Six sigma project selection using data envelopment analysis

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4 authors, including:

U. Dinesh Kumar
Indian Institute of Management Bangalore

Haritha Saranga
Indian Institute of Management Bangalore

David Nowicki
University of North Texas

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U. Dinesh Kumar and Haritha Saranga
Indian Institute of Management, Bangalore, India, and
José E. Ramírez-Márquez and David Nowicki
Department of Systems Engineering and Engineering Management, Stevens Institute of Technology, Hoboken, New Jersey, USA

Abstract

Purpose – The evolution of six sigma has morphed from a method or set of techniques to a movement focused on business-process improvement. Business processes are transformed through the successful selection and implementation of competing six sigma projects. However, the efforts to implement a six sigma process improvement initiative alone do not guarantee success. To meet aggressive schedules and tight budget constraints, a successful six sigma project needs to follow the proven define, measure, analyze, improve, and control methodology. Any slip in schedule or cost overrun is likely to offset the potential benefits achieved by implementing six sigma projects. The purpose of this paper is to focus on six sigma projects targeted at improving the overall customer satisfaction called Big Q projects. The aim is to develop a mathematical model to select one or more six sigma projects that result in the maximum benefit to the organization.

Design/methodology/approach – This research provides the identification of important inputs and outputs for six sigma projects that are then analyzed using data envelopment analysis (DEA) to identify projects, which result in maximum benefit. Maximum benefit here provides a Pareto optimal solution based on inputs and outputs directly related to the efficiency of the six sigma projects under study. A sensitivity analysis of efficiency measurement is also carried out to study the impact of variation in projects' inputs and outputs on project performance and to identify the critical inputs and outputs.

Findings – DEA, often used for relative efficiency analysis and productivity analysis, is now successfully constructed for six sigma project selection.

Practical implications – Provides a practical approach to guide the selection of six sigma projects for implementation, especially for companies with limited resources. The sensitivity analysis discussed in the paper helps to understand the uncertainties in project inputs and outputs.

Originality/value – This paper introduces DEA as a tool for six sigma project selection.

Keywords Six sigma, Data analysis, Optimization techniques, Project planning

Paper type Research paper

1. Introduction

Over the past few years, manufacturing companies have been successful in leveraging six sigma, as a corporate strategy, to reduce the number of defective units from manufacturing processes thereby reducing costs and improving profits. Six sigma is now often thought of as the new mantra in the corporate world. Anonymous (2003) reports that six sigma implementations have resulted in phenomenal returns on investment to the corporate world, more than double the original investment in many cases. The benefits of six sigma are extensively reported in the literature

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(Hendricks and Kelbaugh, 1998; Harry, 1998; Hahn *et al.*, 1999; Lanyon, 2003; Robinson, 2005). However, there are noticeable cases where six sigma failed to deliver the desired results. A survey conducted by the *Aviation Week* magazine among major aerospace companies reported that less than 50 percent of the companies expressed satisfaction with results from six sigma projects, nearly 30 percent were dissatisfied and around 20 percent were somewhat satisfied (Zimmerman and Weiss, 2005). Of significant note, the study identified that 60 percent of the companies in the survey selected opportunities for improvement on an *ad hoc* basis, while only 31 percent relied on a portfolio approach. However, the study shows that companies actually achieve better results when applying the portfolio approach. Among all, the process improvement techniques used in the last five decades, six sigma has clearly emerged as the most effective quality improvement technique as pointed out in a survey conducted by DynCorp (Dusharme, 2003).

In essence, six sigma is an extension of other quality initiatives such as Deming's statistical quality control and total quality management (TQM). Six sigma, as with most of the management strategies on quality initiatives is focused around meeting the customer requirements as its main objective. Six sigma can be defined as a strategy that includes TQM, strong customer focus, additional data analysis tools, financial results and project management (Anbari, 2002; Kwak and Anbari, 2004). Although six sigma originated in the manufacturing industry to reduce the wastes due to manufacturing process deficiencies, it is now used by almost all industries including service industries such as health care management (Krupar, 2003; Antony, 2004; Antony and Fergusson, 2004; Moorman, 2005). Contrary to this wide application potential, none of the other quality improvement initiatives received such high application outside the manufacturing industry.

For many companies, the question is not whether or not to implement six sigma, but how to implement a successful six sigma process improvement project. The selection of process improvement projects is probably the most difficult aspect of six sigma (Pande *et al.*, 2000; Snee, 2001). Bertels (2003) point out that the key characteristics differentiating successful six sigma projects from unsuccessful projects is a well-defined project based on the clear and concise description of the project objectives. Selecting six sigma projects is one of the most frequently discussed issues in the six sigma literature today (Goldstein, 2001; Fundin and Cronemyr, 2003). In TQM literature (Juran, 1989), the projects are differentiated based on their scope. Projects with an objective to meet the specific process-related issues are classified as little q (quality) projects whereas projects with a broader scope are classified as Big Q (Quality) projects. Big Q projects attempt to improve the overall customer satisfaction and try to achieve corporate level objectives. In this paper, we assume that the projects that are being evaluated for selection are Big Q projects. That is, the projects focus on improving overall customer satisfaction.

The implementation of a six sigma project requires multiple resources such as capital and labor (in the form of Black and Green Belts). Based on these resources, a successful six sigma implementation can provide beneficial outputs in the form of an increase in sigma quality level, increase in customer satisfaction and a reduction in cost of poor quality (COPQ). In essence, a six sigma project consumes multiple inputs to produce multiple outputs. Whenever different six sigma projects are competing for implementation, management is interested in identifying those projects that result in the maximum benefit to the organization. Table I provides the list of tools used for six sigma project selection (Banuelas *et al.*, 2006).

