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Measuring batting parameters in cricket: A two-stage regression-OWA method

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ABSTRACT

The selection of cricket players by team selectors and sponsors for endorsement of products is primarily dependent on the performance of players in terms of various parameters in their areas of expertise such as batting or bowling. This paper proposes a two-stage method for measuring and ranking batting parameters in cricket using ordered weighted averaging (OWA) operator and regression. The first stage measures the performance of batsmen using OWA operator followed by ranking of batting parameters using regression. The study reveals that the ranking obtained for batting parameters is not sensitive to changes in the OWA weights. A real dataset of 40 batsmen from Indian Premier League 2011 is considered for analysis purpose. Although this paper focuses only on the batting discipline the results from this paper can be extended to investigate bowling discipline using multiple parameters. These results can be implemented to enhance the quality of decision making.

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1. Introduction

Cricket is a game with huge following in the British Commonwealth Countries as well as some other countries. The game of cricket as played today is more than a century old and the game has evolved through frequent changes over the past few decades. The older versions of cricket are test matches and One Day Internationals (ODIs). Unlike these older formats of cricket, which take longer duration, the latest format of the cricket, Twenty20 game can be completed in shorter period of two and half hours comparable with the time span of other popular team sports. This format was introduced a decade ago in England around 2003 and gained huge popularity among both the spectators on the ground and viewers on the television and resulted in tremendous opportunity gather huge revenue for cricket boards and players. In 2007, the first world cup of Twenty20 was played in South Africa and the cup was won by India. In June 2009, speaking at the annual Cowdrey Lecture at Lord's, former Australian cricketer Adam Gilchrist pushed for Twenty20 to be made an Olympic sport. Twenty20 attracted millions of spectators and viewers of the game through Indian Premier League (IPL) making it a huge economic and entertainment forum. The first IPL organized in India in the year 2008 can be considered a landmark event and a turning point for the world of cricket. Till date, the IPL Twenty20 games have been highly successful in generating popularity and robust earnings for players and organizers. As of 2011, as many as seventeen countries have participated in Twenty20 tournaments around the world. A summary of International Cricket Council (ICC) sanctioned matches played in various formats is available on www.cricinfo.com. The growth in the number of Twenty20 matches in recent years point towards the success of the adoption of Twenty20 cricket format; however, the deviation from technical aspects or the basics of cricket has become a subject of debate. Usually new talented players believe that Twenty20 is about hitting 6s and 4s and tend to ignore

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the basics of the cricket game. Another concern is the inclination of new talented players to focus on making contracts with Twenty20 format of various countries instead of choosing to represent their countries.

Twenty20 game is similar to ODI and played between two teams, the fundamental difference being each team bats for a maximum of 20 overs. Each team is a combination of 11 players taken from different disciplines such as batting, bowling, all-rounder, and wicket keeper. Each bowler can bowl maximum four overs in a match or a maximum of only one-fifth of the total overs to be played per innings. In other formats of cricket, batsmen arrive from and depart to dressing room whereas in Twenty20 format, batsmen come and go from a "row of chairs" visible from all corners of the playground, similar to association football's "Technical area" or a baseball "dugout". In Twenty20 cricket format, the role of a batsman is considered more important in winning the game. It is believed that Twenty20 has tilted the game in favor of batsmen and the scope for bowlers has become more limited in comparison to ODIs. The problem of choosing a set of good batsmen is of paramount importance in all three formats of cricket. We propose a two-stage mathematical procedure using ordered weighted averaging (OWA) operator and regression methods. The first stage measures the performance of players taking five various capabilities such as Highest Score (HS), Average (AVG), Strike Rate (SR), 4s, 6s using OWA operator and then establishes the ranking of parameters using a regression model. The prioritization of various parameters of a player is important for selectors while choosing a set of batsmen for team in any format of the game whereas it is more important in Twenty20 format since the duration of the match is short and the performance expectations from players are high.

