# BY THE NUMBERS

The Newsletter of the Statistical Analysis Committee of The Society for American Baseball Research


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## We're Back................

By Dave Raglin

It's been awhile since our last newsletter. I apologize (blaming a lack of enthuiasm due to the strike), but we're going to try and make it up with a great issue.

In Committee news:

(1) By the time you read this, we will have had our Annual Committee meeting at the SABR Convention in Pittsburgh. More news on this next issue.

(2) Unfortunetly, we were not able to get enough interest to put together a session at the 1995 Joint Statistical Meetings in Orlando. We will try again in 1996...

(3) Rob Wood and I could use some help in running the committee (especially since I start grad school in the fall). Call Rob at 415/961-6574 or me at 703/370-9497.

(4) The questionnaire was a great success. We received a lot of information about Committee members. We asked about available databases. Here's what I got:

- Strikeouts/Wins and Strikeouts/Walks ratios for starting pitchers from 1927-1994
- Closer performances from 1955-1994
- Macmillian stats (plus some others) for all 20th century hitters with 10 years of experience
- (Developing) database on old-time salaries
- Full offensive stats for all teams in the 1980s with estimates of various run estimation formulas (James, Palmer, etc.)
- Gold Glove/Silver Slugger awards
- Pinch hit grand slams
- All MLB players, 1993-1994
- All players with .300-30-100 seasons
- Bibliography of published statistical research articles and books
- ERA and Runs Scored rankings for teams 1977-1990
- Caught stealings and outs on bases in the World Series
- Players with 200 + home runs
- Leaders in offense, active since 1960, 1970, 1980, etc.
- Pacific Coast League stats, 1938-1957

We also have a member looking for team attendance and revenue figures for the last 20 years.

If you have any interest in obtaining copies of any of these databases, please call me at 703/370-9497 or write me at 910 N. Iverson #302, Alexandria, VA 22304. (I'll be moving in late summer to Maryland--you should be able to get the new phone number from either the old number or the address/number from the SABR office.)

## Recent Hall of Fame Voting: Cause for Joy?

By Rob Wood

Recent Hall of Fame balloting by the BBWAA has been applauded as signaling the elevation of the standards for selection. Over the past six years only ten players have been elected by the baseball writers. And even Hall of Fame purists like me must admit that all were deserving: Palmer, Morgan, Carew, Perry, Jenkins, Seaver, Fingers, Jackson, Carlton, and Schmidt.

However, our joy may be premature. The reason why so few have been enshrined may be that the 1990s thus far have seen a true superstar enter the ballot in each year. It is easy to conclude that Dick Allen should not be elected on a ballot which also includes Reggie Jackson, a superior and comparable player in many ways. Similarly, Ron Santo suffers in comparison to Mike Schmidt, and Jim Kaat to Steve Carlton.

Many question the validity of these one-to-one comparisons, arguing instead that a player's Hall of Fame credentials do not diminish regardless of who else is on the ballot. However, I find such comparisons useful as long as they are not given too much weight.

Whenever a superstar enters the ballot, all holdovers, even those not comparable, have a tendency to suffer. Thus, the real test for voters may come in the next three years when no true superstars enter the ballot. In these ballotings, many holdovers may get a "ballot comparison" boost. For example, Phil Niekro, Don Sutton, and Tony Perez may approach the magic 75% level in the absence of obviously superior talent on these ballots.

The tables on the next page contain two measures of a player's worth. TPR (Palmer & Thorn's total player rating given in Total Baseball), is the number of wins the player has contributed to his team over the course of his career, above the contribution expected of a league average player at his position.

The second measure, WMV (Wood-McCleery value), is an index based upon research I have presented in earlier articles. WMV was designed so that a player fully deserving of Hall of Fame selection has an index of 300 (or above), a player not deserving of selection has an index of 230 (or below), with a gray area between 230 and 300.

TPR and WMV are similar as they both take into account the effect a player's ballpark and era have on his statistics. However, the two measures have different tendencies. For hitters, WMV values longevity and skilled defense more than TPR. For pitchers, WMV values longevity and several statistics, including strikeouts, shutouts, winning percentage (relative to team) and saves, which TPR does not. WMV credits players for post-season performance and seasons missed due to injury. To be fair, TPR is a systematic way to estimate a player's true value, whereas WMV is an ad hoc jumble of many statistics trying to get at the same thing.

I cannot resist a few comments on the tables. Both Niekro and Sutton probably deserve enshrinement and will likely make it soon. Garvey and Oliva probably don't and won't. Perez probably doesn't and will. Santo and Allen are well-known sabermetric cases who don't stand a chance.

Jim Rice and Tommy John, first timers in 1995, got 30% and 21%, respectively. History teaches us the percent that a player receives in his first year is very important, so these players have a tough hill to climb.

Some players who have received paltry support deserve much more according to both TPR and WMV; besides Ron Santo and Dick Allen, there are Bobby Bonds, Graig Nettles, Rusty Staub, and Darrel Evans. As a Hall of Fame purist, I would vote for none of them. However, I find interesting the failure of some players to get their just support while others get far more than they deserve.

In summary, unlike the previous several years, no true superstar will enter the Hall of Fame ballot in the next three years. These years' balloting may shed new light on the question of current Hall of Fame standards.

**Table 1: Recent Hall of Fame Votes (percent)**

| | TPR | WMV | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|
| Mike Schmidt | 80 | 372 | | | | | | 97 |
| Phil Niekro | 36 | 307 | | | | 66 | 60 | 62 |
| Don Sutton | 15 | 306 | | | | | 57 | 57 |
| Tony Perez | 10 | 258 | | | 50 | 55 | 58 | 56 |
| Steve Garvey | -6 | 242 | | | | 42 | 36 | 43 |
| Tony Oliva | 27 | 235 | 32 | 36 | 41 | 37 | 35 | 32 |
| Ron Santo | 42 | 289 | 22 | 26 | 32 | 37 | 33 | 30 |
| Jim Rice | 31 | 247 | | | | | | 30 |
| Bruce Sutter | 13 | 268 | | | | | 24 | 30 |
| Jim Kaat | 19 | 245 | 18 | 14 | 27 | 30 | 22 | 22 |
| Tommy John | 27 | 271 | | | | | | 21 |
| Dick Allen | 34 | 286 | 13 | 13 | 16 | 17 | 15 | 16 |
| Minnie Minoso | 26 | 254 | | 9 | 16 | 16 | 10 | 14 |
| Curt Flood | -3 | 214 | 8 | 5 | 10 | 9 | 9 | 13 |
| Joe Torre | 20 | 263 | 12 | 9 | 14 | 15 | 12 | 11 |
| Luis Tiant | 16 | 261 | 9 | 7 | 12 | 15 | 9 | 10 |
| Dave Concepcion | 9 | 228 | | | | | 7 | 9 |
| Bobby Bonds | 33 | 271 | 7 | 9 | 9 | 11 | 8 | 8 |
| Vada Pinson | 5 | 241 | 8 | 7 | 8 | 9 | 10 | 7 |
| Thurmon Munson | 15 | 246 | 7 | 6 | 7 | 9 | 7 | 7 |
| Graig Nettles | 22 | 282 | | | | | 8 | 6 |
| Vida Blue | 10 | 232 | | | 5 | 9 | | 6 |
| Mickey Lolich | 3 | 229 | 6 | 7 | 10 | 10 | 5 | 6 |
| Ron Guidry | 18 | 250 | | | | | 5 | 5 |
| Rusty Staub | 27 | 264 | | 6 | 6 | 8 | 8 | 5 |
| George Foster | 23 | 227 | | | 6 | 7 | | 4 |
| Don Baylor | 14 | 227 | | | | | | 3 |
| Buddy Bell | 23 | 251 | | | | | | 2 |
| Darrell Evans | 35 | 275 | | | | | | 2 |

**Table 2: Future Hall of Fame Ballot First Timers**

| Year | Player | TPR | WMV |
|---|---|---|---|
| 1996 | Keith Hernandez | 34 | 255 |
| | Fred Lynn | 24 | 260 |
| | Dan Quisenberry | 18 | 263 |
| 1997 | Dwight Evans | 33 | 281 |
| | Dave Parker | 22 | 264 |
| 1998 | Bert Blyleven | 33 | 312 |
| | Gary Carter | 30 | 289 |
| | Jack Clark | 29 | 271 |
| | Pedro Guerrero | 17 | 253 |
| | Willie Randolph | 23 | 257 |

| Year | Player | TPR | WMV |
|---|---|---|---|
| 1999 | George Brett | 42 | 349 |
| | Carlton Fisk | 27 | 320 |
| | Dale Murphy | 19 | 232 |
| | Nolan Ryan | 22 | 311 |
| | Dave Stieb | 29 | 246 |
| | Robin Yount | 43 | 314 |

# Predicted ERA

**By Mat Olkin**

It's hard to imagine it now, but when Bill James first presented his Runs Created formula, the whole idea was revolutionary. Of course, his basic approach was that runs scored were the predictable outcome of a combination of elements. Bill tried to measure the number of runs a hitter generated by combining different elements of his batting record. Although we may tend to take the formula for granted, there are still potential new uses for it. I'm here to propose one.

How about this: Runs Created for pitchers. Why not? Just as the hitter has a batting line, a pitcher has an opposition batting line. If we apply the formula to what opposing hitters accomplished against the pitcher, we should get an estimate of how many runs were scored against the pitcher, right?

"Right!" said everyone I asked. Several people told me they'd thought of it before. A few people I talked to had actually gone so far as to apply the method, including the editor of this newsletter, Dave Raglin. I mean, it seems so obvious, it's hard to believe that Bill James didn't do it himself. Actually, he came close: he applied it to teams' opponents' batting totals (see pp. 84-85 of the '87 Abstract). Still, he never took the extra step of applying the formula to individual pitchers, and you'd think there must have been a good reason for that.

There was: 99% of the time, the method doesn't tell you a darned thing. Let's say you do the math, you get a runs created total, and you make adjustments and convert it to a "Predicted ERA". If you do that for about twenty or thirty pitchers, you start to notice something: the "Predicted ERA" almost always comes very close to the pitcher's actual ERA. So you inevitably conclude that you're wasting your time, and - if you're normal - you go watch Seinfeld or something. On the other hand, if you're me, you wonder about that other 1% of the time - the rare cases where a pitcher's "Predicted ERA" differs from his actual ERA.

So, being me and all, I did a little figuring. And you know what I found? The predicted ERA is actually a better predictor of future performance than the ERA itself. For example, take Roger Clemens. He had his first bad year in '93, and many thought he was going into his decline phase. His 4.46 ERA wasn't pretty, but if you look at the rest of his numbers, you'll see that he didn't pitch all that badly (in fact, he pitched better than Frank Viola, who had a much lower ERA). His predicted ERA came in at 3.66, which wasn't so catastrophic. Then, in '94, he went out and showed that he was still Roger Clemens, and that needlessly left a lot of people confused.

I studied a lot of other cases where a pitcher's predicted ERA didn't agree with his ERA. I'd look at the guy's ERA in the following year to see which course it followed. Here's what I found: two-thirds of the time, the "Predicted ERA" is a better predictor than the ERA itself. For this reason, I believe that the "Predicted ERA" is a better than the ERA at measuring a pitcher's ability.

Sounds good so far, huh? Well, here's the rub: it's a pain in the butt to figure. First, it's hard enough to get your hands on pitchers' opponent batting lines, especially during the season. And then you have to do all that multiplying and subtracting... dammit Jim, I'm a law student, not a statistician. I needed to simplify it, if only for the sake of my own sanity.

Luckily, I remembered something Bill James once wrote - I can't remember it exactly, but it was something like: "If you want a shortcut to figuring Runs Created, you can multiply (On-Base %) x (Slugging %) x (Plate Appearances), and the result will be pretty close." It seems that the heart of the Runs Created formula was just On-Base-times-Slugging. I set out to find if there was a simple relationship between that, and a pitcher's ERA. It turned out that there was one - simple enough even for me:

(On-Base %) x (Slugging %) x 31 = "Predicted ERA"

Thirty-one? Why thirty-one? Heck, I don't know. If I could tell you that, I'd tell you why Pi = 3.16. All I know is that it works, and if you want the proof, I'll send it to you. Trust me; I applied the formula to many teams' opposing batting lines, and it seems to be about as accurate as the runs created formula is for team's offensive totals. The best part is that it's so simple: all you need are the guy's opponents' on-base and slugging, which you can get in *Baseball Weekly*. The only problem is that I still don't know what to call it. I'm taking suggestions; please help. "Predicted ERA" sounds too familiar - I know somebody else coined that phrase, but for lack of anything better, I'll call it that, for now at least.

Anyway, when you apply it to individual pitchers, as I said before, it will almost always mirror the guy's actual ERA. The key cases are where there is a disparity between the two measures. You see, our old and trusted friend, the traditional ERA, is not above misleading us - or even outright lying to us. How can this happen?

A starting pitcher, for example, can receive lousy support from his bullpen. When a pitcher comes out of a game with runners on base, his ERA will depend on whether the relievers are able to strand the runners. I watched a lot of Clemens' starts in '93, and his bullpen support was just atrocious. Roger really didn't pitch like a guy with a 4.46 ERA, it's just that every time he left with men on base, the relievers would come in and start throwing napalm.

And the relievers' ERAs are subject to an even greater illusion: random chance. Consider this: a modern reliever may pitch as few as 60 innings. His ERA is determined by the twenty-or-so runs that he is charged with. Suppose that while he's on the mound, some freak thing happens - something that has absolutely nothing to do with that pitcher's ability to get batters out. Let's say that an outfielder goes into the corner in pursuit of a catchable a fly ball, but he falls down, the ball kicks around, and eventually three runs score as a result. Now get this: those three runs will inflate that reliever's seasonal ERA by almost a half of a run.