In this paper, data envelopment analysis (DEA) is used to identify the six sigma projects that result in the maximum benefit to the organization. DEA is an application of operations research that uses linear programming (LP) to obtain an effective, non-parametric efficiency measure. DEA has the ability to compare the multiple input and output parameters simultaneously, so that a scalar measure of overall performance is obtained. Thus, this paper, exploits the ability of DEA to identify the six sigma projects that will result in highest overall performance. Consistent with a DEA formulation, the performance measure is relative efficiency, essentially defined as the distance from the efficiency frontier. Traditionally, project selection is treated as a multi-criteria decision-making (MCDM) problem and most tools available in the literature use some parametric model that assigns a priori weights to the project inputs and outputs. Solution obtained using parametric methods are very sensitive to a priori weights assigned to the inputs and outputs. DEA is a non-parametric method, and does not assume a priori weights for inputs and outputs.

The rest of the paper is organized as follows. The basic concepts of the DEA approach are discussed in Section 2. Section 3 discusses the input and output parameters that are important to study the performance of six sigma projects. A decision model, based on DEA, is developed to choose among different six sigma projects in Section 4. Sensitivity analysis that studies the impact of changes in input and output values on the project benefit is discussed in Section 5. Conclusions and future research are presented in Section 6.

2. Application of DEA for six sigma project selection

2.1 Classical DEA models

Charnes *et al.* (1978) introduced DEA to measure the scale efficiencies of various public sector firms. Central to a DEA model is the notion of a "Decision-making Unit" (DMU). A DMU is an abstract representation of a firm in a given industry that produces a collection of outputs by consuming a set of inputs. In the six sigma project selection problem, the different DMUs constitute the six sigma projects eligible for implementation. Each of these six sigma projects, or DMUs in the DEA vernacular, consumes various amounts of different inputs and produces different quantities of outputs.

Author	Tool(s)
Pyzdek (2000, 2003)	Pareto priority index (PPI), AHP, QFD, theory of constraints (TOC)
Breyfogle *et al.* (2001)	Project assessment matrix
Pande *et al.* (2000)	QFD
Kelly (2002)	Project selection matrix
Adams *et al.* (2003)	Project ranking matrix
Larson (2003)	Pareto analysis
De Feo and Barnard (2004)	Reviewing data on potential projects against specific criteria
Dinesh Kumar *et al.* (2006)	AHP

Source: Banuelas *et al.* (2006)

Table I. Methods used for selection of six sigma projects

In summary, the first DEA approach is known as the CCR model (Charnes *et al.*, 1978) or the constant returns to scale (CRS) model and is based on a LP formulation that determines the relative efficiency of a specific DMU with respect to the remaining DMUs. This formulation can be either input-oriented or output-oriented. For the input-oriented case, the LP formulation checks whether a hypothetical DMU exists (in our case, a hypothetical project) whose outputs are as great as the DMU under consideration by consuming lesser input. For the output-oriented CCR model, the LP formulation checks whether it is possible to create a hypothetical DMU which uses the same quantities of input resources and produces more outputs than the output quantities produced by the DMU under evaluation. For both, the input and output-orientated CCR models, hypothetical DMU is the linear combination of all the DMUs under consideration.

In this paper, the input-oriented CCR model is formulated for the selection of efficient DMUs. The output-oriented CCR model is a relatively straightforward transformation of the proposed model and thus not presented in the paper. Under the input-oriented CCR model, it is assumed that each of the n DMUs, uses m unique inputs that generate s unique outputs. Then, it is of interest to know the relative efficiency of each DMU (six sigma project) to select the most efficient.

Let:

x_{ij} denotes the amount of the ith input consumed by the jth DMU, where $i = 1, \ldots, m$ and $j = 1, \ldots, n$.

y_{kj} denotes the amount of the kth output produced by the jth DMU, where $k = 1, \ldots, s$ and $j = 1, \ldots, n$.

u_j denotes the weight assigned to the jth DMU ($j = 1, 2, \ldots, n$).

In order to calculate the relative efficiency of the lth DMU, the following linear program based on the input-oriented CCR must be solved for each DMU:

$$\text{Min} \quad \theta \tag{1}$$

subject to:

$$u_1 y_{k,j} + u_2 y_{k,j} + \ldots + u_n y_{k,j} \geq y_{k,l} \quad k = 1, 2, \ldots, s \quad j = 1, 2, \ldots, n \tag{2}$$

$$u_1 x_{i,j} + u_2 x_{i,j} + \ldots + u_n x_{i,j} \leq \theta x_{i,l} \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n \tag{3}$$

$$u_j \geq 0 \tag{4}$$

The set of equations represented by equation (2) implies that the output produced by the hypothetical DMU is at least as good as the output produced by the lth DMU for all outputs ($k = 1, 2, \ldots, s$). The set of equation (3) tries to minimize the input consumed by the hypothetical DMU compared to the lth DMU, whose efficiency is θ. If the value of θ is 1, then the lth DMU is considered to be efficient otherwise when $\theta < 1$, the lth DMU is inefficient. The multipliers u_i of the linear combinations of inputs and outputs of hypothetical DMU are weights (that may vary from DMU to DMU) corresponding to each efficiency calculation (i.e. each DMU). Under a six sigma perspective, those projects with an efficiency score of 1 can be potentially chosen for six sigma implementation.

The input-orientated CCR model expressed in equations (1)-(4) assumes CRS. Since, this assumption does not hold in all practical situations, Banker *et al.* (1984) introduced the BCC model under the assumption of varying returns to scale. The input-oriented BCC model is obtained by adding the convexity constraint $\sum_{j=1}^{n} u_j = 1$ to the input-oriented CCR model (1)-(4).

