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Full Length Research Paper

Benchmarking management in military organizations: A non-parametric frontier approach

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Assessing the military organization's performance is an important yet complex issue. It is important to know whether the policy is effective in achieving its goal to advance the operating efficiency; and at the execution level. The aim of this paper is to explore the operating efficiency and the benchmarks of the military outlets by using a non-parametric frontier method: data envelopment analysis. Furthermore, the factor-specific measure and variable returns to scale model are combined together not only to identify the inputs/outputs that are most important but also to distinguish those military outlets which can be treated as benchmarks. The assessment can assist the Ministry of National Defense to improve the military operational management and to help the military outlets in delivering better and efficient services to soldiers, veterans, and their dependents. The potential applications and strengths of DEA in assessing the military organizations are also highlighted.

Key words: Data envelopment analysis, linear programming, military outlet.

INTRODUCTION

Performance evaluation is a fundamental building block of competitive advantage and has received increased attention over the past few years. Traditionally, organizations have always in some way measured performance through financial indicators. However, traditional performance measures, based on cost accounting information, provide little support to organizations interested in a more complete picture of quality. Performance benchmarking analysis should give a lead to people in an organization and make clearer their relationship with strategy. Thus, an organization's performance management system could play an important role in stimulating change and innovation, by both demonstrating the system's linkage with overall strategy and by monitoring progress towards an organizational goal (Simpson and Hill, 2004).

Along with new Defense Laws of the Ministry of National Defense in Taiwan, tightening the defense budget, the reduction of military organizations, and the innovation of military affairs, military mangers need to be more efficient in order to draw, transfer, and control finance resources. Since the Ministry of National Defense has administered "The Armed Forces Reengineering Program", the General Welfare Service Ministry (GWSM), which is composed of 31 military outlets, has not only faced a cutback of organizational structure and staff, but it has also dissolved some of the departments. Therefore, the GWSM urgently requires a performance benchmarking analysis to both enhance its operational management within the military outlets and to allocate its scarce defense resources under the supervision of Ministry of National Defense in Taiwan.

To date, the Ministry of National Defense has undertaken very few studies for helping managers or officers identify how a management system can be changed to improve crucial factors underlying the efficiency of military outlet's operation. However, since an military outlet's performance is a complex phenomenon requiring more than a single criterion to characterize it, traditional performance measurement techniques (Bush et al., 1990; Ingene, 1984; Thurik and Wijst, 1984) have often also been criticized for being inadequate and not taking into account of mix and nature of services provided (Good, 1984).

To overcome the shortcomings mentioned above, DEA has been used extensively for benchmarking analysis (Seiford, 1997; Gattoufi and Oral, 2004; Emrouznejad, 2009; Cook and Seiford, 2009) ever since its introduction by Charnes et al. (1978). DEA has many desirable features which may explain why researchers are interested in using it to investigate the efficiency of converting multiple inputs into multiple outputs. This study attempts to examine the operating efficiency of 31 military outlets by utilizing an extended DEA by Zhu (2000, 2009) incorporating the traditional DEA, the factor-specific measure, and the reference-share measure and, which so far has not been applied for the analysis of performance variation in military issues. The result of this analysis can provide an indication of the order of magnitude of performance differences between military outlets.

The main interest of this study is to examine potential applications of DEA in assessing military outlets' performance and to illustrate the use of input congestion measure and reference-share measure in DEA for evaluating military outlets, which should provide additional managerial insights to managers. The purposes of this paper include:

1. To provide a benchmark analysis based on DEA to investigate military outlets and assist the military managers in improving its operational management.
2. To determine the amount of input congestion and simultaneously identify factors responsible for congestion for an inefficient military outlet.
3. To identify the input/output that is most important and to distinguish those efficient military outlets which can be treated as benchmarks.

This paper proceeds as follows. In Section 2, the related prior studies are reviewed in the military issues. Section 3 introduces the input/output factors used and data collection. Section 4 explains the DEA models. The empirical results and interpretations are provided in section 5. Finally, section 6 concludes with the findings of this study.