Get the point? Since the reliever's ERA is determined by only 20 or 30 "events" (earned runs), it's subject to all sorts of random occurrences. The "predicted ERA", on the other hand, is influenced by every single plate appearance against the pitcher. That being the case, random chance has less opportunity to skew the numbers. Therefore, the "Predicted ERA" can pick out pitchers, especially relievers, who have misleading ERAs.

My favorite illustrations from the '94 season are the perplexing cases of Jose Rijo and Scott Sanders. At first glance, there is simply no comparison between the two. Rijo had another Rijo year, going 9-6 with a 3.08 ERA. Sanders, a young, anonymous Padre ( - how redundant!) apparently did not fare so well. He went 4-8 with a 4.78 ERA. Now, what would you say if I told you that Sanders had actually pitched better than Rijo did? Sounds fishy? Here, I'll show you. These are their opponent batting lines:

| | AB | R | H | 2B | 3B | HR | RBI | BB | SO | Avg | OB | Slg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sanders | 421 | 63 | 103 | 16 | 3 | 10 | | 48 | 109 | .245 | .326 | .368 |
| Rijo | 667 | 73 | 177 | 31 | 4 | 16 | | 52 | 171 | .265 | .321 | .396 |

The fact is, Sanders was better than Rijo at *getting hitters out*. Eventually, this is going to show up in their conventional stats. While I don't expect Sanders to elbow his way into the Cy Young competition, I wouldn't be at all surprised if his ERA next year was comparable to Rijo's.

Let me expose some other ERA frauds. These are the ten luckiest starters of '94 (minimum: 95 IP). These guys got hit a lot harder than their ERAs would have you believe:

| | PredERA | ERA | +/- |
|---|---|---|---|
| Marvin Freeman | 3.67 | 2.80 | -0.87 |
| Jose Rijo | 3.94 | 3.08 | -0.86 |
| Bobby Munoz | 3.48 | 2.67 | -0.81 |
| Pat Rapp | 4.64 | 3.85 | -0.79 |
| Scott Kamieniecki | 4.54 | 3.76 | -0.78 |
| Orel Hershiser | 4.53 | 3.79 | -0.74 |
| Butch Henry | 3.15 | 2.43 | -0.72 |
| Steve Trachsel | 3.91 | 3.21 | -0.70 |
| John Burkett | 4.27 | 3.62 | -0.65 |
| Zane Smith | 3.89 | 3.27 | -0.62 |

Well, I can't say I'm surprised to hear that Butch Henry isn't the next Steve Carlton.

Now, let's look at the starters who were victimized by their own ERA:

| | PredERA | ERA | +/- |
|---|---|---|---|
| Willie Banks | 4.17 | 5.40 | +1.23 |
| John Doherty | 5.27 | 6.48 | +1.21 |
| Scott Sanders | 3.72 | 4.78 | +1.06 |
| Todd Van Poppel | 5.30 | 6.09 | +0.79 |
| Pete Harnisch | 4.66 | 5.40 | +0.74 |
| Denny Neagle | 4.38 | 5.12 | +0.74 |
| Juan Guzman | 4.94 | 5.68 | +0.74 |
| Greg W. Harris | 5.92 | 6.65 | +0.73 |
| Cal Eldred | 3.98 | 4.68 | +0.70 |
| Steve Avery | 3.41 | 4.04 | +0.63 |

Well, for some of those guys, it doesn't tell you much. I mean, Doherty, Van Poppel, Harris... those guys were just plain **bad**, no matter how you cut it. However, we can see that guys like Banks and Neagle are a lot closer to respectability than you would think, and it's nice to know that there's nothing really wrong with Avery.

Time to look at relievers (minimum: 39 IP). The chart at the top of the next page shows the guys who came in, got hit hard, and quietly slipped away with their ERA figures intact:

| | PredERA | ERA | +/- |
|---|---|---|---|
| Steve Reed | 5.94 | 3.94 | -2.00 |
| Rod Beck | 4.36 | 2.77 | -1.59 |
| Tony Castillo | 4.03 | 2.51 | -1.52 |
| Mark Dewey | 4.98 | 3.68 | -1.30 |
| John Habyan | 4.43 | 3.23 | -1.20 |
| Dave Otto | 4.94 | 3.80 | -1.14 |
| Rick Aguilera | 4.70 | 3.63 | -1.07 |
| Ken Ryan | 3.33 | 2.44 | -0.89 |
| Mike Hampton | 4.58 | 3.70 | -0.88 |
| Jeff Nelson | 3.63 | 2.76 | -0.87 |

To me, the real surprise here is Beck. He got a lot of credit for converting all those saves, but on the other hand, he did give up a hit an inning, and served up ten homers in 48 games. That's got to catch up with him. That, or his weight.

Now we'll look at all the relievers who did the job, but ended up getting charged with everyone else's runs:

| | PredERA | ERA | +/- |
|---|---|---|---|
| Jeff Tabaka | 3.36 | 5.27 | -1.91 |
| Greg A. Harris | 6.19 | 7.99 | -1.80 |
| Roberto Hernandez | 3.44 | 4.91 | -1.47 |
| Jesse Orosco | 3.64 | 5.08 | -1.44 |
| John Dopson | 4.81 | 6.14 | -1.33 |
| Dave Stevens | 5.68 | 6.80 | -1.12 |
| Jaime Navarro | 5.59 | 6.62 | -1.03 |
| Scott Bankhead | 3.54 | 4.54 | -1.00 |
| Graeme Lloyd | 4.19 | 5.17 | -0.98 |
| Jeff Russell | 4.22 | 5.09 | -0.87 |

The biggest news here is that White Sox fans can rest assured that their closer is set and ready to go to the World Series.

OK, that's it. If any of you have done some work in this area, I'd love to hear about it. I'm in the membership directory. Thanks.

# The Case for Independent At-Bats

By Frank Monaldo

Several years ago, I was prevailed upon to keep the official statistics for my then 10-year old son's baseball team. After the first two games, I compiled and presented the first set of statistics for the team to the other coaches. I was troubled by the observation that after only a few at-bats the player batting averages were only weakly related to how well I perceived the kids to be hitting. For example, one player, who was slapping the ball hard, was unfortunate enough to line-drive directly to fielders and had an anemic batting average. Whereas a weak hitter had managed to earn a 0.500 batting average on the basis of two at-bats and a hit that was in reality a full-swing bunt.

The situation provoked two questions:

1. How many at-bats does one have to wait until the observed batting average is a good estimate of a player's *intrinsic* batting average? By *intrinsic* batting average, I mean the average a player would achieve, if at the current skill level, the player had an infinite number of at-bats.
2. How statistically independent are adjacent at-bats?

The first question reduces to determining the confidence interval on the estimates of batting average. This question has been considered by others and I provide a brief review here. The second question in more difficult. Recently some major league data has become available that allows me to address this issue. Contrary to my first notions, I will suggest that adjacent at-bats are independent. Of course, the independence of at-bats is extremely relevant to the computation of confidence intervals.

### Confidence Intervals

Let us assume *N* independent at-bats, with an observed batting average of $\mu$. If we assume that the estimates of batting average are normally distributed, then we can be 95% certain that the intrinsic batting, $\mu_i$, average lies in the interval:

$$\mu - 1.96\sqrt{\frac{\mu(1-\mu)}{N}} \langle \mu_i \langle \mu + 1.96\sqrt{\frac{\mu(1-\mu)}{N}}$$

For example, if a player with 100 at-bats has an observed batting average of 0.300, we can be 95% sure that the player's intrinsic batting average lies between 0.210 and 0.390. There is a world of difference between a 0.210 hitter and a 0.390 hitter. Bat 0.210 consistently and you had better have a great glove. Consistently bat 0.390 and you'll find yourself at Cooperstown. Even if one is content with a lower level of certitude, a large number of at-bats is still required. For 70% confidence interval, the coefficient 1.96 is the previous equation would change to 1.04. We could be 70% certain that the intrinsic batting average lies between 0.252 and 0.384.

The requirement for a large number of at-bats tends to make meaningless glib commentary such as, "We had better take him out. He has only a 0.220 batting average against left-handers with men in scoring position." There are probably not nearly enough at-bats in those situations to make any meaningful statements.

### Correlation of At-bats

The computation of the batting average confidence intervals depends upon the number of independent at-bats. The larger the number of independent at-bats, the narrower the confidence interval. My first guess would be that adjacent at-bats are somewhat correlated. One would expect that variables such as the pitcher, the field and the weather would be the same over the course of every two or three at-bats. If it was the case that every two at-bats were correlated, then the *N* used in the previous equation would be one-half the actual number of at-bats. The confidence interval would grow 40% wider. We would be less certain about the instrinsic batting average.

One means of determining whether adjacent at-bats are statistically correlated is to compute the autocorrelation function. The difficulty lies in the fact that in order to perform this calculation one needs a sequence of hitting successes and failures. Specifically one needs an at-bat sequence like 1-0-1-0-0-0-1..., where the 1's represent hits and the 0's represent no hit.

I am grateful to Christopher Albright who compiled such data from Project Scorebook and kindly made it available to me. From this data, it possible for generate hitting sequences for players over the years 1987 through 1990. In all, 500 yearly batting sequences were available.

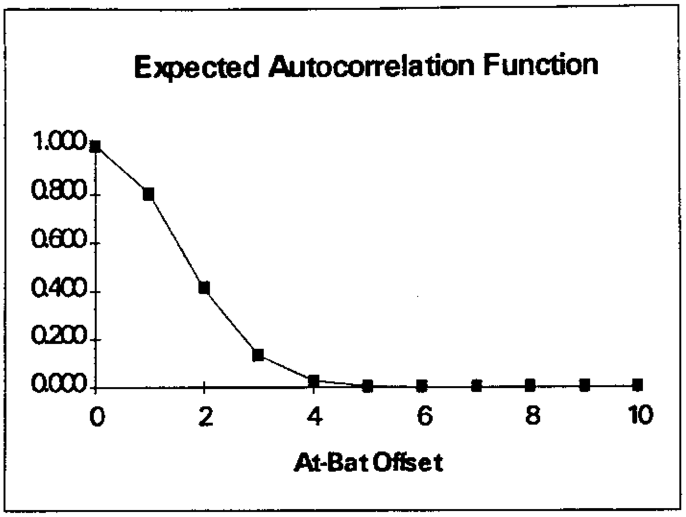
We allow $x(i)$ to represent this sequence, where $i$ goes from 1 to the number of at-bats in the sequence, $N_A$, and $x$ takes on the values of 0 and 1. The autocorrelation function is written as

$$R(j) = \frac{\sum_{i=1}^{N_A} [x(i)-\mu][x(i-j)-\mu]}{\sum_{i=0}^{N} [x(i)-\mu]^2}$$

where $\mu$ is the average of the sequence $x$ and equals the observed batting average from the sequence. The autocorrelation function specifies how correlated at-bats are when separated by $j$ at-bats. The value of the autocorrelation function ranges from 1 to -1. A positive value indicates correlation, 0 indicates no correlation and a negative value indicates anti-correlation.

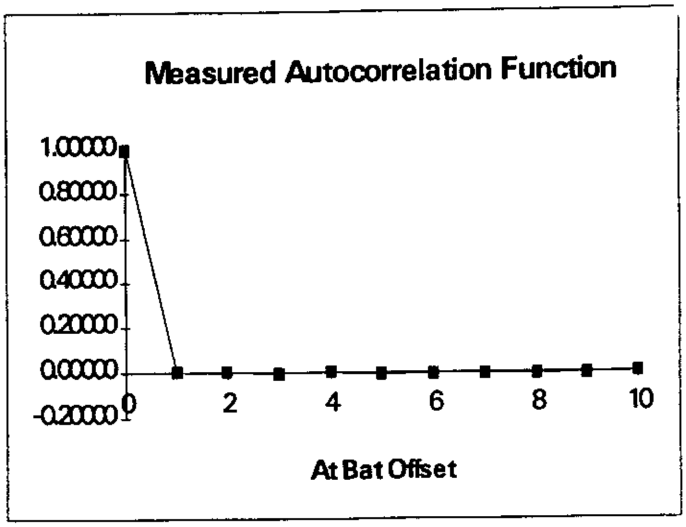
Perhaps some examples will make clear will make clear the meaning of correlation, both positive and negative. The highest possible correlation is 1. If we found $R(4)=1$, it would imply that every time a player got a hit, he would also get a hit four at-bats later. Similarly, every time the player would get out, four at-bats later he got out. A correlation of 0 would mean that it is not possible to predict what will happen four bats later based on the current at-bat. A $R(4)=-1$ would imply that if a player got a hit at a particular at-bat, four at-bats later the player got an out and visa versa.

An examination of the autocorrelation equation shows for $j=0$, the function equals 1. This is not surprising because if you get a hit at this at-bat, zero at-bats later — the same at-bat — you are guaranteed a hit. Autocorrelation functions generally start at the value 1 for $j=0$ and gradually decrease to zero as $j$ increases. If I were to have imagined a typical batting autocorrelation function before this study, I would have expected it to look something like this:




As this autocorrelation function suggests, I expected at-bats to be at least partially correlated over three at-bats. After all, for three at-bats one would likely be facing the same pitcher in the same park under the same lighting and weather conditions.

However, I computed the autocorrelation function for the 500 major league batting sequences. The resulting autocorrelation function is shown below.




Clearly the data show that, at-bats become immediately ccorrelated. The odds of getting a hit on a particular at bat can not be predicted based on the previous at bat. The odds of getting a hit immediately after a hit are the same at the batting average.

**Conclusion**

The contribution of this work is to demonstrate, with actual major league data, that at-bats can be treated as independent events. Batting averages are commonly quoted to three signifcant digits. Given the first equation and the observation that at-bats are not correlated, a player would have to have over 180,000 at-bats for the last digit to be significant — over 180,000 at-bats before one could be 95% certain that batting average measured is intrinsic batting average to within ±0.001. If adjacent at-bats were correlated these confidence limits would be even larger. Even so, caution is called for before making judgments on small sample sizes.

