國立交通大學

管理科學系

博 士 論 文

No. 026

經營績效評估之綜合管理架構研究-
應用於國軍零售供應站

A COMPREHENSIVE MANAGERIAL FRAMEWORK FOR OPERATING PERFORMANCE MEASUREMENT:
Application in Taiwan's Military Welfare Department

研 究 生：王宗誠

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研 究 生：王宗誠　　　Student：Tsung-cheng Wang

指導教授：楊　千　　　Advisor：Chyan Yang

國 立 交 通 大 學

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博 士 論 文

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摘　　　要

本論文主要以探索台灣國軍零售福利站之營運效率並擘劃運用標竿學習法指導營運效率不佳之零售店，學習經營效率極佳之福利站。 幾項實際之營運經驗法則分述如下: （1）台灣國軍零售福利站之技術無效率，其主要由純技術無效率造成，而非規模無效率。 本研究同時也建議福利站之營運經理應先聚焦於純技術無效率之改革，而非先改進其規模無效率。 （2）位於北部地區之零售福利站平均營運績效優於位於中部、南部、及東部之零售福利站。 由上述發現顯示零售福利站所處區域在影響營運績效上扮演一關鍵性腳色。（3）在不同層級對服務滿意度之零售福利站經營績效，確實有非常明顯之影響。（4）對顧客吸引力測度顯示，新營零售福利站為最具吸引力之福利站，如具全球化經營觀點之管理者。 同時，不論用何種評審標準與流程顯示台東零售福利站與其他福利站相比較，均不具競爭力。(5）用資料包絡分析法(DEA）相互關連性可顯示出零售福利站之標竿學習路徑，使吾等可得知如何改進無效率之零售福利站與確認何者是最具績效福利站。故本研究運用 DEA 評估國軍零售福利站之經營效率為重要實務之運用。

關鍵字:資料包絡分析法; 背景依賴資料包絡分析法; 吸引力測度; 進步測度; 零售店; 分層資料包絡分析法.

A COMPREHENSIVE MANAGERIAL FRAMEWORK

FOR OPERATING PERFORMANCE MEASUREMENT:

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ABSTRACT

A comprehensive framework of performance measurement is developed and illustrated through application to in Taiwan's Military Welfare Department. This dissertation aims to explore the operating efficiency and the benchmark-learning roadmap of retail stores for the General Welfare Service Ministry (GWSM) in Taiwan. Several empirical results are shown: (1) the overall technical inefficiencies of GWSM retail stores are primarily due to the pure technical inefficiencies rather than the scale inefficiencies. This also suggests that managers should focus on removing the pure technical inefficiency of retail stores, before improving their scale efficiencies; (2) the retail stores located on north on the average operate better than those on the other three regions. The findings show that the retail store's region plays key role which affects its operating performance; (3) the service-satisfaction levels do have a very significant influence upon retail store's performance; (4) the attractiveness measure shows that Hsinying retail store is the most attractive retail store, i.e. global leader, no matter which evaluation context is chosen, and the progress measure shows that Taitung retail store is the worst retail store; (5) the context-dependent DEA successfully draws the GWSM retail stores' benchmark-learning roadmap to improve the inefficient retail stores progressively and can identify the best retail store. The potential applications and strengths of DEA in assessing the military retail stores are highlighted.

Keywords: Data envelopment analysis; context-dependent DEA; attractiveness measure; progress measure; retail store; stratification DEA Method.

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Tsung-Cheng Wang

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ACRONYMS AND ABBREVIATIONS

BLR-	Benchmark-Learning Roadmap
BCC-	Banker, Charnes, and Coope Model (1984)
CCR-	Charnes, Cooper, and Rhodes Model, (1978)
CRS-	Constant Return to Scale
DEA-	Data Envelopment Analysis
DMU-	Decision Making Unit
DRS-	Decreasing Returns to Scale
GWSM-	General Welfare Service Ministry
IRS-	Increasing Returns to Scale
PTE-	Pure Technical Efficiency
R.O.C.-	Republic of China
SE-	Scale of Efficiency
SFA-	Stochastic Frontier Model
TE-	Technical Efficiency

CONTENTS

Chapter 1. Introduction

1.1 History

In 1955 the President Chiang Kai-shek established Military Welfare Enterprise Management Division in Combined Service Forces. In 1964 it was renamed Military Welfare Department and was then officially under the supervision of Ministry of National Defense (MND) of R.O.C. In 1975 it expanded its service to government employees and staffs of public schools in addition to the welfare supplies in the military. In 1981, it provided additional service to veterans and their dependents. In 1989, its service to government employees and staffs of public schools was cancelled as ordered. Since then it has been in charge of the supply of supplementary foods and products in the military.

Up to now, there are 31 supply stations for daily necessities. General Welfare Service Ministry (GWSM) retail stores provide many benefits. For some Taiwanese military personnel, they remain the only affordable and accessible source of familiar products. For service members, MND's policy of selling goods at below-market prices makes its stores important nonbenefit. The prices of commissary goods are about 10 to 20 percent below commercial market levels.

1.2 Organization and Employees

According to the General Welfare Service Ministry (GWSM) annual report in 2003, the Taiwan’s Military Welfare Department (TMWD) in MND has 788 employees and takes charge of controlling over GWSM’s operation efficiencies. The TMWD divides into North, West, South and East four management divisions. (As in Figure. 1)

- In North region, it has 14 GWSMs such as: Keelung, Beibei,Beijhong, Beisi, Beidong, Beinan, Sioulang, Banciao, Shuanghe, Neiyi, Taoyuan01, Taoyuan02, Guangfu,and Hsinchu.
- In West region, it has 4 GWSMs such as Miaoli, Chiayi, Taichung, and Pinglin.
- In South region, it has 9 GWSMs such as Hsinying, Tainan01, Tainan02, Gaosyong, Zuoying, Kaohsiung, Fongshan, Dailiao, and Pingtung.
- In East region, it has 4 GWSMs such as Taitung, Ilan, Hualian, and Meilun.

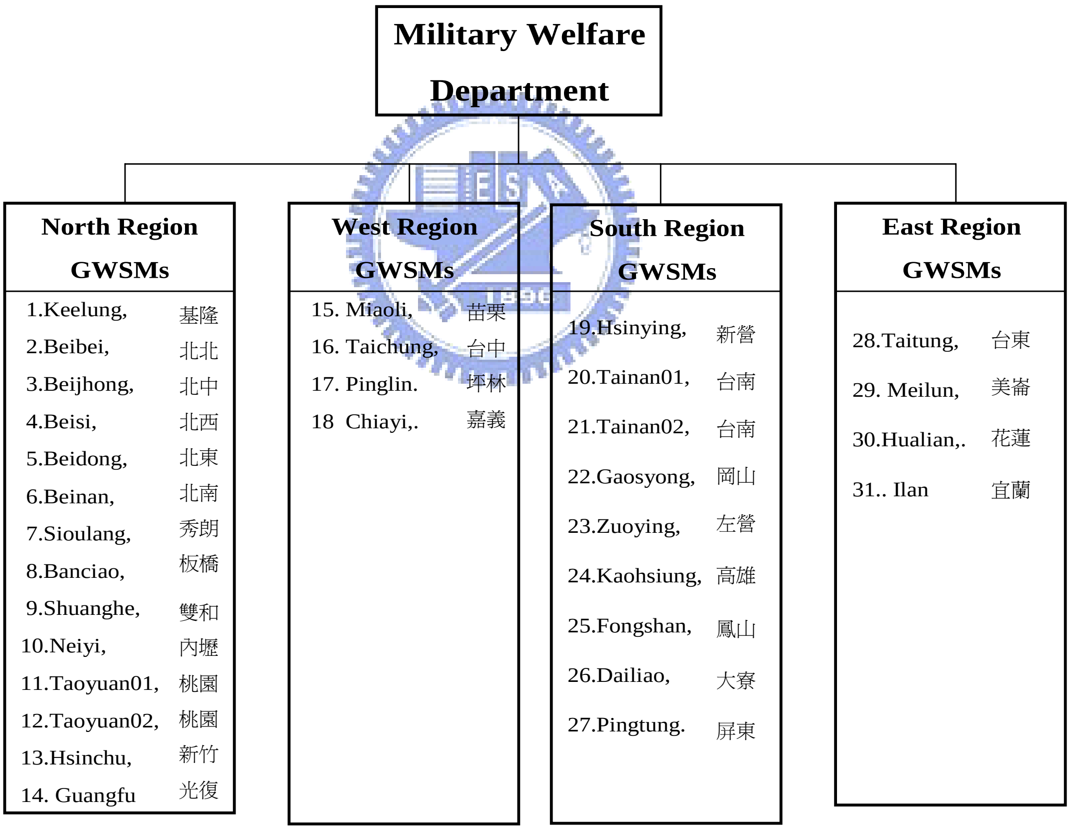

Figure 1. The Organization of Military Welfare Department

1.3 Principles of Management

GWSM retail store is a nonprofit organization, so it creates the following rules for supporting Soldiers (including cadets in military academies), reservists, veterans and their dependents. GWSM made the following rules as their operating principles.

1. Customers first, Quality products first, Quality service first.
2. Meet the needs of the customers.
3. Enhance the service to improve the welfare of the performance.

1.4 Research Motivation

Facing the 'Two Defense Acts' of the MND (i.e. the reorganization of MND), a military base closure program, a reduction in the proportion of defense budget in the total central government budget, and a decrease in national defense manpower, the GWSM urgently requires a performance benchmarking analysis to enhance its operational management within the GWSM retail stores and to allocate its scare defense resources. To date, studies undertaken by the GWSM are few to help managers or officers identify how a management system can be changed to improve crucial factors underlying the efficiency of retail store operations. However, since a retail store's performance is a complex phenomenon requiring more than a single criterion to characterize it, traditional performance measurement techniques (Bush et al.,1990) have often also been criticized for being inadequate and not taking into account of mix and nature of services provided (Good, 1984). For about reasons, it motivates author try to find an effective evaluation method to solve those problems and provide some realistic suggestions to GWSM manager.

1.5 Research Purpose

Due to the importance of GWSM efficiency measurement, the main interest of this study is therefore to address the issues related to the performance benchmarking analysis and the potential applications and strengths of DEA in assessing the GWSM. This study should provide additional managerial insights into retail store in Taiwan. The purposes of this study are as follows:

The first purpose of this study is to provide a benchmarking analysis based on DEA to investigate GWSM in Taiwan and assist the managers in improving the operational management of these retail stores. The second, we also design a decision-making matrix to identify the position of the 31 retail stores, which help the manager and/or authorities to improve their operating efficiencies; Furthermore, we implement the context-dependent DEA to draw the GWSM retail stores' benchmark-learning roadmap to improve the inefficient retail stores progressively and can identify the best retail store.

1.6 Framework of the Dissertation

This dissertation is organized in the following manner as Figure 2 shows: Chapter 1 presents the motives and purposes of the study, and briefly introduces the structure of this work. Prior studies which have influenced this study are discussed in Chapter 2. Chapter 3 proposes a research design that includes the criteria for performance evaluation, the data selection and description, and the introduction of DEA methodology. The empirical results and interpretations are provided in Chapter 4. Finally, Chapter 5 concludes this dissertation.

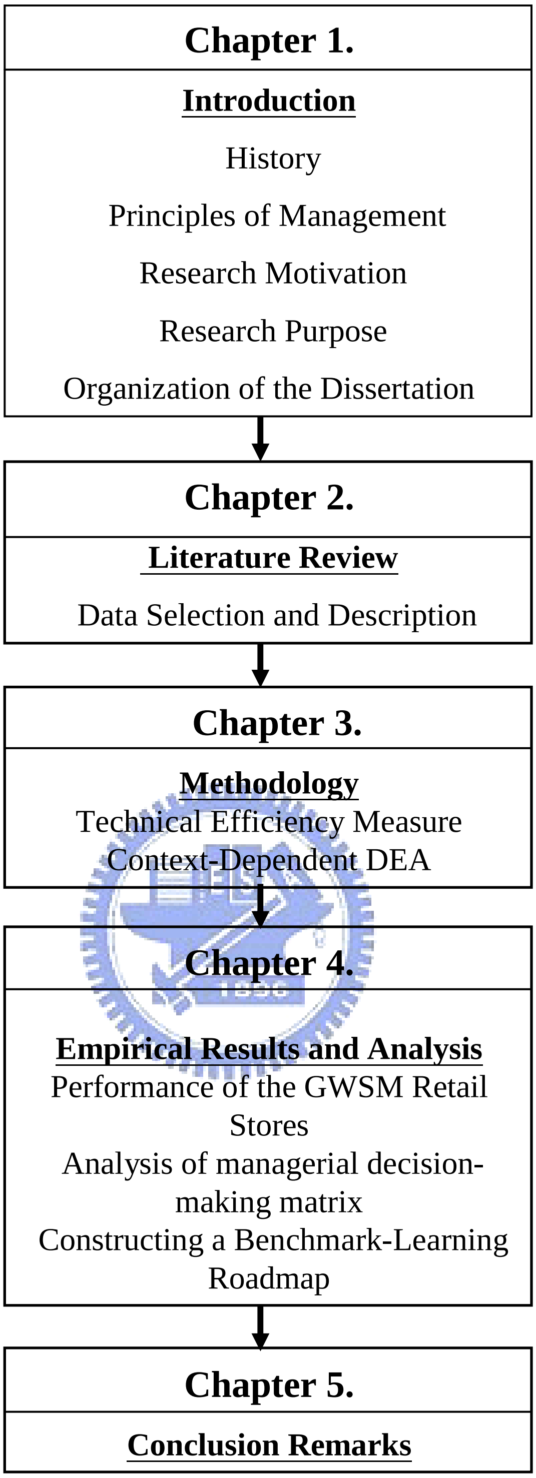

Figure 2. Research Flow Chart

Chapter 2. Literature Review

2.1 Literature Survey

According to the main purposes mentioned above, DEA has been used to measure the retail store performance over the last decade. DEA has many desirable features (Charens et al., 1994) which may explain why researchers are interested in using it to investigate the efficiency of converting multiple inputs into multiple outputs. Furthermore, DEA is also a theory-based, transparent, and reproducible computational procedure. In comparison to the traditional approaches such as ratio analysis and regression analysis (Sherman, 1986), DEA has gained several more advantages. These characteristics include (Lewin et al., 1982):

- capable of deriving a single aggregate measure of the relative efficiencies of units in terms of their utilization of input factors to produce desired outputs;
- able to handle non-commensurate multiple outputs and multiple input factors;
- able to adjust for factors outside the control of the unit being evaluated;
- not dependent on a set of a priori weights or prices for the inputs or the outputs;
- able to handle qualitative factors such as consumer satisfaction, quality of employees, etc.;
- able to provide insights on the possibilities for increasing outputs and/or conserving inputs for the inefficient unit to become efficient;
- able to maintain equity in performance assessment.