LITERATURE REVIEW

Various studies have been done to adopt the DEA method to evaluate military organization performance during the past few years. Charnes et al. (1985) first introduced the term DEA in military organization performance research, which used the input orientated CCR model to analyze the relative efficiency of fourteen tactical fighter wings in the U.S. Air Force using artificial data. Bowlin (1987) implemented a DEA window analysis technique to evaluate the efficiency of U.S. Air Force real-property maintenance activities during the period October 1982 to March 1984, while Roll et al. (1989) used DEA to provide an efficiency measurement of five maintenance units in the Israel Air Force using quarterly data; Bowlin (1989) analyzed the relative efficiency of Air Force accounting and finance offices during the period 1983 to 1985; Clarke (1992) applied DEA to evaluate vehicle maintenance performance at seventeen bases of the U.S. Air Force's Tactical Air Command over the time period 1983–1986.

Bowlin (1995) assessed the financial condition of the aerospace-defense industrial base from 1978 to 1992 in comparison to the Standard & Poors 500 by using DEA. Bowlin (1999) examined the financial performance of defense-oriented business segments compared to non-defense-business segments for the years 1983-1992. Bowlin (2004) extended previous studies of the Civil Reserve Air Fleet (CRAF) program and its participants by assessing the financial condition of the CRAF participants for the time period 1988–1997. Brockett et al. (2004) utilized recently developed methods based on DEA which, when incorporated in the regression, make it possible to distinguish between efficient and inefficient performances. Sun (2004) proposed an alternative DEA method for assessing the performance of joint maintenance shops (JMSs) in the Taiwanese Army over two 6-month periods in 2000, and found that most previously inefficient JMSs, on average, have become relatively more efficient through DEA recommendation remedial actions. Additionally, the definition of input and output variables played critical roles in meaningful applications of DEA.

Despite various works having been completed to investigate the operating performance of different military organization, from the perspective of a research topic, military outlets performance evaluation is rarely taken as a research target. Furthermore, the issues of input congestion measure and efficiency rankings thus far are discussed less frequently. Consequently, this paper contributes three extensions to the existing research. First, this study provides a benchmark analysis based on DEA to investigate Taiwan and assist the MND in improving the GWSM's operational management. Second, a slack-based approach (Cooper et al., 2001b) is implemented to measure the input congestion. This method not only detects input congestion, but also determines the amount of congestion and simultaneously identifies factors responsible for congestion for an inefficient military. Lastly, the factor-specific measure and variable returns to scale (VRS) model (Bank et al., 1984) are combined together not only to identify the inputs/ outputs that are most important but also to distinguish those outlets which can be treated as benchmarks.

DATA SELECTION AND DESCRIPTION

Since an organization's performance is a complex phenomenon requiring more than a single criterion for characterization, it has been generally accepted that a multi-factor performance measurement model can provide a better characterization (Chakravarthy, 1986). Military outlets, 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 systems perspective, based on the resource concept, organizational activities refer to the conversion of inputs in. From a systems perspective, based

Table 1. Descriptive statistics for military outlets.

	Mean	Minimum	Maximum	Std. Dev.	Valid N
Input factor					
Employees (persons)	10	4	16	4	31
Operating expenses (NT$ thousand)	8.495	2.835	23.464	3.793	31
Cost of products (NT$ thousand)	107.687	22.397	230.197	59.638	31
Area of outlet (square meters)	417	56	1246	232	31
Output factor					
Customers (persons)	277.441	41.371	683.803	153.346	31
Net profit (NT$ thousand)	119.351	24.876	255.004	66.181	31

