Benchmarking of R&D performance using interactive data envelopment analysis

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Abstract

This paper aims to assess the performance benchmarking approach to assess competitiveness of research organisations. The unit of analysis is R&D organizations. It uses interactive data envelopment analysis (IDEA). Data were collected from an Indian R&D organization. Superior R&D performance enhances an organization's competitiveness. It is observed the Indian R&D organization, needs to adopt approximately 56% of the best practices from Lockheed Martin and 30.18% of the best practices Kongsberg Gruppen, Thales Group, Furuno and Altas Elektronik respectively. Analysis demonstrates that IDEA utilises the embedded learning effect to form a dynamic and realistic performance profile based on the organization's capabilities.

Keywords: Performance benchmarking, data envelopment analysis, Interactive multiple goal programming

Introduction

In today's dynamic and competitive environment, research and development (R&D) organizations are gearing up to perform with efficiency and efficacy to enhance their product innovation performance (Alegre et al., 2006). In recent decades technological innovation has evolved as a means to stimulate economic growth (Lundvall, 1992). This necessitates conducive policy formulation and effective implementation (USDC, 2000). Organizations are addressing shortening of product life cycles by accelerating the time to market by creating virtual processes across network of both internal as well as external strategic partners (Holtzman, 2008). However, achieving successful innovation is not simple for most organizations as innately innovation is difficult to be comprehended and interpreted (Dougherty, 1996). In the long term a combination of innovative ideas and good organizational innovation management is the key to sustaining competitive organizational innovation (Ahmed, 1998).

The objective of this research is to develop an effective model of performance measurement of a publicly funded R&D laboratory in India and structure a benchmark which it can strive to achieve based on the workings of market leaders in the domain of underwater defence and surveillance systems. The top players include private and publicly funded organizations from Lockheed Martin (USA), Kongsberg Gruppen (Norway), Thales Group (France), Furuno (Japan) and Altas Elektronik (Germany) that are known for their high innovation index. This paper aims to explore the best practices that the Indian laboratory can adopt from the market leaders in the domain of underwater defence and surveillance systems. The Interactive Data Envelopment Analysis (IDEA) technique is used to evaluate the performance. The next section presents the literature on performance benchmarking. Section 3 presents the model, methodology and the data. Results are interpreted in section 4 and section 5 draws the conclusion and practical applicability of this work.

Literature Review

Innovation and Economic Growth

Patents are key indicators of innovation and economic returns are achieved through their commercialization. Public funded R&D organizations are answerable to the society for their performance (Coccia, 2001). Regular evaluations and comparisons become paramount to maintain their accountability therefore, performance measurement is undertaken by decision makers to determine whether efforts put in by these firms are on course (Cook et al., 1995). This process, however, becomes complex as it requires a set of multiple input and output measurement criteria along with a technique that can provide results matching the organizational climate and market scenario.

Benchmarking

Benchmarking is a management method aiming at finding performance gaps in organizations (Maleyeff, 2003). The purpose of benchmarking is to systematically measure and compare performance with the best-in-class to determine what should be improved for achieving superior performance (Ettorchi-Tardy et al., 2012). In particular, performance benchmarking is concerned with measuring, comparing, and improving outcome characteristics (Wolfram Cox et al., 1997). Benchmarking raises the standard of competition in an industry and weeds out the companies that do not or cannot maintain a competitive edge (Bhutta and Huq, 1999). The common steps of the benchmarking process include defining what needs to be benchmarked, identifying the best-in-class for comparison, determining performance gaps, making improvements, and so on (Asif, 2015).

