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An efficiency-driven approach for setting revenue target

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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.

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

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Table 1
Notations.

Index and input parameters
X_i input factor i, $i = 1, 2, \ldots, m$.
Y_r output factor r, $r = 1, 2, \ldots, s$.
x_{ij} input amount of X_i of DMU j, $j = 1, 2, \ldots, n$.
y_{rj} output amount of Y_r of DMU j, $j = 1, 2, \ldots, n$.
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:

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

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

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

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–Cooper) 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:

$$\begin{aligned} E_k^T = \; & \text{Min} \sum_{i=1}^{m} v_i x_{ik} + v_0 \\ \text{s.t.} \; & \sum_{i=1}^{m} v_i x_{ij} + v_0 - \sum_{r=1}^{s} u_r y_{rj} \geq 0, \quad j = 1, \ldots, n, \\ & \sum_{r=1}^{s} u_r y_{rk} = 1, \\ & v_i, \; u_r \geq \varepsilon, \; v_0 \text{ unrestricted in sign.} \end{aligned} \tag{2}$$

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 how much should the output of the DMU be increased? Jahanshahloo et al. [13] developed a method to solve this problem.

3. Proposed approach

DEA and inverse DEA methods are employed in this study since they are powerful tools that have been extensively applied in management problems. Due to the characteristics of the ordinal data considered in the current real-world case, suitable IDEA and inverse IDEA models are developed as core techniques of the proposed approach to deal with the problems of efficiency measurement of existing stores and setting revenue target of a new store. The conceptual flow of the proposed approach is depicted in Fig. 1. The approach is according to the following procedure:

Stage 1. Efficiency measurement of existing stores
A suitable IDEA-CCR model is proposed to measure the aggregate efficiency scores of existing stores which contain strong ordinal input data in last period. The period for efficiency measurement is usually a fiscal year. The IDEA-BCC model is also employed to measure the technical efficiency scores and obtain the values of v_0 of existing stores for classifying them into the types of IRS, CRS or DRS.

Stage 2. Adjusting inputs and outputs of existing stores and calculating the expected aggregate efficiency scores for next period
The status of returns-to-scale of a store is used as a guide for adjusting its input resources and output target. The expected amounts of input and output are increased in next period for existing stores classified as IRS or CRS, while the expected amounts of input are decreased and amount of output will remain the same for a store classified into the DRS type. Then, the expected aggregate efficiency scores in the next period are calculated.

Stage 3. Setting expected aggregate efficiency score and fictitious inputs and output for a new store
Among the group of existing stores, the expected aggregate efficiency score ranked in *c*th percentile is selected as the expected level of the new store. The input and output data of this reference store are used as the fictitious data for the new store such that the aggregate efficiency score of new store is kept at the expected level.

Stage 4. Revising fictitious input data of new store
The fictitious input data of the new store are revised according to allotted data of the establishment proposal.

Stage 5. Using the inverse IDEA-CCR model to set the target of output (business revenue) for a new store
In order to remain the expected aggregate efficiency level of the new store unchanged, a suitable inverse IDEA-CCR model is developed to obtain the target of output for the new store with its revised input data.

4. Simulated application

Since the regional manager in the region of southern Taiwan, where 11 chain stores have been established, is now planning to establish a new store in his region, this case is used to illustrate the implementation of the proposed approach.

4.1. Stage 1

4.1.1. Inputs and outputs

The relative efficiency of each store is calculated via its weighted sum of outputs and weighted sum of inputs. Some factors which are capable of representing the attainment of output and the input resources that the stores have consumed should be selected adequately. According to the managerial judgments, earning money via selling products and providing relevant services for customers is the major task of the stores. Hence, monetary amount of business revenue (in 1000 New Taiwan Dollars; NTD) is served as output factor (Y_1). Regarding the input factors, the regional manager concerns the internal resources related to service manpower, space and expenditures. In the study of Wu et al. [28], population density is contained in the input factors to represent the environmental variable, and then the efficiencies of banks from different regions were assessed and compared. From the outlook on relative efficiency, the more the population (i.e., input), the more the revenue (i.e., output) of a store