In both, the input-oriented CCR and BCC models, the hypothetical DMU is a linear representation of all DMUs, including the DMU under consideration. The next section discusses super efficiency DEA models where the hypothetical DMU is still a linear representation of DMUs, except that the representation does not include the DMU under consideration. The CCR and BCC models are likely to classify more than one DMU as efficient. However, if management is interested in ranking the projects based on their efficiency, then one has to use super efficiency DEA models.

An additional benefit of DEA models is the derivation of what is commonly called a "peer group" of efficient DMU (also called "reference set"). These DMU are the efficient units observed to produce the same or higher level of outputs with same or lesser amounts of inputs in comparison to the inefficient DMU. This enables the analysts to identify any excessive waste of inputs of an inefficient DMU and if there is any scope for improvement in outputs.

2.2 Super efficiency DEA models

The super efficiency models came into prominence as an aid in the sensitivity analysis of classical DEA models (Charnes *et al.*, 1992; Zhu, 1996; Charnes *et al.*, 1996; Seiford and Zhu, 1998a, b). Andersen and Petersen (1993) propose the use of super efficiency DEA models in ranking the relative efficiency of each DMU. Since, 1993, super efficiency DEA models span across a variety of applications. These include measuring technology and productivity changes (Färe *et al.*, 1994), identifying the extreme efficient[1] DMU (Thrall, 1996), and two person ratio efficiency games (Rousseau and Semple, 1995). However, super efficiency DEA models are infeasible when a DMU efficiency result is an extreme point on the efficiency frontier, or when certain zero patterns appear in the data domain. Studies have identified these reasons for infeasibilities in super efficiency DEA models and certain necessary and sufficient conditions are derived to explain these infeasibilities. This information on infeasibilities is also used to locate the endpoint positions of the extreme efficient DMU and in the sensitivity analysis of inputs and outputs (Seiford and Zhu, 1999).

The input-oriented super efficiency CCR model is expressed as (Zhu, 2003):

$$\text{Min} \ \ \theta \tag{5}$$

subject to the constraints:

$$\sum_{\substack{j=1 \\ j \neq l}}^{n} u_j x_{ij} \leq \theta x_{il}, \quad i = 1, 2, \ldots, m \tag{6}$$

$$\sum_{\substack{j=1 \\ j \neq l}}^{n} u_j y_{kj} \geq y_{kl}, \quad k = 1, 2, \ldots, s \tag{7}$$

$$u_j \geq 0, \quad j \neq l \tag{8}$$

To obtain the input-oriented super efficiency BCC model requires adding the following convexity constraint:

$$\sum_{\substack{j=1 \\ j \neq l}}^{n} u_j = 1 \tag{9}$$

The difference between the classical and the super efficiency CCR and BCC models is that for the super efficiency models, the DMU under evaluation (the lth DMU in equations (5)-(8)) is not included in the reference set to compute its efficiency, while it is included in the classical models. In essence, the best practice frontier (efficiency frontier) is constructed by leaving out the lth DMU, and its efficiency score is measured by its distance from the efficiency frontier. Thus, some of the efficient DMUs under the classical DEA models would either attain a super efficiency score greater than 1 or found to be infeasible. Thrall (1996) shows that if the super efficiency CCR model is infeasible or if the super efficiency score is greater than 1 for the input-oriented model then, the lth DMU is classified as an extreme efficient point.

The next section discusses the prominent inputs and outputs relative to the six sigma project selection problem. The input and output selection for DEA analysis is usually done through brainstorming.

3. Input and output parameters for selection of six sigma projects using DEA

The impact to the corporate bottom-line ultimately measures the success of six sigma. Selection of an appropriate six sigma project requires careful analysis. The chosen project should align with the strategic objectives of the organization. Pande *et al.* (2000) classify six sigma project selection criteria into three categories:

(1) business benefits criteria;

(2) feasibility criteria; and

(3) organization impact criteria.

Business benefits criteria include issues such as the impact on customers, the impact on business strategy, and the impact on core competencies, financial impact and urgency. Feasibility criteria for six sigma project selection include criteria such as resources needed, expertise available, complexity, and probability of success. Learning benefits and cross-functional benefits are listed under organizational impact criteria. Harry and Schroeder (2000) propose the following criteria for six sigma project selection:

- defects per million opportunities (DPMO);
- net cost savings;
- COPQ;
- cycle time;
- customer satisfaction;
- capacity; and
- internal performance.

Banuelas *et al.* (2006) list the following six criteria as critical for six sigma project selection:

(1) customer impact;
(2) financial impact;
(3) top management commitment;
(4) measurable and feasible;
(5) learning and growth; and
(6) connected to business strategy and core competence.

It is evident from the literature that the six sigma project selection is a MCDM problem. A DEA model lends itself to solving the six sigma project selection problem since DEA allows multiple, competing factors for consideration. In the proposed DEA models, we use three inputs and five outputs. The input and output criteria used in the DEA model represents most of the project selection criteria reported in the literature. The inputs are:

- project cost;
- project duration; and
- number of Black and Green Belts.

The outputs are:

- customer satisfaction;
- impact on business strategy;
- increase in sigma level;
- financial impact (impact on COPQ); and
- increase in productivity.

Since, most of the inputs and outputs are probabilistic in nature, we have used expected values of input and output values. It should be noted that, one can easily extend the model to include more inputs and outputs depending on the criticality of those criteria.

