Report 3

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Major Research Project Report on Selection of Cricket Team Squad using Data Envelopment Analysis Technique

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CHAPTER 1: INTRODUCTION

This part of the report will provide a detailed overview of the concepts of Decision Making Units (DMUs), efficiency, Data Envelopment Analysis Model, the nature of influence and interest of population in the game of cricket around the world along with the novelties and developments in its format, scope of Data Envelopment Analysis in the measurement and evaluation of performance of Cricket players with varied capabilities.

1.1 Introducing the concept of Data Envelopment Analysis

The accomplishment of superior levels of performance is vital for the success of any firm or organization. As a result, an appropriate management framework is necessarily required for measuring and evaluating the present performance, determining the benchmarks to look up to and/or use in seeking improvements, as well as identifying the reasons as to why some units in a particular organizational framework are not operating efficiently.

Data envelopment analysis (DEA) is a linear programming based technique which is used to compare and measure the relative performance of several similar organizational units (called Decision-Making Units), which consume several inputs to produce several outputs, and where the presence of multiple inputs and outputs makes comparisons relatively difficult. In short, it may be deemed as “a non-parametric approach to efficiency measurement – a technique used in scenarios which require a relative performance of different units to be compared and evaluated.” The units viz. the process, polity, organization, product, etc. under evaluation are termed as Decision-Making Units, often abbreviated as DMUs.

A typical DEA Model has been defined in terms of relative efficiency, decision making units, and input-output variables in figure 1.1 and figure 1.2

> A model and method used to evaluate the relative efficiency or performance or an entity among a set of entities called decision making units (DMUs), where performance cannot be evaluated by a single measurement; instead it involves multiple inputs (resources) and multiple outputs (outcomes), by solving linear programming problems for each decision making unit (DMU) according to the observed data.

Figure 1.1 – Defining Data Envelopment Analysis

The DEA is a method for mathematically comparing differences in DMU productivity based on multiple inputs and outputs. The **ratio of weighted inputs and outputs** produces a single measure of productivity called **relative efficiency**.

The DMUs that have a **ratio of 1** are referred to as **"efficient"**, given the required inputs and produced outputs. The units that have a **ratio less than 1** are **"less efficient"** relative to the most efficient units. Because the weights for the input and the output variables of DMUs are compared to maximize the ratio and then compared to a similar ratio of the best-performing DMUs, the measured productivity is also referred to as "relative efficiency"

Figure 1.2 – Relative Efficiency and Data Envelopment Analysis

Figure 1.3 lists the contrasting feature of Data Envelopment Analysis technique to that of other multivariate statistical models, and the wide usage opportunity that it provides to the researchers and analysts.

A model and method used to evaluate the relative efficiency or performance or an entity among a set of entities called decision making units (DMUs), where performance cannot be evaluated by a single measurement; instead it involves multiple inputs (resources) and multiple outputs (outcomes), by solving linear programming problems for each decision making unit (DMU) according to the observed data.

Figure 1.3 – Contrasting Data Envelopment Analysis from Multivariate Statistical Models.

1.2 Historical Background

Over the past three decades, Data Envelopment Analysis (DEA) has become a powerful, analytical and quantitative tool for performance measurement and evaluation. The application of this technique extends to numerous different types of units/entities involved in a wide range of activities in many contexts across the globe. Although this technique was named & popularized by William Cooper, Eduardo Rhodes and Abraham Charnes in the late 1970s, it was primarily worked upon and utilized by Michael Farrell in the year 1958.

Figure 1.4 depicts the conception and background of Data Envelopment Analysis technique which was primarily introduced to evaluate the non-profit & public sector firms.

(Refer to next page for the figure)

The first DEA model was developed by Charnes, Cooper, and Rhodes (1978), known as **the CCR model**, and used the ratio of weighted outputs to weighted inputs to measure the relative efficiency of DMUs, where the weights were determined via a constrained optimization model. Banker, Charnes, and Cooper's (1984) **BCC model** extended the CCR model by introducing a convexity constraint which allowed for variable returns to scale. The CCR and BCC models are considered radial models because they measure radial distances between DMUs and the efficient frontier; a frontier comprised of a set of DMUs not dominated by any other DMU. Stemming from these early works, several models have since been developed to address specific questions in a variety of operational settings.

Figure 1.4 – Conception and Background of Data Envelopment Analysis Models.

Figure 1.5 depicts the scope and advantage of Data Envelopment Analysis technique for situations where the relative performance of various similar units is to be evaluated and compared.

•DEA can be used to analyse the performance of several units to set a benchmark.
•The analysis can be used to discover the inefficient operations or units even for the most profitable organizations.
•DEA has an advantage over other analysis techniques as it can handle complex relation between multiple inputs and multiple outputs and the units are non-commeasurable.
•DEA techniques are based on linear algebra and are related to linear programming concepts. The technique is similar to mathematical duality relations in linear programming.

Figure 1.5 – Scope of DEA

Given the fact that one cannot turn a blind eye to the significance and application of DEA in various research and analysis fields, it is not a fool-proof technique but does come with some shortcomings as well. The following figure points at one of the most noted short-coming of DEA that is existent ever since its conception.

DEA is a very powerful tool for the efficiency evaluation of decision-making units with multiple inputs and outputs. One of its shortcomings is its **inability to fully rank the decision-making units.** Ever since it was created by Charnes, Cooper, and Rhodes on the basis of Farrel, the question of full ranking has been in the frontline of research

Figure 1.6 – Major Shortcoming of DEA

1.3 Cricket – the true Wonder of the World, A Religion in Indian Speech

In present times, Cricket is regarded as one of the world's prodigious sports - be it in terms of players, viewers, media publishers and virtual-play enthusiasts' interest. As a sport in the Indian Subcontinent including the countries of India, Sri Lanka, Pakistan, Bangladesh and the likes, Cricket and its ever-growing popularity globally makes it a sports wonder of the world in truest sense. The intensity, passion and the sheer scale, on which this sport is not merely played, but also watched, talked about, analyzed and cherished is not surpassed by any of its counterpart worldwide. Surprisingly, not many studies can be found in the literature that address various research affairs related to multiple attributes of this sport. However, it is a relatively contemporary and does prove to be a promising research field in relation to other sports such as tennis, soccer, basketball, etc. The rising interest in club/franchise based cricket and online fantasy cricket league games raises the significance of player selection from the financial as well as sport performance perspective.

The following figure depicts the rising popularity of cricket not merely as a sport but also as a "religion" for many in the Indian context.

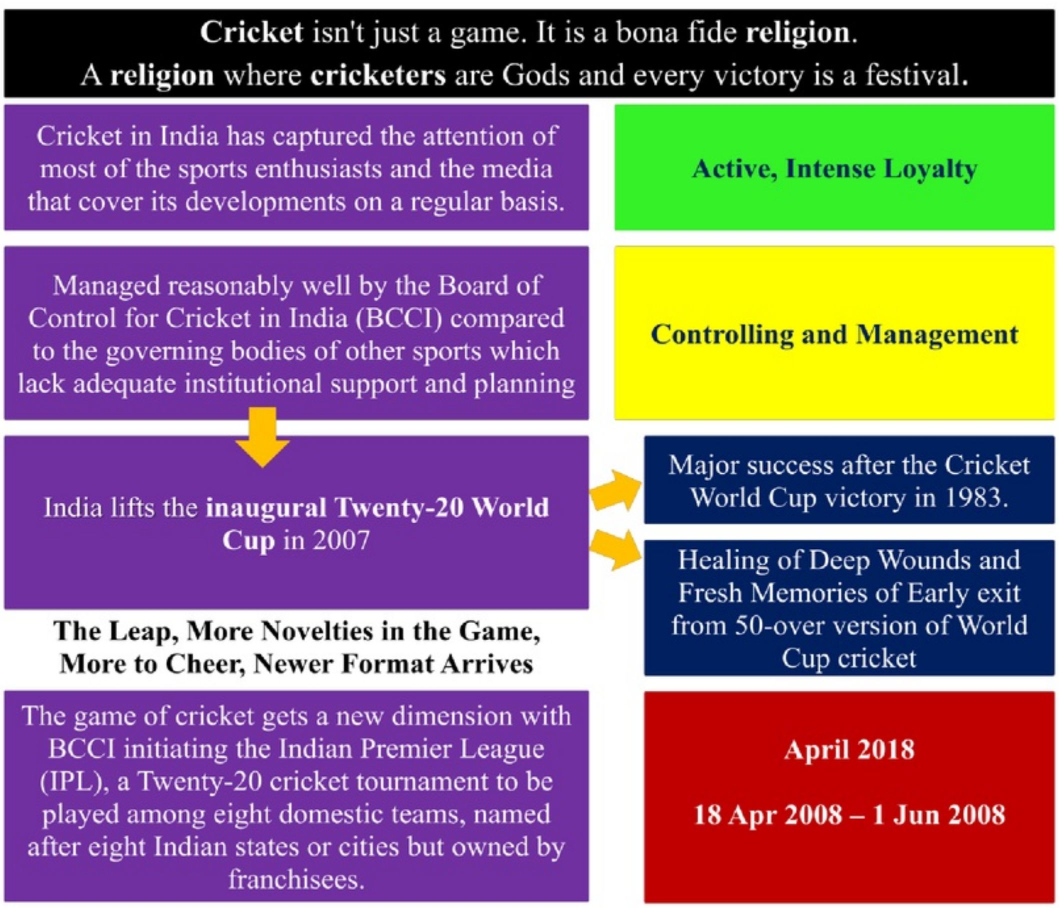

Figure 1.7 – Rising Interest and Popularity of Cricket in India

1.3.1 Indian Premier League

What it Indian Premier League?

The Indian Premier League (IPL) is a franchise-based Twenty20 competition organized by the BCCI, and backed by the ICC. It features the world's best cricketers playing - their affiliation decided by open auction - for eight city-based franchises, owned by a host of businessmen and celebrity consortiums. The first season was held successfully in India in 2008, while the second edition, which coincided with general elections in India, was shifted to South Africa. The tournament returned to India for the third and subsequent editions.

Why has the IPL generated such a buzz?

Two main reasons why. One the football-club concept of the IPL, which is unlike anything cricket has known. The best players from across the world playing, not on the basis of nationality but dictated by market forces. Second, the sheer financial scale of the IPL is unprecedented at this level of cricket. The BCCI made close to $ 1.75 billion solely from the sale of TV rights ($908 million), promotion ($108 million) and franchises (approximately $700 million). There are now several players on contracts worth more than $1 million annually. It's an entire cricket economy - and one unaffected by recession - out there.

Figure 1.8 – Indian Premier League

1.4 Scope of Data Envelopment Analysis in Cricket

Owing to its enhanced vogue and significant developments, particularly in terms of nativity of new professional competitions, the game of cricket has become a paramount attraction in today's time, whose performance in all of its aspects is a vital phenomenon to watch and measure. As a result, more applications and programs that monitor performance in cricket have already started to emerge.

One such example is the Data Envelopment Analysis which objectively evaluates, analyses and ranks the performance of the players by adopting a comprehensive approach towards the game.

The DEA Model takes into account all aspects of the players' game particularly the batting and bowling, trying to create and bring into attention comprehensive statistics, insights, information and knowledge in order to facilitate a better understanding of the game and what is necessary in order to create a winning performance.

It is used for objective evaluation of cricket players with different skill-sets and capabilities which are represented in the form of various input and output variables, thus enabling "experts/pundits of the game" to track teams or players performance on a cumulative level or in different aspects of the game.

Figure 1.9 - Scope of Data Envelopment Analysis in Cricket

CHAPTER 2: LITERATURE REVIEW

This part of the report contains the links to various sources such as published research papers, technical articles, journals, etc. which were consulted while undertaking this project, and will also present the substantive findings, as well as theoretical and methodological contributions to this topic, as derived from them. Surprisingly, not many studies can be found in the literature that address various research affairs related to different attributes of Cricket. Moreover, the relevant literature related to classification of cricket players based on their performance is not very rich either.