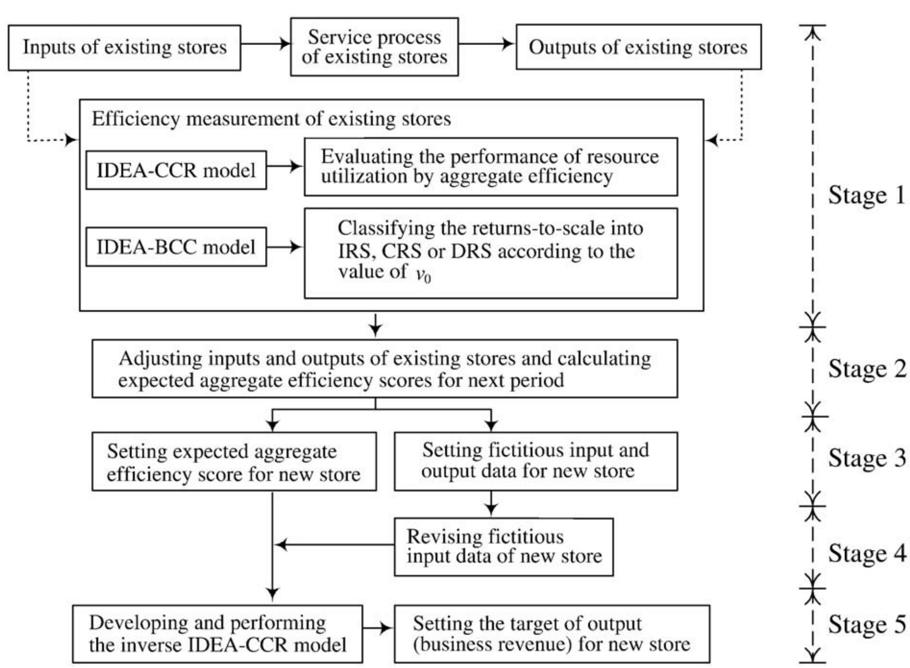

Fig. 1. Conceptual flow of the five-stage approach.

should be. Therefore, the population density in the trade area is also adopted as input factor to represent the external resource in this study. Thus, the input factors consist of manpower (X_1), store floor area (X_2, in 36 square feet), operating expense (X_3, in 1000 NTD) and number of households in the trade area (X_4). Since the number of stores is somewhat low, and in addition, the number of input factors is from three to four and the number of output factors is from one to three in the reference studies [e.g., 2,8,10,11,15,16,20,24,31], hence the numbers of input and output factors used in this study are appropriate. Table 2 shows the input and output measures of the 11 existing stores in last fiscal year. The correlation coefficients between X_i, $i = 1, 2, 3, 4$, and Y_1 are calculated as 0.97, 0.83, 0.88 and 0.78, respectively, where X_1 adopts the total number. The high positive correlations between the four input factors and the output factor show that the isotonic property is preserved for them. Thus, the validity of the inputs and output is justified.

Regarding the input manpower (X_1), there is a characteristic of multiple workers in different ranks. Each store employs workers in these categories to provide the sales service and home improvement consultation for customers. The workers are classified into five ranks, abbreviated as ranks 1 to 5, according to knowledge, expertise and experience, with rank 5 being the highest. For example, the total number of workers employed by store 1 is 77, with 12 in rank 1 and three in rank 5. These three workers in rank 5 include one store manager and two division managers. The company provides different remuneration, welfare and related support (such as salary, bonus, traveling perquisite, learning and training expenditure, private room and others) for each of the five ranks. According to the payments structure, the total amount of resources consumed by a worker in rank ℓ, $\delta(\ell)$, $\ell = 1,\ldots,5$, can be divided into two parts: basic payment of salary and bonus, BP_ℓ, and extra expenditures, EE_ℓ. That is, $\delta(\ell)$ can be expressed as $\delta(\ell) = BP_\ell + EE_\ell$. The higher the rank ℓ, the more the amount of BP_ℓ. With respect to EE_ℓ, although the amount of EE_ℓ is difficult to calculate exactly, the regional manager argues that a worker in the higher ranks consumes much more extra expenditures, viz., $EE_{\ell+1}$ is much more than EE_ℓ. Thus, obviously a worker in rank 5 consumes the most resources, while one in rank 1 consumes the least. Besides, the amounts of $\delta(\ell)$ may be different for the workers in rank ℓ but employed by different stores. In order to quantify the characteristics that workers in different ranks are employed by the stores and different ranks consume different amounts of resources, after consultation with the regional manager, the input values of the five ranks are treated as a strong ordinal relation. The total amount of resources consumed by the workers in different ranks are expressed as $\delta(\ell) < \delta(\ell+1)$, $\ell = 1,\ldots,4$. This relation reveals that a worker in rank ℓ consumes less resources than one in rank $\ell + 1$.