3.1 Expected value of the project cost

Six sigma implementations may require a significant investment of capital. For example, General Electric invested about $1.6 billion between 1996 and 1999 on six sigma (Waxer, 2007). The project cost is an important input for the six sigma project selection. However, it is difficult to predict with accuracy the cost of any project even with new techniques such as activity-based costing (ABC). For this reason, in this paper, we use the expected value of the project cost. A sensitivity analysis is carried out to study the impact of changes in the project cost.

3.2 Expected project duration

Duration of the project plays an important role, since the long-time period needed to implement the project may require higher resource commitment and delays the benefits that can be achieved. As in the case of project cost, since the duration is a random variable, we use the expected value of the project duration in the DEA model.

3.3 Number of Black and Green Belts

Black and Green Belts are the important resources required in six sigma implementation. Snee and Rodenbaugh (2002) proposed a four-stage project selection process; an important task in the method proposed by Snee *et al.* is the identification of Black Belt projects. The availability of appropriate manpower in the form of Black and Green Belts are an important criterion.

The output measures used in the DEA analysis are listed below.

3.4 Expected increase in customer satisfaction

The ultimate goal of any six sigma project is to improve the customer satisfaction, since success of the project heavily depends on how well a project can improve the customer satisfaction. In this paper, we measure the expected increase in customer satisfaction using expected value of the percentage increase in the customer satisfaction value.

3.5 Impact on business strategy

Any six sigma project is expected to assist the organization to improve its competitive position and assist to realize the corporate vision. In this paper, we use a nine-point scale to discriminate various projects with respect to its likely impact on business strategy.

3.6 Financial impact – expected reduction in cost of poor quality

COPQ is commonly used as a key criterion for selection and evaluation of six sigma projects (Bisgaard and Freiesleben, 2004). For manufacturing companies, the direct benefit of six sigma results from reduction in the number of defects due to improved manufacturing processes. Any improvement in sigma level is likely to reduce the COPQ. The COPQ as a result of manufacturing defects is a function of rework cost, excessive use of material, warranty-related costs and unnecessary use of resources. One of the main objectives of six sigma project is to minimize the COPQ. In this paper, we use the expected value of the reduction in COPQ as a result of implementing a six sigma project.

3.7 Expected increase in sigma quality level

A higher sigma level indicates that the process results in a fewer defects, whereas a lower sigma means higher defect rate. Sigma quality level is a measure of process defect rate. Sigma quality level can be used for benchmarking purpose and helps to measure quality of the process. Sigma quality level also helps to set a realistic target for improvement of process quality during the DMAIC cycle of process improvement. Improving a process from 3 to 4 sigma level reduces the number of DPMO from 66,811 to 6,210, whereas improving sigma level from 5 to 6 sigma level reduces the DPMO from 233 to 3.4. However, more effort may be required to improve a process from 5 to 6 sigma level compared to improving a process from 3 to 4 sigma level. Thus, impact of "increase in quality level" to the profitability is an important criterion for selection of a six sigma project.

3.8 Expected increase in productivity

Six sigma aims to improve productivity of the manufacturing system and thus, increase in productivity as a result of six sigma implementation is an important output. Thus, we have three inputs and five outputs. In the next section, we illustrate how DEA can be used to select projects using a hypothetical example.

COPQ, sigma quality level and productivity are related, but the relationship is nonlinear. As the sigma level increases the DPMO decreases at a decreasing rate (Dinesh Kumar *et al.*, 2007). Similarly, as the sigma level increases, the productivity (yield) increases at a decreasing rate. For this reason, we would like to include COPQ, sigma level and productivity as outputs in the DEA model.

4. Illustrative example for selection of projects

In this example, we illustrate how the input-oriented CCR DEA model described in Section 2 is used to select the best amongst competing six sigma projects. Table II shows the inputs and outputs for the 20 hypothetical six sigma projects. Each project here represents an improvement opportunity. As an example, we refer to the DMAIC implementation case-study on locomotive starter batteries reported in Dinesh Kumar *et al.* (2006). In this case, the authors have identified five major causes of failure which affect the reliability of a locomotive starter motor battery used by railways in an Asian country. The objective of the case problem is to identify the best way to improve the reliability of the batteries, which can be achieved through several improvement projects. Each project consumes varying amounts of resources and achieves different levels of reliability improvements.

Let:

x_{ij} the input i used by project j

y_{ij} the output i generated by project j

The input-oriented CCR formulation for project 1 is given by:

Min θ

Subject to:

Input constraints:

$$\sum_{j=1}^{20} x_{1j}u_j \leq 212\theta \quad \text{(Expected project cost)}$$

$$\sum_{j=1}^{20} x_{2j}u_j \leq 70\theta \quad \text{(Expected project duration)}$$

$$\sum_{j=1}^{20} x_{3j}u_j \leq 10\theta \quad \text{(Number of Black and Green Belts)}$$

