An efficiency-driven approach for setting revenue target

Hung-Tso Lin *

Department of Distribution Management, National Chin-Yi University of Technology, Taichung County, Taiwan, Republic of China

ARTICLE INFO

ABSTRACT

This paper addresses the efficiency measurement and revenue setting problems drawn from a home improvement company with 22 chain stores in Taiwan. The top management attaches great importance to efficiency analysis of their stores. Furthermore, when the proposal to establish a new store is under development, the regional manager must determine what efficiency level the new store should achieve and what amount of business revenue it should earn. An approach by using the imprecise DEA (IDEA) and inverse IDEA models as core techniques is proposed to deal with such problems. A simulated application illustrates the implementation of the proposed approach.

© 2010 Elsevier B.V. All rights reserved.

1. Introduction

In popular management theory, goal-setting and efficiency measurement play a pivotal role, expressed in phrases such as "what gets measured, gets done" [22]. From the viewpoint of management practice, questions related to what level of efficiency an organization needs to achieve and how it should set appropriate efficiency target are some of the main issues for managing organizational efficiency [12,21].

In this paper, the issue for measuring efficiencies of existing stores and decision-making problem for setting business revenue target of a new store are addressed. These problems are drawn from a home improvement company in Taiwan. The company has established 22 chain stores to sell do-it-yourself products including more than thirty thousand items and to provide professional design and consultation for home improvement. In order to enhance the service competence to cope with intense competition within the same business sector and to meet the diverse demands of customers, the top management attaches great importance to efficiency analysis. Thus, to obtain an objective efficiency measurement in last period the regional managers must evaluate not only the business revenue earned by the stores in their respective regions, but also the performance of resource utilization in earning that revenue. Furthermore, important considerations have arisen due to the development of a new store establishment proposal. In addition to allotting the input resources for a new store, a regional manager must determine what efficiency level the new store should achieve and how much business revenue

it should earn. Under the target of business revenue, the store manager and the subsidiary workers will devote themselves to develop effective marketing and service plans for delivering the target. Since the company plans to establish new stores each year in different regions, such considerations have become important issues for corporate administration, and so this is thus a problem worthy of investigation.

Each store consumes some resources in implementing the tasks to obtain some concerned results. Conceptually, the relative efficiency of a store is calculated as the ratio of weighted sum of outputs to weighted sum of inputs. Data envelopment analysis (DEA) has been shown to be a powerful tool for measuring the relative efficiencies of the homogenous decision-making units (DMUs). In this study, the chain stores are referred to as homogenous DMUs. DEA and the relevant techniques are employed to deal with the problems under consideration. The rest of this paper is organized as follows. The next section presents the fundamentals of DEA models and the relevant techniques. Section 3 describes the proposed approach consisting of five stages. Section 4 illustrates the implementation of the proposed approach via a simulated application. Finally, conclusions are given in Section 5.

2. DEA models and relevant techniques

DEA is a nonparametric method that can be applied to assess the relative efficiency of each DMU without predetermined weights for the input and output factors and without knowing information on the production function. The CCR model [3] and BCC model [1] are commonly used to evaluate relative aggregate efficiency and technical efficiency, respectively, of each DMU that consumes multiple inputs to produce multiple outputs. For convenience, the momentous notations used in the following description are listed in Table 1. The CCR (Charnes–Cooper–Rhodes) model was developed to establish an

* Postal address: Department of Distribution Management, National Chin-Yi University of Technology, 35, Lane 215, Chung-Shan Road, Section 1, Taiping City, Taichung County, 41101, Taiwan, Republic of China. Tel.: +886 4 23924505x7805; fax: +886 4 23932065.
  E-mail address: htl@mail.ncut.edu.tw.

Table 1
Notations.

Index and input parameters
X_i input factor i, $i = 1, 2, ..., m$.
Y_r output factor r, $r = 1, 2, ..., s$.
x_{ij} input amount of X_i of DMU j, $j = 1, 2, ..., n$.
y_{rj} output amount of Y_r of DMU j, $j = 1, 2, ..., n$.
ε a non-Archimedean small number.
$n_{\ell j}$ number of workers in rank ℓ of DMU j.
BP_ℓ basic payment of salary and bonus of a worker in rank ℓ.
EE_ℓ extra expenditures of a worker in rank ℓ.
$\delta(\ell)$ total amount of resources consumed by a worker in rank ℓ,
  where $\delta(\ell) = BP_\ell + EE_\ell$, $\delta(\ell) < \delta(\ell + 1)$ and $\delta(1) \geq \gamma = BP_1$.
π_ℓ a value to reflect the degree of worker level intensity between
  ranks ℓ and $\ell + 1$.
p_r unit value of Y_r.
x'_{ij} adjusted or revised amount of x_{ij}.
$n'_{\ell j}$ adjusted or revised number of $n_{\ell j}$.

Decision variables
E_k^A aggregate efficiency of DMU k.
E_k^T technical efficiency of DMU k.
E_k^S scale efficiency of DMU k.
v_i weight attached to X_i.
u_r weight attached to Y_r.
$w_{1\ell}$ weight attached to $n_{\ell j}$, where $w_{1\ell} = v_1 \delta(\ell)$.
v_0 a variable used to discriminate the status of returns-to-scale
  of the DMU under evaluation.
y'_{rj} amount target for adjusting or revising y_{rj}.

