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RESEARCH ARTICLE

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Major weapons procurement: An efficiency-based approach for the selection of fighter jets

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This study applies the epsilon-based measure method in data envelopment analysis (DEA) to evaluate processes in procuring fighter jets (FJs), which are indicative of the technology and capability of major weapons. Moreover, multidimensional scaling analysis and sensitivity analysis were included to assess the selection of FJs. The DEA analysis indicates that the overall efficiency of the sample of 26 FJs was 0.824 on average. Besides, procurers rely on price and capability to decide which FJ models to purchase. Overall, the evaluation results can be provided to procurement decision makers even in selecting other types of major weapon in a cost-effective manner.

1 | INTRODUCTION

Procurers typically manage a variety of problems when purchasing major weapons, and they must consider a wide range of aspects when acquiring essential military equipment (Chen, 1996). Subsequently, when countries form armies in preparation for war, appropriate weapons are required to successfully complete military missions (Tung, Huang, Keh, & Wai, 2009). Fighter jets (FJs) are indicative of the technology and capability of major weapons. According to statistics released by Jane's Information Group, the United States currently produces the largest number of FJs, followed by China, Russia, Germany, and Japan. On the basis of various classifications,[1] countries procure different FJ models to meet specific tactical objectives and current demands. Procurers are required to consider a variety of factors when purchasing FJs. Therefore, they rely on a variety of metrics to facilitate their evaluation and selection of major weapons. The formulation of these metrics is a serious challenge for procurers.

The wide range of complex factors involved in the selection of major weapons may be confusing to decision makers, forcing them to act under conditions of uncertainty. The major weapons systems of a country pertain to high-technology products. A series of capital- and technology-intensive design and production processes are required to manufacture such systems (Lee & Yoon, 2015). Major weapons are extremely expensive to produce and purchase. Therefore, they should be cautiously selected using a favorable evaluation method to achieve maximum benefits and to facilitate the formulation of an ideal procurement plan (Dožić & Kalić, 2014).

Organizations rely on numerous metrics to evaluate their operating performance (Chakravarthy, 1986). Similarly, a wide range of evaluation metrics is also required during the procurement of FJs. The data envelopment analysis (DEA) method is often adopted to evaluate decision-making units (DMUs) with multiple inputs and multiple outputs to create multifactor performance measurement models. In addition, models derived through this method are generally coupled with linear programming to determine production frontiers, which serve as the basis for measuring performance.

Methodologically, most common DEA models can be classified into radial and nonradial models. The radial models, represented by Charnes, Cooper, and Rhodes (1978), are built on Debreu–Farrell measure (Debreu, 1951; Farrell, 1957a) and estimate the technical efficiency based on efficiency score in the objective function. However, the nonradial models, represented by Tone (2001),[2] have roots in Pareto–Koopmans measure (Koopmans, 1951) and estimate the technical efficiency based on slacks.

[1]FJs can be classified into jet and piston fighters in terms of production; supersonic and hypersonic fighters in terms of speed; short-range, mid-range, and long-range fighters in terms of flight distance; and air-to-air and air-to-ground fighters in terms of attack.

[2]Additive DEA models introduced by Charnes, Cooper, Golany, Seiford, and Stutz (1985) also measure nonradial inefficiency but are unable to report the efficiency unit in a scalar value (Avkiran & Rowlands, 2008) or do not gauge the depth of inefficiency (Tone, 2001); hence, the SBM is the successor of additive models.

Whereas the former technique deals with proportionate change in input and output quantities, the latter technique relaxes such assumption. For example, in an input-oriented case, a radial model proportionally reduces input quantities; meaning for a DMU with two inputs, a radial model maximizes the reduction rate for the two inputs with the same proportion. However, a nonradial model aims at maximizing the reduction rate that may ignore the proportional changes in input quantities. However, these techniques are not appropriate for problems involving radial and nonradial inputs and outputs concurrently.

The decision making on the procurement of various FJ models would be a great case that might require both radial and nonradial features simultaneously. For example, Tone and Tsutsui (2010) illustrated that DMUs that are standardized under a single administrative system, such as municipal hospitals, tend to have high-affinity values (high correlation), large eigenvalue, and very small epsilon, translating to the fact that there exist proportional changes, and thus, a radial model should suffice to obtain valid efficiency scores. On the other hand, DMUs with higher dispersion, such as museums, are not standardized and possess low-affinity values (low correlation), small eigenvalue, and large epsilon, meaning that the factors behave as of a nonradial model and change nonproportionally. However, DMUs having input factors that are positively correlated but considerably diversified require both proportional and nonproportional model simultaneously. FJs are technologically complicated products manufactured through the years with different learning curves (Bongers & Torres, 2014). As a result, input and output factors vary to some extent while being positively correlated. Thus, the epsilon-based measure (EBM) DEA method, proposed by Tone and Tsutsui (2010), which can produce evaluation outcomes that could meet procurement demands (adjusting both inputs and outputs is important), was adopted in the present study. The results of the evaluation mechanism can be provided to future procurers as a guideline for the procurement of FJs and to future researchers as a reference, thereby facilitating the successful procurement of weapons.

Taken together, the present study focused on the following research objectives. First, the multi-input and multioutput DEA method was incorporated into the selection of FJs to establish an evaluation mechanism that facilitated the decision-making processes of procurement. Second, multidimensional scaling (MDS) analysis and sensitivity analysis were combined to determine the strengths and weaknesses of FJs.

This study makes at least three contributions. First, the adoption of the EBM DEA method overcomes the flaws of conventional DEA models and satisfy the requirement for simultaneous input and output adjustment, thereby enhancing evaluation accuracy and practicality and resolving challenging and complex problems in the selection of major weapons. Second, the results can serve as a reference for R&D activities. Various dimensions are involved in analyzing FJs, and each FJ index has strengths and weaknesses. Third, the hybrid MDS-sensitivity analysis method adopted in the present study indicated the strengths and weaknesses of various FJ indices, thereby maximizing selection with the limited resources available. With that, the present study was able to identify the ideal FJ selection method. Overall, although the evaluation methods currently available entail different processes, the present study identified an evaluation method that accounted for the multiattribute indices of FJs, and this method can be provided to decision makers for evaluating and procuring FJs.

