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AUTHORS' CONTRIBUTIONS

This work was carried out in collaboration between all authors. Authors FA and MA designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors Muhammad Ather Nadeem and Muhammad Asim Nawaz managed the analyses of the study. Author MI managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

The main aim of this paper is to present ranking of 95 National Basketball Association players from 2008 to 2009 to 2015-2016 by using the Slacks-based measure approach. This time period has been chosen because we want players who have played continuously over the entire time period. Constructing a Slacks-based measure model for the ranking of NBA players can aid sports researchers to decide vital factors for the investigation of players, and in addition help managers in the improvement of a particular indicator. This efficiency estimation method is performed in order to indicate that the financial factor is widely recognized and important as one of the significant parameter which shows the ranking of an NBA player that can be utilized by the decision maker or management. However, calculating this sort of model is complex because of plenty of individual player achievements and statistics that entail contemplation. The results of the current paper show that the ranking based on our proposed SBM approach totally differs from that based on the player impact estimate (PIE) measures. It is not surprising because these two rankings are based on different methods. Anyway, we think that both approaches investigate the efficiency of the players from a particular perspective and can complement each other. We believe that both approaches will provide useful information and supports for decision-makers and readers.

Keywords: NBA players; slack-based measures; efficiency.

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1. INTRODUCTION

The National Basketball Association has observed its share of excellent players since its beginning, however in a teambuilding game with an association history which ranges more than 60 years; it is hard to decide the greatest players ever. Not exclusively do insights for various positions must be measured, however singular measurements should also be considered against team measurements. Furthermore, the game of basketball has changed from its beginning, and the importance of certain positions and style of play has changed with it [1], further complex the job of deciding the best basketball players ever. In this manner, a single best way to deal with examine individual execution in this team activity stays elusive. Though, this interesting topic can attract a large number of spectators, range from casuals follower to sports authors and from game researchers to managers to players themselves.

For demographic, economic and sports specific reason, national basketball league (NBL) and basketball association of America (BAA) merged and produced another professional organization in 1949, the national basketball association (NBA). The International Basketball Federation recognizes it as the national governing body for basketball in the United States. In addition to multiple sports markets, NBA commands millions of spectators and fans across the world, especially in China, the Philippines, and Italy (1). Over the last six decades, NBA authorities made short and long-run business decisions that affected in some way the current and future costs, profits and revenues of coaches, players, teams and their owners. The league's clubs struggle for many years as they have to compete with national hockey league (NHL), major league baseball (MLB) and National Football League (NFL) for fans so that they attend and watch their all type of matches. The NBA is one of the most known competitions in the world. It consists of 30 teams (29 from USA and 1 from Canada), assembled into two sessions (East and West) and six divisions (Atlantic, Central, Southeast, Southwest, Northwest, and Pacific). Every year, There are two phases in NBA regular season and playoff. The top eight teams from both sessions (East and West) go to the playoff phase, and two winners from these sessions play for the title. Regarding regular season, each team has to play 82 games, and it is compulsory for each team to attain a good position to gain access to the playoffs.

Unlike other sports and leagues, NBA players are the reason for the success of the league. It has the most active union in all professional sports leagues, so athletes in the NBA have a better playing career with more rights than to other sports leagues. Further. NBA team rosters consist of 13 players compared to the MLB and NFL, in which teams have 25 and 53 players. Respectively, NBA players get a tremendous amount of profits which gives a better opportunity to the player to make headlines and news stories than players in other sports leagues. National Basketball Association is not only one of the biggest sports entertainment but also become a leading business. It involves a great deal of money through marketing sponsorship and broadcasting rights. For example, NBA games are seen in 215 countries and territories in 49 languages, so that the transmission can reach out to most of the world [2].

According to Berri [3], in the world of professional sports, it provides a unique environment to examine and study business and economic issues. It is the only industry where the face, name and life history of every player, coach, manager, etc. is available. Furthermore, he found that the data of the National basketball association not only explains the racial discrimination but also clarifies the whole story from beginning to end. There are many problems with a ranking of the best basketball players during the period 2008-2009 to 2015-2016 through sports metrics or statistical modeling. Initially, the main concern is the contemplation and after that absolute collection of the numerous accessible measurement to incorporate into such investigations, because an individual player can affect the game in numerous ways. Secondly, singular measurements are affected by variables like the offensive approach of play, the pace of play, position play on the court, etc. Therefore, selecting one statistical measure over another may make difficulties towards correctness of the model.

