APPLYING ATHLETES UNLIMITED SOFTBALL SCORING TO MLB BASEBALL: TEAM PARITY AND INDIVIDUAL PERFORMANCE

Applying Athletes Unlimited Softball Scoring to MLB Baseball: Team Parity and Individual Performance

Authors: Soham Mahabaleshwarkar, Philip Maymin

Abstract: Athletes Unlimited developed an alternative scoring system for the sport of softball, designed to produce greater team parity and to highlight individual performance on a more granular level. The system was analyzed and tested on Major League Baseball data from the 2019 season to determine whether individual performance evaluation and team parity changed when the new scoring system was applied to a similarly scored sport.

Introduction

This paper investigates the parity and evaluation implications in the innovative scoring system to be employed by the Athletes Unlimited (AU) professional softball league.

Traditional scoring systems run on a strict win/loss system. By contrast, the AU team scoring system allocates points to the winner of each inning as well as to the winner of the game overall. In addition, the AU individual scoring system allocates points to individual players based on offensive plays and their degree of impact on the game. By creating a scoring system that rewards individual contributions as well as team accomplishments, overall evaluation should improve. Here, we test that hypothesis.

While some historical data exists for United States professional softball, the consistency of both team and individual performance ranges widely and does not paint an accurate picture of closely-matched competition. Major League Baseball, on the other hand, has a long, complete, and stable historical database and provides an excellent testbed to evaluate the efficacy of the new AU scoring system. Using MLB data from the 2019 season, we applied the AU scoring system to answer the following questions:

1. What impact does this scoring system have on team parity?
2. What impact does this scoring system have on individual rankings?

Athletes Unlimited Softball

In brief, the AU scoring system attempts to measure athletic performance at both the team and the individual level in an intuitive manner for both athletes and fans to understand. These points determine cumulative league standings each week, with the top 4 players serving as team captains and conducting draft picks. These aspects of the system are beyond the scope of this paper; for a more thorough description of the AU scoring system, please see the theoretical white paper on team parity.

Individual athletes earn Win Points, MVP Points, and Individual Points. For the purposes of this paper, we consider only Win Points and Individual Points.

Win Points: Athletes earn 50 points for each victory and an additional 10 points for every non-overtime inning they win.

Individual Points:

1) +10 points for walks (including BB, IBB, or HBP)
2) +10 points for sacrifice hits (bunts) or sacrifice flies
3) +10 points for each stolen base (-10 points if caught stealing)
4) +10 points for singles
5) +20 points for doubles
6) +30 points for triples
7) +40 points for home runs
8) Pitchers:
    a. +4 points for each out recorded
    b. -10 points for each earned run allowed

The AU scoring system does not award points on the basis of defense due to a lack of clear and simple defensive metrics (apart from tracking errors), and to avoid encouraging more conservative play in order to avoid mistakes. In addition, errors are inherently dependent on the opportunity to make plays. Players who have more frequent opportunities to make defensive plays based on the likelihood of receiving the ball during a play will usually have a higher error count. This would penalize players in certain defensive positions, such as infielders, if the scoring system simply counted errors.

The rules of play largely follow regulations set forth by the NCAA and WBSC, with games taking place over 7 innings.

Team Parity Methodology

In order to understand the scoring system's effect on team parity, we took five different sample sizes of the MLB season from the middle of the season, to account for specific behaviors that tend to occur at the beginning or end of the season that could potentially skew the results of our analysis (i.e. warm-up period for players at the beginning of the season; injuries and benching as the postseason nears). To more accurately reflect AU's 4-team, 15-game structure, we analyzed data in samples of 4 teams based on divisions and general placement in the league rankings. For this paper, we examined the four middle teams in the league during the MLB's 2019 season: the Arizona Diamondbacks, the Chicago Cubs, the Boston Red Sox, and the New York Mets (which ranked between 12 and 15 in the league during the season overall); as well as the top four teams in the league for the 2019 season: the Houston Astros, the Minnesota Twins, the Los Angeles Dodgers, and the New York Yankees.