By treating X_1 as a compound manpower which consists of multiple workers in five ranks with a strong ordinal relation, then the input amount of X_1 of store j, x_{1j}, can be measured as the sum of products between the number of workers in rank ℓ, $n_{\ell j}$, and the corresponding input amount, $\delta(\ell)$. That is, $x_{1j} = \sum_{\ell=1}^{5} n_{\ell j}\delta(\ell)$. For example, the numbers of workers in ranks 1 to 5 of store 1 are 12, 46, 10, 6 and 3, respectively. Then $n_{11} = 12$, $n_{21} = 46$, $n_{31} = 10$, $n_{41} = 6$ and $n_{51} = 3$. The compound manpower of store 1, x_{11}, is calculated as $x_{11} = 12\delta(1) + 46\delta(2) + 10\delta(3) + 6\delta(4) + 3\delta(5)$. Thus, for store 1, the resources consumed by all workers in the five ranks are included in the input manpower via $\delta(\ell)$ and $n_{\ell 1}$.

The operating expense (X_3) is the expenditures for maintenance of facilities, cleaning, telephone, postage, water, electric power, rent, depreciation and others. The advertising, remuneration, welfare and related support of personnel are not included.

Table 2
Input and output measures of the 11 existing stores.

Store (j)	X_1						X_2	X_3	X_4	Y_1
	5	4	3	2	1	Total				
1	3	6	10	46	12	77	1105	20,432	242,766	421,276
2	3	5	10	46	20	84	1480	16,702	192,812	501,549
3	3	4	6	33	11	57	725	13,250	112,663	308,853
4	3	5	10	38	15	71	1159	16,310	149,268	331,495
5	2	4	5	23	12	46	1089	14,850	103,735	222,646
6	4	5	10	50	27	96	1615	29,728	218,924	642,073
7	2	3	7	17	12	41	753	12,558	55,072	167,886
8	3	5	7	42	13	70	1354	20,229	253,009	350,590
9	3	6	13	48	14	84	1790	24,979	224,362	460,869
10	2	3	3	17	10	35	696	10,268	108,672	139,515
11	3	6	7	49	20	85	1645	20,273	214,626	454,549

4.1.2. Proposed IDEA model

Since the inputs contain strong ordinal data, the suitable output-oriented IDEA-CCR and IDEA-BCC models are developed for measuring the relevant efficiency scores and classifying the returns-to-scale of existing stores into the types of IRS, CRS or DRS. The reason for adopting the output-oriented model is that this orientation is suitable for developing the inverse model, where the objective value shows the target of business revenue (see $y'_{1,12}$ in model (5) later).

In this study, x_{1j} is expressed as $x_{1j} = \sum_{\ell=1}^{5} n_{\ell j}\delta(\ell)$, where $\delta(\ell)$ follows the strong ordinal relation of $\delta(\ell) < \delta(\ell+1)$. Model (2) is rewritten in the following IDEA-BCC form:

$$E_k^T = \text{Min } v_1 \sum_{\ell=1}^{5} n_{\ell k}\delta(\ell) + \sum_{i=2}^{4} v_i x_{ik} + v_0 \tag{3.0}$$

$$\text{s.t.} \quad v_1 \sum_{\ell=1}^{5} n_{\ell j}\delta(\ell) + \sum_{i=2}^{4} v_i x_{ij} + v_0 - u_1 y_{1j} \geq 0, j = 1, \ldots, 11, \tag{3.1}$$

$$u_1 y_{1k} = 1, \tag{3.2}$$

$$\delta(5) > \delta(4) > \delta(3) > \delta(2) > \delta(1) \geq \gamma > 0, \tag{3.3}$$

$$v_1,\ v_2,\ v_3,\ v_4,\ u_1 \geq \varepsilon, v_0 \text{ unrestricted in sign.}$$