In spite of such difficulties, efforts have been made to move forward the theme to rank the most prominent basketball players. This pattern started during the 70s, with James Bill and others testing measurements to in-game action in MLB, and in the next years, this methodology has applied to a basketball game [4]. The terms sport metrics, sabermetrics, analytics, and sport analytics are extensively utilized to show this pattern to test statistical investigation as a method for evaluating in-game movement. The majority of researchers who have tended to the theme of the most prominent basketball players have incorporated offensive factors commonly engaged with the individual discussion on the topic. Oliver [5] noticed the key significance of singular game measurement, for example, assists per game (APG), points per game (PPG), and rebounds per game (RPG) the contribution of players in any investigation. As per Berri [6], the author proposed fixed effects model in two steps, the first one links the statistics of the players with total wins and the other one evaluate the marginal product of the players instead of the inputs. The findings demonstrated that in team wins, points surrendered, and points scored described ninety-five percent of the variance. Moreover, he found the efficiency of a player could be further observationally derived by using the strategy of least squares regressions to match statistics. The author made further modifications and fitted this equation to precisely compute the value of a player based on the production of wins. Such a summary is offered with equation:

$$\text{Production of wins} = [PM + TF + TDF - PA + TA] * \text{Total minutes played} \quad (1)$$

Where PM=per-minute player production, TF= per-minute team tempo factor, TDF=per-minute team defensive factor, PA=average per-minute production at the position, and TA=average player's per-minute production.

Moreover, one more confront related with this kind of investigation is the nonappearance of measurement which is generally utilized in modern basketball however not consistently accounted in previous periods inside the association. These sport measurements would, in general, be defensive, and two missing sport measurements incorporate steals and blocked shots, that were not recorded during the season of 1973-1974 [7]. Since both steals and block shots are extensively acknowledged statistics of individual defensive efficiency, the nonattendance of these measures before the season of 1973-1974 prevents their consideration for any analysis. This shows various confinements to efficiently tending to the subject of "most prominent ever." Therefore, past researchers have not included defensive statistics in their investigations [1], and it is absent from player measurements accounted before that period. In addition to the fact that this eliminates a conceivable measure for contrasting the offensive expertise of players crosswise over chronicled periods, however, the reception of the 3-point shot adjusts the point scored measurement because it enabled a few players to goal more in modern play.

NBA is a team sport, analysts have attempted to interface singular player diversion estimations to group execution. Moreno & Lozano [8] Used a network DEA approach to evaluate the efficiency of 30 NBA teams for the regular season 2009-2010. As input, the authors considered team budget. The output used was games won by the team. They suggested that the said approach presented more discriminating power than to conventional DEA approach. Different researchers have also tested statistical models to measure the execution of NBA players and teams. Such as, Asghar and Asif [9] studied player performance, Ribas et al. [10] addressed rebound location, Sampaio and Janeira [11], investigated key performance indicators, and Sporiš et al. [12] studied the of efficiency players. Even though these investigations tended to basketball player performance, they offer vital understanding into measurable models. For instance, Sampaio & Janeira [11] showed that in close playoff games, the win was discriminated by offensive rebounding. On the other hand, in regular season games which were succeeded by one to eight points, the success was distinguished by successful exchange of free throws (FT). In a recent investigation, analysts discovered 6 variables to clarify 67.52% of the difference in expert player effectiveness. The extracted factors were named:

> "Basic offensive efficiency, errors in posting the defense and realization from the free throw line, the three-point play, basic defensive efficiency and defensive/offensive back line efficiency, defensive aggressiveness on the player in possession of the ball and offensive aggressiveness of the player in possession of the ball." [12].

Even though these recent measurements provide information for coaches and sport analysts to lead team development and modern player, the nonappearance of these measurements in the prior basketball prevents their utilization in the statistical examinations that analyze players since the commencement of the association. Similarly, the available analyses in the literature use diverse data and techniques, that makes it complex to evaluate team efficiency [8] to players production of wins [6] to the influence of coaching and teammates [13]. As a result, queries remain on standardized approaches to measure team and individual performance utilizing statistical methodologies. This is especially obvious for the question of the best players in the history of NBA, and it makes the present investigation necessary to fill this gap.