# Projecting Prospects

**By Daniel Levitt**

I want to share with the Statistical Analysis Committee my reasearch in projecting and ranking the abilities of minor league batters. I have not seen any other process that can not only evaluate all full-season minor leaguer hitters on an age and league equivalent scale, but whose results can be translated into future major league performance projections.

The four available statistics to use in minor league player evaluation consist of (1) the player's age; (2) the level of the league (e.g. AAA, AA, A, etc.); (3) the performance of the player as measured by his batting statistics; and (4) the run context within which the team plays (e.g. the runs scored per game by both the home and away club: for example, this allows comparison between the high scoring Pacific Coast League and the lower scoring American Association).

The ultimate statistic used to evaluate a prospect is his projected major league "offensive won/lost percentage" at age 25. As many readers already know, offensive won/lost percentage (OW%) is a statistic developed by Bill Jame (seems like all the good ones were) to measure the contribution of a players batting statistics within the context of the game. The OW% attempts to estimate the won/lost percentage of a team with nine hitters of similar ability.

# Using Offensive Win-Loss Percentage to Predict Future Stars

| PLAYER | POS | ORG | TEAM | LEVEL | AGE | AVG | AB | H | 2B | 3B | HR | RBI | BB | SO | SB | RC | RC/25.5 | CONTEXT | OW% | MLC | MLEOW | OW25 | OW25C |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Abreu, Bob | OF | HO | JCK | AA | 20 | 0.303 | 400 | 121 | 25 | 2 | 16 | 73 | 42 | 81 | 12 | 72.6 | 6.78 | 4.06 | .736 | 5.42 | .611 | .734 | .734 |
| Green, Shawn | OF | BJ | SYR | AAA | 21 | 0.344 | 433 | 149 | 27 | 3 | 13 | 61 | 40 | 54 | 19 | 87.6 | 8.14 | 4.82 | .740 | 6.18 | .634 | .727 | .727 |
| Ashley, Billy | OF | LA | ABQ | AAA | 24 | 0.345 | 388 | 134 | 19 | 1 | 37 | 105 | 53 | 116 | 6 | 112.5 | 11.43 | 6.01 | .784 | 7.70 | .688 | .708 | .708 |
| Delgado, Carlos | C | BJ | SYR | AAA | 22 | 0.319 | 307 | 98 | 11 | 0 | 19 | 58 | 42 | 58 | 1 | 66.9 | 8.18 | 4.82 | .742 | 6.18 | .637 | .705 | .705 |
| Rodriguez, Alex | SS | SM | CGY | AAA | 18 | 0.311 | 119 | 37 | 7 | 0 | 6 | 21 | 8 | 25 | 2 | 22.1 | 6.97 | 6.67 | .522 | 8.55 | .399 | .618 | .704 |
| Rodriguez, Alex | SS | SM | JAX | AA | 18 | 0.288 | 59 | 17 | 4 | 0 | 1 | 8 | 10 | 13 | 2 | 9.7 | 6.03 | 4.58 | .634 | 6.11 | .494 | .704 | .704 |
| Rodriguez, Alex | SS | SM | APP | A | 18 | 0.248 | 248 | 79 | 17 | 2 | 14 | 55 | 24 | 44 | 16 | 52.7 | 8.35 | 4.57 | .770 | 7.62 | .546 | .745 | .704 |
| Greene, Todd | C | AN | LKE | A+ | 23 | 0.302 | 524 | 158 | 39 | 2 | 35 | 124 | 64 | 96 | 10 | 115.1 | 8.13 | 3.86 | .816 | 5.93 | .653 | .695 | .695 |
| Young, Ernie | OF | OA | TAC | AAA | 25 | 0.284 | 102 | 29 | 4 | 0 | 6 | 16 | 13 | 27 | 0 | 18.7 | 6.54 | 5.02 | .629 | 6.44 | .507 | .507 | .692 |
| Young, Ernie | OF | OA | HVL | AA | 25 | 0.346 | 257 | 89 | 19 | 1 | 14 | 55 | 37 | 45 | 5 | 65.1 | 10.03 | 4.16 | .853 | 5.55 | .765 | .765 | .692 |
| Jeter, Derek | SS | YA | COL | AAA | 20 | 0.349 | 126 | 44 | 7 | 1 | 3 | 16 | 20 | 15 | 10 | 27.4 | 9.09 | 4.68 | .790 | 6.00 | .697 | .801 | .685 |
| Jeter, Derek | SS | YA | ALB | AA | 20 | 0.377 | 122 | 46 | 7 | 1 | 2 | 13 | 15 | 16 | 12 | 27.5 | 10.01 | 4.28 | .846 | 5.70 | .755 | .844 | .685 |
| Jeter, Derek | SS | YA | TAM | A+ | 20 | 0.329 | 292 | 96 | 13 | 3 | 0 | 39 | 23 | 30 | 28 | 43.6 | 6.11 | 4.58 | .640 | 7.05 | .429 | .569 | .685 |
| Hunter, Brian | OF | HO | TCN | AAA | 23 | 0.372 | 513 | 191 | 28 | 6 | 10 | 51 | 52 | 52 | 49 | 111.2 | 9.53 | 5.60 | .743 | 7.18 | .638 | .682 | .682 |
| Hosey, Dwayne | OF | KC | OMA | AAA | 27 | 0.333 | 406 | 135 | 23 | 3 | 27 | 80 | 61 | 85 | 27 | 101.9 | 10.09 | 5.07 | .798 | 6.50 | .707 | .677 | .677 |
| Vitiello, Joe | 1B | KC | OMA | AAA | 24 | 0.344 | 352 | 121 | 28 | 1 | 10 | 61 | 56 | 63 | 3 | 78.7 | 8.74 | 5.07 | .748 | 6.50 | .644 | .666 | .666 |
| Alfonzo, Edgardo | 2B | NY | BNG | AA | 20 | 0.293 | 498 | 146 | 34 | 2 | 15 | 75 | 64 | 55 | 14 | 85.8 | 6.34 | 4.57 | .658 | 6.09 | .520 | .656 | .656 |
| Newfield, Marc | OF | SM | CGY | AAA | 21 | 0.349 | 430 | 150 | 44 | 1 | 19 | 83 | 42 | 58 | 0 | 103.2 | 9.40 | 6.67 | .665 | 8.55 | .547 | .650 | .650 |
| Graffanino, Tony | 2B | AT | GRV | AA | 22 | 0.300 | 440 | 132 | 28 | 4 | 7 | 52 | 50 | 53 | 29 | 69.9 | 6.07 | 3.92 | .705 | 5.23 | .574 | .648 | .648 |
| Greene, Willie | 3B | RE | IND | AAA | 22 | 0.285 | 435 | 124 | 24 | 2 | 23 | 80 | 56 | 88 | 8 | 80.5 | 6.68 | 4.55 | .684 | 5.83 | .568 | .642 | .642 |
| Berrios, Harry | OF | OR | BOW | AA | 22 | 0.250 | 4 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0.5 | 4.38 | 4.64 | .470 | 6.19 | .333 | .406 | .639 |
| Berrios, Harry | OF | OR | FRE | A+ | 22 | 0.348 | 325 | 113 | 13 | 5 | 13 | 72 | 32 | 47 | 42 | 68.5 | 9.15 | 5.23 | .753 | 8.05 | .564 | .638 | .639 |
| Berrios, Harry | OF | OR | ABY | A | 22 | 0.333 | 162 | 54 | 12 | 2 | 6 | 35 | 18 | 23 | 14 | 34.4 | 8.68 | 4.49 | .789 | 7.49 | .573 | .647 | .639 |
| Phillips, J.R. | 1B | SF | PHX | AAA | 24 | 0.300 | 360 | 108 | 28 | 1 | 27 | 79 | 45 | 96 | 4 | 82.7 | 8.43 | 5.20 | .725 | 6.66 | .616 | .638 | .638 |
| Obando, Sherman | OF | OR | ROC | AAA | 24 | 0.330 | 403 | 133 | 35 | 1 | 20 | 69 | 30 | 53 | 1 | 86.6 | 8.20 | 5.08 | .723 | 6.51 | .613 | .636 | .636 |
| Beamon, Trey | OF | PI | CAR | AA | 20 | 0.323 | 434 | 140 | 18 | 3 | 5 | 47 | 33 | 53 | 24 | 66.2 | 5.99 | 4.50 | .639 | 6.00 | .499 | .636 | .636 |
| Damon, Johnny | OF | KC | WIL | A+ | 20 | 0.316 | 472 | 149 | 25 | 5 | 6 | 75 | 62 | 55 | 44 | 80.2 | 6.79 | 4.44 | .700 | 6.83 | .497 | .634 | .634 |
| Morris, Bob | 2B | CC | PEO | A | 21 | 0.354 | 362 | 128 | 33 | 2 | 7 | 64 | 53 | 63 | 7 | 80.9 | 8.95 | 5.05 | .758 | 8.42 | .530 | .634 | .634 |
| Hollins, Damon | OF | AT | DUR | A+ | 20 | 0.270 | 485 | 131 | 28 | 2 | 23 | 88 | 45 | 115 | 12 | 76.6 | 5.61 | 3.69 | .697 | 5.68 | .493 | .631 | .631 |
| Franklin, Micah | OF | RE | CNG | AA | 22 | 0.276 | 279 | 77 | 17 | 1 | 10 | 40 | 33 | 79 | 2 | 44.2 | 5.61 | 4.23 | .638 | 5.63 | .498 | .575 | .631 |
| Franklin, Micah | OF | RE | W-S | A+ | 22 | 0.300 | 150 | 45 | 7 | 1 | 21 | 44 | 27 | 48 | 7 | 46.7 | 11.73 | 5.36 | .827 | 8.25 | .669 | .734 | .631 |
| Malave, Jose | OF | RS | NBR | AA | 23 | 0.299 | 465 | 139 | 37 | 2 | 24 | 92 | 52 | 81 | 4 | 92.6 | 7.29 | 4.61 | .714 | 6.15 | .584 | .630 | .630 |
| Durham, Ray | 2B | WS | NVL | AAA | 22 | 0.296 | 527 | 156 | 33 | 4 | 16 | 66 | 46 | 91 | 34 | 85.4 | 6.15 | 4.39 | .663 | 5.63 | .544 | .620 | .620 |
| Cirillo, Jeff | 3B | MB | NO | AAA | 24 | 0.309 | 236 | 73 | 18 | 1 | 10 | 46 | 28 | 39 | 4 | 46.9 | 7.43 | 4.76 | .709 | 6.11 | .597 | .620 | .620 |
| Perry, Herbert | 1B | IN | CHR | AAA | 24 | 0.327 | 376 | 123 | 20 | 2 | 13 | 70 | 41 | 55 | 9 | 72.7 | 7.46 | 4.82 | .706 | 6.18 | .593 | .616 | .616 |
| Casanova, Raul | C | SD | RC | A+ | 21 | 0.340 | 471 | 160 | 27 | 1 | 23 | 120 | 43 | 97 | 1 | 101.8 | 8.36 | 5.32 | .712 | 8.18 | .511 | .616 | .616 |
| Belk, Tim | 1B | RE | CNG | AA | 24 | 0.309 | 411 | 127 | 35 | 2 | 10 | 86 | 60 | 41 | 13 | 78.1 | 7.18 | 4.23 | .743 | 5.63 | .619 | .642 | .615 |
| Belk, Tim | 1B | RE | IND | AAA | 24 | 0.111 | 18 | 2 | 1 | 0 | 0 | 1 | 1 | 5 | 0 | 0.5 | 0.77 | 4.55 | .028 | 5.83 | .017 | .019 | .615 |
| Cordova, Marty | OF | TW | SLK | AAA | 25 | 0.358 | 385 | 138 | 25 | 2 | 19 | 66 | 39 | 63 | 17 | 93.1 | 9.95 | 6.16 | .723 | 7.90 | .613 | .613 | .613 |
| Cedeno, Roger | OF | LA | ABQ | AAA | 19 | 0.321 | 383 | 123 | 18 | 4 | 4 | 49 | 51 | 57 | 30 | 64.7 | 6.73 | 6.01 | .557 | 7.70 | .433 | .610 | .610 |
| Sutton, Larry | 1B | KC | WIL | A+ | 24 | 0.306 | 480 | 147 | 33 | 1 | 26 | 94 | 81 | 71 | 2 | 105.8 | 8.13 | 4.44 | .770 | 6.83 | .586 | .609 | .609 |
| Arias, George | 3B | AN | LKE | A+ | 21 | 0.280 | 514 | 144 | 28 | 1 | 23 | 80 | 58 | 111 | 6 | 86.0 | 5.98 | 3.86 | .706 | 5.93 | .504 | .609 | .609 |
| Nieves, Melvin | OF | SD | LVG | AAA | 22 | 0.308 | 406 | 125 | 17 | 1 | 25 | 90 | 58 | 138 | 1 | 86.0- | 7.82 | 5.72 | .652 | 7.33 | .532 | .609 | .609 |
| Clark, Tony | 1B | DE | TOL | AAA | 22 | 0.261 | 92 | 24 | 4 | 0 | 2 | 13 | 12 | 25 | 2 | 12.0 | 4.58 | 4.57 | .500 | 5.86 | .379 | .454 | .601 |
| Clark, Tony | 1B | DE | TRE | AA | 22 | 0.279 | 394 | 110 | 25 | 1 | 21 | 86 | 40 | 113 | 0 | 69.0 | 6.19 | 4.11 | .694 | 5.48 | .561 | .635 | .601 |

Projecting the OW% to age 25 for all players gives a common evaluation point at a typical rookie age for minor league batters.

**Specific Methodology:** The process contains seven steps starting form the players raw batting statistics.

(1) Using the raw batting statistics, calculate "runs created" (RC) through the following Bill James formula:

(H+BB-CS)x(TB+.55xSB)/(AB+BB)

(2) Convert runs created to a per-game factor of runs created per 25.5 outs used (RCpG).

(3) Define the team "Context" as the total runs (i.e. both teams combined) scored per game divided by two.