2.2 Data Selection and Description

One major advantage is that DEA has emerged as the leading method for efficiency evaluation in terms of both the number of research papers published and the number of applications to real world problems (Seiford, 1997; Gattoufi et al., 2004). Previous studies that used DEA to investigate the relative efficiency of the retail industry are now described as follows.

According to the former chapter mention about the requirements, we need to find an effective method to satisfy the requirements. Because of the attributes of requirements, DEA has been used extensively for benchmarking analysis ever since its introduction by Charnes et al. (1978). DEA has many desirable features (Charnes et al., 1994) which may explain why researchers are interested in using it to investigate the efficiency of converting multiple inputs into multiple outputs. The previous studies that have used DEA as related to retail industry field are now described as follows. Thomas et al. (1998) implemented DEA to probe the intra-comparative efficiency using 500 domestic retail outlets of a leading specialist retailer in U.S. This study showed that DEA not only helped make sense of the data in deriving an overall efficiency index, but also identified the best practice stores within the organization by focusing on the efficiency frontier. By using the DEA approach, Keh and Chu (2003) adopted a three–stage transformation process to assess the operating efficiency of 13 grocery stores in the U.S. for the years 1988 through 1997. The finding showed that there were increasing returns to scale in grocery retailing.

Barros and Alves (2003) implemented DEA to explore operating efficiency for a Portuguese retail store. This study showed competitiveness should be based on benchmarking the retail outlets which composed the chain. Barros and Alves (2004) estimated total productivity change for a Portuguese retail store chain with the DEA-Malmquist productivity index for the period 1999-2000. This study reported that there is room for improvement in the management of the stores. Barros (2005) utilized the stochastic frontier model (SFA) to assess the technical efficiency of a Portuguese hypermarket retail chain. This study proposed a modification of management procedures in order to enable efficiency to be increased, based on a governance-environment framework. Chen et al. (2005) assessed 13 companies in the retail industry by using the super-efficiency DEA. This analysis indicated that the EB companies performed better in some areas than their non-EB counterpart. Table 1 presents the characteristics of these main previous studies using DEA.

Table 1. Literature survey of the DEA model on the retail industry

Paper	Model	Units	Inputs	Outputs
Thomas, Barr, Cron, and Slocum Jr. (1998)	Assurance Region-CCR	552 domestic retail outlets of the U.S., 1994.	(1) labor, (2) experience, (3) location related costs, (4) internal processes.	(1) sales, (2) profits.
Keh and Chu (2003)	CCR and BCC	13 grocery stores of the U.S.,1988, 1997.	(1) labor, (2) capital.	(1) sales revenue, (2) accessibility, (3) assurance of product delivery, (4).product information, (5) ambience.
Barros and Alves (2003)	CCR and BCC	47 retail outlets of the Portugal, 2000.	(1) number of full-time employees, (2) cost of labors, (3) number of cash-out points, (4) stock, (5) other costs.	(1) sales, (2) operational results.
Barros and Alves (2004)	Malmquist Productivity Index	47 retail outlets of the Portugal, 1999-2000.	(1) number of full-time employees, (2) cost of labors, (3) number of cash-out points, (4) stock, (5) other costs.	(1) sales, (2) operational results.
Barros (2005)	Stochastic Frontier Approach (SFA)	47 retail outlets of the Portugal, 2000.	(1) price of labour, (2) price of capital, (3) sales at constant price, (4) earnings before taxes, (5) population, (6) number of competitors, (7) the rate of part-time workers, (8) average days of staff absenteeism, (9) the purchasing power in the area.	(1) operational cost.
Chen, Motiwalla, and Khan (2005)	Super-efficiency	10 companies of the retail industry of the U.S., 1997-2000.	(1) number of employees, (2) inventory cost, (3) total current assets, (4) cost of sales.	(1) revenue, (2) net income.

To summarize the above studies, few research studies about the retail industry have been conducted in emerging countries (such as Taiwan) while applications of DEA for the evaluation of retail stores have been very limited in the military. The main interest of this study is to address the issues related to the performance benchmarking analysis and to illustrate the use of a context-dependent DEA for evaluating GWSM retail stores, which should provide additional managerial insights into GWSM. The important contributions of this study include: (1) to provide a milestone analysis based on DEA to investigate Taiwan and assist the MND in improving the operational management of GWSM; (2) to design a decision-making matrix to identify the position of the 31 retail stores, which help the manager and/or authorities to improve their operating efficiencies; and (3) to implement the context-dependent DEA to draw the GWSM retail stores' benchmark-learning roadmap to improve the inefficient retail stores progressively and can identify the best retail store.

Chapter 3. Research Design

3.1 Data Selection and Description

GWSM is in charge of the supply of supplementary foods and products in the military and provides its service to the soldiers, veterans, and their dependents. From a system perspective, organizational activities refer to the conversion of inputs in various resources to output. Output is a concrete measurement that an organization has reached its objectives. This study uses the production approach to design the performance model. The performance model measures the performance of retail stores in using four inputs to produce four outputs.

The four input factors are namely the number of full-time employees (in persons), operating expenses (in NT$), cost of products (in NT$), and area of the retail store (in square meters). The employee factor is composed of businessmen, administrators, guards, drivers, and affair employees. These employees keep retail stores operating normally. The cost regarding maintenance, marketing, and administration makes up a so-called operating expense factor which is a necessary input for maintaining operations. The cost of products is used to purchase product so as to provide supplementary foods and products to the soldiers, veterans, and their dependents. The area of the retail store refers to the total floor space used by the operational units of the retail store, measured in square feet. The service outputs are measured in terms of quantitative outputs (number of customers and net profit) and qualitative outputs (consumer-satisfaction index and facilities-satisfaction index) which are the result of a brief questionnaire set to guests after shopping (as in figure 3).

This study investigates thirty-one GWSM retail stores in Taiwan based on the retail stores' operation data shown in the period 2003. Each of these retail stores is treated as a decision making unit (DMU) in the DEA analysis. The 31 retail stores of various geographical dispersion are selected since they are in charge of the supply of supplementary foods and products. The performances of the retail stores are accessed based on the data obtained for the year 2003. The data are extracted from the annual report of the GWSM except for consumer-satisfaction index and the facilities-satisfaction index. The service-satisfaction index can divide into consumer-satisfaction index and the facilities-satisfaction index two parts. We traveled to the 31 GWSM stores and asked for one thousand one hundred and seventeen customers to fill in the Service-Satisfaction Questionnaire (as in appendix A) in two months. We combined consumer-satisfaction index and the facilities-satisfaction index and divided by two which can get the service-satisfaction index. Table 2 presents descriptive statistics for our dataset. In table 2, we can find the mean of net profit is negative that means the general GWSM stores have poor operation performance. This is another reason why we need to do this research for improving the GWSM stores efficiency. Because of the reorganization in MND, the circumstance and Data are dynamic for each year. We only can select the data from the recent published document; otherwise it can not match the real situation. Input/output data are reported as the total number throughout the year and can be found in The Operating Report of General Welfare Service Ministry in Taiwan published by the GWSM in November 2004, the most recent published document.

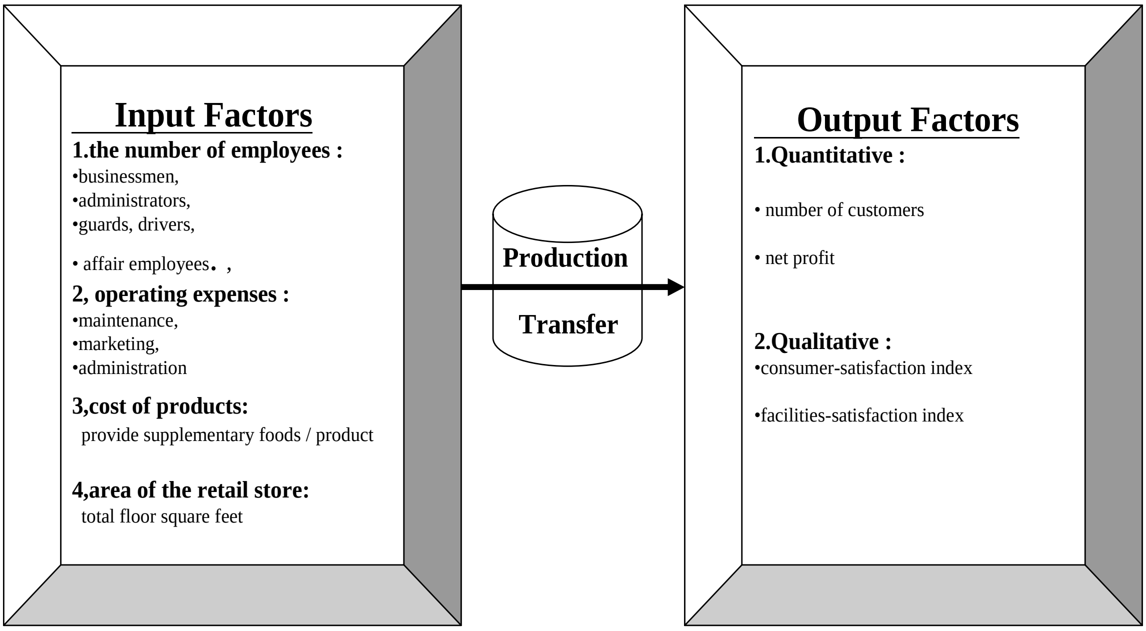

Figure 3. Managerial Performance Model

Table 2. Descriptive statistics for the 31 GWSM retail stores in Taiwan

	Mean	Minimum	Maximum	Std. Dev.	Valid N
Input factors					
Employees (persons)	34	26	47	5	31
Operating expenses (NT$)	10,908,379	5,733,262	17,990,931	3,659,243	31
Cost of products (NT$)	159,846,440	35,446,619	299,696,847	84,295,358	31
Square feet of retail store	1,509	185	3,826	884	31
Output factors					
Customers (persons)	337,676	67,839	696,274	176,170	31
Net profit (NT$)	-2,702,147	-8,169,347	2,887,210	2,621,810	31
Customer-satisfaction index (%)	88.06	77	97	6.17	31
Facilities-satisfaction index (%)	83.58	73	93	6.12	31

Table 3 shows the correlation matrix of inputs x_i and outputs y_i. Notice that all the correlation coefficients are positive. Therefore, these inputs and outputs hold ‘isotonicity’ relations, and thus these variables are justified to be included in the model. Cooper et al. (2001) suggested that the number of retail stores should be at least triple to the number of inputs and outputs considered. In this study the number of retail stores is 31, which is larger than triple the number of inputs (4)/outputs(4), or 31>3(4+4) = 24. It can conform to Golany & Roll experience rules the number of retail stores is larger than triple the number of inputs plus outputs. Consequently, the developed DEA model should hold high construct validity in this study.

Table 3. Correlation coefficients among inputs and outputs

	Net profit	Customers	Customer-Satisfaction index	Facilities-Satisfaction index
Employees	0.1055	0.7813	0.0137	0.0170
	p=0.572	p=0.000	p=0.942	p=0.928
Operating expenses	0.3394	0.1994	0.0856	0.0112
	p=0.062	p=0.282	p=0.647	p=0.952
Cost of products	0.5978	.9659	0.3672	0.3623
	p=0.000	p=0.000	p=0.042	p=0.045
Square feet of retail store	0.0155	0.7746	0.0378	0.0124
	p=0.934	p=0.000	p=0.840	p=0.947

3.2 Methodology: Data Envelopment Analysis Model

3.2.1 Efficiency Measurement Concepts

DEA is known as a mathematical programming method for assessing the comparative efficiencies of a decision making unit (DMU). DEA is a non-parametric method that allows for an efficient measurement, without specifying either the production functional form or weights on different inputs and outputs. This methodology defines a non-parametric best practice frontier that can be used as a reference for efficiency measurement which can be found in Cooper et al. (2000).

The input-oriented technical efficiency implies "by how much can input quantities be proportionally reduced without changing the output quantities produced?" The efficiency frontier presents that each DMU minimizes its inputs, keeping the output level constant. DMUs on the frontier are efficient, while DMUs inside the frontier are inefficient. Consider the case of a single input x and a single output y. In Figure 4, the constant returns to scale (*CRS*) frontier is a simple ray (ray *0C*) through the origin that envelops the data. The efficient DMU at point *C* lies on this frontier and its technical efficiency (*TE*) score equals one. The other four DMU stores (*B, E, D, F*) operating inside the frontier are inefficient. The *TE* score for the DMU operating at point *E* is defined by $\overline{PQ}/\overline{PE}$. However, the CRS assumption is only appropriate when all DMU stores are operating at an optimal scale. Many realistic factors, such as imperfect competition, financial constraints, etc., may cause a DMU not to operate at optimal scale. Thus, there is also a variable returns to scale (VRS) DEA model. In Figure 4, the VRS frontier is the piecewise linear frontier *ABCD*. This general form envelops the data more closely. The DMUs at *B*, *C*, and *D* lying on this frontier are efficient with a score of one. The relative inefficient DMU *E* is given by a pure technical efficiency (PTE) score ($\overline{PR}/\overline{PE}$). The TE is decomposed into PTE and scale efficiency (SE). The *SE* can be estimated by dividing PTE into TE.

