



Research article

PERFORMANCE ANALYSIS OF BOWLERS IN INDIAN PREMIER LEAGUE BY DATA ENVELOPMENT ANALYSIS

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Abstract

This paper uses data envelopment analysis (DEA) to evaluate the performance of bowlers who have been ranked according to the number of wickets they have taken in the tenth edition of Indian Premier League (IPL) 2017. This evaluation determines efficient and inefficient cricket bowlers and ranks them on the basis of DEA scores. The DEA benchmarking analysis also allows identifying strengths and weaknesses of the game of the players. To the ranking of players, the authors used the super-efficiency evaluation. The ranking can be used to choose the required number of players for a cricket team and would be beneficial for franchise owners and team management in prizing the players. The inputs considered for DEA evaluation were number of innings, number of overs bowled and prize of player. Wickets taken by the bowler, bowling average, economy, and strike rate were taken as outputs.

Keywords: Data Envelopment Analysis, Indian Premier League, Benchmarking, Bowler

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INTRODUCTION

Over the past one decade, drastic changes have occurred within the traditional model of cricket primarily due to the creation of Indian Premier League. Shorter games, auction-based salaries, city franchises and revenue derived primarily from broadcasting are some of

the innovations adopted by the IPL C Akthar (2013).

The IPL is the most-attended cricket league in the world and ranks sixth among all sports leagues. The brand value of IPL was estimated to be \$4.5 billion in 2015 by American Appraisal, a Division of Duff & Phelps. According to BCCI, the 2015 IPL season contributed ₹11.5 billion

(\$182 million) to the GDP of the Indian economy (Indian Premier League). Duff & Phelps added that the value of brand IPL has jumped to \$4.16 billion after the 2016 edition.

The Indian Premier League often abbreviated as IPL, is a domestic professional Twenty20 cricket competition in India. The league was founded by the Board of Control for Cricket in India (BCCI). In early 2008, the BCCI announced the launch of the Indian Premier League, a new franchise based T20 league, which is among the first of its kind in the cricketing world. The league was based on the Premier League of England and the NBA in the United States Indian Premier League (2016).

Currently, eight teams are participating in IPL. Players from India as well as from other countries like Australia, South Africa, England, Afghanistan etc are participating in this league. Each team plays each other twice in a double round-robin format. At the conclusion of the league stage, the top four teams qualify for the Playoffs. The top two teams from the league phase play against each other in the first qualifying match, with the winner going straight to the IPL final and the loser getting another chance to qualify for the IPL final by playing the second qualifying match. Meanwhile, the third and fourth place teams from league phase play against each other in an eliminator match and the winner of that match will play the loser from the first qualifying match. The winner of the second qualifying match will move onto the final to play the winner

of the first Qualifying match in the IPL Final match, where the winner will be crowned the Indian Premier League championship.

Bowling aspect in cricket

In the sport of cricket bowling is the action of propelling the ball toward the wicket defended by a batsman. A player skilled at bowling is called a bowler. There are different types of bowlers ranging from fast bowlers, whose primary weapon is pace, through swing and seam bowlers who try to make the ball deviate in its course through the air or when it bounces, to slow bowlers, who will attempt to deceive the batsmen with a variety of flight and spin. A spin bowler usually delivers the ball quite slowly and puts a spin on the ball, causing it to turn at an angle while bouncing off the pitch (Bowling in cricket).

MATERIALS AND METHODS

Data Envelopment Analysis is a linear programming-based technique for measuring the performance efficiency of organizational units which are termed Decision-making Units (DMUs). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs Charnes, Cooper and Rhodes (1978). Decision-making units can include a sports player, team manager, athletic director, coach or a game or part of a game.

The performance of DMUs is assessed in DEA using the concept of efficiency or productivity, which is the ratio of total outputs to total inputs. Efficiencies

estimated by DEA are relative, that is, relative to the best performing DMU (or DMUs if there are more than one best-performing DMUs). The best performing DMU is assigned an efficiency score of unity or 100 percent, and the performance of other DMUs vary, between 0 and 100 percent relative to his best performance Ramanathan (2003)