In model (3), the 3rd constraint (Eq. (3.3)) restricts that the permissible input amounts must satisfy the strong ordinal relation in which a worker in rank ℓ consumes less resources than one in rank $\ell + 1$, and the value of $\delta(1)$ is greater than or equal to the value of γ. The strong ordinal relation of $\delta(\ell+1) > \delta(\ell)$ equates the form of $\delta(\ell+1) - \delta(\ell) \geq \pi$ with $\pi > 0$. Since Zhu [31] showed that the strong ordinal relation with this form is unable to discriminate efficiencies with a strong ordinal relation from those with a weak ordinal relation. Hence, the improved form, $\delta(\ell+1) \geq \pi\delta(\ell), \pi > 1$, was suggested by Zhu to replace it. In this study, the parameter π_ℓ is introduced to reflect the degree of worker level intensity between ranks ℓ and $\ell + 1$. The strong ordinal relation of $\delta(\ell+1) > \delta(\ell)$ in Eq. (3.3) is replaced by the improved form of $\delta(\ell+1) \geq \pi_\ell \delta(\ell), \pi_\ell > 1$.

The determination of π_ℓ is now elaborated in detail. The proportion of $\delta(\ell+1)$ to $\delta(\ell)$ can be expressed as $\delta(\ell+1)/\delta(\ell) = (BP_{\ell+1} + EE_{\ell+1})/(BP_\ell + EE_\ell)$. Since the regional manager argues that $EE_{\ell+1}$ is much more than EE_ℓ, hence he considers that $\delta(\ell+1)/\delta(\ell) \geq BP_{\ell+1}/BP_\ell$, or $\delta(\ell+1) \geq (BP_{\ell+1}/BP_\ell)\delta(\ell)$. Thus, π_ℓ is determined as $\pi_\ell = BP_{\ell+1}/BP_\ell > 1$. By using the average of BP_ℓ for the workers of 11 stores in last fiscal year, the amounts of BP_ℓ (in NTD), $\ell = 1,\ldots,5$, are determined as $BP_1 = 250{,}895$, $BP_2 = 309{,}407$, $BP_3 = 569{,}435$, $BP_4 = 808{,}295$ and $BP_5 = 1{,}680{,}730$. By using these amounts of BP_ℓ, π_1, π_2, π_3 and π_4 are determined as 1.2332, 1.8404, 1.4194 and 2.0793, respectively. The value of γ is set as BP_1 ($= 250{,}895$).

By substituting $\delta(\ell+1)\geq\pi_\ell\delta(\ell)$ for $\delta(\ell+1)>\delta(\ell)$ and making the change of variable $w_{1\ell}=v_1\delta(\ell)$, model (3) now has a linear programming problem format:

$$E_k^T = \text{ Min} \sum_{\ell=1}^{5} n_{\ell k} w_{1\ell} + \sum_{i=2}^{4} v_i x_{ik} + v_0 \tag{4.0}$$

$$\text{s.t.} \sum_{\ell=1}^{5} n_{\ell j} w_{1\ell} + \sum_{i=2}^{4} v_i x_{ij} + v_0 - u_1 y_{1j} \geq 0, j = 1, \ldots, 11, \tag{4.1}$$

$$u_1 y_{1k} = 1, \tag{4.2}$$

$$w_{1,\ell+1} \geq \pi_\ell w_{1\ell}, \ell = 1, 2, 3, 4, \tag{4.3}$$

$$w_{11} \geq v_1 \gamma > 0, \tag{4.4}$$

$$v_1,\ v_2,\ v_3,\ v_4,\ u_1 \geq \varepsilon, v_0 \text{ unrestricted in sign.}$$

Thus, $w_{1\ell}$ is the most favorable weight attached to $n_{\ell k}$ in calculating the best relative efficiency of store k. Regarding the value of ε, Chien et al. [5] pointed out that ε is generally set as 10^{-9}, while Kao et al. [17] considered that 10^{-6} is commonly used in practice. In this study, the value of ε is set as 10^{-8}. When v_0 is set as zero in model (4), the IDEA-BCC model becomes IDEA-CCR form.