To investigate the current operating region to scale inefficient DMU stores, this may be determined by running an additional DEA problem with non-increasing returns to scale (*NIRS*) imposed. This may be determined by running an additional DEA problem with non-increasing returns to scale (*NIRS*) imposed. The *NIRS* DEA frontier is also plotted in Figure 4. The nature of the scale inefficiencies (i.e. due to increasing or decreasing returns to scale) for a particular DMU can be determined by seeing whether the *NIRS TE* score is equal to the *VRS TE* score. If they are unequal (as will be the case for the point *E* in Figure

4), then increasing returns to scale (*IRS*) exist for the DMU. If they are equal (as is the case for point *F* in Figure 4), then decreasing returns to scale (*DRS*) apply.

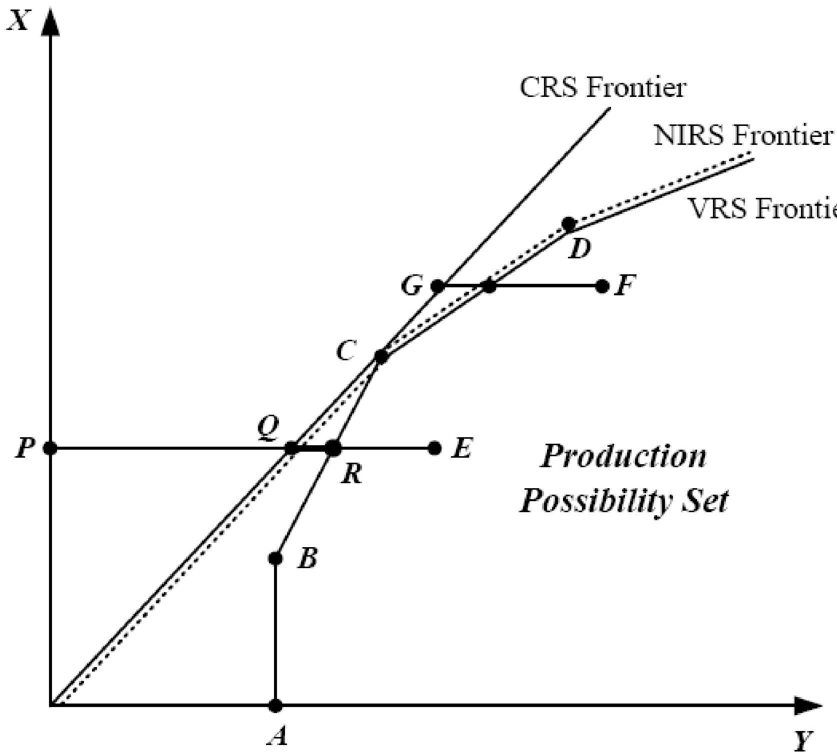

Figure 4. Graphical Illustration of Measuring Technical Efficiency
(Input-Oriented DEA Using a Single Input to Produce a Single Output)

3.2.2 Multiplier Model of the CCR/BCC Model

DEA is a mathematical model that measures the relative efficiency of decision-making units with multiple inputs and outputs but with no obvious production function to aggregate the data in its entirety. Relative efficiency is defined as the ratio of total weighted output to total weighted input. By comparing n units with s outputs denoted by y_{ro}, $r = 1,\dots,s$, and m inputs denoted by x_{io}, $i =,\dots,m$, the efficiency measure h_o for the target DMU_o ($o = 1,\dots,n$) is

$$h_o = Max \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}},$$

where the weights, u_r and v_i, are non-negative. A second set of constraints requires that the same weights, when applied to all DMUs, do not provide any unit with efficiency greater than one. This condition appears in the following set of constraints:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \text{ for } j = 1, \ldots, n.$$

The efficiency ratio ranges from zero to one, with the target DMU_o being considered relatively efficient if it receives a score of one. Thus, each unit will choose weights so as to maximize self-efficiency, given the constraints. The result of the DEA is the determination of the hyper planes that define an envelope surface or Pareto frontier. DMUs that lie on the surface determine the envelope and are deemed efficient, whilst those that do not are deemed inefficient. The formulation described above can be translated into a linear program, which can be solved relatively easily and a complete DEA solves n linear programs, one for each DMU.

$$\begin{aligned} h_o = \ & Max \ \sum_{r=1}^{s} u_r y_{ro} \\ & s.t. \\ & \sum_{i=1}^{m} v_i x_{io} = 1, \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, \ldots, n, \\ & u_r, v_i \ge 0; \quad i = 1, \ldots, m; \quad r = 1, \ldots s, \end{aligned} \tag{1}$$

Eq. (1), often referred to as the CCR model (Charnes et al., 1978), assumes that the production function exhibits constant returns to scale. The BCC model (Banker et al., 1984) adds an additional constant variable, u_o, in order to permit variable returns to scale:

$$
\begin{aligned}
h_o = \ & Max \ \sum_{r=1}^{s} u_r y_{ro} - u_o \\
& s.t. \\
& \quad \sum_{i=1}^{m} v_i x_{io} = 1, \\
& \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_o \leq 0, \quad j = 1, \ldots, n, \\
& \quad u_o \text{ free in sign}, \\
& \quad u_r, v_i \geq 0; \quad i = 1, \ldots, m; \quad r = 1, \ldots s.
\end{aligned}
\tag{2}
$$

It should be noted that the results of the CCR input-minimized or output-maximized formulations are the same, which is not the case in the BCC model. Thus, in the output-oriented BCC model, the formulation maximizes the outputs given the inputs and vice versa.

3.2.3 The Dual Program of the CCR/BCC Model

If a DMU proves to be inefficient, a combination of other efficient units can produce either greater output for the same composite of inputs; use fewer inputs to produce the same composite of outputs or some combination of the two. A hypothetical decision making unit can be composed as an aggregate of the efficient units, referred to as the efficient reference set for inefficient DMU_o. The solution to the dual problem of the linear program directly computes the multipliers required to compile efficient units. The pure technical efficiency (PTE) of the target DMU_o ($o = 1, \ldots, n$) in the BCC model can be computed as a solution to the following linear programming (LP) problem.

$$
\begin{aligned}
& Min \;\; \theta_o \\
& s.t. \\
& \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_o x_{io}, \quad i = 1, \ldots, m, \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, \quad r = 1, \ldots, s, \\
& \quad \sum_{j=1}^{n} \lambda_j = 1, \quad j = 1, \ldots, n, \\
& \quad \theta_o,\ \lambda_j \ge 0;\ \forall\ i \ and \ r.
\end{aligned}
\tag{3}
$$

In the case of an efficient DMU, all dual variables will equal zero except for λ_o and θ_o, which reflect the DMU_o's efficiency, both of which will equal one. If DMU_o is inefficient, θ_o will equal the ratio solution of the primal problem. The remaining variables, λ_j, if positive, represent the multiples by which DMU_o's inputs and outputs should be multiplied in order to compute the composite efficient DMU. If $\sum_{j=1}^{n} \lambda_j = 1$ is dropped from Eq.(3), then the technology is said to exhibit constant returns to scale (CRS). The technical efficiency (TE) of the target DMU_o is defined as $TE = \theta_o$ under the input-oriented CRS model (Charnes et al., 1978).

3.2.4 The Slack-Adjusted CCR/BCC Model

In the slack-adjusted DEA models, see for example model (3), a weakly efficient DMU will now be evaluated as inefficient, due to the presence of input and output oriented slacks s_i^- and s_r^+, respectively. The pure technical efficiency (PTE) of the target DMU_o ($o = 1, \ldots, n$) in the BCC model can be computed as a solution to the following linear programming (LP) problem.

$$
\begin{aligned}
& Min \;\; \theta_o - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_o x_{io}, \quad i = 1, \ldots, m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, \ldots, s, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \theta_o,\ \lambda_j,\ s_i^-,\ s_r^+ \geq 0;\ \varepsilon > 0;\ \forall\ i \ and\ r.
\end{aligned} \tag{4}
$$

The PTE of the target DMU_o is defined as $\text{PTE} = \theta_o$. By varying the index $'o'$ over all DMUs, we arrive at the PTE in each DMU. If $\text{PTE} = 1$ and all input and output slacks, s^- and s^+, are equal to zero, then the DMU_o is technically efficient. If PTE is smaller than one, then DMU_o is technically inefficient. The solution value of λ_j indicates whether DMU_j serves as a role model or peer for DMU_o. If $\lambda_j = 0$, then DMU_j is not a peer. However, if $\lambda_j > 0$, say $\lambda_j = 0.4$, then DMU_j is a peer DMU with a 40 percent weight placed on deriving the target efficient output and input levels for DMU_o. For an inefficient DMU_o, we have the expression in Eq. (5).

$$\theta_o x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j^* + s_i^{-*},\quad i = 1,\ldots,m,$$
$$y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j^* - s_r^{+*},\ \ \mathrm{r} = 1,\ldots,s, \tag{5}$$

where θ_{jo}, s_i^{-*}, s_r^{+*} and λ_j^* are optimal slacks and weights obtained from Eq. (4). The $DMU_o\left(x_{io}, y_{ro}\right)$ can be improved and become efficient by deleting its excess input and augmenting the shortfall output as follows:

$$\hat{x}_{io} = \theta_o x_{io} - s_i^{-*} = \sum_{j=1}^{n} x_{ij}\lambda_j^*,\quad i = 1,\ldots,m,$$
$$\hat{y}_{ro} = y_{ro} + s_r^{+*} \quad = \sum_{j=1}^{n} y_{rj}\lambda_j^*,\ \ \mathrm{r} = 1,\ldots,s. \tag{6}$$

This operation is called BCC-projection.

If $\sum_{j=1}^{n}\lambda_j = 1$ is dropped from Eq.(4), then the technology is said to exhibit constant returns to scale (CRS). The technical efficiency (TE) of the target DMU_o is defined as $TE = \theta_o$ under the input-oriented CRS model (Charnes et al., 1978). The scale efficiency (SE) for the target DMU_o is then obtained as.

$$SE = TE / PTE. \tag{7}$$

The SE represents the proportion of inputs that can be further reduced after pure technical inefficiency is eliminated if scale adjustments are possible. It has a value of less than or equal to one. If the target DMU_o has a value equal to one, then it is operating at the constant returns to scale size. If SE is less than one, then the target DMU_o is scale inefficient and there is potential input savings through the adjustment of its operational scale. Whether the scale inefficient DMU_o should be either downsizing or expanding depends on its current operating scale.

3.2.5 Returns to Scale

There are at least three different basic methods of testing a DMU's returns to scale (RTS) nature which have appeared in the DEA literature. Banker (1984) shows that the CCR model can be employed to test for DMUs' RTS using the concept of most productive scale size (MPSS), i.e. the sum of the CCR optimal lambda values can determine the RTS classification. This method is called the CCR RTS method. Banker et al. (1984) report that a new free BCC dual variable (u_o) estimates RTS by allowing variable returns to scale (VRS) for the CCR model, i.e. the sign of u_o determines the RTS. We call this method the BCC RTS method. Finally, Färe et al. (1985) provide the scale efficiency index method for the determination of RTS using DEA. These three RTS methods, in fact, are equivalent but different presentations (Banker et al., 1996; Färe et al., 1994; Zhu et al., 1995).

The three basic RTS methods have been widely employed in real world situations (Byrnes et al., 1984; Charnes et al., 1989; Zhu, 1996a). However, it has been noted that the CCR and BCC RTS methods may fail when DEA models have alternate optima, i.e. the original CCR and BCC RTS methods assume unique optimal solutions to the DEA formulations. In contrast to the CCR and BCC RTS methods, the scale efficiency index method does not require information on the primal and dual variables and, in particular, is robust even when there exist multiple optima. Since it may be impossible or at least unreasonable to generate all possible multiple optima in many real world applications, a number of modifications or extensions of the original CCR and BCC methods have been developed to deal with multiple optima.

Banker and Thrall (1992) generalize the BCC RTS method by exploring all alternate optima in the BCC dual model, i.e. RTS in their extended technique is measured by intervals for u_o. Banker et al. (1995) further modified the technique to avoid the need for examining all alternate optima. Using the same technique, Banker et al. (1996) introduce a modification to the CCR RTS method by determining the maximum and minimum values of $\sum_{j=1}^{n}\lambda_j$ in the CCR model in order to reach a decision. On the other hand, by the scale efficiency index method, Zhu and Shen (1995) suggest a remedy for the CCR RTS method under possible multiple optima.

According to the recent result of Zhu and Shen (1995), one can easily estimate the returns to scale (RTS) by the CCR and BCC scores and $\sum_{j=1}^{n}\lambda_j$ in any optimal solution to the CCR model without exploring all possible multiple optimal solutions. That is, if CCR score is equal to the BCC score, then CRS (constant return to scale) prevails; otherwise, if the CCR and BCC scores are not equal, then $\sum_{j=1}^{n}\lambda_j < 1$ indicates IRS (increasing returns to scale) and $\sum_{j=1}^{n}\lambda_j > 1$ indicates DRS (decreasing returns to scale).