Perhaps, there is no direct publication for measuring and ranking batting parameters in the cricket literature. However, in recent years some authors have paid attention in different domains of cricket statistics. Kimber and Hansford [11] discussed statistical analysis of batting in cricket. This study was extended by Barr and Kantor [4] by suggesting a mathematical method for comparing and selecting batsmen in cricket. Sharp et al. [17] revisited a partial mathematical approach proposed in Barr and Kantor [4] to choose batsmen based on the average and strike rate of a batsman with subjective choice of a parameter. Sharma et al. [16] discussed how to choose best cricket batsman using ordered weighted averaging. Lemmer [12] proposed a single match approach to strike rate adjustments in batting performance measures for ODI in cricket. [13] suggested a hedonic model of players' wage determination for IPL based on various cricket parameters. Multivariate statistical method such as factor analysis has been employed in Twenty20 cricket by Sharma [15]. For cricket team selection using different mathematical models see Iyer and Shadra [10], Amin and Sharma [3]. The proposed DEA method in Amin and Sharma [3] is used to evaluate cricket players in different abilities for a team selection whereas the current study focuses on ranking batting parameters. In fact, their proposed DEA method cannot be used for the purpose of the current study, as each DEA model for individual batsman assigns different importance weights for the batting parameters. As discussed in Cook et al. [6], DEA is an effective method when decision making units (DMUs) can be viewed as production systems where multiple resources (or inputs) are consumed to produce multiple outputs (or products); however, in all cases defining the actual inputs and outputs may not be easy. Another problem encountered when using DEA is the generation of different importance weight vector for the batting parameters for each batsman which might fail in case of unique ranking.

Among the cricket experts and fans, strike rate is considered as an important measure for good batsmen in Twenty20 format but there is no scientific evidence to support this measure in the literature. This paper is an attempt to provide a scientific basis to prove that strike rate is an important measure for good batsmen in shorter version of cricket using OWA and regression methods.

This paper suggests a new method for measuring batting parameters in cricket using OWA operator and regression methods for prioritizing batting parameters. The OWA operators, originated in Yager [19], represent an aggregation method that maps $\mathbf{x} = (x_1, \ldots, x_n)$ to $F(\mathbf{x}) = \mathbf{wy} = \sum_{i=1}^{n} w_i y_i$, where y_i is the ith largest value $(i = 1, \ldots, n)$ of components of $\mathbf{x}$ and $\mathbf{w} = (w_1, \ldots, w_n)$, $w_i \geqslant 0$ $i = 1, \ldots, n$ and $\sum_{i=1}^{n} w_i = 1$, are the associated weights. Recent years have seen successful applications of OWA in different areas. For example, Tesfamariam and Sadiq [18] used OWA operators for probabilistic risk analysis. Emrouznejad [7] introduced the most preferred OWA operator for considering the role of data in the process of aggregation. Amin and Sadeghi [2] proposed an application of OWA for a metasearch aggregation. Yager and Beliakov [22] developed the use of OWA operators for regression problems. Also, Chang and Cheng [5] suggested an OWA based method for the risk failure analysis.

In this paper we propose a new method for measuring and ranking batting parameters in cricket using OWA and regression. It is shown that for different generated OWA weights, corresponding to various uncertainty levels, the ranking obtained for batting parameters is not sensitive to the change of these weights. The result of this paper can be developed for any other format of cricket and capabilities with multiple parameters. The remainder of this paper is organized as follows: Section 2 gives the concept of OWA operator. Data for 40 IPL batsmen is explained in Section 3. Section 4 gives a method for measuring batting parameters. Conclusion and directions for further research are presented in Section 5.

2. Basic concepts: OWA operators

In OWA operator there are two important measures, the dispersion (or entropy) and the orness, defined as follows, Yager [19].

$$\mathrm{Disp}\,(w_1, \ldots, w_n) = -\sum_{i=1}^{n} w_i Ln(w_i)$$

$$\mathrm{Orness}\,(w_1, \ldots, w_n) = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i$$