For this analysis, we took the entire nine innings of MLB games and proportionally raised the AU Scoring System team points won per game. All extra innings were counted and considered in the scoring model as well and proportionally weighted according to the AU Scoring System.

The measure of team parity we employed was a basic range of the highest and lowest team win percentage over each 15-game sample size. We also analyzed the potential change in league standings from the actual MLB system to the new AU scoring system.

Middle Four Teams Analysis

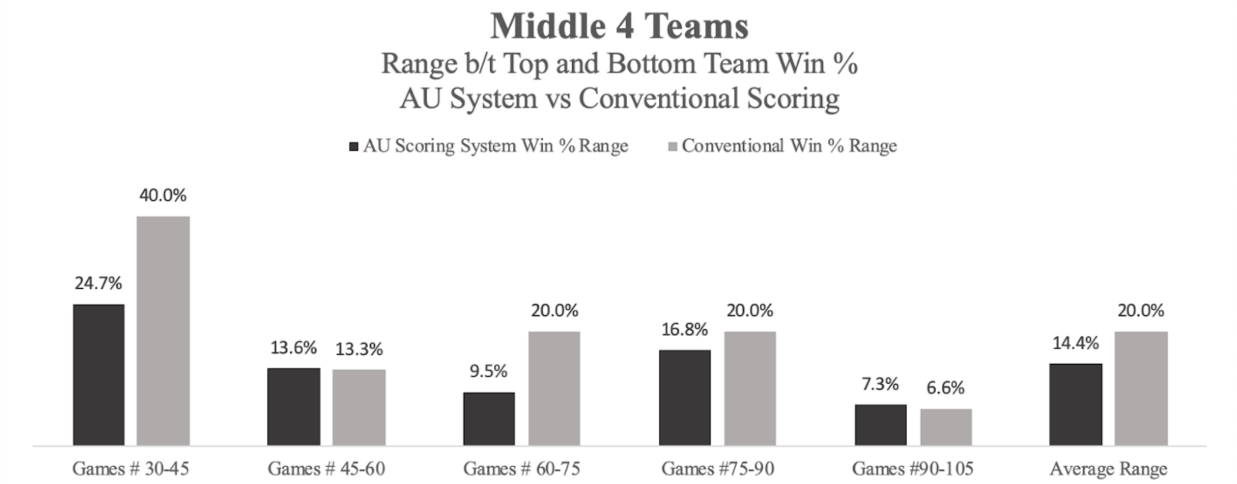
We first performed an analysis on the middle-performing teams of the 2019 MLB season based on the assumption that these teams represented the average level of athletic performance in the league. Teams in the middle of the pack may experience a wider range of competitive ability, thus generating larger gaps in win percentage. If the AU scoring system can improve parity between teams that are not as closely matched, it suggests the efficacy of the model as the foundation for a level playing field.

To identify the win percentage range while observing the MLB conventional scoring system, we set the upper and lower bounds by the highest and lowest performing teams in this sample group, which were the Boston Red Sox (#12) and the New York Mets (#15). When measuring this sample group while observing the AU Scoring Methodology, we found a much smaller range/area between the two curves in this AU Methodology case as compared to the MLB Win %.

Table 1: Win Percentage for Middle Four Teams, AU vs. MLB Comparison

	Middle 4 Teams									
	AU Scoring System Win %					**Conventional Win %**				
	Mets	**Arizona**	**Red Sox**	**Cubs**	**Range**	**Mets**	**Arizona**	**Red Sox**	**Cubs**	**Range**
Games # 30-45	29.9%	47.7%	54.0%	54.6%	**24.7%**	33.3%	60.0%	73.3%	66.6%	**40.0%**
Games # 45-60	49.0%	38.5%	52.0%	44.7%	**13.6%**	53.3%	40.0%	53.3%	46.6%	**13.3%**
Games # 60-75	44.5%	48.6%	54.0%	44.9%	**9.5%**	46.6%	60.0%	66.6%	53.3%	**20.0%**
Games #75-90	34.6%	44.1%	51.4%	37.8%	**16.8%**	33.3%	46.6%	53.3%	40.0%	**20.0%**
Games #90-105	56.3%	51.6%	58.1%	58.9%	**7.3%**	66.6%	60.0%	66.6%	60.0%	**6.6%**
				AU Avg Range	**14.4%**				Conventional Avg Range	**20.0%**