Table 2. Correlation coefficients among inputs and outputs

	Employees	Operating expenses	Cost of products	Area of outlet	Customers	Net profit
Employees	1.000					
Operating expenses	0.945	1.000				
Cost of products	0.817	0.804	1.000			
Area of outlet	0.011	0.034	0.200	1.000		
Customers	0.781	0.775	0.966	0.199	1.000	
Net profit	0.106	0.015	0.598	0.339	0.597	1.000

on the resource concept, organizational activities refer to the conversion of inputs in various resources (or costs) to outputs. Four input factors were therefore selected for the analysis. The four input factors are namely: the number of full-time employees (in persons); operating expenses (in NT$ thousand); cost of products (in NT$ thousand) and area of the outlet (in square meters). The employee factor is composed of businessmen, administrators, guards, drivers, and affair employees. These employees keep outlets 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 outlet refers to the total floor space used by the operational units of the outlet, measured in square meters.

On the other hand, output is a concrete measurement showing that an organization has reached its objectives. The service outputs are measured in terms of the number of customers (in persons) and the net profit (in NT$ thousand). This study uses the production approach to design the performance model. The performance model measures the performance of military outlets in using four inputs to produce two outputs.

This study investigates 31 military outlets, because those military outlets operated in the year 2007. Each of these military outlets is treated as a decision making unit (DMU) in the DEA analysis. The 31 military outlets of various geographical dispersements are selected since they are in charge of the supply of supplementary foods and products. The performances of the military outlets are accessed based on the data obtained for the year 2007. The data are extracted from the annual report of the GWSM. Table 1 presents descriptive statistics for our dataset. 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 2008. Table 2 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. (2001a) suggested that the number of DMUs should be at least triple to the total number of inputs and outputs considered. In this study the number of military outlets is 31, which is larger than triple the number of inputs (4)/outputs (2). Consequently, the developed DEA model should hold a high construct validity in this study.

METHODOLOGY

This section briefly introduces the DEA models used to assess the relative efficiency. Detailed descriptions of the specific evaluation model used in this study are also presented. The procedures adopted are as follows: Firstly, this study employs the traditional DEA models to measure technical, pure technical, and scale efficiencies and further determines the current returns to scale (RTS) for military outlets. Secondly, a slack-based approach (Cooper et al., 2001b) is used to measure the input congestion. Finally, the reference-share measure (Zhu, 2000, 2009) by combining the factor-specific measure and VRS model is used to define a ranking measure. All DEA models are now described as follows.

Traditional DEA Models

It has been noted that DEA, first developed by Farrell (1957) and consolidated by Charnes et al. (1978), is a non-parametric technique that permits the inclusion of multiple inputs and outputs in the production frontier and also measures efficiency in relation to the constructed frontiers. Assume that the objective of each unit (military outlet in our case) is to minimize its inputs, keeping the output level constant in the BCC model. The pure technical efficiency (PTE) of the target unit ($o=1,\ldots,n$) can be computed as a solution to the following linear programming problem:

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

where n is the number of unit; m and s are the number of inputs and outputs respectively. Let x_{ij} and y_{rj} be the amount of the ith input consumed and the amount of the rth output produced by the unit j and ε is the non-Archimedean infinitesimal. The PTE of the target unit is defined as PTE = θ_o. By varying the index 'o' over all unit, we arrive at the PTE in each unit. If PTE is equal to one and all input and output slacks, s_i^- and s_r^+, are equal to zero, then the target unit is technically efficient. If PTE is smaller than one, then the target unit is technically inefficient.

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

$$SE=TE/PTE. \tag{2}$$

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 unit 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 unit is scale inefficient and there is potential input savings through the adjustment of its operational scale. Whether the scale inefficient target unit should be either downsizing or expanding depends on its current operating scale. To determine the current operating region for scale inefficient target unit, following the result of Zhu and Shen (1995), one can easily estimate the returns to scale (RTS) by the TE and PTE scores and $\sum_{j=1}^{n} \lambda_j$ in any optimal solution to the CRS model. That is, if TE is equal to PTE, then CRS prevails; otherwise, if TE is not equal to PTE, 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).

