

An Evaluation of Characteristics of J-League Players Using Data Envelopment Analysis

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We evaluate the performance of J-league players using data envelopment analysis (DEA) in order to try to identify player characteristics from the standpoint of efficiency. We use time played as the input and the numbers of ten basic plays or actions such as goals, assists, crosses, passes, dribbles, tackles, interceptions, clears, blocks and fouls as output. We then analyse the performance of J-league field players using data from the 2008 season based on the CCR (Charnes-Cooper-Rhodes) model. In this analysis, we evaluate field players by position, i.e. forwards, midfielders and defenders, and discuss their characteristics in reference to their efficiency scores, virtual input and output values, reference sets, and their targets for improvement.

Keywords: CCR, DEA, Efficiency, Evaluation, J league

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1. Introduction

In this study, we evaluate the performance of J-league players using data envelopment analysis (DEA) to clarify their characteristics. DEA is a method that allows a relative evaluation of the efficiency of subjects based on the ratio of input to output, and is often used to analyze corporate performance (e.g. Copper et al., 2007). This study compares individual J-league player efficiency utilizing data related to major plays such as number of goals, passes, and dribbles.

DEA has been applied in the past to the evaluation of individual baseball players (Anderson, 1997; Bosca, et al., 2009; Charnes et al., 1995; Cooper et al., 2009; DeOliveria, 2004; Hashimoto, 1993; and Sueyoshi, 1999). Most evaluations of soccer performance, however, focus on teams, such as the evaluation of team performance with player and coach salaries as input and spectator attendance and revenue as output (Haas, 2003), and an evaluation of a team from the standpoint of offensive and defensive skill (Bosca et al., 2009). Hirotsu et al.(2006) attempted to rank players; however, due to difficulties in evaluating different positions with the same scale, the authors settled with a simple description of their

results in reference to the Opta Index (e.g. Opta Index Limited, 2000; J-STATS Opta, 2005).

This study was carried out not for the purpose of ranking players, but to clarify player characteristics utilizing DEA, which can evaluate subjects from various perspectives based on multiple items. Subjects of this study were J-league Division 1 players. We analysed basic play data such as number of goals, passes, and dribbles utilizing the Charnes-Cooper-Rhodes (CCR) model (e.g. Copper et al., 2007), which is the most basic among the existing DEA models, to obtain efficiency scores, and quantify the characteristics of individual players to clarify targets for improvement.

In general, the evaluation of players presents a challenge due to the wide range of items associated with performance, such as differences in opponents and conditions. Validation is also a challenge due to differences in the perspective of individual evaluators. However, it is possible to quantify the characteristics of individual players through a relative evaluation based on multiple items by DEA analysis using annual data to evaluate the efficiency of multifaceted player abilities.

The DEA model used in this study is described in Section 2, and the data used is described in Section

3. In Section 4, we show efficiency scores, discuss the characteristics of individual players, and list targets for improvement. In Section 5, we provide our conclusions.

2. DEA model

In this section, we describe the DEA model used to evaluate individual soccer players. We conduct a relatively evaluation of subjects in terms of output against input using DEA. For example, if we define “goal rate” as the number of goals against minutes played, the goal rate will be the rate of the output (number of goals) against the input (minutes played), based on which the efficiency will be evaluated. In DEA, we set a player whose rate is the greatest as the standard (=1) and evaluate individual players using values between 0 and 1. In other words, DEA is characterized by a relative evaluation based on the best player among the subjects, which is the opposite of the regression analysis method, which evaluates subjects based on average values.

This example of goal rate is equivalent to one input (minutes played) and one output (number of goals). According to 2008 data, Marquinhos had 2608 minutes played and 21 goals ($21/2608 = 0.00805$), which was the largest. For DEA, we convert this to 1 and rate other players with efficiency scores between 0 and 1 relative to Marquinhos.

The goal rate calculated using one input and one output simply reflects a part of the offense ability; however, DEA is characterized by the advantage of being capable of using multiple items. For example, adding the number of passes to the evaluation items as well as the number of goals, the rate can be defined by setting the number of minutes played as input and $u_1 \times$ number of goals + $u_2 \times$ number of passes. Here, u_1 expresses the weight of goals and u_2 expresses the weight of passes, and if the goals are considered ten times as important as passes, they can be evaluated using the sum of the weight ($u_1 = 10$, $u_2 = 1$) as output. It is necessary to consider how to set the weight u_1 and u_2 for fair evaluation. In DEA, individual players can set the weight to maximize their own rate. In other words, in DEA, every player can set u_1 and u_2 values freely within restricted ranges such as nonnegativity constraints, and select weight to maximize their evaluation.

The above concept can be expressed as

$$\text{Rate} = \frac{\text{Virtual output}}{\text{Virtual input}} = \frac{\sum_{r=1}^s u_r y_{rj_0}}{\sum_{i=1}^m v_i x_{ij_0}} \quad (1)$$

In this formula, m represents the number of input items and s is the number of output items.

