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Baseball Evaluation Using DEA Benchmark Approach
：An Application to Japanese Pacific League-1999

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Abstract

This research uses a new analytical approach for baseball evaluation, referred to as "A Bench Mark Approach," [1] by combining DEA (Data Envelopment Analysis) with OERA (Offensive Earned-Run Average). An important feature of the approach is that it can select a best performer among many baseball players and evaluate their ranking scores. The DEA is an evaluation technique of various entities in public and private sectors, whose production activities are characterized by multiple inputs and outputs. The evaluation technique has a shortcoming in examining baseball performance because it produces many efficient baseball players. To overcome such a shortcoming of DEA baseball evaluation, a Slack-Adjusted DEA (SA-DEA) is combined with OERA in [1]. As its real application, the benchmark approach is applied to the evaluation of their offensive records of Japanese baseball players in Pacific League(1999).

1. Introduction

This research uses a new analytical approach, referred to as "A Bench Mark Approach," for baseball evaluation that DEA (Data Envelopment Analysis) is combined with OERA (Offensive Earned-Run Average) [6]. The DEA method, first proposed by Charnes et al. [1], is now widely known as an evaluation technique for performance analysis of various entities, whose production activities are characterized by multiple inputs and outputs. Admitting DEA contributions in performance analysis, however, this study needs to describe that it has a difficulty in evaluating baseball performance. That is, DEA relatively compares the performance of each DMU (Decision Making Unit) with others on an efficiency frontier, consequently having a difficulty in identifying a best performer because multiple DMUs usually comprise the efficiency frontier. This DEA feature is not a serious problem for many decisional cases. However, it produces a difficulty in ranking baseball's offensive records because the sport needs the best individual for its whole performance evaluation. The benchmark approach is proposed to overcome this DEA shortcoming. This research fully utilizes the benchmark approach for the evaluation of Japanese baseball players' offensive efforts.

The OERA, proposed in [2], was originally developed for baseball evaluation, using a Markov chain model. A methodological strength of OERA is that it can incorporate stochastic features, expressing their offensive efforts of baseball players, into its analytical structure. This methodological feature is very important in the evaluation of modern baseball. However, the OERA method has a major drawback; it cannot incorporate several important offensive records (e.g., base steals, double plays and sacrifices) in its analytical framework. The DEA/OERA approach can overcome such an OERA shortcoming because DEA can incorporate these important performance measures into its evaluation.

2. Data Envelopment Analysis

2.1 SA(Slack-Adjusted)-DEA model

To describe the analytical structure of our DEA model in detail, it is assumed that we can access information regarding y_{rj} = the r^{th} output $(r = 1, K , h)$ and x_{ij} = the i^{th} input $(i = 1, K , m)$ of the j^{th} DMU $(j = 1, K , n)$. [The DMU stands for a baseball player in this study.] The Slack-Adjusted DEA is used to measure a DEA efficiency score of a specific k^{th} DMU by the following model:

$$
\begin{aligned}
&\text{min imize} && \theta - \left[\left(\sum_{i=1}^{m} s_i^x \big/ MR_i^x \right) + \left(\sum_{r=1}^{h} s_r^y \big/ MR_r^y \right) \right] \bigg/ (m+h) \\
&\text{subject to} && -\sum_{j=1}^{n} x_{ij}\lambda_j + \theta x_{ik} - s_i^x = 0, \qquad i = 1, K, m, \\
& && \sum_{j=1}^{n} y_{rj}\lambda_j \qquad - s_r^y = y_{rk}, \qquad r = 1, K, h, \\
& && \theta : \text{free}, \lambda_j \geq 0, s_i^x \geq 0 \text{ and } s_r^y \geq 0.
\end{aligned} \tag{1}
$$

As formulated in the objective of (1), the influence of a slack is adjusted by the following data ranges:

$$
MR_i^x = \max_j x_{ij} \ (i = 1, K, m) \text{ and } MR_r^y = \max_j y_{rj} \ (r = 1, K, h). \tag{2}
$$

A SA-DEA efficiency score (η^*) is measured by the following manner:

$$
\eta^* = \theta^* - \left[\left(\sum_{i=1}^{m} s_i^{x^*} \big/ MR_i^x \right) + \left(\sum_{r=1}^{h} s_r^{y^*} \big/ MR_r^y \right) \right] \bigg/ (m+h), \tag{3}
$$

where the superscript "*" indicates optimality.