By using model (4), the technical efficiency score along with the maximum weight and minimum weight are shown in columns 2–4 of Table 3. The status of returns-to-scale is classified by value of v_0 and shown in column 5 of Table 3. None of the stores is classified into DRS type. By using IDEA-CCR model, the aggregate efficiency score along with the maximum weight and minimum weight are obtained and shown in columns 7–9 of Table 3. For the weight determination in calculating the best relative efficiency of each store, all 11 stores put the maximum weight on w_{15}. The minimum weight is put on v_2, v_3 or v_4. According to the descending order of E_j^A, the existing stores are ranked as store 10–5–8–4–9–11–1–7–3–2–6, where store 11 is ranked as the 50th percentile in the group of existing stores. This ranking shows that stores 2 (with $E_2^A=1$) and 6 (with $E_6^A=1$) are the best ones in performance of resource utilization, while store 10 (with $E_{10}^A=1.746$) has the worst performance. This is because stores 2 and 6 produce relatively more outputs and store 10 produces relatively fewer outputs. Note that the output of store 7 ($y_{17}=167{,}886$) is fewer than that of store 5 ($y_{15}=222{,}646$), whereas the aggregate efficiency score of store 7 ($E_7^A=1.045$) is better than that of store 5 ($E_5^A=1.379$). It may be seen somewhat of a surprise, but the reason is due to the evaluation is based on the resources utilization, and store 7 consumes relatively fewer resources in performing its service tasks.

The scale efficiency score of store j can be calculated as $E_j^S=E_j^A/E_j^T$ and is shown in column 6 of Table 3. It can be seen from E_j^A, E_j^T and E_j^S that nine stores are aggregate inefficient. Among these nine stores, five stores (stores 1, 3, 5, 7, and 10) are caused by scale inefficiency, while four stores (stores 4, 8, 9, and 11) are caused by both scale inefficiency and technical inefficiency.

4.2. Stage 2

Since the returns-to-scale of existing stores are classified as either IRS or CRS, the expected input amounts and output targets will be increased in the next period. According to the suggestion of the regional manager, an increment of 2% for Y_1 is set for all 11 stores. Regarding the inputs, the adjustment of X_3 is based on the performance of resource utilization, meaning that with better aggregate efficiency, the increment of X_3 is higher. The other inputs will not be changed in the short-term consideration. As results, the adjusted amounts of X_3 and Y_1, along with the expected aggregate efficiency scores, for the 11 existing stores in next period are shown in columns 8, 10 and 11 of Table 4.

4.3. Stage 3

To set a challenging but attainable goal, the regional manager selects the aggregate efficiency score ranked as the 50[th] percentile in the group of existing stores as the target for the new store (i.e., store 12). This expected efficiency is 1.108 and the reference store is store 11. The input and output data of store 11 are used as the fictitious data of store 12 so that the aggregate efficiency score of store 12 is kept at the expected level. These fictitious data are listed in the last row of Table 4, which show $n_{1,12}=20$, $n_{2,12}=49$, $n_{3,12}=7$, $n_{4,12}=6$, $n_{5,12}=3$, $x_{2,12}=1645$, $x_{3,12}=20{,}577$, $x_{4,12}=214{,}626$ and $y_{1,12}=463{,}640$.