DEA Models

DEA is a “data-oriented” approach for evaluating the performance of a set of peer entities called Decision Making Units DMUs Charnes et al (1978). The basic idea behind DEA is the “relative measurement” of performance, which is generally defined as the effectiveness of a set of DMUs in realizing output(s) created through the utilization of input(s). DEA allows one to identify the best practice

and 100 % efficient DMU(s) and compare these to the inefficient DMU(s). As a result, insight is gained as for how to improve inefficient DMU(s). Although DEA has a strong link to production theory in economics, the tool is also used for benchmarking in operations management, where a set of measures is selected to benchmark the performance of manufacturing and service operations Cook, Tone and Zhu (2014). Data Envelopment Analysis (DEA) is a methodology based upon an interesting application of linear programming. The principles of DEA date back to Farrell (1957), but a mathematical framework to handle frontier analysis could be established only after 20 years. This mathematical formulation was provided by Charnes et al (1978).

The mathematical formulation of DEA with the assumption of CRS¹ was given by Charnes, Cooper, and Rhodes (1978). Let x_i and y_r denote the i^{th} ($i = 1, 2, 3, \dots, m$) i^{th} input and r^{th} ($r = 1, 2, 3, \dots, s$) output of j^{th} DMU; ($j = 1, 2, 3, \dots, n$) respectively. The efficiency of k^{th} – DMU (under evaluation) is defined as:

$$\max h_k(u, v) = \frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m v_i x_{ik}} \quad (1.1)$$

Sub to

$$\frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1; j = 1, 2, 3, \dots, n$$

$$u_r \geq 0 \text{ and } v_i \geq 0; \forall r = 1, 2, 3, \dots, s \text{ and } i = 1, 2, 3, \dots, m$$

Where u_r and v_i are the weight of r^{th} output and weight of the i^{th} input in the j^{th} DMU respectively. The mathematical formulation of the model (1.1) is in the fractional form has

¹ CRS=Constant Returns to Scale is defined as, the variation of inputs results the constant variation in outputs.

an infinite number of solutions. In order to avoid fractional form, we are using transformation given by Charnes and Cooper (1962). The linear form of the mathematical model (1.1) is as below:

$$\max h_k(u, v) = \sum_{r=1}^s u_r y_{rk}$$

Sub to

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0; \forall j = 1, 2, 3, \dots, n. \quad (1.2)$$

$$\sum_{i=1}^m v_i x_{ik} = 1.$$

$$u_r \geq 0 \text{ and } v_i \geq 0; \forall r = 1, 2, 3, \dots, s \text{ and } i = 1, 2, 3, \dots, m$$

The mathematical model is given in the equation (1.2) is linear form but it is not feasible for solving under DMU technique for which we are using the principle of duality in linear programming. The standard form of envelopment model is as follows:

$$u^* = \text{Minimise } u_k$$

Sub to

$$\sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = y_{rk}; r = 1, 2, 3, \dots, s \quad (1.3)$$

$$\sum_{j=1}^n x_{ij} \lambda_j + s_i^- = u_k x_{ik}; i = 1, 2, 3, \dots, m$$

$$s_r^+ \geq 0, s_i^- \geq 0, \text{ and } \lambda_j \geq 0; j = 1, 2, 3, \dots, n.$$

Where s_r^+ and s_i^- are input and output slacks. The DMU_k is said to be efficient if and only if $u^* = 1$ and all slacks must be zero i.e. $s_r^+ = 0, s_i^- = 0$. If $u^* = 1$, but all slacks are not zero. Then DMU under evaluation is weak efficient, and if $u^* < 1$, then the DMU_k under evaluation is inefficient.

In 1984 Banker, Charnes and Cooper extended the CCR model in variable returns to scale process is well known as BCC model Banker, Charnes and Cooper (1984), gives the technical efficiency of DMUs under investigation without any scale effect. The mathematical formulation is given as:

$$\begin{aligned}
 & \theta^* = \text{Minimise } \theta_k \\
 & \text{Sub to} \\
 & \sum_{i=1}^n y_{rj} \theta_j - s_r^+ = y_{rk} ; r = 1, 2, 3, \dots, s \\
 & - \sum_{j=1}^n x_{ij} \theta_j + s_i^+ = -\theta_k x_{ik} ; i = 1, 2, 3, \dots, m. \quad (1.4) \\
 & \sum_{j=1}^n \theta_j = 1 ; j = 1, 2, 3, \dots, n \\
 & \theta_j \geq 0 \text{ and } s_r^+ \geq 0, s_i^- \geq 0.
 \end{aligned}$$

Where s_r^+ and s_i^- are input and output slacks. θ_k is the efficiency score of k^{th} DMU and lie between 0 and 1.