To explain why (2) can avoid the occurrence of zero in multipliers, this article needs to present the following dual model of (3):

$$
\begin{aligned}
&\text{max imize} && \sum_{r=1}^{h} w_r y_{rk} \\
&\text{subject to} && -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{h} w_r y_{rj} \leq 0, \qquad j = 1, K, n, \\
& && \sum_{i=1}^{m} v_i x_{ik} \qquad = 1, \\
& && v_i \geq 1/(m+h)MR_i^x, \qquad i = 1, K, m, \\
& && w_r \geq 1/(m+h)MR_r^y, \qquad \Lambda\, r = 1, K, h,
\end{aligned} \tag{4}
$$

From the last two groups of constraints in (4), this research immediately knows that all the multipliers are always positive on optimality, because they are all restricted by these lower bounds. Thus, (4) can avoid the examination regarding whether zero occurs in multipliers.

2.2 DEA Strengths and Shortcomings

When applying DEA (including SA-DEA and other DEA models) to baseball's offensive evaluation, this article needs to pay attention to the following methodological strengths and shortcomings:

<u>Strengths:</u>

(a) DEA can incorporate important features related to modern baseball (e.g., steals, sacrifices and double plays) into its analytical framework.

(b) An offensive contribution needs to be evaluated from multi-objectives of baseball. In this sense, DEA becomes an important methodological tool for baseball evaluation.

<u>Shortcomings:</u>

(a) DEA may often produce many efficient baseball players even though we search for a single player as the best performer.

(b) DEA may yield multiple solutions on some multipliers.

The above two shortcomings are important in evaluating their offensive records of baseball players. Therefore, this article needs to explore when multiple solutions occur on each multiplier, then presenting how to deal with such a DEA difficulty. [The identification of the best player (the first difficulty of DEA) will be discussed in the proceeding section.]

2.3 When Multiple Solutions Occur on SA-DEA Multipliers

To identify when multiple solutions occur on each multiplier, this research needs to return to Complementary Slackness Conditions (CSC), existing between (1) and (4), which may be mathematically expressed by the following three groups of equations on optimality:

$$\begin{aligned}
&\text{(a)}\quad s_i^{x*}\,(v_i^* - 1/(m+h)MR_i^x) = 0, \quad \text{for } i = 1, K, m,\\
&\text{(b)}\quad s_r^{y*}\,(w_r^* - 1/(m+h)MR_i^y) = 0, \quad \text{for } r = 1, K, h, \text{ and}\\
&\text{(c)}\quad \lambda_j^*(-\sum_{i=1}^{m} v_i^* x_{ij} + \sum_{r=1}^{h} w_r^* y_{rj}) = 0, \quad \text{for } j = 1, K, n.
\end{aligned} \tag{5}$$

The above CSC requirements indicate that for each component,

$$\begin{aligned}
&\text{(a)}\quad \text{if } s_i^{x*} > 0, \text{ then } v_i^* = 1/(m+h)MR_i^x, \quad \text{for } i = 1, K, m,\\
&\text{(b)}\quad \text{if } s_r^{y*} > 0, \text{ then } w_r^* = 1/(m+h)MR_i^y, \quad \text{for } r = 1, K, h, \text{ and}\\
&\text{(c)}\quad \text{if } \lambda_j^* > 0, \text{ then } -\sum_{i=1}^{m} v_i^* x_{ij} + \sum_{r=1}^{h} w_r^* y_{rj} = 0, \quad \text{for } j = 1, K, n.
\end{aligned} \tag{6}$$