Input congestion measure

Input congestion, by definition, presents the increments of inputs which result in a decrease of output. An excessive amount of labor or capital input can be a major source of inefficiency. The problem of input congestion thus far is less discussed in the literature of bank efficiency. This study will use a slack-based approach such as in Cooper et al. (2001b) to measure the input congestion. This method not only detects congestion, but also determines the amount of congestion and simultaneously identifies factors responsible for congestion for an inefficient unit. Input congestion for target unit can be computed as a solution to the following linear programming problem.

$$
\begin{aligned}
& Max \;\; \sum_{i=1}^{m} \delta_i^+ \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j x_{ij} - \delta_i^+ = \theta_o^* x_{io} - s_i^{-*} = \hat{x}_{io}, \quad i=1,\ldots,m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} = y_{ro} + s_r^{+*} = \hat{y}_{ro}, \qquad r=1,\ldots,s, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0,\ s_i^{-*} \geq \delta_i^+,
\end{aligned} \tag{3}
$$

where θ_o^*, s_i^{-*}, and s_r^{+*} are obtained from Eq. (1). The amount of congestion in each input for target unit can then be determined by the difference between each pair of s_i^{-*} and δ_i^{+*}, where δ_i^{+*} are optimal values in Eq. (3). That is,

$$s_i^c = s_i^{-*} - \delta_i^{+*}, i=1,\ldots m, \tag{4}$$

where s_i^c defined in Eq. (4) are called input congestion slacks.

Reference-share measure

To identify the inputs/outputs that are most important or to distinguish those efficient units which can be treated as benchmarks, the reference-share measure (Zhu, 2000; Zhu, 2009) is defined as a ranking measure by combining the factor-specific measure in Equations (5, 6) and VRS model in Equation (1). Here, for a particular inefficient unit d the factor-specific (kth input-specific and qth output-specific) measure comes via the following two linear programming problems and the existing VRS model's best practice frontier. The kth input-specific DEA model can be written as follows:

$$
\begin{aligned}
& \theta_d^{k*} = Min\ \theta_d^k, \quad d \in N, \\
& s.t. \\
& \sum_{j\in E} \lambda_j^d x_{ij} = \theta_d^k x_{kd}, \quad k \in \{1,\ldots,m\}, \\
& \sum_{j\in E} \lambda_j^d x_{ij} \leq x_{id}, \qquad i \neq k, \\
& \sum_{j\in E} \lambda_j y_{rj} \geq y_{rd}, \quad r=1,\ldots,s, \\
& \sum_{j\in E} \lambda_j^d = 1, \\
& \theta_d^k,\ \lambda_j^d \geq 0,\ j \in E.
\end{aligned} \tag{5}
$$

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

$$\phi_d^{q*} = Max\ \phi_d^q, \quad d \in N,$$
$$s.t.$$
$$\sum\nolimits_{j \in E} \lambda_j^d y_{qj} = \phi_d^q y_{qd}, \quad q \in \{1, \ldots, s\},$$
$$\sum\nolimits_{j \in E} \lambda_j^d y_{rj} \geq y_{rd}, \ r \neq q,$$
$$\sum\nolimits_{j \in E} \lambda_j^d x_{ij} \leq x_{id}, \ i = 1, \ldots, m,$$
$$\sum\nolimits_{j \in E} \lambda_j^d = 1,$$
$$\phi_d^q, \lambda_j^d \geq 0, j \in E. \tag{6}$$

Here, E and N respectively represent the index sets for the efficient and inefficient units identified by Equation (1). The factor-specific measures in Equation (5) and Equation (6) 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 Equation (5), the kth input-specific reference-share measure for each efficient unit, $j \in E$, is

$$\Delta_j^k = \sum\nolimits_{d \in N} \lambda_j^{d*} \left(1 - \theta_d^{k*}\right) x_{kd} \Big/ \sum\nolimits_{d \in N} \left(1 - \theta_d^{k*}\right) x_{kd}, \tag{7}$$

where λ_j^{d*} and θ_d^{k*} are optimal values in Equation (5). On the basis of Equation (6), the qth output-specific reference-share measure for each efficient unit, $j \in E$, is

$$\Pi_j^q = \sum\nolimits_{d \in N} \lambda_j^{d*} \left[1 - \left(1/\phi_d^{q*}\right)\right] y_{qd} \Big/ \sum\nolimits_{d \in N} \left[1 - \left(1/\phi_d^{q*}\right)\right] y_{qd}, \tag{8}$$

where λ_j^{d*} and ϕ_d^{q*} are optimal values in Equation (6).