Therefore the objective of the current study is to determine a ranking framework for the best player among the selected players by using Slacks-based measure approach. The current study also contributes in various ways to the literature. Firstly, the sports ranking of participating players in the NBA for an enormous data set of 08 years for the first time. The ranking measured based on this system can more entirely imitate a player's value. Secondly, modeled accurately by using accessible individual match measurement for evaluating players crosswise overtimes in the history of the league. According to best of our knowledge this is the first study that evaluate the ranking of NBA players by using SBM Model over an extensive period. Our proposed method is motivated and feasible on substantial evidence for the sports industry.

The structure of the study is as follows: In section 2 data description and the brief presentation of the SBM and applying that approach for the ranking of basketball players in the context of NBA. Section 5 presents and discusses the results by applying the model to the 95 players in NBA during the season 2008-2009 to 2015-2016. Section 6, the conclusions will suggest the important ideas that could be implemented to improve the performance of NBA players.

2. DATA AND METHODOLOGY

This study gathers the panel data of 95 NBA players during the season 2008-2009 to 2015-2016. Empirical data has been collected from the official website (www.basketball-reference.com). These players are a small part of the total number of players in NBA teams (there were more than 400 players) due to data constrain we, therefore, focus on these 95 NBA players for several reasons. First, we have data of these players over the entire time period. Second, the selected players are strongly representative to investigate the ranking of NBA players. Third, this sample size is computationally feasible using a PC.

Based on the literature review and data availability, we obtain two inputs and seven outputs. There are two inputs used in this study that are: x1: Salary and x2: Minutes Played. The eight output items considered are the y1: field goals, y2: free throws, y3: offensive rebounds, Y4: defensive rebounds, Y5: steals, Y6: blocks and Y7: Points. Table 1 provides detail definitions and units of inputs and outputs variables, whereas the descriptive statistics of the input and output variables are shown in Table 2.

Following Chen, Gong, & Li [14], we use minutes played as input, i.e., the total minutes a player has played on the court. But we use an average value of this measure rather than an absolute value for the current study. We use salary as input, i.e., the more salary a player is paid, the better he should perform during games, and we have used average statistical data (more than one season) that is the same with [15]. Moreover, we use free throws as an output measure because a player may have no option whether to get a chance and take a shot only when the player of the opposite team makes a foul. Different from Moreno et al. [15], we do not categorize different types of points gained by each player such as two-point and three-point. Consequently, we feel that it would be much easier to incorporate a total number of points scored by a player as an output. Other four variables (DefReb, OffReb, FG, STL, BLK,) are regularly used in existing literature such as [6,8,16,17].

Table 1. Definitions of inputs and outputs variables

Variables	Definition
	Inputs
X1:Salary	A fixed, regular payment paid to an employee through an employment contract.
X2:Minutes Played	A measurement which records how many minutes, a player has played on the court.
	Outputs
Y1: Field goals	A field goal is any shot, other than a free throw, that is attempted by a player.
Y2:Free throws	An unopposed shot that is taken at the free throw line, typically awarded to an offensive player who is fouled during the act of shooting.
Y3:Offensive rebounds	An offensive rebound occurs in basketball when an offensive player misses the field goal or free throw attempt and regains possession of the ball.
Y4:Defensive rebounds	A defensive rebound occurs when a defensive player obtains the possession of the ball after an offensive player missed the shot.
Y5: Steals	A statistic awarded to a defensive player who forces a turnover by deflecting or catching a pass off an offensive player.
Y6: Blocks	Blocks committed by a player.
Y7: Points	The number of points a player achieves.

Table 2. Descriptive statistics of the input and output variables

Statistics	X1	X2	Y1	Y2	Y3	Y4	Y5	Y6	Y7
Mean	8110299	1799	311	159	83	249	55	37	836
Std. Dev.	5736209	731	171	123	69	151	35	35	470
Minimum	48849	18	2	2	3	2	3	2	7
25%	3400301	1279	187	72	31	139	31	14	489
50%	6775599	1847	287	126	65	214	49	25	765
75%	11774124	2375	417	218	120	341	74	51	1107
Maximum	30453799	3268	855	755	337	799	217	229	2590

In Data Envelopment Analysis (DEA), there are two kinds of models: radial and non-radial. Radial models are represented by the CCR (Charnes–Cooper–Rhodes) model. They deal with proportional changes of inputs or outputs. On the other hand, the non-radial slacks-based measure of efficiency (SBM) models put aside the assumption of proportionate changes in inputs and outputs, and deal with slacks directly. This may discard varying proportions of original inputs and outputs. The SBM models are designed to meet the following two conditions.