The dispersion constraint can be interpreted as the entropy of the probability distribution in which all the aggregates are equally used. Also, the orness constraint that lies in the unit interval, $\alpha = \text{orness}\ (w_1, \ldots, w_n) \in [0, 1]$, can be viewed as a measure of optimism of a decision maker. For example, $\alpha = 1$ gives unique OWA weights $(w_1, \ldots, w_n) = (1, 0, \ldots, 0)$ which means $F(x_1, \ldots, x_n) = x_k$ where $x_k = \max\{x_i : i = 1, \ldots, n\}$. This case happens when decision maker is purely optimistic and considers only the largest value of alternative $(x_1, \ldots, x_n)$. Also, $\alpha = 0$ is used when decision maker is pure pessimistic. This case is associated with the OWA weights $(w_1, \ldots, w_n) = (0, \ldots, 0, 1)$ and therefore the OWA score is $F(x_1, \ldots, x_n) = x_l$, where $x_l = \min\{x_i : i = 1, \ldots, n\}$. One more special case is related to $\alpha = 0.5$. In this case the orness constraint gives unique OWA weights $(w_1, \ldots, w_n) = (\frac{1}{n}, \ldots, \frac{1}{n})$ and the OWA operator becomes as the simple average. In fact, larger values of α indicate preference for larger values of $\mathbf{x} = (x_1, \ldots, x_n)$ and lower values of α, closer to 0, denote preference for smaller components of $\mathbf{x} = (x_1, \ldots, x_n)$. Furthermore, if decision maker chooses an orness close to the middle, near 0.5, this is an indication of no preference for either large or small values. Apart from the special cases for other orness $\alpha \in (0, 1)$, and $\alpha \neq 0.5$, there exist infinite number of OWA weights satisfying in the orness constraint. The corresponding OWA aggregation has the following property.

$$\min\{x_i : i = 1, \ldots, n\} \leq F(\boldsymbol{x}) \leq \max\{x_i : i = 1, \ldots, n\}$$

This gives an aggregation varying between pure pessimistic and optimistic views depending on the opinions of decision maker. One important issue in the theory and application of OWA operators is the determination of the corresponding OWA weights. A number of methods have been introduced for generating of the OWA weights, Fuller and Majlender [9], Xu [24], Wang and Parkan [23], Emrouznejad and Amin [8]. Wang and Parkan [23] introduced the first linear programming (LP) model, minimax disparity model, to determine the OWA weights. In this paper, without loss of generality, we use the minimax disparity LP model, Wang and Parkan [23], for generation of OWA weights. For a given orness, $0 \leqslant \alpha \leqslant 1$, the minimax disparity LP model proposed in Wang and Parkan [23] can be written as follows.

$$\begin{aligned}
&\min \delta \\
&s.t. \sum_{i=1}^{n} \left(\tfrac{n-i}{n-1}\right) w_i = \alpha \quad \alpha \in [0, 1] \\
&\quad \sum_{i=1}^{n} w_i = 1 \\
&\quad w_i - w_{i+1} \leq \delta \qquad i = 1, \ldots, n-1 \\
&\quad w_i - w_{i+1} \geq -\delta \qquad i = 1, \ldots, n-1 \\
&\quad w_i \geq 0 \quad i = 1, \ldots, n
\end{aligned} \tag{1}$$

The objective of the above model is minimizing the deviation between two consecutive weights as much as possible. To generate the OWA weights for a given orness one needs to solve model (1). In this paper we consider five batting parameters affecting the performance of a cricket batsman. Also, we have considered data for 40 batsmen who played IPL 4. Therefore, the OWA aggregation for a player can be defined as the following equation.

$$F(B_i) = w_1^* x_{1i} + w_2^* x_{2i} + w_3^* x_{3i} + w_4^* x_{4i} + w_5^* x_{5i}$$
$$i = 1, \ldots, 40$$

where B_i denotes the ith batsman $(i = 1, \ldots, 40)$ and $\boldsymbol{x}_i = (x_{1i}, \ldots, x_{5i})$ are the ordered observed batting parameters for the ith player, and $\mathbf{w}^* = (w_1^*, \ldots, w_5^*)$ denote the optimal OWA weights obtained from model (1).

In the OWA literature, we have several publications for generating OWA weights for different applications (see [20,21,1,14]). For instance, the OWA method suggested in [20,21] is useful when the priority among various factors is known whereas the methods in Amin and Emrouznejad [1] and Liu [14] are appropriate when additional constraints, depending on the application, can be incorporated in the process of OWA weights generation. In this paper, we use the most commonly used OWA weights generation model, the minimax disparity model (1) because it is based on the linear programming model and therefore easy in terms of implementation.

