# A Modification of OPS: Widely Used to Measure a Baseball Batter's Performance 

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#### Abstract

Batting average (BA), home runs (HRs), and runs batted in (RBIs) have been the most dominant statistics to measure a baseball batter's performance. Since each of those contains a meaningful interpretation but also some drawback to explain a batter's ability at the same time, often we use those three together. Slugging percentage (SLG) and onbase percentage (OBP) have been used as alternatives of the traditional three statistics. SLG measures how often a batter hits and how valuable the hits are and OBP measures how often a batter reaches bases. Whereas SLG ignores reaching bases by hits by pitched ball or walks, OBP is limited to measure the quality of the hits. A combination of these two is called OPS, the sum of OBP and SLG, which has become more widely used. We introduce a variation of OPS, WOA (weighted offensive average), which is a single number explaining not only a batter's hitting performance but also his non-hitting performance to generate runs for his team such as stolen bases, walks, and etc. This newly developed statistic is based on major league team statistics from the year 2000 to the year 2008.


Key Words: regression, correlation coefficient, longitudinal data, baseball statistics

## 1. Introduction

### 1.1 Who is more valuable batter? Ichiro? Or Matsui?

Two best Japanese batters to play in the major league baseball may be Ichiro Suzuki of New York Yankees (2012~) and Hideki Matsui of Tampa Bay Devil Rays (2012~). They both similarly began their professional baseball career in Japan and moved to the major league after spending 9 years in Japan. As shown in Table 1, Ichiro hits .353 BA with 118 HR and 529 RBIs for Orix Buffalos from 1992 to 2000 and Matsui hits .304 BA with 332 HR and 889 RBIs for Yomiuri Giants from 1994 to 2002. As we can see from those descriptive statistics Ichiro is more likely a slap hitter and Matsui is more likely a slugger. Even though they have different batting style, they have been very valuable for their teams. Who is more valuable?

Table 1: Descriptive career statistics for Ichiro and Matsui in Japan and in major league.

| Japanese league |  |  |  |  | Major league |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Player | Hits | BA | HR | RBIs | Hits | BA | HR |  | RBIs | R |
| :---: |

[^0]We conduct a comparison between Ichiro and Matsui in 2004. As shown in Table 2, Ichiro and Matsui made about the same salary in the year. Ichiro performed better than Matsui in the categories of hits, BA, and OBP in 2004. On the other hand, Matsui did better in HR, RBIs, SLG, and OPS in the year. Especially Matsui has higher OPS than Ichiro (. 912 versus .869). However Ichiro made higher salary in 2008 ( $\$ 17$ mil. versus $\$ 13$ mil.) Does it mean that OPS is not a big factor to explain a batter's salary? Or any better single offensive statistic can explain their difference in salary more precisely?

Table 2: Descriptive baseball statistics for Ichiro and Matsui in the major league in 2004 and salary in 2004 and 2008. Note: The player with bold is better in the category in 2004.

| Player | Salary <br> $(2008)$ | Salary <br> $(2004)$ | Hits | BA | HR | RBIs | OBP | SLG | OPS |
| :---: | :---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| Ichiro | \$17 mil. | $\$ 6.5$ mil. | $\mathbf{2 6 2}$ | $\mathbf{0 . 3 7 2}$ | 8 | 60 | $\mathbf{0 . 4 1 4}$ | 0.455 | 0.869 |
| Matsui | $\$ 13$ mil. | $\$ 7$ mil. | 174 | 0.298 | $\mathbf{3 1}$ | $\mathbf{1 0 3}$ | 0.390 | $\mathbf{0 . 5 2 2}$ | $\mathbf{0 . 9 1 2}$ |