$\sum_{i=1}^m v_i x_{ij_0}$ is the virtual input obtained by adding the weight (v_i) to data (x_{ij_0}) regarding input item i ($=1, 2, \dots, m$) of subject player (j_0) and $\sum_{r=1}^s u_r y_{rj_0}$ is the virtual output obtained by adding the weight (u_r) to the data (y_{rj_0}) regarding output item r ($=1, 2, \dots, s$). For this calculation, the most appropriate weight (v_i and u_r) is determined for each player to maximize the rate within restricted ranges such as nonnegativity constraints.

This study uses minutes played as an input item, and the frequency of ten basic plays and actions, such as the number of goals and passes, as output items (one input and ten output model) as shown below.

Input item (1): Minutes played

Output item (10): Number of goals, assists, passes, crosses, dribbles, tackles, interceptions, clears, blocks and fouls.

Note: Number of passes: Number of passes to a team mate

Number of crosses: Number of crosses to a team mate

Number of dribbles: Number of successful dribbles

Number of fouls: Difference from the largest number of fouls converted by minutes played (evaluate as points)

Minutes played is the only input item; therefore, it is similar to evaluation by adding the weight of each output item per unit time, such as number of goals or passes per unit time. Output items are all frequently pointed out by the Japan Football Association (2002, 2003, 2004), and are considered as major items in the Opta Index Limited (2000) and J-STATS Opata (2005), which are generally recognized as important by the individuals involved in the sport.

The output items comprise on-the-ball plays during games. For example, number of passes per minutes played expresses the level of contribution to games through passes, or on-the-ball plays. Therefore, it is necessary to remember that evaluation of off-the-ball plays and technical aspects such as accuracy of passes has not been possible.

Different from other indexes used as output

items such as the number of goals, the lower the number of fouls, the higher the evaluation of the player. Therefore, the data should be converted for evaluation. In this study, the maximum number of fouls per unit time of all players is set as the base and converted to the number of subject player fouls against the number of minutes played to evaluate the difference between said converted figures and the actual number of subject player fouls. Specifically, the maximum number of fouls per unit time for Hirayama was 78 fouls/1414 min. (= 0.05512 times/min.). Based on this figure, the number of fouls during Hirayama's playing time at 2307 minutes is converted to 127.3 fouls (0.05512×2307). Amaral played 2307 minutes and committed 107 fouls; therefore, the difference between 127.3 and 107 is the equivalent number (20.3) of fouls. This allows the number of fouls to be included in the calculation, which is based on the frequency per unit time, as other output items are.

There are other ways to calculate items for which lower values are better outcomes. For example, using reciprocals as output items or using the actual numbers as input items is possible. However, depending on the handling, differences may result. In the end, head and other coaches must determine the best input and output items. In this study, based on the data conversion mentioned above, we used number of fouls in the same way as other output items; namely, from the viewpoint of frequency per time played.

The input and output items above are nearly the same as those used by Hirotsu et al. (2006). In the Hirotsu study, the values of the above-mentioned output items were converted to correspond to 90 minutes of playing time, with the converted value of each item standardized to set the maximum as 1 and minimum as 0. In this study, however, we used actual data other than the number of fouls to reduce complication. In addition, Hirotsu et al. (2006) used the value acquired by adding the number of crosses and corner kicks as an output item. However, we think using the number of corner kicks with the number of crosses is inappropriate because corner kicks are generally performed by a specific individual, and it may not be suitable to evaluate players by the number of corner kicks to team mates while players on the same team and opponents are mixed in front of the goal. Therefore, we used the number of crosses, but excluded the number of corner kicks from the output items.

The calculation of the efficiency scores using

the above-mentioned input and output items can be formulated in the CCR model shown below. The maximum value obtained by solving a fractional programming problem, which maximizes the rate obtained from formula (2) under the conditions shown in (3) to (5), is the efficiency score of a player (j_o). The number of subjects is 243, and there are one input and ten output items; therefore, $n = 243$, $m = 1$, and $s = 10$.

$$\text{Max } \frac{\sum_{r=1}^s u_r y_{rj_o}}{\sum_{i=1}^m v_i x_{ij_o}} \quad (2)$$

s.t.

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1 \quad (j = 1, \dots, n) \quad (3)$$

$$u_r \geq 0 \quad (r = 1, \dots, s) \quad (4)$$

$$v_i \geq 0 \quad (i = 1, \dots, m) \quad (5)$$

Solving this fractional programming problem for each player (j_o) ($j_o = 1, 2, \dots, n$) makes it possible to calculate the efficiency score and the most appropriate weight for each player. A player whose efficiency is 1 is considered efficient and to have excellent ability. (Strictly speaking, a player whose efficiency rate is 1 and whose weights, v_i and u_r , are positive is considered efficient. Player efficiency can also be checked with a slack variable (Cooper et al., 2007). In this study, all players with an efficiency rate of 1 satisfied the condition and were considered efficient.) Players who are not efficient are inefficient, which, simply stated, means that they are not as good as other players. We used DEA-Solver-PRO, DEA calculation software produced by SEITECH, based on Cooper et al., (2007) for the calculation.

3. Data

We acquired 2008 J-league Division 1 data for the above-mentioned eleven input and output items aggregated at Data Stadium Inc. and evaluated J-league players who had greater than 900 minutes of timed played. Data Stadium Inc. aggregates the frequency of plays and actions during games by

classifying them into approximately 300 items. Among the data, we used only those items necessary for analysis in this study.