I. Units invariant: The measure should be invariant concerning the units of data.
II. Monotone: The measure should be monotone decreasing in each slack in input and output.

The SBM DEA model [18] is used to measure the efficiency of 95 NBA players, which is equivalent to the Enhanced Russell Measure (ERM) independently proposed by Pastor et al. [19], is non-radial and tries to minimize the ratio of average inputs reductions and outputs increases, instead of making a radial reduction of inputs or radial increase of outputs. Since every NBA player tries to obtain as many points/wins as possible for his team (in order to qualify for playoffs and be able to sign new contract) and simultaneously to reduce the production of the opponents player (in order to build a reasonable representation of possible alternatives and strategies), the use of a non-oriented SBM model is fully justified.

3. RESULTS AND DISCUSSION

The empirical results of the study have been presented in this section, starting with simple descriptive statistics of the data before presenting the SBM based results. Table 2 presents the descriptive statistics of the variables that have been used in evaluating ranking of the sample of 95 NBA players from period 2008-2009 to 2015-2016 including their minimum, mean, maximum, 25%, 50%, 75%, and standard deviation values. As for the efficiency assessment, the Slack-based measure (SBM) efficiency scores and player impact estimate (PIE) measures are shown for every player in Table 3. It can be noted that a larger SBM and PIE % score indicates better performance.

As shown in Table 3, the 2nd, 5th and 8th column shows the Slacks-based measure (SBM) efficiency whereas the 3rd, 6th and 9th column demonstrates the Player Impact Estimate (PIE) efficiency score. In Table 3, we find that the SBM scores for most efficient players are close to each other with the exception of four players, i.e., K. Durant, A. Varejao, A. Miller, and N. Mohammed. These four players have a higher efficiency scores than the others. K. Durant who is an All-Star player and wins NBA Finals most valuable player (MVP) in 2016 and 2017, is the efficient player with an SBM efficiency of 1. A. Varejao is also the efficient player with an SBM efficiency of 1 and wins best defensive player of the regular season in 2010 and Euro League champion award in 2003. A. Miller also wins many awards such as WAC player of the year, NBA assist leader and NBA all-rookie first team with an SBM efficiency of 1. N. Mohammed who is also an ALL-Star player with an SBM efficiency of 1. While R. Stuckey, J. Jack and K. Hinrich demonstrates the lowest efficiency score by 0.213, 0.292 and 0.292.

On the other hand, K. Durant is on the top with highest efficiency score (PIE) 18.40% following T. Duncan (15.93%), D. Wade (15.90%), K. Love (15.55%), D. Howard (15.46%), P. Gasol (15.18%) and R. Westbrook (15.14%) respectively. These values shows that the players are efficient over the entire period. While L. Amundson has the lowest efficiency score 2.88% by PIE following by the R. Foye (6.92%), K. Hinrich (7.30%), C. Brewer (7.6%), N. Mohammed (7.43%), N. Young (7.45%), M. Belinelli (7.66%) and N. Hilario (7.88%) respectively. The efficiency score of both approaches are different. N. Mohammed is on the top by SBM efficiency, but he has lowest efficiency score by PIE%. It is not surprising as both efficiency scores are evaluated on different methods.

In addition, Table 4 shows the full ranking of NBA players ordered by SBM efficiency scores in column 2nd, 5th, and 8th. As shown in the NBA official website (www.nba.com), player impact estimate (PIE) measures a player's overall statistical contribution against the total statistics in games they play in and yields results which are comparable to other advanced statistics (e.g., the Player Efficiency Rating (PER) using a simple formula. It is a major improvement to the stat 'efficiency' (EFF) rating. The 3rd, 6th, and 9th columns thus show the corresponding ranking ordered by the PIE.

In Table 4, we find that the ranking on SBM efficiency for A. Varejao, A. Miller, K. Durant and N. Mohammed have the highest ranking/score. These value indicate that these four players are more efficient than to other players. Whereas R. Sessions has the lowest ranking (95) based on SBM following by R. Hibbert (94), J. Jack (92), K. Hinrich (92) and R. Hollins (91). These values indicate that these players have declined efficiency over the sample period. The improvement or decline in efficiency is due to the technical efficiency or technological progress or both.