Performance Measurement

It is difficult to evaluate and compare performance of R&D or innovation in absolute terms because R&D is risky, uncertain, intangible and complex (Bremser and Barsky, 2004) apart from having multiple output parameters (Brown and Svenson, 1998). But relative efficiencies can be used to calculate the performance of such organizations that use innovation as a means to establish competitive advantage in their domain (Zhu, 2014). Firm performance has usually been the dependent variable of empirical studies. However, innovation performance can be considered as an intermediate variable between firm performance and business processes. Furthermore, previous research has shown a definitive link between innovation performance and firm performance (Calantone et al., 1995). Studies such as R&D measurement system for Korean researchers (Kim and Oh, 2002), model to measure the effectiveness of research units (Roy *et al.*, 2003) and developing evaluation criteria for multi-disciplinary R&D projects in China for ranking and rewarding (Wang *et al.*, 2005) have been conducted. A mathematical model and research laboratories evaluation (RELEV) function with k-indices and two performance functions using discriminant analysis with direct and Wilks method has been given by Coccia (2001, 2004). Data envelopment technology has also been used in Taiwan for 31 computer and peripherals firms by taking selective input and output measures (Chen et al., 2004). Firm's R&D performance is analysed using the best worst method (Salimi and Rezaie, 2018). Epure (2016) talks of benchmarking for routines and organizational knowledge as a managerial accounting approach to measurement of performance with feedback. R&D performance of government research institutes using a bottom-up DEA approach has been measured and improved in Lee and Lee (2015). Developing a R&D process improvement system to simulate the performance of R&D activities is yet another take on the recent research scenario in this domain (Lee et al., 2017). Literature suggests use of multiple dimensions to assess the performance of R&D (Gallarza et al., 2017; Zobel, 2017). It has been observed from the literature that studies have been conducted at the level of researchers and R&D projects in various disciplines (Henttonen, 2016) while some studies have formulated performance measurement functions for national R&D organizations (Maistry et al., 2017). Chen et al. (2004) have used the DEA technique by taking selective input-output measures without using weighed data. DEA combined with Interactive Multiple Goal Programming have been used to benchmark UK university departments (Post and Spronk, 1997).

Methodology

Selection of performance benchmarks is vital for organizational planning and control as it constitutes external restrictions and managerial preferences as well as organizational policy considerations and technical production possibilities. A combination of the performance measurement technique, Data Envelopment Analysis (DEA) and the interactive decision procedure, Interactive Multiple Goal Programming (IMGP) has been proposed in this paper under the resulting performance benchmarking procedure, Interactive Data Envelopment Analysis (IDEA).

Data Envelopment Analysis

DEA measures the relative performance of decision making units (DMUs) in a setting of multiple input and output variables, say m and s respectively. A combination of fractions (or lambda's) of one or more observed DMUs forms one or more hypothetical composite DMUs based on certain assumptions of technical production relationships. These composite DMUs act as comparators for the observed DMUs with their performance levels taken as lambda weighted averages of the constituent observed DMUs. This method implicitly assumes that the continuous, linear inputs are substitutable and the outputs are transformable, with constant-returns-to-scale properties. The collection of input-output combinations of all feasible DMUs forms the smallest subset in the input-output space consistent with the aforementioned observed combinations and production assumptions known as the DEA production possibility set (PPS) (Bogetoft, 2012). Having constructed the PPS structure, reference units from the PPS are selected to act as performance benchmarks for the observed DMUs which consume each DMU's lowest possible fraction of current input levels to produce at least that DMU's current output levels. These reference units are identified simultaneously by solving the following linear programming problem:

$$\min_{\lambda_{kj}} \sum_{k=1}^{n} \theta_k$$

$$s.t. \sum_{j=1}^{n} \lambda_{kj} y_{rj} \geq y_{rk}, k = 1, \dots, n; r = 1, \dots, s; \text{ (1)}$$

$$\sum_{j=1}^{n} \lambda_{kj} x_{ij} \leq \theta_k x_{ik}, k = 1, \dots, n; i = 1, \dots, m;$$

$\lambda_{kj} \geq 0, k = 1, \ldots, n; j = 1, \ldots, n.$

This method selects the reference unit for each DMU which maximizes its relative efficiency, subject to the condition that the production function is monotone increasing and concave, enveloping almost all DMUs. The dual formulation of the problem (1) illustrates this point perfectly, as under:

$$\max_{u_{ro}, v_{io}} \sum_{k=1}^{n} h_k = \sum_{k=1}^{n} \sum_{r=1}^{s} u_{rk} y_{rk}$$

$$s.t. \sum_{i=1}^{m} v_{ik} x_{ik} = 1, k = 1, \ldots, n; \quad (2)$$

$$\sum_{r=1}^{s} u_{ro} y_{rk} - \sum_{i=1}^{m} v_{io} x_{iij}, k = 1, \ldots, n; \; j = 1, \ldots, n;$$

$$u_{rk}, v_{ik} > 0, k = 1, \ldots, n; r = 1, \ldots, s; i = 1, \ldots, m.$$

Notation: h_k, $\theta_k$are efficiency scores of DMU$_k$, y_{rj} quantity of rth output for jth DMU, x_{ij} quantity of ith input for jth DMU, u_{rj}weight of rth output for jth DMU; v_{ij} weight of ith input for jth DMU, λ_{kj} proportion of jth DMU in reference unit of kth DMU.