---

efficiency frontier based on the Pareto optimum concept. The aggregate efficiency of the DMU under evaluation, say DMU k, can be calculated by the following output-oriented DEA-CCR model:

$$E_k^A = \text{Min} \sum_{i=1}^{m} v_i x_{ik} \tag{1.0}$$

$$\text{s.t.} \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0, \quad j = 1, ..., n, \tag{1.1}$$

$$\sum_{r=1}^{s} u_r y_{rk} = 1, \tag{1.2}$$
$$v_i, \ u_r \geq \varepsilon.$$

By the restriction of the above constraints, the efficiencies of all DMUs have a lower bound of 1. DMU k is aggregate efficient when E_k^A is equal to 1 and aggregate inefficient if E_k^A is greater than 1. The value of E_k^A equals 1 indicating that DMU k lies on the efficiency frontier and is thus regarded as relatively efficient. Alternatively, DMU k does not lie on the efficiency frontier and is regarded as relatively inefficient. Regarding the determination of weights v_i and u_r, each DMU is allowed to select the most favorable weights in measuring its relative efficiency provided that all DMUs with the same weights will not be resulted in efficiency score of less than 1. However, to prevent unfavorable factors from being ignored in the evaluation by setting a weight of zero to them, all weights should be greater than a non-Archimedean small number ε.

In model (1), when the objective function (Eq. (1.0)) is set as $E_k^A = \text{Max} \sum_{r=1}^{S} u_r y_{rk}$ and the 2nd constraint (Eq. (1.2)) as $\sum_{i=1}^{m} v_i x_{ik} = 1$, then the model is known as input-oriented DEA-CCR model and the efficiencies of all DMUs have a upper bound of 1.

The main advantage of CCR model is that it can be used to measure the aggregate efficiency of each DMU for evaluating its performance of resource utilization. However, the limitation of CCR model is that it is based on the assumption of constant returns-to-scale. In order to establish a variable returns-to-scale efficiency frontier for measuring the technical efficiency, the BCC (Banker–Charnes–Coo-

per) model was developed by introducing a variable, v_0, to reveal the status of returns-to-scale at specific points on the efficiency frontier. By employing the treatment of v_0 in the BCC model [16,18], the output-oriented DEA-BCC model for measuring the technical efficiency of DMU k can be represented as follows:

$$E_k^T = \text{Min} \sum_{i=1}^{m} v_i x_{ik} + v_0$$

$$\text{s.t.} \sum_{i=1}^{m} v_i x_{ij} + v_0 - \sum_{r=1}^{s} u_r y_{rj} \geq 0, \quad j = 1, ..., n, \tag{2}$$

$$\sum_{r=1}^{s} u_r y_{rk} = 1,$$
$$v_i, \ u_r \geq \varepsilon, \ v_0 \text{ unrestricted in sign}.$$

DMU k is technical efficient when $E_k^T = 1$ and technical inefficient if $E_k^T > 1$. The value of v_0 can be positive, zero or negative indicating that DMU k presents DRS (decreasing returns-to-scale), CRS (constant returns-to-scale) or IRS (increasing returns-to-scale), respectively. When v_0 is set as zero in model (2), the model is known as CCR.

The aggregate efficiency is used to explore the performance of resource utilization, while the technical efficiency is used to explore the performance of operation. By using the technical efficiency, the reasons causing aggregate inefficiency (i.e., inefficiency in resource utilization) can be specified. Since the aggregate efficiency can be decomposed into the technical efficiency and the scale efficiency [1], the scale efficiency can be obtained by calculating the ratio of aggregate efficiency to technical efficiency and then used to assess the adequacy of the scale. A DMU is aggregate efficient if and only if it is both technical efficient and scale efficient. If a DMU is aggregate inefficient, then the technical efficiency and scale efficiency scores can be used to detect the sources of aggregate inefficiency, viz., whether it is caused by technical inefficiency, by scale inefficiency or by both [23].

In the conventional DEA, the input and output data can be expressed exactly. This type of model has been extensively applied in real-world cases [e.g., 2,11,16,24,25]. In practice, uncertain information, which is expressed such as bounded data, ordinal data or ratio-bounded data, occurs because of uncertainty. The mixture of uncertain information is referred to as imprecise data, and the associated method as imprecise DEA (IDEA). There have been many studies discussing the treatment of imprecise data and the application of the IDEA model [e.g., 6,8,9,15,19,26,28]. These IDEA models were developed to treat the case of mixtures of interval and ordinal data together with crisp number, or the case of incorporating fuzzy data into interval and ordinal data. With respect to the solution to IDEA model, it can either be solved using the standard linear DEA model by converting imprecise data into exact data [e.g., 30–32] or converted into a linear program by scale transformations and variable alternations [e.g., 7]. Chen [4] showed alternative ways to convert the ordinal data into bounded data and further into a set of exact data, and then investigated the work mechanisms of multiplier IDEA and primal IDEA.

Previous studies of DEA and IDEA were applied to measure the relative efficiency scores of the DMUs under given amounts of inputs and outputs. In recent years, a few studies have discussed the inverse DEA problem. Jahanshahloo et al. [14] reviewed these studies and classified the addressed problems into two types. The first type is related to how much the amounts of input and output should be adjusted so that the efficiency level of the DMU concerned remains unchanged or at least maintains its current efficiency status. Some methods were proposed to deal with this problem [27,29]. The second type is concerned with the problem that: if certain amounts of inputs are increased to a particular DMU, and assuming that the DMU improves its current efficiency level with respect to other DMUs, then