(4) Calculate the OW% for the batter based on his runs created relative to the team context using the following formula:

$$\frac{RCpG^2}{RCpG^2 + Context^2}$$

The calculation for the OW% is based on the Pythagorean theorem. As regards baseball, OW% is based on the observation that a teams won/lost percentage can be approximated by the formula:

$$\frac{RunsScored^2}{RunsScored^2 + RunsAgainst^2}$$

(5) Adjust the team context by the major league equivalency of the subject league using the following factors.

| League Level | Adjustment Factor |
|---|---|
| AAA | .78 |
| AA | .75 |
| A+ (Calif., Car & FSL) | .65 |
| A (Midwest & Sally) | .60 |

The adjustment factors are generally derived from Bill James' formulas for calculating major league equivalencies, data presented in ESSENTIAL BASEBALL 1994 by Norm Hitzges and Dave Lawson, and my own analysis.

(6) The major league equivalent OW% is calculated using the team context in (3) multiplied by the factor in (5) as the Context for the calculation.

(7) The final step consists of calculating the players projected OW% at age 25. The batters OW% in (6) above is adjusted to project his performance at age 25 using the adjustment factors in the table below.

| Age | Year-to-Year Change | Cumul Chnge to 25 |
|---|---|---|
| 18 | 1.09 | 1.56 |
| 19 | 1.08 | 1.43 |
| 20 | 1.07 | 1.33 |
| 21 | 1.06 | 1.24 |
| 22 | 1.06 | 1.17 |
| 23 | 1.05 | 1.10 |
| 24 | 1.05 | 1.05 |
| 25 | 1.04 | 1.00 |
| 26 | 1.04 | .96 |
| 27 | .97 | .93 |
| 28 | .96 | .90 |

The adjustment factors are generally derived from Bill James' formulas for calculating major league equivalencies, James' Brock2 formulas, data presented in ESSENTIAL BASEBALL 1994 by Norm Hitzges and Dave Lawson, and my own analysis.

For a player on more than one team in a year, his OW% for each team is averaged (weighted by At Bats).

**Results:** The players evaluated using the discussed methodology include the 148 top prospects whose statistics are provided by the USA Today On-line Information service. The accompaining chart shows the top prospects accorting to the system.

Most of those players are highly rated in almost any ranking. Some highly touted prospects who rank fairly low (OW% at age 25 below .500) include Mike Tucker (.496), Rich Becker (.475), Howard Battle (.472), Todd Hollandsworth (.470), Ray Holbert (.451), Quilvio Veras (.386), Billy Hall (.368) and Joe Randa (.355).

**Caveats:** The most important caveat in the above analysis is that it is based on only one year's play. Obviously injury, personal problems, on simply the random fluctuations in a career can cause any single year to not be representative of a players ability. Evaluation over additional seasons clearly adds value.

Secondly the growth patterns of a player's ability varies. Some peak earlier than others; some never learn to hit pitching above the high A level; and the whole gamut of human differences cause projecting future abilities even a couple years into the future suspect at best. Another important reason for caution lies in estimating the relative competition of the four league levels. Although my adjustment factors appear reasonable and are based on solid information, more research clearly needs to be done in this area, especially the A leagues.

The statistics included in the USA Today Information service do not include triples or caught stealing. As I had no desire to look up and enter those statistics for every player, I estimated triples at .03 x Doubles + .10 x Stolen Bases, and Caught Stealing at .50 x Stolen Bases. I think the loss of accuracy to the overall projections from these estimates very small.

I believe my analysis advances the knowledge in the sabermetric evaluation of minor league players. I look forward to the thoughts of committee members on this analysis. Please feel free to call or write with any questions or comments.

# Relative Production Potential

**By Tony Blengino**

While some evaluate prospects primarily on tools, and others on statistics, very few others focus on players' performance in relation to their peers. Also, many others do not take prospects' ages into consideration when determining their value. Therefore, most other lists of "Future Stars" include names like Ron Coomer. Coomer is a 28-year-old, eight-year minor league vet who, by divine providence, landed in the Pacific Coast League, a hitters' paradise in 1994. Of course, he hit .338 with 22 homers and 123 RBI - a surefire star, right? Well, no. Relative to the league, he wasn't that great, and he's well beyond the age at which a "real" prospect enters the major leagues.

Relative Production Potential measures a minor leaguer's offensive production relative to his league, adjusted for the age of that player in relation to his peers. Production is based on the two most important offensive statistics: on-base percentage and slugging percentage. This method adjusts for exaggerated statistics such as those posted in the Pacific Coast and California Leagues, making it possible to compare prospects at different levels. The end result is an ordered list of the 279 minor leaguers who established some level of major league production.

While the top of the 1993 list was largely populated by major league-ready players who went on to make major league impacts in 1994, the 1994 Top 10 is, on balance, younger and less well known. This method does not purport to predict the prospects most likely to have an impact NEXT YEAR - the method projects long-term potential.

Two of the prospects in the Top 10 are most likely totally unknown to even most hardcore baseball fans. However, some previously unknown players who ranked highly on last year's list have gone on to certify themselves as "mainstream" prospects in 1994 - but names like Bob Abreu, Karim Garcia and Richard Hidalgo didn't appear on any other Top Prospects' list besides this one prior to 1994. RPP can also be used to analyze the relative strength of individual minor league systems.

**Methods**

The first step in the evaluation process is the calculation of OBP and SLG for all starters for full-season minor league teams. To capture them all, all players with greater than 300 at bats were included, as well as any players with fewer at bats, but who led their team in at-bats at a given position. In some cases, players who met neither qualification, but who split their season at multiple levels, were qualified at the level where they accumulated the most at bats.

Each player's OBP and SLG is compared to the average of all the qualifiers in his league. Each player is awarded points in the amount of the number of standard deviations his OBP and SLG are above or below the league average. For instance, Carlos Delgado of the Triple-A Syracuse Chiefs in the Blue Jays' organization had an OBP 2.02 standard deviations above the average of his peers, and a SLG 1.85 standard deviations above the average of his peers. This gives him an unadjusted RPP score of 3.87, which is excellent.

For each league, the sum of all OBP and SLG factors is zero. This enables hitters' leagues to be fairly compared to pitchers' leagues. By comparison, the vaunted Marlins' Triple-A outfield of Nigel Wilson, Carl Everett and Darrell Whitmore had similar raw numbers to Delgado - but relative to their league, they were much more ordinary.

After calculating unadjusted RPP for all minor league starters, the population of top minor league prospects can be assembled. This is where a prospect's age becomes critical. This is where would-be prospects like Ron Coomer get burned. RPP is age-adjusted for each player, based on the optimal age for a player at a given minor league level. For Triple-A the optimal age is 22, for Double-A, it's 21, for High-A (California, Carolina and Florida State Leagues), it's 20, and for Low-A (Midwest and South Atlantic Leagues), it's 19.

First, all starters who were at or below their level's optimal age (July 4 cutoff date) are placed in the prospect pool. Next, all players who are one year above optimal age, and have positive unadjusted RPP, are placed in the pool. All players who are two years above the optimal age who have unadjusted RPP of at least 1.00 are placed in the pool. Lastly, all players three years above the optimal age who have unadjusted RPP of at least 2.00 are placed in the pool. The pool is now full - 279 players qualified in 1994. The pool includes players who performed at high offensive levels, as well as some who did not, but who were among the youngest in their leagues.

Each qualifier's unadjusted RPP is then adjusted for age. For each year younger than his league's optimal age, a player's RPP is increased by 1.00; for each year older than his league's optimal age, a player's RPP is decreased by 1.00. This process brings together two seemingly starkly different seasons. Roger Cedeno, 19, a Dodgers' Triple-A outfielder, had unadjusted RPP of 0.33, adjusted upward by 3.00 to 3.33, ranking him 11th. Ernie Young, 24, an A's Double-A outfielder, had an incredible unadjusted RPP of 6.40 adjusted downward by 3.00 to 3.40, ranking him 10th.

**Relative Organizational Strength**

This system makes it quite simple to compare relative strength of minor league systems. By assigning the #1 prospect with a point value of 279, and lowering each successive prospect's value by one, a cumulative organizational RPP can be calculated. The Top Five were Toronto (2,541 points), Cleveland (2,453), Los Angeles (2,438), Atlanta (2,012) and Montreal (1,925). The Blue Jays, though still the best, saw their depth cut in 1994. They had 14 of the top 95 prospects in 1993, but "only" eight of the top 83 in 1994. The Bottom Five organizations were Colorado (181), Texas (608), St. Louis (752), San Francisco (763) and Philadelphia (846).

# Relative Production Potential

| 1994 Rank | 1993 Rank | Name | Pos | Age | Level | Team | Org | Rel OBP | Rel SLG | Rel Tot | Age Adj | RPP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | Alex Rodriguez | SS | 18 | LO-A | APP | SEA | 1.27 | 3.30 | 4.57 | 1.00 | 5.57 |
| 2 | | Jeff Abbott | OF | 21 | LO-A | SBN | CWS | 4.12 | 3.08 | 7.20 | -2.00 | 5.20 |
| 3 | 24 | Karim Garcia | OF | 18 | HI-A | VB | LA | -0.11 | 2.61 | 2.50 | 2.00 | 4.50 |
| 4 | 74 | Shawn Green | OF | 21 | AAA | SYR | TOR | 1.97 | 1.39 | 3.36 | 1.00 | 4.36 |
| 5 | 18 | Bob Abreu | OF | 20 | AA | JAC | HOU | 1.03 | 2.24 | 3.27 | 1.00 | 4.27 |
| 6 | 4 | Carlos Delgado | DH | 22 | AAA | SYR | TOR | 2.02 | 1.85 | 3.87 | 0.00 | 3.87 |
| 7 | | Marc Newfield | OF | 21 | AAA | CLG | SEA | 1.14 | 1.65 | 2.79 | 1.00 | 3.79 |
| 8 | | Charles McBride | 3B | 20 | LO-A | MAC | ATL | 1.95 | 2.83 | 4.78 | -1.00 | 3.78 |
| 9 | 70 | Billy Ashley | OF | 23 | AAA | ABQ | LA | 1.62 | 3.13 | 4.75 | -1.00 | 3.75 |
| 10 | 30 | Ernie Young | OF | 24 | AA | HUN | OAK | 2.94 | 3.46 | 6.40 | -3.00 | 3.40 |
| 11 | 9 | Roger Cedeno | OF | 19 | AAA | ABQ | LA | 0.98 | -0.65 | 0.33 | 3.00 | 3.33 |
| 12 | 88 | Scott Romano | 3B | 22 | HI-A | TAM | NYY | 1.99 | 3.17 | 5.16 | -2.00 | 3.16 |
| 13 | 85 | Trey Beamon | OF | 20 | AA | CAR | PIT | 1.32 | 0.80 | 2.12 | 1.00 | 3.12 |
| 14 | 19 | Edgardo Alfonzo | SS | 20 | AA | BNG | NYM | 1.06 | 0.87 | 1.93 | 1.00 | 2.93 |
| 15 | 65 | Desi Relaford | SS | 20 | HI-A | RIV | SEA | 2.30 | 0.58 | 2.88 | 0.00 | 2.88 |
| 16 | 35 | Derek Jeter | SS | 20 | HI-A | TAM | NYY | 1.64 | 1.19 | 2.83 | 0.00 | 2.83 |
| 17 | | Ruben Rivera | OF | 20 | LO-A | GRN | NYY | 1.07 | 2.71 | 3.78 | -1.00 | 2.78 |
| 18 | | Bob Morris | 2B | 21 | LO-A | PEO | CHI | 2.79 | 1.85 | 4.64 | -2.00 | 2.64 |
| 19 | 56 | Johnny Damon | OF | 20 | HI-A | WLM | KC | 1.66 | 0.77 | 2.43 | 0.00 | 2.43 |
| 20 | 7 | Arquimedez Pozo | 2B | 20 | AA | JAX | SEA | 0.36 | 1.05 | 1.41 | 1.00 | 2.41 |
| 21 | 34 | Tom Evans | 3B | 19 | LO-A | HAG | TOR | 1.33 | 1.07 | 2.40 | 0.00 | 2.40 |
| 22 | | Raul Casanova | C | 21 | HI-A | RAN | SD | 1.34 | 2.00 | 3.34 | -1.00 | 2.34 |
| 23 | | Jason Thompson | 1B | 23 | HI-A | RAN | SD | 2.51 | 2.73 | 5.24 | -3.00 | 2.24 |
| 24 | | Enrique Wilson | SS | 18 | LO-A | COL | CLE | 0.39 | 0.83 | 1.22 | 1.00 | 2.22 |
| 25 | | Scott Rolen | 3B | 19 | LO-A | SPT | PHL | 1.07 | 1.15 | 2.22 | 0.00 | 2.22 |
| 26 | | Torii Hunter | OF | 18 | LO-A | FTW | MIN | 0.29 | 0.80 | 1.09 | 1.00 | 2.09 |
| 27 | 25 | Alex Gonzalez | SS | 21 | AAA | SYR | TOR | 0.83 | 0.24 | 1.07 | 1.00 | 2.07 |
| 28 | 160 | Jason Kendall | C | 20 | HI-A | SAL | PIT | 1.65 | 0.41 | 2.06 | 0.00 | 2.06 |
| 29 | | Mel Nieves | OF | 22 | AAA | LV | SD | 0.80 | 1.25 | 2.05 | 0.00 | 2.05 |
| 30 | 40 | David Bell | 3B | 21 | AAA | CHR | CLE | 0.45 | 0.58 | 1.03 | 1.00 | 2.03 |
| 31 | | Sherman Obando | OF | 24 | AAA | ROC | BAL | 1.28 | 2.75 | 4.03 | -2.00 | 2.03 |
| 32 | | Bob Henley | DH | 21 | LO-A | BUR | MTL | 1.50 | 2.29 | 3.79 | -2.00 | 1.79 |
| 33 | 143 | Charles Johnson | C | 22 | AA | POR | FLA | 0.94 | 1.81 | 2.75 | -1.00 | 1.75 |
| 34 | 13 | Willie Greene | 3B | 22 | AAA | IND | CIN | 0.69 | 1.05 | 1.74 | 0.00 | 1.74 |
| 35 | 97 | Joe Vitiello | 1B | 24 | AAA | OMA | KC | 2.39 | 1.34 | 3.73 | -2.00 | 1.73 |
| 36 | | Carlos Mendez | DH | 20 | LO-A | RCK | KC | 1.24 | 1.41 | 2.65 | -1.00 | 1.65 |
| 37 | | Troy O'Leary | OF | 24 | AAA | NO | MIL | 1.85 | 1.79 | 3.64 | -2.00 | 1.64 |
| 38 | 28 | Brian Giles | OF | 23 | AAA | CHR | CLE | 1.70 | 0.92 | 2.62 | -1.00 | 1.62 |
| 39 | | Matt Lawtón | OF | 22 | HI-A | FTM | MIN | 2.54 | 1.04 | 3.58 | -2.00 | 1.58 |
| 40 | 149 | Jose Vidro | 2B | 19 | HI-A | WPB | MTL | 0.44 | 0.12 | 0.56 | 1.00 | 1.56 |
| 41 | | Ricky Ledee | OF | 20 | LO-A | GRN | NYY | 1.23 | 1.27 | 2.50 | -1.00 | 1.50 |
| 42 | 208 | Willis Otanez | 3B | 21 | HI-A | VB | LA | 0.77 | 1.70 | 2.47 | -1.00 | 1.47 |
| 43 | 180 | Brian Hunter | OF | 23 | AAA | TUC | HOU | 1.79 | 0.65 | 2.44 | -1.00 | 1.44 |
| 44 | 33 | Richard Hidalgo | OF | 19 | LO-A | QUAD | HOU | -0.17 | 1.59 | 1.42 | 0.00 | 1.42 |
| 45 | | Mike Warner | DH | 23 | HI-A | DUR | ATL | 2.16 | 2.26 | 4.42 | -3.00 | 1.42 |
| 46 | | Harry Berrios | OF | 22 | HI-A | FRD | BAL | 1.95 | 1.44 | 3.39 | -2.00 | 1.39 |
| 47 | | Pat Watkins | OF | 21 | HI-A | WIN | CIN | 0.87 | 1.47 | 2.34 | -1.00 | 1.34 |
| 48 | 84 | Jose Malave | OF | 23 | AA | NBR | BOS | 0.94 | 2.39 | 3.33 | -2.00 | 1.33 |
| 49 | 68 | Chris Stynes | 2B | 21 | AA | KNX | TOR | 0.61 | 0.72 | 1.33 | 0.00 | 1.33 |
| 50 | | Wilton Guerrero | SS | 19 | HI-A | VB | LA | 0.50 | -0.18 | 0.32 | 1.00 | 1.32 |
| 51 | 151 | Ray Durham | 2B | 22 | AAA | NAS | CWS | 0.34 | 0.94 | 1.28 | 0.00 | 1.28 |