The number of players who played more than 900 minutes, which is equivalent to more than 10 games, a number totalling approximately one third of the total number of games per year, was 243, including 55 forwards (FW), 102 midfielders (MF), and 86 defenders (DF). The players who played different positions for each game were categorized into the position they played most often. The figures for the input and output items of the top and bottom 20 players are shown in **Table 1**. For example, Marquinhos made 21 goals, which is the top among all players. Nakamura passed 1850 times, which exceeded Endo and marked the top. Amaral committed 107 fouls, whose equivalent was 20.3 after converting the figure into time played.

Table 1 shows that the FW position accounts for the majority of top positions for number of goals, and that the DF position accounts for all the top positions for number of clears. There are 50 to 80 players who showed “0” for number of goals and assists. However, because of the impact of the difference of roles due to their positions, we decided to evaluate players by position in this study. The input and output item data shown in Table 1 reveals the characteristics of each player. In the next section, we discuss and explain DEA results based on this data.

4. Results and Discussion

4.1. Efficiency score

Table 2 and **3** show the efficient players and the efficiency scores for inefficient players with their efficiency scores, respectively. The efficiency scores were obtained by classifying players into three positions, FW, MF, and DF, and by solving the fractional programming problem (2) – (5) using the values for eleven input and output items described in Section 2. Table 2 gives figures for 113 players in total, including 27 FW (a), 50 MF (b), and 36 DF (c), whose efficiency scores were 1. The number of players with efficiency scores of 1 is associated with the number of input and output items. In general, the greater the number of input and output items, the higher the number of players with efficiency scores of 1. In this study, Almost half of the subject players were considered to be efficient.

Table 2 shows that the majority of players ranked at the top for the input and output items in Table 1, including Marquinhos and Nakamura; that is, the efficient players. Efficient players in Table 1 are highlighted in gray. In regard to FW, Marquinhos and Juninho, who are positioned at the top in the number of goals and dribbles respectively, were considered efficient. Other FWs also exhibit specific characteristics and are considered efficient. Similarly, among MFs and DFs, players, who exhibit specific characteristics in their respective positions, including Nakamura, Kim, and Shimomura, who occupied the top positions in certain output items, such as the number of passes, tackles, and blocks, are considered to be efficient. Although Nakamura exceeded Endo in the number of passes, placing him in the top spot, Endo had 1758 passes during 2368 minutes of play while Nakamura had 1850 during 3049 minutes of play. This gives Endo the higher rate and rates him as efficient. Although Tomita is top in the number of clears, his standing drops to inefficient after the number is converted to passes/time played. The reference frequency given in Table 2 will be explained later.

This method of calculation has great potential for use in clarifying player characteristics. For example, three players, Murakami (MF), Shibata and Fujiyama (DF), have not been selected as members of the Japan national team, have been told that they are not in the future plans of their respective clubs, and are not ranked high in the input and output items shown in Table 1. They are good players, but not necessarily highly regarded generally. Of course, it is impossible to evaluate players by statistical data alone because there are too many factors associated with performance. However, these three players are considered efficient according to this data, which suggests the possibility of discovering player characteristics from different perspectives. We will continue discussing this point in the following sections.

Table 3 shows inefficient players; that is, players with scores of less than 1. Inefficient MF scores are 0.775 or greater and the range of MF scores is the smallest. As an individual player, Tomita had the largest number of clears; however, his score is 0.999, which makes him inefficient. While Tese is considered an excellent player in general, the figures in this study show him to be inefficient, which is surprising. However, superiority or inferiority among the players

Table 2 Efficient players and reference frequency

(a)FW

Player	Reference Frequency	Player	Reference Frequency	Player	Reference Frequency
França	15	Marquinhos	5	Amaral	1
Nagai	15	Iio	5	Nakayama	1
Edmilson	11	Maki,S	4	Tanaka,T	1
Takahashi,D	11	Akamine	4	Davi	0
Bare	10	Fukai	3	Johnsen	0
Okazaki	10	Yano	3	Lavrič	0
Juninho	9	Leandro,A	2	Lucas	0
Sugimoto,K	8	Leandro,S	2	Yoshihara	0
Hulk	5	Tamada	2	Bandai	0

(b)MF

Player	Reference Frequency	Player	Reference Frequency	Player	Reference Frequency	Player	Reference Frequency
Yasuda	26	Ogura	7	Fujimoto	3	Kikuchi	0
Myojin	23	Murakami,K	6	Magnum	2	Yoshida,T	0
Endo	19	Otani	6	Kurisawa	2	Sakamoto	0
Nakamura,K	19	Ito,T	5	Kobayashi,Y	2	Edamura	0
Kudo	18	Kim	4	Yoshimura	1	Ueda	0
Ogawa	18	Suganuma	4	Yamase	1	Chiba	0
Komano	16	Ishikawa,N	4	Matsuoka	1	Murai	0
Danilo	13	Taniguchi	4	Saito,M	1	Hyodo	0
Hirakawa	11	Chugo	4	Soma	1	Haga	0
Konno	9	Diego	3	Tanaka,H	1	Homma	0
Oota	9	Shimomura	3	Roberto	0	Suzuki,N	0
Suzuki,S	9	Ogasawara	3	Kawai	0		
Marcos Paulo	7	Watanabe	3	Kawamura	0		