4.4. Stage 4

The previous fictitious inputs of store 12 are revised according to the company's establishment proposal and then used to determine its output target so that its expected efficiency level remains unchanged. The revisions of fictitious input data of store 12 in the establishment proposal are elaborated as follows. By quoting from the marketing department's investigation, the number of households in the trade area (X_4) of store 12 is provided as 201,530. Hence, the fictitious data $x_{4,12}=214{,}626$ is revised as $x'_{4,12}=201{,}530$. The regional manager assumes that there are relationships between X_4 and X_2, between X_2 and X_3 and between X_2 and X_1. Hence, the regression model is used to determine the amounts of input factors X_1, X_2 and X_3 for store 12. Regarding the allotment of X_2, the regression model used is $\hat{X}_2=\hat{\beta}_0+\hat{\beta}_4 X_4$. From the data shown in Table 4, the correlation coefficient of 0.772 and the p-value of 0.005 for the test H_1:$\beta_4\neq 0$ indicate that this regression model is proper for use under two-sided test at the 0.05 level of significance. Thus, the value of X_2 for store 12 is

Table 3
Efficiency measurement results.

Store (j)	BCC model				E_j^S	CCR model		
	E_j^T	Max. weight	Min. weight	Status of returns-to-scale		E_j^A	Max. weight	Min. weight
1	1	w_{15}	v_3,v_4	IRS	1.107	1.107	w_{15}	v_3,v_4
2	1	w_{15}	v_2	IRS	1	1	w_{15}	v_2
3	1	w_{15}	v_3	IRS	1.004	1.004	w_{15}	v_4
4	1.233	w_{15}	v_2	IRS	1.037	1.279	w_{15}	v_2
5	1	w_{15}	v_2	IRS	1.379	1.379	w_{15}	v_3
6	1	w_{15}	v_2,v_3	CRS	1	1	w_{15}	v_2,v_3
7	1	w_{15}	v_3	IRS	1.045	1.045	w_{15}	v_3
8	1.229	w_{15}	v_2,v_4	IRS	1.094	1.345	w_{15}	v_2,v_4
9	1.105	w_{15}	v_3,v_4	IRS	1.006	1.112	w_{15}	v_3,v_4
10	1	w_{15}	v_3	IRS	1.746	1.746	w_{15}	v_4
11	1.053	w_{15}	v_2,v_3	IRS	1.052	1.108	w_{15}	v_2,v_4

Table 4
Adjusted data and expected aggregate efficiency in the next period.

Store (j)	X_1					X_2	X_3	X_4	Y_1	Expected E_j^A
	5	4	3	2	1					
1	3	6	10	46	12	1105	20,738	242,766	429,702	1.107
2	3	5	10	46	20	1480	17,036	192,812	511,580	1
3	3	4	6	33	11	725	13,449	112,663	315,030	1.002
4	3	5	10	38	15	1159	16,555	149,268	338,125	1.278
5	2	4	5	23	12	1089	14,999	103,735	227,099	1.379
6	4	5	10	50	27	1615	30,323	218,924	654,914	1
7	2	3	7	17	12	753	12,746	55,072	171,244	1.045
8	3	5	7	42	13	1354	20,431	253,009	357,602	1.341
9	3	6	13	48	14	1790	25,354	224,362	470,086	1.112
10	2	3	3	17	10	696	10,371	108,672	142,305	1.741
11	3	6	7	49	20	1645	20,577	214,626	463,640	1.108
12	*3*	*6*	*7*	*49*	*20*	*1645*	*20,577*	*214,626*	*463,640*	*1.108*

allotted to be 1358 by this regression model. The fictitious data $x_{2,12}=1645$ is revised as $x'_{2,12}=1358$. For the budget of X_3, the correlation coefficient of 0.837 and the p-value of 0.001 for the test H_1:$\beta_2 \neq 0$ similarly indicate that $\hat{X}_3=\hat{\beta}_0+\hat{\beta}_2 X_2$ is proper for use. Thereby, the amount of X_3 for store 12 is budgeted as 19,524. The fictitious data $x_{3,12}=20{,}577$ is revised as $x'_{3,12}=19{,}524$. With respect to the disposition of X_1, the regression model $\hat{X}_1=\hat{\beta}_0+\hat{\beta}_2 X_2$ is respectively used for proposing the numbers of workers in the five ranks. The correlation coefficients of 0.699, 0.844, 0.692, 0.810 and 0.645 and the p-values of 0.016, 0.001, 0.018, 0.002 and 0.032 for ranks 1 to 5, respectively, support the use of the regression model. The numbers of workers in ranks 1 to 5 are allotted as 16, 41, 9, 5 and 3, respectively. The fictitious data $n_{1,12}=20$, $n_{2,12}=49$, $n_{3,12}=7$, $n_{4,12}=6$ and $n_{5,12}=3$ are revised as $n'_{1,12}=16$, $n'_{2,12}=41$, $n'_{3,12}=9$, $n'_{4,12}=5$ and $n'_{5,12}=3$.