3.2.6 Context-Dependent DEA

1. Stratification DEA Method

The context-dependent DEA (Seiford and Zhu, 2003) is introduced as follows. Let $J^1 = \{DMU_j,\ j = 1,\ldots,n\}$ (the set of all n $DMUs$) and interactively define $J^{l+1} = J^l - E^l$ where $E^l = \{DMU_k \in J^l \,|\, \phi(l,k)\}$, and $\phi(l,k)$ is the optimal value to the following LP when DMU_k is under evaluation.

$$
\begin{aligned}
&\underset{\lambda_j,\phi(l,k)}{Min}\ \phi(l,k) \\
&s.t. \\
&\sum_{j\in F(J^l)} \lambda_j x_{ij} \le \phi(l,k)\, x_{ik}, \\
&\sum_{j\in F(J^l)} \lambda_j y_{rj} \ge y_{rk}, \\
&\phi(l,k),\ \lambda_j \ge 0;\ \forall\ i\ and\ r,\ j \in F\left(J^l\right),
\end{aligned}
\tag{8}
$$

Where $j \in F\left(J^l\right)$ means $DMU_j \in J^l$, i.e., $F(.)$ represents the correspondence from a DMU set to the corresponding subscript index set. When $l = 1$, Eq.(8) becomes the original input-oriented CCR model, Eq.(1), and E^1 consists of all the frontier $DMUs$. These $DMUs$ in set E^1 define the first-level best-practice frontier. When $l = 2$, Eq. (8) gives the second-level best-practice frontier after the exclusion of the first-level frontier $DMUs$. And so on. In this manner, we identify several levels of best-practice frontiers. We call E^l the lth-level best practice frontier. The following algorithm accomplishes the identification of these best-practice frontiers by Eq.(8).

- Step 1: Set $l = 1$. Evaluate the entire set of $DMUs$, J^1, by Eq.(8) to obtain the first-level frontier $DMUs$, set E^1 (the first-level best-practice frontier).
- Step 2: Exclude the frontier $DMUs$ from future DEA runs. $J^{l+1} = J^l - E^l$. (If $J^{l+1} = \varnothing$ then stop).
- Step 3: Evaluate the new subset of 'inefficient' $DMUs$, J^{l+1}, by Eq.(8) to obtain a new set of efficient $DMUs$ E^{l+1} (the new best-practice frontier).
- Step 4: Let $l = l + 1$. Go to step2.
- Stopping rule: $J^{l+1} = \varnothing$, the algorithm stops.

2. Attractiveness Measure

Now, based upon these evaluation contexts E^l $(l = 1,\ldots,L-1)$, we can obtain the relative attractiveness measure by the following LP:

$$\begin{aligned}
& H_q^*(d) = \underset{\lambda_j, H_q(d)}{Min} H_q(d), \quad d = 1,\ldots,L-l_o, \\
& s.t. \\
& \sum_{j \in F\left(E^{l_o+d}\right)} \lambda_j x_{ij} \le H_q(d) x_{iq}, \;\; i = 1,\ldots,m, \\
& \sum_{j \in F\left(E^{l_o+d}\right)} \lambda_j y_{rj} \ge y_{rq}, \qquad r = 1,\ldots,s, \\
& H_q(d),\; \lambda_j \ge 0;\; \forall\; i \;and\; r,\; j \in F\left(E^{l_o+d}\right),
\end{aligned} \tag{9}$$

where $DMU_q = \left(x_{iq}, y_{rq}\right)$ is from a specific level E^{l_o}, $l_o \in \{1,\ldots,L-1\}$. In Eq.(4), each best-practice frontier of E^{l_o+d} represents an evaluation context for measuring the relative attractiveness of $DMUs$ in E^{l_o}. The larger the value of $H_q^*(d)$, the more attractive the DMU_q is. Because this DMU_q makes itself more distinctive from the evaluation context E^{l_o+d}. We are able to rank the $DMUs$ in E^{l_o} based upon their attractiveness scores and identify the best one.

3. Progress Measure

To obtain the progress measure for specific $DMU_q = \left(x_{iq}, y_{rq}\right) \in E^{lo}$, $l_o \in \{2,\ldots,L\}$, we use the following LP:

$$
\begin{aligned}
& G_q^*(g) = \underset{\lambda_j, G_q(g)}{Min}\, G_q(g), \quad g = 1,\ldots,l_o - 1, \\
& s.t. \\
& \sum_{j \in F\left(E^{l_o - g}\right)} \lambda_j x_{ij} \le G_q(g)\, x_{iq}, \;\; i = 1,\ldots,m, \\
& \sum_{j \in F\left(E^{l_o - g}\right)} \lambda_j y_{rj} \ge y_{rq}, \qquad r = 1,\ldots,s, \\
& G_q(g),\; \lambda_j \ge 0;\; \forall\; i \text{ and } r,\; j \in F\left(E^{l_o - g}\right).
\end{aligned} \tag{10}
$$

Each efficient frontier, $E^{l_o - g}$, contains a possible target for a specific DMU in E^{l_o} to improve its performance. The progress measure here is a level-by level improvement. For a larger $1/G_q^*(g)$, more progress is expected for DMU_q. Thus, a smaller value of $1/G_q^*(g)$ is preferred.

Chapter 4. Empirical Results and Analysis

4.1. Performance of the GWSM Retail Stores

An input-orientated DEA model is chosen to calculate the overall technical efficiency scores for 31 retail stores because the objective of the GWSM is to provide fine effective service with least input resources to soldiers , reservists, veterans, and their dependents. The technical efficiency (TE, Mean=0.820) is decomposed into pure technical efficiency (PTE, Mean=0.864) and scale efficiency (SE, Mean=0.950), and the nature of returns to scale (RTS) is reproduced in Table 4. The result reveals that the overall technical inefficiencies of the GWSM retail stores are primarily due to the pure technical inefficiencies rather than the scale inefficiencies, because mean of SE equal 0.95 close to 1. It is mean that SE has a little tolerance to improve non the less mean of PTE only equal 0.864 has a lot tolerance to improve. This also suggests that managers should focus firstly on removing the technical inefficiency of retail stores, and then retail stores can be subject to improving their scale efficiencies.

As regards to the pure technical efficiency (PTE), it is found that, on average, retail stores can produce the same level of measured output with 13.60% less inputs, holding the current input ratios constant. Using a t-test, we reject the null hypothesis that the sample mean is one at the 5% level of significance. Approximately 45.16% of retail stores need to reduce their inputs if they are to become efficient. The rest of the retail stores are regarded as efficient. This indicates that overall retail stores still have room for improving their pure technical efficiencies.

We further investigate the relationship between efficient score and region of retail stores. There are four regions for the GWSM retail stores: North, West, South, and East. To determine whether differences exist in region characteristic, a non-parametric statistical analysis (Kruskal-Wallis test) is used (Brockett et al., 1996) for unknown distribution scores. A non-parametric statistical analysis is presented in Table 5. Table 5 reveals that those retail stores located on north region perform better on average than the other three regions in pure technical efficiency. The findings show that retail stores located on north region are more competitive and they should provide examples of operating practice. Using a Kruskal-Wallis test shows no significant difference in pure technical efficiency at the 5 percent level for the four regions.

The scale efficiency is defined by the ratio of a TE score to a PTE score. If the ratio is equal to one, then a retail store is scale efficient; otherwise, if the ratio is less than one, then a retail store is scale inefficient. This t-test indicates that the scale efficiency ratios are significantly less than one, which means that serious scale inefficiencies occur in these 31 retail stores. This is evidence showing that a scale problem really does exist in the GWSM retail stores, which can be treated as support for future mergers and acquisitions between retail stores.

This study further investigates the status of returns to scale for retail stores. From Table 4 we observe that the average scale efficiency of 0.950 suggests further potential input savings of 5% if it is possible for a retail store to operate at the constant returns to scale technology. Approximately 41.5% of the retail stores are constant returns to scale (CRS). There are nearly 32.3% of the retail stores that operate at decreasing returns to scale (DRS). The DRS retail stores represent stores need to be reduced in size and become efficient stores. On the other hand, about one-third of the retail stores operate at increasing returns to scale (IRS). The IRS stores in the latter group could be consolidated with other small units to achieve the optimal size. However, an across-the-board policy for downsizing these retail stores is not recommended because those retail stores are on different resource basis and location. It is more appropriate to consider the retail stores on a case-by-case basis before any restructuring policy is implemented.

Table 4. Efficiency scores of the 31GWSM retail stores

DMU No.	DMU	TE	PTE	SE	$\sum\lambda$	RTS	Location	Service-satisfaction Index*
1	Keelung	1.000	1.000	1.000	1.000	CRS	North	0.900
2	Beibei	1.000	1.000	1.000	1.000	CRS	North	0.905
3	Beijhong	0.725	0.747	0.970	1.172	DRS	North	0.895
4	Beisi	0.967	1.000	0.967	1.964	DRS	North	0.910
5	Beidong	0.877	1.000	0.877	1.395	DRS	North	0.920
6	Beinan	0.925	0.936	0.988	1.123	DRS	North	0.905
7	Sioulang	1.000	1.000	1.000	1.000	CRS	North	0.915
8	Banciao	1.000	1.000	1.000	1.000	CRS	North	0.910
9	Shuanghe	0.882	0.906	0.973	1.107	DRS	North	0.810
10	Neiyi	0.820	0.864	0.950	0.920	IRS	North	0.845
11	Taoyuan01	0.731	0.734	0.996	1.036	DRS	North	0.765
12	Taoyuan02	0.794	0.799	0.994	0.988	IRS	North	0.820
13	Hsinchu	1.000	1.000	1.000	1.000	CRS	North	0.905
14	Guangfu	0.980	1.000	0.980	0.908	IRS	North	0.820
15	Miaoli	0.846	0.893	0.947	0.862	IRS	West	0.780
16	Taichung	1.000	1.000	1.000	1.000	CRS	West	0.835
17	Pinglin	0.771	0.786	0.981	1.102	DRS	West	0.800
18	Chiayi	0.682	0.807	0.845	1.828	DRS	West	0.790
19	Hsinying	1.000	1.000	1.000	1.000	CRS	South	0.935
20	Tainan01	0.684	0.735	0.930	1.364	DRS	South	0.805
21	Tainan02	0.745	0.811	0.919	0.884	IRS	South	0.815
22	Gaosyong	0.596	0.616	0.968	0.865	IRS	South	0.790
23	Zuoying	1.000	1.000	1.000	1.000	CRS	South	0.930
24	Kaohsiung	1.000	1.000	1.000	1.000	CRS	South	0.910
25	Fongshan	1.000	1.000	1.000	1.000	CRS	South	0.920
26	Dailiao	1.000	1.000	1.000	1.000	CRS	South	0.785
27	Pingtung	1.000	1.000	1.000	1.000	CRS	South	0.925
28	Taitung	0.572	0.640	0.892	0.836	IRS	East	0.750
29	Meilun	1.000	1.000	1.000	1.000	CRS	East	0.925
30	Hualian	0.982	1.000	0.982	1.127	DRS	East	0.900
31	Ilan	0.614	0.720	0.854	0.854	IRS	East	0.785
	Mean	0.820	0.864	0.950	0.920			0.845

* Service-satisfaction index = (Customer-satisfaction index + Facilities-satisfaction index)/2

* TE = PTE * SE

Table 5. Non-parametric statistical analysis of location for the 31 GWSM retail stores

Location	Number of retail stores	Mean	Kruskal-Wallis test (p-value)
North	14	0.928	0.6483
West	4	0.872	
South	9	0.907	
East	4	0.840	

4.2. Analysis of managerial decision-making matrix

By combining the results of pure technical efficiency and service-satisfaction index, we design a decision-making matrix to identify the position of the 31 retail stores, which help the managers and/or authorities to improve their operating efficiencies. A pure technical efficiency/ satisfaction index matrix of retail store is presented in Fig. 5. All retail stores fall into four zones: I, II, III, and IV. Each retail store is classified into a zone by examining (1) whether the pure technical efficiency is equal to or less than 1, (2) whether the satisfaction index is greater than or smaller than 0.9. This matrix can act as a managerial decision-making matrix for further improving efforts that is contributive to managers. Retail stores located in the four zones are described below.

Zone I: Those retail stores enjoy high level in both pure technical efficiency and satisfaction index dimensions. Fourteen retail stores are included here: Keelung, Beisi, Sioulang, Hsinchu, Zuoying, Beibei, Beidong, Banciao, Hsinying, Kaohsiung, Meilun, Fongshan, Pingtung, and Hualian retail stores. These retail stores appear to be good role model, which can be treated as benchmarks to others. The findings also show that the retail stores located on Zone I have better competitive advantage than the other ones.

Zone II: The retail store experiences a higher satisfaction-index, but a lower pure technical efficiency. Beinan retail store is included. It is suggested that Beinan should place more emphasis on activities of improving operating efficiency.

Zone III: Those retail stores which perform inferior both in satisfaction-index and pure technical efficiency. Thirteen retail stores, Gaosyong, Neiyi, Taitung, Ilan, Shuanghe, Taoyuan02, Chiayi, Tainan02, Taoyuan01, Miaoli, Pinglin, Beijhong, and Tainan01 retail stores, are classified here. This suggests that managers should focus firstly on improving the service quality of retail stores, and then retail stores can be subject to improving operating efficiency.

Zone IV: Those retail stores which have high pure technical efficiency, but low satisfaction-index. Three retail stores are included here: Guangfu, Taichung, and Dailiao retail stores. It is suggested that these retail stores should place more emphasis on activities of improving the service quality of retail stores.

Looking at all the retail stores the correlation coefficient between pure technical efficiency and satisfaction index is 0.737 which is significant at the 5% level. Thus there is significant association between pure technical efficiency and service-satisfaction index, indicating a strong tendency for relatively high satisfaction index to go with good pure technical efficiency. This indicates that the customer/facilities satisfaction levels do have a very significant influence upon retail store’s performance. Therefore, managers should expect to spend most of their efforts in this area for inefficient retail stores.