Figure 1: Win Percentage Range for Middle Four Teams, AU vs. MLB Comparison



Conventional MLB:
Average: 19.98%
Standard Deviation: 11.175
Confidence Interval: 7.53 - 14.81

AU Scoring:
Average: 14.34%
Standard Deviation: 6.27
Confidence Interval: 3.11 - 9.38

On average, the AU scoring system has a significantly lower average range difference and standard deviation than the MLB scoring system. A closer range and smaller standard deviation imply closer matches, more equal teams and greater team-wise parity in the league.

Top Four Teams Analysis

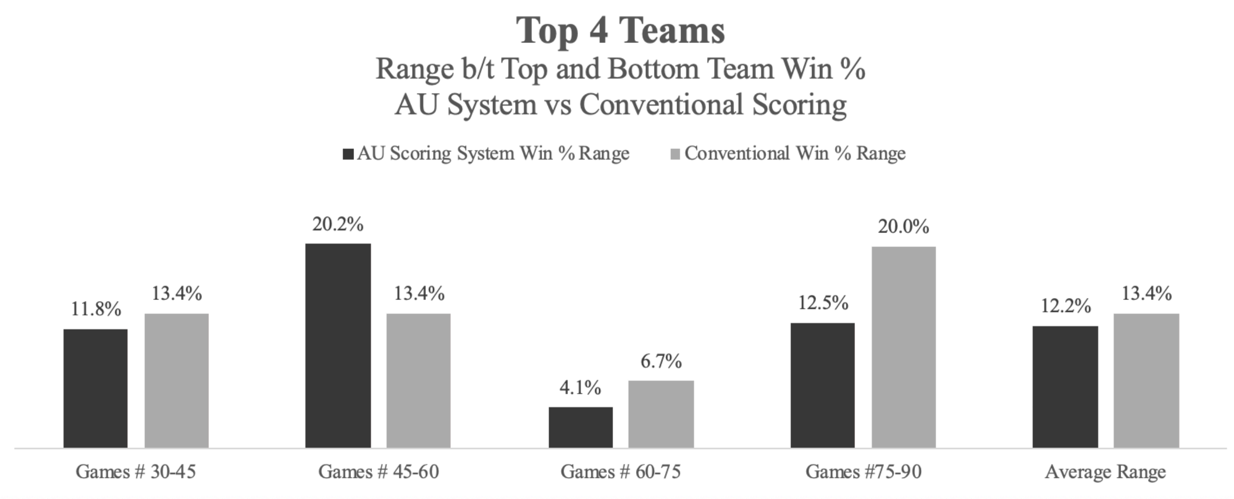
After observing improved parity in the middle of the MLB pack, we next performed a similar analysis on the top MLB teams of the 2019 season to see if the AU scoring system could also make a measurable impact on these statistically high achievers. Teams at the top of the league standings tend to experience smaller gaps in win percentages, since consistency in team performance is a key factor in rising to the top. If the AU scoring system can improve or maintain parity at this level, it will suggest that the model remains fair for teams at any standing.

To identify the win percentage range while observing the MLB conventional scoring system, we set the upper and lower bounds by the highest and lowest performing teams in this sample group, which were the Los Angeles Dodgers (#2) and the Minnesota Twins (#4). When measuring this sample group while observing the AU Scoring Methodology, we once again found a much smaller range/area between the two curves in this AU Methodology case as compared to the MLB Win percentage.