### 1.2 Why new single offensive statistic needed?

James (1985) explains why he believes runs created (RC) is an essential measurement of batting ability in his book. "With regard to an offensive player, the first key question is how many runs have resulted from what he has done with the bat and on the base-paths. Willie McCovey hit . 270 in his career, with 353 doubles, 46 triples, 521 home runs and 1,345 walks - but his job was not to hit doubles, nor to hit singles, nor to hit triples, nor to draw walks or even hit home runs, but rather to put runs on the scoreboard. How many runs resulted from all of these things?" After that many researchers have focused on making a model to measure a batter's ability to contribute to generate runs for his team. Another effort to measure a batter's performance more precisely was introduced by by Thorn and Palmer (1984). It is called an On-base plus slugging (OPS) which is simply the sum of OBP and SLG. There have been studied by several slightly varied statistics of OPS. One example of those is called Gross production average (GPA) introduced by Gleeman (2003). GPA is obtained by (the sum of SLG and 1.8 times OBP)/4. It presents better relative weight to its two components OBP and SLG and its scale is somewhat similar to the already familiar BA. However both OBP and SLG contain the interpretation of BA, any statistics based on those two would depend on BA doubly. We introduce a new variation of OPS, WOA (weighted offensive average), which solves the problem of the redundancy of BA and explains a batter's non-hitting performance to generate runs for his team such as stolen bases, walks, and etc. Basic baseball terminologies are displayed in Table 3.

## 2. Dataset and models

### 2.1 Dataset

As we mentioned before, we only consider offensive statistics not pitching statistics. The dataset described in this paper contains team's batting statistics as well as players' batting statistics for 14 American League (AL) and 16 National League (NL) from 2000 to 2008. Therefore we use 270 teams' offensive statistics ( 30 teams for 9 years). And we use all 147 players' and 142 players' batting statistics those who were qualified in the seasons of 2008 and 2012, respectively.

Table 3: Basic baseball terminologies and their abbreviations

| Abbreviation | Meaning | Abbreviation | Meaning |
| :---: | :---: | :---: | :---: |
| AB | At Bats | BA | Batting Average |
| PA | Plate Appearances | BB | Base on Balls |
| R | Runs | HBP | Hit By Pitched Ball |
| H | Hits | BB | Base on Balls |
| 2B | Doubles | SB | Stolen Bases |
| 3B | Triples | CS | Caught Stealing |
| HR | Home Runs | SF | Sacrifice Flies |
| TB | Total Bases | SLG | Slugging Percentage |
| RBI | Runs Batted In | OBP | On Base Percentage |

### 2.2 Models

Batting average measures the percentage of hits a batter earns for his total at bats. It provides a strong measure of a batter's ability to produce hits. However it fails to measure the quality of hits and also fails to detect a batter's ability to reach bases by nonhits such as BB and HBP. As the formula shown in Table 4, slugging measures the quality of a batter's hits in addition to the ability to produce hits. However still it cannot detect a batter's ability to reach bases by non-hits. Let us assume that there are two players A and B. And we assume that player A has $\mathrm{AB}=5$ and $\mathrm{H}=1(1 \mathrm{HR})$ and player B has $\mathrm{AB}=5$ and $\mathrm{H}=4$ (4 singles). Then the SLG for player A and player B are the same as .800 whereas the BA for player $\mathrm{A}=.200$ is much lower than the one for player $\mathrm{B}=.800$. Even though their SLG are same, player B is not a power hitter like player A though his ability producing hits is good. An alternative to solely measure a batter's ability as a power hitter is called the Isolated power (ISO). By the formula given in Table 4, ISO for player $\mathrm{A}=.600$ (.800-.200) is much higher than the one for player $\mathrm{B}=.000=(.800-.800)$. We introduce a variation to ISO which is called the Pure slugging percentage (pSLG). pSLG is defined by ISO/( $3 * \mathrm{BA}$ ) $=(\mathrm{TB}-\mathrm{H}) /(3 * \mathrm{H})$. Note that ISO measures how many extra bases per AB but pSLG measures how many extra bases per hit over three. It means the theoretical scale for pSLG is between 0 and 1 . On-base percentage (OBP) accounts for a batter's ability to reach bases not only by hits but also by non-hits such as BB or HBP. However it fails to measure the quality of hits and considers BB and HR as the same value.