4.5. Stage 5

Under the input and output data of all 12 stores depicted in Table 4, the relative aggregate efficiency of store 12 is calculated as $E^A_{12}=1.108$. Consider the situation that the input amounts of store 12 are changed from the fictitious input amounts (i.e., $n_{1,12}=20$, $n_{2,12}=49$, $n_{3,12}=7$, $n_{4,12}=6$, $n_{5,12}=3$, $x_{2,12}=1645$, $x_{3,12}=20{,}577$ and $x_{4,12}=214{,}626$) to the proposal input amounts (i.e., $n'_{1,12}=16$, $n'_{2,12}=41$, $n'_{3,12}=9$, $n'_{4,12}=5$, $n'_{5,12}=3$, $x'_{2,12}=1358$, $x'_{3,12}=19{,}524$ and $x'_{4,12}=201{,}530$). Then, what is the output target of store 12 (i.e., $y'_{1,12}$) to keep its expected aggregate efficiency score, E^A_{12}, unchanged? That is, what amount of Y_1 should store 12 earn to keep E^A_{12} at the level of 1.108? This problem belongs to the inverse DEA [27,29]. Since $E^A_{12}=1.108>1$, the inverse DEA-CCR model $(\hat{P})$ [27] is employed to develop an inverse IDEA-CCR model for obtaining the output target of store 12, $y'_{1,12}$, in this case. The proper inverse IDEA-CCR model is proposed as follows (see the development in Appendix):

$$
\begin{aligned}
y'_{1,12} &= \text{Min} \sum_{\ell=1}^{5} n'_{\ell,12} w_{1\ell} + \sum_{i=2}^{4} v_i x'_{i,12} \\
\text{s.t.} & \sum_{\ell=1}^{5} n_{\ell j} w_{1\ell} + \sum_{i=2}^{4} v_i x_{ij} - u_1 y_{1j} \geq 0, j = 1, \ldots, 12, \\
& u_1 E^A_{12} \geq 1, \\
& w_{1,\ell+1} \geq \pi_\ell w_{1\ell}, \ell = 1,2,3,4, \\
& w_{11} \geq v_1 \gamma > 0, \\
& v_1, v_2, v_3, v_4, u_1 \geq \varepsilon.
\end{aligned}
\tag{5}
$$

The value of $y'_{1,12}$ obtained by model (5) is 443,849, which is the target value of business revenue for store 12 in next period. For determining this value of $y'_{1,12}$ in model (5), the maximum weight is w_{15} while the minimum weight is v_4. The store manager and the subsidiary workers of store 12 should devote themselves to develop effective marketing and service plans for delivering this target. Under the expected input and output data of stores 1 to 11 depicted in Table 4 as well as the proposal input data of store 12, if the business revenue delivered by store 12 in next period is the same as $y'_{1,12}$, then the aggregate efficiency score of store 12 will remain unchanged, viz., stay at the level of 1.108. Of course the aggregate efficiency score of store 12 will be better than 1.108 if the business revenue delivered is greater than $y'_{1,12}$. Thus, the output target (i.e., $y'_{1,12}=443{,}849$) is viewed as the minimal amount of business revenue which store 12 should deliver in next period so that its aggregate efficiency score can at least maintain the expected level.

5. Conclusions

It is seen in the literature that goal-setting and efficiency measurement play a pivotal role in current management theory and practice. In order to manage organizational efficiency, the questions related to what level of efficiency an organization needs to achieve and how it should set appropriate efficiency target for the organization need to be resolved.