Till the completion of 20th century and around, various measures such as Average and Striking Rate of the Batsman were mostly used to analyze the cricket performance of a batsman. On the contrary, the variables such as bowling average, average runs conceded per over, and bowler's strike rate were considered to evaluate a bowler's performance. Preston and Thomas (2000) discussed the batting strategies in the limited over format of the cricket, primarily One Day International Matches.

The inability and inadequacy of the exiting metrics in limited overs cricket to measure the performance of the cricketers and access their true capability was pointed out by Lewis (2005), following which an alternative performance metric was suggested which included further expanding the scope of Duckworth & Lewis' practice to take into account the scenario/condition in which the respective cricketers performed.

A ranking scheme was developed and presented by Lemmer (2004) in his studies conducted during 2004, 2006 which classified the batsmen and the bowlers based on the performance data taken from One-day International (ODI) matches and Test cricket. Post the inaugural season of the ICC T20 World Cup, Lemmer (2008) also analyzed the performance of cricketers in the tournament during his research in 2008.

In the same year, Van Staden (2008) conducted an analysis to evaluate the performance of various all-rounders, that is the players who possessed both batting as well as bowling

capabilities, and further classified them as ideal, batting and bowling allrounder. The dataset used by Van Staden was extracted from the statistics of IPL Season I.
The contrast between limited over edition of cricket and its Twenty20 counterpart are being highlighted by Bhattacharya, Gill, and Swartz (2011).

Sharp, Brettenny, Gonsalves, Lourens, and Stretch (2011) and Lemmer (2011), have pointed out that the selectors often pick a team of eleven players who can participate in a given match. However, it is a common practice to select a squad of fifteen players so as to provide flexibility of choosing a playing XI to the skipper as well as the coaching staff of the cricket team.

There are various constraints to selection of a cricket team which apply to the total number of batsmen, bowlers, wicket-keepers and all-rounders to be picked up in the playing XI as all the available cricketers with varying capabilities cannot participate together in a given match. Thus, getting the best combination of playing XI on the paper before the toss is never an easy task. The application of mathematical modeling may be used to simplify this task to a certain extent. Sharda & Iyer (2009) have devised a neural network approach to aid in the selection of the best possible combination of players in a cricket team. Sharp et al. (2011) and Lemmer (2011) have further proposed a model of integer programming to make a selection of the desired cricket squad.

CHAPTER 3: RESEARCH METHODOLOGY ADOPTED

This section will represent the application of Data Envelopment Technique in order to evaluate the cricket players based on their performance in some past tournament and/or overall statistics of the player under consideration.

A suitable aggregation method is needed in order to compare and evaluate the performance of the players with different capabilities, and when numerous factors pertaining to the players' performance are to be considered simultaneously. The Data Envelopment Analysis is a linear programming aggregation model that computes the scores of the players objectively rather than subjecting the players to qualitative, subjective computations. Also, the objective of this report is to posit a DEA model, which can be used to determine the relative efficiency of the cricket players and also suggest plausible corrective solution(s) to the Decision Making Units (DMUs), here the individual players, for improving their performance if they stand inefficient based on their respective performance scores. These DMUs are represented in terms of their inputs and outputs, and not in the form of their operating details.

A DMU is regarded to be efficient when it is capable of deriving the maximum or most output from the inputs available/supplied to it. In general, a DEA aggregation model is capable of performing objective computations on multiple inputs and multiple outputs.
In this report, a novel DEA application is introduced for measuring the performance of cricketers with different capabilities. This is the followed by determining the ranking of the players from the highest to the lowest score and choosing the squad for the team of players under consideration – World XI (from the dataset of International as well as Indian Players) as well as National Cricket Squad for the ICC World Cup(from the dataset of Indian Players). The purpose of DEA is to identify efficient DMUs, the cricketers in this context when they are characterized by multiple outputs and multiple inputs.

When the performance evaluation analysis is to be performed on multidimensional Inputs and Outputs, then it is required to make use of weighting factors to produce an overall efficiency measure.

Figure 3.1 elicits a conceptual description of a typical Decision-Making Unit with 2 inputs and 3 outputs.

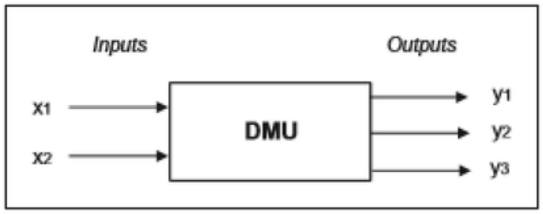

Figure 3.1 - Conceptual Description of a Decision-Making Unit

Let x_1 and x_2 be the two inputs given to the DMU and y_1, y_2 and y_3 be the three outputs obtained from the same DMU.

As stated earlier that whenever we are dealing with multi-dimensional inputs and/or outputs, then we are required to make use of weighting factors for the inputs as well as outputs in order to compute an overall efficiency measure.

Let (v_1, v_2) and (u_1, u_2, u_3) be the weights assigned to the inputs (x_1 and x_2) and outputs (y_1, y_2 and y_3) respectively. These weights represent the respective coefficients for the output as well as input variables. The coefficients which are related to outcome variables depict the relative reduction in efficiency with reduction of one unit from the output or outcome variable. The coefficients which are related to input/incoming/supplied variables denote the relative increase in efficiency with reduction of every unit from the input/supplied variable.

Thus, the aggregate value of two inputs viz. x_1 and x_2 computes to $\mathbf{v_1x_1 + v_2x_2}$

Similarly, the total value of three outputs, y_1, y_2 and y_3 computes to $\mathbf{u_1y_1 + u_2y_2 + u_3y_3}$

Here, the input quantities, x_1 and x_2 are obtained from existent data while the weights/coefficients (v_1 and v_2) are determined from the analysis. Likewise, the output quantities y_1, y_2 and y_3 are obtained from existent data and the corresponding weights/coefficients (u_1, u_2, u_3) are determined in the analysis.

The measure of efficiency is therefore derived/computed as weighted outputs divided by weighted inputs, which is mathematically expressed as –

$$\text{Efficiency, E} = \frac{u1y1 + u2y2 + u3y3}{v1x1 + v2x2}$$

The figure below elicits the working of a typical DEA Model that computes of multiple inputs and multiple output variables.

A typical DEA Model (CCR model) uses a linear programming model to assign weights or to determine coefficients that are chosen in a manner that assigns a best set of weights/coefficients to each of the unit. CCR stands for Charnes, Cooper and Rhodes, who introduced DEA in 1978. In CCR model we arrange the information available from the data into a matrix format with X to be input matrix and Y to be output matrix. The data is for "n" decision making units, "m" inputs and "s" outputs similar to the one presented below. The inputs and outputs are assumed to be known and all positive.

Input Data Matrix

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

Output Data Matrix

$$Y = \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ y_{s1} & y_{s2} & \cdots & y_{sn} \end{pmatrix}$$

Figure 3.2 – Input and Output Data Matrices

Now, the efficiency of each of the DMUj (Decision Making Unit), with j = 1, 2, … n is to be measured so that we can determine relative efficiency and identify inefficient units. If there are 'n' DMUs, we need 'n' optimizations, one for each DMU using following notations.

DMU_k: DMU which will be evaluated in a particular trial, with k = 1, 2, … n. This notation will be used for the DMU in the objective function. The same DMU in the constraints will follow the notation DMUj as defined next.

DMUj : DMUs with j= 1,2,…..n

v_i: Coefficient for input i, with i = 1,2,…..q

u_r: Coefficient for output r, with r = 1,2,…..t.

The DEA model can be presented to maximize the efficiency of DMU_k, θ_k, by writing the objective function of k[th] DMU as given below.

$$\text{Max Ek} = \frac{u1y1k + u2y2k + \dots \dots .. + us.ytk}{v1x1k + v2xk + \dots \dots .. + vm.xqk}$$

The model will now be subjected to the following constraints –

$$\frac{u1y1j + u2y2j + \dots \dots .. + ut.ytj}{v1x1j + v2x2j + \dots \dots .. + vq.xqj} \leq 1$$

$$v1, v2, \dots .., vq \geq 0$$

$$u1, u2, \dots .., ut \geq 0$$

Note –

- 1, 1j, …… sj are the subscripts of u, y respectively in the numerator.
- Likewise, 1, 1j, …… mj are the subscripts of v, x respectively in the denominator.

The fractional programming model can then be transformed into a linear programing model. This is done by scaling each of the inputs to 1 and rewriting the constraints as mentioned below.

Objective Function – (For the k[th] DMU),

$$\text{Max Ek} = u1y1k + u2y2k + \dots \dots .. + ut.ytk$$

Subject to -

$$v1x1k + v2x2k + \dots \dots .. + vq.xqk = 1$$

$$u1y1j + u2y2j + \dots \dots .. + us.ysj \leq v1x1j + v2x2j + \dots \dots .. + vq.xqj$$

(with j = 1, 2, …n)

$$v1, v2, \dots .., vq \geq 0$$

$$u1, u2, \dots .., ut \geq 0$$

The model discussed and presented above determines the best combination of weights or coefficients corresponding to each output and input variable, while maximum efficiency rating is designated to the kth DMU. On solving the linear programming model for DMU_k, the kth DMU will be efficient only if the model results in:

Condition 1 - The optimal efficiency of kth DMU being equal to 1,

Condition 2 - There are no Slacks present, that is, "All slacks are zero."

In the case when the efficiency of any DMU equates to less than 1, then that DMU is regarded as inefficient. The slack components for the DMUs which are not efficient will be non-zero, which means that the DMU is utilizing some inputs in excess as compared to the efficient units in for producing the same output level. All the inefficient DMUs will have a corresponding set of efficient entities or units that would serve as a reference set to enhance the performance of inefficient ones.

The above presented models can be solved using any optimization software or using excel. On solving the above linear programming models in Excel for all the units, only the efficiency for the DMU under consideration and the respective weights for the input and output variables can be found. Finding the efficiency (and the weights for corresponding input and output variables) for each DMU can be a very time consuming and a tedious task. Therefore, it is suggested that an appropriate optimization software/tool such as DEA Solver – LV (Learning Version) should be used for performing such complex computations.

About DEA Solver – Learning Version

There are 2 types of DEA-Solver, the "Learning Version" (termed as "DEA-Solver-LV"), and "Professional Version" (termed as "DEA-Solver-PRO."). DEA-Solver-LV 1.0 which has been used for analysis in this study includes 7 DEA model clusters and can perform analysis for up to fifty DMUs. More about the DEA Solver and its applications will be discussed in the later sections subsequently.

3.1 Dataset for Analysis

The training dataset for analysis in this study has been obtained data from the recently concluded Indian Premier League 2019 (12^{th} Edition). For the sake of reference, a brief overview of IPL 12 is also presented in this section, which is then succeeded by a discussion of cricketers' varying skillsets and the application of the proposed DEA model to evaluate the performance of the players in their respective capabilities and subsequently rank them based on their performance scores.

S.No.	Title/Context	Description
1.	Tournament Name	2019 Indian Premier League
2.	Cricket format	Twenty20
3.	Schedule/Duration	23 Mar 2019 – 12 May 2019
4.	Total Number of Participating Teams	8
5.	Tournament Format	Double Round-robin and Knockout
6.	Selection criteria for Players/Teams	Via an auction
7.	Number of Players auctioned (2019 only)	60
8.	Overseas Players allowed per team per match	4
9.	Total Matches Played	60
10.	Champions	Mumbai Indians
11.	Runners Up	Chennai Superkings

Table 3.1 Brief Overview of IPL 2019

Player Capability	Performance Dimension/Statistic	Meaning/Description
Batting	Runs Scored (Runs)	This is the base parameter. The batsman has to score runs to be of any use to the team.
	Not Outs (NO)	A batsman is not out if he comes out to bat in an innings and has not been dismissed by the end of the innings. The batter is also not out while his innings is still in progress.
	Balls Faced (BF)	The total number of balls received, including no-balls but not including wide balls.
	Highest Score (HS)	For a batsman, the highest individual score (HS) is the maximum number of runs scored in one match during a tournament.
	Average (avg)	The average batting performance is expressed by R/m where R denotes the number of runs scored and m the number of times the batsman was out.