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 unit makes to the potential input (output) improvement in inefficient units. The terms Δ_j^k and Π_j^q are weighted optimal lambda values across all inefficient units. 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 Equation (7) and Equation (8) that an efficient unit which does not act as a referent unit for any inefficient unit will have zero reference-share measure. The bigger the reference-share measure is, the more important an efficient unit is in benchmarking.

RESULTS AND ANALYSES

Operating performance analysis

Based on the controllable aspects from a manager's point of view, the performance model in this study is run under the assumption of input minimization (also known as input orientation). Technical efficiency (TE, Mean=0.859) is broken down into pure technical efficiency (PTE, Mean=0.900)) and scale efficiency (SE, Mean=0.952), and the nature of returns to scale (RTS) is reproduced in Table 3. The results reveal that the overall technical inefficiencies of Asian container ports are primarily due to pure technical inefficiencies rather than scale inefficiencies. The low pure technical efficiency in comparison to scale efficiency suggests that inefficiencies are mostly due to inefficient management practices. The result suggests that the overall technical inefficiencies of the military outlets are primarily due to the pure technical inefficiencies, not the scale inefficiencies. The low pure technical efficiency in comparison to scale efficiency suggests that inefficiencies are mostly due to inefficient management practices. This also suggests that military managers should focus firstly on improving their management practices to the market requirements, and then military outlets can be subject to improving their scale efficiencies. With regards to pure technical efficiency (PTE), it is found that, on average, military outlets can produce the same level of measured output with 10 % fewer inputs, holding the current input ratios constant. Using a t-test, this study rejects the null hypothesis that the sample mean is one at the 5% level of significance. Approximately 48.4% of military outlets need to reduce their inputs if they are to become efficient. The rests of outlets are regarded as efficient. This indicates that the numbers of outlets still have room for improving their pure technical efficiencies.

The scale efficiency is defined by the ratio of a CRS score to a VRS score. If the ratio is equal to one, then an outlet is scale efficient; otherwise, if the ratio is less than one, then an outlet 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 military outlets in performance model (p-value = 0.000). This is evidence showing that a scale problem really does exist in the military outlets, which can be treated as support for future mergers and acquisitions between military outlets.

This study further investigates the status of returns to

Table 3. Efficiency scores and reorganization alternative for military outlets.