The rest of the present study has been organized into four parts. The following part reviews relevant prior studies. The third part deals with the research design of the present study, focusing on the input/output mix, prerequisite of DEA, and the methodology used. The fourth part presents the results and a discussion of the results through the hybrid MDS-sensitivity analysis method. Finally, the fifth part concludes the present study with some implications.

2 | LITERATURE REVIEW

Procuring FJs is an important issue, especially when FJ selections are bound by limited military procurement budget. Besides, technological research and development (R&D) is constantly conducted to enhance the capabilities of FJs, rendering them irreplaceable in terms of attack and defense capabilities (Bongers & Torres, 2014). Military aircraft require the most advanced aeronautical engineering technologies and technical models available, as well as various high-technology machine and electronic systems and materials (Hobday, 2000). Therefore, using the right selection method to get the best weapon becomes an important consideration.

A broad range of methods is currently available for selecting major weapons. Chen (1996) presented a new approach to evaluate the performance of weapon systems using simplified fuzzy arithmetic operations to make the process faster as compared with Mon, Cheng, and Lin (1994) who used complicated entropy weight calculations. Cheng and Lin (2002) proposed a model to evaluate the best main battle tank using fuzzy decision theory. Fu (2007) adopted a fuzzy decision analysis method to investigate military production plants, advising them to center their management and operations on production and service operation funds to attain their annual governance plans and expected revenue goals. Cheng and Mon (1994) proposed an algorithm to evaluate weapon system using analytical hierarchy process (AHP), developed by Saaty (1980), based on fuzzy scales. The AHP approach is a very practical multiple criteria decision-making (MCDM) tool and has been substantially utilized by practitioners in read case scenarios. In this approach, a decision problem is evaluated by creating a reciprocal matrix built on pairwise comparison between alternatives with regard to the attributes. As a result, the alternatives will be ranked and provide the decision maker with the weight scores that are real numbers. Taking a step further, Dağdeviren, Yavuz, and Kılınç (2009) recommended a model to analyze the structure and find the weights of each criterion of weapon selection problem using AHP and then applied fuzzy TOPSIS (the technique for order performance by similarity to ideal solution), developed by Hwang and Yoon (1981), to rank the weapons. The authors claimed that their model has improved the efficiency of the decision-making process in weapon selection by eliminating many procedures involved in AHP-fuzzy AHP solution.

Although the application of strength, weakness, opportunity, and threat (SWOT) analysis in a single framework does not render a noteworthy outcome in a decision-making process, there are a few studies who combined such methodology with other advanced techniques in evaluating decision alternative, particularly in weapon selection field

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of research. For example, Ahlat (2015) combined SWOT and AHP in military decision making. Yogi, Rizal, Ahmadi, and Suharyo (2017) conducted a feasibility analysis of the naval base as part of an integrated fleet weapon system using SWOT and AHP.

As pointed by Cheng (1999), the performance evaluation of weapon systems are MCDM problems because they are complex and require multifactor analysis. The above-reviewed studies utilized various techniques to evaluate military and weapon selection decision-making. In fact, there is no better or worse approach to follow; however, the choice of a technique depends on the objective of a researcher and whether a particular technique is suitable for the decision-making problem under investigation. As such, DEA provides an opportunity to compare DMUs based on the efficiency scores in a multifactor setting, transforming inputs to outputs. Hence, DEA resembles MCDM and is a valuable approach to be used alternatively or as a supplement to MCDM (Nakayama, Arakawa, & Yun, 2002; Opricovic & Tzeng, 2003; Yılmaz & Yurdusev, 2011).

Although the application of DEA cannot be traced in major weapon selection domain, Inman, Anderson, and Harmon (2006), reexamining the data from Martino (1993) for the period of 1960–1982 pointed that technology forecasting using DEA (TFDEA) is a powerful approach for predicting complex technological trends and first flight of FJs. Sun (2002a) adopted DEA and proposed an evaluation method for 21 lathe machines, which could be used by military buyers. The results indicated that the proposed evaluation method assisted procurers in purchasing the most favorable items. In another military-related study but not in major weapon selection, Sun (2004) applied DEA to evaluate the efficiency of joint maintenance shops (JMS) in the Taiwanese Army; the DEA findings, particularly the suggestions for improvement, help most inefficient joint maintenance shops become relatively more efficient. Besides, Bowlin (2004) examined the financial stability of the Civil Reserve Air Fleet of the United States Department of Defense by using DEA. Yang, Wang, and Lu (2007) also utilized DEA to evaluate the performance of military retail stores for Taiwan's General Welfare Service Ministry. The above review of literature shows that there is a dearth of research on major weapon selection using traditional DEA technique, let alone advanced suitable models in achieving a more accurate outcome. Table 1 summarizes the strengths, limitations, and applications of the aforementioned evaluation methods.

In the present study, the multi-input and multioutput DEA method was thus adopted to measure the standards for selecting FJs when limited resources are available. Specifically, the EBM DEA method proposed by Tone and Tsutsui (2010) was employed to overcome the flaws of conventional DEA models and obtain evaluation results suitable for procurement purposes.

3 | RESEARCH DESIGN

3.1 | Estimating efficiency by epsilon based efficiency

Several studies used the DEA method to measure performance because of its advantages. DEA can handle many inputs and outputs and results at the same time while comparing them with each other. DEA has some limitations; hence, this paper used the EBM method (Tone & Tsutsui, 2010). The EBM method is both radial and nonradial model in a unified framework. The EBM method has several advantages. First, it is objective when weighing different DMUs. Second, it enables every DMU to follow standards and make good decisions to achieve higher efficiency. Finally, it can determine whether the DMU should increase or decrease input or output. It maintains objectivity when measuring performance efficiency. The EBM computation process is described as follows.