Super efficiency

The super-efficiency for n -DMUs using m -input and s -output can be defined as let x_{ij} and y_{rj} denote i^{th} input; $i=1, 2, 3, \dots, m$ and r^{th} output; $r=1, 2, 3, \dots, s$ respectively of the j^{th} DMU; $j=1, 2, 3, \dots, n$. The super -efficiency can be calculated by using the mathematical model as given below, under the assumption that DMU under evaluation should be efficient:

$$\begin{aligned}
 & \theta^* = \text{Minimise } \theta_k \\
 & \text{Sub to} \\
 & \sum_{\substack{j=1 \\ j \neq 0}}^n \theta_j x_{ij} \leq \theta_k x_{i0} ; i = 1, 2, 3, \dots, m \quad (1.5) \\
 & \sum_{\substack{j=1 \\ j \neq 1}}^n \theta_j y_{rj} \geq y_{r0} ; r = 1, 2, 3, \dots, s \\
 & \sum_{j=1}^n \theta_j = 1 ; \theta_j (j \neq 0) \geq 0
 \end{aligned}$$

RESULTS AND FINDINGS

In this study, three inputs and four outputs were taken as regarded in Table 1. The inputs being the number of innings², overs³ bowled by the bowler, and prize⁴ of the player. The outputs considered were

wickets⁵ taken by the bowler, average⁶, economy⁷, and strike rate⁸ of the player. The data for this study was taken from authentic and reliable sources from the tenth edition of Indian Premier League 2017(Sports, 2017; Statistics IPL, 2017).

TABLE - I
INPUTS AND OUTPUTS FOR DAE

Decision-Making Units		Inputs				Outputs			
DMUs	Player	Inn	Ov	Bid Amt	Wkt	Avg	Econ	S/R	
DMU1	Bhuvnesh Kumar	14	52.2	4.25	26	14.19	7.05	12	
DMU2	Jaydev Unadkat	12	45.5	0.3	24	13.41	7.02	11.4	
DMU3	Jasprit Bumrah	16	59.2	1.2	20	22	7.41	17.8	
DMU4	Mitchell McClenaghan	14	54	0.3	19	26.68	9.38	17	
DMU5	Imran Tahir	12	47	0.5	18	20.5	7.85	15.6	
DMU6	Rashid Khan	14	54	4	17	21.05	6.62	19	
DMU7	Sandeep Sharma	13	48	4.2	17	23.41	8.29	16.9	
DMU8	Umesh Yadav	14	48.3	0.85	17	24.11	8.45	17.1	
DMU9	Chris Woakes	13	44	2.6	17	22.7	8.77	15.5	
DMU10	Pawan Negi	12	32.1	1	16	12.31	6.12	12	
DMU11	Siddarth Kaul	10	35.4	0.1	16	18.75	8.41	13.3	
DMU12	Axar Patel	14	48	0.75	15	24.13	7.54	19.2	
DMU13	N Counter-Nile	8	28.2	3.5	15	15.2	8.04	11.3	
DMU14	Pat Cummins	12	46.1	4.5	15	24.86	8.07	18.4	
DMU15	Y Chahal	13	43.3	0.1	14	23.78	7.65	18.6	

² The number of innings in which the batsman actually bowled.

³ The number of overs bowled.

⁴ Prize of the player is the amount of money paid by the franchise to the player or bid amount.

⁵ The number of wickets taken by the bowler.

⁶ The average number of runs conceded per wicket. (Ave = Runs/W)

⁷ The average number of runs conceded per over. (Econ = Runs/Overs bowled).

