Player Contribution

a method for allocating credit
for a team's performance
to the individual contributors
on a hockey team.

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Introduction

"Player Contribution" (PC) is a method for allocating credit for a team's performance to the individual contributors on a hockey team. More precisely, it is a way of allocating a team's wins to individual players. It puts offense, defense and goaltending performance on the same page, in the same currency.

Defense has always been the toughest part of the game to isolate. The real power of Player Contribution is its ability to get at defensive contribution in a meaningful way. The way to do that is to isolate the component parts of the game. If you identify offense and goaltending, the rest must be defense. Study situational play to break defense down into smaller, more homogeneous pieces. Identify defensive responsibilities by position. Once you have done all that, the pieces become easier to understand and defense becomes easier to quantify.

The Player Contribution method is basically:

1. Determine Team "Marginal Goals" (MG)
2. Allocate Marginal Goals to
   Marginal Goals Created (MGC) and Marginal Goals Prevented (MGP)
3. Split MGP into
   Marginal Goals Defense (MGD) and Marginal Goals Goaltending (MGG)
4. Allocate MGC and MGD to "Situations"
   (Even Handed, Power Play, Shorthanded, Penalties)
5. Translate Marginal Goals to Wins and to Player Contribution (PC)
6. Allocate MGC to Individual Players (PCO)
7. Allocate MGD to Individual Players (PCD)
8. Allocate MGG to Individual Goaltenders (PCG)

If the method is effective (and I will argue both that it is and that it has some gaps), it can help answer such questions such as:

- "How much did Todd Bertuzzi's penalty taking hurt Vancouver?"
- "Who is the best defensive forward in the NHL?"
- "How good will Colorado be without Patrick Roy?"
- "Who are league's most effective penalty killers?"
- "How far is St. Louis away from winning the Stanley Cup?"
- "What does Derian Hatcher's signing mean for the Red Wings? And is he worth it?"

First I need to give credit where it is due. Player Contribution is rooted firmly in the work of Bill James. His "Win Shares" system for baseball was the inspiration for my work and his methodology has been adapted here. I take no credit for the fundamental thinking. But James points out that he decided, in making Win Shares, to "worry about the small stuff". My work departs substantially from his because hockey ain't baseball and the devil is in the details.

I began this work in the fall of 2002 and completed it ("Version 3.0") in the summer of 2003. Very late in the process I discovered that Iain Fyffe had published his Point Allocation method in the spring of 2002. Iain's inspiration and objective were exactly the same as mine. At the highest level, his basic methodology is the same as mine. We diverge in the details. I think that I have sweated more details than Iain. But after a career of model building, I would be the first to tell you that a more complex model is not necessarily a better model. In the spring of 2003, Tom Awad also published a method for getting at player contribution called "Goals Versus Average". In it he did some math that gets to something like my "Goal Allowance Rates". Goal Allowance Rates are central to the understanding of defense and I developed this independently. I believe that my approach is more rigorous than Tom's. But we both tried to use this concept in the same way.

And now for some disclaimers:

- Player Contribution looks at marginal performance. We effectively draw a line in the sand and say: players to the left contributed negative value, players to right contributed positive value. Mathematically, the consequences are clear. In reality, the line is fuzzy.

- Player Contribution attempts to allocate a team's success to individual players. Although we will use the system to answer "what if" questions about the presence or absence of a player, this is treacherous ground. A team is a complex process, full of interactions and synergies. Not all of an individual's on-ice contribution to the team is captured by Player Contribution. And the off-ice contribution is clearly absent.

- There is no measure of coaching in Player Contribution. Yet coaching and systems seem to matter a great deal. Players get the credit for good coaching (sorry Jacques Lemaire).

- Player Contribution was constructed to take advantage of all that we currently know. It is only really usable for leagues and seasons in which we know all the statistics that are used. To use Player Contribution historically requires some significant simplifications. I have been working on this, but the results are disappointing so far.

- This analysis is about the regular season. The playoffs are a different world. In particular, the playoffs are a tournament involving the league's best teams. You can determine Player Contribution during the playoffs, but you cannot expect regular season PC rates to continue into the post season because the playing field is no longer level.

- The analysis discussed is of the NHL's 2002-03 season. Certain "factors" would vary from season to season. You need to apply the theory of Player Contribution to look at other seasons [1].

This paper was originally written in August, 2003 (Version 3.0). Subsequently I have enhanced the method as described in this paper (April 2004, Version 3.2). The principal change in Version 3.2 was the method of determining defensive contribution.

[1] See http://www.HockeyAnalytics.com/research.html for analysis of other seasons.

Predicting Wins

It is all about wins! Winning is everything. Success is denominated in wins. But how do teams win games? And how do players help teams win games?

This paper attempts to answer the second question.

The answer to the first question is pretty basic. Over the course of a season, **a team will win more games than it loses if it scores more goals than it allows.** Although a team only needs to outscore its opposition by a single goal to win a single game, the bigger the goal differential over the course of the season, the better the team's winning percentage will be.

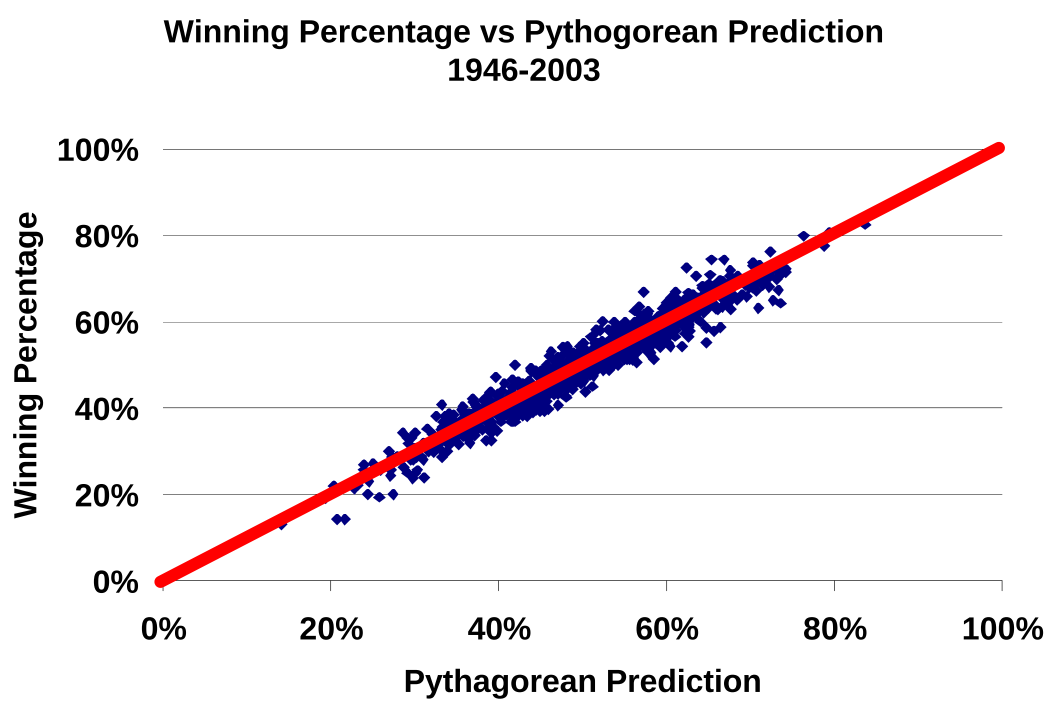
It has been well established in baseball circles that the "Pythagorean Relationship" of runs scored to runs allowed does a very good job of predicting the winning percentage of a baseball team. The same theory can and does apply in hockey. The formula is generally expressed:

Predicted Winning Percentage $= GF^2 / (GF^2 + GA^2)$

But I prefer the following equivalent expression, which demonstrates that it is the **ratio** of GA to GF that drives the formula:

Predicted Winning Percentage $= 1 / (1 + (GA/GF)^2)$

To illustrate, I have charted below the predicted and actual winning percentages for the NHL from the 1945-46 season through 2002-03. Note that, when calculating actual



winning percentage, a tie is counted as half a win. The prediction would be perfect if all the data points sit on the solid line. You can see that the predictive quality of the Pythagorean Relationship is quite high:

Since WWII, the Pythagorean formula predicts winning percentage with about 93.5% accuracy (the formula can be enhanced slightly with a more exotic exponent). The unexplained variation of 6.5% can only be due to either (a) a model deficiency, (b) random factors ("luck") or (c) non-random factors ("clutch play" or "choking").

A great deal of research has been done on this relationship in baseball. Most believe that the unexplained variation is due to luck. In hockey, there has been occasional sustained over or under-performance. But it is more often the case that, when a team exceeds (lags) the predicted winning percentage of the formula in any given year, it is unlikely to sustain that over (under) performance, and therefore demonstrate an ability to win (lose) close games the following year. Another way of looking at it is that the Pythagorean prediction of this season's winning percentage is actually a more powerful predictor of winning percentage in the following season than is this season's winning percentage. Of course, the unexplained variation could be due to a "lurking variable", something missing from the model. But no one has found it yet.

Why do we care about predicting wins? **If we have a simple formula that predicts wins with a high degree of accuracy, then that formula must be capturing the vital elements of a win.** Pythagoras tells us that, if we know goals for and goals against, we know almost all we need to know about what creates wins. And, if we could allocate goals for and goals against to individual players, we might be able to translate this strong predictor of wins to the player level.

Can we do this? The problem with the utility of Pythagoras is that it is a "non-linear" formula. Non-linear formulae don't "add up". The whole is not the sum of the parts.

The problem can be seen this way. Say you have a completely average team (Team A) which both scores and allows the league average of 205 goals. You don't have to do the math to see that this team will have an expected winning percentage of .500. If Team A scores or prevents 5 additional goals over the course of an 82 game season, it will be expected to win an additional game along the way (or convert two ties to wins, or two losses to ties).

