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An analysis of strikers ranking in Barclays premier league football using multi-criterion decision making approach

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Abstract
Football is one of the popular outdoor sports and followed by many. It has evolved now with a concrete business model. With the advent of sponsorships and rich ownership, football clubs are investing more on buying and transfers of players. We believe there are various methods of estimating a player to assess its value. Our study is based on supervised learning and tried to propose a rating system which assigns a rank to football players (our research is limited to Strikers in this paper). We wanted to give a fair indication of player assessment for the transfer window for the subsequent tournaments.

Keywords: Premier league, business of football, sports analytics, strikers ranking, supervised learning

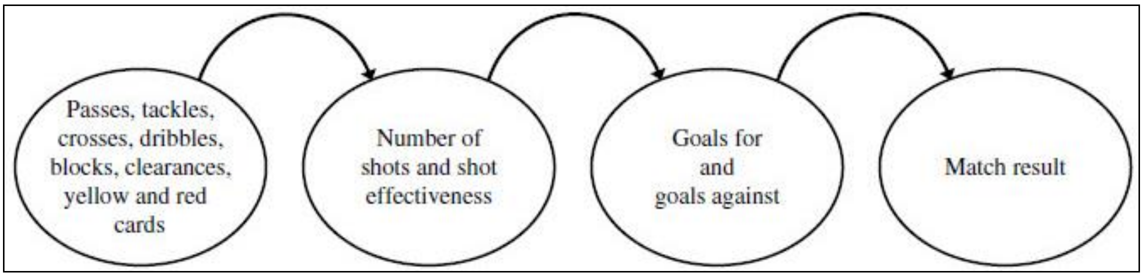
Introduction

A sport like football require no formal introduction. It is played in almost all part of the world with equal enthusiasm. It is also one of the most watched sports and this factor make it a lucrative option for marketer to engage the prospective customer. This characteristic of the sports has been utilised for marketing communication by the business firms. As, by the basic law of demand and supply, we have more firms to air their information and lesser time or attention span available with the customer, the cost of marketing is significantly higher. Further, it also depends upon the intensity of play and degree of competitiveness in the gameplay. The coveted 11-player team is responsible for keeping more audience hooked with them and their all games. So, better the player skill set, it can attract more fans and audience towards their game. This underline fact is the important factor to know which player a team should include in their team within their resource constraints. Thus, it makes a business sense for the team management to know the players monetary worth to take the decision for final eleven of your team.

Business Model

The Barclays Premier League ("BPL") is one of the prestigious football tournaments of Europe. It is related with England. It has top twenty teams competing for the championship. The best players are attracted from different nations to join the different clubs in BPL. Based on a season's performance, a player's net worth can increase or decrease. If a player has performed well, it may be sought after by a bigger club with higher price tag. A successful player transaction means, the buying club has better skillset, the selling club has earned monetary resource (as they may have bought the player at lesser investment in the previous season) and the player has increased its net worth.

One visual representation can be seen as proposed by the McHale, I. G., Scarf, P. A., & Folker, D. E. (2012) [3] as:



A game of football requires majorly four sets of player skills which are carefully chosen within the playing eleven. They are – goalkeeper, defenders, midfielders and strikers. Now, the big question always persists is which player the best or, who are the top 10 or top 25 players. Each of the above set of players require difference performance metrics to measure their ranking. For our study, we have analysed only the strikers (forward players) and the performance metrics are taken by the sports data website Opta Sports. The position of strikers can be understood from below image.

(Image courtesy – bostonglobe.com)

Multi Criteria Decision Making

It is a method of decision analysis process which is based upon different conflicting criteria to evaluate a situation or performance. Analytic Hierarchy Process (AHP) and TOPSIS are two important tools to measure the multi criteria decision making. In our study we have taken Topsis analysis tool for the quantitative calculations.

Topsis

It's an acronym for Technique for Order of Preference by Similarity to Ideal Solution. In this method first an evaluation matrix is made for n number of criteria and m number of alternatives. Then the matrix is normalised. Then the assigned weights of n criteria are incorporated and finally the weighted matrix is obtained. Using the calculation formula for Topsis the best and worst alternatives are obtained.

Review of Literature

Hadley, L. *et al.* (2000) [4] used the Poisson regression model for performance evaluation in National Football League. The measure is based on a production process where player skills are converted into games won. Govan, A. Y., & Meyer, C. D. (2006) [8] used Google's webpage ranking method to create an algorithm for ranking National Football League (NFL) teams. Govan, A. *et al.* (2009) [9] also developed a model called Offense-Defense model to generate team ratings. McHale *et al.* (2012) [3] has developed player performance index for football players. The rating is based on six sub-indices (viz, Modelling Match Outcome, Points Sharing, Appearance, Goal-Scoring, Assists and Clean Sheet) a final equation model based on these indices. Deng, W. *et al.* (2012) [7] has discussed importance of ranking system of players and in the field of tennis the probability that the higher-ranked player tops the lower-ranked opponent is proportional to the rank difference between the pair.

Barrow, D. *et al.* (2013) [6] has studied the different ranking systems across various sports and concluded that different ranking system has different predictive accuracy. Brooks, J. *et al.* (2016) [5] studied about quantitative evaluation of football players based on goals scored, assists made, and shots taken. They developed a model Shot Prediction Model for players' ranking. Brown, S. (2017) [1] has emphasised on players' rating for rewarding those players who initiate and contribute to the game. The method adopted was based on Google's PageRank.

Aronson, A. (2017) [2] has studied tennis players and suggested improvements on ATP method of ranking. The study has also focussed on predictive analysis that how a good rating system can predict the players' win or progress in the tournament.