The most improved organization was San Diego moving from 20th place in 1993 to 6th place in 1994, while Houston suffered the greatest drop, going from 2nd in 1993 to 13th in 1994.

**Conclusion**

Relative Production Potential is a minor league performance evaluation system for position players. Measurement of players' OBP and SLG relative to their leagues', adjusted for players' ages, gives an unbiased view of players' long-term major league potential. Performance can be viewed within league context, and can be compared across leagues and levels. Though the system is relatively new, it has already unearthed prospects such as Karim Garcia, Bob Abreu, Richard Hidalgo, etc. ahead of most of the baseball establishment. Next year's "discoveries" are likely somewhere on this list.

# Trend Du Jour

**By Dave Raglin**

Baseball is an ever-changing game. There are new strategies being developed every season. Some happen all of a sudden, but some also just become part of the game on a gradual basis; before you know it, it's a common practice. Such is the case of the "left-handed middle reliever to pitch to one batter".

The trend of middle relief pitchers who pitch many games but very few innings (well below one inning per game) is a very recent trend. Before 1991, the record for the lowest innings pitched per game in a season (with at least 40 games) was held by Joe Hoerner of the 1973 Braves and Royals. Hoerner pitched 32.0 innings in 42 games that season--a ratio of .762 innings per game. In the last four seasons, 16 pitchers have had a lower ratio. This paper examines that trend and the pitchers who are part of it.

The full page chart accompaning this paper lists the 22 pitchers with 40 games in a season and a ratio of less than .800 (really, it's 21 plus Jim Poole of the 1994 Orioles, who had a .535 ratio in 38 games of the strike-shortened season). Detailed data was available for 22 of the 23 pitcher/seasons from the STATS, Inc. Player Profiles books and STATS Online except for Horener in 1973. The detailed statistics below are for those 22 pitchers. Several things stand out:

- All 23 pitchers are left-handers. The record by lowest innings pitched per game by a righthander is Jeff Nelson of the 1993 Mariners (60.0 IP, 71 G, .845 ratio). There is a trend towards righthanders who pitch few innings per game, but it is not as strong as for lefthanders.
- Who started the trend and why did it start? In 1990 and before, there are not only no pitchers on the list (except for Hoerner), but no one even close. Two people made the list in 1991, Candelaria under Lasorda and McClure (mostly) for Joe Torre, and a few were close. As I recall, one of the ramifications of the labor agreement following the 1990 lockout was that rosters would go back up to 25 from 24 in 1991. Maybe after surviving for a few years with 24 men, some managers decided to invent a whole new job with the extra man.
- Several guys make multiple appearances on this list--Tony Fossas three times, and John Candelaria, Rick Honeycutt, Vince Horseman, Paul Assenmacher, and Bob McClure twice, even though several of these players played on different teams during this period. Fossas is now with the Cardinals and is on the way to making the list again.

Look at the managers who are using this strategy. Tony LaRussa's has had two pitchers make the list a total of three times; in fact two in one season. Tommy Lasorda has two pitchers on the list for three pitcher/seasons, Gene Lamont has two pitchers on the list, and Fossas' three seasons on the list were for Butch Hobson. It may be becoming a common strategy, it is not universally used yet. It tends to be used by younger managers and veteran "geniuses".

- It may be the "lefthander to pitch to one batter" trend, but they usually pitch to more than one batter. As the chart shows, none of these guys average less than two batters per game. In Fossas' historic 1992 season, he pitched to one batter in about 30 of his 60 games, getting him out about 23 times (a .233 on-base percentage). In Candelaria's 1992 season, he pitched to one batter about 23 times, getting him out about 15 times (a .346 on-base percentage).
- Although they presumably were called in to get the tough left-handed hitter, 18 of the 21 actually had more plate appearances (at-bats plus walks) against right-handed batters. They were better against lefthanders, some dramatically so (ten of the 22 had on-bse percentages 100 points higher against righthanders). Fossas is the best example. He cannot get righthanders out, but he is death on lefthanders. Presumably he is brought in either against a good lefthanded batter his manager knows will not be pinch hit for, or he is brought in to get the opposing manager to take out a certain lefthanded hitter.
- These are not great pitchers. You can tell that just by looking at their stats. They can do one thing--throw a good breaking pitch that lefthanders cannot pull (look at the slugging percentages against lefthanded batters). They are finness pitchers. That also shows up in the fact that they are groundball pitchers. If they were great pitchers, they would not be in this role.

I expect this trend to continue to grow. If it wasn't for the strike, there probably would have been 7-8 pitchers on the list in 1994. As mentioned earlier, even when these pitchers change teams, they tend to take the role with them. Is it a good role? Is it worth a roster spot for a pitcher with 30-50 innings a season? I'm not going to argue with LaRussa and Lasorda, and as long as respected minds in the game like those continue to use it, it will grow, just like the five-man rotation and the relief ace coming in for the save.

# The Pitchers With The Lowest Innings Pitched Per Game Ratio In A Season

| | | | | | | | | | | | | vs Lefthanders | | | vs Righthanders | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| # | Name | Team | Year | L/R | G/F/N | IP | G | IP/G | W-L-S | ERA | PA/G | OBP | SLG | PA | OBP | SLG | PA |
| 1. | Tony Fossas | Boston | 1992 | L | G | 29.7 | 60 | .494 | 1-2-2 | 2.43 | 2.08 | .254 | .321 | 59 | .463 | .509 | 66 |
| 2. | John Candelaria | Los Angeles | 1992 | L | F | 25.3 | 50 | .507 | 2-5-5 | 2.84 | 2.08 | .328 | .385 | 57 | .292 | .179 | 47 |
| 3. | Jim Poole | Baltimore | 1994 | L | N | 20.3 | 38 | .535 | 1-0-0 | 6.64 | 2.55 | .476 | .579 | 42 | .397 | .604 | 55 |
| 4. | Tony Fossas | Boston | 1993 | L | G | 40.0 | 71 | .563 | 1-1-0 | 5.18 | 2.42 | .215 | .157 | 76 | .396 | .529 | 96 |
| 5. | John Candelaria | Los Angeles | 1991 | L | N | 33.7 | 59 | .571 | 1-1-2 | 3.74 | 2.27 | .206 | .207 | 63 | .392 | .690 | 71 |
| 6. | Al Osuna | Houston | 1993 | L | F | 25.3 | 44 | .576 | 1-1-2 | 3.20 | 2.23 | .400 | .417 | 47 | .208 | .245 | 51 |
| 7. | Rick Honeycutt | Texas | 1994 | L | G | 25.0 | 42 | .595 | 1-2-1 | 7.20 | 2.74 | .423 | .608 | 52 | .400 | .509 | 63 |
| 8. | Vince Horseman | Oakland | 1993 | L | G | 25.0 | 40 | .625 | 2-0-0 | 5.40 | 2.83 | .418 | .326 | 54 | .328 | .346 | 59 |
| 9. | Joe Klink | Florida | 1993 | L | G | 37.7 | 59 | .638 | 0-2-0 | 5.02 | 2.76 | .333 | .243 | 87 | .405 | .446 | 76 |
| 10. | Jesse Orosco | Milwaukee | 1992 | L | N | 39.0 | 59 | .661 | 3-1-1 | 3.23 | 2.63 | .328 | .418 | 60 | .278 | .333 | 95 |
| 11. | Steve Frey | San Francisco | 1994 | L | N | 31.0 | 44 | .705 | 1-0-0 | 4.94 | 2.95 | .306 | .476 | 46 | .448 | .603 | 84 |
| 12. | Rick Honeycutt | Oakland | 1992 | L | G | 39.0 | 54 | .722 | 1-4-3 | 3.69 | 2.98 | .313 | .339 | 65 | .337 | .393 | 96 |
| 13. | Bob McClure | Calif/StLou | 1991 | L | N | 32.7 | 45 | .726 | 1-1-0 | 4.96 | 3.11 | .319 | .311 | 69 | .397 | .538 | 71 |
| 14. | Mike Munoz | Detroit | 1992 | L | G | 48.0 | 65 | .738 | 1-2-2 | 3.00 | 3.14 | .259 | .219 | 80 | .384 | .425 | 124 |
| 15. | Vince Horseman | Oakland | 1992 | L | N | 43.3 | 58 | .747 | 2-1-1 | 2.49 | 3.03 | .302 | .243 | 85 | .374 | .420 | 91 |
| 16. | Scott Radinsky | Chicago AL | 1993 | L | N | 54.7 | 73 | .749 | 8-2-4 | 4.28 | 3.38 | .287 | .261 | 94 | .351 | .379 | 153 |
| 17. | Paul Assenmacher | Chicago AL | 1994 | L | N | 33.0 | 44 | .750 | 1-2-1 | 3.55 | 2.93 | .246 | .280 | 53 | .342 | .348 | 76 |
| 18. | Omar Daal | Los Angeles | 1993 | L | G | 35.3 | 47 | .752 | 2-3-0 | 5.09 | 3.21 | .326 | .338 | 85 | .433 | .571 | 66 |
| 19. | Bob McClure | St. Louis | 1992 | L | F | 54.0 | 71 | .761 | 2-2-0 | 3.17 | 3.15 | .272 | .407 | 101 | .405 | .426 | 123 |
| 20. | Joe Hoerner | Atlan/KanCty | 1973 | L | -- | 32.0 | 42 | .762 | 4-2-6 | 5.63 | ---- | ---- | ---- | ---- | ---- | ---- | ---- |
| 21. | Tony Fossas | Boston | 1994 | L | G | 34.0 | 44 | .773 | 2-0-1 | 4.76 | 3.36 | .286 | .273 | 63 | .384 | .615 | 85 |
| 22. | Kevin Wickander | Cleve/Cincin | 1993 | L | F | 34.0 | 44 | .773 | 1-0-0 | 6.09 | 3.80 | .408 | .386 | 70 | .429 | .670 | 97 |
| 23. | Paul Assenmacher | Ch NL/NY AL | 1993 | L | G | 56.0 | 72 | .778 | 4-3-0 | 3.38 | 3.22 | .314 | .380 | 101 | .344 | .364 | 131 |

| Year | # |
|---|---|
| Pre 1991 ................ | 1 |
| 1991 ...................... | 2 |
| 1992 ...................... | 7 |
| 1993 ...................... | 8 |
| 1994 ...................... | 5 |

| Type | # |
|---|---|
| Groundball . | 10 |
| Neutral ....... | 8 |
| Flyball ........ | 4 |

| PA % vs LHB | # |
|---|---|
| 35 - 39% ........... | 4 |
| 40 - 44% ........... | 10 |
| 45 - 49% ........... | 5 |
| 50 - 57% ........... | 3 |

| Better Vs | # |
|---|---|
| LH Batters ....... | 16 |
| RH Batters ...... | 6 |

Better: comparing OBP*SLG

PAs -- Plate Appearances is AB + BB, close enough in most situations.
G/F/N -- Groundball/Flyball/Neutral pitcher: G is a G/F ratio of 1.50+, F is a ratio of 1.00 or less.
Note: A pitcher must have 40 apperances to make the list and a IP/G ratio of under .800
(Jim Poole was made an exception because he was so close in a strike year, and his IP/G ratio was so low)

# COMPUTER SIMULATION OF MAJOR LEAGUE BASEBALL: Does the Sum of the Parts Equal the Whole?

**by Dave Everett**

Computer simulation of major league baseball is a bit of an odyssey..... The hope is that my using individual performance statistics, and then simulating individual batter/pitcher match-ups, you end up with team Won/Lost results that are similar to the actual team results.