Table 3.2 Description of Batting Parameters (Runs, NOs, BFs, HS, Avg)

Player Capability	Performance Dimension/Statistic	Meaning/Description
Batting	Strike Rate (SR)	The average number of runs scored per 100 balls faced. (SR = [100 * Runs]/BF)
	Boundaries (Combination of 4s and 6s hit by a Batsman)	**4s:** The number of 4's the batsmen has scored. **6s:** The number of 6's the batsmen has scored.
	Milestones (Combination of Half Centuries and Centuries Scored by a Batsman)	**Half-Centuries(50):** The number of innings in which the batsman scored fifty to ninety-nine runs (centuries do not count as half-centuries as well). **Centuries (100):** The number of innings in which the batsman scored one hundred runs or more.
	Matches (Mat/M)	Number of matches played. (also Played (Pl).)
	Innings (Inns)	The number of innings in which the batsman actually batted.

Table 3.3 Description of Batting Parameters (SR, 4s, 6s, 50s, 100s, Mat, Inns)

Player Capability	Performance Dimension/Statistic	Meaning/Description
Bowling	Overs Bowled (Ov)	The number of overs bowled. 1 Over = 6 legitimate Balls
	Runs Conceded (RC)	The number of runs scored by the batsman against the balls bowled by bowler.
	Dot Balls (DB)	The number of balls for which the bowler conceded zero runs.
	Average (AVE)	The average number of runs conceded per wicket. (Ave = Runs/W)
	Economy Rate (Econ)	The average number of runs conceded per over. (Econ = Runs/Overs bowled).
	Strike Rate (S/R)	The average number of balls bowled per wicket taken. (SR = Balls/W)
	Wickets Taken (W)	The number of times a bowler dismissed a batsman on a legitimate ball.
	Four wickets in an innings (4w)	The number of innings in which the bowler took *exactly* four wickets, sometimes recorded alongside 5w.

Table 3.4 Description of Bowling Parameters

Player Capability	Capability Parameter/Dimension	Input / Output Variable
Batting (3 Inputs , 7 Outputs)	Matches Played (Mat)	Input (I)
	Innings Played (Inns)	Input (I)
	Bowls Faced (BF)	Input (I)
	Not Outs (NO)	Output (O)
	Runs Scored (Runs)	Output (O)
	Highest Score (HS)	Output (O)
	Average (Avg)	Output (O)
	Strike Rate (SR)	Output (O)
	Milestones (Half and Full Centuries)	Output (O)
	Boundaries Hit (4s and 6s hit)	Output (O)
Bowling (4 Inputs , 6 Outputs)	Matches Played (Mat)	Input (I)
	Innings Played (Inns)	Input (I)
	Overs Bowled	Input (I)
	Runs Conceded	Input (I)
	Average (Avg)	Output (O)*
	Economy Rate (Eco)	Output (O)*
	Strike Rate (SR)	Output (O)*
	Wickets Taken	Output (O)
	Dot Balls	Output (O)
	Four Wicket Hauls (4w)	Output (O)

Table 3.5 Input – Output Characteristics of Player Capabilities

* These attributes of bowling performance are actually the outputs of a bowler; however they are regarded better if they are lesser quantitatively, therefore as DEA outputs we shall be using the inverse of these values.

It can be said that higher is the measure/magnitude of the outcomes, the better the player in the respective ability performs. Therefore, the seven outcomes of batsmen as enlisted in Table 3.5 viz. Not Outs (NO), Highest Score (HS), Average (Avg), Strike Rate (SR), Milestones (Half and Full Centuries), Runs Scored (Runs), Boundaries Hit (4s and 6s hit) define the seven outputs for the DEA method. Likewise, there are 6 important outputs for the bowling capability viz. Average (Avg), Economy Rate (Eco), Strike Rate (SR), Wickets Taken, Dot Balls, Four Wicket Hauls (4w). All these are essential measures to be taken into consideration when evaluating the performance of a cricketer in their respective capability zones in limited over edition of cricket.

3.2 Selection of DEA Model, Number of Decision Making Units

Selection of DEA Model

The CCR model (by Charnes, Cooper and Rhodes, 1978) is based on the assumption that constant return to scale exists at the efficient frontiers. The CRS assumption is only appropriate when all the DMUs are operating at an optimal scale. Banker, Charnes and Cooper (1984) suggested an extension of CRS model to account for variable returns to scale (VRS). It captures the pure resource-conversion efficiencies, irrespective of whether the DMUs operate at IRS, CRS or DRS.

CCR - Input Oriented Vs CCR - Output Oriented

BCC- Input Oriented Vs BCC- Output Oriented

Input orientated is a term used in conjunction with the BCC and CCR ratio models, to indicate that an inefficient unit may be made efficient by reducing the proportions of its inputs but keeping the output proportions constant.

Input minimization is the DEA mode adopted when the analysis tries to minimize the amount of inputs used to produce the specified outputs. (The opposite of input minimization is output maximization).

Output orientated model indicates that an inefficient unit may be made efficient by increasing the proportions of its outputs while keeping the input proportions constant.

Output maximization is the DEA mode adopted when the analysis tries to maximize the outputs produced for a fixed amount of inputs.

In this study, an increase in a Player's inputs does not produce a proportional change in the resulting outputs, as a result, the DMU (Player) exhibits variable returns to scale. This means that as the unit changes its scale of operations its efficiency will either increase or decrease. This is in contrast to Constant returns in which an increase in a unit's inputs leads to a proportionate increase in its outputs i.e. there is a one-to-one, linear relationship between inputs and outputs.

Therefore, it is suggested that **BCC – O Model** may be used for the analysis of the desired dataset. In the chosen dataset, one cannot attempt to minimize the inputs as the format of the tournament is fixed , so are the number of matches, the number of overs to be bowled in an innings, the number of overs allowed per bowler, the maximum number of overs available per side to bat, etc..

Criteria for Selection of number of Decision Making Units for analysis

Banker et al. (1989), suggest a rough rule of thumb. Let p be the number of inputs and q be the number of outputs used in the analysis, then the sample size (n) should satisfy

$$\mathbf{n >= max\ \{p \times q, 3(p + q)\}}$$

Player Capability	Number of Inputs (p)	Number of Outputs (q)	p + q	p x q	Maximum of {p × q, 3(p + q)}
Batting	3	7	10	3 x 7 = 21	30
Bowling	4	6	10	4 x 6 = 24	30

Table 3.6 – Selection criteria for appropriate number of Decision Making Units

Therefore, we have selected a set of 30 batsman and 30 bowlers from the dataset obtained from IPL 12 for evaluating the performance and selecting the best combination of players for forming the squad for World XI Team (including Indian as well as Overseas Players).
The same approach has been followed to select the best combination of players to form the squad for National Cricket Team of India for the upcoming ICC World Cup. (For this analysis, 30 Indian Batsman as well as 30 Indian Bowlers are analysed for their performance in the recently concluded IPL.)

3.3 Working with DEA-Solver LV Software

Step 1	Preparation of Dataset File	The dataset file should be prepared in an Excel Workbook before the execution of DEA-Solver. The file must comply with BCC-O Model requirements.

	A	B	C	D	E	F	G	H	I	J
1	PLAYER	(I)Mat	(I)Inns	(I)Overs Bowled	(I)Runs Conceeded	(I)Avg	(I)Econ	(I)SR	(O)Wickets Taken	(O)Dot Balls

Figure 3.3 Preparation of Data file for DEA Model along with an illustration

Figure 3.3 illustrates how the dataset is to be prepared in the Microsoft Excel for DEA Model analysis. One must take due care to add "(I)" parameter against each input variable and "(O)" against each output variable before running the analysis. The primary of the first row of the excel sheet (Row 1) depicts the Name of the problem/Decision Making Unit, which is Player (Cell A1) in this study; and Input-Output variables viz. Matches Played, Overs Bowled, and son on (Cells B1, C1, … , K1).

Step 2	Entering/Recording the Data Values	The second and subsequent rows contain the nominal data of the first DMU and the values of input-output variables for the corresponding I/O items. The process continues up to the last DMU.

	A	B	C	D	E	F	G	H	I	J
1	PLAYER	(I)Mat	(I)Inns	(I)Overs Bowled	(I)Runs Conceeded	(I)Avg	(I)Econ	(I)SR	(O)Wickets Taken	(O)Dot Balls
2	ImranTahir	17	17	64.2	431	16.57	6.69	14.84	26	149
3	Kagiso Rabada	12	12	47	368	14.72	7.82	11.28	25	113
4	Deepak Chahar	17	17	64.3	482	21.9	7.47	17.59	22	190
5	Shreyas Gopal	14	14	48	347	17.35	7.22	14.4	20	107
6	Jasprit Bumrah	16	16	61.4	409	21.52	6.63	19.47	19	169
7	Khaleel Ahmed	9	9	34.5	287	15.1	8.23	11	19	87
8	Mohammed Shami	14	14	54	469	24.68	8.68	17.05	19	119
9	Yuzvendra Chahal	14	14	49.2	386	21.44	7.82	16.44	18	117
10	Rashid Khan	15	15	60	377	22.17	6.28	21.17	17	166
11	Harbhajan Singh	11	11	44	312	19.5	7.09	16.5	16	117

Figure 3.4 Entering/Recording the Data Values for DEA Model along with an illustration

The selected data set must be entered or recorded in the Excel Workbook in such a manner such that there is at least one blank column at right and one blank row at bottom. This specifies the end of the dataset region. The data entry must always start from the top-left cell that is, A1.

As a precautionary measure, one should never make use of the following names for the datasheets –

"Summary", "Score", "Projection", "Weight", "WeightedData", "Slack", "RTS", "Rank" and "Graph"

These are some of the keywords that are reserved for the DEA Solver software.

Once the data file is prepared in an Excel worksheet, one should not forget to save it and close it before running the analysis.

Step 3	Starting the DEA Solver	Click on the file "DEA Solver-LV" to begin the DEA-Solver.

Figure 3.5 Starting the DEA Solver

Once the "DEA Solver-LV" file is opened, simply follow the steps that appear on the screen to get started with the analysis.

Figure 3.6 View of Home Screen of DEA Solver LV

Click on "Click here to Start" option from the Home Screen of DEA Solver LV. Thereafter, click on "OK" button of Introduction Screen to proceed to the Model Selection Screen.

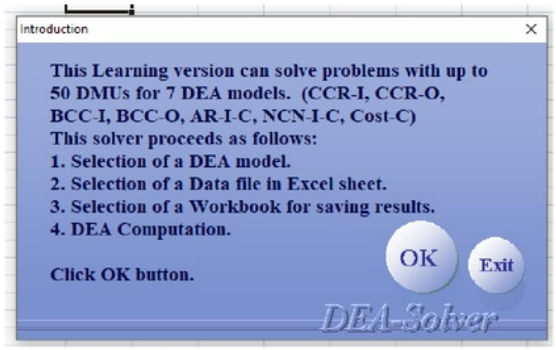

Figure 3.6 View of Introduction Screen of DEA Solver LV

As discussed in the earlier sections, choose the BCC-O Model for performing the desired analysis.