(c)DF

Player	Reference Frequency	Player	Reference Frequency	Player	Reference Frequency
Shibata	28	Minowa	7	Tsutsumi	2
Nakazawa,Y	21	Nakatani	6	Moniwa	2
Marcus Tanaka	20	Leandro	5	Takagi,K	1
Fujiyama	19	Shimohira	5	Yamaguchi	1
Bajalica	16	Kaga	5	Ishikawa	1
Yoshida,M	15	Kamata	5	Nagatomo	1
Araiba	12	Abe,Y	4	Kakuda	0
Murayama	11	Komiyama	3	Kobayashi,R	0
Hattori	10	Matsuo	3	Matsuda	0
Nasu	8	Kaji	2	Tokunaga	0
Abe,S	7	Ichikawa	2	Uchida,J	0
Mizumoto	7	Uemoto	2	Uchida,A	0

Table 3 Inefficient players and their efficiencies

(a)FW

Player	Efficiency	Player	Efficiency	Player	Efficiency
Tese	0.991	Maeda,R	0.903	Tashiro	0.818
Marques	0.978	Okubo	0.899	Anderson	0.816
Takahara	0.977	Sakata	0.894	Rôni	0.811
Hiramoto	0.941	Yamazaki,M	0.889	Ooguro	0.805
Lee	0.939	R.Cullen	0.879	Ueslei	0.800
Tahara	0.937	Ohshima	0.875	Reinaldo	0.795
Hara	0.930	Takamatsu	0.850	Alessandro	0.780
Yanagisawa	0.920	Arai,T	0.847	Yazima	0.735
Hirayama	0.915	Cabore	0.820		
Nishizawa	0.914	Koroki	0.820		

(b)MF

Player	Efficiency	Player	Efficiency	Player	Efficiency
Ponte	0.993	Yazawa	0.954	Marcio	0.885
Kobayashi,D	0.992	Uchida,T	0.954	Hosogai	0.883
Hashimoto	0.991	Nakamura,N	0.951	Davidson	0.876
Yamagishi	0.990	Kajiyama	0.950	Claiton	0.876
Kataoka	0.989	Lopes	0.946	Sunakawa	0.866
Honda	0.980	Vitor Junior	0.943	Matsushita	0.862
Kurihara	0.979	Naruoka	0.940	Kanazawa,S	0.846
Yamane	0.977	Emerson	0.938	Sato,Y	0.844
Fernandinho	0.976	Sugawara	0.935	PoPo	0.838
Edmilson	0.975	Aoki,T	0.927	Fujimoto,C	0.831
Suzuki,K	0.972	Fujita,S	0.919	Kanazaki	0.817
Terakawa	0.971	Botti	0.916	Hyodo	0.816
Futagawa	0.970	Koga,S	0.915	Shibasaki	0.791
Nozawa	0.964	Hanyu	0.915	Fukunishi	0.789
Mori	0.963	Alex	0.913	Nishi	0.780
Motoyama	0.957	Rodrigo	0.912	Yamada,N	0.775
Inuzuka	0.957	Asari	0.909		
Tanaka,H	0.957	Saeki	0.897		

(C)DF

Player	Efficiency	Player	Efficiency	Player	Efficiency
Tanaka,Y	0.9996	Aoki,R	0.955	Masushima	0.892
Tomita	0.999	Tanaka,M	0.951	Aoyama,N	0.889
Kanazawa,J	0.996	Wada	0.946	Saito,D	0.886
Takeuchi	0.994	Horinouchi	0.946	Iwashita	0.881
Igawa	0.979	Kitamoto	0.946	Oiwa	0.878
Kobayashi,Y	0.979	Teshima	0.945	Inoha	0.865
Hato	0.975	Nagata	0.942	Kobayashi,T	0.861
Tsuboi	0.970	Fukaya	0.940	Sahara	0.860
Masukawa	0.968	Nakazawa,S	0.935	Tsubouchi	0.854
Bosnar	0.967	Ito,H	0.932	Iwase	0.848
Morishige	0.966	Terada	0.929	Kodama	0.843
Tsuchiya	0.965	Ishibitsu	0.928	Tomisawa	0.837
Ikeda	0.962	Fujita,Y	0.919	Okubo	0.830
Nishizawa	0.960	Chiyotanda	0.918	Nishijima	0.818
Kurakawa	0.960	Sidiclei	0.915	Chano	0.778
Ikeuchi	0.960	Kurihara	0.912	Koga,M	0.746
Hiraoka	0.956	Uchiyama	0.903		

in this study is simply a relative relationship based on input and output items. For example, although Tese is considered inefficient, we have to remember that it does not make him inferior as an FW.