Step 1:

This study used the variable-returns-to-scale (VRS)-nonoriented slacks-based measure (SBM) model to find slacks and project DMUs to efficient frontiers, particularly the unique efficient DMU. Throughout this paper, this study deals with n DMUs ($j = 1, \ldots, n$) having m inputs($i = 1, \ldots, m$) and s outputs($r = 1, \ldots, s$). The input and output matrices are denoted by $\mathbf{X} = [x_{ij}] \in R^{m \times n}$ and $\mathbf{Y} = [y_{rj}] \in R^{s \times n}$, respectively. Assume $\mathbf{X} > 0$ and $\mathbf{Y} > 0$.

VRS-nonoriented SBM model is as follows:

$$\begin{aligned}
&Min \left(1-\frac{1}{m}\sum\nolimits_{i=1}^{m}\frac{s_i^-}{x_{io}}\right) \Big/ \left(1+\frac{1}{s}\sum\nolimits_{r=1}^{s}\frac{s_r^+}{y_{ro}}\right)\\
&Subject\ to\\
&x_{io}=\sum\nolimits_{j=1}^{n}x_{ij}\lambda_j+s_i^- \quad i=1,\ldots,m,\\
&y_{ro}=\sum\nolimits_{j=1}^{n}y_{rj}\lambda_j-s_r^+ \quad r=1,\ldots,s,\\
&\sum\nolimits_{j=1}^{n}\lambda_j=1\\
&\lambda_j \geq 0(\forall j), s_i^- \geq 0(\forall i), s_r^+ \geq 0(\forall r).
\end{aligned} \tag{1}$$

The optimal slacks s^{-*} and s^{+*} are utilized to define the projected input and output for target DMU by the following:

$$\begin{aligned}
\bar{x}_{io} &= x_{io} - s_i^{-*}, \quad i = 1,\ldots,m,\\
\bar{y}_{ro} &= y_{ro} + s_r^{+*}, \quad r = 1,\ldots,s.
\end{aligned} \tag{2}$$

Although the SBM model may produce different projections, they are on the efficient frontiers of the production possibility set. Thus, n VRS-efficient DMUs can be denoted by the following:

$$\begin{bmatrix}\bar{\mathbf{X}}\\ \bar{\mathbf{Y}}\end{bmatrix} = \begin{bmatrix}\bar{x}_{11} & \cdots & \bar{x}_{1n}\\ & \cdots & \\ \bar{x}_{m1} & \cdots & \bar{x}_{mn}\\ \bar{y}_{11} & \cdots & \bar{y}_{1n}\\ & \cdots & \\ \bar{y}_{s1} & \cdots & \bar{y}_{sn}\end{bmatrix} = \begin{bmatrix}\bar{\mathbf{x}}_{\mathbf{1}}\\ \cdots\\ \bar{\mathbf{x}}_{\mathbf{m}}\\ \bar{\mathbf{y}}_{\mathbf{1}}\\ \cdots\\ \bar{\mathbf{y}}_{\mathbf{s}}\end{bmatrix}. \tag{3}$$

All constant-returns-to-scale-efficient DMUs are included in this set along with VRS-efficient DMUs.

Step 2:

We calculated the "diversity index, $D(\bar{\mathbf{x}}_{\mathbf{t}}, \bar{\mathbf{x}}_{\mathbf{h}})$" of any two input vectors $\bar{\mathbf{x}}_{\mathbf{t}} \in R^n$ and $\bar{\mathbf{x}}_{\mathbf{h}} \in R^n$ as follows:

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TABLE 1 Performance evaluation methods

Evaluation method	Strength	Weakness	Applicability
Fuzzy decision analysis	1. Handles evaluation and measurement problems relating to message ambiguity2. Simplifies complex structures and handles nonlinear and incomplete models	1. Unable to clearly provide suggestions for improvement2. Unable to process multi-input and multioutput problems3. Easily influenced by the subjectivity of the decision maker	Project selection decisions
Analytic hierarchy process	1. Presents qualitative data in a quantitative format 2. Presents data in an organized structure and simplifies evaluation processes	1. Unable to clearly provide improvement suggestions2. Unable to process multi-input and multioutput problems3. Easily influenced by the subjectivity of the decision maker	Project selection decisions
SWOT (strength, weakness, opportunity, threat)	1. Handles internal organization conditions to highlight strengths and weaknesses2. Handles external environmental conditions to highlight opportunities and threats	1. Unable to clearly provide improvement suggestions 2. Unable to process multi-input and multioutput problems3. Easily influenced by the subjectivity of the decision maker	Project selection decisions
Data envelopment analysis	1. Handles multi-input and multioutput problems2. Assumptions are not required3. Provides clear improvement suggestions4. Provides DMU returns to scale5. Production function pattern designation is not required	1. Reliability increases concurrently with the homogeneity of the DMUs2. Highly sensitive to data and easily influenced by erroneous extremes	Multi-input and multioutput project decision problems

$$
\begin{aligned}
&F_j^{t,h} = \ln\left(\bar{x}_{tj}/\bar{x}_{hj}\right)\ (t,h=1,\dots,m;j=1,\dots,n),\\
&\bar{F}^{t,h} = \frac{1}{n}\sum\nolimits_{j=1}^{n} F_j^{t,h},\\
&D(\bar{x}_t,\bar{x}_h) = \left(\sum\nolimits_{j=1}^{n}\left|F_j^{t,h}-\bar{F}^{t,h}\right|\right)/n\left(Max\left[F_j^{t,h}\right]\text{-}Min\left[F_j^{t,h}\right]\right).
\end{aligned}
\tag{4}
$$

The "diversity index, $D(\bar{\mathbf{y}}_\mathbf{t},\bar{\mathbf{y}}_\mathbf{h})$" of any two output vectors is calculated by using the same process.

Step 3:

The "affinity matrix, $AF(t,h)$" is calculated by formula (5).