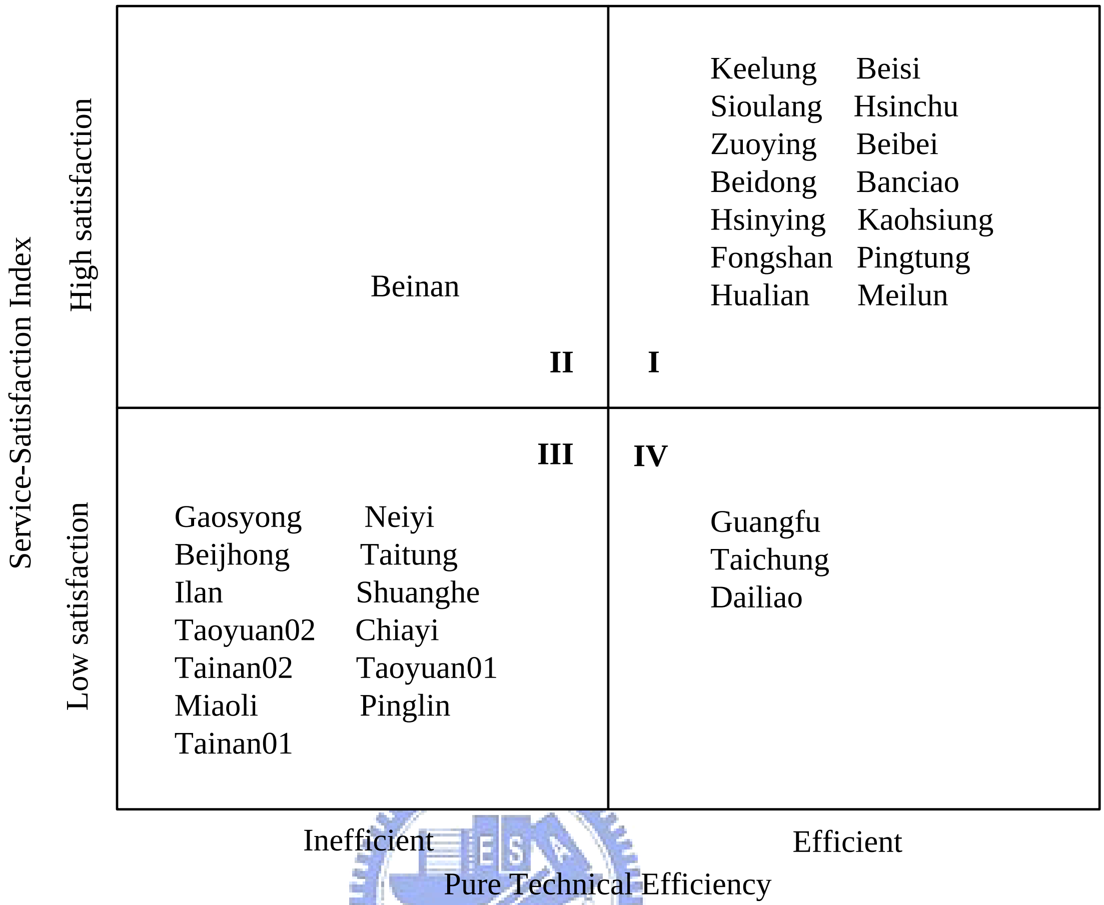

Figure 5. Service-satisfaction index/pure technical efficiency cross-tabulation

4.3. Constructing a Benchmark-Learning Roadmap

After identifying the efficient *DMU*, the role it plays in being benchmarked by other inefficient *DMUs* is also important. Previously, various efforts have been devoted to develop methods without priority information to identify the benchmark in DEA. One way to accomplish such a task is to count the number of times a particular efficient DMU acts as a reference DMU (Smith and Mayston, 1987). Andersen and Petersen (1993) presented the procedure referred to as the super-efficiency CCR model for ranking efficient units. Their basic idea is to compare the *DMU* under evaluation with all other *DMUs* in the sample, i.e., the *DMU* itself is excluded. Seiford and Zhu (1999) offered a super-efficiency BCC model in which increasing, constant, and decreasing returns to scale are allowed. The model is based on a reference technology constructed from all other DMUs. Li and Reeves (1999) proposed a multiple criteria approach that is called Multiple Criteria DEA, which focuses on solving two key problems: a lack of discrimination and inappropriate weighting schemes. To identify the inputs/outputs that are most important or to distinguish those efficient *DMUs* which can be treated as benchmarks, the reference-share measure (Zhu 2000) is defined as a ranking measure by combining the factor-specific measure and BCC model. Tone (2002) wrote a super-efficiency model using the slacks-based measure of efficiency. The detail description for above methodologies can check in appendix A. To summarize the above previous studies, the benchmarks derived from the proposed methods above can possibly become unimitable or unattainable goals for the inefficient *DMUs* immediately. A series of step-by-step benchmarks (or called 'a benchmark-learning roadmap') for an inefficient retail store to learn and gradually improve its operating efficiency seems to be more realistic and reasonable.

In this section the context-dependent DEA, by incorporating stratification DEA, attractiveness measure, and progress measure, can draw the GWSM retail stores' benchmark-learning roadmap to improve the inefficient retail stores progressively and can identify the best retail store. By using stratification DEA model, Eq. (3), we can get the first-level best-practice frontier when l=1. When l=2, Eq. (3) gives the second-level best-practice frontier. Then, the third-level frontier when l=3, and so on. Before continued to explain, it needs to make a definition for attractive and progress. Progress meaning the second level or third level needs to catch up the first or second level learning curve distance, in another word, it real means is falling behind degree from level two or three to level one. Attractive meaning the first level which takes the lead level two or level three degree, that is to say, level two or level three needs do their efforts to come up with level one or level three needs to improve it's performance to catch up with level two's performance. (as in Figure 6)

In this research, the three levels of efficient frontiers are reported in Table 6. According to Morita, Hirokawa, and Zhu (2005), the benchmark targets of the inefficient retail stores on level 3 should take retail stores on level 2 as initial targets to improve efficiency in the first stage. In the second stage, after retail stores on level 3 achieve the second-level efficient frontier, these on level 3 can use the first-level efficient frontier as secondary benchmarks for improvement and so on to proceed stage by stage. We call this composition of learning tracks for retail stores in different levels as a 'benchmark-learning roadmap.' Note that as pointed out in Chen, Morita, and Zhu (2005), the levels obtained using Eq. (3) do not necessarily follow the order of the TE scores. For instance, five retail stores (Beijhong, Miaoli, Pinglin, Tainan01, and Taoyuan01) on the third-level have a larger TE score than does Chiayi on the second-level.

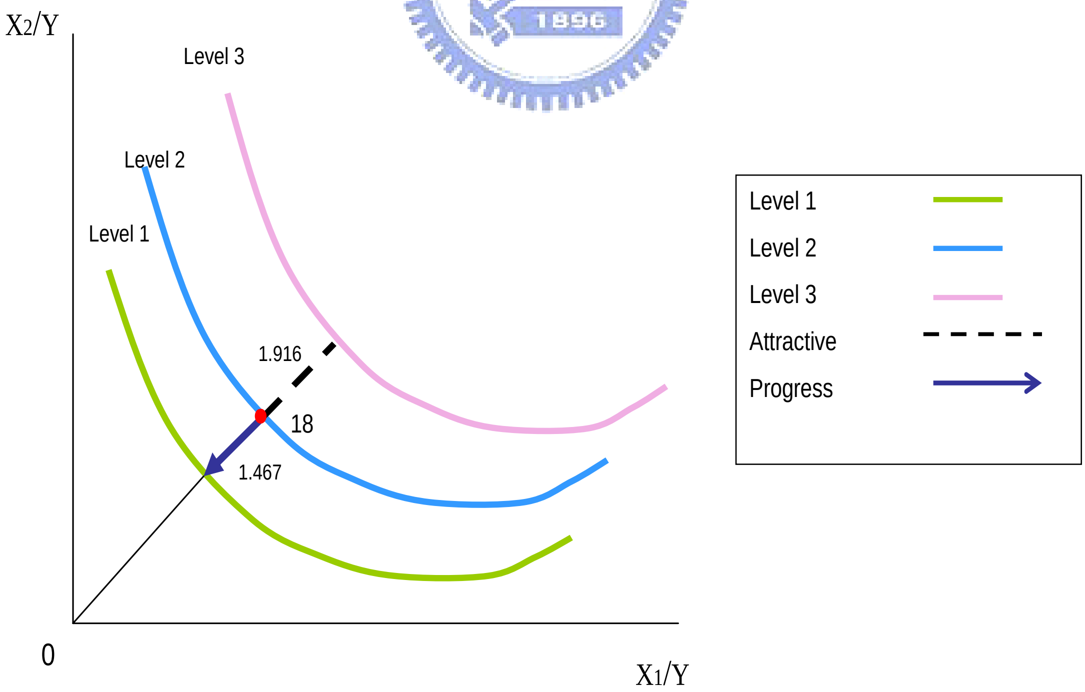

Figure 6. Context-DEA Figure: Attractive and Progress Measurement Values

Table 6. Levels of efficient frontiers

First-Level			Second-Level			Third-Level		
DMU No.	DMU Name	TE	DMU No.	DMU Name	TE	DMU No.	DMU Name	TE
2	Keelung	1	1	Neiyi	0.820	4	Beijhong	0.725
3	Beibei	1	5	Beisi	0.967	15	Miaoli	0.846
8	Sioulang	1	6	Beidong	0.877	17	Pinglin	0.771
9	Banciao	1	7	Beinan	0.925	20	Tainan01	0.684
13	Hsinchu	1	10	Shuanghe	0.882	22	Gaosyong	0.596
16	Taichung	1	12	Taoyuan02	0.794	30	Taitung	0.572
19	Hsinying	1	14	Guangfu	0.980	31	Ilan	0.614
23	Zuoying	1	18	Chiayi	0.682	11	Taoyuan01	0.731
24	Kaohsiung	1	21	Tainan02	0.745			
25	Fongshan	1	28	Hualian	0.982			
26	Dailiao	1						
27	Pingtung	1						
29	Meilun	1						

We now turn to the attractiveness measure and the progress measure (Eqs. 4 and 5) of the 31 retail stores when different efficient frontiers are chosen as evaluation contexts.

Table 7 gives the results. The number of the right of each score indicates the ranking position by the attractiveness measure and progress measure ((1) represent the top-rank position). As regards to the attractiveness measure, when the second-level is chosen as the evaluation context, Hsinying in first-level is the best retail store because it has the largest attractiveness score of 5.196. The retail stores in first-level can be ranked by using attractiveness measure in the order of Hsinying Meilun, Dailiao, Hsinchu, Keelung, Taichung, Pingtung, Kaohsiung, Beibei, Zuoying, Fongshan, Sioulang, and Banciao retail stores. Results also show that 11 out of the 13 retail stores on the first level are located on the north and south regions, indicating that retail stores located on north and south regions are more competitive. When the third-level is chosen as the evaluation context, Hsinying is still the best retail store, as followed by Meilun retail store. The findings show that Hsinying retail store is the most attractive retail store, i.e. global leader, no matter which evaluation context is chosen.

As regards to the progress measurement, when the first-level is chosen as the evaluation context, Taitung retail store is the worst retail store in the third-level because it has the largest progress score of 1.750. The retail stores in third-level can be ranked by using progress measure. When the second-level is chosen as the evaluation context, Taitung is still the worst retail store in the third-level. The findings show that Taitung retail store is the worst retail store, no matter which evaluation context is chosen. Note that the ranking position is change for Dailiao, Hsinchu, Keelung, Taichung, Pingtung, Kaohsiung, Beibei, Zuoying, Fongshan, Sioulang, and Banciao retail stores in first-level when evaluation context is changed. This demonstrates that the performance of retail stores can be dependent on the evaluation background (Zhu, 2003).

Table 7. Attractive and progress scores for the retail stores in different evaluation context

First-Level DMU	Evaluation Context		Second-Level DMU	Evaluation Context		Third-Level DMU	Evaluation Context	
	Second-Level	Third-Level		First-Level	Third-Level		First-Level	Second-Level
	1st-Degree[a]	2nd-Degree[a]		1st-Degree[b]	1st-Degree[a]		1st-Degree[b]	2nd-Degree[b]
Keelung	1.626 (5)	2.244 (9)	Neiyi	1.219 (7)	1.834 (6)	Beijhong	1.379 (4)	1.169 (3)
Beibei	1.437 (9)	2.122 (11)	Beisi	1.034 (3)	2.024 (2)	Miaoli	1.182 (1)	1.092 (1)
Sioulang	1.306 (12)	2.143 (10)	Beidong	1.140 (6)	1.911 (5)	Pinglin	1.297 (2)	1.163 (2)
Banciao	1.147 (13)	2.712 (6)	Beinan	1.081 (4)	1.411 (10)	Tainan01	1.463 (5)	1.203 (5)
Hsinchu	1.917 (4)	2.632 (7)	**Shuanghe**	1.134 (5)	**2.521** (1)	Gaosyong	1.678 (7)	1.227 (6)
Taichung	1.593 (6)	3.633 (3)	Taoyuan02	1.260 (8)	1.565 (8)	**Taitung**	**1.750 (8)**	**1.325 (8)**
Hsinying	**5.196 (1)**	**7.412 (1)**	Guangfu	1.020 (2)	1.932 (3)	Ilan	1.628 (6)	1.187 (4)
Zuoying	1.399 (10)	1.840 (12)	Chiayi	1.467 (10)	1.916 (4)	Taoyuan01	1.367 (3)	1.278 (7)
Kaohsiung	1.470 (8)	3.355 (4)	Tainan02	1.341 (9)	1.640 (7)			
Fongshan	1.343 (11)	1.633 (13)	**Hualian**	**1.019 (1)**	1.545 (9)			
Dailiao	2.234 (3)	2.739 (5)						
Pingtung	1.585 (7)	2.279 (8)						
Meilun	**3.202 (2)**	**4.525 (2)**						

Note:

1. [a]This represents attractive.
2. [b]This represents progress.
3. First level is the best performance then the second level, the third level represents the worst performance.
4. Ranks are given in parenthesis.

According to Seiford and Zhu (2003), for retail stores that are not located on the first or last level of efficient frontier, we can characterize their performance by their attractiveness and progress scores. Each retail store in the second-level is classified into a zone by examining (1) whether the attractiveness score is greater than or less than 1.80, (2) whether the progresses score is greater than or smaller than 1.25. In Figure 7 the attractiveness and progress scores give a two-by-two matrix to classify the retail stores in the second-level. A good performer shows high attractiveness and low progress and, a wrong performer shows low attractiveness and high progress. A high progress indicates that the retail store needs to improve its outputs substantially, and a high attractive indicates that the retail store have better competitive advantage than the other ones. Retail stores have been split subjectively into four groups plotted respectively in the zones of LH, HH, HL, and LL. The retail stores in each group are summarized as follows.