Now let's look at an exceptional team (Team B) that scores 287 goals (40% more than our average team) and allows only 123 goals (40% less). This team would have an expected winning percentage of .840 (or 69 wins in 82 games). To achieve one additional expected win it would need to score 14 additional goals. This makes sense. Given that Team B wins so many games already, randomly sprinkling an additional 5 goals scored around the season is less likely to have the impact that it would have for Team A. The problem of non-linearity is that "cost" of an additional win varies with the degree of success of the team.

At the individual player level, this says that the impact of adding Mario Lemieux to Team A is much greater than the impact of adding Mario Lemieux to Team B. Furthermore, the order in which you "add" players to a team affects their contribution. If Team B already has Mario, he is worth more than if the team is considering adding Mario. So you cannot simply add up individual performance, as predicted by the Pythagorean relationship, to arrive at team performance. Pythagoras says, rightly, that a team is a complex thing.

Step 1: Determine Marginal Goals

The good news is there is a pretty good **linear** approximation to the Pythagorean Relationship over the normal ranges of goals scored and allowed. Pythagoras is based on the **square** of the **ratio** of GA/GF. This approximation relies on the **difference** between GF and GA. "Marginal Goals" is defined as follows:

Marginal Goals = Goals For – Goals Against + League Average Goals For
MG = GF – GA + GF<

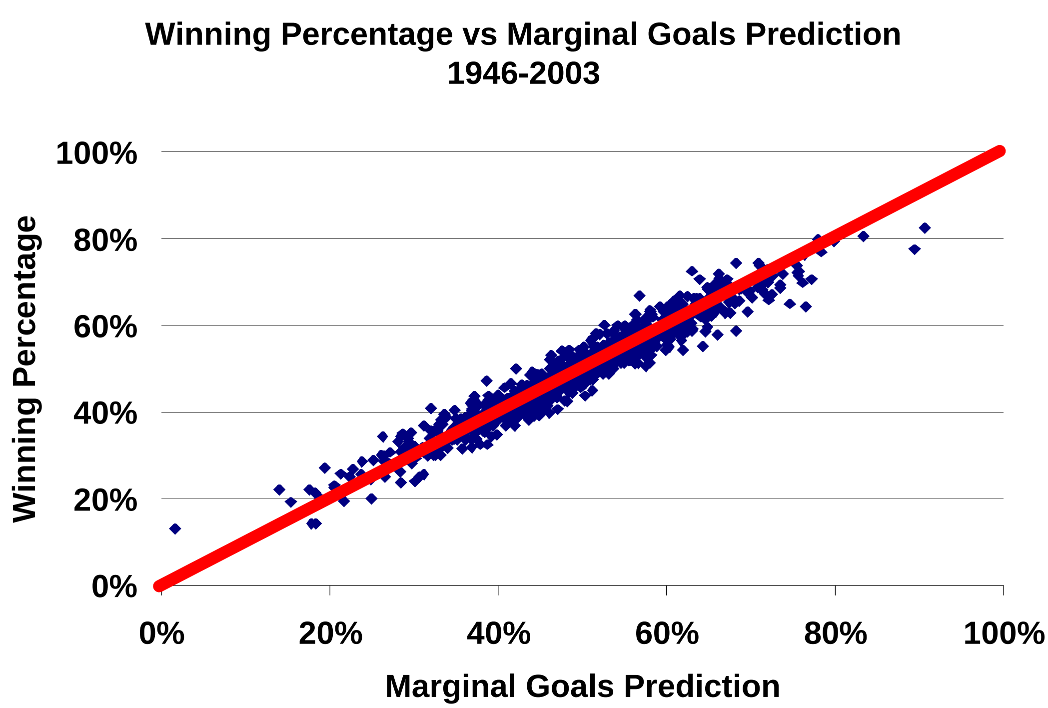
Note that I will be using "XX<" to mean the league average for the statistic "XX". Also note that GF< = GA<.

When you look at this formula, you can see that every team starts with a certain credit (League Average Goals For) and gets and additional credit (or slapped with a debit) depending on the degree to which is scores more goals than it allows.

A consequence of this definition is that Marginal Goals gives us a simple prediction of wins:

Predicted Winning Percentage = MG / (2 x GF<)

Marginal Goals is not quite as good a predictor of winning percentage as the Pythagorean approach. It explains 93.3% of the variation we see in winning percentage (vs. 93.5% for Pythagoras). But for the purposes of this work it is usually good enough. Below are the predicted and actual winning percentages for the NHL from the 1945-46 season through 2002-03. Note that the graph is a bit "S" shaped. Extremely poor teams tend to outperform the prediction while extremely good teams tend to under perform the



prediction. But the Marginal Goals approximation works pretty well for teams with a winning percentage between 30% and 70%. As you can see, this is covers most of the data.

The premise of Marginal Goals is that a team comprised of “marginal” players would score and prevent some goals, but would win no games. What is a marginal player? Mathematically, a marginal player is simply a player contributing at the level of a line drawn “in the sand” somewhere near the bottom end of major league performance. Although not quite true, you can think of him as “replacement player” -- a good player in the minors or the guy on the end of the bench.

There is an apparent anomaly here. A team with zero Marginal Goals is presumed to win zero games. But Pythagoras will tell us that this is not true, that such a team will win some games. That is not the point. Most teams function well above zero. What we are really interested in is the establishment of the level of individual performance which will not add anything to a team’s success. As team success is very close to a linear function of over the range of performance that matters, extrapolating that line to the level of zero performance tells us how to get to “marginal performance”.

For individuals we start with an assumption that there is a threshold rate of goal scoring which marginal players achieve. That rate of scoring must have zero “contribution” to the team. It is easier to think of this in terms of replacement players. Since that marginal player is easily replaced with another marginal player, his performance must have zero “value”. As scoring improves, the player’s contribution increases above zero. We can apply the same logic to defense. If a player’s defense is below a certain level, he is replaced. As it improves beyond a threshold, we observe a positive contribution to the team. Actually, for skaters, these two factors get combined. You can be a sub-marginal defensive player if your offense rescues you. If a goaltender fails to stop enough shots, he sits. Otherwise … well, you get it.

Can a player have a negative contribution? The theory says that such a player would not get to play as there are other players available with higher skills. In reality, players can have negative value. The coach may not detect the performance. A team’s talent pool may be too thin. The coach may run out of options. There is some “friction” in the movement of players from minors to the NHL. All of these things say that negative contribution can emerge.

A nice consequence of the definition of Marginal Goals is that it gives us a simple measure of the impact of additional (or fewer) goals: Marginal Goals / Wins (a tie is half a win). Across the league the average marginal goals per win is simply the average number of goals scored per game (since each game results in a win, or two ties):

Average Marginal Goals per Win = (GF< + GA<) / GP = 2 x GF< / GP

We can think of the “cost” of a win as Marginal Goals / Win. In 2002-03, MG/W ranged from 5.9 for San Jose to 4.6 for Atlanta. The average was 5.3. When scoring is up, the cost of a win is obviously higher. Teams averaged 4.0 goals scored per game in the

1981-82 season, making the average cost of a win 8.0 Marginal Goals. MG/W ranged from 9.3 for Washington to 7.2 for the New York Rangers.

Keep 5.3 MG/W in mind as we proceed. When we talk about 5 Marginal Goals, you can translate that to about 1 win (at least for 2002-03). But also remember that MG/W does vary by team. Some teams are more efficient than others at translating goals into wins. This can be a consequence of limitations of Marginal Goals (recall that extremely poor teams are more efficient than predicted). It can also be a result of some intangible (clutch play or choking). But over the normal range of team performance, it is most often just plain luck. I can demonstrate this, but I won't do it here.

Step 2: Allocate Marginal Goals to Offense and Defense

Consider the following two teams, each of which would be expected to have a .500 record:

Team A scores 240 goals and allows 240 goals
Team B scores 170 goals and allows 170 goals.

Clearly Team A is a better offensive team and Team B is a better defensive team. But they are still expected to be .500 teams. If we define:

Marginal Goals Created = MGC = GF - (GF< x Threshold Percentage)
Marginal Goals Prevented = MGP = (GF< x (1 + Threshold Percentage)) - GA

we have a way of measuring the differing ways in which Team A and teams B get to the same result. But note that the formulae are constructed so that:

MGC + MGP = GF – GA + GF< = Marginal Goals

regardless of the Threshold Percentage.

You can interpret MGC as goals scored (credit) in excess of some minimum standard (debit). You can interpret MGP as goals against (debit) subtracted from some maximum standard (credit). We will be using credits and debits to build the rest of Player Contribution.

Marginal Goals was formulated to express its offensive and defensive components. But what is the right Threshold Percentage? An obvious one might be 50%. Mathematically, this would put 50% of the weight on each of offense and defense (and for this reason, I will now call the Threshold Percentage the Defensive Attribution or DA).

Bill James argues for baseball that the Defensive Attribution is 52%, placing more weight on defense. His rationale (which runs on for a few pages) is summarized as:

> " a) I am convinced that it is as logical to do this as it is not to do it, and
> b) it causes problems if your don't"

So much for science. James' argument is essentially that the results of his Win Shares calculation fit the data better with a DA of 52% than with a DA of 50% or with a DA of 54%.

It does make sense to me that, in hockey, the DA should be greater than 50%. When the average number of goals scored / allowed per game is in the range of 2.5 to 4.0, it would seem to take a great deal of defensive effort to keep the goals allowed down to this level. If you don't believe me, just watch the NHL All Star game. How many players are sent in on a forecheck? When do you do a line change? Do you want a defenseman jumping into the rush? How do you feel about the break out pass up the middle of the defensive zone? The answers to questions like these depend on how much you want to risk a defensive crisis. Most coaches don't want this risk. I contend that the game is significantly more than 50% defense.