Table 4: Baseball statistics and their formulas

| Statistic | Formula | Statistic | Formula |
| :--- | :--- | :--- | :--- |
| PA | AB+BB+HBP+SF | SLG | TB/AB |
| BA | H/AB | OPS | OBP+SLG |
| TB | $\mathrm{H}+2 \mathrm{~B}+2 * 3 \mathrm{~B}+3 * \mathrm{HR}$ | GPA | $\left(1.8^{*}\right.$ OBP+SLG)/4 |
| OBP | $(\mathrm{H}+\mathrm{BB}+\mathrm{HBP}) / \mathrm{PA}$ | ISO | SLG-BA $=(\mathrm{TB}-\mathrm{H}) / \mathrm{AB}$ |

As we see in Table 5, in response to the deficiencies of SLG and OBP, many have turned to combinations of OBP and SLG. RC (Runs Created) and TA (Total Average) are examples to use a mixture of OBP and SLG). On-base plus slugging (OPS) has been more popular because of its easy formula as a short form to measure contribution as a batter. Let us consider another example. Let us assume that Player C has $\mathrm{PA}=20, \mathrm{AB}=17$, $\mathrm{H}=3$ ( 3 HR ), and $\mathrm{BB}=3$ and player D has $\mathrm{PA}=20, \mathrm{AB}=15, \mathrm{H}=6$ ( 5 singles and one 2 B ),
and $\mathrm{BB}=5$. Then ( $\mathrm{BA}, \mathrm{OBP}, \mathrm{SLG}$ ) for player $\mathrm{C}=(.176, .300, .706$ ) and (BA, OBP, SLG) for player $\mathrm{D}=(.400, .550, .467)$. Thus player C is much better than player D in BA and OBP but not in SLG. It turns out the OPS for player C (1.006) is almost the same as the one for player $\mathrm{D}(1.017)$ even we may feel player D is better because he generates fewer outs. Since SLG and OPS are highly correlated ( $\mathrm{r}=.97$ ), while the correlation coefficient between OBP and OPS is .89 , OPS may not differentiate SLG. And it's harder to generate .100 of OBP than .100 of SLG. GPA (Gross Production Average) is basically the weighted average of OBP and SLG with the weights 1.8 and 1 . The weights come from the linear weights in the regression equation of RPG (Runs per game for a team) on a team's OBP and SLG. And GPA makes a balance of OBP and SLG in terms of their correlation coefficients with GPA (. 94 versus .93 ). From our dataset, the regression results: $\mathrm{RPG}=-5.94+10.7 * \mathrm{SLG}+18.5 * \mathrm{OBP}$ with $\mathrm{R}^{2}=90.4 \%$. The ratio of 18.5 and 10.7 is 1.73 which is close to 1.8 of the weight in GPA.

Table 5: The comparison of several batting statistics. The newly developed statistic WOA with bold is able to measure all of these categories and its scale is similar to BA.

| Statistics | Accuracy | Power | Reaching Bases <br> by non-hits | Running | Q1 | Q3 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| BA | O | X | X | X | .261 | .297 |
| SLG | O | O | X | X | .406 | .506 |
| ISO | X | O | X | X | .134 | .226 |
| pSLG | X | O | X | X | .162 | .267 |
| OBP | O | X | O | X | .328 | .373 |
| OPS | O | O | O | X | .743 | .874 |
| GPA | O | O | O | X | .253 | .292 |
| WOA | O | $\mathbf{O}$ | $\mathbf{O}$ | $\mathbf{O}$ | $\mathbf{. 2 6 3}$ | $\mathbf{. 2 9 8}$ |