Zone LH: Those retail stores enjoy low progress and high attractiveness scores. Five retail stores are included here: Neiyi, Beisi, Beidong, Shuanghe, and Guangfu retail stores. The findings show that the retail stores located on Zone LH have better competitive advantage than the other ones in the second-level.

Zone HH: The retail store experiences a higher progress and attractiveness scores. Chiayi retail store is included. It is suggested that Chiayi retail store should place more emphasis on activities of improving its outputs substantially.

Zone HL: The retail store experiences a higher progress and lower attractiveness scores.

Taoyuan02 and Tainan02 retail stores are included. It is suggested that Taoyuan02 and Tainan02 retail stores should put forth efforts on learning more capabilities for effective outcomes such as enhancing the activities of operational management and relocating the resources between inputs and outputs. Further, these retail stores must draw up a short-term or middle-term plan to enhance its' competitive advantage.

Zone LL: Those retail stores which have a lower progress and lower attractiveness scores. Two retail stores are included here: Beinan and Hualian retail stores. It is suggested that these retail stores must make up a short-term or middle-term plan to enhance its' competitive advantage for moving up into the Zone LH.

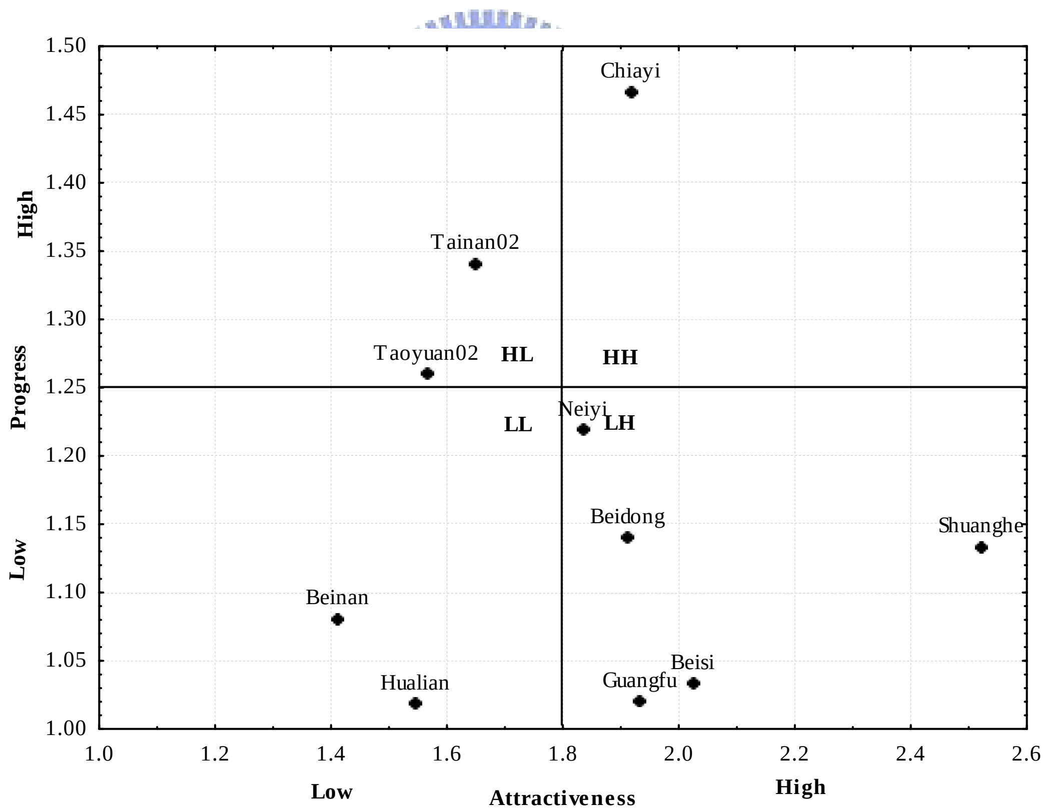

Figure 7. Attractiveness/progress score for the retail stores in the second-level

4.4 Discussion

According to the efficiency scores (as in table 4), service-satisfaction index/pure technical efficiency cross-tabulation (as in figure 6), and attractive and progress scores for the retail stores in different evaluation context (as in table 7), we can draw a reorganization alternative map of 31 GWSM stores and the map shows us the whole picture of each GWSM store's RTS and location.(as in figure 8) The Taiwan's map will divide into North, West, South and East four parts and discuss the analysis results.

In North area, there have 14 GWSM stores because this area lives around one fourth populations in Taiwan announced by Ministry of the Interior 2004 annual report. Only in Taipei City has 5 GWSM stores but 4 of them belong to DRS, the reasons are Taipei is Capital in Taiwan and its economical and business activities are popular so the famous companies want to set up the big sale markets or outlets in Taipei city. In the meanwhile, GWSM stores will encounter the competition from the above big outlets so we suggest Beibei (CRS) needs to keep operating because of excellent performance and Beijhong (DRS), Beisi (DRS), Beidong(DRS), Beinan (DRS) four stores, Beisi and Beinan should reduce their size and improve their service to become CRS and deactivate Beijhong and Beidong owing to their poor TE in Taipei city. In Taipei County, Shuanghe (DRS) store is inefficient, we suggest it should merge in Banciao (CRS) let it becomes more competitive. In Taoyuan County, we suggest Taoyuan01 (DRS) store should shut down and re-allocated the resources to Taoyuan02 (IRS) because of the inefficiency and many deactivated military units. It can let Taoyuan02 increasing its size and become CRS. In Hsinchu, Hsinchu (CRS) store has good performance so it needs keep providing service to customers but Guangfu (IRS) store we suggest MND to keep this store and improve its size to ideal scale.

In West area, Miaoli store (IRS) in Miaoli County has a poor performance and not reach constant scale but we suggest that should enlarge its scale and become constant return to scale because Miaoli only has one GWSM and GWSM belongs to nonprofit organization. Pinglin (DRS) store in Taichung city should deactivate because of its inefficiency and many troops are dissolved in Taichung. In Chiayi County, Chiayi (DRS) store should uphold and try to improve the poor performance because Chiayi, Yulin, Changhua and Nantou Counties only has this GWSM store and at the same time Chiayi has a lot of military bases including an air force base. Just like we mention in chapter 1 “GWSM retail store is a nonprofit organization and their main purpose is supporting soldiers, reservists, veterans and their dependents”.

In South area, Tainan County, Tainan01 (DRS) store should merge into Tainan02 (IRS) store and Tainan02 store can improve scale, performance and save the manpower cost. In Kaohsiuang and Pingtung, there are the key position of military units and schools in Taiwan so six of them can reach CRS only Gaosyong (IRS) store belongs to IRS and has the worst operation performance (Te=0.565) in South area. In Gaosyong, there has R.O.C. Air Force Academy, Air Force Institute of Technology, and Gaosyong Air Force Base etc. It should have enough loyal customers, but it has poor performance should have the problems of operation skills, so we need focus on the management skill. The remnants of the five GWSM stores, we suggest keep improving their Service-satisfaction to become the benchmark GWSM stores in Taiwan.

In East area, Taitung (DRS) store has the worst performance in 31 GWSM stores, but Taitung County has an AFB and a lot of military units, and it only has one GWSM so we suggest keeping this store and improving its service quality and operation performance. In Hualian, we suggest Hualian (DRS) store can merge into Meilun (CRS) store because of its inefficiency and Hualian population is less. In Ilan, we suggest keep Ilan (IRS) store because Ilan only has one GWSM store we need consider the purpose for supporting the military customers.

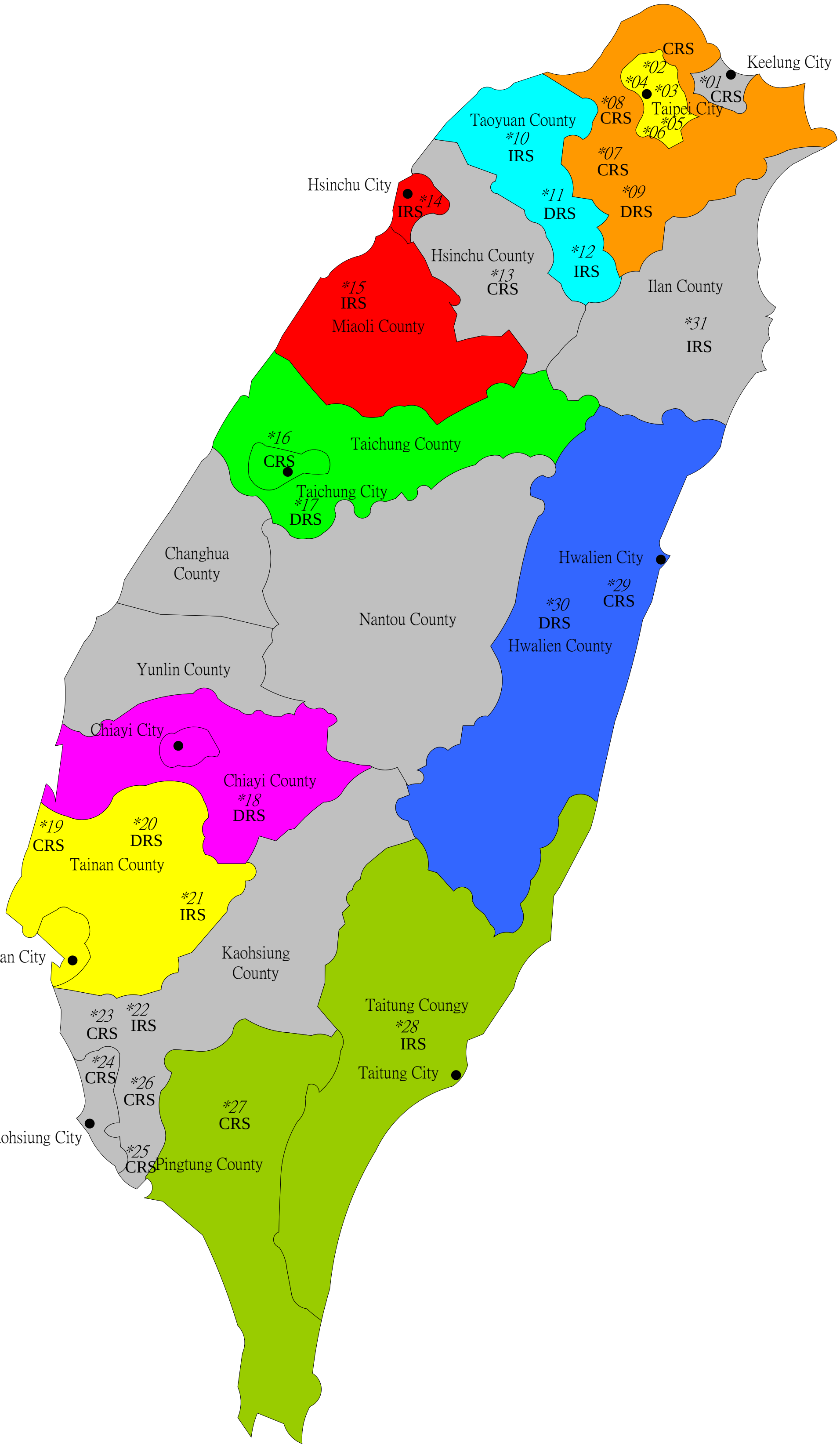

Figure 8. Map of GWSM"s RTS and Location.

Chapter 5. Concluding Remarks

5.1 Conclusions

Although the retail industry efficiency has been widely discussed in previous literature and DEA technique is frequently used, there are still some important points not touched. Few research studies about the retail industry have been conducted in emerging countries (such as Taiwan) while applications of DEA for the evaluation of military retail stores have been very limited. This study provides a milestone analysis based on DEA to investigate Taiwan and assist the MND in improving the GWSM stores operational management with insights in resource allocation. Additionally, the application of context-dependent DEA thus far is rarely discussed in the literature of retail industry. This paper therefore aims to explore the operating efficiency of military retail stores and the application of context-dependent DEA from a more complete viewpoint.

The findings are now briefly enumerated as follows. Firstly, the overall technical inefficiencies of GWSM retail stores are primarily due to the pure technical inefficiencies rather than the scale inefficiencies. This also suggests that managers should focus on removing the pure technical inefficiency of retail stores, before improving their scale efficiencies. Secondly, the retail stores located on north on the average operate better than those in the other three regions. The findings show that the retail store's region plays key role which affect its operating performance. Thirdly, the customer/facilities satisfaction levels do have a very significant influence upon retail store' performance. Therefore, managers should expect to spend most of their efforts in this area for inefficient retail stores. Fourthly, the attractiveness measure shows that Hsinying retail store is the most attractive retail store, i.e. global leader, no matter which evaluation context is chosen, and the progress measure shows that Taitung retail store is the worst retail store. Fifthly, the context-dependent DEA successfully draws the GWSM retail stores' benchmark-learning roadmap to improve the inefficient retail stores progressively and can identify the best retail store. Last, the assessment herein can assist the Ministry of National Defense to improve the operational management of GWSM and contribute to the GWSM retail stores in delivering better and efficient services to the soldiers, veterans, and their dependents.

5.2 Suggestions

In real situation for improving GWSM performance, we suggest that MND needs focus on the future priorities as follows:

1. Sales Promotion:

   Even though GWSM services for specific customers, it still needs for attracting the people's sighting and purchasing desire. Because of the competition by civilian's big sales market such as Kmart, Carrefour, RT-Mart, MATSUSEI etc., customers want to compare the price, quality of products with the big market store. If GWSM does not use the fancy way to attract and maintain the customers, they will be closed very soon because no people want to walk in GWSM.

2. Enhance Quality Control Process:

   Because the living standard of military already promoted in recent years, the customers do not care the little price difference but they do more care about the quality of merchandise. So GWSM needs effectively control over the suppliers' merchandise, it can fit normal standards fresh, good looking and high quality, that we can hold the customers for a long time. If customers met one time for buying an unqualified products, they will never walk in your store again.