Output constraints:

$$\sum_{j=1}^{20} y_{1j}u_j \geq 11 \quad \text{(Percentage increase in customer satisfaction level)}$$

$$\sum_{j=1}^{20} y_{2j}u_j \geq 4 \quad \text{(Impact on business strategy)}$$

Table II.
Inputs and outputs for 20 hypothetical projects

	Inputs				Outputs			
Project number	Expected project cost	Expected project duration in days	Number of black and Green Belts	Percentage increase in customer satisfaction	Impact on business strategy	Financial impact	Expected increase in sigma quality	Expected percentage increase in productivity
1	212	70	10	11	4	331	0.24	20
2	199	63	3	29	8	342	0.77	23
3	214	88	5	28	4	333	0.33	10
4	280	77	8	29	6	303	0.48	10
5	263	72	11	19	2	240	0.41	11
6	203	70	11	21	5	306	0.52	17
7	196	61	3	31	9	345	0.78	21
8	215	79	5	22	5	264	0.27	6
9	281	71	8	17	3	239	0.66	19
10	233	66	6	10	6	338	0.3	16
11	263	84	10	27	8	310	0.88	19
12	198	60	3	32	8	341	0.51	22
13	220	80	4	15	7	308	0.31	7
14	284	79	6	23	4	325	0.31	7
15	214	87	7	19	7	314	0.54	5
16	235	80	5	27	2	236	0.34	17
17	200	63	4	33	8	339	0.83	23
18	217	75	11	13	5	313	0.74	7
19	198	63	3	31	8	343	0.87	22
20	227	70	5	10	6	317	0.46	17

$$\sum_{j=1}^{20} y_{1j}u_j \geq 331 \quad \text{(Financial impact – reduction in CoPQ)}$$

$$\sum_{j=1}^{20} y_{1j}u_j \geq 0.24 \quad \text{(Increase in sigma level)}$$

$$\sum_{j=1}^{20} y_{1j}u_j \geq 20 \quad \text{(Increase in productivity)}$$

An equivalent model must be developed for each of the remaining projects. Then, each of these models are solved with the simplex method to obtain optimal values of θ. The models that provide an optimal value for θ (which is equal to 1) are the projects considered for potential implementation while the remaining projects are rejected for six sigma implementation because of their inefficiency. Table III gives the efficiency values for each project using CCR and BCC input-oriented models.

Table III shows five projects being CCR efficient and six projects BCC efficient, and hence qualify for implementation of six sigma process. However, in situations where resources are limited, one would like to select the projects that would benefit the most, so that the resource allocation is most appropriate. Since, the classical CCR and BCC models do not rank the efficient projects, we use the super efficiency DEA model described in Section 2.2 to rank the efficient projects in the order of their super efficiency. Super efficiency DEA model for project 1 is given by:

Project number	Input-oriented CCR efficiency	Input-oriented BCC efficiency
1	0.887	0.925
2	1.000	1.000
3	0.884	0.916
4	0.707	0.779
5	0.587	0.833
6	0.856	0.966
7	1.000	1.000
8	0.698	0.912
9	0.733	0.853
10	0.901	0.909
11	0.762	1.000
12	1.000	1.000
13	0.795	0.891
14	0.724	0.759
15	0.834	0.916
16	0.696	0.834
17	1.000	1.000
18	0.824	0.903
19	1.000	1.000
20	0.799	0.866

Table III.
The input-oriented CCR and BCC efficiency scores for the 20 projects

Objective: Min θ
Subject to:
Input constraints:

$$\sum_{j=2}^{20} x_{1j}u_j \leq 212\theta \quad \text{(Expected project duration)}$$

$$\sum_{j=2}^{20} x_{2j}u_j \leq 70\theta \quad \text{(Expected project duration)}$$

$$\sum_{j=2}^{20} x_{3j}u_j \leq 10\theta \quad \text{(Number of Black and Green Belts)}$$

Output constraints:

$$\sum_{j=2}^{20} y_{1j}u_j \geq 11 \quad \text{(Percentage increase in customer satisfaction level)}$$

$$\sum_{j=2}^{20} y_{2j}u_j \geq 4 \quad \text{(Impact on business strategy)}$$

$$\sum_{j=2}^{20} y_{1j}u_j \geq 331 \quad \text{(Financial impact – reduction in CoPQ)}$$

$$\sum_{j=2}^{20} y_{1j}u_j \geq 0.24 \quad \text{(Increase in sigma level)}$$

$$\sum_{j=2}^{20} y_{1j}u_j \geq 20 \quad \text{(Increase in productivity)}$$

Table IV gives the ranking of projects based on the input-oriented CCR super efficiency scores. The five efficient projects from Table III, namely 2, 7, 12, 17 and 19 are ranked fourth, first, third, fifth and second, respectively. Thus, project 7 should be given top priority for six sigma implementation and rest of the projects follow in the above order based on the availability of resources.

An application of BCC super efficiency model resulted in five infeasibilities in the super efficiency scores out of six BCC efficient projects. Thus, it is not possible to rank them based on the BCC super efficiency scores, and hence we are not reporting the scores.

Table V lists the weights and the corresponding "peer" group of projects for each project. For efficient projects, the weight is equal to one, implying, the project is its own "peer" group. For each inefficient project, there exists a linear combination of efficient projects, which are called their "peer" group of projects that can be used as a benchmark for future improvements by the inefficient project. For example, the linear

Project number	CCCR super efficiency scores	Super efficiency ranking
7	1.136	1
19	1.115	2
12	1.056	3
2	1.045	4
17	1.045	5
10	0.901	6
1	0.887	7
3	0.884	8
6	0.856	9
15	0.834	10
18	0.824	11
20	0.799	12
13	0.795	13
11	0.762	14
9	0.733	15
14	0.724	16
4	0.707	17
8	0.698	18
16	0.696	19
5	0.587	20

Table IV. The input-oriented CCR super efficiency scores and the corresponding ranks for the 20 projects

		Weights and the corresponding peer projects			
Project number	$\sum_{j=1}^{20} u_j$	Weight	First peer project number	Weight	Second peer project number
1	0.959	0.9594	7		
2	1.000	1	2		
3	0.965	0.9652	7		
4	0.904	0.8458	12	0.0585	17
5	0.702	0.1933	7	0.5081	12
6	0.887	0.8869	7		
7	1.000	1	7		
8	0.765	0.7652	7		
9	0.830	0.0903	12	0.7396	17
10	0.991	0.9912	12		
11	1.011	1.011	19		
12	1.000	1	12		
13	0.893	0.8927	7		
14	0.953	0.9530	12		
15	0.910	0.9101	7		
16	0.818	0.8181	17		
17	1.000	1	17		
18	0.909	0.5670	7	0.3422	19
19	1.000	1	19		
20	0.923	0.6032	7	0.3192	12