But I will come at this issue from a more scientific angle. There are normally 6 players on the ice. Five of these players are expected to play both offense and defense. On an average team, these "skaters" will play offense half the time and defense half the time. One player, the goaltender, is a defensive specialist. Hence we have 5 players playing offense half the time (5/6 x 1/2) and defense half the time (5/6 x 1/2) and the goaltender fully devoted to defense (1/6). This suggests that 7/ 12 (58.3%) of the team's resources are allocated to defense. The percentage rises if you factor in penalties. But I have used a DA of 58.3%. Keep in mind that this is the most critical assumption I will make. I will discuss it further at the end of this paper.

Once you have DA, you can determine MGC and MGP. Here is what these calculations look like for the 2002-03 season:

2002-03 Team Marginal Goals Created, Prevented and Total

TEAM	GF	GA	Wins *	MGC	MGP	MG	MG/W
Anaheim	203	193	44.5	76.0	151.6	227.7	5.1
Atlanta	226	284	34.5	99.0	60.6	159.7	4.6
Boston	245	237	41.5	118.0	107.6	225.7	5.4
Buffalo	190	219	32.0	63.0	125.6	188.7	5.9
Calgary	186	228	35.5	59.0	116.6	175.7	4.9
Carolina	171	240	27.5	44.0	104.6	148.7	5.4
Columbus	213	263	33.0	86.0	81.6	167.7	5.1
Chicago	207	226	36.5	80.0	118.6	198.7	5.4
Colorado	251	194	48.5	124.0	150.6	274.7	5.7
Dallas	245	169	53.5	118.0	175.6	293.7	5.5
Detroit	269	203	53.0	142.0	141.6	283.7	5.4
Edmonton	231	230	41.5	104.0	114.6	218.7	5.3
Florida	176	237	30.5	49.0	107.6	156.7	5.1
Los Angeles	203	221	36.0	76.0	123.6	199.7	5.5
Minnesota	198	178	47.0	71.0	166.6	237.7	5.1
Montreal	206	234	34.0	79.0	110.6	189.7	5.6
Nashville	183	206	33.5	56.0	138.6	194.7	5.8
New Jersey	216	166	51.0	89.0	178.6	267.7	5.2
NY Islanders	224	231	40.5	97.0	113.6	210.7	5.2
NY Rangers	210	231	37.0	83.0	113.6	196.7	5.3
Ottawa	263	182	56.0	136.0	162.6	298.7	5.3
Philadelphia	211	166	51.5	84.0	178.6	262.7	5.1
Phoenix	204	230	36.5	77.0	114.6	191.7	5.3
Pittsburgh	189	255	30.0	62.0	89.6	151.7	5.1
San Jose	214	239	32.5	87.0	105.6	192.7	5.9
St. Louis	253	222	46.5	126.0	122.6	248.7	5.3
Tampa Bay	219	210	44.0	92.0	134.6	226.7	5.2
Toronto	236	208	47.5	109.0	136.6	245.7	5.2
Vancouver	264	208	51.5	137.0	136.6	273.7	5.3
Washington	224	220	43.0	97.0	124.6	221.7	5.2
Average	217.7	217.7	41.0	90.7	127.0	217.7	5.3

- *"Wins" are calculated as Wins + Ties / 2*

The method gives about twice as much offensive credit to St. Louis as it does to Pittsburgh even though it scored just 34% more goals. The method presumes that a team of marginal players would have scored 127 (58% x 217.7) goals and that only goals in excess of this threshold made a difference.

The method gives St. Louis about twice as much defensive credit as Atlanta. The method presumes that a team of marginal players would have allowed 344 (158% x 217.7) goals and that only goals prevented below this threshold made a difference.

Edmonton was the league's most average team. The Oilers scored 231 goals and allowed 230. This translates to 218.7 Marginal Goals. Edmonton "won" 41.5 games and the average win cost 5.3 goals. Ottawa was the league's best team (56.0 wins and 298.7 MG) and Carolina went from the 2001-02 Stanley Cup finals to being the worst team in the league (27.5 wins and 148.7 MG). We already know this, but MGC and MGP are important steps on the road to Player Contribution.

Let's have a quick look at the worst 5 offensive and defensive teams since 1945-46:

Team Marginal Goals Created and Prevented
Worst Teams Since 1945-46

Worst Offensive Teams			Worst Defensive Teams		
Team	Season	Marginal Goals Created	Team	Season	Marginal Goals Prevented
NY Islanders	1973	21	Washington	1975	-12
Washington	1975	21	Chicago	1951	21
Kansas City	1975	24	Chicago	1954	24
Ottawa	1993	24	Chicago	1947	26
Tampa Bay	1998	25	Boston	1962	28

This data shows that even very bad teams still generate, with one exception, positive marginal goals. The symmetry between these two data sets is also an endorsement of the method and of our selection of 58.3% as the DA. The 1975 Capitals are the worst team to skate since World War 2. Washington's truly awful defensive team of 1975 is a clear outlier in the data. How can you have negative Marginal Goals Prevented? Only by having a team of sub-marginal defensive players. But note that no other team has ever been close to such a performance. If we were to adjust the DA to get Washington's MGP up to zero, the DA would have to be 63%. That would destroy the symmetry of the results. That doesn't feel right. So the 1975 Capitals will just have to remain a team of sub-marginal defensive players

The 1975 Capitals illustrate again the difference in the predictive quality of the Pythagorean Method and Marginal Goals. The Caps collected 21 points in 80 games, scoring 181 goals and allowing 446. Pythagoras predicts 23 points for the team – not bad. Marginal Goals predicts only 3 points for this team – not good. This is demonstration of the limitations of the Marginal Goals approximation to the Pythagorean Method. It is least effective for extreme teams. It will understate the predicted performance of very poor teams and overstate the predicted performance of outstanding teams.

Step 3: Allocate Marginal Goals Prevented to Skaters and Goaltending

Because Marginal Goals is a linear equation, the total must equal the sum of the parts:

Marginal Goals Prevented = Marginal Goals Defense + Marginal Goals Goaltending
or
MGP = MGD + MGG

Since we know the whole, if we can get either part we know both parts. Defense is an elusive thing to measure. So we will get at it by measuring the impact of goaltending.

Let's start with a theory of goal prevention**. The role of the defender is to minimize both the quantity and the quality of shots on goal.** On a 2 on 1, a defender is doing a good job if he is able to take away the pass while forcing the puck carrier to a bad angle. A shot is likely, but the defender is working at reducing its quality. A bad angle is a lower quality shot. A pass might result in a higher quality shot. Once a shot has been taken, the defender's job is to worry about the rebound. Perhaps this shot can be prevented. If allowed, it may well be of high quality.

The role of the goaltender is to stop shots. He will face shots of varying quality. A goaltender playing behind a poor defense may have either or both of more shots or more dangerous shots.

For the moment, let's assume that all goaltenders face an array of shots that are of similar quality. If that is the case, save percentage will tell us much of we want to know about a goaltender's contribution to a team's success. The other pieces are his exposure to shots and the save percentage of a "marginal goaltender".

Using the basic method of credits and debits:

MGG = Marginal Goals Goaltending
= Scoring Opportunities x Save Percentage - Scoring Opportunities x Save Percentage Threshold
= Scoring Opportunities x (Save Percentage - Save Percentage Threshold)
= (Shots on Goal – Empty Net Goals) x (Save Percentage – Save Percentage Threshold)
or
MGG = (SOG – ENG) x (SV% -SPT)

Alternatively:
MGG = Threshold Goals – Actual Goals
= (Shots on Goal – Empty Net Goals) x (1–Save Percentage Threshold) – (Goals Against–Empty Net Goals)
or
MGG = (SOG – ENG) x (1 – SPT) – (GA – ENG)
= (SOG – ENG) x (1 – SPT) – (SOG x (1 – SV) – ENG)

What is the right Save Percentage Threshold? Let's go back to offense for a moment. Setting DA to 58% means that a team with scoring 42% below league average will be considered "marginal". In other words, a player with offense at 58% of the norm has no value. It is difficult to prove, but this is the presumed level at which a player flunks out of the NHL. The same is true for defense. When a player has defense that is worse than 158% of normal, he is thought to be a marginal player.

When do goaltenders tend to flunk out of the NHL? This is a tricky question to answer since there are so few goaltenders and some sub-marginal players play more than a few games below this level. The SPT clearly is a function of the openness of the game.

I have set the 2002-03 Save Percentage Threshold (SPT) to 89.3%. This is the level at which MGG equals 16.67%, or 1/6th, of league Marginal Goal totals. The following formula forces SPT to be 1/6th:

SPT = .893 =1 - (GA x 7/6 - ENG) / (SOG - ENG)

The result of using 89.3% for SPT is that there are some goaltenders playing at a sub-marginal level. But it is clear from their playing time that the coach would prefer someone else in the net.

The level of SPT turns out to be a very material assumption. In the recent past, an average team faces about 2300 shots per season. In 2002-03, lowering SPT by 1% results in 23 additional Goals Saved **per team** to be attributed to goaltending. This is the equivalent of about 4 wins. That's a lot. This is the reason why I forced MGG to be 16.67% of MG.

Let's now revisit the assumption that all goaltenders face an array of shots that are of similar quality. Historically, available statistics have forced us to make this assumption. We were stuck with the following simple model of goal prevention:

GA = SOG x (1 – SV)

We knew that Shots on Goal (SOG) was a defensive responsibility, so we have historically attributed it to the team. We knew that Save Percentage (SV) was more a goaltender statistic than a team statistic, so we have historically attributed it to goaltenders. I consider this to be a material, over simplification of goaltending. A defense that is good at minimizing shot quality will just have their goaltending look better!

To deal with this deficiency, I conducted a study [2] of the 2002-03 season game event logs and was able to construct a measurement of "shot quality". I defined SQA (Shot Quality Against) such that a team SQA of 1.05 means that the team is giving up shots which are 5% more "dangerous" than those of an average team (and 0.95 to be 5% less dangerous). That team would have, all other things being equal, 5% more goals against than an average team

Below are the results of the study, sorted from best (lowest shot quality allowed) to worst. As you can see, SQA ranges from .915 to 1.087. This is a big range. NHL teams

[2] See http://www.HockeyAnalytics.com/Research_files/Shot_Quality.pdf

averaged 218 goals against in the 2002-03 season. A swing of +/- 8.5% goals means +/- 19 goals for an average team, worth almost 4 wins over the course of the season. A team that both gives up a lot of shots and allows more dangerous shots will have the effect multiplied.