3. Data for 40 batsmen

We collected data from www.cricinfo.com for IPL session 4 (2011). The data are collected for top 40 batsmen based on average performance of batsmen. The five important parameters of a batsmen are Highest Score (HS) in a match, Average (Avg), Strike Rate (S/R), numbers of 4s and 6s hit by a batsman. 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*. The batting strike rate can be expressed as R/b where R denotes the number of runs scored and b denotes the number of *balls* faced by a player. Data for 40 batsmen is given in Appendix A. Also, we use SPSS 18.0 for data analysis.

4. Measuring batting parameters

In this section, we propose a two-stage OWA-regression method to prioritize batting parameters including, HS, Avg, S/R, 4s, and 6s for 40 players chosen from IPL 4. In the first stage we use OWA method for finding the performance of batsmen. This gives the OWA aggregation for players using three different orness levels. The last column in Appendix A shows the OWA scores for 40 batsmen corresponding to $\alpha = 0.6$. For this case we first solve model (1) and obtain the following optimal OWA weights.

$$\boldsymbol{w}^* = (w_1^*, \ldots, w_5^*) = (0.28, 0.24, 0.20, 0.16, 0.12)$$

Now, consider the first row in Appendix A. This row is related to the batsman who received the highest OWA score for $\alpha = 0.6$, that is, Chris Gayle. His observed batting data are

$$\begin{aligned}
\mathbf{x}_{\text{Chris Gayle}} &= (\text{HS}, \text{Avg}, \text{S/R}, 4\text{s}, 6\text{s}) \\
&= (107, 99.5, 196.1, 38, 30)
\end{aligned}$$

So, his OWA score can be calculated as

Table 1
OWA regression for $\alpha = 0.6$.

	Unstandardized coefficients	Standard error	Standardized coefficients (beta)	t Stat	*P*-value
Intercept	−.185	.087	–	−2.117	.042
HS	.241	.001	.428	237.067	.000
Avg	.199	.001	.268	249.901	.000
S/R	.281	.001	.438	430.000	.000
4s	.160	.002	.165	104.251	.000
6s	.120	.003	.053	37.515	.000

Table 2
OWA regression for $\alpha = 0.65$.

	Unstandardized coefficients	Standard error	Standardized coefficients (beta)	t Stat	*P*-value
Intercept	−.278	.131	–	−2.117	.042
HS	.262	.002	.444	171.506	.000
Avg	.199	.001	.256	166.193	.000
S/R	.322	.001	.479	328.047	.000
4s	.141	.002	.138	60.928	.000
6s	.080	.005	.034	16.730	.000

Table 3
OWA regression for $\alpha = 0.7$.

	Unstandardized coefficients	Standard error	Standardized coefficients (beta)	t Stat	*P*-value
Intercept	−.370	.175	–	−2.117	.042
HS	.282	.002	.458	138.726	.000
Avg	.198	.002	.244	124.339	.000
S/R	.362	.001	.516	277.070	.000
4s	.121	.003	.113	39.266	.000
6s	.041	.006	.016	6.338	.000

$$F(\text{Chris Gayle}) = 0.28 * \text{S/R} + 0.24 * \text{HS} + 0.20\text{Avg} + 0.16 * 4\text{s} + 0.12 * 6\text{s} = 110.1568$$

The OWA scores of the other batsmen are obtained similarly. Now, we can use the OWA scores of the players as dependent variable in the following regression model.

$$y_i = \beta_0 + \beta_1\text{HS}_i + \beta_2\text{Avg}_i + \beta_3(\text{S/R})_i + \beta_4(4\text{s})_i + \beta_5(6\text{s})_i + \varepsilon_i \quad i = 1, \ldots, 40$$

where five batting capabilities, HS, Avg, S/R, 4s, and 6s, are our independent variables, and β_j ($j = 0, \ldots, 5$) are parameters. Also, the residual terms, ε_i $i = 1, \ldots, 40$, are independent random variables with mean of zero. The residual terms have a constant variance across the observations, denoted as lacking *heteroscedasticity* (nonconstant variance). Therefore, the estimated regression equations become as below.