Table V. Weights and corresponding peer projects for each of the project in the CCR efficiency analysis combination of project 12 and project 17 perform better than project 4, itself. In other words, a linear combination of each input of efficient projects 12 and 17 are lesser than the corresponding inputs of project 4, while a linear combination of each output of efficient projects 12 and 17 are greater than or equal to the corresponding outputs of project 4. Which essentially means that there exists a set of weights such that the weighted average of projects 12 and 17 perform better than project 4, in terms of either inputs (keeping same level of outputs) or outputs (keeping same level of inputs) or both. These weights can be determined using the DEA programs. The corresponding weights of this linear combination are listed in the column before the project number in Table V. Thus, one should read the linear combination peer group or the reference set for project 4 as follows: 0.846* project 12 + 0.059* project 17. Thus, this particular linear combination of projects 12 and 17 outperforms project 4 and hence renders project 4 as inefficient compared to the efficiency frontier formed by projects 12 and 17.

5. Sensitivity analysis

In this section, sensitivity of the efficiency scores is tested to determine to what extent the data perturbations can be tolerated, using various super efficiency models. Charnes *et al.* (1992), Rousseau and Semple (1995) and Charnes *et al.* (1996) developed sensitivity analyses using super efficiency DEA models, assuming simultaneous proportional change in all inputs and outputs for the specific DMU under consideration, while data for the remaining DMUs is assumed to be fixed. The super efficiency sensitivity approach used in this paper is developed by Zhu (2003), who simultaneously considers the data perturbations in all the DMUs, namely the specific DMU under consideration as well as the remaining DMUs in the sample. The sensitivity results from this approach are stable and unique, as they use optimal values of the super efficiency models. The measure specific input-oriented BCC super efficiency model with test DMU l not included in the left hand side of the constraints is used to analyze the BCC sensitivity of input i, as described below:

$$\theta_l^{i^*} = \mathrm{Min}\,\theta_l^i \quad l \in N \tag{10}$$

subject to the constraints:

$$\sum_{\substack{j=1 \\ j\neq l}}^{n} u_j x_{ij} = \theta_l^i x_{il}, \quad i \in I \tag{11}$$

$$\sum_{\substack{j=1 \\ j\neq l}}^{n} u_j x_{ij} \leq x_{il}, \quad i \notin I \tag{12}$$

$$\sum_{\substack{j=1 \\ j\neq l}}^{n} u_j y_{kj} \geq y_{kl}, \quad k = 1, 2, \ldots, s \tag{13}$$

$$\sum_{j=1}^{n} u_j = 1 \tag{14}$$

$$u_j \geq 0, \quad \forall j = 1, \ldots, N \tag{15}$$

Note that set I consists of the inputs whose stability with respect to data perturbations is being tested. The corresponding output-oriented measure specific super efficiency model for the output sensitivity analysis is given below:

$$\phi_l^{k^*} = \mathrm{Max}\,\phi_l^k \tag{16}$$

subject to the constraints

$$\sum_{\substack{j=1\\ j\neq l}}^{n} u_j y_{kj} \geq \phi_l^k y_{kl}, \quad k \in K \tag{17}$$

$$\sum_{\substack{j=1\\ j\neq l}}^{n} u_j y_{kj} \geq y_{kl}, \quad k \notin K \tag{18}$$

$$\sum_{\substack{j=1\\ j\neq l}}^{n} u_j x_{ij} \leq x_{il}, \quad i = 1, \ldots, m \tag{19}$$

$$\sum_{j=1}^{n} u_j = 1 \tag{20}$$

$$\phi_l^k \geq 0, \quad u_j \geq 0, \quad \forall j = 1, \ldots, N \tag{21}$$

Here, set K contains the outputs that are subjected to the sensitivity analysis. Note that a decrease in any input or an increase in any output would not worsen the efficiency score of an efficient DMU. Therefore, these sensitivity models are only focused on an increase in any input or a decrease in any output of the DMU l under consideration. The sensitivity models test the stability of the efficiency scores, when all the remaining DMUs work at improving their efficiencies against the deteriorating performance of the test DMU l. The larger (smaller) the optimal values to the input-oriented (output-oriented) super efficiency DEA models described above, the greater the stability of the DMU l in preserving the efficiency, when the inputs and outputs of all DMUs are changed simultaneously and unequally (Zhu, 2003). Since, we are using super efficiency models, some of the sensitivity values may result in infeasibilities. The infeasibility indicates that the corresponding DMU remains efficient (BCC or CCR based on whether the convexity constraint is imposed or not) to any simultaneous data perturbations in the corresponding inputs/outputs considered for the sensitivity analysis.