From (6), this research obtains the following proposition:

<u>Proposition 1</u>: Using (1), measure the efficiency of the k^{th} DMU and then compute the following numbers:

$$\begin{aligned}
&\#(RF_k) = \text{the number of } \left\{ j \in J \,\middle|\, \lambda_j^* > 0 \text{ in } (1) \right\},\\
&\#(S_k^x) = \text{the number of} \left\{ i \,\middle|\, s_i^{x*} > 0 \text{ in } (1) \right\}, \text{and}\\
&\#(S_k^y) = \text{the number of} \left\{ r \,\middle|\, s_r^{y*} > 0 \text{ in } (1) \right\}.
\end{aligned} \tag{7}$$

Then, DEA multipliers of (7) have the following possible three cases on optimality:

(a) $m + h > \#(RF_k) + 1 + \#(S_k^x) + \#(S_k^y)$, then multiple solutions occur on some multipliers ,

(b) $m + h = \#(RF_k) + 1 + \#(S_k^x) + \#(S_k^y)$, then a unique solution occurs on all the multipliers, or

(c) $m + h < \#(RF_k) + 1 + \#(S_k^x) + \#(S_k^y)$, then no solution is found on some multipliers .

[Proof]

Dual form (4) consists of n+1+m+h constraints and m+h unknown multipliers. Here, "1" indicates the number of the constraint $(\sum_{i=1}^{m} v_i x_{ik} = 1)$ in (4). It is true that all the m+h multipliers become positive on optimality of (4), but the number of binding (equality) constraints may become less than n+1+m+h on its optimality. The CSC requirements of (6) indicate the number of equality constrains used for optimality = $\#(RF_k) + 1 + \#(S_k^x) + \#(S_k^y)$, which is less than or equal to n+1+m+h. Consequently, the three cases of Proposition 1 are proved by comparing the number of positive multipliers (m+h) with that of equality constraints, $\#(RF_k) + 1 + \#(S_k^x) + \#(S_k^y)$, on optimality of (7)..

Q.E.D.

2.4 Dealing with Multiple Solutions

In the preceding section, this article discusses when and why multiple solution(s) occur on DEA multipliers. Now, a simple but important question may occur in our mind. How do we deal with such non-uniqueness when it occurs? To answer the question, this article proposes a use of the following DEA formulation to obtain the upper and lower bounds of $v_i = (i = 1, K, m)$ of the k^{th} DMU:

$$
\begin{aligned}
\max./\min \quad & v_i \\
\text{subject to} \quad & -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{h} w_r y_{rj} \le 0, \quad j \in RF_k \\
& \sum_{i=1}^{m} v_i x_{ik} = 1, \\
& \sum_{r=1}^{h} w_r y_{rk} = \eta^*, \\
& v_i \ge 1/(m+h)MR_i^x, \quad i = 1, K, m, \text{ and} \\
& w_r \ge 1/(m+h)MR_r^y, \quad r = 1, K, h,
\end{aligned}
\tag{8}
$$

where its lower bound is determined by minimizing the objective of (11) and its upper bound is obtained by replacing the objective from minimization to maximization. $RF_k = \left\{ j \in J \middle| \lambda_j^* > 0 \text{ in}(3) \right\}$ is a reference set of the k^{th} DMU. Similarly, the upper and lower bounds of $w_r = (r = 1, K, h)$ are determined by

$$
\begin{aligned}
\max./\min \quad & w_r \\
\text{subject to} \quad & -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{h} w_r y_{rj} \le 0, \quad j \in RF_k \\
& \sum_{i=1}^{m} v_i x_{ik} = 1, \\
& \sum_{r=1}^{h} w_r y_{rk} = \eta^*, \\
& v_i \ge 1/(m+h)MR_i^x, \quad i = 1, K, m, \text{ and} \\
& w_r \ge 1/(m+h)MR_r^y, \quad r = 1, K, h,
\end{aligned}
\tag{9}
$$

along with an exchange between maximization and minimization. There are two important features associated with (8) and (9), both need to be clearly specified here. One of the two is that these DEA models incorporate the level of η^* in these formulations. A supporting rationale on this modification is due to the fact that all the DEA multipliers have multiple solutions under the same efficiency score (η^*). The other important feature is that the number of constraints for $-\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{h} w_r y_{rj} \le 0$ is reduced from "n" (the number of the whole DMUs) to the size of RF_k in (8) and (9), so that the two DEA models can considerably reduce these computational efforts, in particular dealing with a large number of DMUs.