$$\hat{y}_i = b_0 + b_1\text{HS}_i + b_2\text{Avg}_i + b_3(\text{S/R})_i + b_4(4\text{s})_i + b_5(6\text{s})_i \quad i = 1, \ldots, 40$$

where $\hat{y}_i$ is estimated value for performance of the *i*th batsman ($i = 1, \ldots, 40$), and b_j ($j = 0, \ldots, 5$) are estimated coefficients. The second stage of our method computes the estimated parameters of the above model corresponding to data shown in Appendix A. The results are displayed in Table 1.

As shown in Table 1, the most important batting parameters are S/R, HS, Avg, 4s and 5s in the decreasing order of importance.

Similarly, we obtain the OWA scores of 40 batsmen corresponding to values of α 0.65 and 0.70. Tables 2 and 3 present the results of regression model obtained in the second stage of the proposed model.

The proposed hypotheses are as follows

$$\text{H}_0 : \beta_i = 0$$

$$\text{H}_a : \beta_i \neq 0$$

The results summarized in Tables 1–3 correspond to various degrees of orness. The regression analysis in the second stage of our proposed method explained a statistically significant variance by the model as the value of adjusted R^2 is close to 100% which implies a higher degree of appropriateness.

The null hypotheses proposed above are rejected as all *p*-values are less than 5% level of significance. Hence, the coefficients of all parameters of batsmen are statistically significant and can be ranked based on the beta values. Therefore, the ranked parameters from the most to least are S/R, HS, Avg, 4s, and 6s. For example, considering $\alpha = 0.6$ as the optimistic level, the Beta values are S/R

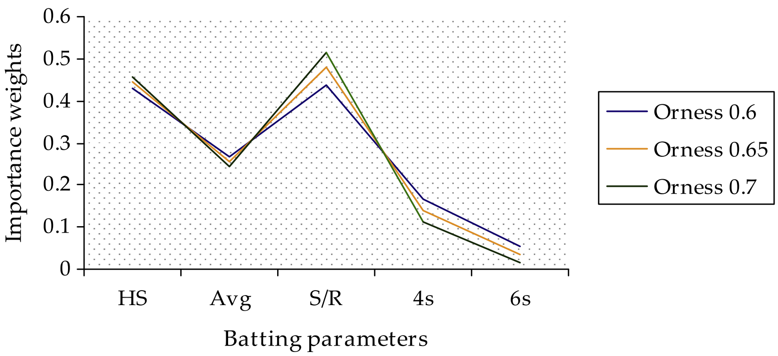

Fig. 1. Importance weights for batting parameters.

(0.438), HS (0.428), Avg (0.268), 4s (0.165), and 6s (0.053). For different OWA weights, the ranking of batting parameters does not change. In OWA different weights can be generated through different levels of optimism of decision maker. In this regard, we used three different orness values, 0.60, 0.65, and 0.70, indicating different levels of decision-maker optimism uncertainty. In all cases, we have the same ranking of batting parameters as below:1. S/R, 2. HS, 3. Avg, 4. 4s, 5. 6s (see Tables 1–3).

Fig. 1 shows the importance weights given to the parameters for different orness levels. It also indicates that the changes of OWA weights, obtained from different orness levels, does not affect the ranking of batting parameters. As shown by the three different curves, S/R has the highest value, followed by HS and other three parameters.

On the basis of these mathematical results we can claim that S/R is the most important parameter to choose a batsman for Twenty20 format. Appendix A shows that Chris Gayle and Virender Sehwag are on the rank 1 and 2, respectively with highest S/R. In Twenty20 format higher S/R means the batsman is consuming less balls and scoring more runs. In Twenty20 format, it is essential to maintain high S/R and have less focus on safeguarding the loss of wickets since the probability of losing all wickets in a matter of twenty overs is quite reduced. If a batsman maintains high S/R it follows that the values of other parameters of batsman are likely to be better. Runs scored with low S/R even without losing wickets can lead to higher chances of a defeat rather than a win in Twenty20 format. While using the best selection procedure to choose a batsman, there is no guarantee that he will perform very well in the succeeding matches. If good batsmen are selected the chances of success of the team would be higher. It is the responsibility of the selector to choose a set of good batsman to ensure the success of a team.