4.2. Virtual input and output values

Virtual input and output values can be used to identify which items contribute to efficiency scores of 1 among players. The values for each virtual input $\sum_{i=1}^m v_i x_{ij0}$ and virtual output $\sum_{r=1}^s u_r y_{rj0}$ item described in Section 2 show this. **Table 4** shows the results for each item that contributed to an efficiency score of 1. It is also possible to determine which input and output items should be regarded as important by checking the weight of v_i and u_r , rather than virtual input and output; however, because the weight values vary depending on the scale (unit) of input and output items, it is easier to compare items with the values of each virtual input and output item, which is a function of weight multiplied by input and output item. As total values of both virtual input and output items for the efficient players equal 1, the values shown in Table 4 express the contribution of each item, making it possible to distinguish the characteristics of individual players.

For example, the virtual output values for Nagai (FW) in Table 4 (a) show that his efficiency score is 1 as a result of the number of goals, passes, and crosses, namely, 0.25, 0.54, and 0.21 respectively, and the frequency of the goals, passes, and crosses per time played contributes to his efficiency, with the number of passes in particular being highly regarded. Similarly, França is highly regarded due to his frequency of assists.

With only a partial solution to the fractional programming problem (2) to (5), it is not possible to set the most appropriate weight value, meaning that the virtual input and output value provides only an example of player characteristics. However, even such an example can indicate the degree of contribution of the input and output items to achieving an efficiency score of 1. Therefore, it is useful in discovering player characteristics.

The example of Murakami, described in Section 4.1, shows that the number of goals, passes, dribbles, intercepts, and clears per time played contributed at the rate of 0.04, 0.32, 0.08, and 0.38 respectively, as shown in Table 4, to yield the determination that he is efficient. In other words, when we consider such

contribution rates, no player exceeds Murakami, indicating that these rates are helpful in clarifying certain of Murakami's characteristics. Similarly, the characteristics of Shibata and Fujiyama can also be read from the results shown in Table 4. Of course it is left up to head and other coaches to decide how to apply such results; however, DEA is meaningful as a useful means of clarifying player characteristics that are difficult to identify by other methods of analysis.

4.3. Reference set and lambda value

Table 5 shows the results for the reference set and lambda value of inefficient players. Here we describe the results using Tese (FW) shown in Table 5 (a) as an example.

Tese is inefficient in relation to players such as Edmilson, Hulk, Nagai, Maki, and Akamine in terms of reference set and lambda value. In this case, the values of ten output items for Tese are inferior to the values obtained from the combination of Edmilson, Hulk, Nagai, Maki, and Akamine, rendering clarification of Tese's characteristics problematic. There is always a group of efficient players, however, that an inefficient player can be compared with. In other words, when we focus on inefficient players, there is always a group of efficient players that can serve as a model toward which the inefficient player should improve. Such a group of players is called a reference set.

Applying the virtual method to players whose input and output values are obtained by multiplying an appropriate coefficient (lambda value) with the input and output items of a group of players which serve as a reference set and summing them up shows inefficient players to be inferior to such virtual players under weights that said inefficient players select to their advantage. Incidentally, the fraction of the rate of inefficient players shown in (1) and the rate of the virtual players represent the efficiency score of inefficient players.

Specifically, when Tese is compared with a virtual player obtained by summing up five players, Edmilson, Hulk, Nagai, Maki, and Akamine, with the lambda values, 0.56, 0.08, 0.02, 0.09, and 0.53 respectively, Tese is rated inefficient. Although Tese is widely acknowledged to be an excellent player, he is inferior to the virtual player with the characteristics of these five players that comprise the reference set. When the efficiency score of this virtual player is

Table 4 Virtual input and output of the efficient players

(a)FW

No.	Player	Virtual Input	Virtual Output									
		Time	Goal	Assist	Pass	Cross	Dribble	Tackle	Interception	Clear	Block	Foul
1	França	1.00	0.03	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	Nagai	1.00	0.25	0.00	0.54	0.21	0.00	0.00	0.00	0.00	0.00	0.00
3	Edmilson	1.00	0.43	0.27	0.00	0.00	0.00	0.13	0.00	0.17	0.00	0.00
4	Takahashi	1.00	0.00	0.00	0.00	0.23	0.00	0.32	0.01	0.43	0.00	0.00
5	Bare	1.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.60
6	Okazaki	1.00	0.51	0.00	0.40	0.00	0.00	0.09	0.00	0.00	0.00	0.00
...
22	Davi	1.00	0.76	0.00	0.00	0.00	0.09	0.00	0.00	0.15	0.00	0.00
23	Johnsen	1.00	0.23	0.00	0.42	0.00	0.00	0.00	0.00	0.21	0.14	0.00
24	Lavrič	1.00	0.17	0.00	0.11	0.00	0.00	0.00	0.00	0.72	0.00	0.00
25	Lucas	1.00	0.17	0.00	0.62	0.03	0.00	0.19	0.00	0.00	0.00	0.00
26	Yoshihara	1.00	0.00	0.00	0.00	0.00	0.00	0.41	0.59	0.00	0.00	0.00
27	Bandai	1.00	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.88	0.00	0.05