Table 3. Efficiency score for slack-based measure and player impact estimate process

DMU	SBM efficiency	PIE%	DMU	SBM efficiency	PIE%	DMU	SBM efficiency	PIE%
A. Jefferson	0.529	14.49	J. Nelson	0.324	9.49	M. Williams	0.633	9.93
A. Stoudemire	0.501	12.86	J. Dudley	0.349	8.43	M. Ellis	0.583	10.48
A. Varejao	1	10.88	J. Jack	0.292	10.72	N. Mohammed	1	7.43
A. Iguodala	0.747	11.38	J. Smith	0.759	7.93	N. Hilario	0.561	7.88
A. Miller	1	11.13	J. Thompson	0.556	8.51	N. Collison	0.649	12.65
A. Bargnani	0.432	9.43	J. McGee	0.495	9.58	N. Young	0.321	7.45
A. Bogut	0.570	12.08	J. Green	0.514	9.05	N. Batum	0.373	10.15
B. Udrih	0.403	9.65	J. Noah	0.624	12.63	P. Gasol	0.627	15.18
B. Diaw	0.535	9.51	J. Calderon	0.590	11.56	P. Millsap	0.606	12.91
B. Wright	0.535	11.98	K. Durant	1	18.40	P. Pierce	0.521	12.03
B. Bass	0.409	10.16	K. Garnett	0.652	7.93	R. Rondo	0.337	12.86
C.J. Miles	0.640	8.06	K. Love	0.376	15.55	R. Sessions	0.207	11.44
C. Anthony	0.531	14.42	K. Martin	0.635	10.10	R. Foye	0.363	6.92
C. Butler	0.617	8.68	K. Hinrich	0.292	7.30	R. Felton	0.575	10.10
C. Frye	0.436	8.21	K. Bryant	0.494	13.94	R. Lopez	0.541	8.78
C. Kaman	0.450	11.18	K. Koufos	0.665	8.76	R. Stuckey	0.213	10.15
C. Paul	0.528	18.10	K. Humphries	0.407	9.93	R. Hibbert	0.351	9.26
C. Brewer	0.385	7.36	K. Korver	0.547	9.01	R. Gay	0.385	11.48
D. Lee	0.455	13.45	L. Aldridge	0.578	14.16	R. Westbrook	0.411	15.14
D. West	0.658	13.10	L. Barbosa	0.502	9.20	R. Hollins	0.301	4.85
D. Williams	0.665	12.98	L. James	0.573	20.58	S. Hawes	0.407	9.88
D. Harris	0.442	10.56	L. Amundson	0.929	2.88	T. Sefolosha	0.661	8.30
D. Nowitzki	0.586	4.79	L. Scola	0.490	11.54	T. Young	0.442	10.53
D. Gooden	0.848	11.18	L. Deng	0.455	10.87	T. Duncan	0.594	15.93
D. Howard	0.395	15.46	M. Ginobili	0.595	13.54	T. Allen	0.618	9.11
D. Wade	0.440	15.90	M. Gortat	0.601	12.28	T. Parker	0.415	13.33
E. Brand	0.692	9.55	M. Belinelli	0.330	7.66	T. Ariza	0.463	9.74
E. Ilyasova	0.493	10.27	M. Speights	0.511	10.44	T. Chandler	0.565	11.45
G. Dragic	0.385	10.53	M. Williams	0.723	9.48	V. Carter	0.620	9.70
J.J. Barea	0.440	10.26	M. Barnes	0.636	8.73	Z. Randolph	0.605	13.79
J.R. Smith	0.774	9.55	M. Conley	0.487	11.71	Z. Pachulia	0.593	9.30
J. Crawford	0.905	10.22	M. Dunleavy	0.319	9.29			

On the other hand, the ranking of 95 NBA players based on PIE is totally different from SBM ranking. L. James is on the top with highest ranking 1, following by the K. Durant (2), C. Paul (3), T. Duncan (4), D. Wade (5). The ranking of L. James based on Slacks-based measure (SBM) is totally different from PIE, his ranking is 39^{th}. It is not surprising because these two rankings are based on different methods. While L. Amundson has the lowest ranking (95) followed by D. Nowitzki (94), R. Hollins (93), R. Foye (92) and K. Hinrich (91) respectively.