3. Integrated sale market conditions:

Integrating GWSM's marketing information and avoiding duplicated investments, different area has different operating strategies. For example, GWSM in Taipei, the merchandises need sale delicate products, otherwise, it will lose the competition powers, but in low income areas, it should sale par goods, if not, GWSM will threaten the customers. Therefore, MND should integrate each GWSM conditions and share the information to improve operation efficiency.

4. Merge and deactivate the inefficient GWSM:

MND should refer to the GWSM efficiencies by above research, then; can decide which retail store should merge and deactivate because of the poor efficiency, bad location, and low competition. MND can relocated the resources and maintain the efficient stores, therefore, GWSM can survive in the future and support for military soldiers (including cadets in military academies), reservists, veterans and their dependents.

A further investigation would be the examination of performance over time (panel data) by using the Malmquist productivity change index techniques. Such an approach would allow a dynamic view of the multidimensional performance of retail stores. It is also hoped that the models and methods implemented in this study can bring about other related researches to a variety of industries.

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Appendix A: Service-Satisfaction Questionnaire

國軍福利站滿意度問卷調查

親愛的顧客您好!

國軍福利站之設立宗旨是為服務勞苦功高的三軍同胞、軍事院校學生、退伍榮民及上述人員眷屬，為提升福利站之服務品質以提高顧客滿意度，本研究針對福利站之硬體設施及服務品質之滿意度，設計下列問卷，敬請親愛的顧客能以您自身的體驗填答下列問卷，俟問卷分析完畢後，即將及結果交送福利總處，供其作為改善設施及服務品質之參考，再次感謝您的協助。

敬祝　　　　　　　購物愉快

交通大學管理學院管理科學系 敬上

指導教授: 楊千

研究生: 王宗誠，盧文民

Eail:jamesw0728@yahoo.com.tw

第一部分　基本資料

1. 性別：

□ 男　　□ 女

2. 年齡：

□18 歲~30 歲　□30~50 歲　□50~60 歲　□60~歲以上

3. 職業：

□軍公教人員　□軍校學生　□ 榮民 □ 眷屬 □ 其他

4. 每月收入：

□ 10,000 元以下　□ 10,001~30,000 元　□ 30,001~50,000 元

□ 50,001~100,000 元　□ 100,000 元以上

5. 教育程度：

□ 小學 □ 國中 □ 高中、職 □ 大專院校　□ 研究所以上

第二部份　消費狀況

1.請問您會到福利站消費的原因

□較近□服務項目多樣化□商品的多樣化□服務度態度 □較便宜

□其他_____

2.請問您多久到福利站去消費

☐每週一次☐每週 2-3 次☐每月一次以上 ☐其他_____

3.您平均每次到福利站消費的金額

☐300 以下 ☐500 以下 ☐1000 以下 ☐2000 以下 ☐2000 以上

4.下列幾家販售商店,您比較喜歡到哪一家便利商店消費(請按照優先順填寫)

______福利站 ______家樂福______大潤發______松青_____愛買

5. 大潤發與松青一天經營 24 小時對你來說有比較方便嗎?

☐ 沒差 ☐方便 ☐非常方便

6. 你覺得上述超商會取代福利站嗎?

☐會 ☐不會 ☐不知道

7.你滿意目前福利站整體提供的服務嗎?

☐滿意 ☐不滿意 ☐沒意見

8.你覺得福利站有需要改進的地方嗎?

第三部份

服務滿意度

	很不滿意	不太滿意	無意見	滿意	非常滿意
1、店員的親切度	☐1	☐2	☐3	☐4	☐5
2、店員的衣著及服儀	☐1	☐2	☐3	☐4	☐5
3、店員的結帳速度	☐1	☐2	☐3	☐4	☐5
4、商品是否多樣化--包含熱食、飲料、零食、蔬果,生鮮及日用品等等	☐1	☐2	☐3	☐4	☐5
5、商品是否新鮮每天是否定時更新食品	☐1	☐2	☐3	☐4	☐5
6、是否經常推出特惠商品	☐1	☐2	☐3	☐4	☐5
7、過年過節之禮盒及禮品供應式樣是否滿意	☐1	☐2	☐3	☐4	☐5
8、商品是否維持良好品質及外觀	☐1	☐2	☐3	☐4	☐5
9、商品退換手續是否簡便,服務員態度是否良好	☐1	☐2	☐3	☐4	☐5

10、商品價格與大賣場比是否具競爭力 □1 □2 □3 □4 □5

設施滿意度

1、福利站是否座落在住家、辦公室的附近 □1 □2 □3 □4 □5

2、汽機車停車是否方便 □1 □2 □3 □4 □5

3、是否有接駁轉運之服務 □1 □2 □3 □4 □5

4、福利站外觀是否明顯美觀 □1 □2 □3 □4 □5

5、是否設置儲物箱或物品代管之服務 □1 □2 □3 □4 □5

6、商場面積是否足夠與舒適 □1 □2 □3 □4 □5

7、內部動線設計是否順暢舒適 □1 □2 □3 □4 □5

8、商品陳列是否整齊及以相同商品歸類陳列 □1 □2 □3 □4 □5

9、商場內光線是否充足 □1 □2 □3 □4 □5

10 整體設施及地面是否清潔舒適 □1 □2 □3 □4 □5

感謝您接受我們的問卷調查，更謝謝您的寶貴意見！

APPENDX B: Ranking Extensions to DEA Model

1. Super Efficiency (Andersen and Petersen, 1993)

Andersen and Petersen (1993) developed a new procedure for ranking efficient units. The methodology enables an extreme efficient unit k to achieve an efficiency score greater than one by removing the kth constraint in the multiplier model, as shown in model (a.1).

$$
\begin{aligned}
h_k = \; & Max \; \sum_{r=1}^{s} u_r y_{rk} \\
& s.t. \\
& \quad \sum_{i=1}^{m} v_i x_{ik} = 1, \qquad\qquad (a1) \\
& \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1,\ldots,n, \;\; j \ne k \\
& \quad u_r, v_i \ge 0; \;\; i = 1,\ldots,m; \;\; r = 1,\ldots s.
\end{aligned}
$$

The dual formulation of the super-efficient model, as seen in model (a.2), computes the distance between the Pareto frontier, evaluated without unit k, and the unit itself i.e. for $J = \{ j = 1,\ldots,n, \; j \ne k \}$.

$$
\begin{aligned}
& Min \;\; \theta_k \\
& s.t. \\
& \quad \sum_{j=1, j\ne k}^{n} \lambda_j x_{ij} \le \theta_k x_{ik}, \quad i = 1,\ldots,m, \qquad\qquad (a2) \\
& \quad \sum_{j=1, j\ne k}^{n} \lambda_j y_{rj} \ge y_{rk}, \quad r = 1,\ldots,s, \\
& \quad \theta_k, \; \lambda_j \ge 0; \; \forall \; i \; and \; r; \; j = 1,\ldots,n.
\end{aligned}
$$

However, there are two problematic areas with this methodology. First, the super-efficient methodology can give “specialized” DMUs an excessively high ranking (Sueyoshi, 1999). The second problem lies with an infeasibility issue, which if it occurs, means that the super-efficient technique cannot provide a complete ranking of all DMUs (Seiford and Zhu, 1999).

2. Cross-Evaluation (Doyle and Green, 1994)

The cross-evaluation matrix was first development by Sexton et al. (1986), inaugurating the subject of ranking in DEA. Indeed, as Doyle and Green (1994) argued, decision-makers do not always have a reasonable mechanism from which to choose assurance regions, thus they recommend the cross-evaluation matrix for ranking units. The basic idea is to use DEA in a peer-appraisal instead of a self-appraisal, which is calculated by the CRS (constant returns to scale) model. A peer-appraisal means that the efficiency score of a DMU is achieved when evaluated with the optimal weights (input and output weights obtained by the output-oriented CRS model) of other $DMUs$. Thus, for each DMU there are $(n-1)$ cross-efficiency scores where n represents the total number of $DMUs$. Averaging the cross-efficiency scores of DMU_k by using the weighting scheme of other $DMUs$, we can compute the mean cross-efficiency score of DMU_k by the following formulation:

$$CEM_k^{Mean} = \sum_{j=1}^{n} \left(\sum_{r=1}^{s} u_{rj} y_{rk} \Big/ \sum_{i=1}^{m} v_{ij} x_{ik} \right) \Big/ (n-1), \quad j \neq k . \qquad \text{(a3)}$$

Here, CEM_k^{Mean} becomes an index for effectively differentiating between good and poor performers. Thus, the performer of the $DMUs$ can be ranked based on mean cross-efficiency scores. Table A1 summaries a generalized CEM. The zth row and the kth column represent the efficiency measure of DMU k by the optimal weights for DMU z (E_{zk}).

As indicated by Baker and Talluri (1997), a limitation of the CEM evaluated from the classic DEA model is that input/output weights (optimal weights) obtained from this formulation may not be unique. This condition occurs if multiple optimum solutions exist, because one scheme can be favorable to one DMU and not favorable to another, or vice versa. Doyle and Green (1994) propose aggressive and benevolent formulations to solve this ambiguity. Doyle and Green not only maximize the efficiency of the target DMU, but also take a second goal into account. This second goal, in the case of aggressive formulation, minimizes the efficiency of the composite DMU constructed from $(n-1)$ $DMUs$. The outputs and inputs of a composite DMU are obtained by summing the corresponding outputs and inputs of all the other $DMUs$ except the target DMU. The weights obtained from this formulation make the efficiency of the target DMU the best that it can be, and all other $DMUs$ are the worst. Thus, the CEM in Eq. (a4), which is evaluated from these weights, is more meaningful.

The aggressive formulation is generally used when relative dominance among the $DMUs$ is to be identified. The formulation is shown below:

$$
\begin{aligned}
Min \quad & \sum_{r=1}^{s} u_r \left(\sum_{j \neq k}^{n} y_{rj} \right) \\
s.t. \quad & \\
& \sum_{i=1}^{m} \left(v_i \sum_{j \neq k}^{n} x_{ij} \right) = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad \forall j \neq k, \\
& \sum_{r=1}^{s} u_r y_{rk} - \theta_{kk} \sum_{i=1}^{m} v_i x_{ij} = 0, \\
& v_i, u_r \geq 0, \quad \forall\ i \text{ and } r,
\end{aligned}
\tag{a4}
$$

where DMU_k is the target DMU, $\sum_{r=1}^{s} u_r \left(\sum_{j \neq k}^{n} y_{rj} \right)$ is the weighted output of composite DMU, $\sum_{i=1}^{m} \left(v_i \sum_{j \neq k}^{n} x_{ij} \right)$ is the weighted input of composite DMU, and θ_{kk} is the efficiency of DMU_k obtained from Eq. (1). The benevolent formulation uses the same set of constraints except that the efficiency of the composite DMU is maximized. As reported by Angulo-Meza and Lins (2002), these two formulations give very similar results, which is why only one of these formulation is used, generally the aggressive formulation.

A DMU potentially becomes as 'false positive' when it is exhibiting a high efficiency score by heavily weighting on a few favorable inputs and outputs. The self-appraisal and peer-appraisal are used in computing a false positive index (FPI) (Baker and Talluri, 1997). The FPI relates to the percentage increment in efficiency that a DMU achieves when moving from peer-appraisal to self-appraisal. This FPI is similar to the maverick index suggested by Doyle and Green (1994). It is calculated by using Eq. (a5). The higher the value of FPI_k is, the more 'false positive' the DMU_k will be. FPI is defined as:

$$FPI_k = \left(\theta_{kk} - CEM_k^{Mean}\right) \Big/ \left(CEM_k^{Mean}\right), \tag{a5}$$

where θ_{kk} is the self-appraisal efficiency of DMU_k, and CEM_k^{Mean} is the mean cross-efficiency score of DMU_k.

Table A1 A Generalized Cross-Efficiency Matrix

Rating DMU	Rated DMU						
	1	2	3	$\cdots$	k	$\cdots$	n
1	E_{11}	E_{12}	E_{13}	$\cdots$	E_{1k}	$\cdots$	E_{1n}
2	E_{21}	E_{22}	E_{23}	$\cdots$	E_{2k}	$\cdots$	E_{2n}
3	E_{31}	E_{32}	E_{33}	$\cdots$	E_{3k}	$\cdots$	E_{3n}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
z	E_{z1}	E_{z2}	E_{z3}	$\cdots$	E_{zk}	$\cdots$	E_{zn}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\cdots$	$\vdots$
n	E_{n1}	E_{n2}	E_{n3}	$\cdots$	E_{nk}	$\cdots$	E_{nn}
CEM^{Mean}	$E_{\bullet 1}$	$E_{\bullet 2}$	$E_{\bullet 3}$	$\cdots$	$E_{\bullet k}$	$\cdots$	$E_{\bullet n}$

3. Infeasibility of Super-Efficiency Model (Seiford and Zhu, 1999)

Seiford and Zhu (1999) presents super efficiency VRS (SE-VRS) model. The SE-VRS model is based on based on a reference technology constructed from all other DMUs. The super efficiency of DMU k is evaluated by solving the LP problem below:

$$
\begin{aligned}
&\theta_k^* = Min \quad \theta_k \\
&s.t. \\
&\quad \sum_{j=1,\, j\neq k}^{n} \lambda_j x_{ij} \leq \theta_k x_{ik}, \quad i = 1, \dots, m, \\
&\quad \sum_{j=1,\, j\neq k}^{n} \lambda_j y_{rj} \geq y_{rk}, \quad r = 1, \dots, s, \\
&\quad \sum_{j=1,\, j\neq k}^{n} \lambda_{\mathrm{j}} = 1 \\
&\quad \theta_k,\ \lambda_j \geq 0;\ \forall\ i\ and\ r;\ j = 1, \dots, n,
\end{aligned}
\qquad \text{(a6)}
$$

where θ_k^* is the optimal value for DMU k to the input-oriented SE-VRS model.