For a given batter, you pick a random number, then evaluate the batter's probability of various outcomes, based upon his actual batting statistics -- of all his plate appearances, what percentage of the time did he hit a single or double, strike out or receive a base on balls, etc. Naturally, there are many other factors that could be considered: left/right-handed performance, ball park factors, defensive skills, to name a few.

However, regardless of the degree of complexity, a computer simulation almost always centers around picking a random number to determine the outcome for each batter's appearance.

One of the problems with this type of computer simulation is that the results of the simulation can vary significantly, sometimes dramatically, from one simulation to another. A team might win 100 games in a simulation of a season, but might win only 80 in the next. These types of swings in the results are inevitable due to the element of chance in selecting the random numbers which drive the simulation. This inconsistency makes it impossible to draw any meaningful conclusions from the simulation because the results of one simulation may be completely different from the results of the next.

## SUMMARY

Although simulation results vary considerably when running an individual season, I will show that the results become more and more consistent as more simulations are run. By running a larger number of simulations and calculating the average results of the simulations, we can obtain consistent and meaningful results.

## HOW THE SIMULATION WORKS

The simulations that I will describe here have all been generated by a computer simulation program that I have developed. The program simulates full major league seasons by creating individual batter/pitcher match-ups. The outcome for an individual batter is determined by evaluating his actual statistics, adjusted to reflect the quality of the pitcher he is facing. All game decisions -- such as baserunner advances, defensive throws to bases, pitching changes -- are made by the program. Lineups and pitching rotations are selected based on how players have been used in the past. The program can re-create seasons that have already been played, or can forecast future seasons.

The program uses individual batting and pitching statistics obtained from the STATS, Inc. Season Final Statistics. The program simulates a full major league season in approximately two minutes (running on a 486/50 personal computer).

## HOW CONSISTENT ARE THE RESULTS?

In this section, I will show how the consistency of the simulation improves as a higher number of seasons is simulated. For the purposes of discussing the consistency of the simulation, I will refer to the American League in 1993, the last complete season.

1-Season Simulation. To begin our comparison, we'll look at the results of simulating a single full season 10 separate times, and comparing the results. Table 1 shows the results of the ten 1-season simulations.

**Table 1:**
**Simulated Results of Ten Single-Season Simulations**

1-Season Simulation
American League, 1993
Run #1

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| TOR | 103 | 59 | 0.636 | 0 |
| BAL | 88 | 74 | 0.543 | 15 |
| DET | 88 | 74 | 0.543 | 15 |
| NYY | 84 | 78 | 0.519 | 19 |
| BOS | 81 | 81 | 0.500 | 22 |
| MIL | 74 | 88 | 0.457 | 29 |
| CLE | 71 | 91 | 0.438 | 32 |
| *West* | | | | |
| TEX | 89 | 73 | 0.549 | 0 |
| CHW | 87 | 75 | 0.537 | 2 |
| OAK | 79 | 83 | 0.488 | 10 |
| KC | 78 | 84 | 0.481 | 11 |
| SEA | 73 | 89 | 0.451 | 16 |
| MIN | 71 | 91 | 0.438 | 18 |
| CAL | 68 | 94 | 0.420 | 21 |

1-Season Simulation
American League, 1993
Run #2

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| TOR | 90 | 72 | 0.556 | 0 |
| BAL | 89 | 73 | 0.549 | 1 |
| BOS | 89 | 73 | 0.549 | 1 |
| NYY | 89 | 73 | 0.549 | 1 |
| DET | 86 | 76 | 0.531 | 4 |
| CLE | 78 | 84 | 0.481 | 12 |
| MIL | 69 | 93 | 0.426 | 21 |
| *West* | | | | |
| CHW | 93 | 69 | 0.574 | 0 |
| KC | 90 | 72 | 0.556 | 3 |
| TEX | 78 | 84 | 0.481 | 15 |
| OAK | 77 | 85 | 0.475 | 16 |
| CAL | 71 | 91 | 0.438 | 22 |
| SEA | 71 | 91 | 0.438 | 22 |
| MIN | 64 | 98 | 0.395 | 29 |

1-Season Simulation
American League, 1993
Run #3

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| BOS | 87 | 75 | 0.537 | 0 |
| DET | 87 | 75 | 0.537 | 0 |
| TOR | 85 | 77 | 0.525 | 2 |
| MIL | 81 | 81 | 0.500 | 6 |
| NYY | 79 | 83 | 0.488 | 8 |
| BAL | 78 | 84 | 0.481 | 9 |
| CLE | 75 | 87 | 0.463 | 12 |
| *West* | | | | |
| TEX | 94 | 68 | 0.580 | 0 |
| CHW | 89 | 73 | 0.549 | 5 |
| SEA | 84 | 78 | 0.519 | 10 |
| OAK | 78 | 84 | 0.481 | 16 |
| KC | 75 | 87 | 0.463 | 19 |
| MIN | 74 | 88 | 0.457 | 20 |
| CAL | 68 | 94 | 0.420 | 26 |

1-Season Simulation
American League, 1993
Run #4

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| DET | 98 | 64 | 0.605 | 0 |
| TOR | 92 | 70 | 0.568 | 6 |
| BAL | 89 | 73 | 0.549 | 9 |
| BOS | 85 | 77 | 0.525 | 13 |
| NYY | 85 | 77 | 0.525 | 13 |
| MIL | 84 | 78 | 0.519 | 14 |
| CLE | 66 | 96 | 0.407 | 32 |
| *West* | | | | |
| CHW | 88 | 74 | 0.543 | 0 |
| SEA | 83 | 79 | 0.512 | 5 |
| KC | 81 | 81 | 0.500 | 7 |
| TEX | 76 | 86 | 0.469 | 12 |
| MIN | 72 | 90 | 0.444 | 16 |
| CAL | 70 | 92 | 0.432 | 18 |
| OAK | 65 | 97 | 0.401 | 23 |

1-Season Simulation
American League, 1993
Run #5

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| DET | 102 | 60 | 0.630 | 0 |
| NYY | 97 | 65 | 0.599 | 5 |
| BAL | 93 | 69 | 0.574 | 9 |
| TOR | 84 | 78 | 0.519 | 18 |
| BOS | 83 | 79 | 0.512 | 19 |
| CLE | 77 | 85 | 0.475 | 25 |
| MIL | 65 | 97 | 0.401 | 37 |
| *West* | | | | |
| CHW | 91 | 71 | 0.562 | 0 |
| TEX | 88 | 74 | 0.543 | 3 |
| SEA | 84 | 78 | 0.519 | 7 |
| KC | 76 | 86 | 0.469 | 15 |
| CAL | 69 | 93 | 0.426 | 22 |
| OAK | 69 | 93 | 0.426 | 22 |
| MIN | 56 | 106 | 0.346 | 35 |

1-Season Simulation
American League, 1993
Run #6

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| TOR | 97 | 65 | 0.599 | 0 |
| BAL | 95 | 67 | 0.586 | 2 |
| NYY | 93 | 69 | 0.574 | 4 |
| BOS | 91 | 71 | 0.562 | 6 |
| CLE | 79 | 83 | 0.488 | 18 |
| DET | 79 | 83 | 0.488 | 18 |
| MIL | 66 | 96 | 0.407 | 31 |
| *West* | | | | |
| CHW | 90 | 72 | 0.556 | 0 |
| TEX | 84 | 78 | 0.519 | 6 |
| KC | 78 | 84 | 0.481 | 12 |
| SEA | 78 | 84 | 0.481 | 12 |
| OAK | 75 | 87 | 0.463 | 15 |
| CAL | 70 | 92 | 0.432 | 20 |
| MIN | 59 | 103 | 0.364 | 31 |

1-Season Simulation
American League, 1993
Run #7

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| NYY | 96 | 66 | 0.593 | 0 |
| BOS | 89 | 73 | 0.549 | 7 |
| TOR | 86 | 76 | 0.531 | 10 |
| DET | 85 | 77 | 0.525 | 11 |
| BAL | 81 | 81 | 0.500 | 15 |
| CLE | 68 | 94 | 0.420 | 28 |
| MIL | 64 | 98 | 0.395 | 32 |
| *West* | | | | |
| TEX | 96 | 66 | 0.593 | 0 |
| CHW | 82 | 80 | 0.506 | 14 |
| SEA | 82 | 80 | 0.506 | 14 |
| KC | 79 | 83 | 0.488 | 17 |
| CAL | 78 | 84 | 0.481 | 18 |
| MIN | 76 | 86 | 0.469 | 20 |
| OAK | 72 | 90 | 0.444 | 24 |

1-Season Simulation
American League, 1993
Run #8

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| DET | 104 | 58 | 0.642 | 0 |
| TOR | 94 | 68 | 0.580 | 10 |
| BOS | 85 | 77 | 0.525 | 19 |
| BAL | 83 | 79 | 0.512 | 21 |
| NYY | 83 | 79 | 0.512 | 21 |
| MIL | 73 | 89 | 0.451 | 31 |
| CLE | 70 | 92 | 0.432 | 34 |
| *West* | | | | |
| CHW | 94 | 68 | 0.580 | 0 |
| TEX | 82 | 80 | 0.506 | 12 |
| KC | 81 | 81 | 0.500 | 13 |
| SEA | 81 | 81 | 0.500 | 13 |
| CAL | 70 | 92 | 0.432 | 24 |
| MIN | 67 | 95 | 0.414 | 27 |
| OAK | 67 | 95 | 0.414 | 27 |

1-Season Simulation
American League, 1993
Run #9

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| TOR | 103 | 59 | 0.636 | 0 |
| BAL | 92 | 70 | 0.568 | 11 |
| DET | 89 | 73 | 0.549 | 14 |
| NYY | 89 | 73 | 0.549 | 14 |
| BOS | 86 | 76 | 0.531 | 17 |
| CLE | 82 | 80 | 0.506 | 21 |
| MIL | 70 | 92 | 0.432 | 33 |
| *West* | | | | |
| CAL | 86 | 76 | 0.531 | 0 |
| CHW | 82 | 80 | 0.506 | 4 |
| TEX | 80 | 82 | 0.494 | 6 |
| SEA | 78 | 84 | 0.481 | 8 |
| OAK | 72 | 90 | 0.444 | 14 |
| KC | 69 | 93 | 0.426 | 17 |
| MIN | 56 | 106 | 0.346 | 30 |

1-Season Simulation
American League, 1993
Run #10

| | W | L | Pct. | GB |
|---|---|---|---|---|
| *East* | | | | |
| TOR | 101 | 61 | 0.623 | 0 |
| NYY | 89 | 73 | 0.549 | 12 |
| CLE | 86 | 76 | 0.531 | 15 |
| BOS | 80 | 82 | 0.494 | 21 |
| DET | 77 | 85 | 0.475 | 24 |
| BAL | 75 | 87 | 0.463 | 26 |
| MIL | 75 | 87 | 0.463 | 26 |
| *West* | | | | |
| TEX | 87 | 75 | 0.537 | 0 |
| SEA | 84 | 78 | 0.519 | 3 |
| CHW | 80 | 82 | 0.494 | 7 |
| KC | 77 | 85 | 0.475 | 10 |
| OAK | 77 | 85 | 0.475 | 10 |
| CAL | 76 | 86 | 0.469 | 11 |
| MIN | 70 | 92 | 0.432 | 17 |

By glancing through the results of these 10 simulations, it is clear that the results of the simulations are very inconsistent. In the 10 single-season simulations, four different teams (Toronto, Detroit, Boston, and New York) won the AL East, and three different teams (Chicago, Texas, and California) won the AL West. Detroit had the most inconsistent results: the Tigers twice had over 100 wins, yet twice finished under .500; four times they finished in first place, yet three times finished in fifth place.

Table 2 makes it easier to see how widely the results varied. The number of wins is indicated for each team, for each of the 10 simulations (for example, Baltimore had 88 wins in the first season simulation, 89 wins in the second simulation, etc.). The columns to the right show summary information for each team: average number of wins for the 10 simulations; the highest and lowest number of wins from the 10 simulations; the span of wins between their best and worst results (again using Baltimore as an example.... the Orioles' best result was 95 wins, their worst result 75 wins, for a span of 20); and the standard deviation of the results for the 10 simulations. The standard deviation is a useful measure to see how much the simulation results varied for the 10 simulations.

Half of the A.L. teams had a span of 20 or more wins between their best and worst showing. The largest span was Detroit, with a whopping range of 27. Boston, which had the narrowest span of results, still had a swing of 11 wins between their best and worst results.