It came as no surprise to me that New Jersey lead the league in this metric, allowing 8.5% fewer goals than an average team because of its ability to minimize shot quality. Philadelphia and Minnesota are also not surprising teams to see on the SQA leader board. These three teams have a reputation for solid defense.

At the other end of the list were St. Louis, Florida and the Rangers. St. Louis and Florida were bookends in one respect. The Blues were thought to have awful goaltending whereas the Panthers were thought to possess outstanding goaltending. The SQA index tells us clearly that both of these teams had better goaltending than previously thought. And, obviously, the reverse is true. When a team is at the top of the SQA list, it means that its goaltenders faced softer shots and that their statistics are misleadingly good.

Shot Quality 2002-03

	SQA
NJD	0.915
PHI	0.935
MIN	0.947
CAL	0.953
TOR	0.956
TB	0.965
BUF	0.969
OTT	0.970
ANA	0.972
DAL	0.972
WAS	0.973
DET	0.976
PHO	0.980
MON	0.982
CHI	0.996
PIT	0.996
NAS	1.000
VAN	1.004
COL	1.018
EDM	1.018
SJ	1.022
CAR	1.024
BOS	1.027
NYI	1.037
CBJ	1.041
ATL	1.045
LA	1.048
NYR	1.057
FLA	1.078
STL	1.087

So now we are in a position to use a model that does a better job of isolating the responsibilities of goaltending and defense:

GA = SQA x SOG x (1 – SQNSV)

where SQA is the Shot Quality Against Index and SQNSV is the Shot Quality Neutral Save Percentage.

In this model we attribute both SQA and SOG to the defense and SQNSV to goaltending. Clearly SQNSV is a better measure of the goaltender's contribution to team success than is SV. You can think of it as the save percentage one would expect with no variation in shot quality from team to team.

How do you calculate SQNSV? The two models both give us Goals Against, so:

SOG x (1 – SV) = SQA x SOG x (1 – SQNSV),
or
(1 – SV) = SQA x (1 – SQNSV),
which means
SQNSV = 1 – (1- SV) / SQA

Below is a calculation of SQNSV for each team in the NHL in 2002-03, sorted from best to worst. I have included the team Save Percentage so that you can see what a huge difference this makes in our view of goaltending. Florida's goaltending, basically Roberto Luongo, jumps 7 positions into second place (but in a virtual tie for first). The Rangers also move up 7 positions to 10^{th}. Meanwhile, the Devils' goaltending slips 7 places to 14^{th}.

How does SQA affect the calculation of MGG? Use the final definition and replace SV with SQNSV:

MGG = (SOG – ENG) x (1 – SPT) – (SOG x (1 – SQNSV) – ENG)

I will show the results of this calculation during my discussion of the next step.

Shot Quality Neutral Save Percentage 2002-03

	SV	Rank	SQNSV	Rank
MIN	0.924	1	0.919	1
FLA	0.913	9	0.919	2
COL	0.916	5	0.918	3
ANA	0.919	2	0.916	4
DAL	0.918	3	0.916	5
PHI	0.918	4	0.912	6
DET	0.914	8	0.912	7
MON	0.913	10	0.911	8
TOR	0.914	6	0.910	9
NYR	0.905	17	0.910	10
NAS	0.909	14	0.909	11
WAS	0.910	12	0.908	12
OTT	0.910	11	0.908	13
NJD	0.914	7	0.906	14
TB	0.909	13	0.905	15
VAN	0.905	16	0.905	16
PHO	0.906	15	0.905	17
CBJ	0.900	20	0.904	18
NYI	0.900	21	0.904	19
CHI	0.904	19	0.903	20
SJ	0.900	22	0.902	21
BUF	0.905	18	0.902	22
LA	0.897	28	0.901	23
BOS	0.898	24	0.901	24
STL	0.892	29	0.900	25
CAR	0.897	27	0.900	26
EDM	0.898	25	0.899	27
PIT	0.899	23	0.899	28
ATL	0.890	30	0.895	29
CAL	0.897	26	0.892	30

Step 4: Allocate Marginal Goals to Situations

What do I mean by "situations"? The NHL currently tracks and publishes data on three situations: even handed, short handed and power play. There are refinements to this that might help us better understand the game: 5 on 5, 4 on 4, 3 on 3, 5 on 4, 5 on 3, 4 on 3, 4 on 5, 3 on 5 and various empty net situations. But we don't have this data and it would be limited in any case.

Why should we care about this? Offensive and defensive performance and expectations clearly vary amongst these three situations. We expect offense on the power play. We don't expect it while short handed. By breaking the game into smaller bits, we get more homogeneous data and gain a better understanding of the game. Take defenseman Andy Delmore (NAS) for example. He played 71 games, logging an average of 17 minutes per game, and scored 18 goals. That makes him look like a good offensive defenseman with some probable defensive weakness. But if you look at the situational data, the picture becomes clearer. He played an average of about 7 minutes per game on the power play, scoring 14 power play goals, and only 10 minutes per game even handed (an average defenseman plays about 15 minutes per game even handed). He played 7 minutes all season killing penalties! The picture now comes clearly in focus. This guy is a role player: all offense and no defense.

Except for one refinement, the allocation of marginal goals to situations is pretty simple. We already defined:

$MGC \quad = GF - (GF< \times DA)$

So let's just break it into its component parts:

$MGC^{EH} \quad = GF^{EH} - (GF^{EH}< \times DA)$ -- *Even Handed*
$MGC^{PP} \quad = GF^{PP} - (GF^{PP}< \times DA)$ -- *Power Play*
$MGC^{SH} \quad = GF^{SH} - (GF^{SH}< \times DA)$ -- *Short Handed*

We can do the same for Marginal Goals Prevented, except that we need to take note of the part that has already been allocated to goaltending. To do that let's define:

$G \quad = MGG / MGP$ -- *the percentage of MGP allocated to goaltending*

Then:

$MGD \quad = MGP – MGG \quad = (1 – G) \times MGP$
$MGD^{EH} \quad = (1 – G) \times ((GA^{EH}< \times (1 + DA)) – GA^{EH})$
$MGD^{PP} \quad = (1 – G) \times ((GA^{PP}< \times (1 + DA)) – GA^{PP})$
$MGD^{SH} \quad = (1 – G) \times ((GA^{SH}< \times (1 + DA)) – GA^{SH})$

Note that GF< = GA< for all situations.

Below are the results for 2002-03:

2002-03 Team Marginal Goals Created, Defense and Goaltending by Situation

	Offense						Defense					Goaltending		
TEAM	MGC	MGC %	EH	PP	SH	MGP	MGD	MGD %	EH	PP	SH	MGG	MGG %	G
Anaheim	76.0	33%	51.3	21.2	3.5	151.6	88.3	39%	53.6	4.2	30.5	63.4	28%	42%
Atlanta	99.0	62%	66.3	29.2	3.5	60.6	50.2	31%	27.4	-1.5	24.3	10.4	7%	17%
Boston	118.0	52%	88.3	24.2	5.5	107.6	87.8	39%	62.9	0.9	24.0	19.8	9%	18%
Buffalo	63.0	33%	43.3	16.2	3.5	125.6	99.3	53%	65.7	0.9	32.7	26.4	14%	21%
Calgary	59.0	34%	46.3	12.2	0.5	116.6	113.2	64%	82.6	2.1	28.5	3.4	2%	3%
Carolina	44.0	30%	19.3	23.2	1.5	104.6	83.6	56%	63.2	2.5	17.9	21.0	14%	20%
Columbus	86.0	51%	42.3	36.2	7.5	81.6	48.8	29%	26.4	1.9	20.5	32.9	20%	40%
Chicago	80.0	40%	72.3	4.2	3.5	118.6	90.7	46%	58.2	3.2	29.3	27.9	14%	24%
Colorado	124.0	45%	90.3	33.2	0.5	150.6	86.9	32%	65.3	3.5	18.1	63.7	23%	42%
Dallas	118.0	40%	86.3	27.2	4.5	175.6	125.4	43%	89.3	4.4	31.7	50.3	17%	29%
Detroit	142.0	50%	94.3	41.2	6.5	141.6	93.9	33%	62.4	5.4	26.1	47.8	17%	34%
Edmonton	104.0	48%	74.3	21.2	8.5	114.6	94.3	43%	63.5	3.4	27.5	20.3	9%	18%
Florida	49.0	31%	32.3	14.2	2.5	107.6	30.3	19%	21.4	0.9	8.0	77.4	49%	72%
Los Angeles	76.0	38%	55.3	17.2	3.5	123.6	97.9	49%	65.8	6.4	25.6	25.7	13%	21%
Minnesota	71.0	30%	49.3	17.2	4.5	166.6	104.4	44%	67.7	4.5	32.2	62.3	26%	37%
Montreal	79.0	42%	72.3	9.2	-2.5	110.6	55.7	29%	34.3	3.1	18.3	55.0	29%	50%
Nashville	56.0	29%	35.3	23.2	-2.5	138.6	99.7	51%	72.7	3.0	24.0	39.0	20%	28%
New Jersey	89.0	33%	85.3	1.2	2.5	178.6	150.0	56%	90.8	6.8	52.4	28.6	11%	16%
NY Islanders	97.0	46%	65.3	24.2	7.5	113.6	77.2	37%	53.7	4.8	18.6	36.5	17%	32%
NY Rangers	83.0	42%	59.3	20.2	3.5	113.6	65.9	33%	51.1	2.4	12.4	47.8	24%	42%
Ottawa	136.0	46%	88.3	48.2	-0.5	162.6	132.3	44%	92.9	3.4	36.1	30.3	10%	19%
Philadelphia	84.0	32%	68.3	12.2	3.5	178.6	136.9	52%	99.8	3.2	34.0	41.7	16%	23%
Phoenix	77.0	40%	57.3	20.2	-0.5	114.6	78.7	41%	66.0	0.8	11.9	35.9	19%	31%
Pittsburgh	62.0	41%	32.3	31.2	-1.5	89.6	67.7	45%	38.6	1.6	27.5	21.9	14%	24%
San Jose	87.0	45%	53.3	33.2	0.5	105.6	77.7	40%	56.7	1.6	19.4	27.9	14%	26%
St. Louis	126.0	51%	74.3	45.2	6.5	122.6	102.0	41%	78.3	4.3	19.4	20.7	8%	17%
Tampa Bay	92.0	41%	55.3	35.2	1.5	134.6	100.6	44%	65.9	5.3	29.4	34.0	15%	25%
Toronto	109.0	44%	74.3	28.2	6.5	136.6	91.8	37%	62.6	3.5	25.8	44.9	18%	33%
Vancouver	137.0	50%	77.3	52.2	7.5	136.6	104.2	38%	77.9	1.6	24.7	32.5	12%	24%
Washington	97.0	44%	71.3	22.2	3.5	124.6	82.5	37%	62.3	5.4	14.8	42.1	19%	34%