Table 2: Win Percentage for Top Four Teams, AU vs. MLB Comparison

Top 4 Teams										
	AU Scoring System Win %					Conventional Win %				
	Astros	Yankees	Twins	Dodgers	Range	Astros	Yankees	Twins	Dodgers	Range
Games # 30-45	67.1%	55.3%	64.3%	60.6%	**11.8%**	80.0%	66.6%	66.6%	66.6%	**13.4%**
Games # 45-60	49.9%	56.8%	58.5%	70.1%	**20.2%**	66.6%	73.3%	80.0%	73.3%	**13.4%**
Games # 60-75	52.0%	54.6%	51.0%	50.5%	**4.1%**	60.0%	53.3%	60.0%	60.0%	**6.7%**
Games #75-90	52.3%	56.3%	45.6%	58.1%	**12.5%**	53.3%	53.3%	73.3%	73.3%	**20.0%**
				AU Avg Range	**12.2%**				Conventional Avg Range	**13.4%**

Figure 2: Win Percentage Range for Top Four Teams, AU vs. MLB Comparison



Conventional MLB:
Average: 13.4%
Standard Deviation: 4.7
Confidence Interval: 1.76 - 7.64

AU Scoring:
Average: 12.15%
Standard Deviation: 5.70
Confidence Interval: 2.62 - 8.78

The AU scoring system has a similar average range difference and standard deviation to the MLB conventional scoring system. The MLB 2019 season had four exceptionally close matched teams at the top, and the existing system was exceptionally good at maintaining parity at this level.

The analysis performed here demonstrates that the AU scoring system improves on the conventional MLB model by improving on parity in the middle of the league, bringing the whole league closer together competitively speaking. In a league model where athletes are routinely drafted onto different teams, improved team parity across the board reduces the negative impact of a team loss on an individual player. Being drafted onto a "worse" team is no longer a player's ill-fated destiny, but simply a setback that can be overcome.

Individual Parity Methodology

The AU scoring system is unique in its measurement of individual performance in addition to team performance. It is important that the system rewards players accurately based on their performance on the field. In order to determine whether the AU scoring system properly evaluates individual contributions, we took the top 200 offensive players of the MLB season according to their offensive Wins Above Replacement (WAR) statistic. This non-standardized sabermetric baseball statistic measures a player's total contributions to their team by placing a numeric value on the number of additional wins the player's team has achieved versus what would be expected if the player were replaced. It is one of the few all-encompassing metrics that measures the overall performance of an individual player. WAR is also context, league, and park neutral. As a result, WAR can be used to compare players between years, leagues, and teams. However, WAR is not a perfect holistic measurement, which is discussed later in the paper.

To observe whether or not the AU scoring system properly evaluates individual production, the results of this analysis should be evaluated based on the similarity in individual rankings between WAR and AU. Further, the range of scores between WAR and AU can also illustrate the degree of separation in each system. We calculated the top individual player scores of the MLB 2019 season according to AU's scoring methodology.

An example calculation for an individual (Cody Bellinger) through the season and the points accumulated is shown in Figure 3.

Figure 3: Application of AU individual scoring system to Cody Bellinger of the LA Dodgers