(b)MF

No.	Player	Virtual Input	Virtual Output									
		Time	Goal	Assist	Pass	Cross	Dribble	Tackle	Interception	Clear	Block	Foul
1	Yasuda	1.00	0.00	0.00	0.33	0.36	0.31	0.00	0.00	0.00	0.00	0.00
2	Myojin	1.00	0.00	0.00	0.61	0.00	0.00	0.00	0.18	0.21	0.00	0.00
3	Endo	1.00	0.00	0.31	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	Nakamura,K	1.00	0.00	0.39	0.52	0.00	0.07	0.02	0.00	0.00	0.00	0.00
5	Kudo	1.00	0.05	0.00	0.00	0.00	0.14	0.00	0.66	0.00	0.15	0.00
6	Ogawa	1.00	0.65	0.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	Komano	1.00	0.00	0.00	0.15	0.85	0.00	0.00	0.00	0.00	0.00	0.00
8	Danilo	1.00	0.27	0.71	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	Hirakawa	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.80
10	Konno	1.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.75	0.00
...
15	Murakami,K	1.00	0.04	0.00	0.32	0.00	0.08	0.00	0.18	0.38	0.00	0.00
...
41	Yoshida.T	1.00	0.57	0.03	0.08	0.31	0.00	0.00	0.00	0.00	0.00	0.00
42	Sakamoto	1.00	0.00	0.00	0.00	0.00	0.00	0.11	0.24	0.29	0.00	0.35
43	Edamura	1.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.40
44	Ueda	1.00	0.00	0.52	0.23	0.00	0.02	0.00	0.17	0.00	0.06	0.00
45	Chiba	1.00	0.00	0.00	0.00	0.00	0.00	0.04	0.19	0.21	0.00	0.56
46	Murai	1.00	0.00	0.00	0.00	0.00	0.66	0.00	0.34	0.00	0.00	0.00
47	Hyodo	1.00	0.05	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
48	Haga	1.00	0.00	0.00	0.00	0.00	0.00	0.07	0.19	0.19	0.50	0.04
49	Homma	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.14	0.31	0.27
50	Suzuki,N	1.00	0.02	0.00	0.00	0.09	0.00	0.00	0.00	0.19	0.67	0.03

(c)DF

No.	Player	Virtual Input	Virtual Output									
		Time	Goal	Assist	Pass	Cross	Dribble	Tackle	Interception	Clear	Block	Foul
1	Shibata	1.00	0.20	0.00	0.00	0.00	0.00	0.33	0.00	0.47	0.00	0.00
2	Nakazawa,Y	1.00	0.03	0.00	0.01	0.00	0.00	0.26	0.00	0.00	0.00	0.70
3	Marcus Tanaka	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	Fujiyama	1.00	0.00	0.00	0.00	0.00	0.00	0.60	0.40	0.00	0.00	0.00
5	Bajalica	1.00	0.00	0.00	0.27	0.00	0.00	0.68	0.00	0.05	0.00	0.00
6	Yoshida,M	1.00	0.00	0.00	0.69	0.00	0.00	0.23	0.00	0.08	0.00	0.00
7	Araiba	1.00	0.08	0.32	0.00	0.43	0.17	0.00	0.00	0.00	0.00	0.00
8	Murayama	1.00	0.00	0.03	0.19	0.04	0.02	0.00	0.13	0.00	0.55	0.03
9	Hattori	1.00	0.00	0.15	0.66	0.19	0.00	0.00	0.00	0.00	0.00	0.00
10	Nasu	1.00	0.00	0.00	0.08	0.02	0.00	0.12	0.05	0.59	0.00	0.14
...
27	Takagi,K	1.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.79
28	Yamaguchi	1.00	0.02	0.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	Ishikawa,N	1.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.11	0.86
30	Nagatomo	1.00	0.13	0.29	0.00	0.18	0.40	0.00	0.00	0.00	0.00	0.00
31	Kakuda	1.00	0.00	0.69	0.00	0.01	0.08	0.21	0.00	0.00	0.00	0.00
32	Kobayashi,R	1.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.97
33	Matsuda	1.00	0.00	0.07	0.70	0.00	0.00	0.13	0.10	0.00	0.00	0.00
34	Tokunaga	1.00	0.00	0.00	0.00	0.04	0.11	0.31	0.00	0.00	0.15	0.40
35	Uchida,J	1.00	0.00	0.88	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00
36	Uchida,A	1.00	0.00	0.16	0.28	0.15	0.05	0.00	0.00	0.00	0.36	0.00