MGC% = MGC / MG
MGD% = MGD / MG
MGG% = MGG / MG
G = MGG / MGP, goaltending's share of goal prevention

These results already tell us some interesting things about the way teams work. We don't need marginal goals to tell us that Detroit, Vancouver and Ottawa were the top offensive teams or that New Jersey, Philadelphia and Dallas were the best defensive teams. But here are some observations that are a consequence of this analysis:

- Carolina and Florida were the league's worst offensive teams. Nashville (29%) was the team least reliant on offense. They had a lot of company: Carolina, Minnesota, Florida, Philadelphia, New Jersey, Buffalo and Anaheim also had a low percentage of their Marginal Goals from offense. Atlanta was way out ahead at the other end of the list with 62% of marginal goals attributable to offense. Boston, Columbus, Detroit, St. Louis and Vancouver were other teams relying on offense.

- Calgary had the league's 5th best defense but destroyed it with an absence of goaltending. MGG for the Flames was 3 (2% of all their Marginal Goals). Atlanta had little goaltending (MGG = 10 or 7% of MG). Only 8% of the Blues Marginal Goals came from goaltending. The St. Louis offense created 126 goals (4th in league) and the defense saved 102 goals (8th). What would it have taken for St. Louis to win the Cup? Maybe free agent Ed Belfour. Adding Belfour (I am sneaking ahead here, but enjoy the fun) might have added about 25 Marginal Goals to St. Louis and brought them very close to Dallas and Detroit, the Western Conference leaders in Marginal Goals. Furthermore, St. Louis had the third lowest shots on goal total. Their offense may have opened up significantly with Belfour in the crease.

- Florida was, by far, the team most dependent on goaltending. Fully 49% of the Panthers Marginal Goals came from the crease. And 72% of MGP was in goal. Florida allowed more shots on goal than any team in the league and allowed the second poorest shot quality. Yet goaltending, mainly Roberto Luongo, rescued the team time and time again. Yes, the most impactful goaltending in the league came from Florida (MGG of 77). Three other teams collected more than 60 Marginal Goals from goaltending – Colorado, Anaheim and Minnesota.

- Calgary, Carolina and New Jersey were the three teams most dependent on defense (MGD% of 64%, 56% and 56%). New Jersey was way out in front with the league's best defense (MGD of 150). If we carve out goaltending, we can see the strong team defense of Philadelphia and Ottawa (MGD of 137 and 132). Florida, Montreal and Columbus were least dependent on defense (MGD% of 19%, 29% and 29%). And the worst defensive teams were Florida, Columbus and Atlanta (MGD of 30, 49 and 50).

- New Jersey had a power outage. Even handed, the Devils had an offense that is similar to Ottawa or Dallas. Maybe the problem with the power play was that it is too focussed on defense? This analysis says that they prevented more goals on the power play (MGD^{PP} of 7) than they created (MGC^{PP} of 1). Shocking! A dive into the details reveals that the New Jersey power play problem was one of a lack of opportunity (303 opportunities, last in the league) compounded by a lack of execution (11.9% power play percentage, also last in the league). More on this below.

- New Jersey's league leading MGD of 150 is clearly driven by short handed situations (MGD^{SH} = 52). Again we have a very unusual confluence of events. New Jersey had both the lowest number of short handed opportunities in the league and the best penalty killing.

- Even handed, the Devils defense (MGD^{EH} = 91) ranks behind Ottawa and Philadelphia. But was it really third best? Because New Jersey was last in the league in drawing penalties and last in the league in taking penalties, they must have been first in the league in even handed minutes. I estimate that New Jersey was even handed about 3.25 more minutes per game than average. That works out to about 4.4 extra games playing even handed. New Jersey's even handed goals against average is estimated to be 1.98 (goals against per 60 minutes of even handed play). If you add

8.75 goals to the Devils MGD^{EH} they virtually tie Philadelphia. If you look at the GAA^{EH} (which brings goaltending back into the mix), the Devils ranked third behind Dallas and Philadelphia. No matter which way you slice it, New Jersey had a very good defense.

Because MGD + MGG = MGP, whatever we allocate to goaltending, we take away from defense. Although the use of SQA has improved our understanding of goal prevention, there is still considerable potential for distortion in MGD vs MGG. If you look at the results of this analysis and feel that a team's goaltending is over or under rated, then you must also conclude that team defense is accordingly under or over rated. I will have some more to say on this when we talk about individual goaltenders.

Below is a graphical display of the relative impact of situational play across the NHL in 2002-03.

But I promised you a refinement. At the team level we know something about the triggering event for short handed situations – penalties. We know, for example, that New Jersey (264) and Toronto (426) allowed the lowest and highest numbers of short handed situations in 2002-03. Short handed opportunities are highly correlated to the number of minor penalties taken. New Jersey (314) also had the lowest number of minor penalties while Toronto was the third highest (490). So it would seem to be a useful refinement to split MGD^{SH} into the part associated with the **penalty kill** and the part associated with **penalty taking**. Below I will treat penalties as a fourth "situation", even though it is an "event" rather than a situation.

Shorthanded Situations

To split Marginal Goals Shorthanded into the penalty killing and penalty taking pieces, we need to do some algebra:

Let:

SHO = Short Handed Opportunities (SHO< is the league average)
PK = Penalty Killing Percentage (PK< is the league average)
G = Percentage of MGP allocated to goaltending
DA = Defensive Attribution (58%)

Then:

$$MGD^{SH} = (1\text{-}G) \times [(1+DA) \times GA^{SH}< - GA^{SH}]$$
$$= (1\text{-}G) \times [(1+DA) \times SHO< \times (1 - PK<) - SHO \times (1 - PK)]$$
$$= (1\text{-}G) \times [(1+DA) \times SHO< \times (1 - PK<) - SHO \times (1 - PK) + (1+DA) \times SHO \times (1\text{-}PK<) - (1+DA) \times SHO \times (1 - PK<)]$$
$$= (1\text{-}G) \times [(1+DA) \times (SHO< \times (1 - PK<) - SHO \times (1 - PK<)) + (1+DA) \times SHO \times (1\text{-}PK<) - SHO \times (1 - PK)]$$
$$= (1\text{-}G) \times [\underline{(1+DA) \times (1 - PK<) \times (SHO< - \mathbf{SHO})} + \underline{\mathbf{SHO} \times ((1+DA) \times (1 - PK<)) - (1 - \mathbf{PK})}]$$

I have highlighted the team based moving parts in the formula. And I have underlined the two parts of MGD^{SH}. Part 1 depends on the deviation of the number of short handed opportunities from then league average. Part 2 depends on the actual number of short handed opportunities and the penalty killing effectiveness compared to the league average. The first part we will treat as the penalty taking piece (MGD^{SHO}). The last part we will take as the penalty killing piece (MGD^{SHK}). This means:

$$MGD^{SHO} = (1\text{-}G) \times (1+DA) \times (1 - PK<) \times (SHO< - SHO)$$
$$\text{or} \quad = (1\text{-}G) \times (1+DA) \times (GA^{SH}< - SHO \times (1 - PK<))$$

$$MGD^{SHK} = (1\text{-}G) \times SHO \times ((1+DA) \times (1 - PK<)) - (1 - PK))$$
$$\text{or} \quad = (1\text{-}G) \times ((1+DA) \times SHO \times (1 - PK<) - GA^{SH})$$

I chose this decomposition of MGD^{SH} so as to make penalty taking neutral across the league. This means that some teams will have positive MGD^{SHO} and others will have negative MGD^{SHO}. There are an infinite number of ways to split MGD^{SH} into two pieces. This one relies on the premise that a certain level of penalty taking is normal. It also sets up Player Contribution for use across time.

Version 2 of these formulae let us see the decomposition in another way. MGD^{SHK} charges debits equal to short handed goals against. But the credit is not based on the league average of short handed goals against. Instead it is based on team SHO and league average, penalty killing effectiveness. When you combine these two factors in this fashion, you are taking the effect of the teams' penalty killing out of the credits.