The standardized weighted average of all input and output levels is taken in such a way that no DMU is over efficient and all outputs are strictly positive while all inputs are weighed strictly negative.

Interactive Multiple Goal Programming

In the case of multiple inputs and outputs in the PPS, it becomes difficult to assign weights and obtain a benchmark that is practically implementable for any DMU. Combining DEA with interactive decision procedures from the Multiple Criteria Decision Making theory (MCDM) has been suggested in literature (Andre et al., 2010).

Interactive Data Envelopment Analysis

The collection of input-output variables of some composite DMU from the production possibility set (PPS) creates an initial performance profile to act as a proposed performance benchmark. Improvements feasible with the DEA PPS are then made on this profile. The potential improvements along with the initial profile are presented to the decision maker who indicates whether the updated profile is satisfactory and if not, which input and output levels need to be rectified, and to what extent. Successive iterations reduce the set of feasible performance profiles, keeping only those alternatives which align with the best practices until the desired benchmarked state is finally reached. This procedure involves selection of a feasible performance profile, improvement of potential performance variables, readjustment of selected performance profile and reiteration of the above steps till desired benchmark in achieved. IDEA assumes the standard DEA production technology with constant-returns-to-scale properties, continuous linear local input substitutability and output transformability in this article. However, IDEA can also accommodate varied assumptions other than those mentioned above. The IMPG procedure can be combined with virtual weight constraints by restricting the dual input-output weights to the closed convex cones V for inputs and U for outputs. These polar cones have vectors spanning in the direction normal to the hyperplanes bounding V and U. The selected composite DMU is projected in all directions in the graph to find the many DEA efficient reference units which form the upper feasibility boundaries for aspiration levels of benchmarking. These performance levels are not feasible at the same time as they are solutions to multiple independent optimizations focused on single and not multiple input and output formulations. The linear programming problems for the computations of maximum feasible, separately calculated input observations and output augmentations for DMU o (o∈ {1… n}) are as follows:

$$\min_{\lambda_{oj}} \sum_{j=1}^{n} \lambda_{oj} x_{ij}$$

$$s.t. \left\{\sum_{j=1}^{n} \lambda_{oj} x_{ij} - X_{io}, i = 1, \dots, m\right\} \epsilon - V^*, \quad (3)$$

$$\left\{\sum_{j=1}^{n} \lambda_{oj} y_{rj} - Y_{ro}, r = 1, \dots, s\right\} \epsilon - U^*,$$

$$\lambda_{oj} \geq 0, j = 1, \dots, n;$$

$$\max_{\lambda_{oj}} \sum_{j=1}^{n} \lambda_{oj} y_{rj}$$

$$s.t. \left\{\sum_{j=1}^{n} \lambda_{oj} x_{ij} - X_{io}, i = 1, \dots, m\right\} \epsilon - V^*, \quad (4)$$

$$\left\{\sum_{j=1}^{n} \lambda_{oj} y_{rj} - Y_{ro}, r = 1, \dots, s\right\} \epsilon - U^*,$$

$$\lambda_{oj} \geq 0, j = 1, \dots, n.$$

Where y_{rj} is the *quantity* of the *r*th output for *j*th DMU, x_{ij} quantity of the *i*th input for *j*th DMU, λ_{oj} proportion of the *j*th DMU in reference unit for DMU *o*, Y_{ro} aspiration level for *r*th output of DMU *o,* X_{io}aspiration level for *i*th input of DMU *o*, V^* negative polar cone of input weight cone *V*, U^* negative polar cone of output weight cone *U*.

The production possibility set (PPS) of inputs and outputs with its literature backing is provided in Table 1.