In the nonoriented case, we calculate the input affinity matrix $AF(t,h) \in R^{m\times m}$with the elements.

$$AF(t,h) = 1-2D(\bar{\mathbf{x}}_\mathbf{t},\bar{\mathbf{x}}_\mathbf{h})\ (t,h=1,\dots,m), \tag{5}$$

All elements of the matrix $AF(t,h)$ satisfy the bounds: $1 \geq AF(t,h) \geq 0(\forall(t,h))$. The affinity matrix of any two output vectors is calculated by using the same process.

Step 4:

The largest eigenvalue (ρ_x) and eigenvector (w_x) of the input affinity matrix are calculated.

We define ε_x and w^- in the EBM as follows:

$$
\begin{aligned}
\varepsilon_x &= \frac{m-\rho_x}{m-1}\ \ (if\ m>1)\\
&= 0\quad (if\ m=1)\\
w^- &= \frac{w_x}{\sum_{i=1}^{m} w_{xi}}.
\end{aligned}
\tag{6}
$$

The ε_x and w^- satisfy the $0 \leq \varepsilon_x \leq 1$ and $ew^- = 1$ in the input matrix. The output matrix of the ε_y and w^+ is calculated by using the same process.

Step 5:

Use of $\varepsilon_x(\varepsilon_y)$ in the VRS-nonoriented EBM of efficiency. This fractional program can be solved by using the Charnes–Cooper transformation (Charnes and Cooper, 1962).

$$
\begin{aligned}
&r^* = Min\left(\theta-\varepsilon_x\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}\right)\Big/\left(\eta+\varepsilon_y\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}}\right)\\
&Subject\ to\\
&\theta x_{io}-\sum_{j=1}^{n} x_{ij}\lambda_j - s_i^- = 0\ i=1,\dots,m,\\
&\eta y_{ro}-\sum_{j=1}^{n} y_{rj}\lambda_j + s_r^+ = 0\ r=1,\dots,s,\\
&\sum_{j=1}^{n}\lambda_j = 1,\\
&\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0,
\end{aligned}
\tag{7}
$$

where $\varepsilon_x(\varepsilon_y)$ is a key parameter that combines the radial $\theta(\eta)$ from inputorientedBanker, Charnes, and Cooper (1984) - BCC model (output-oriented BCC model) and the nonradial slacks term. Parameters $\varepsilon_x(\varepsilon_y)$ must be supplied prior to the efficiency measurements.

3.2 | Selection of inputs and outputs

As discussed earlier, the EBM DEA method proposed by Tone and Tsutsui (2010) was employed in the present study to evaluate FJ models. The evaluation results can be provided to relevant decision makers as a reference for procuring FJs or for improving R&D. As mentioned in Section 2, the application of DEA in military decision making is sparse and possibly none in FJ selection. In fact, Yu (2016) highlighted that aircraft do not have clearly quantifiable and definitive inputs and outputs; the selection of the variables depends on the context of the study and the data availability. Hence, to select the inputs and outputs required for DEA analysis, this study revisited the origin of choosing the right variables. Cooper, Seiford, and Tone (2006) pointed that efficiency evaluation relates to resources used and benefits utilized when production approach is assumed. An efficiency analysis using DEA, in a conventional form, a more efficient unit is the one producing more outputs relative to consuming fewer inputs within which the conversion of inputs to outputs defines the general organizational activities. Similarly, in the context of decision making for FJ procurers, inputs are the resources and outputs are the benefits that involve in the decision to select an FJ, that is, the conversion.

To this end, the basic capabilities of FJs were categorized into five input and output analysis variables. Input variables comprised FJ price (P) and maximum takeoff weight (MTW). P referred to the cost of manufacturing FJs. For FJ procurers, the price of an aircraft is basically the initial resource quantity. In the closely relevant studies in the aircraft efficiency domain, MTW of the fleet is used as the flight equipment input (e.g.Distexhe & Perelman, 1994, Pereira, de Carvalho Chaves, & Mello, 2013). Also, Defersha, Salam, and Bhuiyan (2012) utilized MTW as the main cost driver of main landing gear when estimating cost efficiency using DEA. MTW affected flight speed and thrust. Heavy FJs require increased thrust and speed to maintain flight balance; thus, they require more energy, and modifications for such jets should be minimal.

Output variables comprised total thrust (TT), maximum flight speed (MFS), and combat radius (CR). These outputs are particular indicators benefits for FJs, which might be different from other aircraft. In a study of aero-engine performance analysis, Zhu, Liang, and Zhan (2017) highlighted that military aircraft need fast speed, wide CR, and huge thrust-weight ratio, among others, for better performance outcomes (Foster, 2018). TT refers to the lift and flight power of the FJs; MFS refers to the horizontal speed of FJs in midair; CR refers to the maximum combat range of FJs between the takeoff and combat zone. The latter output, CR, is essentially an outcome in the process of conversion in the production efficiency because it delineates the tolerance of an FJ for air refueling capacity. Collectively, the three output variables encompassed the flight, technology, and combat range of FJs. Figure 1 illustrates that the research framework is illustrated, and Table 2 describes the definitions of the input and output variables.

3.3 | Preliminary requirements of DEA

In applying the EBM method, the present study checks that the following basic DEA requirements were fully met to ensure the effectiveness of the epsilon DEA method.

TABLE 2 Definitions of inputs and outputs

Variable	Definition
Inputs	
FJ price (P)Maximum takeoff weight (MTW)	The cost of manufacturing FJs.The maximum weight that is more than gravity an FJ is allowed to attempt during a takeoff.
Outputs	
Total thrust (TT)	The lift and flight power of the FJs.
Maximum flight speed (MFS)	The horizontal speed of FJs in midair.
Combat radius (CR)	The maximum combat range of FJs between the takeoff and combat zone.