Power Play Situations

What about the power play? At the team level we know something about the triggering event for power play situations – opposition penalties. In 2002-03, Carolina drew 497 minor penalties to lead the league. Sure enough, the Hurricanes tied the Maple Leafs with a league leading 420 power play opportunities. New Jersey trailed the league, drawing only 352 minor penalties and having only 303 power plays. We can use the logic developed for short handed situations to separate penalty drawing from the power play:

Let:
PPO = Power Play Opportunities (PPO< is the league average)
PP = Power Play Percentage (PP< is the league average)
DA = Defensive Attribution (58%)

Then:

$$
\begin{aligned}
MGC^{PP} &= GF^{PP} - DA \times GF^{PP}< \\
&= PPO \times PP - DA \times PPO< \times PP< \\
&= PPO \times PP - DA \times PPO< \times PP< + DA \times PPO \times PP< - DA \times PPO \times PP< \\
&= PPO \times PP - PPO \times DA \times PP< + DA \times PPO \times PP< - DA \times PPO< \times PP<) \\
&= \mathbf{PPO} \times (\mathbf{PP} - DA \times PP<) + DA \times PP< \times (\mathbf{PPO} - PPO<)
\end{aligned}
$$

This is completely analogous to the short handed math:

$$
\begin{aligned}
MGC^{PPO} &= DA \times PP< \times (PPO - PPO<) \\
\text{or} \quad &= DA \times (PPO \times PP< - GF^{PP}<) \qquad \text{-- Power Play Opportunities}
\end{aligned}
$$

$$
\begin{aligned}
MGC^{PPP} &= PPO \times (PP - DA \times PP<) \;\; \text{or} \\
&= GF^{PP} - DA \times PPO \times PP< \qquad \text{-- Power Play Production}
\end{aligned}
$$

This decomposition of MGC^{PP} also makes penalty drawing approximately neutral across the league. This means that some teams will have positive MGC^{PPO} and others will have negative $MGCP^{PPO}$. The second version of MGC^{PPP} shows that the power play goal scoring threshold is set relative to league average power play efficiency, given the actual number of power play opportunities.

Here are the results of this approach for 2002-03:

2002-03 Team Marginal Goals Created and Marginal Goals Defense Power Play and Short Handed

TEAM	MGCPP	MGCPPP	MGCPPO	MGDSH	MGDSHK	MGDSHO
Anaheim	21.2	22.6	-1.4	30.5	26.0	4.5
Atlanta	29.2	28.4	0.8	24.3	22.7	1.6
Boston	24.2	27.8	-3.6	24.0	26.6	-2.6
Buffalo	16.2	17.1	-0.8	32.7	32.8	-0.1
Calgary	12.2	9.7	2.5	28.5	35.2	-6.7
Carolina	23.2	17.7	5.5	17.9	24.0	-6.1
Columbus	36.2	31.7	4.5	20.5	27.7	-7.2
Chicago	4.2	9.5	-5.2	29.3	30.6	-1.3
Colorado	33.2	33.2	0.0	18.1	17.6	0.5
Dallas	27.2	30.6	-3.4	31.7	28.6	3.1
Detroit	41.2	45.4	-4.2	26.1	28.6	-2.5
Edmonton	21.2	19.0	2.2	27.5	25.0	2.5
Florida	14.2	15.7	-1.5	8.0	7.5	0.5
Los Angeles	17.2	18.0	-0.7	25.6	27.6	-1.9
Minnesota	17.2	16.9	0.3	32.2	23.3	8.9
Montreal	9.2	13.8	-4.6	18.3	12.3	6.0
Nashville	23.2	17.9	5.3	24.0	22.2	1.8
New Jersey	1.2	6.9	-5.7	52.4	30.8	21.5
NY Islanders	24.2	22.2	2.1	18.6	26.1	-7.5
NY Rangers	20.2	22.5	-2.3	12.4	16.2	-3.8
Ottawa	48.2	45.5	2.7	36.1	29.6	6.5
Philadelphia	12.2	15.6	-3.3	34.0	29.1	4.9
Phoenix	20.2	18.1	2.1	11.9	20.8	-8.8
Pittsburgh	31.2	31.5	-0.2	27.5	25.4	2.1
San Jose	33.2	32.0	1.2	19.4	18.5	0.9
St. Louis	45.2	42.5	2.7	19.4	25.1	-5.7
Tampa Bay	35.2	32.5	2.7	29.4	20.4	9.1
Toronto	28.2	28.6	-0.3	25.8	36.9	-11.1
Vancouver	52.2	46.7	5.5	24.7	30.1	-5.4
Washington	22.2	25.3	-3.0	14.8	18.5	-3.7

Let's look at what this says about penalties:

- New Jersey (21.5 MGD^{SHO}) won 3 or 4 games by staying out of the penalty box! Tampa Bay (9.1), Minnesota (8.9), Ottawa (6.5) and Montreal (6.0) all won at least a game by avoiding penalties.

- Toronto (-11.1 MGD^{SHO}) lost about two games through its lack of discipline. Phoenix (-8.8), NY Islanders (-7.5), Columbus (-7.2), Calgary (-6.7), Carolina (-6.1), St. Louis (-5.7) and Vancouver (-5.4) also hurt themselves a great deal through penalties.

- Carolina (MGCPPO = 5.5), Vancouver (5.5) and Nashville (5.3) each won an extra game by drawing lots of penalties. New Jersey (-5.7) and Chicago (-5.2) each lost an extra game by drawing few penalties.

- Toronto (36.9) lead the league in MGD^{SHK}. The Leafs took a lot of penalties yet they were relatively effective at killing them. Montreal (12.3) and Florida (7.5) trailed the league in this metric. Both teams relied heavily on goaltending while killing penalties poorly.

- There is greater variation in the penalty taking results than in the penalty drawing results. This makes sense as it is much easier to take a penalty than to draw one.

Step 5: Translate Marginal Goals to Player Contribution

So far we have been dealing with team data. Now it is time to start looking at individuals. Our objective is to allocate a team's success to individual players. We have defined Marginal Goals, making sure that it is "linear" (ie the whole is the sum of the parts). We have shown that MG is highly correlated to wins. Player Contribution will connect the dots and position us to apportion team wins to individuals.

Player Contribution = Player Contribution Factor x Marginal Goals
or
PC = PCF x MG
where
PCF = PCSF / (MG / W)

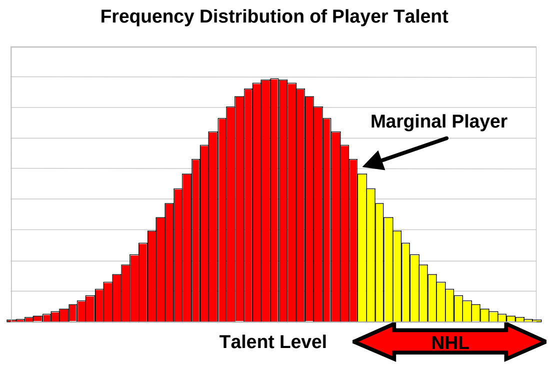
If you rework the terms, you see that Player Contribution is just a "scaling factor" (PCSF) times marginal goals divided by the "cost" of a win (Marginal Goals / (Wins + Ties / 2). The last piece of this formula translates Marginal Goals into "wins". PCF varies from team to team to mirror the variation in MG/W from team to team.

The scaling factor is introduced to adjust the resolution of the system. At the team level, I find it makes more sense to think of team performance in terms of Marginal Goals and wins. But once you start slicing the data down to the individual level, the pieces tend to look pretty small. So I have introduced a scaling factor as a kind of magnifying glass. I could have picked any factor. I picked PCSF = 20, partially because there are 20 players on a team but mainly because I got the kind of granularity of the results I was seeking. It is easier to see and feel the difference between PC = 80 and PC = 83, whereas it is harder to see the difference between PC = 4.02 and PC = 4.13. Just remember to divide by 20 if you want to get at the impact on wins and divide by 10 if you want to get at the impact on points.

We give something up when we make this translation. Marginal Goals is not perfectly predictive of wins. When teams are efficient or inefficient at winning games, it is usually not repeated the next season, it is usually due to luck. As a consequence, Marginal Goals may be a fairer measure of an individual player's efforts. But … by performing this translation, we adjust for the deficiencies of Marginal Goals. More importantly, we can perform a comparison of players over time. A win is a win and there is no better currency of success. And a Player Contribution "Point" has the same value today as it had in 1980, when goals were much cheaper.

So far we have been working with team data to allocate Marginal Goals to the constituent pieces of the game. Now we want to start figuring out the contribution of individuals to team success.

The first thing to observe (see below) about individuals is that the distribution of talent around average is no where close to being symmetrical. There are more players performing at 90% of average than at 110% of average. There are way more players performing at 70% of average than at 130% of average. This observation makes sense.



NHL players are the best hockey players in the world. They represent the "tail" of the distribution of all hockey players. When you are working with distributional tails, averages are meaningless. Working with deviations from average is a slippery slope. That is why we want to try to identify marginal performance (debits) and measure performance above this level (credits).

The second thing to note is that a player's contribution to a team's success is the product of "opportunity to play" and "performance". A "talented" player who gets little ice time (eg due to injury), will have little contribution. A journeyman getting lots of ice time will generate some contribution. Obviously, more talented players tend to get more ice time. But don't confuse player "contribution" with player "talent". Although contribution and talent are highly correlated, a talented player could be sitting on the bench in Ottawa (zero contribution), get traded to Pittsburgh and play a great deal (some contribution). If you want to get at talent, you have to equalize your measure of "opportunity". This will become most evident when we look at goaltenders. A goaltender playing behind a poor defense will have a greater contribution than if he were playing behind a strong defense.

Step 6: Allocate Marginal Goals Created to Individual Players

The approach we will take to individuals mirrors the approach used for teams. If individual performance adds up to team performance, then we have properly allocated team success. Recall that:

MGC = GF - (GF< x DA)
and therefore
PCO = PCF x MGC

On an individual level this translates to:

Individual MGC = Individual Goals Created – Individual Goals Threshold

In other words, we need to allocate team scoring to individuals (credits) and then allocate the threshold level of offense to individuals (debits).