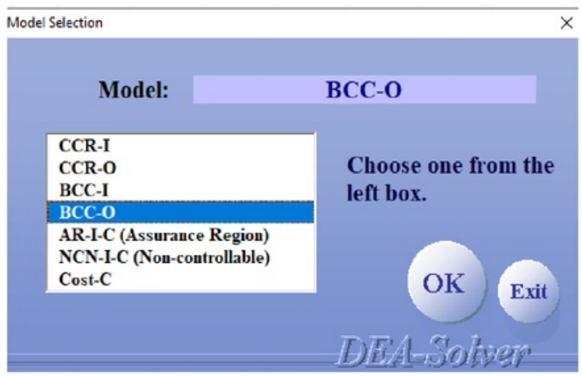

Figure 3.7 View of Model Selection Screen of DEA Solver LV

Upon selection of the appropriate model for analysis, select and open the dataset file created in Step 1 to run the analysis.

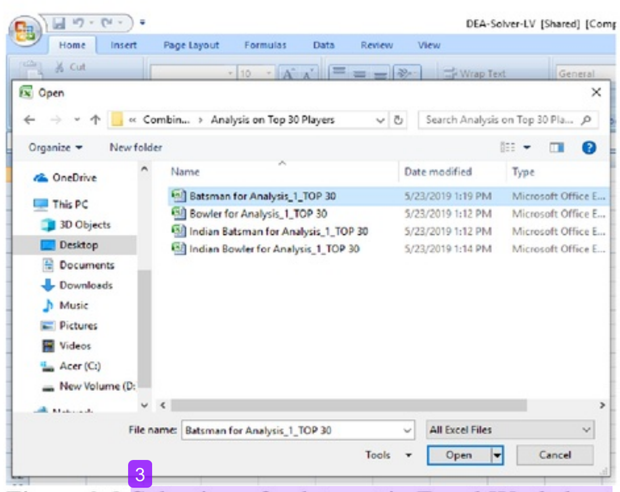

Figure 3.8 Selection of a data set in Excel Worksheet

Prior to running the analysis on the desired dataset, choose the Workbook name for saving the computation results.

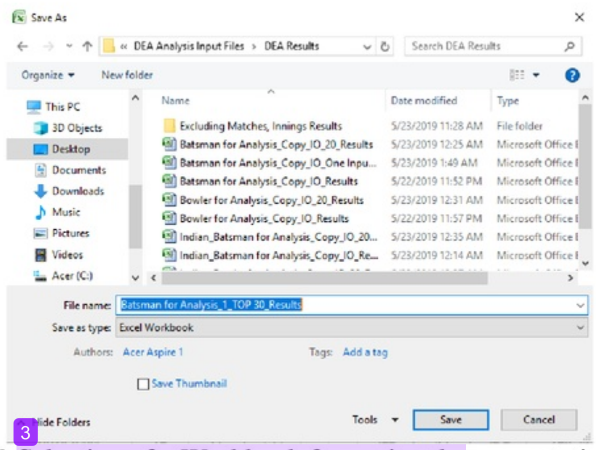

Figure 3.9 Selection of a Workbook for saving the computation results.

Finally, click on Run option from the Running DEA window to perform the desired computation.

Figure 3.10 View of DEA computation window.

CHAPTER 4: RESULTS AND FINDINGS

This section presents the results of the analysis performed on different datasets which are used to assess, evaluate the performance of the cricketers, and rank them in the order of their DEA performance scores. Furthermore, based on the ranking obtained for each of the player, a squad is formed for World XI team which includes Indian as well as Overseas Players. Another squad is formed for the selection of the Indian National Team for the upcoming ICC World Cup in England 2019 as well as to form basis for the selection of squad for the upcoming ICC T20 World Cup in Australia and New Zealand in 2020. This squad is prepared by analysis and comparing the performance of Indian Players exclusively. The results of each analysis are saved in the chosen/desired Excel file (workbook).

Serial No.	Worksheet Name	Results Produced
1.	Worksheet "Summary"	This worksheet shows statistics on data and a summary report of results obtained.
2.	Worksheet "Score"	This worksheet contains the DEA-score, reference set, λ -value for each DMU in the reference set, and ranking of efficiency scores.
3.	Worksheet "Projection"	This worksheet contains projections of each DMU onto the efficient frontier analyzed by the chosen model.
4.	Worksheet "WeightedData"	This worksheet shows the optimal weighted I/O values. v_i: Coefficient for input i, with i = 1,2,.....m u_r: Coefficient for output r, with r = 1,2,.....s.
5.	Worksheet "RTS"	In case of the BCC, models, the returns-to-scale characteristics are recorded in this worksheet. For BCC inefficient DMUs, returns-to-scale characteristics are those of the (input or output) projected DMUs on the frontier.
6.	Graphsheet "Graph1"	This graphsheet exhibits the bar chart of the DEA scores. One can redesign this graph using the Graph functions of Excel.
7.	Graphsheet "Graph2"	This graphsheet exhibits the bar chart of the DEA scores in the ascending order.

Table 4.1 – Results of computation depicted by various worksheets generated during analysis

4.1 Results of Analysis of Player Performance in different capabilities.

The following table shows the DEA scores, obtained by DEA model, for the top 30 batsmen.

Rank	DMU	Score
1	Jos Buttler	1
1	David Warner	1
1	KL Rahul	1
1	Sanju Samson	1
1	Hardik Pandya	1
1	Andre Russell	1
1	Chris Gayle	1
1	MS Dhoni	1
1	AB de Villiers	1
1	Jonny Bairstow	1
11	Shikhar Dhawan	0.965416
12	Shubman Gill	0.953317
13	Ajinkya Rahane	0.921053
14	Virat Kohli	0.91661
15	Nitish Rana	0.912958
16	Manish Pandey	0.908893
17	Prithvi Shaw	0.907649
18	Rishabh Pant	0.899069
19	Chris Lynn	0.883866
20	Shane Watson	0.881078
21	Quinton de Kock	0.875563
22	Faf du Plessis	0.85124
23	Steve Smith	0.81145
24	Suryakumar Yadav	0.768838
25	Rohit Sharma	0.763116
26	Ambati Rayudu	0.755725
27	Shreyas Iyer	0.749829
28	Parthiv Patel	0.745235
29	Mayank Agarwal	0.740824
30	Suresh Raina	0.684739

Table 4.1 – Results of Analysis of Batting Performance (Rank, Score)

Based on the above results, we can see that Jos Buttler, David Warner, KL Rahul, Sanju Samson, Hardik Pandya, Andre Russell, Chris Gayle, MS Dhoni, AB de Villiers, Jonny Bairstow are the top batsmen based on their DEA scores. For inefficient set of batsmen, the proposed DEA model can be used to improve their performance by comparing them with their superior peers and suggesting the improvement or corrective actions to be at par with them (superior peers).

The following table shows the DEA scores, obtained by DEA model, for the top 30 bowlers.

Rank	DMU	Score
1	Sam Curran	1
1	ImranTahir	1
1	Kagiso Rabada	1
1	Deepak Chahar	1
1	Shreyas Gopal	1
1	Andre Russell	1
1	Khaleel Ahmed	1
1	Navdeep Saini	1
1	Jofra Archer	1
1	Rashid Khan	1
1	Harbhajan Singh	1
1	Lasith Malinga	1
1	Ravindra Jadeja	1
1	Amit Mishra	1
1	Chris Morris	1
1	Rahul Chahar	1
1	Bhuvneshwar Kumar	1
18	Jasprit Bumrah	0.998318
19	Ishant Sharma	0.937167
20	Yuzvendra Chahal	0.905277
21	Hardik Pandya	0.820168
22	Mohammed Shami	0.818772
23	Sunil Narine	0.783745
24	Axar Patel	0.769096
25	Krunal Pandya	0.743958
26	Ravichandran Ashwin	0.734647
27	Sandeep Sharma	0.72289
28	Piyush Chawla	0.716353
29	Dwayne Bravo	0.685805
30	Jaydev Unadkat	0.64278

Table 4.2 – Results of analysis for Bowling Performance (Rank, Score)

Based on the above results, we can see that Sam Curran, ImranTahir, Kagiso Rabada, Deepak Chahar, Shreyas Gopal, Andre Russell, Khaleel Ahmed, Navdeep Saini, Jofra Archer, Rashid

Khan, Harbhajan Singh, Lasith Malinga, Ravindra Jadeja, Amit Mishra, Chris Morris, Rahul Chahar, Bhuvneshwar Kumar are the top bowlers based on their DEA scores. For inefficient set of bowlers, the proposed DEA model can be used to improve their performance by comparing them with their superior peers and suggesting the improvement or corrective actions to be at par with them (superior peers).

The following table shows the DEA scores, obtained by DEA model, for the top 30 **Indian batsmen** only.

Rank	DMU	Score
1	Ravindra Jadeja	1
1	KL Rahul	1
1	Shikhar Dhawan	1
1	Rishabh Pant	1
1	Axar Patel	1
1	Rahul Tripathi	1
1	Riyan Parag	1
1	MS Dhoni	1
1	Mandeep Singh	1
1	Hardik Pandya	1
1	Ajinkya Rahane	1
1	Sarfaraz Khan	1
1	Parthiv Patel	1
1	Dinesh Karthik	1
1	Sanju Samson	1
1	Nitish Rana	1
17	Virat Kohli	0.993613
18	Prithvi Shaw	0.988845
19	Manish Pandey	0.96374
20	Rohit Sharma	0.950169
21	Shubman Gill	0.946
22	Mayank Agarwal	0.89904
23	Suryakumar Yadav	0.845798
24	Suresh Raina	0.838044
25	Shreyas Iyer	0.836594
26	Robin Uthappa	0.805864
27	Krunal Pandya	0.768483
28	Ambati Rayudu	0.737805
29	Vijay Shankar	0.700797
30	Kedar Jadhav	0.69691

Table 4.3 – Results of analysis for Batting Performance of Indian Batsmen (Rank, Score)

Based on the above results, we can see that Ravindra Jadeja, KL Rahul, Shikhar Dhawan, Rishabh Pant, Axar Patel, Rahul Tripathi, Riyan Parag, MS Dhoni, Mandeep Singh, Hardik Pandya, Ajinkya Rahane, Sarfaraz Khan, Parthiv Patel, Dinesh Karthik, Sanju Samson, Nitish Rana are the top Indian batsmen based on their DEA scores.

The following table shows the DEA scores, obtained by DEA model, for the top 30 Indian bowlers only.

Rank	DMU	Score
1	Washington Sundar	1
1	Deepak Chahar	1
1	Shreyas Gopal	1
1	Jasprit Bumrah	1
1	Khaleel Ahmed	1
1	Navdeep Saini	1
1	Yuzvendra Chahal	1
1	Harbhajan Singh	1
1	Ravindra Jadeja	1
1	Amit Mishra	1
1	Bhuvneshwar Kumar	1
1	Rahul Chahar	1
13	Varun Aaron	0.96148738
14	Ishant Sharma	0.9340233
15	Mohammed Shami	0.92105263
16	Mohammed Siraj	0.89978525
17	Siddarth Kaul	0.87126437
18	Prasidh Krishna	0.85304315
19	Umesh Yadav	0.84827975
20	Hardik Pandya	0.82649954
21	Shardul Thakur	0.81857472
22	Dhawal Kulkarni	0.81350867
23	Axar Patel	0.80437103
24	Ravichandran Ashwin	0.79541132
25	Krunal Pandya	0.77924645
26	Sandeep Sharma	0.77259475
27	Murugan Ashwin	0.76619895
28	Piyush Chawla	0.72966235
29	Kuldeep Yadav	0.69606004
30	Jaydev Unadkat	0.64980545

Table 4.4 – Results of analysis for Batting Performance of Indian Bowlers (Rank, Score)

Based on the above results, we can see that Washington Sundar, Deepak Chahar, Shreyas Gopal, Jasprit Bumrah, Khaleel Ahmed, Navdeep Saini, Yuzvendra Chahal, Harbhajan Singh, Ravindra Jadeja, Amit Mishra, Bhuvneshwar Kumar, Rahul Chahar are the top Indian bowlers based on their DEA scores.