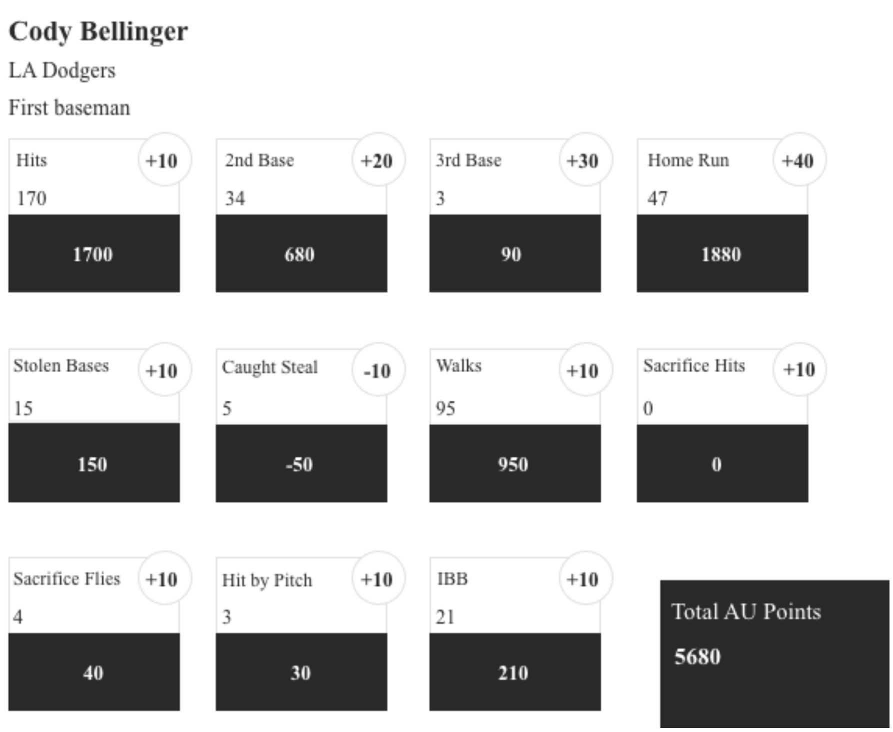


Table 3: Top 20 Offensive Players in the MLB 2019 season according to AU Scoring

	Player	Team	Position	AU Score
1	Cody Bellinger	LA Dodgers	Right fielder	**5680**
2	Alex Bregman	Houston Astros	Third baseman	**5500**
3	Christian Yelich	Milwaukee Brewers	Right fielder	**5390**
4	Pete Alonso	NY Mets	First baseman	**5360**
5	Mike Trout	LA Angels	Center fielder	**5300**
6	Anthony Rendon	LA Angels	Third baseman	**5200**
7	Marcus Semien	Oakland Athletics	Shortstop	**5200**
8	Mookie Betts	LA Dodgers	Right fielder	**5150**
9	Xander Bogaerts	Boston Red Sox	Shortstop	**5140**
10	Freddie Freeman	Atlanta Braves	First baseman	**5110**
11	Rafael Devers	Boston Red Sox	Third baseman	**5110**
12	Jorge Soler	Kansas City Royals	Right fielder	**5090**
13	Ronald Acuna Jr.	Atlanta Braves	Center fielder	**5070**
14	Nolan Arenado	Colorado Rockies	Third baseman	**5030**
15	Juan Soto	Washington Nationals	Left fielder	**4990**
16	Bryce Harper	Philadelphia Phillies	Right fielder	**4960**
17	Eugenio Suarez	Cincinnati Reds	Third baseman	**4940**
18	Carlos Santana	Cleveland Indians	First baseman	**4890**
19	Trevor Story	Colorado Rockies	Shortstop	**4870**
20	J.D. Martinez	Boston Red Sox	Right fielder	**4830**

Table 4: Top 20 Offensive Players in the MLB 2019 season according to MLB Offensive WAR