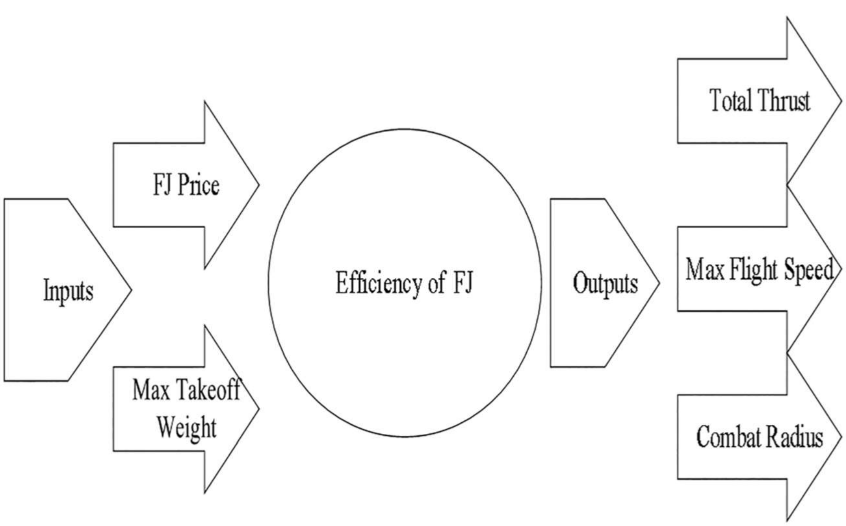

FIGURE 1 The research framework

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3.3.1 | Homogeneity of the DMUs

Farrell (1957a) indicated that DMUs with homogeneous characteristics produce significant evaluation outcomes in DEA. However, this limitation was broadened in recent years. The DMUs in the present study were focused on a common objective (FJ model selection); hence, they were homogeneous.

3.3.2 | Minimum number of DMUs

The input and output variables were selected in accordance with the FJs introduced in *Jane's World Aircraft Recognition Handbook* published in 2003. A total of 26 FJ models presented in this book feature accessible and comprehensive data; hence, they were selected as the DMUs of this study, and other jet models mentioned in the handbook were excluded from this study. Moreover, Golany and Roll (1989), Cooper et al. (2006), and Dyson et al. (2001) suggested that the appropriate number of DMUs selected for DEA should be at least double the number of input and output variables. Therefore, the 26 FJ models selected in the present study to serve as the DMUs created a stable and reliable research framework. The descriptive statistics of the input and output variables are presented in Table 3.

3.3.3 | Positive correlation between input and output variables

Golany and Roll (1989) adopted correlation analysis to verify the correlations between input and output variables. The researchers found that an increase in input produced a proportionate amount of output. In the present study, a Spearman correlation analysis was adopted to determine the correlation between the input and output variables. The untabulated pairwise correlation coefficient values ranged between 0.415 and 0.674, suggesting that the variables achieved positive correlations. These values confirmed that the variables met the requirements of DEA and that the input and output variables could be incorporated into the performance measurement model.

3.3.4 | Importance indicators

The directions of input and output relationships were examined to verify the importance and meaning of the input and output variables (Sun, 2002b). Lewin, Morey, and Cook (1982) indicated that logistic regression was more effective than linear regression because the returns to scale could be increased or decreased. Moreover, the estimated coefficients of log-log regression models can be interpreted flexibly, meaning that the percentage change in an output is for each 1% change in an input. This argument reaffirms the adequacy of the variables selected in the present study. The regression analysis results for the input and output variables are displayed in Table 4. The explanatory power for TT, MFS, and CR were 51.6%, 22.4%, and 28.7%, respectively, suggesting that an increase in input actuated a proportionate increase in output and that the input and output variables performed exceptionally well. TT significantly influenced P and MTW, MFS significantly influenced MTW, and CR significantly influenced MTW. In summary, the input and output variables selected in the present study were closely associated with one another. Therefore, these variables served as the "importance indicators."

4 | EMPIRICAL RESULTS

4.1 | Efficiency Analysis for the FJs

Table 5 shows the diversity matrix, which was estimated via Equation (4), whereas Table 6 indicates the affinity matrix, which was gauged through Equation (7). Table 7 reports the efficiency scores achieved by the 26 FJs. The mean efficiency of 82.4% in Table 7 suggested that 17.6% of inputs could be saved provided that an FJ manufacturer is able to operate at diminishing cost or increasing returns to scale. It is noteworthy that the efficiency score obtained from the EBM model not only reflects the scale of production but also

TABLE 4 Regression analysis of the relationship between inputs and outputs

	Outputs		
Inputs	TT	MFS	CR
Constant	26.906*	1.039***	353.611**
P	0.003**	3.483	0.000
MTW	0.002**	1.733*	0.026*
R^2	0.516	0.224	0.287
1.1.1.1.1. *F*	14.309	4.616	6.043

*Significance level at 10%.
**Significance level at 5%.
***Significance level at 1%.

TABLE 3 Descriptive statistics of inputs and outputs

Variable	Unit	Mean	*SD*	Q1	Q3
P	U	4,957.846	4,534.678	18,800.000	400.000
MTW	KG	19,238.920	10,199.970	38,000.000	1,650.000
TT	KN	89.641	46.625	191.000	16.370
MFS	M	1.545	0.541	2.500	0.770
CR	KM	854.308	452.584	1,700.000	100.000

Abbreviations: KG, kilogram; KM, kilometer; KN, 1,000 newton; M, Mach; U, USD million.

TABLE 5 Diversity matrix

Variable	P	MTW
P	0	0.125
MTW	0.125	0

TABLE 6 Affinity matrix

Variable	P	MTW
P	1	0.751
MTW	0.751	1

TABLE 7 Efficiency of the 26 FJs

FJ	Efficiency	FJ	Efficiency
FC-1	1.000	T-50	0.860
FTC-2000	1.000	AV-8	0.704
K-8J	1.000	Su-25	0.344
L-159	1.000	Su-27	1.000
M2000-5	0.863	Su-30	0.837
Rafale	0.482	Su-35	1.000
TD-1	1.000	Yak-130	0.446
AMX	0.464	JAS-39	1.000
IDF	1.000	F-15	1.000
Mako	0.789	F-18	0.332
Typhoon	0.841	F-22	1.000
T-4	0.466	F-35	1.000
F-2	1.000	F-16	1.000
Overall mean	0.824		

represents the manufacturer's efficiency in terms of input/output transformation. In summary, FC-1, FTC-2000, K-8J, L-159, TD-1, IDF, F-2, Su-27, Su-35, JAS-39, F-15, F-22, F-35, and F-16 were identified as the best performing FJs, which can be the references that other FJs can learn. Other FJs such as M2000-5, Typhoon, T-50, and Su-30 that are with efficiency scores of 0.8 or greater still needed to enhance their efficiencies.