Need of the study

The sports are no longer remained only a recreational thing. It follows a business model and the performance indicators are required for rewarding the best performers. The indicators also serve as benchmark for others. Further, the money involve in the sports are justified by the investing in players as an asset based on their ranking.

Scope of the study

We have studied only the Barclays Premier League in 2017-18 season. The analysis can be conducted for forthcoming seasons also. The study can be extended to various other leagues viz, La Liga (Spain), Bundesliga (Germany), Ligue 1 (France), Eredivisie (Netherlands), Serie A (Italy) etc. It can also extend to another sports league viz, NBA (Basketball), MLB (Baseball), IPL (Cricket) etc.

Limitations

Choosing the performance criteria for evaluation is always debatable. A good knowledge of game is required. Criteria can be more than what we have chosen in our study.

Research Methodology

We have observed the data and the various criteria. The Strikers' specific data is segregated and analysed. Suppose we have n criteria for performance measurements, then the evaluation matrix is made out of this. We have taken 50 players as rated by whoscored.com. For our study we have taken Offensive players rating and chosen the performance indicators as "Total Mins Played", "Goals", "Assists" and "Fouls per game". Here first three parameters are positive (More is better) in nature and last one is negative. (Means less is better).

The data looks like below: First 10 rows

R	Player	Mins	Goals	Assists	Fouled
1	Sergio Agüero Manchester City	1969	21	6	0.7
2	Kevin De Bruyne Manchester City	3085	8	16	0.9
3	Mohamed Salah Liverpool	2922	32	10	0.8
4	Eden Hazard Chelsea	2433	12	4	2.4
5	Harry Kane Tottenham	3083	30	2	1.1
6	David Silva Manchester City	2437	9	11	1.2
7	Raheem Sterling Manchester City	2593	18	11	1.8
8	Leroy Sané Manchester City	2423	10	15	0.8
9	Paul Pogba Manchester United	2151	6	10	1.9
10	Fernandinho Manchester City	2885	5	3	0.8

We have used library called "Topsis" in R software for data analysis.
Steps:
> View (topsis_sports) #file name
> d<-as.matrix (topsis_sports) #converted in matrix
> w<-c(1,1,1,1)
> i<-c("+","+","+","-")
> a<-topsis (d, w, i)
Alt. row score rank
1. 1 0.5797450 3
2. 2 0.5569232 6
3. 3 0.7917959 1
4. 4 0.3035280 35
5. 5 0.5885747 2
6. 6 0.4749214 11

First six entries of data look like above. It shows that the original serial number of one has rank 3, serial number 2 is rank 6, serial number 3 is rank 1 and so on.

Output Data as per ascending order of ranking

Original serial number	Name	Club	Rating	Final rank
3	Mohamed Salah	Liverpool	0.791796	1
5	Harry Kane	Tottenham	0.588575	2
1	Sergio Agüero	Manchester City	0.579745	3
8	Leroy Sané	Manchester City	0.570115	4
7	Raheem Sterling	Manchester City	0.567616	5
2	Kevin De Bruyne	Manchester City	0.556923	6
17	Romelu Lukaku	Manchester United	0.55079	7
12	Roberto Firmino	Liverpool	0.535729	8
11	Christian Eriksen	Tottenham	0.516605	9
18	Riyad Mahrez	Leicester	0.47729	10
6	David Silva	Manchester City	0.474921	11
45	Alexandre Lacazette	Arsenal	0.437036	12
44	Dele Alli	Tottenham	0.395042	13
23	Mesut Özil	Arsenal	0.390356	14
29	César Azpilicueta	Chelsea	0.388036	15
9	Paul Pogba	Manchester United	0.37125	16
21	Aaron Ramsey	Arsenal	0.371186	17
20	Sadio Mané	Liverpool	0.37055	18
46	Ben Davies	Tottenham	0.333788	19
35	Nacho Monreal	Arsenal	0.332909	20
10	Fernandinho Manchester	City	0.332309	21
49	Harry Maguire	Leicester	0.330335	22
34	Marcos Alonso	Chelsea	0.330025	23
13	Shkodran Mustafi	Arsenal	0.329114	24
39	Andros Townsend	Crystal Palace	0.327931	25
24	N'Golo Kanté	Chelsea	0.325632	26
42	Cesc Fàbregas	Chelsea	0.323743	27
25	Chris Smalling	Manchester United	0.322027	28
33	Nicolás Otamendi	Manchester City	0.317967	29
40	Joseph Gomez	Liverpool	0.317783	30
50	Antonio Valencia	Manchester United	0.314905	31
16	James Tomkins	Crystal Palace	0.31391	32
28	Nemanja Matic	Manchester United	0.308754	33
41	Christopher Schindler	Huddersfield	0.306457	34
4	Eden Hazard	Chelsea	0.303528	35
37	Kurt Zouma	Stoke	0.299175	36
32	Wilfred Ndidi	Leicester	0.298578	37
19	Emre Can	Liverpool	0.297915	38
30	Shane Duffy	Brighton	0.297502	39
22	Jan Vertonghen	Tottenham	0.290073	40
43	Ryan Shawcross	Stoke	0.288633	41

31	Fabian Delph	Manchester City	0.280597	42
38	Ashley Young	Manchester United	0.273784	43
26	James Tarkowski	Burnley	0.273401	44
48	Laurent Koscielny	Arsenal	0.252954	45
36	Ben Mee	Burnley	0.249148	46
27	Phil Jones	Manchester United	0.241334	47
14	Wilfried Zaha	Crystal Palace	0.232335	48
15	Alexis Sánchez	Arsenal	0.193985	49
47	Ruben Loftus-Cheek	Crystal Palace	0.115257	50

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