2.469	-55.24%	1.667	3.667	4.667
Training	2.250	4.312	-2.062	-47.82%	2.500	4.000	4.000
Cost	2.000	0.900	1.100	122.17%	1.000	1.250	1.000
Outputs							
Impact	3.588	3.588	0.000	0.00%	4.000	4.647	4.235
Satisfaction	2.000	4.048	-2.048	-50.59%	4.000	5.000	5.000

The data in Table 5 shows the amount of inefficiency as identified for DMU_7 when compared to its efficiency reference set. The 'original' column contains the values for DMU_7 as gathered from the survey results. The values for each DMU in the reference set are also the values as gathered from the survey. Each target value was assigned by the DEA model and is a weighted composite value of the DMUs in the reference set. For example, the target for *voluntariness* was calculated by the following formula: $5x_1 + 1x_2 + 2x_3 = 1.409$ where x_i represents the weight assigned to each DMU in the reference set. The target values are a representation of what the inputs and outputs could have been if DMU_7 operated more efficiently. In other words, the target is an indication of how much the input use could be optimized in order to achieve the same or a better output level. With efficiency of only 45% (see Table 3), DMU_7 has the worst rating in the analysis. In comparison with the other companies its input- and output deficiencies are quite large, especially its bad *satisfaction* rating of 2 which is 50.59% below the target *satisfaction* of 4.048. Only *impact* had no variance from the target. However the *impact* is still inadequate compared to the *impact* achieved by the companies in its reference set which are all equal to or above 4.647. Although a value of 2 for *cost* is actually good, the model wants to lower *cost* even more. The reason for this is: compared to other companies, the same (bad) level of outputs could have been achieved with less *cost*. The distressing variables are those of *voluntariness*, *support* and *vertical use*.

In order to gain even more insight into the problems identified, the company itself must be considered in more detail. This would be possible by delving deeper into the survey results, but a personal more in-depth analysis of the company itself will yield the best results. DMU_7's bad *satisfaction*-rating of XP is obvious when one considers the company's bad levels of *vertical use*, *support* and *training.* The overall recommendation would be to increase SDM-use which will on its part lead to a better *impact* and *satisfaction*. Amongst recommendations to increase efficiency for DMU_7 are:

- Make the use of XP more mandatory. In other words, decrease the level of *voluntariness*;
- Increase *management support*. Management should drastically consider increasing their SDM *support*. This is important as management controls company resources. Effective communication may affect *management support* as perceived by developers positively;
- Invest in more formal training, whether externally or in-house. *Training* may also be a vehicle to increase developer support; and
- *Costs* regarding the SDM should be reasonable. *Voluntariness* and *cost* had the largest contribution to inefficiency.

For further comments on the results of the preceding DEA evaluation, a more in-depth analysis of the individual company is necessary which is beyond the scope of this paper.

6. CONCLUSION

This study proposed a method of evaluating post-implementation SDM use by means of the linear programming method Data Envelopment Analysis. Evaluation criteria (inputs and outputs) were identified in the literature and were used in the DEA model. A major advantage of DEA is its ability to deal with multiple inputs and outputs in contrast to the more conventional regression-based approaches where assessment is against average performance. An input-orientated DEA model was used to classify companies' SDM-use as efficient or inefficient in respect to how good inputs (*vertical use, voluntariness, support, training,* and *cost*) were utilized to produce the achieved level of outputs (*impact* and *satisfaction*).

The applicability of DEA to evaluate the efficiency of SDMs after implementation was demonstrated using XP. It is a requirement for DEA to have a homogenous set of DMUs, therefore different companies using the same SDM were compared to each other. After each evaluation the companies were divided into two categories namely efficient companies (with an efficiency rating of one) and inefficient companies (with an efficiency rating less than one).

Instead of just identifying inefficient DMUs and their reference sets, additional insight about the degree of inefficiency can be provided by DEA. The true managerial value of DEA comes to its strength when results are analyzed individually. This ability was demonstrated in this paper as one of the inefficient companies from the evaluation were randomly selected and assessed. An individual analysis enables one to identify specific areas needing improvement.

A limitation regarding DEA is that it does not provide a measure of absolute efficiency because an efficient DMU is only efficient relative to the other DMUs in the analysis. This emphasizes the importance of having a representative sample.

In an era where there is a reappraisal of the efficiency of system development methodologies, it is critical to have a valid and reliable method of evaluation. This paper contributed to the dearth of research on post-implementation efficiency of system development methodologies by presenting DEA as a method to evaluate companies' efficient use of XP.

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