The issue for measuring efficiencies of existing stores and decision-making problem for setting business revenue target of a new store are addressed in this study. The problems are drawn from a home improvement company with 22 chain stores in Taiwan. 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 management. To obtain an objective efficiency measurement, the regional managers should not only evaluate the monetary amount of business revenue earned by the stores in their respective regions, but also quantify the performance of resource utilization in earning that revenue. Furthermore, some important considerations arise when developing a proposal to establish a new store. In addition to allotting the input resources for the new store, a regional manager must determine what efficiency level the new store should achieve and how much business revenue it should earn. As the company plans to establish new stores each year in different regions, such affairs have become important issues for administration practices, and is thus a problem worthy of investigation. A five-stage approach is developed to deal with the problems under consideration. Since the problems contain strong ordinal data, the suitable IDEA and inverse IDEA models are developed as core techniques of the proposed approach. A simulated application considering the 11 chain stores established in the region of southern Taiwan is presented to illustrate the implementation of the proposed approach.

For efficiency measurement, four inputs (manpower, store floor area, operating expense and number of households in the trade area) and one output (monetary amount of business revenue) are adopted to suit the managerial requirements. Regarding the input manpower, the workers in different ranks are transformed into compound manpower that includes all workers. An IDEA-CCR model is developed to obtain the aggregate efficiency for detecting the performance of resource utilization of existing stores, while the BCC model is employed to obtain the value of v_0 for detecting the status of returns-to-scale. The input and output amounts of existing stores are then adjusted according to the status of returns-to-scale.

In the process of establishing a new store, the regional manager must set a challenging but attainable efficiency level for the new store and allot the amounts of input resources for it. Then, the target of business revenue should be properly set for the new store. This target is viewed as the minimal amount of business revenue which the new store should deliver in next period so that its aggregate efficiency score can at least maintain the expected level. Under the efficiency-driven thinking of the regional manager, an inverse IDEA-CCR model is proposed to set the target of business revenue for the new store.

The regional manager agrees that the proposed approach is an effective technique to solve the problems encountered. It will be implemented as a decision support tool in the near future.

Appendix A

The inverse DEA-CCR model $(\hat{P})$ [27] can be rewritten as follows:

$$
\text{Max} \sum_{r=1}^{s} p_r y'_{rk}
$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \le x'_{ik}, \quad i = 1, \ldots, m,$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge E_k^A y'_{rk}, \quad r = 1, \ldots, s,$$

$$y'_{rk} \ge y_{rk}, \quad r = 1, \ldots, s,$$

where $x'_{ik} = x_{ik} + \Delta x_{ik} \ge x_{ik}$ and $y'_{rk} = y_{rk} + \Delta y_{rk} \ge y_{rk}$.

The dual of model $(\hat{P})$ is as follows with removing the conditions of $x'_{ik} \ge x_{ik}$ and $y'_{rk} \ge y_{rk}$:

$$\text{Min} \sum_{i=1}^{m} v_i x'_{ik}$$

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

$$u_r E_k^A \ge p_r, \quad r = 1, \ldots, s,$$

$$v_i, u_r \ge \varepsilon.$$

In this study, since the sole output, Y_1, stands for monetary amount of business revenue, hence its unit value can be set as one, viz., $p_1 = 1$. By letting the target store k as store 12, changing the product $v_1 x'_{1k}$ as $v_1 x'_{1k} = v_1 x'_{1,12} = v_1 \sum_{\ell=1}^{5} n'_{\ell,12} \delta(\ell) = \sum_{\ell=1}^{5} n'_{\ell,12} w_{1\ell}$, changing the product $v_1 x_{1j}$ as $v_1 x_{1j} = v_1 \sum_{\ell=1}^{5} n_{\ell j} \delta(\ell) = \sum_{\ell=1}^{5} n_{\ell j} w_{1\ell}$ and adding the constraints (shown in Eqs. (4.3) and (4.4)) to satisfy the strong ordinal relation for input manpower in this case, model (5) is proposed.

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