⁸ The average number of balls bowled per wicket taken. (SR = Balls/W)

DMU16	Karan Sharma	9	30.4	3.2	13	16.46	6.97	14.1
DMU17	Mohit Sharma	14	45.4	6.5	13	31.53	8.97	21
DMU18	Andrew Tye	6	21	0.5	12	11.75	6.71	10.5
DMU19	Ben Stokes	12	44	14.5	12	26.33	7.18	22
DMU20	Chris Morris	9	31	7	12	20	7.74	15.5
DMU21	Kuldeep Yadav	11	41	0.4	12	28.33	8.29	20.5
DMU22	Dan Christian	13	40	1	11	27.09	7.45	21.8
DMU23	Shardul Thakur	12	38.1	0.2	11	28.63	8.25	20.8
DMU24	Lasith Malinga	12	44.5	7.5	11	34.72	8.52	24.4
DMU25	Basil Thampi	12	44.4	0.85	11	38.54	9.49	24.3
DMU26	Krunal Pandya	13	40.0	2	10	27.30	6.82	24.00
DMU27	Sunil Narine	15	59.0	9.5	10	41.20	6.98	35.40
DMU28	Zaheer Khan	11	40.1	4	10	31.30	7.79	24.10
DMU29	Amit Mishra	14	38.5	3.5	10	34.30	8.83	23.30
DMU30	Mohammed Siraj	6	23.0	2.6	10	21.20	9.21	13.80

Data source: <http://www.iplt20.com/>

Inn: Innings, **Ov:** Overs, **Bid Amt:** Bid Amount in Crore, **Wkt:** Wickets, **Avg:** Average, **Econ:** Economy, **S/R:** Strike Rate

In this section, we are analyzing the performance of thirty bowlers as DMUs. For calculating the efficiency scores the software *DEA Frontier-Solver* was used and super efficiency was calculated manually in excel using solver. We obtain several efficiency measures including CCR, BCC and scale efficiency in input orientation case in the following Table 2. The CCR efficiency is the best indicator if the DMUs are working on the

optimal scale; otherwise, BCC efficacy indicator is good. The BCC efficiency has the property that it divides the overall efficiency into two mutually exclusive components as pure technical efficiency and scale efficiency. The scale efficiency can be calculated by taking the ratio of CCR to BCC efficiency estimates. The following Table (2) represents the various efficiency estimates.

TABLE – II
CCR, BCC, SCALE & SUPER EFFICIENCY

DMUs	Input-Oriented Efficiency		Benchmarks	Scale-eff	Super-eff	Final Rank
	CCR	BCC				
B Kumar	0.929	1.000	DMU1	0.929	1	12
J Unadkat	1.000	1.000	DMU2	1	10.404	1
J Bumrah	0.669	1.000	DMU3	0.669	2.029	3
M						
Clenaghan	0.908	1.000	DMU4	0.908	1	11
			DMU2,11,18,21,2			
I Tahir	0.868	0.937	5	0.926	0.937	19
R Khan	0.665	0.836	DMU2,25,27,30	0.795	0.836	25
S Sharma	0.699	0.880	DMU2,25,29,30	0.794	0.880	24
U Yadav	0.775	0.899	DMU2,4,11,25,30	0.862	0.899	22
C Woakes	0.742	0.969	DMU2,4,25,30	0.765	0.969	16
P Negi	0.872	0.971	DMU2,18,29	0.898	0.971	15
S Kaul	1.000	1.000	DMU11	1	1.878	5
A Patel	0.767	0.884	DMU2,23,25,26	0.867	0.884	23
Counter-						
Nile	0.943	1.000	DMU13	0.943	1.067	8
P Cummins	0.712	0.884	DMU2,25,27,30	0.805	0.884	23
Y Chahal	1.000	1.000	DMU15	1	2.129	2
K Sharma	0.846	0.952	DMU2,18,27,29	0.888	0.952	17
M Sharma	0.769	0.923	DMU2,25,29,30	0.833	0.923	20
A Tye	1.000	1.000	DMU18	1	1.245	7
			DMU2,18,27,29,3			
B Stokes	0.832	0.916	0	0.908	0.916	21
			DMU2,18,27,29,3			
C Morris	0.853	0.950	0	0.897	0.950	18
K Yadav	1.000	1.000	DMU21	1	1.050	10
D Christian	0.962	0.976	DMU2,18,23,26	0.985	0.976	14
S Thakur	1.000	1.000	DMU23	1	1.947	4
			DMU2,25,27,29,3			
L Malinga	0.913	0.977	0	0.934	0.977	13
B Thampi	1.000	1.000	DMU25	1	1	12
K Pandya	1.000	1.000	DMU26	1	1.050	10
S Narine	1.000	1.000	DMU27	1	1	12
Z Khan	1.000	1.000	DMU28	1	1.019	11
A Mishra	1.000	1.000	DMU29	1	1.062	9
M Siraj	1.000	1.000	DMU30	1	1.871	6