Since our explanatory variables SLG and OBP are highly correlated ( $\mathrm{r}=.75$ ), there exists "multicollinearity". Kutner (2004) says in his book: "The simple interpretation of regression coefficients is often unwarranted with highly correlated explanatory variables". Since BA is a component of both OBP and SLG, we may want break OBP and SLG down into BA and some non-BA part. And hopefully they are not highlycorrelated to avoid the effects of "multicollinearity". Let us define reaching bases by nonhitting performace ( nP ) measures a batter's ability to reach the bases by non-hits such as BB, HBP, or SB. It is obtained by $2.8^{*}(\mathrm{~B} \%-\mathrm{CS} \%)+\mathrm{SB} \%$, where $\mathrm{B} \%=(\mathrm{BB}+\mathrm{HBP}) / \mathrm{PA}$, $\mathrm{CS} \%=\mathrm{CS} / \mathrm{PA}$ and $\mathrm{SB} \%=\mathrm{SB} / \mathrm{PA}$. Here the weights 2.8 come from the linear weights in the regression equation of RPG on a team's $\mathrm{B} \%, \mathrm{CS} \%$, and $\mathrm{SB} \%$. Then we realize $\mathrm{OBP}=(\mathrm{H}+\mathrm{BB}+\mathrm{HBP}) / \mathrm{PA}=(\mathrm{H} / \mathrm{PA})+(\mathrm{BB}+\mathrm{HBP}) / \mathrm{PA} \approx \mathrm{BA}+\mathrm{B} \%$ and $\mathrm{SLG}=\mathrm{BA}+\mathrm{ISO}$ to use the formulas given in Table 4. Since $\mathrm{OBP} \approx \mathrm{BA}+\mathrm{B} \%$ and $\mathrm{SLG}=\mathrm{BA}+\mathrm{ISO}$, we may consider the regression of RPG on BA, ISO, and B\%. Since pSLG gives a similar interpretation with ISO ( $\mathrm{r}=.94$ ) and nP gives a similar interpretation with $\mathrm{B} \% ~(\mathrm{r}=.92$ ). pSLG and nP would replace by ISO and B\%. Another advantage to use them as explanatory variables along with BA to explain RPG is because they have much smaller correlation with BA ( $\mathrm{r}=.02$ for pSLG and $\mathrm{r}=.10$ for nP ) as shown in Figure 1. And also nP accounts for a batter's running ability. Now we regress RPG on BA, pSLG and WBS\%. From 2000 to 2008 (14 American and 16 National league teams for nine seasons $=270$ teams), the regression result is that $\mathrm{RPG}=-7.14+34.3 * \mathrm{BA}+$ $8.29 * \mathrm{pSLG}+4.31 * \mathrm{nP}$ with $\mathrm{R}^{2}=90.9 \%$. The ratios of $34.3,8.29$, and 4.31 are similar to 8:2:1 which is used in the new proposed statistic WOA (weighted offensive average). The
formula for WOA is given by WOA $=(8 * \mathrm{BA}+2 * \mathrm{pSLG}+\mathrm{nP}) / 10.5$. The reason why we divide by 10.5 is to make the scale of WOA similar to already familiar BA. Then the new regression is given by $\mathrm{RPG}=-7.12+44.8^{*}$ WOA with $\mathrm{R}^{2}=90.9 \%$.

Figure 1: The matrix plot of BA, pSLG, and $n P$.


As shown in Table 6, regression coefficients of RPG on WOA by year and by league have been consistent.

Table 6: Regression coefficients of RPG on WOA by year and by league

| intercept |  | slope |
| :---: | ---: | ---: |
| TOT | -7.12 | 44.8 |
| AL | -6.62 | 43.1 |
| NL | -7.15 | 44.7 |
| 2000 | -7.15 | 45.1 |
| 2001 | -6.54 | 42.7 |
| 2002 | -7.30 | 45.5 |
| 2003 | -6.82 | 43.7 |
| 2004 | -8.13 | 48.5 |
| 2005 | -6.95 | 43.9 |
| 2006 | -7.20 | 44.9 |
| 2007 | -6.65 | 43.0 |
| 2008 | -6.29 | 41.6 |