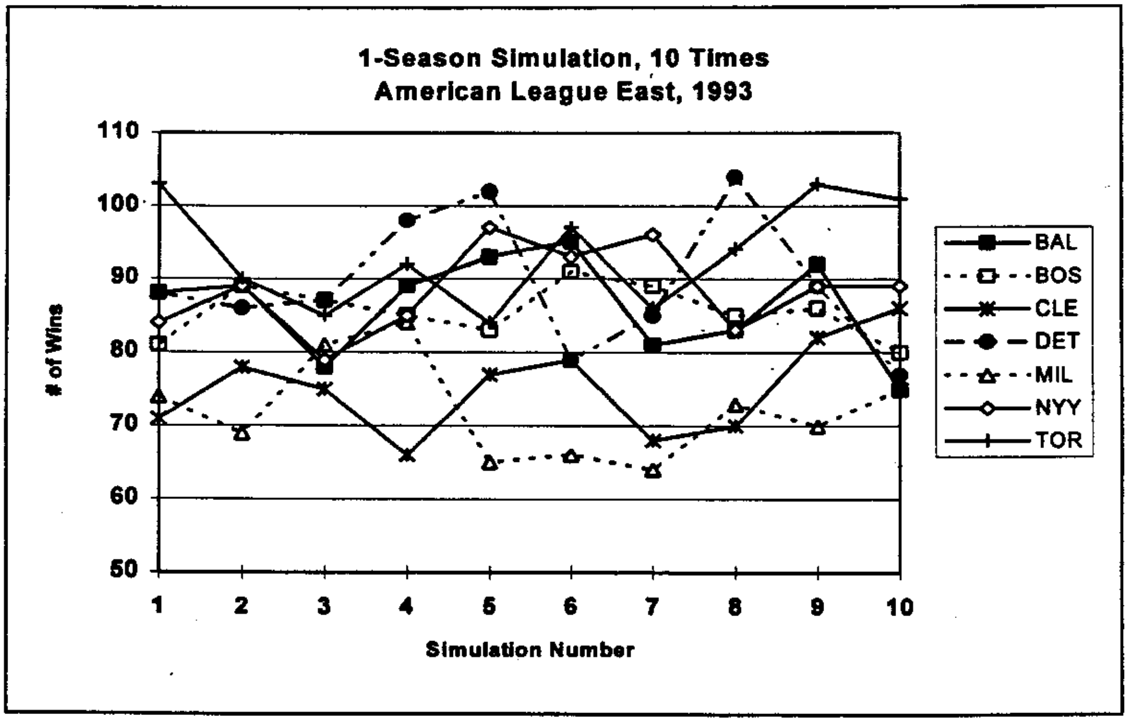
**Table 2**

**1-Season Simulation**
American League, 1993
(Number of Wins)

| | Simulation Number | | | | | | | | | | Summary Info | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Team | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Avg. | High | Low | Range | StdDev |
| BAL | 88 | 89 | 78 | 89 | 93 | 95 | 81 | 83 | 92 | 75 | 86.3 | 95 | 75 | 20 | 6.7 |
| BOS | 81 | 89 | 87 | 85 | 83 | 91 | 89 | 85 | 86 | 80 | 85.6 | 91 | 80 | 11 | 3.6 |
| CAL | 68 | 71 | 68 | 70 | 69 | 70 | 78 | 70 | 86 | 76 | 72.6 | 86 | 68 | 18 | 5.8 |
| CHW | 87 | 93 | 89 | 88 | 91 | 90 | 82 | 94 | 82 | 80 | 87.6 | 94 | 80 | 14 | 4.8 |
| CLE | 71 | 78 | 75 | 66 | 77 | 79 | 68 | 70 | 82 | 86 | 75.2 | 86 | 66 | 20 | 6.4 |
| DET | 88 | 86 | 87 | 98 | 102 | 79 | 85 | 104 | 89 | 77 | 89.5 | 104 | 77 | 27 | 9.1 |
| KC | 78 | 90 | 75 | 81 | 76 | 78 | 79 | 81 | 69 | 77 | 78.4 | 90 | 69 | 21 | 5.3 |
| MIL | 74 | 69 | 81 | 84 | 65 | 66 | 64 | 73 | 70 | 75 | 72.1 | 84 | 64 | 20 | 6.7 |
| MIN | 71 | 64 | 74 | 72 | 56 | 59 | 76 | 67 | 56 | 70 | 66.5 | 76 | 56 | 20 | 7.4 |
| NYY | 84 | 89 | 79 | 85 | 97 | 93 | 96 | 83 | 89 | 89 | 88.4 | 97 | 79 | 18 | 5.8 |
| OAK | 79 | 77 | 78 | 65 | 69 | 75 | 72 | 67 | 72 | 77 | 73.1 | 79 | 65 | 14 | 4.9 |
| SEA | 73 | 71 | 84 | 83 | 84 | 78 | 82 | 81 | 78 | 84 | 79.8 | 84 | 71 | 13 | 4.7 |
| TEX | 89 | 78 | 94 | 76 | 88 | 84 | 96 | 82 | 80 | 87 | 85.4 | 96 | 76 | 20 | 6.6 |
| TOR | 103 | 90 | 85 | 92 | 84 | 97 | 86 | 94 | 103 | 101 | 93.5 | 103 | 84 | 19 | 7.3 |

Figure 1 illustrates this same information graphically, limited to the A.L. East for less cluttered viewing. The spaghetti appearance of the results confirms what we suspected: the results of a single-season simulation are inconsistent and unreliable.[1]

**Figure 1**




<u>10-Season Simulation</u>. Now that we've tried running a single season at a time, let's run 10 seasons at a time, and then calculate the average number of wins for each team. We'll do this 10 times (simulating 10 seasons each time), and then compare the results of the ten simulations to see how consistent they are.

Table 3 shows the results of the ten simulations. Let me make clear what these numbers represent. Looking at Baltimore's results, Simulation Number #1 shows that Baltimore won 89.4 games. This means that Baltimore won an average of 89.4 games in the ten seasons that were simulated. We don't see the season-by-season details here, but in the 10 simulated seasons, Baltimore won 894 games, for an average of 89.4 per season. Similarly, in the second 10-season simulation the Orioles won 856 games, for an average of 85.6 wins per season.

A review of Table 3 shows that the results across the ten simulations have become considerably more consistent. Detroit, which ranged between 77 and 104 wins in the ten single-season simulations, had results within a much narrower band -- 85.0 and 92.3 wins. The results of other teams smoothed out similarly.

**Table 3**

**10-Season Simulation**
American League, 1993
(Number of Wins)

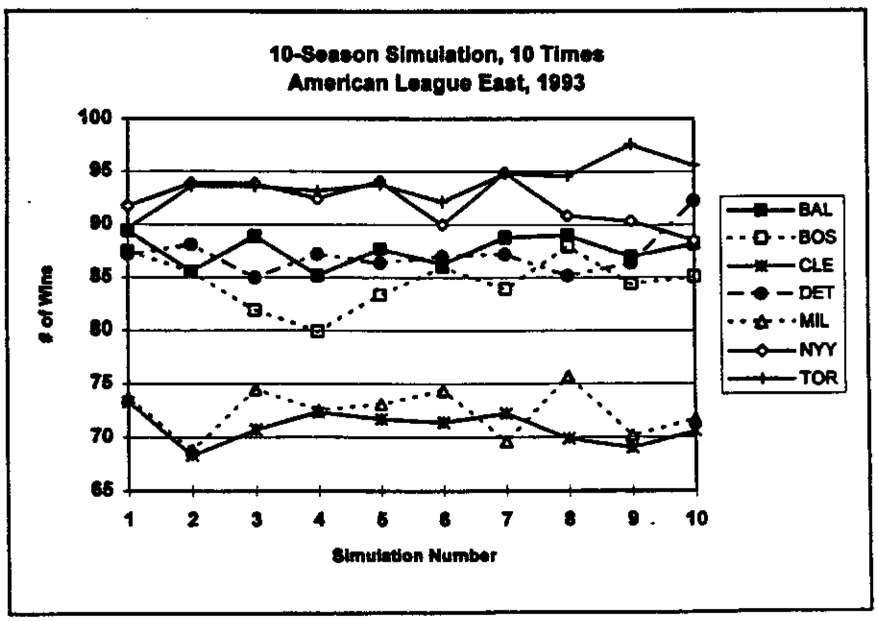
| | Simulation Number | | | | | | | | | | Summary Info | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Team | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Avg. | High | Low | Range | StdDev |
| BAL | 89.4 | 85.6 | 88.9 | 85.2 | 87.7 | 86.3 | 88.8 | 89.0 | 87.0 | 88.2 | 87.6 | 89.4 | 85.2 | 4.2 | 1.5 |
| BOS | 87.5 | 85.6 | 81.8 | 79.9 | 83.3 | 86.0 | 83.9 | 88.0 | 84.4 | 85.1 | 84.6 | 88.0 | 79.9 | 8.1 | 2.5 |
| CAL | 71.3 | 72.6 | 73.2 | 72.4 | 69.5 | 70.1 | 70.3 | 70.7 | 73.8 | 70.8 | 71.5 | 73.8 | 69.5 | 4.3 | 1.4 |
| CHW | 86.4 | 92.9 | 86.5 | 86.8 | 91.3 | 88.8 | 86.6 | 87.2 | 89.1 | 89.9 | 88.6 | 92.9 | 86.4 | 6.5 | 2.3 |
| CLE | 73.3 | 68.3 | 70.7 | 72.3 | 71.7 | 71.4 | 72.2 | 69.9 | 69.0 | 70.6 | 70.9 | 73.3 | 68.3 | 5.0 | 1.6 |
| DET | 87.2 | 88.1 | 85.0 | 87.2 | 86.4 | 87.0 | 87.2 | 85.2 | 86.4 | 92.3 | 87.2 | 92.3 | 85.0 | 7.3 | 2.0 |
| KC | 78.2 | 81.6 | 79.1 | 80.9 | 78.6 | 81.4 | 80.2 | 75.5 | 77.6 | 77.7 | 79.1 | 81.6 | 75.5 | 6.1 | 1.9 |
| MIL | 73.7 | 68.8 | 74.5 | 72.5 | 73.1 | 74.4 | 69.6 | 75.7 | 70.2 | 71.7 | 72.4 | 75.7 | 68.8 | 6.9 | 2.3 |
| MIN | 68.2 | 70.3 | 69.6 | 69.1 | 64.7 | 68.3 | 66.6 | 70.0 | 72.3 | 67.5 | 68.7 | 72.3 | 64.7 | 7.6 | 2.1 |
| NYY | 91.8 | 93.9 | 93.9 | 92.5 | 94.1 | 90.0 | 94.9 | 90.9 | 90.4 | 88.5 | 92.1 | 94.9 | 88.5 | 6.4 | 2.1 |
| OAK | 73.7 | 70.4 | 74.3 | 72.3 | 76.6 | 73.8 | 71.0 | 74.6 | 72.9 | 75.9 | 73.6 | 76.6 | 70.4 | 6.2 | 2.0 |
| SEA | 82.0 | 81.2 | 80.7 | 84.7 | 79.6 | 82.9 | 84.4 | 82.2 | 80.1 | 80.0 | 81.8 | 84.7 | 79.6 | 5.1 | 1.8 |
| TEX | 81.6 | 81.1 | 82.2 | 85.0 | 83.6 | 81.4 | 83.5 | 80.5 | 83.2 | 80.2 | 82.2 | 85.0 | 80.2 | 4.8 | 1.5 |
| TOR | 89.7 | 93.6 | 93.6 | 93.2 | 93.8 | 92.2 | 94.8 | 94.6 | 97.6 | 95.6 | 93.9 | 97.6 | 89.7 | 7.9 | 2.1 |

Although these results are much more consistent than the results of the single-season simulation, there are still quite a few variations in the results. For example, comparing the results of Toronto and New York, each team bettered the other five times out of the ten. Likewise, Baltimore's and Detroit's finishes flip-flopped, with Baltimore edging Detroit six times and Detroit beating Baltimore four times.

Figure 2 shows the 10-season simulation results graphically. Notice that the lines for each team are flatter than they were in Figure 1 (the single-season simulation), which is a sign of progress. If the results of the simulation were exactly the same every time we ran the simulation, the line for each team would be perfectly horizontal.

So if we want to run a simulation once and be confident that we'll get reliable results, we need to simulate more than 10 seasons.

**Figure 2**



200-Season Simulation. If our consistency improved considerably by simulating 10 seasons at a time, let's see what will happen if we run 200 seasons at a time. We'll simulate 200 seasons at a time, and do this ten separate times.

Table 4 and Figure 3 show the results of the ten 200-season simulations. Notice that these results are much more consistent than the 10-season simulations. Look at the Blue Jays/Yankees comparison: in the 10-season simulation they each beat the other team in 5 of the 10 simulations; however, running a 200-season simulation, Toronto won every time, and with a consistent margin of approximately three games. Baltimore was the third place finisher in every simulation. Boston and Detroit are neck and neck; their results are very close, and each team bettered the other several times. The results of Milwaukee and Cleveland were similarly close, although Milwaukee edged Cleveland in 8 of the 10 simulations by very narrow margins.

Looking at the ranges of wins in Table 4, notice that *every team had a range of less than 2 wins* across all ten simulations. This is a big improvement over the ranges of wins (from 11 all the way up to 27) that we saw in the single-season simulations!

The standard deviations in Table 4 also help us gauge how consistent the simulation results have become. Let's use the Yankees to illustrate. The Yankees' average number of wins for the 10 simulations was 91.6, with a standard deviation of 0.4. This means if we run a 200-season simulation we can expect the simulated results for the Yankees to be between 90.8 wins and 92.4 wins ninety-five percent of the time. (This interval is calculated by starting with the average of 91.6, and adding and subtracting two times the standard deviation.)

Figure 4 illustrates the results of the 200-season simulation for the American League West. The results for the teams have flattened for these teams as well, again due to the large number of seasons that we have simulated.