To further identify the most efficient FJ, this study also examined the number of times that efficient FJs were the role models for inefficient FJs. Specifically, the frequency of reference for the efficient FJs called the reference set was also scrutinized. Table 8 presents the best possible references in terms of the specifications of FJs. The frequency column of Table 8 reveals the classification of the FJs as either niche FJs (FJs with special focus) or broad FJs (FJs with wide-ranging functions). Whereas broad FJs are normally the references for other FJs, niche FJs are not the reference point for other FJs. In Table 8, the 16 niche FJs are with zero frequency of reference to other FJs and are marked with an asterisk each. Because niche FJs should be facing modest competition, this study consistently found that some expensive FJs such as FC-1, F-22, and F-16 were efficient. However, other expensive FJs were less efficient. Although more expensive FJs were found to be more efficient, this study found that cost and efficiency are correlated at the level of 0.038, which is not significant.

4.2 | Targets of improvements for inefficient FJs

To become efficient, the DEA frontier projection is among one of the numerous ways available. The EBM model produces ideal levels of input/output combinations and thus potential improvements in reducing certain inputs that can contribute to improved efficiency scores for inefficient FJs (Tone & Tsutsui, 2010). Specifically, manufacturers of FJs may refer to the related information in Table 9 to enhance the performance attributes of their FJs. Whereas the "Target" columns suggest the optimal levels of inputs and outputs, the right columns show the amounts of inputs and outputs that an inefficient FJ should be using or producing to become efficient, and the left columns show the possible improvement as a percentage of the current level. An FJ manufacturer may probably need to focus on performance-related factors, although it may not always be possible for the manufacturer to easily modify any specific attributes of an inefficient FJ model due to potential great subsequent costs and practicality.

4.3 | FJ sensitivity analysis and MDS cluster analysis

A sensitivity analysis was performed to reveal the strengths and weaknesses of each FJ model. Each input and output variable was individually excluded from the analysis process to isolate the highly influential sensitive variables. The results displayed in Table 10 showed that removing P, MTW, and TT caused attaining the greatest differences between the original average efficiency score and those without each of P, MTW, and TT, respectively, suggesting that these variables were crucial capacity indicators. Favorable flight stability and aerobatic performance can only be achieved when a balance among the costs, part and component structures, and operating limitations is maintained in the design of FJs.

The efficiency score for F-15 FJs converged with its original efficiency score of 1 after P, MTW, TT, MFS, and CR were individually excluded, suggesting that the capabilities of this particular model were not affected by any of the input and output variables. In other words, the efficiency value for F-15 FJs remained unchanged regardless of which variable was eliminated. These results indicated that the capabilities of this particular model are desirable. The reason for this might be that the F-15 is an American FJ designed specifically for all-weather and high mobility purposes. Its efficiency derives from its low wing load and high thrust-to-weight ratio. The F-15 is able to make tactical maneuvers without decelerating and can safely and effectively engage in the aerial assault. Therefore, the F-15 is the ideal model for procurement to enhance current combat capabilities and is also the ideal learning target for the modification of R&D units. For other FJs,

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TABLE 8 Reference sets for the 26 FJs

FJ	EBM model Reference set				Frequency
FC-1*	FC-1				0
FTC-2000	FTC-2000				1
K-8J	K-8J				5
L-159	L-159				1
M2000-5*	Su-27	JAS-39	F-15		0
Rafale*	IDF	F-2	JAS-39	F-15	0
TD-1	TD-1				4
AMX*	K-8J	TD-1	JAS-39		0
IDF	IDF				3
Mako*	K-8J	TD-1	JAS-39		0
Typhoon*	Su-27	JAS-39	F-15		0
T-4*	K-8J	L-159	IDF	JAS-39	0
F-2	F-2				3
T-50*	F-2	F-15	F-35		0
AV-8*	TD-1	F-2	JAS-39		0
Su-25*	K-8J	L-159	IDF	JAS-39	0
Su-27	Su-27				3
Su-30*	Su-27	JAS-39	F-15		0
Su-35*	Su-35				0
Yak-130*	FTC-2000	K-8J	JAS-39		0
JAS-39	JAS-39				11
F-15	F-15				5
F-18*	TD-1	F-2	JAS-39		0
F-22*	F-22				0
F-35	F-35				1
F-16*	F-16				0

Notes.: An FJ marked with "*" is a niche FJ.

TABLE 9 Target and potential improvement (%)

FJ	Target					Potential Improvement (%)				
	P	MTW	TT	MFS	CR	P	MTW	TT	MFS	CR
M2000-5	4,626.9	15,158.9	110.9	2.2	1,200.0	−15.8	−13.3	16.7	0.0	0.0
Rafale	3,652.5	11,802.7	97.9	2.0	1,100.0	−51.8	−51.8	29.5	0.0	0.0
AMX	1,393.1	6,036.8	49.1	1.1	468.2	−53.5	−53.5	0.0	38.4	26.5
Mako	1,736.7	10,262.4	90.0	1.6	450.1	−21.0	−21.0	0.0	11.6	28.6
Typhoon	4,237.3	20,930.9	102.3	2.0	1,389.0	−50.4	−10.9	13.7	0.0	0.0
T-4	871.9	6,295.1	28.8	0.9	600.0	−53.3	−53.3	75.9	0.0	0.0
T-50	4,169.6	27,224.2	147.0	2.0	1,100.0	−12.2	−26.4	0.0	45.2	0.0
AV-8	2,512.4	9,852.7	96.7	1.7	578.8	−29.6	−29.6	0.0	100.4	246.6
Su-25	1,550.1	6,062.8	44.1	1.1	650.0	−65.5	−65.5	0.0	47.8	0.0
Su-30	3,193.4	29,506.1	123.0	2.3	1,500.0	−29.0	−14.4	0.0	37.3	0.0
Yak-130	669.7	4,594.3	23.3	0.8	427.8	−55.3	−55.3	8.1	0.0	327.8
F-18	3,124.8	7,778.8	94.4	1.8	611.4	−66.7	−66.7	19.2	0.0	13.8