Outlet	TE	PTE	SE	$\sum\lambda$	RTS	Region	Reorganization alternative
Keelung	1.000	1.000	1.000	1.000	CRS	North	Keelung
Beibei	0.961	1.000	0.961	0.858	IRS	North	**Beibei + Beijhong**
Beijhong	0.725	0.747	0.970	1.172	DRS	North	
Beisi	0.967	1.000	0.967	1.964	DRS	North	**Beisi + Beidong +Beinan**
Beidong	0.877	0.906	0.968	1.395	DRS	North	
Beinan	0.925	0.936	0.988	1.123	DRS	North	
Sioulang	1.000	1.000	1.000	1.000	CRS	North	Beinan
Panchiao	1.000	1.000	1.000	1.000	CRS	North	**Panchiao+Shuanghe**
Shuanghe	0.882	0.906	0.973	1.107	DRS	North	
Taoyuan01	0.731	0.734	0.996	1.036	DRS	North	**Taoyuan01+Taoyuan02+Neiyi**
Taoyuan02	0.794	0.799	0.994	0.988	IRS	North	
Neiyi	0.760	0.864	0.880	0.828	IRS	North	
Hsinchu	1.000	1.000	1.000	1.000	CRS	North	Hsinchu
Guangfu	0.946	1.000	0.946	0.836	IRS	North	**Guangfu + Miaoli**
Miaoli	0.814	0.893	0.912	0.742	IRS	West	
Taichung	1.000	1.000	1.000	1.000	CRS	West	**Taichung + Pinglin**
Pinglin	0.771	0.786	0.981	1.102	DRS	West	
Chiayi	0.682	0.807	0.845	1.828	DRS	West	**Chiayi + Dailiao**
Dailiao	0.678	1.000	0.678	0.516	IRS	South	
Sinying	1.000	1.000	1.000	1.000	CRS	South	**Sinying+ Tainan01 +Tainan02**
Tainan01	0.684	0.735	0.930	1.364	DRS	South	
Tainan02	0.719	0.811	0.887	0.820	IRS	South	
Gangshan	0.594	0.616	0.965	0.847	IRS	South	**Gangshan + Zuoying**
Zuoying	1.000	1.000	1.000	1.000	CRS	South	
Kaohsiung	1.000	1.000	1.000	1.000	CRS	South	Kaohsiung
Fongshan	1.000	1.000	1.000	1.000	CRS	South	Fongshan
Pingtung	1.000	1.000	1.000	1.000	CRS	South	**Pingtung + Taitung**
Taitung	0.572	0.640	0.892	0.836	IRS	East	
Meilun	1.000	1.000	1.000	1.000	CRS	East	Meilun
Hualian	0.982	1.000	0.982	1.127	DRS	East	**Hualian + Ilan**
Ilan	0.564	0.720	0.784	0.761	IRS	East	

Note: TE = PTE x SE. RTS: IRS denotes increasing returns to scale; CRS denotes constant returns to scale; DRS denotes decreasing returns to scale. '+' denotes the abbreviation for the merger.

Table 4. Descriptive and summary statistics for inputs congestion.

Input factor	Number of outlets with slack	Mean	Total slack (percent of total inputs)
Employees	5	9	1.8
Operating expenses (NT$ thousand)	9	7829	6.43
Cost of products (NT$ thousand)	6	36828	1.14
Area of outlet (square meters)	8	5248	35.06

scale for military outlets. The result in Table 3 (with an average scale efficiency of 0.952) suggests that a military outlet can save input by 4.8% by operating at the constant returns to scale technology. Approximately 35.5% of the military outlets are constant returns to scale (CRS). There are nearly 32.3% of the military outlets that operate at decreasing returns to scale (DRS). These military outlets could be reduced in size. On the other hand, about one-third of the outlets operate at increasing returns to scale (IRS). The military outlets in the latter group could be consolidated with other small units to achieve the optimal size.

To improve the resource utilization of the military outlets and reduce the number of military outlets, this study proposes a possible reorganization alternative to GWSM. The reorganization alternative should consider three criteria including region, returns to scale, and pure technical efficiency. For example, the Beibei is relatively pure technically efficient, but in the stage of increasing returns to scale, suggesting that Beibei has caught managerial know-how to operate an outlet efficiently, however, it has not yet achieved their optimal scale or still lack scale efficiency. The Beijhong is relatively pure technically inefficient, but in the stage of decreasing returns to scale, suggesting that Beijhong does not perform efficiently and it needs to become smaller to attain scale efficiency. So Beibei and Beijhong are combined to improve the pure technical efficiency and achieve economies of scale. Beisi, Beidong, and Beinan are in the stage of decreasing returns to scale, suggesting that they need to become smaller to attain scale efficiency. Therefore, Beisi, Beidong, and Beinan are combined to avoid an over-utilized resource and achieve economies of scale.

To summarize the above results, further mergers and acquisition among military outlets should be considered so as to achieve economies of scale. Summary of the reorganization alternative is presented in Table 3. Although GWSM has not reorganized the 31 military outlets, this study proposes the direction for reorganizing the military outlets and provides feasible alternative.