**Table 4**

**200-Season Simulation**
American League, 1993
(Number of Wins)

| | Simulation Number | | | | | | | | | | Summary Info | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Team | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Avg. | High | Low | Range | StdDev |
| BAL | 88.3 | 87.8 | 88.0 | 89.2 | 88.6 | 88.7 | 89.1 | 89.1 | 87.3 | 88.3 | 88.4 | 89.2 | 87.3 | 1.9 | 0.6 |
| BOS | 86.6 | 86.5 | 86.9 | 86.3 | 86.8 | 86.2 | 86.5 | 86.9 | 86.9 | 87.0 | 86.6 | 87.0 | 86.2 | 0.8 | 0.3 |
| CAL | 71.7 | 71.4 | 72.6 | 72.5 | 71.9 | 71.7 | 72.6 | 72.0 | 72.0 | 71.5 | 72.0 | 72.6 | 71.4 | 1.2 | 0.4 |
| CHW | 87.5 | 87.8 | 88.6 | 88.5 | 88.2 | 87.8 | 87.9 | 88.4 | 88.9 | 88.3 | 88.2 | 88.9 | 87.5 | 1.4 | 0.5 |
| CLE | 71.9 | 72.2 | 71.6 | 71.2 | 72.4 | 71.7 | 71.2 | 71.4 | 71.9 | 71.5 | 71.7 | 72.4 | 71.2 | 1.3 | 0.4 |
| DET | 86.7 | 87.1 | 87.0 | 86.6 | 86.4 | 87.2 | 86.5 | 86.2 | 86.8 | 86.6 | 86.7 | 87.2 | 86.2 | 1.0 | 0.3 |
| KC | 78.9 | 78.6 | 78.8 | 78.3 | 78.7 | 78.5 | 79.6 | 79.2 | 78.8 | 79.1 | 78.9 | 79.6 | 78.3 | 1.3 | 0.4 |
| MIL | 72.7 | 72.3 | 71.7 | 71.8 | 72.4 | 71.5 | 72.0 | 72.0 | 72.0 | 72.3 | 72.1 | 72.7 | 71.5 | 1.2 | 0.4 |
| MIN | 68.5 | 68.7 | 68.3 | 68.1 | 68.6 | 69.2 | 68.7 | 67.5 | 68.0 | 68.1 | 68.4 | 69.2 | 67.5 | 1.7 | 0.5 |
| NYY | 91.4 | 91.3 | 91.7 | 91.8 | 92.1 | 92.0 | 90.9 | 91.4 | 91.9 | 91.7 | 91.6 | 92.1 | 90.9 | 1.1 | 0.4 |
| OAK | 72.4 | 72.4 | 71.6 | 71.5 | 71.5 | 72.3 | 72.0 | 71.4 | 72.5 | 72.0 | 71.9 | 72.5 | 71.4 | 1.0 | 0.4 |
| SEA | 81.3 | 81.7 | 80.9 | 81.0 | 80.6 | 81.3 | 80.9 | 81.3 | 80.8 | 81.2 | 81.1 | 81.7 | 80.6 | 1.2 | 0.3 |
| TEX | 81.6 | 81.5 | 82.4 | 82.4 | 81.5 | 81.5 | 81.8 | 82.2 | 82.0 | 82.5 | 81.9 | 82.5 | 81.5 | 1.0 | 0.4 |
| TOR | 94.5 | 94.8 | 93.8 | 94.8 | 94.3 | 94.6 | 94.3 | 95.0 | 94.3 | 94.0 | 94.4 | 95.0 | 93.8 | 1.2 | 0.4 |

Conclusions about Consistency. In order for a computer simulation to be useful, it must produce results that are consistent. If a forecast is run several times, the results of those runs need to be very similar; otherwise, there is no way to know which of the several runs is "correct".

By simulating a large number of seasons and calculating average results for each team, we can obtain consistent and meaningful results. When we run a 200-season simulation, the simulated results become very stable. This is significant because we can run a single 200-season simulation and be confident that the results are close to "correct". For this paper I have run ten separate 200-season simulations; however, the results of the ten runs are so similar that I could have used the results from any of the ten simulations.

Figure 3

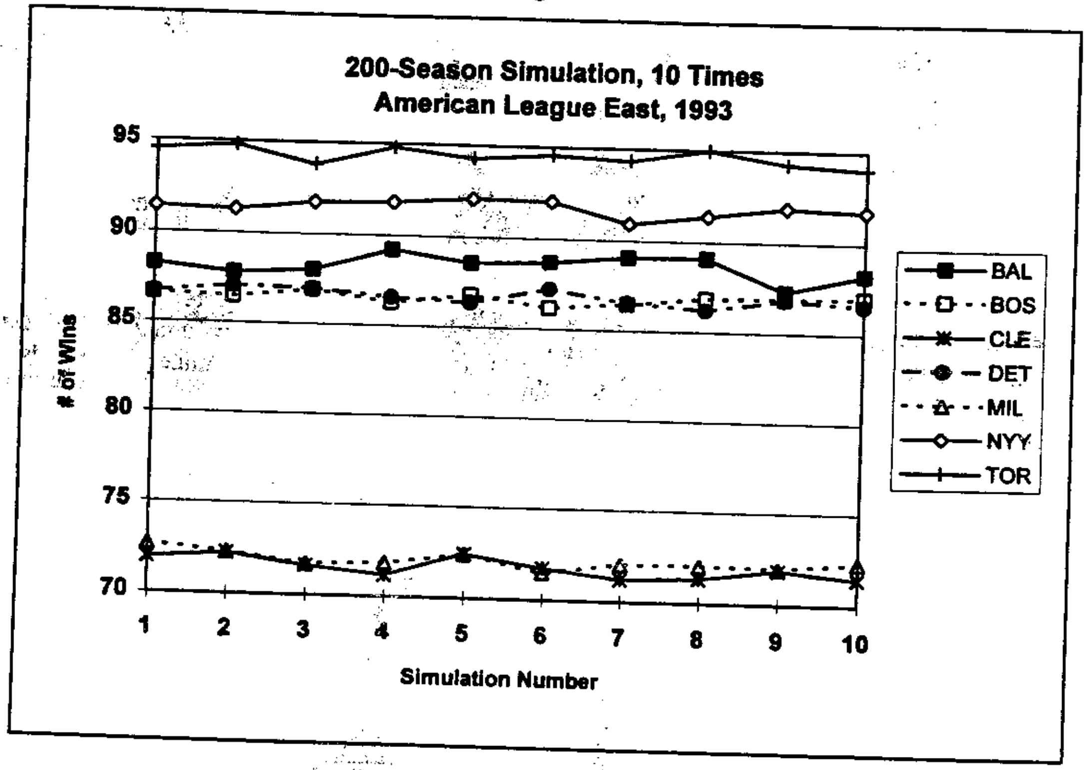
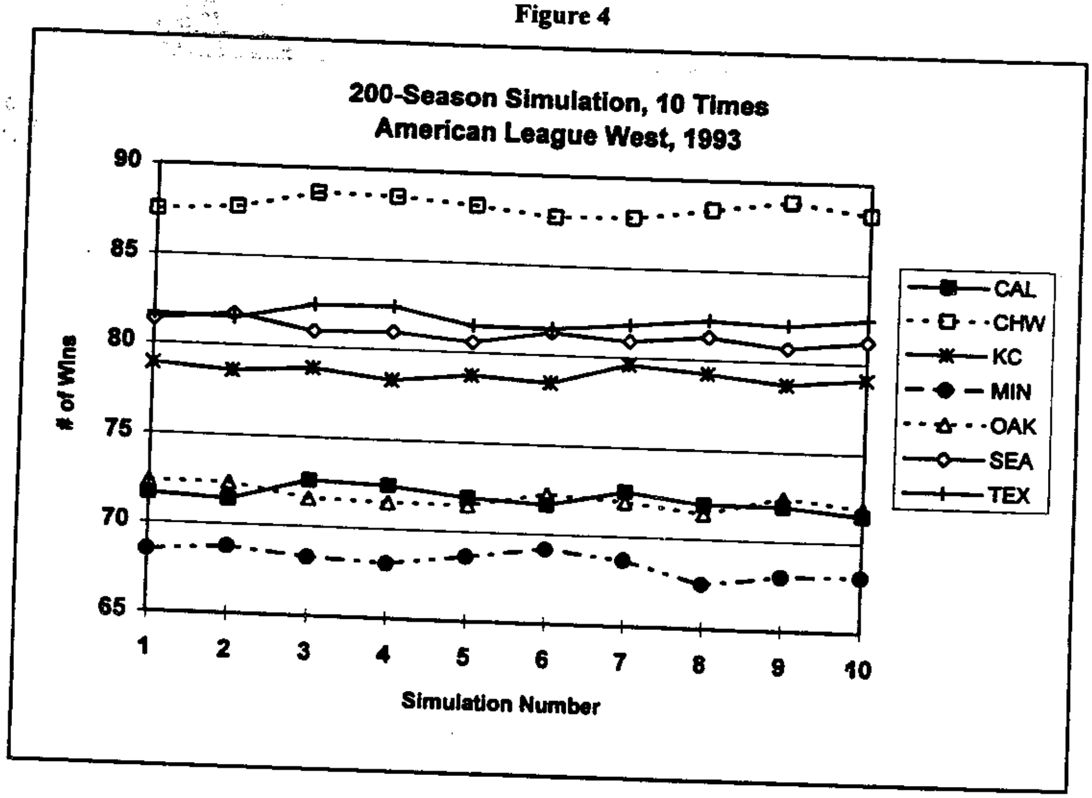



Figure 4



## HOW ACCURATE ARE THE RESULTS?

Okay, now that we can obtain **consistent** simulation results, let's see how **accurate** they are. I have re-created the last three full major league seasons: 1993, 1992, and 1991. For each of these three seasons, I have run a single 200-season simulation and then compiled the average results for each team.

Perhaps the most striking thing about the simulated results for the three seasons is how accurately the division champions were simulated. Of the 12 division champions in this time period, 11 of them were correctly identified. The sole exception was the 1992 AL West, in which both Minnesota and Chicago were simulated to narrowly beat real-life division champion Oakland.

In each of the three seasons that were simulated, there was a range of how close the simulated team results were to the actual results. For the three seasons combined, the simulated and actual results were within 2½ games for approximately one-third of the teams (28 out of 80), and were within 5 games for approximately two-thirds of the teams (53 out of 80). See the table below.

**Simulated vs. Actual Results**
**(Number of Teams)**

| | | # of Wins Difference | | | | | |
|---|---|---|---|---|---|---|---|
| Year & League | | <2.5 | 2.6-5.0 | 5.1-7.5 | 7.6-10 | >10 | Total |
| 1993 | AL | 5 | 7 | 2 | 0 | 0 | 14 |
| | NL | 5 | 3 | 2 | 1 | 3 | 14 |
| | Total | 10 | 10 | 4 | 1 | 3 | 28 |
| 1992 | AL | 4 | 5 | 2 | 2 | 1 | 14 |
| | NL | 4 | 3 | 2 | 2 | 1 | 12 |
| | Total | 8 | 8 | 4 | 4 | 2 | 26 |
| 1991 | AL | 7 | 2 | 1 | 3 | 1 | 14 |
| | NL | 3 | 5 | 1 | 2 | 1 | 12 |
| | Total | 10 | 7 | 2 | 5 | 2 | 26 |
| | | | | | | | |
| 3-Season Totals | | 28 | 25 | 10 | 10 | 7 | 80 |

In each of the three seasons that were simulated, there were a handful of teams whose simulated results were significantly different than their actual results. Here are the teams for which there was the largest differences between simulated and actual results.

<u>"Overachievers"</u> (actual results were much better than simulated)

1993: Expos, Giants
1992: Athletics, Angels, Pirates
1991: Tigers, Angels, Padres

<u>"Underachievers"</u> (actual results were much worse than simulated)

1993: Mets, Padres
1992: Mariners, Phillies, Dodgers
1991: Orioles, Indians, Mets, Reds

There is a noticeable pattern to these results: the "overachieving" teams are strong clubs, and the "underachieving" teams are weak clubs. Of the overachieving clubs, all of them except for the 1992 Angels had a winning record. The nine underachieving clubs, on the other hand, had an average record of 66 wins and 96 losses, and six of the nine underachieving teams finished last in their respective divisions.

There are many possible explanations for differences between simulated and actual results. Some explanations relate to the fact that the computer simulation program is not as sophisticated or realistic as it could be. Other explanations relate to the sometimes quirky results of the actual seasons that have been played.

Computer simulation program. There are several ways in which the computer simulation program could be expanded, to possibly improve the accuracy of the simulated results. For example, the following factors are not included in the simulation program:

- defensive skills
- baserunner quality (the program currently includes basestealing, but not other baserunning skills)
- pinch-hitting and in-game substitutions of fielders
- ballpark adjustment factors
- left- and right-handed batting and pitching adjustments
- ground-to-air ratios (more accurate results for batter outs)

Actual season results. In a real-life baseball season, there are a number of reasons why the team with the better individual performances may not necessarily win the most games. Some teams may win more close games (1-run games and extra inning games). Some teams may win quite a few games in which they are "outplayed" by the other team; for example, a team might be out-hit 10 hits to 3 hits, but might still win the game if one of their hits was a home run with runners on base. These real-life deviations, in which a team does significantly better or worse than could reasonably be expected from their individual performances, depend upon factors that cannot be forecast or simulated.

**CONCLUSION**

By running a larger number of simulations and calculating the average results of the simulations, it is possible to obtain consistent results for major league baseball. The results indicate the team results that can be expected by combining the performances levels of individual batters and pitchers. I have reached no conclusions about how to explain the differences between simulated and actual results. For those teams whose actual records were significantly better than the computer simulation showed, it would be interesting to determine whether these teams were "good" (by taking advantage of circumstances, and getting the most out of their individual performances), or just "lucky" (by benefiting from the sequence of hits, or by outscoring their opponents despite having inferior individual performances).

Understanding the differences between simulated and actual results would raise the possibility of using computer simulation as a forecasting tool (simulating the effects of player trades, changes in batting order, etc.) in addition to simulating seasons that have already been played.

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[1] The inconsistent results of a single-season simulation are very similar to the results documented by Doug Pappas in his June 23, 1993 paper entitled "Tinkering Ever with Chance". When Doug simulated the 1992 season twenty times, every team had at least an 18-game spread between its best and worst record.

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Thanks for reading this issue of *By The Numbers*. Submit articles to Dave Raglin at the address on page 1 or via the Internet at 73730.3354@ compuserve.com. Articles mailed must be on an IBM-format diskette. The next issue of *By the Numbers* will be September, 1995, and there will be a letters section, so send in your comments to this issue's articles.