Table 5 Reference sets for inefficient players

(a)FW

No.	Player	Reference set and Lambda value													
28	Tese	Edmilson	0.56	Hulk	0.08	Nagai	0.02	Maki,S	0.09	Akamine	0.53				
29	Marques	Edmilson	0.13	Juninho	0.28	Bare	0.32	Sugimoto,K	0.04						
30	Takahara	Bare	0.06	França	0.95	Fukai	0.30	Iio	0.27						
31	Hiramoto	Juninho	0.01	Nagai	0.06	Okazaki	0.16	Takahashi,D	0.42	Fukai	0.24	Sugimoto,K	0.12		
32	Lee	Edmilson	0.18	Hulk	0.12	França	0.01	Okazaki	0.06	Takahashi,D	0.39	Iio	0.17		
33	Tahara	Edmilson	0.03	Nagai	0.38	Maki,S	0.26	Takahashi,D	0.10	Yano	0.04				
...				
50	Rôni	Bare	0.04	França	0.74	Marquinhos	0.09	Okazaki	0.25	Sugimoto,K	0.13				
51	Ooguro	Juninho	0.06	França	0.32	Tamada	0.14								
52	Ueslei	Leandro,A	0.07	Nagai	0.95	Maki,S	0.23	Takahashi,D	0.27	Yano	0.11				
53	Reinaldo	Juninho	0.05	Nagai	0.55	Takahashi,D	0.14	Sugimoto,K	0.07						
54	Alessandro	França	0.05	Marquinhos	0.33	Okazaki	0.77	Akamine	0.15						
55	Yazima	Edmilson	0.45	Amaral	0.09	Nagai	0.00	Okazaki	0.10	Takahashi,D	0.02	Nakayama,G	0.03		

(b)MF

No.	Player	Reference set and Lambda value															
51	Ponte	Endo	0.14	Komano	0.22	Ogawa	0.07	Chugo	0.01	Tanaka	0.01						
52	Kobayashi,D	Danilo	0.18	Komano	0.05	Kurisawa	0.11	Kudo	0.58	Ogawa	0.03	Murakami,K	0.19	Taniguchi	0.04		
53	Hashimoto	Yasuda	0.08	Endo	0.01	Komano	0.26	Nakamura,K	0.23	Hirakawa	0.07	Myojin	0.40				
54	Yanagisawa	Ito,T	0.08	Nakamura,K	0.11	Hirakawa	0.49	Suzuki,S	0.20								
55	Kataoka	Endo	0.07	Yoshimura	0.06	Ogura	0.40	Murakami,K	0.50	Myojin	0.21						
56	Honada	Danilo	0.02	Marcos Paulo	0.09	Yasuda	0.01	Endo	0.01	Kudo	0.00	Konno	0.21	Chugo	0.21	Myojin	0.02
57	Kurihara	Diego	0.14	Ogawa	0.03	Kobayashi,Y	0.10	Oota	0.22	Watanabe	0.19						
58	Yamane	Kim	0.30	Ogura	0.05	Matsuoka	0.20										
59	Fernandinho	Magnum	0.19	Yasuda	0.56	Ogawa	0.23	Oota	0.02								
60	Edmilson	Diego	0.04	Kobayashi,Y	0.28	Saito,M	0.23	Taniguchi	0.07	Watanabe	0.01	Hirakawa	0.10	Myojin	0.53		
...		
93	Kanazawa,S	Yasuda	0.10	Ito,T	0.09	Hirakawa	0.00	Myojin	0.23	Suzuki,S	0.02						
94	Sato,Y	Kudo	0.07	Konno	0.43	Otani	0.02	Myojin	0.48	Suzuki,S	0.08						
95	PoPo	Yasuda	0.09	Komano	0.17	Ogawa	0.37	Ishikawa,N	0.03	Oota	0.08	Nakamura,K	0.01				
96	Fujimoto,C	Magnum	0.04	Yasuda	0.24	Endo	0.15	Komano	0.11	Ogawa	0.19	Nakamura,K	0.04				
97	Kanazaki	Yasuda	0.28	Kudo	0.24	Ogawa	0.06	Oota	0.62								
98	Hyodo	Yasuda	0.03	Endo	0.31	Komano	0.02	Ogura	0.15	Hirakawa	0.20	Myojin	0.14				
99	Shibasaki	Marcos Paulo	0.65	Yasuda	0.00	Endo	0.10	Shimomura	0.05	Komano	0.02	Kudo	0.08				
100	Fukunishi	Yasuda	0.16	Endo	0.17	Kurisawa	0.04	Taniguchi	0.11	Nakamura,K	0.31	Myojin	0.12				
101	Nishi	Danilo	0.07	Yasuda	0.04	Konno	0.44	Ogawa	0.14	Myojin	0.08						
102	Yamada,N	Yasuda	0.29	Endo	0.09	Nakamura,K	0.13	Hirakawa	0.12	Myojin	0.10						