The following table shows the Returns to Scale characteristics obtained for the top 30 batsmen included in the dataset.

No.	DMU	Score	RTS	RTS of Projected DMU
1	David Warner	1	Constant	
2	KL Rahul	1	Decreasing	
3	Quinton de Kock	0.8755633		Decreasing
4	Shikhar Dhawan	0.9654164		Decreasing
5	Andre Russell	1	Constant	
6	Chris Gayle	1	Decreasing	
7	Rishabh Pant	0.8990692		Constant
8	Virat Kohli	0.9166102		Constant
9	Shreyas Iyer	0.749829		Constant
10	Jonny Bairstow	1	Constant	
11	AB de Villiers	1	Constant	
12	Suryakumar Yadav	0.7688378		Constant
13	MS Dhoni	1	Constant	
14	Chris Lynn	0.8838656		Constant
15	Rohit Sharma	0.7631158		Decreasing
16	Hardik Pandya	1	Constant	
17	Shane Watson	0.8810776		Decreasing
18	Faf du Plessis	0.8512397		Constant
19	Ajinkya Rahane	0.9210526		Constant
20	Suresh Raina	0.6847394		Constant
21	Parthiv Patel	0.7452346		Constant
22	Prithvi Shaw	0.9076488		Constant
23	Manish Pandey	0.9088935		Constant
24	Nitish Rana	0.912958		Constant
25	Sanju Samson	1	Constant	
26	Mayank Agarwal	0.7408242		Constant
27	Steve Smith	0.81145		Constant
28	Jos Buttler	1	Constant	
29	Shubman Gill	0.9533172		Constant
30	Ambati Rayudu	0.7557252		Constant

Table 4.5 – Returns to Scale Characteristics for Batting Performance

The following table shows the Returns to Scale characteristics obtained for the top 30 bowler included in the dataset.

No.	DMU	Score	RTS	RTS of Projected DMU
1	Imran Tahir	1	Constant	
2	Kagiso Rabada	1	Constant	
3	Deepak Chahar	1	Constant	
4	Shreyas Gopal	1	Increasing	
5	Jasprit Bumrah	0.998318		Increasing
6	Khaleel Ahmed	1	Constant	
7	Mohammed Shami	0.818772		Constant
8	Yuzvendra Chahal	0.905277		Constant
9	Rashid Khan	1	Constant	
10	Harbhajan Singh	1	Increasing	
11	Lasith Malinga	1	Constant	
12	Ravindra Jadeja	1	Increasing	
13	Ravichandran Ashwin	0.734647		Increasing
14	Hardik Pandya	0.820168		Constant
15	Rahul Chahar	1	Increasing	
16	Ishant Sharma	0.937167		Constant
17	Bhuvneshwar Kumar	1	Constant	
18	Chris Morris	1	Increasing	
19	Krunal Pandya	0.743958		Constant
20	Sandeep Sharma	0.72289		Constant
21	Amit Mishra	1	Increasing	
22	Jofra Archer	1	Constant	
23	Dwayne Bravo	0.685805		Constant
24	Navdeep Saini	1	Constant	
25	Andre Russell	1	Increasing	
26	Axar Patel	0.769096		Constant
27	Sunil Narine	0.783745		Constant
28	Piyush Chawla	0.716353		Constant
29	Sam Curran	1	Increasing	
30	Jaydev Unadkat	0.64278		Increasing

Table 4.6 – Returns to Scale Characteristics for Bowling Performance

The following table shows the Returns to Scale characteristics obtained for the top 30 **Indian** batsmen included in the dataset.

No.	DMU	Score	RTS	RTS of Projected DMU
1	KL Rahul	1	Constant	
2	Shikhar Dhawan	1	Constant	
3	Rishabh Pant	1	Constant	
4	Virat Kohli	0.993612934		Constant
5	Shreyas Iyer	0.836593605		Constant
6	Suryakumar Yadav	0.845797734		Constant
7	MS Dhoni	1	Constant	
8	Rohit Sharma	0.950169306		Increasing
9	Hardik Pandya	1	Constant	
10	Ajinkya Rahane	1	Constant	
11	Suresh Raina	0.838043538		Constant
12	Parthiv Patel	1	Increasing	
13	Prithvi Shaw	0.988844647		Constant
14	Manish Pandey	0.963739539		Constant
15	Nitish Rana	1	Constant	
16	Sanju Samson	1	Constant	
17	Mayank Agarwal	0.899039894		Constant
18	Shubman Gill	0.946		Constant
19	Ambati Rayudu	0.737804878		Constant
20	Robin Uthappa	0.805863771		Constant
21	Dinesh Karthik	1	Constant	
22	Vijay Shankar	0.700797356		Constant
23	Krunal Pandya	0.76848251		Constant
24	Sarfaraz Khan	1	Constant	
25	Mandeep Singh	1	Constant	
26	Kedar Jadhav	0.696909555		Constant
27	Riyan Parag	1	Constant	
28	Rahul Tripathi	1	Constant	
29	Axar Patel	1	Constant	
30	Ravindra Jadeja	1	Constant	

Table 4.7 – Returns to Scale Characteristics for Batting Performance of Indian Batsman

The following table shows the Returns to Scale characteristics obtained for the top 30 **Indian** bowler included in the dataset.

No.	DMU	Score	RTS	RTS of Projected DMU
1	Deepak Chahar	1	Constant	
2	Shreyas Gopal	1	Constant	
3	Jasprit Bumrah	1	Constant	
4	Khaleel Ahmed	1	Constant	
5	Mohammed Shami	0.9210526		Constant
6	Yuzvendra Chahal	1	Constant	
7	Harbhajan Singh	1	Constant	
8	Ravindra Jadeja	1	Increasing	
9	Ravichandran Ashwin	0.7954113		Constant
10	Hardik Pandya	0.8264995		Constant
11	Rahul Chahar	1	Constant	
12	Ishant Sharma	0.9340233		Constant
13	Bhuvneshwar Kumar	1	Constant	
14	Krunal Pandya	0.7792465		Constant
15	Sandeep Sharma	0.7725948		Constant
16	Amit Mishra	1	Increasing	
17	Navdeep Saini	1	Constant	
18	Axar Patel	0.804371		Constant
19	Piyush Chawla	0.7296623		Constant
20	Jaydev Unadkat	0.6498054		Constant
21	Shardul Thakur	0.8185747		Constant
22	Umesh Yadav	0.8482798		Constant
23	Mohammed Siraj	0.8997853		Constant
24	Siddarth Kaul	0.8712644		Constant
25	Dhawal Kulkarni	0.8135087		Constant
26	Murugan Ashwin	0.7661989		Increasing
27	Washington Sundar	1	Constant	
28	Kuldeep Yadav	0.69606		Constant
29	Prasidh Krishna	0.8530431		Constant
30	Varun Aaron	0.9614874		Constant

Table 4.8 – Returns to Scale Characteristics for Bowling Performance of Indian Bowlers

4.2 Squad Selection for World XI Team

In this section, we shall collectively analyze the results of DEA model in terms of DEA Scores, Ranking of players, and also the Returns to Scale characteristics as presented in Tables 4.1, 4.2, 4.5 and 4.6. This analysis will eventually help us to form a squad of players from which the World XI team may be picked up/selected.

Collective Analysis of Batting Performance using Scores & Returns To Scale Characteristics

Rank	Player	Score	RTS
1	Jos Buttler	1	Constant
1	David Warner	1	Constant
1	KL Rahul	1	Decreasing
1	Sanju Samson	1	Constant
1	Hardik Pandya	1	Constant
1	Andre Russell	1	Constant
1	Chris Gayle	1	Decreasing
1	MS Dhoni	1	Constant
1	AB de Villiers	1	Constant
1	Jonny Bairstow	1	Constant

Table 4.9 – Collective Analysis of Batting Performance (Rank, RTS)

Rank	DMU	Score	RTS
1	Sam Curran	1	Increasing
1	ImranTahir	1	Constant
1	Kagiso Rabada	1	Constant
1	Deepak Chahar	1	Constant
1	Shreyas Gopal	1	Increasing
1	Andre Russell	1	Increasing
1	Khaleel Ahmed	1	Constant
1	Navdeep Saini	1	Constant
1	Jofra Archer	1	Constant
1	Rashid Khan	1	Constant
1	Harbhajan Singh	1	Increasing
1	Lasith Malinga	1	Constant
1	Ravindra Jadeja	1	Increasing
1	Amit Mishra	1	Increasing
1	Chris Morris	1	Increasing
1	Rahul Chahar	1	Increasing
1	Bhuvneshwar Kumar	1	Constant

Table 4.10 – Collective Analysis of Bowling Performance (Rank, RTS)

Therefore, the best cricket team squad for World XI team, identified by DEA method applied to IPL-12 player statistics is depicted in the following table.

Player in the Squad	Capability
Jos Buttler	Batsman, Wicket Keeper
David Warner	Batsman
Sanju Samson	Batsman
Hardik Pandya	Batsman, All Rounder
Andre Russell	Batsman, Bowler, All Rounder
MS Dhoni	Batsman, Wicket Keeper
AB de Villiers	Batsman
Jonny Bairstow	Batsman, Wicket Keeper
Sam Curran	Bowler
Shreyas Gopal	Bowler
Harbhajan Singh	Bowler
Ravindra Jadeja	Bowler, All Rounder
Amit Mishra	Bowler
Chris Morris	Bowler
Rahul Chahar	Bowler

Table 4.12 – Best Team Squad based on performance in IPL 12 for World XI Team

Note – There are players who may be efficient but owing to squad restrictions, not all of them can be picked up for the squad. As a result, the players are chosen in accordance with their Returns of Scale – with highest priority given to Increasing Returns to Scale followed by Constant Returns to Scale & Decreasing Returns to Scale.

4.2 Squad Selection for National Cricket Team Squad

In this section, we shall collectively analyze the results of DEA model in terms of DEA Scores, Ranking of players, and also the Returns to Scale characteristics as presented in Tables 4.3, 4.4, 4.7 and 4.8. This analysis will eventually help us to form a squad of players from which the National Cricket team may be picked up/selected.

Collective Analysis of Batting Performance using Scores & Returns To Scale Characteristics

Rank	Player	RTS
1	Ravindra Jadeja	Constant
1	KL Rahul	Increasing
1	Shikhar Dhawan	Increasing
1	Rishabh Pant	Increasing
1	Axar Patel	Constant
1	Rahul Tripathi	Constant
1	Riyan Parag	Constant
1	MS Dhoni	Increasing
1	Mandeep Singh	Constant
1	Hardik Pandya	Increasing
1	Ajinkya Rahane	Constant
1	Sarfaraz Khan	Constant
1	Parthiv Patel	Increasing
1	Dinesh Karthik	Increasing
1	Sanju Samson	Increasing
1	Nitish Rana	Constant

Table 4.13 – Collective Analysis of Batting Performance (Rank, RTS)

Collective Analysis of Bowling Performance using Scores & Returns To Scale Characteristics

Rank	DMU	RTS
1	Washington Sundar	Constant
1	Deepak Chahar	Constant
1	Shreyas Gopal	Increasing
1	Jasprit Bumrah	Increasing
1	Khaleel Ahmed	Constant
1	Navdeep Saini	Constant
1	Yuzvendra Chahal	Increasing
1	Harbhajan Singh	Increasing
1	Ravindra Jadeja	Increasing
1	Amit Mishra	Increasing
1	Bhuvneshwar Kumar	Increasing
1	Rahul Chahar	Constant

Table 4.14 – Collective Analysis of Bowling Performance (Rank, RTS)

Therefore, the best cricket team squad for National Cricket team, identified by DEA method applied to IPL-12 player statistics is depicted in the following table.