Thrall (1996) shows that the SE-CRS model can be infeasible. However, Thrall (1996) fails to recognize that the output-oriented SE-CRS model is always feasible for the trivial solution which has all variables set equal to zero. Moreover, Zhu (1996b) shows that the input-oriented SE-CRS model is infeasible if and only if a certain pattern of zero data occurs in the inputs and outputs. Figure A1 illustrates how the SE-VRS model works the infeasibility for the case of a single output and a single input case. We have three VRS frontier DMUs, *A, B, and C*. $\overline{AB}$ exhibits IRS and $\overline{BC}$ exhibits DRS. The SE-VRS model evaluates point *B* by reference to *B'* and *B"* on section $\overline{AC}$ through output-reduction and input-increment, respectively. In an input-oriented SE-VRS model, point *A* is evaluated against *A'*. However, there is no referent DMU for point *C* for input variations. Therefore, the input-oriented SE-VRS model is infeasible at point *C*. Similarly, in an output-oriented

SE-VRS model, point *C* is evaluated against *C'*. However, there is no referent DMU for point A for output variations. Therefore, the output-oriented SE-VRS model is infeasible at point *A*. Note that point A is the left most end point and point *B* is the right most end point on this frontier.

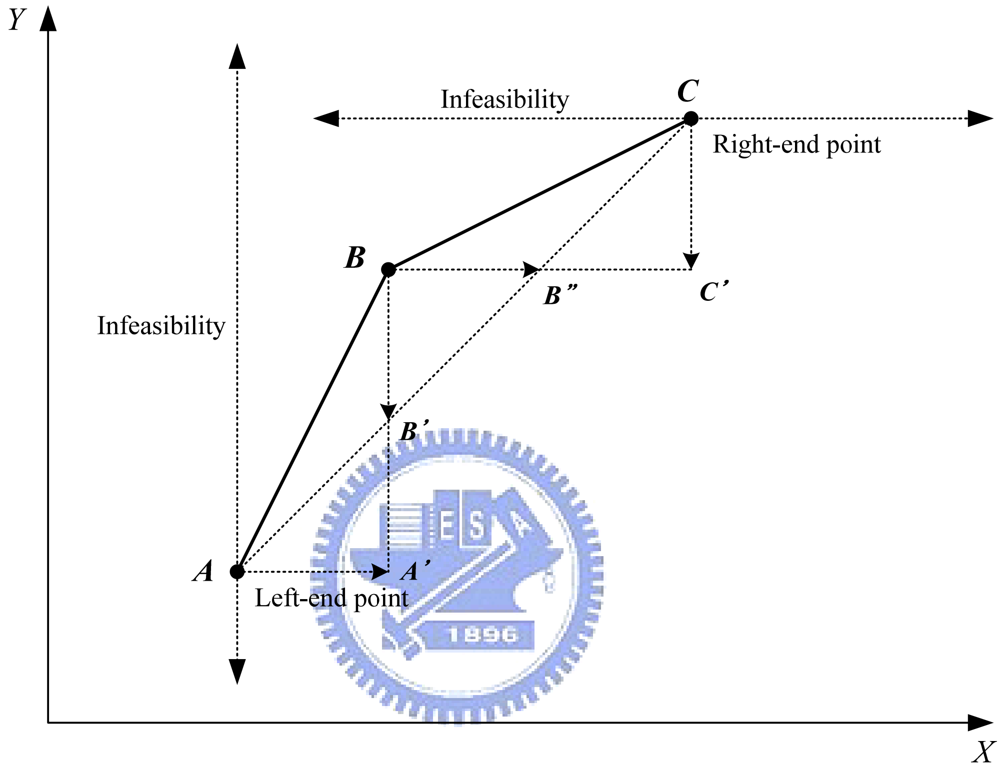

Figure A1 Infeasibility of Super-Efficiency Model

4. A Multiple Objective Approach (Li and Reeves, 1999)

Li and Reeves (1999) present a multiple objective approach that they called Multiple Criteria DEA – MCDEA, which focuses on solving two key problems: lack of discrimination and inappropriate weighting schemes. MCDEA introduces three objective functions into a LP problem. The first objective function seeks minimization of the inefficiency of a target DMU *k*, measured by d_k, such that the weighted sum of outputs is less than or equal to the weighted sum of inputs for each DMU. Thus, we can say that DMU *k* is not efficient its efficiency score would be $\theta_k = 1 - d_k$. The second objective function aims at the minimization of the maximum deviation, for which the restriction included in the new formulation, $M - d_i \geq k \ \ (i = 1, \ldots, n)$, makes *M* the maximum deviation. The third objective function seeks maximization of the deviation of all DMUs. All three objective functions are based on the deviation variable. The LP problem is as follows:

$$
\begin{aligned}
& Min\ d_k \text{ (or } Max\ \theta_k = \sum_{r=1}^{s} u_r y_{rk} \text{)} \\
& Min\ M \\
& Min\ \sum_{j=1}^{n} d_i \\
& s.t. \\
& \sum_{i=1}^{m} v_i x_{io} = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \qquad j = 1, \ldots, n, \\
& M - d_j \geq 0, \qquad i = 1, \ldots, n, \\
& u_r,\ v_i \geq 0, \qquad \forall\ r,\ i,\ and\ j.
\end{aligned}
\tag{a7}
$$

5. Non-Oriented Super-SBM model (Tone, 2002)

In most DEA models, the best performers share the full efficient status denoted by the score unity, and from experience we know that plural DMUs usually exist with this 'efficient' status. The Super-efficiency model discriminates these efficient DMUs. The basic concept is that we delete the efficient DMU concerned from the production possibility set (PPS) and measures the distance from the DMU to the remaining PPS. If the distance is small, then the super-efficiency of the DMU is judged to be lower as the DMU only marginally outperforms other DMUs. On the contrary, if the distance is large, then the super-efficiency of the DMU is high compared with the remaining DMUs. Hence, it makes sense to rank the efficient DMUs in the order of the distance thus obtained. The main problem is how to define the 'distance' between an efficient DMU and the PPS formed by excluding the DMU. The non-oriented super-SBM model (2002) is a well-known solution to evaluate the super-efficiency $DMU_o\left(x_{io}, y_{ro}\right)$ $(o = 1,\ldots,n)$ by solving the following fractional program:

$$
\begin{aligned}
\text{Min} \quad & \eta_o = \left(\frac{1}{m}\sum_{i=1}^{m}\bar{x}_i / x_{io}\right) \Big/ \left(\frac{1}{s}\sum_{r=1}^{s}\bar{y}_r / y_{ro}\right) \\
s.t. \quad & \\
& \bar{x} \geq \sum_{j=1,\, j\neq o}^{n} x_{ij}\lambda_j, \quad i = 1,\ldots,m, \\
& \bar{y} \leq \sum_{j=1,\, j\neq o}^{n} y_{ij}\lambda_j, \quad r = 1,\ldots,s, \\
& \sum_{j=1}^{n}\lambda_j = 1, \\
& \bar{x} \geq x_{io}, \bar{y} \leq y_{ro}, \bar{y} \geq 0, \lambda_j \geq 0.
\end{aligned}
\tag{a8}
$$

The fractional program can be transformed into LPs. See Tone (2002) for detailed discussions.

6. Reference-share measure (Zhu, 2000)

To identify the inputs/outputs that are most important or to distinguish those efficient $DMUs$ which can be treated as benchmarks, the reference-share measure (Zhu 2000) is defined as a ranking measure by combining the factor-specific measure in Eqs. (a9, a10) and BCC model. Lewin et al. (1982) and Torgersen et al. (1996) report the application for output-specific efficiency measures which are derived from the radial component and non-zero slacks. Here, for a particular inefficient DMU_d the factor-specific (kth input-specific and qth output-specific) measure comes via the following two linear programming problems and the existing BCC model's best practice frontier.

The kth input-specific DEA model can be written as follows:

$$\begin{aligned}
&\theta_d^{k*} = Min\ \theta_d^k, \quad d \in N, \\
&s.t. \\
&\sum_{j \in E} \lambda_j^d x_{ij} = \theta_d^k x_{kd,} \quad k \in \{1,\ldots,m\}, \\
&\sum_{j \in E} \lambda_j^d x_{ij} \le x_{id,} \qquad i \ne k, \\
&\sum_{j \in E} \lambda_j y_{rj} \ge y_{rd}, \quad r = 1,\ldots,s, \\
&\sum_{j \in E} \lambda_j^d = 1, \\
&\theta_d^k,\ \lambda_j^d \ge 0,\ j \in E.
\end{aligned} \tag{a9}$$

The qth output-specific DEA model can be written as follows:

$$
\begin{aligned}
&\phi_d^{q*} = Max\ \phi_d^q, \quad d \in N, \\
&s.t. \\
&\sum_{j\in E} \lambda_j^d y_{qj} = \phi_d^q y_{qd,} \quad q \in \{1, \ldots, s\}, \\
&\sum_{j\in E} \lambda_j^d y_{rj} \geq y_{rd}, \ r \neq q, \\
&\sum_{j\in E} \lambda_j^d x_{ij} \leq x_{id,} \ \ i = 1, \ldots, m, \\
&\sum_{j\in E} \lambda_j^d = 1, \\
&\phi_d^q, \lambda_j^d \geq 0, j \in E.
\end{aligned}
\tag{a10}
$$

Here, E and N respectively represent the index sets for the efficient and inefficient $DMUs$ identified by BCC model. The factor-specific measures in Eq. (a9) and Eq. (a10) determine the maximum potential decrease of an input and increase of an output while keeping other inputs and outputs at current levels. These factor-specific measures are still multi-factor performance measures, since all related factors are considered in a single model.

On the basis of Eq. (a9), the kth input-specific reference-share measure for each efficient DMU, $j \in E$, is

$$\Delta_j^k = \sum\nolimits_{d\in N} \lambda_j^{d*} \left(1-\theta_d^{k*}\right) x_{kd} \Big/ \sum\nolimits_{d\in N} \left(1-\theta_d^{k*}\right) x_{kd}, \tag{a11}$$

where λ_j^{d*} and θ_d^{k*} are optimal values in Eq. (a9). On the basis of Eq. (a10), the qth output-specific reference-share measure for each efficient DMU, $j \in E$, is

$$\Pi_j^q = \sum\nolimits_{d\in N} \lambda_j^{d*} \left[1-\left(1/\phi_d^{q*}\right)\right] y_{qd} \Big/ \sum\nolimits_{d\in N} \left[1-\left(1/\phi_d^{q*}\right)\right] y_{qd}, \tag{a12}$$

where λ_j^{d*} and ϕ_d^{q*} are optimal values in Eq. (a10).

The reference-share Δ_j^k (or Π_j^q) depends on the values of $\lambda_j^{d^*}$ and $\theta_d^{k^*}$ (or $\lambda_j^{d^*}$ and $\phi_d^{k^*}$). Note that $\left(1-\theta_d^{k^*}\right)\cdot x_{kd}$ and $\left[1-\left(1/\phi_q^{d^*}\right)\right]y_{qd}$ characterize the potential decrease on the kth input and increase on the qth output, respectively. Therefore, the reference-share here measures the contribution that an efficient DMU makes to the potential input (output) improvement in inefficient $DMUs$.

Terms Δ_j^k and Π_j^q are weighted optimal lambda values across all inefficient $DMUs$. The weights,

$$\left[\left(1-\theta_d^{k^*}\right)x_{kd}\Big/\sum\nolimits_{d\in N}\left(1-\theta_d^{k^*}\right)x_{kd}\right] \text{ and } \left\{\left[1-\left(1/\phi_d^{k^*}\right)\right]y_{qd}\Big/\sum\nolimits_{d\in N}\left[1-\left(1/\phi_d^{k^*}\right)\right]y_{qd}\right\},$$

are normalized, and therefore we have $\sum_{j\in E}\Delta_j^k=1$ and $\sum_{j\in E}\Pi_j^q=1$. It is very clear from Eq. (a9) and Eq. (a10) that an efficient DMU which does not act as a referent DMU for any inefficient DMU will have zero reference-share measure. The bigger the reference-share measure is, the more important an efficient DMU is in benchmarking.

Resume

Name: 王宗誠 (Wang, Tsung-Cheng)

Colonel Tsung-Cheng (James) Wang graduated from the Air Force Institute of Technology in 1996 with an M.S. in logistics management. He was a program manager at the for Air Force Headquarters in Taiwan for the Indigenous Defense Fighter, F-16, and Mirage 2000-5 acquisition programs (including offset administration) between 1988 to 1999. From 1999 to 2000, he was a system analysis officer for defense investment in office of Ministry of National Defense. In 2000 the Taiwanese government formulated a National Defense Law; he is one of the original designers for the Armament Bureau of MND. Since 2001 he is has been chief instructor, of the division of armament and acquisition management of National Defense Management College, National Defense University. Currently, he got his Ph.D. degree at the Institute of Management Science, National Chiao-Tung University, Taiwan.

Published paper:

1. Chyan Yang, Tsung-Cheng Wang, and Wen-Min Lu (2006) "Performance Measurement in Military Provision: The Case of Retail Stores of General Welfare Service Ministry in Taiwan“. AJPOR (*Asia-Pacific Journal of Operational Research*), (SCI)
2. Chyan Yang, and Tsung-Cheng Wang (2006) “VIKOR Method Analysis of Interactive Trade in Policy-Making” , BRC (*The Business Review, Cambridge*), (ABI)
3. Chyan Yang, and Tsung-Cheng Wang, (2006) “Multi-Criteria Analysis of Offset Execution Strategies in Defense Trade: A Case in Taiwan”, JAAB (*The Journal of American Academy of Business*), (ABI)

4. Chyan Yang, and Tsung-Cheng Wang, (2006) "Interactive Trade Decision-Making Thinking for Arms Sale", DISAM (*Defense Institute of Security Assistance Management Journal*).

Email: jamesw0728@gmail.com.tw