(c)DF

No.	Player	Reference set and Lambda value													
37	Tanaka,Y	Abe,Y	0.08	Abe,S	0.16	Yoshida,M	0.23	Matsuo	0.25	Fujiyama	0.04	Nasu	0.02	Hattori	0.06
38	Tomita	Yoshida,M	0.91	Shibata	0.78	Nakazawa,Y	0.05	Marcus Tanaka	0.05						
39	Kanazawa,J	Kaga	0.04	Komiyama	0.04	Fujiyama	0.22	Hattori	0.17						
40	Takeuchi	Shimohira	0.21	Kaji	0.00	Yoshida,M	0.20	Komiyama	0.07	Matsuo	0.25	Araiba	0.44		
41	Igawa	Bajalica	0.23	Yoshida,M	0.52	Uemoto	0.17	Marcus Tanaka	0.02	Fujiyama	0.58				
42	Kobayashi,Y	Leandro	0.00	Kaga	0.09	Mizumoto	1.18	Minowa	0.36						
43	Hato	Abe,S	0.07	Ichikawa	0.26	Araiba	0.03	Murayama	0.97	Marcus Tanaka	0.14				
44	Tsuboi	Bajalica	0.55	Kaga	0.13	Mizumoto	0.07	Minowa	0.18						
45	Masukawa	Yoshida,M	0.48	Shibata	0.25	Nakazawa,Y	0.27	Marcus Tanaka	0.10						
46	Bosnar	Shibata	0.77	Nakazawa,Y	0.60										
...
77	Kobayashi,T	Yoshida,M	0.16	Shibata	1.50										
78	Sahara	Shibata	0.55	Nakazawa,Y	0.26	Fujiyama	0.61	Nasu	0.12						
79	Tsubouchi	Takagi,K	0.02	Shibata	0.60	Araiba	0.62	Marcus Tanaka	0.07						
80	Iwase	Shibata	0.34	Mizumoto	0.08	Nakazawa,Y	0.48	Fujiyama	0.28	Nasu	0.23				
81	Kodama	Abe,S	0.18	Shimohira	0.67	Yoshida,M	0.02	Shibata	0.03	Nakazawa,Y	0.04	Marcus Tanaka	0.23		
82	Tomisawa	Shimohira	0.13	Kamata	0.25	Marcus Tanaka	0.38	Minowa	0.26						
83	Okubo	Yoshida,M	0.04	Shibata	0.77	Nakatani	0.02								
84	Nishijima	Bajalica	0.11	Yoshida,M	0.02	Shibata	0.91	Araiba	0.07	Marcus Tanaka	0.12				
85	Chano	Bajalica	0.16	Shibata	0.42	Araiba	0.01	Nakazawa,Y	0.39	Fujiyama	0.02	Nasu	0.13		
86	Koga,M	Bajalica	0.15	Leandro	0.18	Yoshida,M	0.13	Shibata	0.92	Mizumoto	0.01	Minowa	0.44		

set at 1, Tese's efficiency score is 0.991, as shown in Table 3 (a). In order for Tese to be rated as efficient under the current most appropriate weight, he should set the virtual player as his target.

Furthermore, the lambda value shows that Tese combines Edmilson and Akamine, whose coefficients are larger. The reference set for Tese is significantly different from Marques and Takahara; therefore, Tese as a player is different from Marques and Takahara. Table 5 does not show all the inefficient players due to space limitations. However, the information given can be used to identify reference players or as reference information to distinguish the type of players.

The more efficient players that are included in the reference sets of inefficient players, the more the players become the target for inefficient players. Reference Frequency in Table 2 shows the frequency of efficient players appearing in the reference set of inefficient players. According to Table 2, França, Nagai, Yasuda, and Shibata, whose reference frequencies are high, appear in the reference set of many players in each position, and they represent the players with the desirable characteristics for each position. Meanwhile, 26 efficient players, including Davi and Johnsen, do not appear at all. This means that there are no players who set these 26 players as their target, and indicates that they are peculiar players or players with unique styles. As seen above, the reference frequency in the reference set is an index to distinguish the characteristics of efficient players.

4.4. Examples of improvement

DEA has the advantage of being capable of clearly indicating improvement targets for inefficient players. For example, Tese is considered inefficient due to the existence of a virtual player comprising Edmilson, Hulk, Nagai, Maki, and Akamine. In order for Tese to reach the level of the virtual player maintaining his most appropriate weight, he should improve in the areas shown in **Table 6**; namely, increasing the number of goals to 14.1 or greater, passes to 517.5 or greater, crosses to 8.6 or greater, dribbles to 30.3 or greater, tackles to 18.4 or greater, intercepts to 3.2 or greater, clears to 34.4 or greater, blocks to 32.8 or greater, and fouls to 51.7 or less. This is one specific set among countless targets for improvement. Table 6 also shows examples of targets for improvement for

other players.

5. Conclusion

We described the results of an evaluation of the characteristics of J-league players utilizing DEA. In this study, we used time played as an input item and the annual frequencies of ten basic plays and actions, such as goals and passes, as output items for analysis by CCR to obtain efficiency scores for players. We indicated the characteristics of efficient players with virtual input and output items, and indicated the reference sets, lambda values, and targets for improvement of inefficient players. Through DEA, we were able to suggest the possibility of identifying characteristics of individual players and evaluating their multilateral abilities from the standpoint of efficiency.

We created input and output item data based on the annual performance of individual players in the 2008 season. The evaluation of players varies depending on the data used; therefore, it is desirable to select the ideal period for this method by checking results with head and other coaches. We will continue this study to develop this as a supplementary method for utilization at the discretion of coaches.

Although we chose one input and ten output items for this study, these can be freely changed based on the intention of the individual or group conducting the analysis. Changing items may identify new player characteristics. In particular, because the role of individual players differs by position, choosing input and output items for each position would make it possible to evaluate players according to their roles. In addition, we used a basic CCR model in this study; however, using other DEA models for analyses may yield different results, which may lead us to the identification of different characteristics. We hope that our study will expand and deepen the usability and validity of the evaluation method through more analyses on soccer players utilizing DEA.

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