And as shown in Figure 2, WOA explains RPG as the best single statistic over OPS and GPA. The correlation coefficients between RPG and OPS, GPA and WOA are .946, .951, and .953 , respectively. Table 7 shows the correlation comparison between RPG and pSLG, nP, ISO, BA, OBP, SLG, OPS, GPA, and WOA by year and by league. As always WOA explains RPG at the best even though the differences are slight. As shown in Figure 3, we are confident that WOA is a good predictor for generating runs for a team through the comparative box-plots of RPG and FRPG (fitted RPG on WOA). The descriptive statistics for BA and WOA are almost identical. As shown in Table 8, (minimum, $\mathrm{Q}_{1}$, median, $\mathrm{Q}_{3}$, maximum) for BA and WOA are (.240, .259, .266, .272, .294 ) and (.239, .258, .266, .272, .292), respectively. And (mean, SE) for BA and WOA
are ( $.266, .0006$ ), respectively. Table 9 shows the top ten WOA players in 2004. There exist some agreements between WOA and OPS. However some disagreement also exists. Let us go back to the example of Ichiro and Matsui. After careful calculation, WOA for Ichiro in 2004 (.317) is higher than WOA for Matsui in 2004 (.311). It may make the difference of their salaries in 2008. We remind that the Matsui was considered better than Ichiro in the comparison of OPS (. 912 versus .869 ) and GPA (. 306 versus .300 ).

Figure 2: The matrix plot of RPG, OPS, GPA, and WOA.


Table 7: The correlation comparison between RPG and pSLG, nP, ISO, BA, OBP, SLG, OPS, GPA, and WOA by year and by league. Bold represents the statistic with the highest correlation among them.

| RPG vs. | TOT | AL | NL | 2000 | 2001 | 2002 |
| :---: | :--- | :--- | :--- | :--- | :--- | :--- |
| pSLG | 0.491 | 0.519 | 0.545 | 0.398 | 0.552 | 0.454 |
| nP | 0.503 | 0.626 | 0.522 | 0.452 | 0.564 | 0.438 |
| ISO | 0.728 | 0.729 | 0.763 | 0.684 | 0.762 | 0.736 |
| BA | 0.786 | 0.766 | 0.767 | 0.797 | 0.843 | 0.830 |
| OBP | 0.882 | 0.898 | 0.878 | 0.942 | 0.926 | 0.836 |
| SLG | 0.895 | 0.886 | 0.903 | 0.870 | 0.879 | 0.915 |
| OPS | 0.946 | 0.947 | 0.952 | 0.929 | 0.934 | 0.935 |
| GPA | 0.951 | 0.955 | $\mathbf{0 . 9 5 6}$ | 0.946 | 0.947 | 0.929 |
| WOA | $\mathbf{0 . 9 5 3}$ | $\mathbf{0 . 9 5 7}$ | $\mathbf{0 . 9 5 6}$ | $\mathbf{0 . 9 5 2}$ | $\mathbf{0 . 9 5 5}$ | $\mathbf{0 . 9 3 6}$ |
|  |  |  |  |  |  |  |
| RPG vs. | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
| pSLG | 0.661 | 0.582 | 0.539 | 0.359 | 0.277 | 0.479 |
| nP | 0.586 | 0.501 | 0.466 | 0.337 | 0.438 | 0.505 |
| ISO | 0.853 | 0.781 | 0.672 | 0.634 | 0.584 | 0.698 |
| BA | 0.889 | 0.803 | 0.705 | 0.671 | 0.764 | 0.677 |
| OBP | 0.916 | 0.875 | 0.783 | 0.799 | 0.875 | 0.837 |
| SLG | 0.952 | 0.928 | 0.789 | 0.854 | 0.886 | 0.905 |
| OPS | 0.974 | $\mathbf{0 . 9 7 0}$ | 0.879 | $\mathbf{0 . 9 3 4}$ | 0.951 | 0.945 |
| GPA | 0.973 | $\mathbf{0 . 9 7 0}$ | 0.894 | 0.933 | 0.958 | 0.943 |
| WOA | $\mathbf{0 . 9 7 7}$ | $\mathbf{0 . 9 7 0}$ | $\mathbf{0 . 8 9 5}$ | $\mathbf{0 . 9 3 4}$ | $\mathbf{0 . 9 5 9}$ | $\mathbf{0 . 9 4 9}$ |

Figure 3: The comparative box-plots of RPG and FRPG (fitted RPG on WOA) by year.