In the current study, sensitivity of BCC efficiency results is analyzed for each of the inputs, Expected Project Cost, Expected Project duration, and Number of Black and Green Belts, using the input-oriented measure specific super efficiency model (10)-(15) and for the outputs customer satisfaction level, impact on business strategy, financial impact, sigma quality level and productivity using the output-oriented measure specific super efficiency model (16)-(21). The corresponding sensitivity results for the BCC efficient projects along with the BCC efficiency scores are reported in Table VI below. As one can note from the table, the input and output sensitivity results are "infeasible" for all the BCC efficient projects except for projects 2 and 11 implying that

Table VI.
Sensitivity results for all the inputs and outputs of BCC efficient projects

Project no.	BCC efficiency	Project cost	Project duration	Black and Green Belts	Customer satisfaction	Business strategy	Financial impact	Sigma quality	Increase in productivity
1	0.92	0.92	0.86	0.30	3.00	2.25	1.04	3.63	1.15
2	1.00	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	0.96
3	0.92	0.92	0.68	0.60	1.18	2.25	1.04	2.64	2.30
4	0.78	0.70	0.78	0.37	1.14	1.50	1.14	1.82	2.30
5	0.83	0.75	0.83	0.27	1.74	4.50	1.44	2.13	2.09
6	0.97	0.97	0.86	0.27	1.57	1.80	1.13	1.67	1.35
7	1.00	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
8	0.91	0.91	0.76	0.60	1.50	1.80	1.31	3.23	3.83
9	0.85	0.70	0.85	0.37	1.94	3.00	1.44	1.32	1.21
10	0.91	0.84	0.91	0.50	3.30	1.50	1.02	2.90	1.44
11	1.00	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	0.99	Infeasible
12	1.00	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
13	0.89	0.89	0.75	0.75	2.20	1.29	1.12	2.81	3.29
14	0.76	0.69	0.76	0.50	1.43	2.25	1.06	2.82	3.29
15	0.92	0.92	0.69	0.43	1.74	1.29	1.10	1.62	4.60
16	0.83	0.83	0.75	0.60	1.22	4.50	1.46	2.57	1.35
17	1.00	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
18	0.90	0.90	0.81	0.27	2.54	1.80	1.10	1.18	3.29
19	1.00	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
20	0.87	0.86	0.86	0.60	3.30	1.50	1.09	1.90	1.35

all the BCC efficient projects, except for project 2 and 11 are stable and remain BCC efficient to any data changes to each of the inputs and outputs, keeping the other inputs/outputs constant. The infeasibilities in the sensitivity results imply that the corresponding DMUs are extreme efficient as a result of some inputs (outputs), and will remain extreme efficient no matter how much its remaining inputs (outputs) are increased (decreased), while the corresponding inputs (outputs) of the remaining DMUs are decreased (increased) (Seiford and Zhu, 1998b). Project 2, on the other hand, is also stable with respect to all inputs/outputs except for productivity output, while project 11 is stable with respect to all input/outputs except for sigma quality output. None of the inefficient projects have any infeasibilities, implying that the inefficient projects are not infinitely stable for any data perturbations in any of the inputs/outputs[2]. Note that, in case of inputs, the larger the sensitivity values, the greater the stability, but in case of output sensitivity results, the smaller the sensitivity values, the greater the stability of efficiency scores. The infeasibilities in all the inputs/outputs of efficient projects establish the robustness of our efficiency estimation to the data perturbations and confirm that the efficient projects indeed are the optimum choices for the six sigma implementation. Note that, one can also calculate the sensitivity values for multiple sets of inputs and outputs, i.e. when there is simultaneous change in multiple inputs and outputs. For a detailed description of sensitivity and stability analyses, please refer to Zhu (2003).

So far, the above discussion on sensitivity analysis had been focused on the robustness of efficiency scores for the efficient projects. However, the sensitivity scores obtained using the above-described super efficiency models can also be used to determine the critical inputs/outputs for both efficient as well as inefficient projects. For example, let us first consider the input-oriented super efficiency BCC model defined by model (10)-(15). This model results in one of the following cases for each project:

(1) $\theta_l^{i^*} < 1$;
(2) $\theta_l^{i^*} = 1$;
(3) $\theta_l^{i^*} > 1$; and
(4) infeasible.

Case (1) occurs for the inefficient projects and indicates that if the project l reduces it is ith input by $\theta_l^{i^*}$th proportion, then it can catch up with the frontier and become efficient. Cases (2), (3) and (4) typically occur for efficient projects. Case (4) in particular (infeasibility) implies that the efficient project is stable with respect to ith input and no amount of increase in that input can make project l inefficient and hence one does not have to be concerned about this particular input. However, Cases (2) and (3) indicate that if project l increases it is ith input by more than $\theta_l^{i^*}$th proportion, keeping all other inputs and outputs constant, it will become inefficient and hence there is a cause for concern. The critical input (Zhu, 2003) for efficient projects is defined as that input, which makes the project's efficient status most vulnerable, in other words, the input i corresponding to the $\min\{\theta_l^{i^*}, \forall i\}$. Similarly, the critical input for an inefficient project is defined as that input, by improving which, the inefficient project can catch up with the frontier with minimum effort, in other words, the input i corresponding to the $\max\{\theta_l^{i^*}, \forall i\}$.

Similarly, one can identify the critical outputs for both efficient projects and inefficient projects using the super efficiency BCC output-oriented sensitivity model (16)-(21) and the definition of sensitivity values, in similar lines to the description of critical inputs given above. In case of the output-oriented model, critical output for an efficient DMU is the minimum proportionate reduction in output which will make project l inefficient, i.e. output "k" corresponding to $\max\{\phi_l^{k^*}, \forall k\}$. On the other hand, the critical output for an inefficient DMU is that output, by increasing which, project l can catch up with the frontier and become efficient with minimum effort, i.e. output "k" corresponding to $\min\{\phi_l^{k^*}, \forall k\}$. Note that $\phi_l^{k^*} \leq 1$ for efficient projects (apart from the infeasibility, in which case that particular output is stable for any fluctuations and has no cause for concern) and $\phi_l^{k^*} > 1$ for inefficient projects. For a more detailed description on how to determine critical inputs and critical outputs, the reader is advised to refer to Zhu (2003).