3. Offensive Earned-Run Average

The OERA is index measurement of offensive effectiveness of a certain batter. A unique feature of OERA is that the approach can be formulated by a Markov chain model. The definition is as follows.

Definition:The OERA score is defined as "the number of earned runs per game that a batter could score if he batted in all nine positions in the line-up" [2, p.731].
[See the research works [3, 4] in which a more detailed description can be found for the definition on OERA.]

OERA assumptions are established for mathematical convenience. When applying OERA to Japanese baseball evaluation, which might be slightly different from American baseball, this research needs to restructure it from the perspective of Japanese sport management. That is, when watching news in Japan, sport commentators and team managers often speak about the importance of sacrifices in baseball games. Each sacrifice is considered as a symbol of a team play effort in Japan, because a batter sacrifices his performance to improve a scoring position for his team. Therefore, the first assumption (i.e., sacrifices are not counted at all in OERA) needs to be dropped in the evaluation of offensive efforts.

In addition to the sacrifices, we need to incorporate the number of base steals, that make our baseball games more exciting, into our offensive evaluation. As mentioned previously, the number of steals is usually excluded from OERA. Hence, this research needs to include the number of base steals in our performance evaluation. Moreover, the fifth assumption (i.e., no double plays in OERA) needs to be dropped in our baseball evaluation. It can be easily imagined that there are many double plays in modern baseball games. The double play often destroys the chance of a scoring position, so influencing a final result (win or loss) of many games. Therefore, it is easily thought that the number of double plays needs to be incorporated into our baseball evaluation.

4. Benchmark Approach: A Combined Use of SA-DEA/OERA

To classify many efficient baseball players identified by SA-DEA, this study uses OERA as additional information [6]. These SA-DEA efficient players are referred to as "benchmark batters" and the level of their current efficiency scores (100% efficiency) is referred to as "a benchmark point". Our benchmark approach consists of the following three computations:

(a) <u>OERA Indexes</u>: To incorporate their resulting OERA scores into SA-DEA, the following OERA index (u_j^*) is computed:

$$u_j^* = 1 + \left[\left\{ \mathrm{OERA}_j - \min_j(\mathrm{OERA}_j) \right\} / \left\{ \max_j(\mathrm{OERA}_j) - \min_j(\mathrm{OERA}_j) \right\} \right] \quad \text{for} \quad j \in E, \tag{10}$$

where OERA_j is the OERA score of the j^{th} player measured and E is a set of baseball players whose SA-DEA scores are rated as efficiency. In (10), the OERA index of each SA-DEA efficient player is reevaluated on the range from 100% (bottom) to 200% (best). [Note that inefficient players belong to the range of less than 100%.]

(b) <u>Benchmark Multipliers</u>: To obtain final multiplier estimates of $w_r\,(r = 1, \ldots, h)$ and $v_i\,(i = 1, \ldots, m)$ in the manner that $u_j^* = \sum_{r=1}^{h} w_i y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij},\ j \in E$, this study proposes a use of the following goal programming model:

$$\begin{aligned}
&\text{minimize} && \sum_{j \in E} (d_j^+ + d_j^-) \\
&\text{subject to} && u_j^* \Big(\sum_{i=1}^{m} v_i x_{ij}\Big) - \sum_{r=1}^{h} w_r y_{rj} - d_j^+ + d_j^- = 0, \quad && j \in E \\
& && \min_{j \in E} \underline{v}_{ij} \le v_i \le \max_{j \in E} \overline{v}_{ij}, && i = 1, \ldots, m, \\
& && \min_{j \in E} \underline{w}_{rj} \le w_i \le \max_{j \in E} \overline{w}_{rj}, && r = 1, \ldots, h.
\end{aligned} \tag{11}$$

where, d_j^+ and d_j^- are two groups of deviations for $j \in E$ such that

$$d_j^+ = u_j^* \Big(\sum_{i=1}^{m} v_i x_{ij}\Big) - \sum_{r=1}^{h} w_r y_{rj} \quad \text{and} \quad d_j^- = \sum_{r=1}^{h} w_r y_{rj} - u_j^* \Big(\sum_{i=1}^{m} v_i x_{ij}\Big) \quad \text{for} \quad j \in E.$$

The objective of (11) and the first group of constraints indicate

$$u_j^* - d_j^{\prime +} + d_j^{\prime -} = \sum_{r=1}^{h} w_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij}, \quad \text{where} \quad d_j^{\prime +} = d_j^+ / \sum_{i=1}^{m} v_i x_{ij} \quad \text{and} \quad d_j^{\prime -} = d_j^- / \sum_{i=1}^{m} v_i x_{ij}.$$

The minimization of the sum of total deviations in (11) implies that on its optimality $\sum_{r=1}^{h} w_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij}$ becomes close to u_j^* as much as possible. This type of multiplier estimation can be considered as a special form of the L_1-metric estimation. An important feature of (11) is that all the multipliers are estimated under the restriction of these upper and lower bounds. The resulting multiplier estimates measured by (11) are referred to as "benchmark multipliers," all of which can serve as a computational basis for the following benchmark indexes:

(c) Benchmark Indexes: Let $\hat{w}_r$ and $\hat{v}_i$ be benchmark multipliers of (11), then a new measure, or Benchmark Index (BI), of the j^{th} baseball player is measured by

$$\text{Benchmark Index: } BI(j) = \sum_{r=1}^{h} \hat{w}_r y_{rj} \Big/ \sum_{i=1}^{m} \hat{v}_i x_{ij} \quad \text{for} \quad j \in E. \tag{12}$$

The computation of the benchmark indexes for all efficient baseball players indicates the end of the whole computation process of our benchmark approach.

5. Evaluation of Japanese Baseball Players

The benchmark approach is applied to evaluate their offensive records of Japanese baseball players in Pacific League (1999). Japanese professional baseball consists of two leagues: Central and Pacific Leagues. Each league has six teams, so totaling twelve professional baseball teams in Japan.

A data set used in this study is 1999-Baseball Record Book (in Japanese) published by Baseball Magazine Inc., Tokyo (2000). Thirty-two batters are selected for our performance evaluation according to their batting averages. As mentioned previously, there are six teams (Blue Wave, Marines, Lions, Fighters, Hawks, Buffaloes) in the Japanese Pacific League. We must pay attention to the fact that we use "bats", "singles", "doubles", "triples", "homeruns", and "walks" for OERA. Meanwhile, DEA utilizes "at bats" and "double plays" as input measures as well as "singles", "doubles", "triples", "homeruns", "runs batted in", "steals", "sacrifices", and "walks" as output measures. DEA, SA-DEA, OERA, and Benchmark index are documented of Table 1. Empirical findings in Table 1 may be summarized as follows:

Finding 1: As a result of our slack-adjustment, all the multipliers become positive and the number of DEA efficient batters is reduced from eighteen (in Table 1) to nine players (in Table 1). Nine baseball players, Jojima (Hawks), Ogasawara (Fighters), Pulliam (BlueWave), Yoshioka (Buffaloes), Kataoka (Fighters), Ozeki (Lions), Hori (Marines), Nakamura (Buffaloes), Suzuki (Lions), change their DEA scores from 100% efficiency (in Table 1) to some levels of inefficiency. For example, Jojima (Hawks) exhibits 100% in his DEA efficiency score, but 93.16% in his SA-DEA, thus producing his efficiency decline (6.84% =100-93.16).