Table 1: Input and Output Variables for IDEA Procedure

SN	Performance Dimension	Literature
1	New technologies or products developed	Guellec, 2010; Dobni, 2008
2	Revenue generated	Fuchs, 2010; Chiesa, 2009; Wang, 2007
3	Average resource mobilization (in business days)	Chiesa, 2009, Lofsten, 2014
4	Amount spent on fine-tuning organizational infrastructure and training of employees	Alegre, 2006; Dobni, 2008
5	Average productivity for a single project (in months)	Lynch and Cross, 1991
6	Employees hired at different levels	Lee, 2005; Alegre, 2006; Dobni, 2008
7	Average number of prototypes developed or experiments undertaken	Zhang and Doll, 2001; Valle and Avella, 2003
8	R&D expenditure	Lee, 2005; Alegre, 2006

Here, the input (x_i) and output (y_r) dimensions are-

x_1: average resource mobilization,

x_2: revenue generated,

y_1: R&D expenditure,

y_2: new technologies or products developed,
y_3: average productivity for a single project,
y_4: average number of prototypes developed or experiments undertaken,
y_5: amount spent on fine-tuning organizational infrastructure and training of employees,
y_6: employees hired at different levels.

The design of performance measurement systems depends on the decision maker's need for comprehensiveness of measurement (Chiesa et al., 2007), the type of R&D process being measured, that is basic research, new product development or applied research (Karlsson et al., 2004), the type of uncertainty characterizing R&D projects and the technology strategy pursued by the firm (Devila, 2000). In DEA, inputs and outputs are selected carefully so as to get effective and useful results. The input variables here represent the time taken for resources and raw material to reach the firm from the supplier (Chiesa, 2009, Lofsten, 2014), and revenue generated through the R&D activities (Fuchs, 2010; Chiesa, 2009; Wang, 2007). On the other hand, multiple output variables such as, the amount required for training the employees and readjusting the organizational infrastructure to support new R&D activities (Alegre, 2006; Dobni, 2008), new technologies developed under innovation (Guellec D, 2010; Dobni, 2008), overall R&D expenditure which is the most important of all input criteria (Lee, 2005; Alegre, 2006), prototypes and experiments undertaken (Zhan and Doll, 2001; Valle and Avella, 2003), the number of employees hired at different levels like scientists, consultants, managers and such others (Lee, 2005; Alegre, 2006; Dobni, 2008), and average productivity for R&D projects (Lynch and Cross, 1991) elaborate how the performance of a firm can be assessed.

The weights assigned to each measure have been derived from the judgement of scientists and R&D managers, secondary sources and annual reports of the organizations in question between 2016 and 2017. Using MS Excel, the DEA model has been applied to achieve an initial benchmarking profile.

Table 2: Weights Assigned to Output Levels

SN	Performance Dimension (outputs)	Weights
1	R&D expenditure	0.39
2	New Technologies or Products Developed	0.23
3	Average Productivity for a single project	0.07
4	Average Number of Prototypes developed or Experiments undertaken	0.12
5	Amount spent on fine-tuning organizational infrastructure and training of employees	0.09
6	Employees hired at different levels	0.10

The applied IDEA benchmarking procedure starts by generating an efficiency frontier consisting of the input-output levels (production possibility set or PPS) of all companies and laboratories whose data has been collected for this study. Time, cost and quality, along with organizational structure are key measures based on which the PPS is developed. The names of the seven decision making units in this study are named as DMUs A, B, C, D, E, F and G. All DMUs are mapped on the efficiency frontier which appears concave and qualifies five out of the seven companies as efficient. Now improvements on this performance profile that are feasible within the DEA Production Possibility Set (PPS) are computed. The X-axis represents the consolidated, weighted average of inputs and the Y-axis shows the weighted average of output variables.

