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Goal directed benchmarking for organizational efficiency

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ABSTRACT

In this paper, we extend the standard data envelopment analysis (DEA) model to include longer term top management goals. This extension is in recognition of the fact that benchmarking for decision making units (DMUs) is more than a purely monitoring process, and includes a component of future planning. The new model uses a goal programming structure to find points on the efficient frontier which are realistically achievable by DMUs, but at the same time achieving a closer approach to long term organizational goals (as distinct from the local performance of individual DMUs). Consideration is given to the possibility of adjusting constraints on the DMU by investment in extended inputs or new technologies, in which case minimization of associated investment costs becomes an additional management objective.

1. Introduction

Data envelopment analysis (DEA) has become a widely recognized tool for the evaluation of organizational efficiency, and a number of extensions and applications have been reported [e.g. 3,15,6,2]. Results from DEA include evaluation of the efficiency of "decision making units" (DMUs) in the data base, a non-parametric estimate of the best practice frontier of the production possibility set (PPS) relating outputs produced to inputs consumed, and a consequent provision of benchmark performance levels on the efficient frontier of the PPS for the inefficient DMUs.

A number of writers [e.g. 10,16,1,5] have commented on the links between DEA and multiple criteria decision analysis (MCDA), while others in a similar sense have discussed means of incorporating judgemental management goals in DEA [e.g. [4,15]. Cooper [5] warned, however, that a superficial mathematical similarity between methods of DEA and MCDA should not obscure fundamental organizational differences between management monitoring and control on the one hand, and management planning on the other hand. The assessment of the historical efficiency of a DMU is part of monitoring and control, and the thrust of DEA is to be as objectively fair as possible in making such assessments. The concern of MCDA with values and goals is essentially prospective, and relates to planning, i.e. the process of moving from where we are to where we want to be.

Nevertheless, one of the standard outputs of a DEA analysis is the establishment of "benchmarks" for each inefficient DMU, with the implication that these may serve as targets towards which the DMU should aspire. The point of departure for the present paper is that such targets move from pure monitoring and control to planning, and as such should include value judgements from group management as to what is desirable in addition to what is achievable technically. In fact, future targets can meaningfully be set even for efficient DMUs; they may be efficient in terms of their current inputs and outputs, but there may still be room for improvement in the sense of moving closer to overall management objectives. The theme of the present paper is thus to propose means of specifying benchmarks within a framework similar to that of DEA, but incorporating future management goals.

In the next section we introduce some basic notation and review standard DEA models. The basic form of the proposed new model is described in Section 3, and is extended in Section 4 to include costs of new investments that may be needed. The approach is illustrated by a numerical example in Section 5. In a concluding section we indicate further extensions that could easily be incorporated.

2. Model formulation

We adopt some standard DEA nomenclature. Let n be the number of DMUs, m the number of inputs and s the number of outputs, and then define x_{ij} as the amount of input i used (cost incurred or resource used) by DMU j and y_{rj} as the amount of output (product or service) r produced by DMU j.

Now consider DMU k, for $k \in \{1, \ldots, n\}$. In principle, an empirical benchmark performance profile for DMU k may be

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constructed as a linear combination of selected DMUs, i.e. in the form

$$\left.\begin{aligned} x^*_{ik} &= \sum_{j=1}^{n} \lambda_j x_{ij} \\ y^*_{rk} &= \sum_{j=1}^{n} \lambda_j y_{rj} \end{aligned}\right\} \tag{1}$$

for some appropriately chosen set of weights $\lambda_j \geq 0$ (possibly subject to restrictions such as $\sum_{i=1}^{n} \lambda_j \leq 1$ to model non-increasing returns to scale). The sets of inputs and outputs defined in this way for all combinations of λ_j are assumed to characterize the *production possibility set* (*PPS*).

The conventional DEA models include two approaches for choosing the λ_j weights, termed the input and output oriented forms, respectively, both defined by solutions to LP problems as described below.