Finding 2: A major shortcoming of OERA is that the Markov chain approach cannot incorporate the numbers of base steals, double plays, and sacrifices into its computation process. Such a shortcoming can be found in Table 1, as well. For example, Kosaka (Marines), who stole 31 bases, was the second base stealer in 1999. His effort is neglected and ranked as the twenty-second in OERA. Furthermore, Ozeki (Lions) made 32 sacrifices for his team in 1999. Even though his contribution is highly appreciated by his team (Lions), Ozeki is ranked as the twenty-sixth offensive performer in OERA. Their empirical results clearly indicate a methodological shortcoming of OERA.

As mentioned previously, the benchmark approach uses SA-DEA, as its preparatory treatment, which selects the following nine efficient baseball players as benchmark batters from Table 1:

Table1: Comparison among Performance Evaluation Alternatives

Batter (Team)	Evaluation Alternatives			
	DEA Efficiency	SA-DEAEfficiency	OERA Score	Benchmark Index (SA-DEA/OERA)
Ichiro (BlueWave)	1 (1)	1 (1)	9.437 (1)	1.755 (3)
Matsui (Lions)	1 (1)	1 (1)	7.447 (3)	1.628 (4)
Jojima (Hawks)	1 (1)	0.932 (14)	6.407 (10)	0.932 (14)
Rose (Buffaloes)	1 (1)	1 (1)	9.020 (2)	1.925 (1)
Tani (BlueWave)	0.975 (21)	0.885 (20)	4.795 (22)	0.885 (20)
Clark (Buffaloes)	0.913 (29)	0.814 (28)	6.912 (6)	0.814 (28)
Ogasawara (Fighters)	1 (1)	0.911 (16)	6.417 (9)	0.911 (16)
Pulliam (BlueWave)	1 (1)	0.898 (18)	6.231 (11)	0.898 (18)
Morozumi (Marines)	1 (1)	1 (1)	4.094 (28)	1.267 (9)
Kosaka (Marines)	1 (1)	1 (1)	5.042 (21)	1.780 (2)
Oshima (BlueWave)	1 (1)	1 (1)	5.830 (16)	1.325 (8)
Yoshioka (Buffaloes)	1 (1)	0.939 (12)	6.084 (13)	0.939 (12)
Yoshinaga (Hawks)	1 (1)	1 (1)	7.180 (4)	1.361 (7)
Kataoka (Fighters)	1 (1)	0.927 (15)	6.168 (12)	0.927 (15)
Kaneko (Fighters)	0.968 (23)	0.821 (27)	4.259 (27)	0.821 (27)
Otomo (Lions)	0.989 (19)	0.938 (13)	5.157 (20)	0.938 (13)
Tanaka (Fighters)	0.884 (31)	0.791 (31)	5.422 (18)	0.791 (31)
Taguchi (BlueWave)	0.945 (27)	0.806 (30)	3.887 (29)	0.806 (30)
Matsunaka (Hawks)	1 (1)	1 (1)	6.827 (7)	1.578 (5)
Ozeki (Lions)	1 (1)	0.969 (10)	4.294 (26)	0.969 (10)
Hori (Marines)	1 (1)	0.910 (17)	5.460 (17)	0.910 (17)
Shibahara (Hawks)	0.982 (20)	0.897 (19)	4.443 (23)	0.897 (19)
Nakamura (Buffaloes)	1 (1)	0.879 (21)	6.651 (8)	0.879 (21)
Suzuki (Lions)	1 (1)	0.945 (11)	5.979 (15)	0.945 (11)
Hatsushiba (Marines)	0.960 (25)	0.873 (22)	6.038 (14)	0.873 (22)
Omura (Buffaloes)	0.971 (22)	0.810 (29)	2.966 (31)	0.810 (29)
Akiyama (Hawks)	0.819 (32)	0.747 (32)	4.376 (24)	0.747 (32)
Noguchi (Fighters)	0.965 (24)	0.846 (26)	3.263 (30)	0.846 (26)
Furankurin (Fighters)	1 (1)	1 (1)	6.933 (5)	1.531 (6)
Kokubo (Hawks)	0.907 (30)	0.873 (22)	5.356 (19)	0.873 (22)
Hamana (Hawks)	0.959 (26)	0.850 (25)	2.953 (32)	0.850 (25)
Iguchi (Hawks)	0.936 (28)	0.851 (24)	4.334 (25)	0.851 (24)