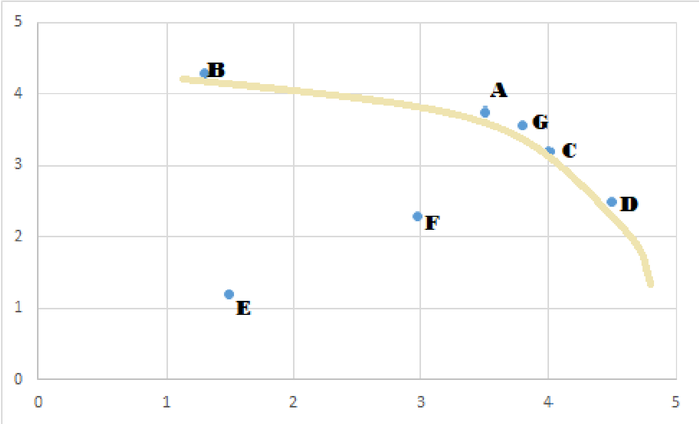

Figure 1: Efficiency Frontier

It is observed that DMU- E, which is the Indian laboratory in question, needs to adopt approximately 56% of the best practices from DMU- B (Lockheed Martin) and 30.18% of the best practices from a composite DMU consisting of DMUs A, C, D and G which are Kongsberg Gruppen, Thales Group, Furuno and Altas Elektronik respectively. The decision maker at the Indian laboratory is presented the initial profile and the potential enhancements, who then has to indicate whether the proposed performance profile is a satisfactory performance benchmark; if not, which of the input-output levels should be enhanced, and to what extent. By successively altering the performance profile from iteration to iteration, the set of feasible performance profiles is gradually reduced by keeping only those alternatives that meet the higher standards, until a satisfactory performance benchmark is identified. In this case, the penultimate performance profile developed on the third iteration consists of recalibrated goals based on the best practices from the influencing DMUs as seen in the table below. The ultimate iteration is, in fact, dynamic and dependent on successful implementation of the preceding stage.

Results and Discussion

The output table 3 shows that the employees hired at different levels can be increased without any concessions on other performance dimensions. To some extent, even the expenditures (R&D and employee training) can be worked upon. However, the remaining three outputs separately cannot be modified without altering or lowering the performance standards of other input-output variables. Therefore, it was suggested to the Accordingly, the input-output levels were adjusted and potential improvements recalculated. It can hence be seen that a constrained DEA model which incorporates priori formulated restrictions to input and output levels cannot offer a feasible solution. However, IDEA avoids unfeasible solutions by computing upper feasibility boundaries before aspiration levels can be specified at each iteration. The decision maker can stop at whichever iteration (or run) s/he feels satisfied with. The numbers in bold italics shows the final output of the IDEA procedure with the selected third performance profile based upon performance improvements in two iterations. Since, the penultimate stage or the third run has recently been implemented; the next phase will be incorporated by the Indian laboratory upon successful adaptation of the previous stage or if there is any change in environmental variables.

Table 3: Results from the Benchmarking Iterations

Performance Dimension	Run	Performance Profile	Upper feasibility boundary	Performance Improvements
R&D expenditure	1 2 3	1840 1900 ***2200***	2000 2400 2500	160 500 ***300***
New Technologies or Products Developed	1 2 3	21 28 ***42***	25 30 50	4 2 ***8***
Average Productivity for a single project	1 2 3	30 36 ***45***	35 39 50	5 3 ***5***
Average Number of Prototypes developed or Experiments undertaken	1 2 3	13 15 ***27***	15 20 35	2 5 ***8***
Amount spent on fine-tuning organizational infrastructure and training of employees	1 2 3	360 360 ***386***	379 392 392	19 32 ***6***
Employees hired at different levels	1 2 3	450 450 ***450***	497 515 465	47 65 ***15***

Conclusion

Findings suggests that performance of the Indian R&D organization is poor compared with best in class players such as Lockheed Martin, Kongsberg Gruppen, Thales Group, Furuno and Altas Elektronik. In order to enhance performance the Indian R&D organization needs to utilize the expenditure by hiring more employees like managers and skilled workforce and enhance the organizational infrastructure for facilitating innovation-oriented activities.

The paper attempts the use of DEA along with IMGP in the form of IDEA to provide an efficiency frontier with proposed benchmarks for the aforementioned performance dimensions. Instead of creating a rigid and ideal benchmarking profile, IDEA utilizes the embedded learning effect to form a malleable and realistic performance profile based on the firm’s capabilities for R&D improvement. Using the procedure detailed throughout the paper, it can be successfully inferred that the integrated IDEA methodology provides a more flexible approach and realistic performance benchmarking technique as opposed to the traditional method of data envelopment analysis. Also, such a technique has not yet been incorporated to study innovation performance in R&D organizations which makes this work unique and novel in itself. For developing countries striving to innovate and reach the level of developed countries in terms of research and development, such a technique can prove useful in quickly escalating towards the desired goal practically and realistically.

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