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TABLE 10 Sensitivity analysis

FJ	Original value of efficiency	Delete P	Delete MTW	Delete TT	Delete MFS	Delete CR
RFC-1	1.000	0.132	1.000	1.000	1.000	0.988
FTC-2000	1.000	0.185	0.357	1.000	0.925	1.000
K-8J	1.000	0.381	1.000	1.000	1.000	1.000
L-159	1.000	0.206	0.785	1.000	1.000	0.618
M2000-5	0.863	0.866	0.385	0.863	0.772	0.824
Rafale	0.482	0.363	0.240	0.482	0.426	0.475
TD-1	1.000	0.125	1.000	1.000	1.000	1.000
AMX	0.464	0.127	0.139	0.312	0.464	0.464
IDF	1.000	0.542	0.910	1.000	1.000	0.996
Mako	0.789	0.127	0.207	0.689	0.789	0.789
Typhoon	0.841	0.891	0.312	0.839	0.756	0.450
T-4	0.466	0.122	0.303	0.466	0.451	0.369
F-2	1.000	0.500	1.000	1.000	1.000	1.000
T-50	0.860	0.550	0.878	0.410	0.862	0.732
AV-8	0.704	0.118	0.149	0.287	0.704	0.704
Su-25	0.344	0.094	0.135	0.324	0.344	0.309
Su-27	1.000	1.000	1.000	1.000	1.000	0.261
Su-30	0.837	0.855	0.664	0.753	0.839	0.498
Su-35	1.000	1.000	1.000	1.000	1.000	0.476
Yak-130	0.446	0.160	0.268	0.446	0.425	0.446
JAS-39	1.000	1.000	0.222	1.000	1.000	1.000
F-15	1.000	1.000	1.000	1.000	1.000	1.000
F-18	0.332	0.071	0.080	0.332	0.288	0.332
F-22	1.000	1.000	1.000	0.410	0.554	1.000
F-35	1.000	1.000	1.000	0.327	1.000	1.000
F-16	1.000	1.000	0.342	0.273	1.000	1.000
Average	0.824	0.338	0.375	0.481	0.614	0.720

in particular, the FC-1, removing the P variable attained the greatest difference between the original efficiency value (1–0.132) and the new one without the P variable than did individually removing the remaining input and output variables. These results indicated that price is an important capability indicator that significantly influenced the procurement and modification R&D of this model. The FC-1 project was originally developed in Pakistan. However, a lack of resources forced the Pakistani government to seek overseas financial support, later collaborating with the United States. This ultimately increased the price of the FC-1. Thus, P should be considered during the modification R&D of the FC-1 FJ to improve its efficiency value. Removing the P variable of the IDF also attained a greater difference in terms of efficiency value (1–0.542) than did individually removing the other input and output variables. These results indicated that price is an important capability indicator that strongly influenced the procurement and modification R&D of this model. The IDF is the first self-developed FJ in Taiwan. Initially, Taiwan lacked the necessary technology to develop FJs. It later received technical guidance from the United States and designed its first domestic jet engine, complete with a fast-responding digital control system. U.S. support substantially increased the price of the FJ. Thus, self-development capabilities should be improved to eliminate the need to seek external assistance.

MDS was adopted to examine the characteristics of FJs. MDS involves plotting the similarities and preferences of a specific number of respondents onto a multidimensional space, using the distance between the plotted points to illustrate the content of the data. This method is particularly useful for analyzing large amounts of information, where a schematic representation enables researchers to more thoroughly comprehend the data and understand the correlations among the data. In addition, hierarchy analysis was conducted in the form of a cluster analysis combined with a sensitivity analysis (Punj & Stewart, 1983). Following prior studies (Jain, 2010; Steinley, 2006; Steinley & Brusco, 2011), the number of clusters was determined in advance for useful segmentation solution (Punj & Stewart, 1983), and the FJs were classified into four clusters as shown in Figure 2; MDS results showed that the maximum explanatory power was R^2 = .981, and thus, the cluster solution is stable over time (Punj & Stewart, 1983). The results of the analysis were as follows.

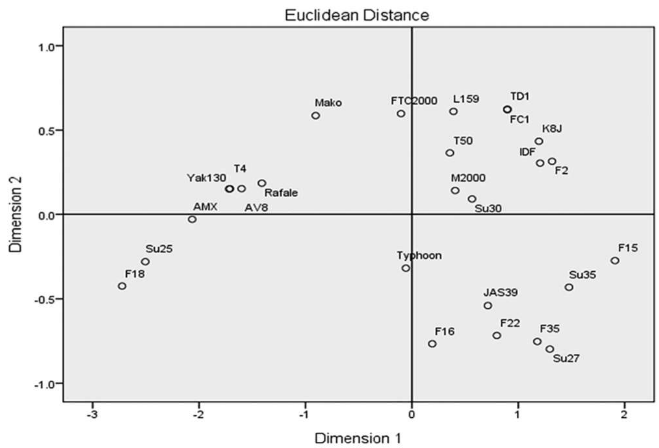

FIGURE 2 Multidimensional Analysis

Cluster 1 comprised seven models, namely, the F-22, F-35, JAS-39, F-16, Su-27, Su-35, and F-15. The models in this cluster were those with high efficiency and high performance, achieving an average efficiency score of 1, which was greater than the overall average efficiency score of 0.824. The characteristics of these models suggest that advanced modern designs and production techniques are required to achieve favorable capabilities. In addition, well-trained pilots must maximize FJ capability. Moreover, these FJs are advantageous for their reasonable prices. Procurers can consider the models in this cluster when acquiring FJs to enhance air combat capabilities and secure national airspace. The F-22 FJ, commonly known as the F-22 Raptor, demonstrated superior stealth (by reducing radar cross-section, rendering it difficult to detect) and attack capabilities, capable of simultaneously tracking 30 airborne and 16 surface targets. This model is also affordable when considering its combat capabilities.