Note: Each number within the parenthesis indicates a rank order.

Ichiro (BlueWave), Matsui (Lions), Rose (Buffaloes), Morozumi (Marines), Kosaka (Marines), Oshima (BlueWave), Yoshinaga (Hawks), Matsunaka (Hawks), Furankurin (Fighters).
Using their OERA indexes listed in Table 1 and (6), this study estimates benchmark multipliers as follows:

$\hat{v}_1$ (At Bats) = 0.00053, $\hat{v}_2$ (Double Plays) = 0.00476, $\hat{w}_1$ (Singles) = 0.00077,
$\hat{w}_2$ (Doubles) = 0.00263, $\hat{w}_3$ (Triples) = 0.01000, $\hat{w}_4$ (Homeruns) = 0.00649,
$\hat{w}_5$ (Runs Batted In) = 0.00099, $\hat{w}_6$ (Steals) = 0.00313, $\hat{w}_7$ (Sacrifices) = 0.00238,
and $\hat{w}_8$ (Walks) = 0.00146.

Using the above benchmark multipliers, we compute benchmark indexes of all the nine efficient players. The SA-DEA scores of all the remaining inefficient players become their benchmark indexes without any change.

<u>Finding 3:</u> All the thirty batters are rated from 0 to 200(%) in the benchmark index, in which the half range between 0 and 100(%) is obtained from SA-DEA and the remaining range above 100 (%) is computed by (6) and (7).

<u>Finding 4</u>: Ichiro (BlueWave) the best offensive player in OERA, is now rated as the third performer in our benchmark ranking. Meanwhile, Rose (Buffaloes) the second performer in OERA, becomes the best batter in our ranking order. Their ranking changes are due to the fact that the magnitudes of the two benchmark multipliers, $\hat{w}_2$ (Doubles) = 0.00263, $\hat{w}_4$ (Homeruns) = 0.00649, are larger than those of the other benchmark multipliers. Rose (Buffaloes) outperforms Ichiro (BlueWave) in terms of these performance measures (doubles, Homeruns) and therefore, Rose (Buffaloes) becomes better than Ichiro (BlueWave) in our benchmark ranking. Consequently, such an evaluation change

occur between the two players.

Finding 5: Another interesting finding can be found in his rank change of Kosaka (Marines); he increases his rank from the 21^{th} in OERA to the 2^{th} in our benchmark ranking, due to the number of his sacrifices. This study also finds the remarkable rank change of Nakamura (Buffaloes) who is rated as the 8^{th} performer in OERA, but rated as the 21^{th} performer in our benchmark rating, because of his many (21) double plays. Thus, it may be easily confirmed that these performance measures (such as steals, sacrifices and double plays) newly incorporated in SA-DEA influence our benchmark ranking scores.

6. Conclusion

A new analytical approach, referred to as a "benchmark approach," is fully utilized in our baseball evaluation. The benchmark approach has the following four computation processes: First, SA-DEA classifies all baseball players into either efficient or inefficient groups. Second, OERA is applied to all the players. The efficient batters are ranked and their OERA indexes are computed on the basis of their OERA scores. Third, a goal programming model estimates benchmark multipliers based upon the upper and lower bounds of SA-DEA multipliers and OERA indexes. Finally, the benchmark indexes are determined by the benchmark multipliers.