Input congestion analysis

Input congestion, a concept from the areas of transportation and agriculture, refers to the situation that, when holding the usage of other inputs constant, reductions in the usage of a proper subset of inputs may generate an increase in one or more outputs. After projecting an inefficient unit onto the frontier by a proportional (radial) input decrease, the input congestion measure is calculated in order to provide information about the effect on output improvement through further individual input reduction. In this section, this study uses a slack-based approach following Cooper et al. (2001b) to capture input congestion and identify its sources and amounts.

Table 4 presents a summary of inputs congestion after radial technical inefficiency is removed. Holding the level of outlets operation constant, on average, five outlets could reduce the number of employees by 9 persons; 9 outlets could reduce their use of total operating expense by 7828,889 NT$; 6 outlets could reduce the cost of products by 36828,079 NT$; and 8 outlets could reduce area of outlet by 5,248 (square meter). Their excessive use of inputs accounts for about 1.8% to 35.06% of total inputs. Almost 26 % of outlets underutilize the area of outlet. The result denotes that inefficient outlets are lack of the ability to integrate their resources, especially in the area of outlet. The result suggests that downsizing the area of these inefficient outlets is recommended.

Benchmark analysis

Multiple efficient units are a characteristic embedded in the principle of DEA. Ever since the pioneering work of Andersen and Petersen (1993), many efforts have been made to discriminate between efficient units. Extensive reviews on these efforts can be found in Angulo-Meza and Lins (2002) and Adler et al. (2002). Adler et al. (2002) compared six ranking methods, while Angulo-Meza and Lins (2002), on the other hand, classified the related methodologies into two types: those that incorporate additional information such as weight restrictions or a preference structure into the model and those that do not use or minimize such exogenous information.

In the current study the reference-share measure defines a ranking measure by using the factor-specific measure and VRS model. This study can now identify the inputs/outputs that are most important or distinguish those outlets which can be treated as benchmarks. In this section, ranking list of the performance model for all

Table 5. Reference-share measure for efficient military outlets.

Outlet	Input factors								Output factors				Average
	Employees (%)		Operating expenses (%)		Cost of products (%)		Area of outlet (%)		Customers (%)		Net profit (%)		Rank
Hsinchu	51.44	(1)	54.41	(1)	11.05	(4)	7.67	(3)	3.65	(5)	45.91	(1)	2.5
Sinying	2.30	(7)	30.40	(2)	31.64	(1)	66.62	**(1)**	18.87	(3)	29.82	(2)	2.6
Taichung	0.00	(12.5)	2.94	(4)	5.31	(6)	11.59	(2)	12.49	(4)	0.00	(11)	6.58
Beisi	1.74	(8)	2.30	(5)	5.61	(5)	2.20	(6)	2.69	(7)	0.00	(11)	7
Panchiao	5.93	(5)	0.00	(12)	0.00	(12)	6.94	(4)	3.57	(6)	4.89	(4)	7.17
Fongshan	0.00	(12.5)	2.16	(6)	14.64	(3)	0.00	(12.5)	22.78	(2)	0.00	(11)	7.83
Zuoying	4.82	(6)	0.00	(12)	0.13	(7)	0.00	(12.5)	0.54	(9)	3.89	(5)	8.5
Hualian	0.00	(12.5)	0.00	(12)	27.62	(2)	0.00	(12.5)	34.12	(1)	0.00	(11)	8.5
Keelung	0.00	(12.5)	7.40	(3)	0.00	(12)	0.00	(12.5)	0.47	(10)	15.49	(3)	8.83
Meilun	12.18	(3)	0.00	(12)	0.00	(12)	3.59	(5)	0.00	(13.5)	0.00	(11)	9.42
Pingtung	12.39	(2)	0.39	(7)	0.00	(12)	0.00	(12.5)	0.00	(13.5)	0.00	(11)	9.6
Sioulang	0.00	(12.5)	0.00	(12)	0.00	(12)	0.58	(8)	0.83	(8)	0.00	(11)	10.58
Guangfu	9.19	(4)	0.00	(12)	0.00	(12)	0.00	(12.5)	0.00	(13.5)	0.00	(11)	10.8
Dailiao	0.00	(12.5)	0.00	(12)	4.00	(6)	0.00	(12.5)	0.00	(13.5)	0.00	(11)	11.17
Kaohsiung	0.00	(12.5)	0.00	(12)	0.00	(12)	0.81	(7)	0.00	(13.5)	0.00	(11)	11.33
Beibei	0.00	(12.5)	0.00	(12)	0.00	(12)	0.00	(12.5)	0.00	(13.5)	0.00	(11)	12.25