2002-03 Assists per Goal by Team and Situation

Team	Overall	Even Handed	Power Play	Short Handed
ANA	1.75	1.68	1.98	1.25
ATL	1.62	1.55	1.88	0.88
BOS	1.67	1.64	1.88	1.00
BUF	1.71	1.67	1.88	1.13
CAL	1.69	1.67	1.83	1.00
CAR	1.67	1.57	1.91	1.17
CBJ	1.70	1.61	1.94	1.25
CHI	1.69	1.65	1.92	1.25
COL	1.78	1.73	1.96	1.40
DAL	1.70	1.70	1.85	0.67
DET	1.71	1.65	1.97	0.73
EDM	1.72	1.72	1.84	1.31
FLA	1.63	1.59	1.88	0.43
LA	1.68	1.62	1.96	1.00
MIN	1.65	1.62	1.87	0.89
MON	1.66	1.60	1.90	1.50
NAS	1.66	1.62	1.79	-
NJD	1.70	1.70	1.83	1.14
NYI	1.73	1.69	1.98	1.08
NYR	1.63	1.53	1.98	1.00
OTT	1.74	1.69	1.87	1.25
PHI	1.64	1.56	1.94	1.25
PHO	1.76	1.71	1.95	1.25
PIT	1.77	1.77	1.80	1.00
SJ	1.72	1.69	1.81	1.40
STL	1.76	1.75	1.86	1.18
TB	1.77	1.76	1.86	1.00
TOR	1.74	1.70	1.97	1.00
VAN	1.73	1.64	1.97	1.33
WAS	1.78	1.81	1.86	0.63
Average	1.71	1.67	1.90	1.06

Credits: Measuring Offense

One could take the following positions on the creation of goals:

1. Only the goal scorer created the goal; or

2. Playmaking counts too. Give credit for assists.

3. Being on the ice when a goal is scored counts too. The screen, the hit, the pick and the threat of a pass all contribute to goals.

I have used the second measure of offensive contribution. The third measure is tempting, but a bit far from the beaten path.

The NHL allocates up to two assists per goal, but assists are not necessarily worth twice what goals are worth. It is pretty clear from the distribution of paychecks, goals and assists around the league that goal scoring is a more valued skill. I will take the position that goal scoring is 50% of offense (ie a goal scored is a credit of 0.50) and playmaking is worth the rest. I know of no research on the relative value of goals versus assists. So you will just have to live with my best guess.

There are, on average, about 1.71 assists per goal in the NHL. So we need to make sure that each assist gets a credit more like 0.25 x 2.0 / 1.71. Actually, we will do this on a team by team, situation by situation basis so that the credits total the goals scored for the team (see table below).

So our formula for Goals Created is:

Goals Created = 0.5 x (Goals + Assists / (Team Assists / Team Goals)) -- by Situation

Here is the calculation for Alexander Mogilny of Toronto:

GC^{EH} = 18.66 = 0.5 x (25 + 21 / 1.70)
GC^{PP} = 8.34 = 0.5 x (5 + 23 / 1.97)
GC^{SH} = 2.50 = 0.5 x (3 + 2 / 1.00)
GC = 29.51

This definition of offense changes the way we see players. Below are the Goals Created leaders and their raw scoring data. Notice the big demotion for points leader Peter Forsberg as he was much more of a play maker than a sniper. And, in general, power play assists are worth less than even handed assists which are, in turn, worth less than short handed assists. Finally note that team context creeps into the calculation. As is shown above, the short handed assists of Federov and Modano end up being worth more than those of Mogilny and Sundin because Detroit and Dallas had fewer short handed assists per goal than did Toronto.

2002-03 Goals Created Leaders

Player	Team	G	A	PTS	GCEH	GCPP	GCSH	GC
Markus Naslund	VAN	48	56	104	20	20	0	40
Milan Hejduk	COL	50	48	98	25	13	0	38
Todd Bertuzzi	VAN	46	51	97	21	17	0	38
Joe Thornton	BOS	36	65	101	24	12	1	37
Glen Murray	BOS	44	48	92	25	10	1	36
Peter Forsberg	COL	29	77	106	26	10	0	36
Dany Heatley	ATL	41	48	89	20	15	1	35
Pavol Demitra	STL	36	57	93	22	12	0	34
Zigmund Palffy	LA	37	48	85	22	9	2	33
Marian Hossa	OTT	45	35	80	20	12	0	32
Sergei Fedorov	DET	36	47	83	20	10	2	32
Mario Lemieux	PIT	28	63	91	16	16	0	32
Mike Modano	DAL	28	57	85	19	10	2	31
Brett Hull	DET	37	39	76	19	10	1	30
Alexander Mogilny	TOR	33	46	79	19	8	3	30
Vincent Lecavalier	TB	34	44	78	19	9	1	29
Jaromir Jagr	WAS	36	41	77	17	11	1	29
Mats Sundin	TOR	37	35	72	15	11	3	29
Daniel Alfredsson	OTT	27	52	79	17	11	0	28
Paul Kariya	ANA	25	56	81	16	12	1	28

Debits: Determining Threshold Performance

The NHL differentiates between even handed, power play and short handed situations. Each of these has a different profile of the offensive and defensive expectations and results for forwards and defensemen.

Of the skaters in the NHL today, forwards outnumber defensemen roughly 2 to 1. These relationships are a function of roster size. Today's roster of 20 suggests a team of 12 forwards, 6 defensemen and 2 goaltenders. When roster size was 17, the usual split was 10 forwards and 5 defensemen (again 2 to 1), but there was greater variability. It is obvious that defensemen do not have the same "exposure" to the game as do forwards. . We will use the data available to us and distinguish between forwards and defensemen.

The clearest picture of "exposure" is revealed by ice time. The usual split of ice time is 40% for defensemen (2 vs 3), but this becomes about 50% in 4 on 4 situations (a subset of even handed situations), 50% on the penalty kill and about 33% on the power play (see table).

It is also pretty clear that defensemen do not have the same offensive role as forwards. In 2002-2003, defensemen accounted for only 21% of offense (as we have defined it) despite getting 41% of the ice time (see table). This split changes when we look at situational data. Defensemen tend to contribute more offense on the special teams.

If we put ice time and goal creation information together, we come up with the (average) Goal Creation Rate by position and situation (see table). This is simply Goals Created divided by ice time (in minutes) and represents the league average number of goals created per minute by situation and position.

We want to allocate the offensive and defensive "responsibility" (or the threshold level of performance)

2002-03 Time on Ice (Minutes)
by Situation and Position

Situation	Even Handed	Power Play	Short Handed	Total
TOI Forwards	335,786	60,303	35,373	431,462
TOI Defensemen	230,325	29,396	35,657	295,377
Total TOI	566,111	89,699	71,030	726,839
% TOI Defensemen	40.7%	32.8%	50.2%	40.6%

2002-03 Goals Created
by Situation and Position

Situation	Even Handed	Power Play	Short Handed	Total
GC Forwards	3,623	1,354	176	5,153
GC Defensemen	875	431	53	1,360
GC Total	4,498	1,786	229	* 6,513
% GC Defensemen	19.5%	24.1%	23.3%	20.9%

** Note that goaltenders assisted on 39 goals (all presumed to be even handed) and therefore are credited with 18 Goals Created.*

2002-03 Goal Creation Rates
by Situation and Position

Situation	Even Handed	Power Play	Short Handed	Total
GCR Forwards	0.01079	0.02247	0.00497	0.01194
GCR Defensemen	0.00380	0.01466	0.00149	0.00460

fairly to forwards and defensemen. To get at this for offense is fairly simple. We know the Goal Creation Rates by situation by forwards and by defensemen. So the debit for a given player would simply be:

DA x GCR x T (by situation and position)
where T = player Time on Ice in minutes

And this means that:

PCO = PCF x MGC = PCF x (GC – DA x GCR x T)

So here is the calculation of Player Contribution (excluding penalty drawing) for Alexander Mogilny based on Toronto's PCF of 3.87 (=20 / 5.2):

PCO^{EH} = 49 = 3.87 x (18.66 -0.58 x 0.01079 x 944)
PCO^{PPP} = 15 = 3.87 x (8.34 – 0.58 x 0.02247 x 338)
PCO^{SH} = 8 = 3.87 x (2.50 – 0.58 x 0.00497 x 181)

For penalty drawing, there is absolutely no data. The NHL could easily ask referees to identify the fouled player, but unfortunately they don't. All we have is ice time data and MGC^{PPO}, the calculated team propensity to draw penalties, relative to the league average. So what we will do is allocate MGC^{PPO} to players in proportion to their share of team total ice time. This approach assumes that that forwards and defensemen have an equal propensity to **draw** penalties. I have no way of proving or disproving this. Later I will show you that forwards and defensemen have an equal propensity to **take** penalties.

For Alexander Mogilny this number is basically zero:

PCO^{PPO} = 0 = 3.87 x -0.3 x 1463 / 24048 = $PCF \times MGC^{PPO}{}_{TOR} \times T / \Sigma_{TOR}\, T$

Which means that for Alexander Mogilny:

PCO = 72 = 49 + 15 + 8 + 0

Results

Offensive Player Contribution leaders are shown below for forwards and defensemen, for even handed and power play situations and overall.