The BCC super efficiency sensitivity models are applied to identify the critical inputs and outputs for the current sample of 20 projects. The BCC sensitivity values for all the inputs/outputs, the corresponding critical values and critical inputs are reported in Table VII. As one can recall from the sensitivity results listed in Table VI, all the six BCC efficient projects show infeasibilities corresponding to all the inputs/outputs except for projects 2 and 11. Thus, the four BCC efficient projects (7, 12, 17 and 19) do not have any critical inputs or outputs, while for project 2, productivity output turns out to be the critical output, for project 11, sigma quality is found to be the critical output. Note that the critical input values are either infeasible or greater than 1 for all the efficient projects and less than 1 for all the inefficient projects (similarly, the critical output values are either infeasible or less than 1 for all the efficient projects and greater than 1 for all the inefficient projects). The most important finding of the critical value analysis is the fact that "Project Cost" is the most critical input for most of the inefficient projects (9), which is followed by "Project Duration" for five inefficient projects. The most critical output for the inefficient projects is found to be "Financial Impact" for a total of 11 projects, which is then followed by "Productivity" and "Customer satisfaction" for two projects each and finally "sigma quality" for one project. Thus, the critical input and output analysis indicates that, efficient use of "Project Cost" followed by "Project Duration" provides the maximum scope for the inefficient projects to catch up with the frontier with minimum effort. Similarly ensuring higher impact on financial performance enables a project to catch up with the frontier on the output side. It may be possible that, due to inefficient or lack of measurement systems, one is unable to capture the impact of process improvements in a given project, which may get reflected in the data. Therefore, not just focusing on the financial performance through six sigma process improvements, but also having the systems in place to measure the impact on financial performance plays a major role in appropriate selection of six sigma projects. This finding is not surprising as one of the major drawbacks in any quality implementation programs is the lack of proper measurement system that can capture the improvements in terms of tangible impact on financial performance to convince the management the usefulness of the program.

6. Conclusions and future research

Several process improvement techniques have come and gone in the past five decades. Although these techniques did improve quality and productivity of products

Project no.	BCC efficiency	Critical input values	Critical inputs	Critical output values	Critical outputs
2	1.00	Infeasible	None	0.956522	Increase in productivity
7	1.00	Infeasible	None	Infeasible	None
11	1.00	Infeasible	None	0.99	Sigma quality
12	1.00	Infeasible	None	Infeasible	None
17	1.00	Infeasible	None	Infeasible	None
19	1.00	Infeasible	None	Infeasible	None
6	0.97	0.97	Project cost	1.13	Financial impact
1	0.92	0.92	Project cost	1.04	Financial impact
3	0.92	0.92	Project cost	1.04	Financial impact
15	0.92	0.92	Project cost	1.10	Financial impact
8	0.91	0.91	Project cost	1.31	Financial impact
10	0.91	0.91	Project duration	1.02	Financial impact
18	0.90	0.90	Project cost	1.10	Financial impact
13	0.89	0.89	Project cost	1.12	Financial impact
20	0.87	0.86	Project cost	1.09	Financial impact
9	0.85	0.85	Project duration	1.21	Increase in productivity
16	0.83	0.83	Project cost	1.22	Customer satisfaction
5	0.83	0.83	Project duration	1.44	Financial impact
4	0.78	0.78	Project duration	1.14	Customer satisfaction
14	0.76	0.76	Project duration	1.06	Financial impact

Table VII. BCC efficiency scores, critical input and output values and the corresponding critical inputs and outputs for the entire sample manufactured by some companies, many failed to get any benefit out of these quality improvement programs. One of the main reasons for the failure of a process improvement initiative in most cases can be identified as "wrong project selection". Although it is claimed that the impact of six sigma has been much higher than any of the previous quality improvement programs, failure to select the right projects will also result in failure of six sigma implementation. In this paper, a DEA-based project selection model is developed for six sigma project selection. The efficient DMUs (projects) based on CCR DEA models are selected for implementation.

DEA can be used as a hybrid tool along with techniques such as quality function deployment (QFD), failure modes, effects and criticality analysis (FMECA) and analytic hierarchy process (AHP). QFD is a tool mainly created to capture the customer requirements (voice of customers) and how the customer requirements can be satisfied. QFD uses benchmarking to set target for various technical requirement derived from voice of customers and DEA can be used for benchmarking. FMECA allows the designers to identify potential failure modes and their effects and classifies them based on their criticality. FMECA is not designed as a project selection tool. AHP has been used by many practitioners as a project selection tool. AHP and project prioritization matrix use subjective judgments of the decision-making group. The output of DEA is basically a Pareto optimal solution. In this paper, our focus was on Big Q projects, however, the methodology can also be applied for selection of little *q* projects.

The sensitivity analysis suggests that the BCC efficiency scores of the sample six sigma projects in general are stable to the perturbations in data. The critical input and output analysis using the BCC sensitivity models shows that only couple of the efficient projects are vulnerable to variations in "Productivity" and "sigma Quality" outputs while the inefficient projects can improve their efficiency ratings by focusing on efficient use of "Project Cost," "Project Duration" and through achievement of higher "Financial impact."

Notes

1. The DMU at the extreme points of the efficiency frontier are termed as extreme efficient. For further description of extreme efficient DMU, see Zhu (2003).
2. Note that, since only extreme efficient DMUs have infinite stability, the inefficient DMUs obviously will never be infinitely stable.

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Corresponding author

U. Dinesh Kumar can be contacted at: dineshk@iimb.ernet.in