Input oriented: Find the benchmark which gives the greatest improvement in inputs over DMU k, while still achieving the same outputs:

$$\left.\begin{aligned} &\text{Minimize} \quad E \\ &\text{Subject to :} \\ &\quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq E x_{ik} \quad (i = 1, \ldots, m) \\ &\quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk} \quad (r = 1, \ldots, s) \\ &\quad \lambda_j \geq 0 \quad (j = 1, \ldots, n) \end{aligned}\right\} \tag{2}$$

Output oriented: Find the benchmark which gives the greatest improvement in outputs over DMU k, while still using the same inputs:

$$\left.\begin{aligned} &\text{Maximize} \quad F \\ &\text{Subject to :} \\ &\quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik} \quad (i = 1, \ldots, m) \\ &\quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq F y_{rk} \quad (r = 1, \ldots, s) \\ &\quad \lambda_j \geq 0 \quad (j = 1, \ldots, n) \end{aligned}\right\} \tag{3}$$

In both approaches, additional constraints may be imposed in order to restrict the range of applicability of the benchmark (domain of the PPS), e.g. $\sum_{j=1}^{n} \lambda_j \leq 1$ in order to represent situations in which decreasing marginal returns to scale apply.

Many have recognized that alternatives to the pure input or output oriented benchmarks may well be desirable. Thanassoulis and Dyson [17] introduce other projections on to the efficient frontier of the PPS by identifying inputs and or outputs which the decision maker wishes to optimize (while projecting from the position of the DMU on to the efficient frontier). In even earlier work, Golany [7] introduced a form of interactive goal programming to allow the decision maker to explore the PPS. He constructs a form of payoff table, by maximizing a scaled form of each output in turn. This table can interactively be modified by changing the scaling in response to choices by the decision maker. Zhu [20] and Neto and Angulo-Meza [12] extend the formulations in (2) and (3) by replacing the E and/or F variables by different target ratios for each input and/or output, for example ϕ_r for each output measure and φ_i for each input measure, so that the relevant constraints become

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \varphi_i x_{ik} \quad (i = 1, \ldots, m)$$

and/or

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \phi_r y_{rk} \quad (r = 1, \ldots, s).$$

Multiobjective programming approaches are then used to search for combinations of the ϕ_r and φ_i which best represent the objectives of the decision maker when finding a most preferred point on the efficient frontier.

While the models mentioned above certainly include decision maker preferences in projecting DMU k on to the efficient frontier, the emphasis is primarily on a preferred direction of projection, rather than on a more fundamental structuring and assessment (in a multicriteria decision analysis sense) of decision maker preferences and values. Longer term planning does require consideration of more extensive goals on both inputs and outputs, to which we now turn.

3. GP-based benchmarking

At this stage, we wish to integrate longer term or more fundamental planning goals into the determination of benchmarks for each DMU. Halme et al. [9] and Joro et al. [11] made direct use of multiattribute value function theory, and suggested interactive procedures for finding points in the efficient frontier which were most preferred. Gouveia et al. [8] proposed a conversion of the inputs and outputs into utilities before applying projections, so that the direction of projection has a more explicit measure of decision maker preferences.

Yang et al. [19] introduce an approach more allied to the goal programming structure developed in this section. They develop an interactive procedure for exploring projections from DMU k on to the efficient frontier of the PPS, by viewing the problem as a multiobjective optimization of the outputs for composite DMUs which use no more inputs than those of DMU k. This multiobjective problem is solved by minimizing weighted deviations from the ideal outputs according to a Chebychev norm.

The approach which we now propose is aimed at satisfying the following properties:

- Decision maker preferences (which we shall express in terms of goals) can be specified externally to the observed DMUs (i.e. may well extend beyond the current PPS).
- Such preferences (goals) may be expressed in terms of inputs and/or outputs, depending on the context of the problem.
- Benchmarking should not be restricted to inefficient DMUs only; if the inputs and outputs of an efficient DMU (in the standard DEA sense) are far from the decision makers goals, it is appropriate to provide amended targets.
- The resulting benchmarks must be realistic in the sense of lying within the PPS (but see the final section on extending the PPS), and not being too far removed from the current position of the DMU (as changes in organizational profiles cannot be achieved overnight).

More formally now, suppose that the decision maker, in moving from a purely monitoring role to a future planning role, proposes a set of explicit goals for DMU k (which may be unique to this DMU, or which may represent a common set of goals for all DMUs). At this point it is assumed that the DMU itself (i.e. its management) has control over its own inputs and outputs. We shall later consider constraints on the DMU's freedom of choice.

Let these goals be defined as follows:

- g_{ik} be the goal or aspiration level specified for input i of DMU k; and
- h_{rk} be the goal or aspiration level specified for output r of DMU k.