In this study, the benchmark approach is applied to the performance evaluation of Japanese baseball players' offensive efforts. Such results are summarized in five empirical findings. As a future extension of our investigation, we need to extend our research into the performance evaluation of their defensive efforts of baseball players [4]. Furthermore, the DEA model can be linked to a stochastic process of Chance-Constraint DEA (CC-DEA) [5]. Such is another important future research direction.

Supplement

A data set used in this study is documented in table2. (The source of this data set is 1999-Baseball Record Book (in Japanese) published by Baseball Magazine Inc., Tokyo (2000).)

Table2:Offensive records of 32 batters(Pacific League-1999)

Batter (Team)	Batting Average	Bats	At Bats	Double Plays	Singles	Doubles	Triples	Homeruns	Runs Batted In	Steals	Sacrifices	Walks
Ichiro (BlueWave)	0.3430	411	468	5	91	27	2	21	68	12	0	52
Matsui (Lions)	0.3300	539	609	7	130	29	4	15	67	32	8	56
Jojima (Hawks)	0.3060	493	539	13	100	33	1	17	77	6	6	39
Rose (Buffaloes)	0.3010	491	565	7	69	38	1	40	101	5	0	71
Tani (BlueWave)	0.2910	532	594	13	123	17	4	11	62	24	8	50
Clark (Buffaloes)	0.2870	509	573	20	85	32	0	29	84	4	0	57
Ogasawara (Fighters)	0.2850	547	608	6	93	34	4	25	83	3	0	56
Pulliam (BlueWave)	0.2803	446	502	14	84	21	0	20	85	0	0	55
Morozumi (Marines)	0.2801	432	475	1	95	19	5	2	33	10	14	29
Kosaka (Marines)	0.2801	482	586	2	104	18	10	3	40	31	42	60
Oshima (BlueWave)	0.2798	361	462	2	84	15	1	1	33	5	28	70
Yoshioka (Buffaloes)	0.2760	420	486	9	74	28	1	13	57	12	9	56
Yoshinaga (Hawks)	0.2750	346	418	5	66	12	1	16	38	0	0	69
Kataoka (Fighters)	0.2742	423	489	8	78	19	4	15	63	1	0	62
Kaneko (Fighters)	0.2740	416	473	11	91	17	3	3	29	4	18	39
Otomo (Lions)	0.2699	415	510	8	90	14	4	4	26	13	26	67
Tanaka (Fighters)	0.2697	508	556	14	89	23	2	23	74	2	0	45
Taguchi (BlueWave)	0.2690	524	569	9	110	21	1	9	56	11	14	30
Matsunaka (Hawks)	0.2684	395	462	11	59	20	4	23	71	5	5	58
Ozeki (Lions)	0.2681	373	464	6	86	9	4	1	34	16	32	57
Hori (Marines)	0.2660	421	493	11	73	28	3	8	50	5	12	58
Shibahara (Hawks)	0.2630	464	539	3	98	15	4	5	26	22	15	60
Nakamura (Buffaloes)	0.2607	514	601	21	80	23	0	31	95	3	1	83
Suzuki (Lions)	0.2607	468	555	11	77	30	2	13	81	3	0	79
Hatsushiba (Marines)	0.2600	457	517	14	63	33	1	22	85	1	0	56
Omura (Buffaloes)	0.2590	494	533	6	104	19	3	2	36	7	19	19
Akiyama (Hawks)	0.2560	386	420	12	69	16	2	12	44	3	3	30
Noguchi (Fighters)	0.2400	391	420	11	64	22	1	7	46	5	11	16
Furankurin (Fighters)	0.2380	428	521	11	49	23	0	30	80	2	0	86
Kokubo (Hawks)	0.2340	465	538	8	59	24	2	24	77	4	3	64
Hamana (Hawks)	0.2260	354	422	4	64	10	4	2	27	5	29	38
Iguchi (Hawks)	0.2240	370	424	13	53	15	1	14	47	14	4	47

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