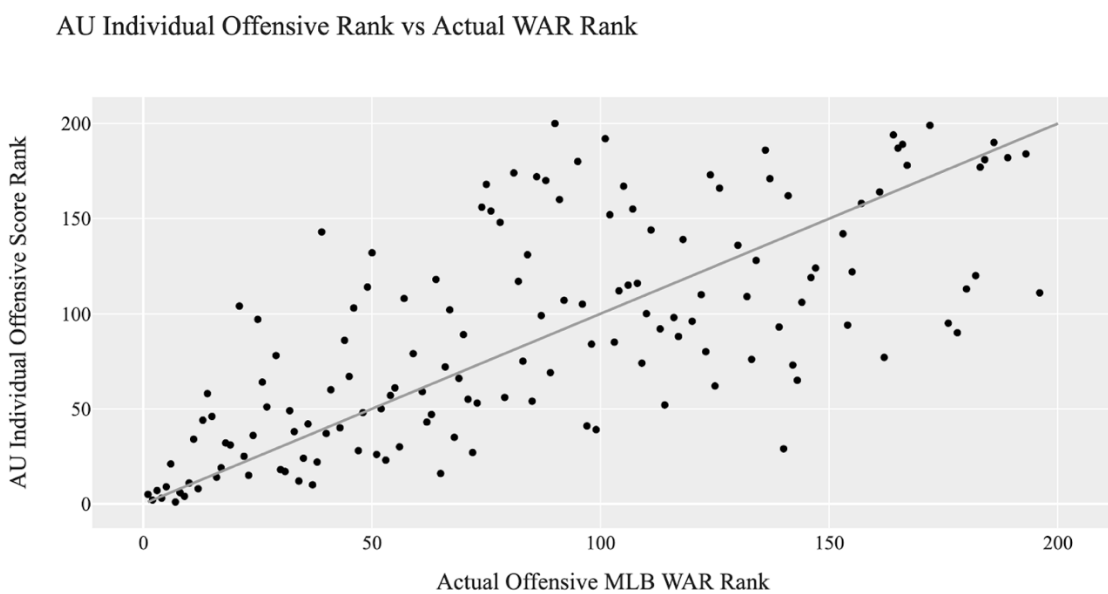
	Player	Team	Position	WAR
1	Mike Trout	LA Angels	Center fielder	**8.3**
2	Alex Bregman	Houston Astros	Third baseman	**7.7**
3	Marcus Semien	Oakland Athletics	Shortstop	**7.5**
4	Christian Yelich	Milwaukee Brewers	Right fielder	**7.3**
5	Xander Bogaerts	Boston Red Sox	Shortstop	**7.1**
6	Ketel Marte	Arizona Diamondbacks	Center fielder	**6.6**
7	Cody Bellinger	LA Dodgers	Right fielder	**6.6**
8	Anthony Rendon	LA Angels	Third baseman	**6.4**
9	Pete Alonso	NY Mets	First baseman	**5.8**
10	Rafael Devers	Boston Red Sox	Third baseman	**5.7**
11	Jorge Polanco	Minnesota Twins	Shortstop	**5.4**
12	Mookie Betts	LA Dodgers	Right fielder	**5.2**
13	DJ LeMahieu	NY Yankees	Second baseman	**5.2**
14	Yoan Moncada	Chicago White Sox	Third baseman	**5.2**
15	George Springer	Houston Astros	Right fielder	**5.1**
16	Nolan Arenado	Colorado Rockies	Third baseman	**5.0**
17	Trevor Story	Colorado Rockies	Shortstop	**4.9**
18	Jonathan Villar	Miami Marlins	Second baseman	**4.8**
19	Matt Chapman	Oakland Athletics	Third baseman	**4.8**
20	Ronald Acuna Jr.	Atlanta Braves	Center fielder	**4.8**

Analysis

Nearly all of the MLB Top 20 offensive players, according to their WAR scores, make an appearance in the top 20 offensive players according to the AU scoring methodology. This suggests that the AU scoring system generally reflects the individual performance of athletes as measured by conventional empirical metrics. In a system where teams change weekly and where compensation is directly impacted by the individual's performance, it is important that the system can reflect that athlete's performance accurately, no matter which team they are drafted on.

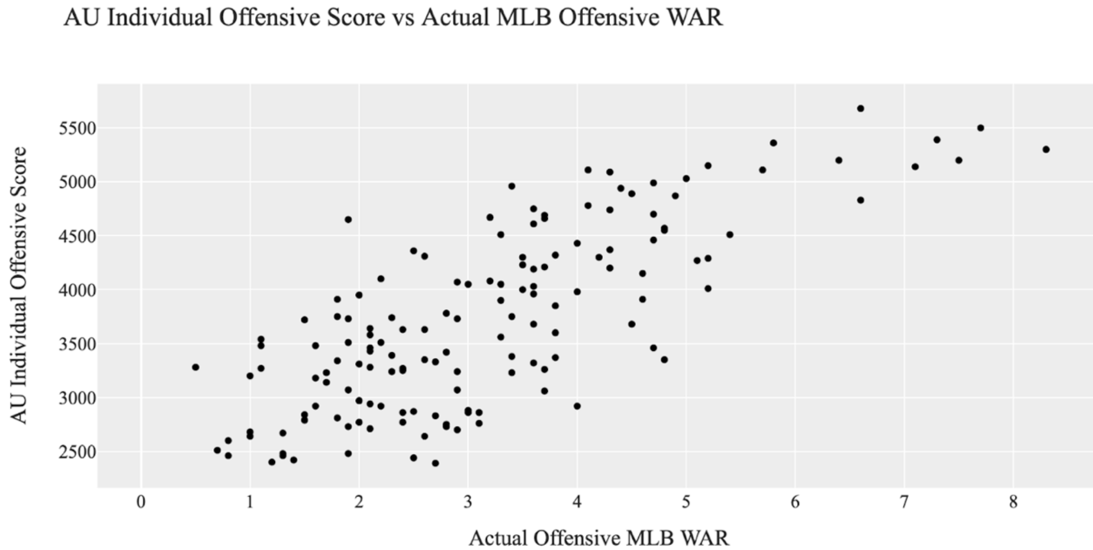
We can further analyze the degree of continuity between these two systems by measuring the correlation between them, both by player rankings in the season and by their WAR scores. Figures 4 and 5 show scatterplots examining these correlations.