Note: Ranks are given in parenthesis, and ties are assigned mid-rank.

those efficient outlets is given. In Table 5, the reference-share measures are reported for the performance model, with the ranking in parenthesis and ordered by the average ranking of the efficient outlets. There are 16 pure technical efficient in the performance model. Of the total 96 reference-share measures, 18 reference-share measures are greater than 10%.

Hsinchu, which is a particular technically efficient outlet, has the biggest reference-share in employees, operating expenses, and net profit. Hsinchu is therefore an important benchmark as the above factors are concerned, while for other input/output factors Hsinchu is still efficient but not in the leading place. As the cost of products and area of outlet are concerned, Sinying plays a leading role in terms of the cost of products and the area of outlet given the current levels of other inputs/outputs. Hualian plays a leading role in terms of number of customers given the current levels of other inputs/outputs. Those outlets which have a reference-share measure of zero are self-evaluators in Table 5. Even if these outlets are efficient, they are revealed as being too different in the input/output space either to be a reference to other units or to be referenced.

Although the reference-share measures give a different ranking list according to the input/output factors which they are measured by, the result of this analysis is robust. The ranking lists all are very similar, with ranking correlation coefficients ranging from 0.664 to 0.774 at the 5% level of significance. Therefore, the ranking list shows a clear and stable indication of the outlets that may be pointed out as benchmarks referred by others.

Conclusion

Although the military organization's efficiency has been widely discussed in previous literature and the DEA technique is frequently used, there are still some important points not touched upon. From the perspective of a research topic, few research studies about the military organizations have been conducted in emerging countries (such as Taiwan) while applications of DEA for the evaluation of outlets have been very limited in the military issues. This study provides a benchmark analysis based on DEA to investigate Taiwan and assist the MND in improving the military operational management with insights into resource allocation and competitive advantage. From the perspective of research methods, the problem that many units are easily calculated as being efficient in DEA is usually ignored. The problem of input congestion measure thus far is less discussed in the literature of military organization. This paper therefore aims to explore the efficiency, the input congestion, and the benchmarks of the military outlets from a more complete viewpoint.

The findings can briefly be concluded as the follows. Firstly, the overall technical inefficiencies of military outlets are primarily due to the pure technical inefficiencies, not the scale inefficiencies. This suggests that managers should focus firstly on removing the pure technical inefficiency, and then outlets can subject to improve their scale efficiencies. Secondly, according to three criteria including region, returns to scale, and pure technical efficiency, this study proposes the direction for reorganizing the military outlets and provides feasible alternative. Thirdly, the congestion analysis denotes that inefficient outlets are lack of the ability to integrate their resources, especially in the area of military outlet. The result suggests that downsizing the area of these inefficient military outlets is recommended. Fourthly, the reference-share measures give a different ranking list according to the input/output factors which they are measured by, the result of this analysis is robust. The ranking list shows a clear and stable indication of the outlets that may be pointed out as benchmarks referred by others.

Our findings serve as a guideline in the defense economics for coping with issues relating to a military's operation performance. Further investigation can examine the performance over time by using the Malmquist productivity change index techniques. Such an approach allows for a dynamic view of the multidimensional performance of military outlets. It is also hoped that the models and methods implemented in this study can bring about other related research to a variety of industries.

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