Table 8: Descriptive summary of BA, WOA, and GPA by league.

| TOT | Var | Mean | SE | Min | $\mathrm{Q}_{1}$ | Med | $\mathrm{Q}_{3}$ | Max |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | BA | 0.266 | 0.0006 | 0.240 | 0.259 | 0.266 | 0.272 | 0.294 |
|  | WOA | 0.266 | 0.0006 | 0.239 | 0.258 | 0.266 | 0.272 | 0.292 |
|  | GPA | 0.257 | 0.0007 | 0.228 | 0.249 | 0.257 | 0.263 | 0.285 |
| AL | Var | Mean | SE | Min | Q ${ }_{1}$ | Med | $\mathrm{Q}_{3}$ | Max |
|  | BA | 0.269 | 0.0009 | 0.240 | 0.263 | 0.269 | 0.277 | 0.290 |
|  | WOA | 0.268 | 0.0010 | 0.239 | 0.259 | 0.269 | 0.275 | 0.292 |
|  | GPA | 0.259 | 0.0010 | 0.229 | 0.250 | 0.259 | 0.266 | 0.285 |
| NL | Var | Mean | SE | Min | Q ${ }_{1}$ | Med | $\mathrm{Q}_{3}$ | Max |
|  | BA | 0.263 | 0.0008 | 0.243 | 0.256 | 0.263 | 0.268 | 0.294 |
|  | WOA | 0.264 | 0.0008 | 0.239 | 0.258 | 0.264 | 0.271 | 0.288 |
|  | GPA | 0.255 | 0.0008 | 0.228 | 0.248 | 0.255 | 0.262 | 0.282 |

Table 9: Top 10 WOA players in 2004 along with their GPA, OPS, BA, HR, and RBIs.

| Rk | Player | WOA | GPA | Rk | OPS | Rk | BA | Rk | HR | Rk | RBI | Rk |
| ---: | :--- | ---: | :--- | ---: | :--- | ---: | :--- | ---: | ---: | ---: | ---: | ---: |
| 1 | Pujols | 0.370 | 0.371 | 1 | 1.114 | 1 | 0.357 | 2 | 37 | 4 | 116 | 9 |
| 2 | Jones | 0.360 | 0.355 | 2 | 1.044 | 2 | 0.364 | 1 | 22 | 59 | 75 | 78 |
| 3 | Ramirez | 0.345 | 0.344 | 3 | 1.031 | 3 | 0.332 | 3 | 37 | 4 | 121 | 6 |
| 4 | Bradley | 0.338 | 0.337 | 4 | 0.999 | 4 | 0.321 | 6 | 22 | 59 | 77 | 72 |
| 5 | Berkman | 0.333 | 0.331 | 5 | 0.986 | 5 | 0.312 | 11 | 29 | 29 | 106 | 17 |
| 6 | Holliday | 0.326 | 0.319 | 9 | 0.947 | 11 | 0.321 | 6 | 25 | 41 | 88 | 50 |
| 7 | Teixeira | 0.326 | 0.323 | 6 | 0.962 | 9 | 0.308 | 14 | 33 | 15 | 121 | 6 |
| 8 | Rodriguez | 0.324 | 0.320 | 8 | 0.965 | 7 | 0.302 | 27 | 35 | 11 | 103 | 21 |
| 9 | Quentin | 0.322 | 0.320 | 7 | 0.965 | 7 | 0.288 | 56 | 36 | 9 | 100 | 26 |
| 10 | Youkilis | 0.320 | 0.318 | 10 | 0.958 | 10 | 0.312 | 11 | 29 | 29 | 115 | 10 |

## 3. Conclusion

We have studied OPS, the sum of OBP and SLG, which has become more widely used and variations of OPS. We proposed a variation of OPS, WOA (weighted offensive average), which is a single number explaining not only a batter's hitting performance but also his non-hitting performance to generate runs for his team such as stolen bases, walks, and etc. This newly developed statistic was based on major league team statistics from the year 2000 to the year 2008. We showed WOA is the best single statistic to explain to produce runs for a team. We would like to develop salary model based on the newly developed statistic WOA. We may add the player's popularity, the indicators for salary arbitrary and free agent. And we would like to add antedependence models for the covariance.

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