Cluster 2 comprised seven models, namely, the FC-1, TD-1, L-159, IDF, F-2, FTC-2000, and K-8J. The models in this cluster were those with high efficiency and moderate capabilities, achieving an average efficiency score of 1, which was greater than the overall average efficiency score of 0.824. The models were similar to those in Cluster 1 in terms of efficiency. However, these models were designed specifically for the combat needs of their countries of manufacture. The prices of the models in this cluster are also higher than those in Cluster 1 because the resources used to make them were relatively more expensive. Despite these weaknesses, the models in this cluster demonstrated exceptional combat capabilities. They were also designed with ample thrust that allowed them to achieve rapid lift. Therefore, procurers can consider purchasing the models in this cluster to enhance air combat capabilities. The F-2 is the core component of the Japan Air Self-Defense Force. This model can hold four anti-submarine missiles and two air missiles. The F-2 can maintain a favorable flight speed and a CR of approximately 800 km with a full load and a full tank. Although the F-2 demonstrates favorable cruise time and attack capability, the R&D of relevant technologies was costly. Therefore, the main weakness of the F-2 is its high cost.

Cluster 3 comprised four models, namely, the Typhoon, Su-30, M2000-5, and T-50. The models in this cluster were those with moderate efficiency and capabilities, achieving an average efficiency score of 0.850, which was greater than the overall average efficiency score of 0.824. These FJs were developed to meet tactical needs. Moreover, the average efficiency values for the functions were relatively similar, indicating that these models were adaptable to a wide range of situations. Therefore, procurers can consider the models in this cluster when seeking to enhance tactical combat capabilities. The Typhoon is a twin-engine FJ with distinct wing design and is equipped for air-to-air combat (namely, this model is difficult to detect and can carry eight missiles) and air-to-surface assault (equipped with a special radar system for accurate bombing). Thus, this model is a multi-purpose FJ.

Cluster 4 comprised eight models, namely, the Su-25, F-18, AMX, T-4, Yak-130, Rafale, Mako, and AV-8. The models in this cluster were those with low efficiency and capabilities, achieving an average efficiency score of 0.505, which was lower than the overall average efficiency score of 0.824. Although the efficiency value was relatively low, flight speed was the key strength of this cluster. During a war, different circumstances demand specific combat capabilities. Therefore, procurers can review the models in this cluster to determine whether they meet the requirements of particular combat missions. The Su-25 is a simple FJ with considerable firepower, easy steering, and high flight speed. Therefore, the survivability of this model on the battlefield is extremely high, rendering it ideal for rugged environments and battlefronts. However, this model is less flexible than others, rendering it comparatively inefficient but still useful.

5 | CONCLUSIONS

Major weapons have been continuously improved and remodeled over time. However, the procurement and R&D of these weapons require immense funding. Therefore, the present study adopted a multi-input and multioutput EBM DEA method for the selection of FJs. In addition, MDS was employed to examine the strengths and weaknesses of FJs. The MDS results can serve as a reference for the R&D of FJs. The findings of the present study were as follows.

First, the overall average efficiency value of the target FJs was 0.824, suggesting that the efficiency only requires an average improvement of 17.6% to achieve the efficient frontier; hence, the overall relative performance for price and capabilities achieved favorable standards. Among the FJs, 14 achieved an efficiency value of 1, suggesting that although the strengths of these models were different (price and capability), they achieved similar performance standards. For example, the IDF exhibited superior TT and MFS but inferior P, whereas the F-16 exhibited superior P and TT but inferior MTW.

Second, a sensitivity analysis was performed to determine the strengths and weaknesses of the various FJs. The results indicated that the F-15 exhibited high standards in both price and capability. Therefore, the F-15 is a tactical and highly mobile FJ suitable for different weather conditions. Its high mobility renders it an effective air assault weapon and thus the ideal model for improving national defense. By contrast, the FC-1 performed poorly in P. The

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collaboration of other countries was required during the R&D of this model because of the lack of resources, raising the price of this model. Thus, P should be modified to enhance the efficiency of this model.

Lastly, MDS was employed to cluster the FJ models with similar characteristics. The FJs were grouped into four clusters. Cluster 1 comprised models with superior performance in price and capability. Procurers can consider the models in this cluster when seeking to enhance air combat capabilities. Cluster 2 comprised models with superior performance in capability but slightly higher marked prices than Cluster 1 models. Procurers can consider the acquisition of these models based on national defense requirements. Cluster 3 comprised models that demonstrated favorable MFS and TT. Procurers can consider these models when the MFS and TT characteristics of FJs are deemed most critical. Cluster 4 comprised models that demonstrated superior flight speed. Procurers can consider these models under special circumstances or meet special requirements. The clusters were distinguished on the basis of the FJ characteristics. The clustering results can be provided to procurement departments as a reference for comparing FJ capabilities.

There are some important implications of this study in management. Specifically, this study indicated that complex problems in the selection of major weapons can be solved by simultaneously adjusting input and output using the EBM DEA method; thereby enhancing evaluation accuracy and practicality. Besides, this study showed the strengths and weaknesses of various FJs, as well as clustering of the FJs; all of which facilitate the successful procurement of weapons. The evaluation results can be provided to procurement decision makers. In summary, procurers rely on price, metrics, and dimensions to decide which FJ models to purchase. Multipurpose metrics are typically used in the evaluation process, highlighting the necessity of a suitable evaluation method to select the FJs most suited to the requirements of militaries in different countries. Moreover, the evaluation method proposed in the present study can be used to select other types of major weapon when limited resources are available, providing procurement decision makers with a selection method.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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