5. Concluding remarks

Choosing a batsman is an important issue in various formats of cricket. This paper developed a two-stage method for measuring and ranking batting parameters in cricket using ordered weighted averaging (OWA) and regression. The paper justified that the changes in the OWA weights have no effect on the ranking of the batting parameters. The outcome of this method can be applied in other sports for prioritizing the abilities of a player with multiple parameters. Sponsors for endorsement of their products are also interested in prioritization of various parameters of players as they are brand ambassadors of their products. Sponsors pay a huge amount of money to players based on the basis of superior potential performance in future. The approach proposed in this paper can also assist sponsors to choose good player at the initial stage of his career.

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Appendix A

See Table A1.

Table A1
OWA scores for 40 batsmen_Orness 0.6.

Rank	Player name	HS	Avg	S/R	4s	6s	OWA score
1	Chris Gayle	107	99.5	196.1	38	30	110.1568
2	Virender Sehwag	119	38.55	176.7	51	18	96.5556
3	Paul Valthaty	120	37.6	141.9	46	16	85.3292
4	Subramaniam Badrinath	71	87.25	133.7	33	8	78.1716
5	Shaun Marsh	95	36.6	141.3	37	12	77.0468
6	Rohit Sharma	87	47.83	130.5	24	12	72.252
7	Michael Hussey	83	49.12	122.4	48	3	72.0644
8	Sachin Tendulkar	100	46.38	111.8	42	5	71.886
9	Virat Kohli	71	55.29	122.1	40	12	70.1204
10	Jesse Ryder	60	24.82	154.2	36	10	69.5112
11	Brendon McCullum	81	26.82	130.5	31	12	67.7524
12	Tirumalsetti Suman	36	20	190.5	3	3	66.8144
13	Gautam Gambhir	75	38.12	123.5	35	2	66.0384
14	Manoj Tiwary	61	69.25	111.7	19	12	64.2432
15	Dinesh Karthik	69	27.11	130.5	27	7	63.6764
16	Sunny Sohal	62	24.38	138.3	23	6	62.88
17	Murali Vijay	74	26	119.1	25	14	61.9824
18	David Warner	77	25.09	116.5	30	7	61.7468
19	Mahela Jayawardene	76	24.42	115.4	34	5	61.462
20	Tillakaratne Dilshan	59	28.25	125.6	33	3	60.6068
21	Venugopal Rao	60	29.09	119.9	29	12	59.856
22	Rahul Dravid	66	29.9	107.6	39	2	58.414
23	Bharat Chipli	61	27.43	123.9	19	4	58.3296
24	Eoin Morgan	66	17.38	124.1	18	3	57.3068
25	Aiden Blizzard	37	19.33	148.7	12	0	56.3076
26	Shikhar Dhawan	54	22.73	119.1	27	5	55.76
27	Jean-Paul Duminy	55	23.14	126.6	8	6	55.2648
28	Ross Taylor	47	36.2	119.1	11	7	54.4624
29	Ajinkya Rahane	52	22.4	125.8	11	2	54.1952
30	Manish Pandey	59	29.57	106.2	22	5	53.916
31	Shane Watson	49	24.56	114.5	22	8	53.2148
32	Srikkanth Anirudha	64	20.75	112.2	6	3	52.2348
33	Andrew Symonds	44	42.33	106.7	9	3	50.7076
34	Brad Hodge	39	25.12	114.2	18	5	49.84
35	Albie Morkel	30	22.5	130.4	5	5	49.6204

Table A1 (*continued*)

Rank	Player name	HS	Avg	S/R	4s	6s	OWA score
36	Ryan McLaren	51	40.5	98.78	7	1	49.2384
37	Stuart Binny	30	37	119.4	2	1	48.458
38	Ashok Menaria	34	18.62	120.2	7	9	47.7288
39	Dwaraka Ravi Teja	30	20.67	120.4	12	2	47.2032
40	Sunny Singh	20	10.75	138.7	6	1	46.8688

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