Figure 4: Scatterplot of Top 200 Player Rankings according to MLB Offensive WAR vs. AU Offensive Score



The correlation calculated between the AU Rank and the Actual WAR Rank is **0.698**.

Figure 5: Scatterplot of Top 200 Players according to MLB Offensive WAR vs. AU Offensive Score



The correlation calculated between the AU Offensive Score and the Actual MLB WAR Score is **0.766** which demonstrates a high correlation - and thus high continuity - between these systems.

Further Discussion: Drawbacks to WAR

As mentioned previously, the WAR statistic, while impressive in its ability to generate holistic scores, is an imperfect empirical comparison to the AU scoring system. During this analysis, we identified a few MLB players that perform well in the AU scoring system, but do not appear in the top 20 MLB players according to WAR:

1. Freddie Freeman, 1st Baseman (AU: 10, MLB: 36)
2. Jorge Soler, Right Fielder/DH (AU: 12, MLB: 33)
3. Juan Soto, Left Fielder (AU: 15, MLB: 22)
4. Bryce Harper, Right Fielder (AU: 16, MLB: 64)
5. Eugenio Suarez, 3rd Baseman (AU: 17, MLB: 30)
6. Carlos Santana, 1st Baseman/DH (AU: 18, MLB: 29)

There are three major contributing factors to this discrepancy, which are briefly summarized as follows. In-depth discussion of the specific mechanics and calculations mentioned here are beyond the scope of this paper. For more information on the statistics that are mentioned in this discussion, please visit https://www.baseball-reference.com/about/war_explained.shtml.

Positional Adjustment

Certain defensive positions are more difficult to play than others and thus have greater impact on the likelihood of a team victory. WAR attempts to factor in these discrepancies by assigning point values to positions. For example, according to Baseball Reference's calculation of WAR, the position multiplier (see figures below) is multiplied by the total innings played at such position and normalized by dividing by 1,350 innings:

1. +10.0 for a catcher
2. +7.5 for a shortstop
3. +3.0 for a second baseman
4. +2.5 for a center fielder
5. +2.0 for a third baseman
6. −7.5 for a left fielder
7. −7.5 for a right fielder
8. −10 for a first baseman
9. −15.0 for a designated hitter.

The AU scoring system does not measure differences in performance between positions because it does not incorporate defensive performance into its overall methodology. Not only does this avoid the inevitable complexity of factoring defensive value into a new system, it prioritizes simplicity in order for fans to quickly understand and follow the events of a game. This discrepancy between the AU scoring system and WAR is the primary reason the AU scoring system awards certain MLB players more than they traditionally experience.

Park Factor Adjustment

The MLB is a national league with venues across the country. While all major league baseball fields follow some standard dimensions and regulations, there are variations that impact the likelihood of certain offensive events. There are also discrepancies in climate, altitude, and weather that can impact the velocity and properties of baseballs and equipment, such as bats. WAR uses a complex equation to modify offensive statistics for these variations. A simple way to review the impact of "park factor" is to compare standard On-Base Plus Slugging (OPS) to OPS+. In contrast to the MLB, a major component of the Athletes Unlimited softball league is that the entire season is set to take place in one market (and thus one field). Since players will never leave the market to compete for league standings, adjusting for park factor becomes irrelevant. This difference between the AU scoring system and WAR can also factor into the discrepancy in MLB individual performance from the analysis.