Player in the Squad	Capability
Ravindra Jadeja	Batsman, Bowler, All Rounder
KL Rahul	Batsman, Wicket-Keeper
Shikhar Dhawan	Batsman
Rishabh Pant	Batsman, Wicket-Keeper
MS Dhoni	Batsman, Wicket-Keeper
Hardik Pandya	Batsman, All-Rounder
Parthiv Patel	Batsman, Wicket-Keeper
Dinesh Karthik	Batsman, Wicket-Keeper
Sanju Samson	Batsman
Shreyas Gopal	Bowler
Jasprit Bumrah	Bowler
Yuzvendra Chahal	Bowler
Harbhajan Singh	Bowler
Amit Mishra	Bowler
Bhuvneshwar Kumar	Bowler

Table 4.15 – Best Team Squad based on performance in IPL 12 for National Team

CHAPTER 6: LIMITATIONS OF THE STUDY

The aggregation model proposed as a part of this study is a non-parametric technique in which statistical hypothesis testing is difficult. The outputs viz. Runs scored, Wickets taken, etc.. are not the parametric functions of the inputs viz. Balls faced, Runs conceded, etc. Thus, there is no direct relationship between the Input and Output Variables. As a result, the formation and testing of statistical hypothesis is very difficult. It must be noted that data accuracy be given due priority as hypothesis testing is not feasible/possible.

Also, the efficiency measured through the proposed model in this study is relative in nature, as a result of which the comparison of the performance of a DMU can be made with only those DMUs which are in the reference set. For instance, if a highly skilled player is rested from the IPL season in order to remain fit for other International tournaments, then his efficiency/performance cannot be taken as a benchmark for comparison as he does not contribute to the reference set (dataset of IPL).

This technique is found to be sensitive to the choice of the input-output factors as well as the number of DMUs chosen for evaluation. The results of computation have been found to be influenced by the size of dataset entries. For small sample sizes, the discretionary power of model is seemingly reduced.

One must take due note of Zero and negative values of any input or output. The data entries must be corrected by adding an appropriate number to all the data entries to offset the difference, if any of the data entry in the given dataset is zero or negative.

The proposed methodology with the pre-decided input-output variables is applicable only for limited overs edition of cricket (particularly T20 format). The choice of variables is likely to vary drastically for performance evaluation in different formats and editions of the game.

The window analysis has not been prescribed as a part of this literature. However, it may become a vital analysis component when a fixed number of players are to be selected for playing a particular match or tournament and all the players of the squad are ranked equally with same performance score. There are players who may be efficient but owing to squad restrictions, not all of them can be picked up for the squad. As a result, the players are chosen in accordance with their Returns of Scale – with highest priority given to IRS followed by CRS & DRS.

The non-discretionary variables like the interest of public in the sport, the availability of cricketing resources, facilities to a player, the experience of playing in county leagues, etc.. have not been taken into consideration or controlled, which may not result in a fairer assessment across players from different nations as it would have otherwise resulted had the non-discretionary variables been taken control of.

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ANNEXURES

IPL 2019 - 12th Edition Dataset - Batting Statistics

PLAYER	(I)Mat	(I)Inns	(I)BF	(O)NO	(O)Runs	(O)HS	(O)Avg	(O)SR	(O) Milestones	(O)Boundaries Hit
David Warner	12	12	481	3	692	100	69.2	143.86	9	78
KL Rahul	14	14	438	4	593	100	53.9	135.38	7	74
Quinton de Kock	16	16	398	2	529	81	35.26	132.91	4	70
Shikhar Dhawan	16	16	384	2	521	97	34.73	135.67	5	75
Andre Russell	14	13	249	5	510	80	56.66	204.81	4	83
Chris Gayle	13	13	319	2	490	99	40.83	153.6	4	79
Rishabh Pant	16	16	300	4	488	78	37.53	162.66	3	64
Virat Kohli	14	14	328	1	464	100	33.14	141.46	3	59
Shreyas Iyer	16	16	386	2	463	67	30.86	119.94	3	55
Jonny Bairstow	10	10	283	3	445	114	55.62	157.24	3	66
AB de Villiers	13	13	287	4	442	82	44.2	154	5	57
Suryakumar Yadav	16	15	324	3	424	71	32.61	130.86	2	55
MS Dhoni	15	12	309	8	416	84	83.2	134.62	3	45
Chris Lynn	13	13	290	1	405	82	31.15	139.65	4	63
Rohit Sharma	15	15	315	2	405	67	28.92	128.57	2	62
Hardik Pandya	16	15	210	7	402	91	44.66	191.42	1	57
Shane Watson	17	17	312	1	398	96	23.41	127.56	3	62
Faf du Plessis	12	12	321	2	396	96	36	123.36	3	51
Ajinkya Rahane	14	13	285	2	393	105	32.75	137.89	2	54
Suresh Raina	17	17	314	2	383	59	23.93	121.97	3	54
Parthiv Patel	14	14	268	1	373	67	26.64	139.17	2	58
Prithvi Shaw	16	16	264	1	353	99	22.06	133.71	2	54
Manish Pandey	12	11	263	4	344	83	43	130.79	3	40
Nitish Rana	14	11	235	2	344	85	34.4	146.38	3	48
Sanju Samson	12	12	230	3	342	102	34.2	148.69	1	41
Mayank Agarwal	13	13	234	1	332	58	25.53	141.88	2	40
Steve Smith	12	10	275	3	319	73	39.87	116	3	34
Jos Buttler	8	8	205	1	311	89	38.87	151.7	3	52
Shubman Gill	14	13	238	5	296	76	32.88	124.36	3	31
Ambati Rayudu	17	17	303	6	282	57	23.5	93.06	1	27

Figure 1 - Batting Performance Dataset (Overall Top 30 Batsmen)

IPL 2019 - 12th Edition Dataset - Bowling Statistics

PLAYER	(I)Mat	(I)Inns	(I)Overs Bowled	(I)Runs Conceeded	(I)Avg	(I)Econ	(I)SR	(O)Wickets Taken	(O)Dot Balls	(O)Corrected 4w
ImranTahir	17	17	64.2	431	16.57	6.69	14.84	26	149	3
Kagiso Rabada	12	12	47	368	14.72	7.82	11.28	25	113	3
Deepak Chahar	17	17	64.3	482	21.9	7.47	17.59	22	190	1
Shreyas Gopal	14	14	48	347	17.35	7.22	14.4	20	107	1
Jasprit Bumrah	16	16	61.4	409	21.52	6.63	19.47	19	169	1
Khaleel Ahmed	9	9	34.5	287	15.1	8.23	11	19	87	1
Mohammed Shami	14	14	54	469	24.68	8.68	17.05	19	119	1
Yuzvendra Chahal	14	14	49.2	386	21.44	7.82	16.44	18	117	2
Rashid Khan	15	15	60	377	22.17	6.28	21.17	17	166	1
Harbhajan Singh	11	11	44	312	19.5	7.09	16.5	16	117	1
Lasith Malinga	12	12	44.5	438	27.37	9.76	16.81	16	91	3
Ravindra Jadeja	16	16	54	343	22.86	6.35	21.6	15	128	1
Ravichandran Ashwin	14	14	55	400	26.66	7.27	22	15	110	1
Hardik Pandya	16	16	42.3	390	27.85	9.17	18.21	14	94	1
Rahul Chahar	13	13	47	308	23.69	6.55	21.69	13	125	1
Ishant Sharma	13	13	46	349	26.84	7.58	21.23	13	122	1
Bhuvneshwar Kumar	15	15	59	461	35.46	7.81	27.23	13	168	1
Chris Morris	9	9	33	306	23.53	9.27	15.23	13	68	1
Krunal Pandya	16	16	46	335	27.91	7.28	23	12	94	1
Sandeep Sharma	11	11	42.4	352	29.33	8.25	21.33	12	82	1
Amit Mishra	11	11	40	270	24.54	6.75	21.81	11	83	1
Jofra Archer	11	11	43	291	26.45	6.76	23.45	11	121	1
Dwayne Bravo	12	12	41.1	330	30	8.01	22.45	11	74	1
Navdeep Saini	13	13	48	397	36.09	8.27	26.18	11	141	1
Andre Russell	14	12	30.1	287	26.09	9.51	16.45	11	61	1
Axar Patel	14	14	51	364	36.4	7.13	30.6	10	110	1
Sunil Narine	12	12	44.2	347	34.7	7.82	26.6	10	96	1
Piyush Chawla	13	13	44.3	399	39.9	8.96	26.7	10	87	1
Sam Curran	9	9	33	323	32.3	9.78	19.8	10	60	2
Jaydev Unadkat	11	11	37.2	398	39.8	10.66	22.4	10	58	1

Figure 2 - Bowling Performance Dataset (Overall Top 30 Bowlers)

IPL 2019 - 12th Edition Dataset – Indian Batsmen Statistics

PLAYER	(I)Mat	(I)Inns	(I)BF	(O)NO	(O)Runs	(O)HS	(O)Avg	(O)SR	(O)Corrected Milestones	(O)Boundaries Hit
KL Rahul	14	14	438	4	593	100	53.9	135.38	8	75
Shikhar Dhawan	16	16	384	2	521	97	34.73	135.67	6	76
Rishabh Pant	16	16	300	4	488	78	37.53	162.66	4	65
Virat Kohli	14	14	328	1	464	100	33.14	141.46	4	60
Shreyas Iyer	16	16	386	2	463	67	30.86	119.94	4	56
Suryakumar Yadav	16	15	324	3	424	71	32.61	130.86	3	56
MS Dhoni	15	12	309	8	416	84	83.2	134.62	4	46
Rohit Sharma	15	15	315	2	405	67	28.92	128.57	3	63
Hardik Pandya	16	15	210	7	402	91	44.66	191.42	2	58
Ajinkya Rahane	14	13	285	2	393	105	32.75	137.89	3	55
Suresh Raina	17	17	314	2	383	59	23.93	121.97	4	55
Parthiv Patel	14	14	268	1	373	67	26.64	139.17	3	59
Prithvi Shaw	16	16	264	1	353	99	22.06	133.71	3	55
Manish Pandey	12	11	263	4	344	83	43	130.79	4	41
Nitish Rana	14	11	235	2	344	85	34.4	146.38	4	49
Sanju Samson	12	12	230	3	342	102	34.2	148.69	2	42
Mayank Agarwal	13	13	234	1	332	58	25.53	141.88	3	41
Shubman Gill	14	13	238	5	296	76	32.88	124.36	4	32
Ambati Rayudu	17	17	303	6	282	57	23.5	93.06	2	28
Robin Uthappa	12	11	245	3	282	67	31.33	115.1	2	39
Dinesh Karthik	14	13	173	6	253	97	31.62	146.24	3	37
Vijay Shankar	15	14	193	3	244	40	20.33	126.42	1	24
Krunal Pandya	16	15	150	5	183	42	16.63	122	1	24
Sarfaraz Khan	8	5	143	2	180	67	45	125.87	2	24
Mandeep Singh	13	12	120	9	165	33	41.25	137.5	1	15
Kedar Jadhav	14	12	169	4	162	58	18	95.85	2	23
Riyan Parag	7	5	126	1	160	50	32	126.98	2	23
Rahul Tripathi	8	7	118	2	141	50	23.5	119.49	2	16
Axar Patel	14	12	88	7	110	26	18.33	125	1	14
Ravindra Jadeja	16	9	88	7	106	31	35.33	120.45	1	12

Figure 3 - Batting Performance Dataset (Top 30 Indian Batsmen)