The results reveals that the DMUs 2, 15, 18, 21, 23, 25, 26, 27, 28, 29, and 30 are CCR efficient whereas DMUs 1, 2, 3, 4, 11, 13, 15, 18, 21, 23, 26, 27, 28, 29, and 30 are BCC efficient as indicated in Table 2. DMUs 1, 3, 4, 11, 13 are BCC efficient but as per CCR they are inefficient, it is because variable returns to scale scores measure pure technical efficiency only. However, the constant return to scale is composed of a nonadditive combination of purely technical and scale efficiencies. A ratio of the overall efficiency scores provides a scale efficiency measurement which is calculated under the column “Scale-efficiency”.

Global technical efficiency is achieved by DMUs 2, 15, 18, 21, 23, 26, 27, 28, 29, and 30. Prize of the player plays an important role in determining the efficiency as we can observe from Table 1 DMUs 2, 15, 18, 21, and 23 are having prize less than one crore. However, the remaining five DMUs, their prize is

higher but they have maintained good average, economy, and strike rate as compared to inefficient DMUs. DMUs 13 and 22 are close to efficiency frontier but the reason of their inefficiency is due to slackness in inputs. In order to provide the inefficient players with information about how to reach the efficiency frontier, the optimization results of the input-oriented DEA model assuming variable returns to scale are indicated in Table 3.

The analysis reveals that there are a number of CCR and BCC efficient units, which restricts one to rank them. For inefficient units one can directly rank them according to their respective scores, while it is not possible for efficient ones, as all are having the same efficiency score as one, in order to discriminate between them we used super efficiency model which gives the score as greater than one. On the basis of super efficiency scores ranking of all DMUs was done and their ranks are displayed in “Final rank” column.

TABLE - III
DEA OPTIMIZATION RESULTS

Inefficient DMU	Input Slacks			Output Slacks			
	Inning s	Over s	Prize in INR	Wicket s	Averag e	Econom y	Strike Rate
DMU5	0.000	2.083	0.000	0.000	+1.052	0.000	0.000
DMU6	0.000	0.154	0.000	0.000	+2.424	+0.881	0.000
DMU7	-0.187	0.000	-2.881	0.000	+1.103	+0.000	0.000
DMU8	-1.058	0.000	-0.000	0.000	+1.017	0.000	0.000
DMU9	-1.435	0.000	-1.545	0.000	+0.451	0.000	0.000
DMU10	-2.817	0.000	-0.263	0.000	+2.109	+0.895	0.000
DMU12	-0.230	0.000	0.000	0.000	+2.120	+0.447	0.000

DMU14	0.000	0.288	-1.323	0.000	+0.000	+0.061	0.000
DMU16	0.000	0.000	-1.588	0.000	+0.894	+0.156	0.000
DMU17	-1.264	0.000	-4.778	0.000	+0.620	0.000	0.000
DMU19	0.000	0.000	-8.817	0.000	+0.114	0.000	0.000
DMU20	0.000	0.000	-4.432	0.000	+0.351	0.000	0.000
DMU22	-0.300	0.000	0.000	0.000	+0.369	+0.138	0.000
DMU24	0.000	0.000	-3.972	0.000	+0.000	+0.193	0.000

Source: Own calculation

In Table 3, the negative sign (-) indicates the amount of input reduction and positive sign (+) amount of output increase necessary for the inefficient DMUs to reach the efficiency frontier. The optimization results suggest that none of the DMUs will reach the efficiency frontier by input reduction only but they have to increase outputs also.

CONCLUSION

In this study, Data Envelopment Analysis (DEA) was utilized to analyze the relative efficiency of top thirty wicket taking bowlers in IPL 17. It was observed from the analysis that prizing of players plays an important role in determining a

DMU efficient or inefficient. The results reveal that almost all the DMUs whose prize was less than one crore were highly efficient and got top ranks. Among them, Jaydev Unadkat got the first rank on the basis of super efficiency score as in spite of low prize he manages to have enough outputs. Ben Stokes was the highest paid player in the tournament but he proved to be inefficient and stood at number 22 as per new ranking. In order to achieve his position on the frontier, his prize amount has to be reduced from 14.5 to 8.225 crore. It can be concluded that data envelopment analysis appears to be a suitable tool for measuring the efficiency of bowlers in IPL 17.

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