Other Adjustments

Finally, there are minor differences in the weight of offensive events between the AU scoring system and WAR. A WAR statistic that is useful to reference for these calculations is known as Weighted On-Base Average (wOBA). Examples of differences include: singles are weighted more heavily than walks in WAR, whereas AU scores singles and walks equally; and getting caught stealing incurs a heavier penalty than successfully stealing, whereas AU weighs the reward and the penalty equally. Additionally, WAR calculates point valuations for specific events that the AU scoring system does not, such as the impact of hitting a ground ball that results in a double play, or participating in the execution of a double play. For the sake of simplicity, the AU scoring system does not account for all variations of offensive events such as the ones listed above. These discrepancies, while small in comparison to the whole, can add up and make discrepancies larger than expected.

Conclusion

The simulations we performed with the MLB data demonstrate that the AU scoring system has greater team parity in the league and aligns with conventional measures of individual performance. The model has greater opportunities to empower athletes and create better and more balanced sports leagues, and it has far-reaching consequences for increased competition, which can lead to a better experience for both fans and athletes. Further discussion could be dedicated to the implementation of a similar system in the MLB and to think of the butterfly effect on the various decisions and implications it may have. How would player behavior change? How would team coaches and captains approach the draft? How would approaches to teamwork evolve as players have fairer chances to represent themselves individually? The AU scoring system has the potential to set a new precedent for athletic competition by making the game fairer and more intuitive for players and fans alike.

About the Authors

Soham Mahableshwarkar is a graduate student at New York University pursuing a Masters in Computer Science specializing in Data Analytics, having previously completed his undergraduate degree in Computer Engineering from University of Pune. He is the co-founder and CEO of Scriblr, a literature tech company he founded in 2019 aiming to change the way readers and writers both create and consume books. He previously founded FuzzyMonster Studios, a game development studio venture and Gamer Unit, a game review website during his high school years. He is currently a Data Science intern at Athletes Unlimited.

He is a published poet with his debut poetry collection ‘Reveries' launched in 2017 and is currently working on the final draft of his fiction novel, *Dreamcatcher*. He has previously co-written research papers as part of his undergraduate curriculum in the fields of Computer Vision and Neural Networks as well.

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Dr. Philip Z. Maymin is a professor of analytics and the director of the Master of Science in Business Analytics program at the Fairfield University Dolan School of Business. He is the founding managing editor of Algorithmic Finance and the co-founder and co-editor-in-chief of the Journal of Sports Analytics. He is the Chief Technology Officer for the Esports Development League (ESDL), an Insight Partner with Essentia Analytics, an advisor to Athletes Unlimited, and an affiliate of the Langer Mindfulness Institute, and has been an analytics consultant with several NBA teams.

He holds a Ph.D. in Finance from the University of Chicago (dissertation chair: Richard H. Thaler), a Master's in Applied Mathematics from Harvard University, and a Bachelor's in Computer Science from Harvard University. He also holds a J.D. and is an attorney-at-law admitted to practice in California.

He was a finalist for the 2010 Bastiat Prize for Online Journalism. He was awarded a Wolfram Innovator Award in 2015. He won the Wolfram Live Coding Challenge in 2016 and second place in 2018, and he won the Wolfram One-Liner Competition in 2015, 2016, 2018, and 2019. He was named one of the Top 50 Data and Analytics Professionals in the US and Canada by Corinium in 2018. He is the only person to have won both the Grand Prize for Best Research Paper (2018) and the Hackathon (2020) at the MIT Sloan Sports Analytics Conference.

His popular writings have been published in dozens of media outlets ranging from Bloomberg to Forbes to the New York Post to American Banker to regional newspapers, and his research has been profiled in dozens more, including The New York Times, Wall Street Journal, USA Today, Financial Times, Boston Globe, NPR, BBC, Guardian (UK), CNBC, Newsweek Poland, Financial Times Deutschland, and others.

His research on behavioral and algorithmic finance has appeared in Quantitative Finance, North American Journal of Economics and Finance, Journal of Portfolio Management, Journal of Wealth Management, Journal of Applied Finance, and Financial Markets and Portfolio Management, among others, and his textbook Financial Hacking was recently published by World Scientific.