IPL 2019 - 12^{th} Edition Dataset – Indian Bowlers Statistics

PLAYER	(I)Mat	(I)Inns	(I)Overs Bowled	(I)Runs Conceeded	(I)Avg	(I)Econ	(I)SR	(O)Wickets Taken	(O)Dot Balls	(O)Corrected 4w
Deepak Chahar	17	17	64.3	482	21.9	7.47	17.59	22	190	1
Shreyas Gopal	14	14	48	347	17.35	7.22	14.4	20	107	1
Jasprit Bumrah	16	16	61.4	409	21.52	6.63	19.47	19	169	1
Khaleel Ahmed	9	9	34.5	287	15.1	8.23	11	19	87	1
Mohammed Shami	14	14	54	469	24.68	8.68	17.05	19	119	1
Yuzvendra Chahal	14	14	49.2	386	21.44	7.82	16.44	18	117	2
Harbhajan Singh	11	11	44	312	19.5	7.09	16.5	16	117	1
Ravindra Jadeja	16	16	54	343	22.86	6.35	21.6	15	128	1
Ravichandran Ashwin	14	14	55	400	26.66	7.27	22	15	100	1
Hardik Pandya	16	16	42.3	390	27.85	9.17	18.21	14	94	1
Rahul Chahar	13	13	47	308	23.69	6.55	21.69	13	125	1
Ishant Sharma	13	13	46	349	26.84	7.58	21.23	13	122	1
Bhuvneshwar Kumar	15	15	59	461	35.46	7.81	27.23	13	168	1
Krunal Pandya	16	16	46	335	27.91	7.28	23	12	94	1
Sandeep Sharma	11	11	42.4	352	29.33	8.25	21.33	12	82	1
Amit Mishra	11	11	40	270	24.54	6.75	21.81	11	83	1
Navdeep Saini	13	13	48	397	36.09	8.27	26.18	11	141	1
Axar Patel	14	14	51	364	36.4	7.13	30.6	10	110	1
Piyush Chawla	13	13	44.3	399	39.9	8.96	26.7	10	87	1
Jaydev Unadkat	11	11	37.2	398	39.8	10.66	22.4	10	58	1
Shardul Thakur	10	9	30	281	35.12	9.36	22.5	8	65	1
Umesh Yadav	11	11	37.5	371	46.37	9.8	28.37	8	88	1
Mohammed Siraj	9	9	28.1	269	38.42	9.55	24.14	7	69	1
Siddarth Kaul	7	7	27	242	40.33	8.96	27	6	56	1
Dhawal Kulkarni	10	10	35	335	55.83	9.57	35	6	77	1
Murugan Ashwin	10	10	34	255	51	7.5	40.8	5	59	1
Washington Sundar	3	3	9	74	18.5	8.22	13.5	4	21	1
Kuldeep Yadav	9	9	33	286	71.5	8.66	49.5	4	54	1
Prasidh Krishna	11	11	40.2	377	94.25	9.34	60.5	4	95	1
Varun Aaron	5	5	12	116	29	9.66	18	4	28	1

Figure 4 - Bowling Performance Dataset (Top 30 Indian Bowlers)

Performance Evaluation and Comparison Charts – Batting Performance

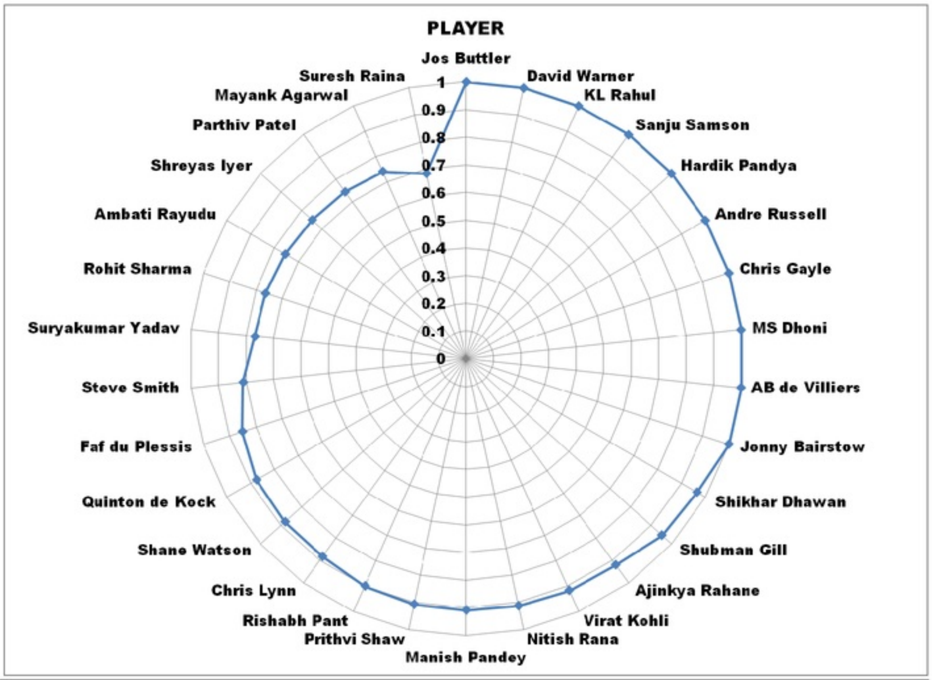

Figure 5 - Batting Performance Efficiency Radar Map (Overall Top 30 Batsmen)

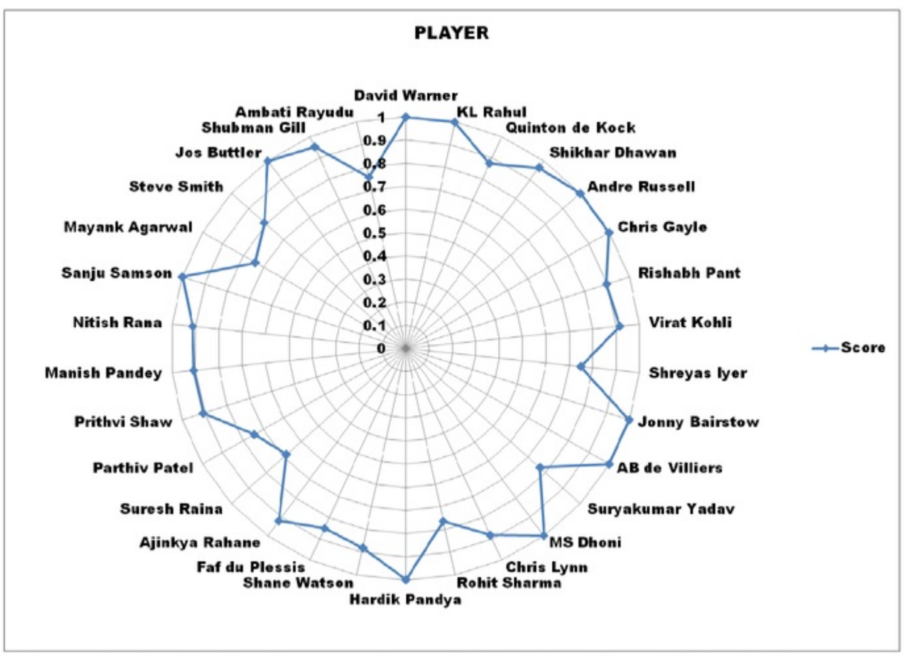

Figure 6 - Batting Performance Score Radar Map (Overall Top 30 Batsmen)

Performance Evaluation and Comparison Charts – Bowling Performance

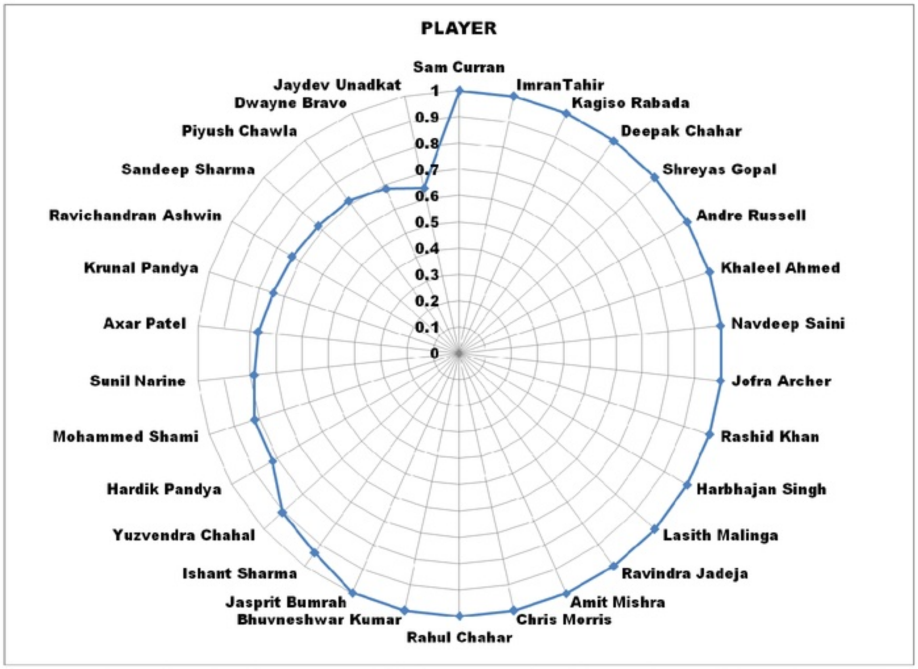

Figure 7 - Bowling Performance Efficiency Radar Chart (Overall Top 30 Bowlers)

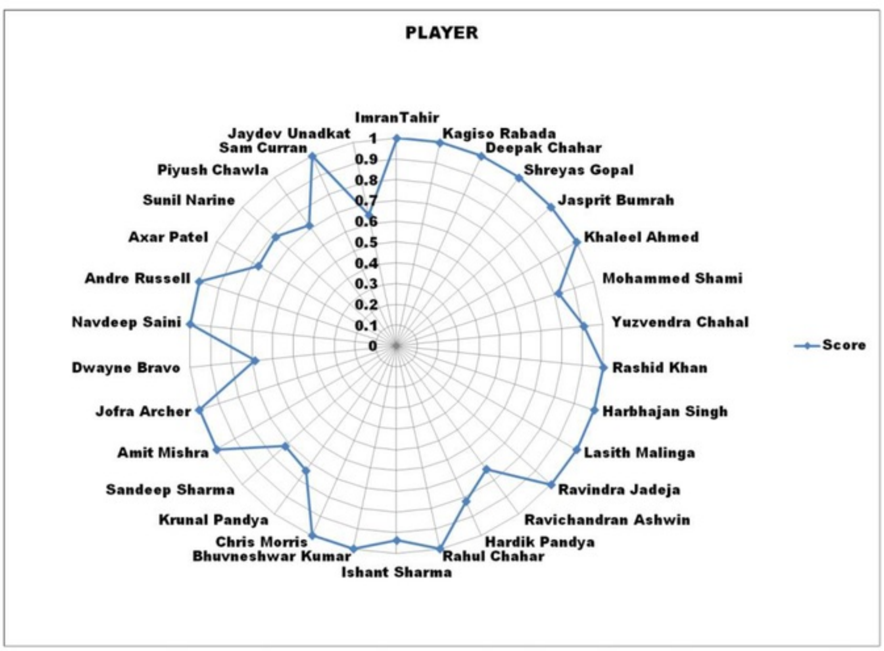

Figure 8 - Bowling Performance Score Radar Chart (Overall Top 30 Bowlers)

Performance Evaluation and Comparison Charts – Batting Performance (Indian Batsmen)