The ranking based on our proposed SBM approach totally differs from that based on the PIE. The Spearman correlation is 0.368 under 5% level of significance (two-tailed). The players in the top positions of the ranking for the SBM approach are even in the bottom positions of the ranking for the PIE approach. It is not surprising because these two rankings are based on different methods. Our proposed approach is based on DEA efficiency analysis. Namely, both inputs and outputs are considered to assess a player's performance while the PIE approach only considers output metrics. Moreover, the measurement for the input and/or output variables is different for the SBM approach and the PIE approach. Of course, the approach itself for calculation is also different. Anyway, we think that both approaches investigate the efficiency of the players from a particular perspective and can complement each other. We believe that both approaches will provide useful information and supports for decision-makers and readers.

Table 4. Efficiency ranking by both approaches

DMU	Ranking on SBM efficiency	Ranking on PIE	DMU	Ranking on SBM efficiency	Ranking on PIE	DMU	Ranking on SBM efficiency	Ranking on PIE
A. Jefferson	49	10	J. Nelson	88	65	M. Williams	22	55
A. Stoudemire	55	21	J. Dudley	85	80	M. Ellis	36	45
A. Varejao	1	39	J. Jack	92	41	N. Mohammed	1	89
A. Iguodala	10	35	J. Smith	9	84	N. Hilario	42	86
A. Miller	1	38	J. Thompson	43	79	N. Collison	18	23
A. Bargnani	70	67	J. McGee	56	61	N. Young	89	88
A. Bogut	40	26	J. Green	52	73	N. Batum	82	51
B. Udrih	76	60	J. Noah	24	24	P. Gasol	23	8
B. Diaw	46	64	J. Calderon	34	30	P. Millsap	28	20
B. Wright	46	28	K. Durant	1	2	P. Pierce	51	27
B. Bass	73	50	K. Garnett	17	84	R. Rondo	86	21
C.J. Miles	19	83	K. Love	81	6	R. Sessions	95	34
C. Anthony	48	11	K. Martin	21	53	R. Foye	83	92
C. Butler	27	78	K. Hinrich	92	91	R. Felton	38	53
C. Frye	69	82	K. Bryant	57	13	R. Lopez	45	75
C. Kaman	64	36	K. Koufos	13	76	R. Stuckey	94	51
C. Paul	50	3	K. Humphries	74	55	R. Hibbert	84	70
C. Brewer	78	90	K. Korver	44	74	R. Gay	78	32
D. Lee	62	16	L. Aldridge	37	12	R. Westbrook	72	9
D. West	16	18	L. Barbosa	54	71	R. Hollins	91	93
D. Williams	13	19	L. James	39	1	S. Hawes	74	57
D. Harris	65	42	L. Amundson	5	95	T. Sefolosha	15	81
D. Nowitzki	35	94	L. Scola	59	31	T. Young	65	43
D. Gooden	7	36	L. Deng	62	40	T. Duncan	32	4
D. Howard	77	7	M. Ginobili	31	15	T. Allen	26	72
D. Wade	67	5	M. Gortat	30	25	T. Parker	71	17
E. Brand	12	62	M. Belinelli	87	87	T. Ariza	61	58
E. Ilyasova	58	47	M. Speights	53	46	T. Chandler	41	33
G. Dragic	78	43	M. Williams	11	66	V. Carter	25	59
J.J. Barea	67	48	M. Barnes	20	77	Z. Randolph	29	14
J.R. Smith	8	62	M. Conley	60	29	Z. Pachulia	33	68
J. Crawford	6	49	M. Dunleavy	90	69			

4. CONCLUSION AND PRACTICAL IMPLICATIONS

A plethora of studies investigate the assessment of performance ranking of, particularly in the sports industry, but little attention has been paid to performance ranking of NBA players. The present study uses Slacks-based measures to measure the ranking of 95 NBA players during the period 2008-2009 to 2015-2016.

The results obtained from Table 3, shows that the Slacks-based measure (SBM) scores for most efficient players are close to each other except four players, i.e., K. Durant, A. Varejao, A. Miller, and N. Mohammed. This might be an exceptional case, and the outcomes might be different for various applications/examples [20]. However, it is motivating and deserves for further investigation on the potential reasons. The ranking based on our proposed SBM approach totally differs from that based on the PIE. The players in the top positions of the ranking for the SBM approach are even in the bottom positions of the ranking for the PIE approach. It is not surprising because these two rankings are based on different methods. But both rankings provide useful information for decision support. By utilizing such findings, NBA coaches and executives may enhance decision making in the process of player selection based on their ranking. They can also determine significant variables for the growth of players. Moreover, NBA players can improve their ranking and status in the eyes of recruiters, spectators, and managers.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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