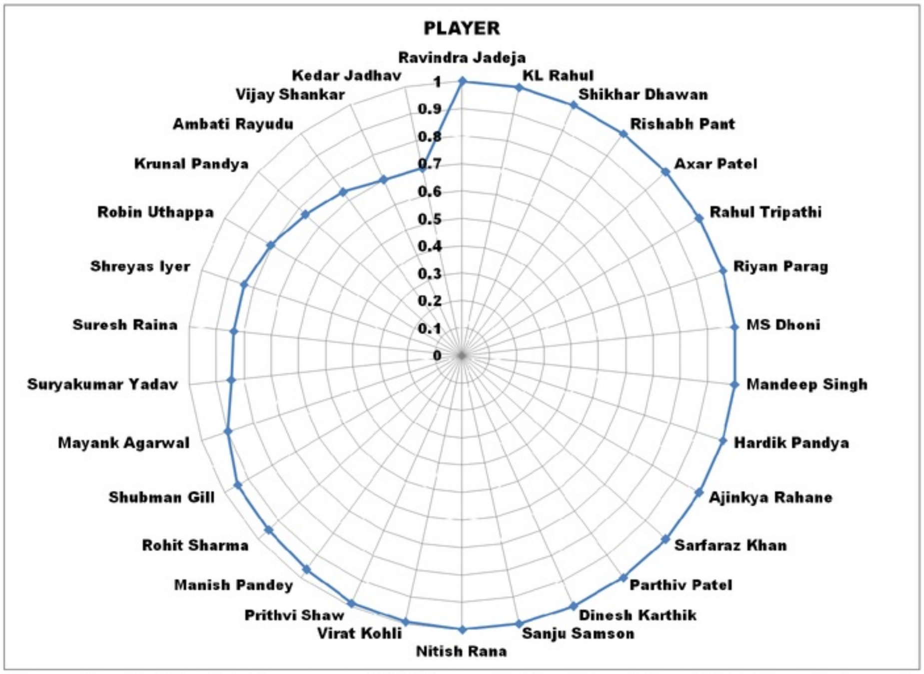

Figure 9 - Batting Performance Efficiency Radar Map (Top 30 Indian Batsmen)

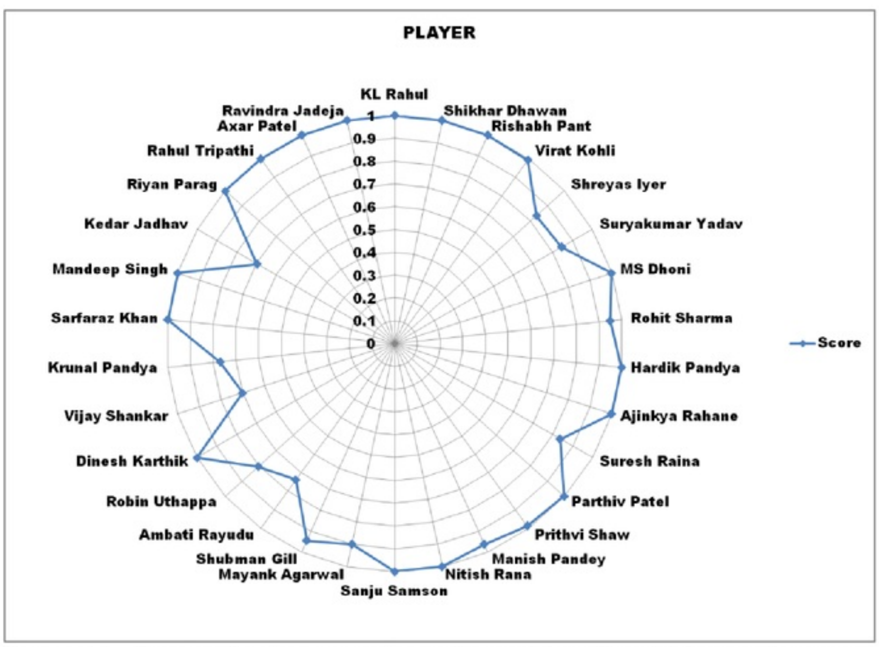

Figure 10 - Batting Performance Score Radar Map (Top 30 Indian Batsmen)

Performance Evaluation and Comparison Charts – Bowling Performance (Indian Bowlers)

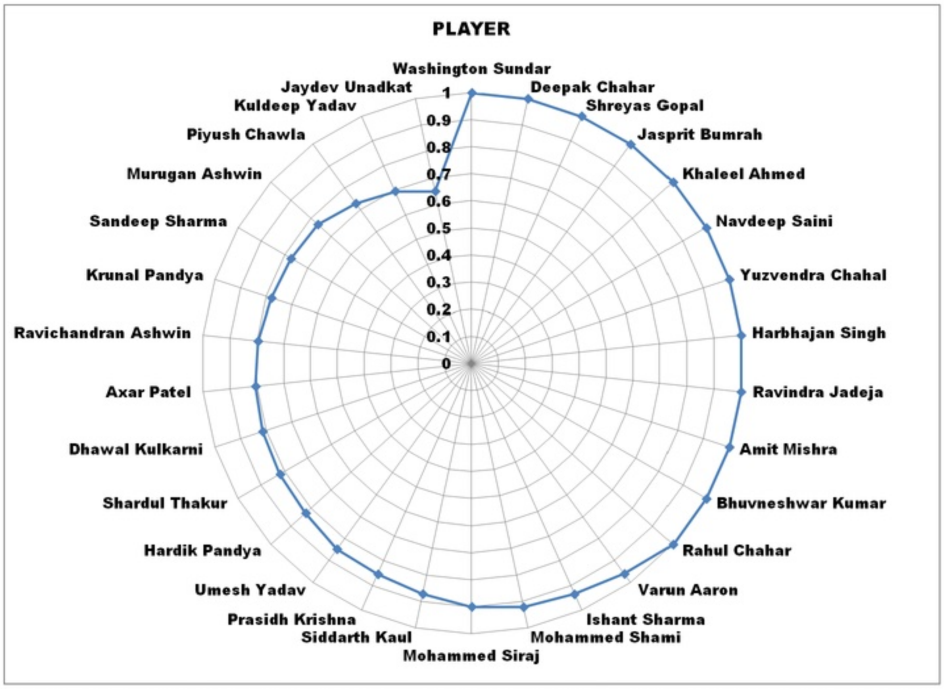

Figure 11 - Bowling Performance Efficiency Radar Chart (Top 30 Indian Bowlers)

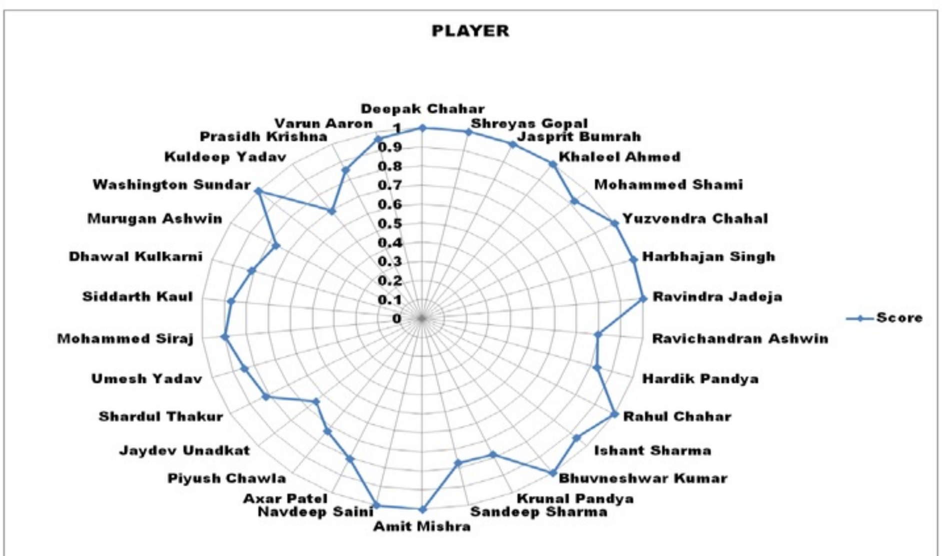

Figure 12 - Bowling Performance Score Radar Chart (Top 30 Indian Bowlers)

Weighted Scores of Input & Output Variables (Batsman)

No.	DMU	Score	VX(0)	VX(1)	VX(2)	VX(3)	UY(1)	UY(2)	UY(3)	UY(4)	UY(5)	UY(6)	UY(7)
1	David Warner	1	0	1	0	0	0.314132	0.685868	0	0	0	0	0
2	KL Rahul	1	0.7476074	0	0	0.252393	0.142409	0	0.478901	0	0	0.172281	0.206409
3	Quinton de Kock	0.875563	1.1421219	0	0	0	0	2.30E-02	0.194365	0	0	0	0.78264
4	Shikhar Dhawan	0.965416	1.0358224	0	0	0	0	2.12E-03	0.527937	0	0	0	0.46994
5	Andre Russell	1	0	0	0	1	9.01E-02	0.90987	0	0	0	0	0
6	Chris Gayle	1	0.3760998	0.560013	0	6.39E-02	0	0	8.89E-02	0	0	0	0.911054
7	Rishabh Pant	0.899069	0.7595742	0	0	0.352687	6.83E-02	0.583406	0.348303	0	0	0	0
8	Virat Kohli	0.91661	0.6420778	0	0	0.448899	0	0.611282	0.388718	0	0	0	0
9	Shreyas Iyer	0.749829	0.6796194	0	0	0.654018	0	1	0	0	0	0	0
10	Jonny Bairstow	1	0	0.704003	0	0.295997	0.26657	0.646095	8.73E-02	0	0	0	0
11	AB de Villiers	1	0	0.321929	0	0.678071	0.182359	0	0.301365	0	0	0.516276	0
12	Suryakumar Yadav	0.768838	0.7693471	0	0	0.531317	0	0.669305	0.330695	0	0	0	0
13	MS Dhoni	1	0	1	0	0	1	0	0	0	0	0	0
14	Chris Lynn	0.883866	0.4420721	0	0	0.689322	0	0	0.502086	0	0	0.352435	0.145479
15	Rohit Sharma	0.763116	1.3104171	0	0	0	0	0.0202	0.184461	0	0	0	0.79534
16	Hardik Pandya	1	0	0.615385	0	0.384615	1	0	0	0	0	0	0
17	Shane Watson	0.881078	1.1349738	0	0	0	0	0	0.573186	0	0	5.43E-04	0.426271
18	Faf du Plessis	0.85124	1.1747573	0	0	0	0	0	0.932039	0	0	6.80E-02	0
19	Ajinkya Rahane	0.921053	1.0857143	0	0	0	0	0	1	0	0	0	0
20	Suresh Raina	0.684739	0.8748671	0	0	0.585543	0	0.687506	0.312494	0	0	0	0
21	Parthiv Patel	0.745235	0.8540109	0	0	0.487848	0	0.653594	0.346406	0	0	0	0
22	Prithvi Shaw	0.907649	0.2905036	0	0	0.811244	0	0	0.878124	0	0	0	0.121876
23	Manish Pandey	0.908893	-0.140843	0.659849	0	0.581233	0.362824	0	0.335133	0	0	0.302043	0
24	Nitish Rana	0.912958	0.4209082	0	0	0.674432	4.03E-02	0	0.624209	0	0	0.335528	0
25	Sanju Samson	1	0	8.35E-02	0	0.916509	0	0	1	0	0	0	0
26	Mayank Agarwal	0.740824	-2.75E-02	0.421748	0	0.955559	0	0	0	0	1	0	0
27	Steve Smith	0.81145	8.11E-02	0	0.432649	0.718576	0.203871	0	0.450937	0	0	0.345193	0
28	Jos Buttler	1	0	0.149401	0	0.850599	0	0.534069	0.465931	0	0	0	0
29	Shubman Gill	0.953317	-1.348526	0	0.985498	1.411997	0.657312	0	0	0	0	0.342688	0
30	Ambati Rayudu	0.755725	0.8131313	0	0	0.510101	1	0	0	0	0	0	0

Figure 13 - Weighted Scores of Input & Output Variables (Top 30 Batsman)

Report 3

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