2002-03 Offensive Player Contribution by Situation and Position

Forwards								
Even Handed			**Power Play**			**Overall**		
Player	**Team**	**PCOEH**	**Player**	**Team**	**PCOPPP**	**Player**	**Team**	**PCO**
Peter Forsberg	COL	66	Markus Naslund	VAN	51	Markus Naslund	VAN	98
Glen Murray	BOS	61	Dany Heatley	ATL	40	Dany Heatley	ATL	94
Milan Hejduk	COL	61	Todd Bertuzzi	VAN	40	Milan Hejduk	COL	91
Joe Thornton	BOS	59	Mario Lemieux	PIT	40	Todd Bertuzzi	VAN	90
Ilya Kovalchuk	ATL	54	Milan Hejduk	COL	31	Joe Thornton	BOS	88
Pavol Demitra	STL	53	V. Damphousse	SJ	28	Peter Forsberg	COL	87
Dany Heatley	ATL	53	Marian Hossa	OTT	28	Glen Murray	BOS	82
Zigmund Palffy	LA	51	Dave Andreychuk	TB	28	Pavol Demitra	STL	81
Marian Hossa	OTT	50	Paul Kariya	ANA	27	Marian Hossa	OTT	78
Sergei Fedorov	DET	50	Joe Thornton	BOS	27	Mario Lemieux	PIT	75

Defensemen								
Even Handed			**Power Play**			**Overall**		
Player	**Team**	**PCOEH**	**Player**	**Team**	**PCOPPP**	**Player**	**Team**	**PCO**
Sergei Gonchar	WAS	34	Al MacInnis	STL	29	Sergei Gonchar	WAS	59
Nicklas Lidstrom	DET	28	Mathieu Schneider	LA/DET	26	Al MacInnis	STL	56
Scott Niedermayer	NJD	27	Derek Morris	COL	24	Nicklas Lidstrom	DET	53
Tom Poti	NYR	26	Nicklas Lidstrom	DET	23	Dan Boyle	TB	43
Al MacInnis	STL	24	Sergei Gonchar	WAS	22	Mathieu Schneider	LA/DET	40
Greg de Vries	COL	24	Sergei Zubov	DAL	22	Sergei Zubov	DAL	40
Tomas Kaberle	TOR	22	Dan Boyle	TB	21	Tom Poti	NYR	37
Eric Desjardins	PHI	22	Andy Delmore	NAS	19	Tomas Kaberle	TOR	35
Dan Boyle	TB	21	Dick Tarnstrom	PIT	18	Derek Morris	COL	35
Andrei Markov	MON	21	Jaroslav Modry	LA	17	Rob Blake	COL	34

These lists are not too surprising. Offense is already visibly measured. How the PCO metric differs from scoring points is that we have:

(a) revalued goals and assists (see Hejduk vs Forsberg),

(b) "taxed" ice time (more heavily in power play situations and more lightly in short handed situations) to level the playing field (see Delmore), and

(c) reflected the impact of goal creation on team wins (see Heatley).

Is the positional and situational analysis worth the effort?

For positions it clearly is. Defensemen account for 41% of ice time but only 21% of offense. If we did not do have a method that reflected this positional difference, we would be expecting defensemen to produce nearly twice the offense that they do. Our conclusions would therefore punish defensemen. Al MacInnis' offensive stats (16 goals and 52 assists, 9 and 28 on the power play) look a lot like those of teammate Doug Weight (15 goals and 52 assists, 7 and 29 on the power play). But, coming from a defenseman, his performance is more impressive. So the method gives MacInnis a PCO score of 57 and Weight a PCO score of 39, the difference being the higher "tax" applied to forwards.

For situational play the story is less clear. It is pretty obvious at the team level that the special teams do perform in a fashion that deviates materially from the average. Recall that New Jersey had a terrible power play, both in terms of opportunities and success. Patrik Elias, Jeff Friesen, Scott Gomez, Jamie Langenbrunner and Joe Nieuwendyk each spent over 200 minutes on the power play and collected only 19 goals and 32 assists between them. This translates to PCO^{PPP} of 15 (MGC^{PPP} of 3.74) between the five of them of them, barely above 58% of the league average and the same as Alexander Mogilny alone. Yet in even handed situations, these five guys were the Devils' top offensive performers, have a total PCO^{EH} of 170.

To evaluate the impact of using situational analysis for offense, I compared the calculation of PCO to a calculation ignoring situational play. Those players most advantaged by the use of the situational approach factors were, not surprisingly, penalty killers. In 2002-03 the biggest positive PCO differential would have applied to Luke Richardson (CBJ), who had a differential of +7. Kevyn Adams (CAR), Sean Pronger (CBJ), Kirk Maltby (DET), Kris Draper (DET), Antti Laaksonen (MIN), Wes Walz (MIN), Kent Manderville (PIT), Tim Taylor (TB) and Trevor Letowski (VAN) all had a PCO differential of +6. Each of these players logged over 200 minutes of short handed ice time. Richardson spent 437 minutes on the penalty kill.

Those players most advantaged by ignoring situational differences spent a lot of time on the power play. In 2002-03 the biggest negative PCO reductions applied to Sergei Gonchar (WAS) and Andy Delmore (NAS), with a differential of –8. Yannick Tremblay (ATL), Cliff Ronning (MIN), Kimmo Timonen (NAS), Mario Lemieux (PIT), Todd Bertuzzi (VAN) and Markus Naslund (VAN) each had differentials of –7. Lemieux spent 394 minutes on the power play, the lowest time from this group of players.

The situational analysis is worth the effort. The data is there. The computers crunch the numbers. The results are a more accurate measurement of offensive **contribution**. On offense, recognizing situational play results in a lower ice time "tax" for penalty killers and a higher ice time "tax" for the power play. It is the same story as for defensemen, just more subtle. On defense, situational analysis is even more rewarding. As you will see below, forwards have defensive responsibility which varies substantially by situation. To give them defensive credit for ice time on the power play would be a travesty. We know that penalty killing is a serious defensive assignment. We need to have this reflected. Situational analysis is key to Player Contribution.

Step 7: Allocate Marginal Goals Defense to Individual Players

We are so used to looking at statistics from the bottom up, that it is easy to forget that there is a top down approach too. On offense, bottom up works. Individual goals and assists add to team goals and assists. If we observe that a team is a good offensive team we already who is contributing to that.

Measuring defense is much more subtle than measuring offense. There is no conventional bottom up approach. When we observe a good defensive team we do not know who made it so. What we would love to have in hockey is the concept of an error, some degree of blame for each goal. But we don't. All we are left with is inference, getting at defense from the top down.

So here is the game plan. If we look at a team's performance and subtracting out offense (MGC) and goaltending (MGG), the rest must be defense (MGD). And we have already subdivided MGD into its situational components. What is left is to determine individual contribution to defense. To do that, we will use all that we know about that contribution.

Recall that:

MGP = ((1+DA) x GA<) – GA
and that
MGD = MGP – MGG = (1 – G) x MGP
which means
MGD = (1 – G) x ((1+DA) x GA<) – GA)

Our approach for allocating defense to individuals will generally parallel this:

Individual MGD = (1 – G) x (Individual Goals Threshold – Individual Goals Against)
and
PCD = PCF x MGD

We will again do this situationally. The benefit of this approach for defense is that we look at homogeneous situations. And we can quickly get a good understanding of defense for about 25% of the game -- power plays and short handed situations.

Goal Allowance Rates

To proceed, we are going to need "Goal Allowance Rates".

Let: T *=Time (in minutes) on Ice for a player*

$\Sigma_{LG}{}^{F}T$ *= Aggregate Time (in minutes) on Ice for Forwards in the NHL*
$\Sigma_{LG}{}^{D}T$ *= Aggregate Time (in minutes) on Ice for Defensemen in the NHL*

${}^{F}GCR$ *= The Rate of Goal Creation per Minute of Ice Time for Forwards*
${}^{D}GCR$ *= The Rate of Goal Creation per Minute of Ice Time for Defensemen*

${}^{F}GAR$ *= The Rate of Goal Allowance per Minute of Ice Time for Forwards*
${}^{D}GAR$ *= The Rate of Goal Allowance per Minute of Ice Time for Defensemen*

Let's first look at even-handed situations. We calculated GCR before:

GCR^{EH} = Goals Created / Time on Ice = GC^{EH} / T^{EH}, while even handed, either for forwards or defensemen

It is the average number of goals created, while even handed, per minute of play. GAR is the defensive analogy -- the rate at which goals are **allowed** per minute of ice time. We know the situational goals against. But how do we allocate them by position? By inference …

Because of how we calculated it, we know that:

$$^{F}GCR^{EH} \times \Sigma_{LG}\, {}^{F}T^{EH} + {}^{D}GCR^{EH} \times \Sigma_{LG}\, {}^{D}T^{EH} = GF^{EH} = GA^{EH}$$

The same must be true for Goal Allowance Rates:

$$^{F}GAR^{EH} \times \Sigma_{LG}\, {}^{F}T^{EH} + {}^{D}GAR^{EH} \times \Sigma_{LG}\, {}^{D}T^{EH} = GA^{EH} = GF^{EH}$$

This just says that GAR times ice time (separately for forwards and defensemen) equals Goals Against.

Our second insight comes from the following logic. If defensemen get 41% of the ice time but generate only 21% of the offense, they must be carrying a heavier defensive burden. The reverse is true for forwards. They carry 79% of the offensive load, but only get 59% of the ice time. In order for all players to be whole, we need the rate at which forwards generate "value" to be equal to the rate at which defensemen generate "value". What is "value"? We already have a model for this.

On offense, value is goals created in excess of a threshold. Generically, this looks like:

Offensive Value Generation Rate $= (GF - DA \times GF) / T = (1-DA) \times GF / T = (1-DA) \times GCR = GCR \times 5/12$

On defense, value is related to goal prevention -- goals allowed below a threshold, adjusting for the goals allocated to goaltending:

Defensive Value Generation Rate $= (1-G<) \times ((1+DA) \times GA - GA) / T = (1-G<) \times DA \times GAR$
$= (5/7)^{*} \times (7/12) \times GAR = GAR \times 5/12$

**(1-G<) is 5/7 under our basic assumptions*

Note that, under our basic assumptions, the rate of goal prevention turns out to be the rate of goal allowance times a positive constant. Mathematically, the second constraint looks like this:

$$^{F}GCR^{EH} \times 5/12 + {}^{F}GAR^{EH} \times 5/12 = {}^{D}GCR^{EH} \times 5/12 + {}^{D}GAR^{EH} \times 5/12$$
or
$$^{F}GCR^{EH} + {}^{F}GAR^{EH} = {}^{D}GCR^{EH} + {}^{D}GAR^{EH}$$

This simply says that goal creation and prevention (allowance) rates for forwards must add up to goal creation and prevention (allowance) rates for defensemen.

When you manipulate the second equation, you end up with two equations in two unknowns:

$$ {}^{F}GAR^{EH} \times \Sigma_{LG}\, {}^{F}T^{EH} + {}^{D}GAR^{EH} \times \Sigma_{LG}\, {}^{D}T^{EH} = GF^{EH} $$
$$ {}^{F}GAR^{EH} - {}^{D}GAR^{EH} = {}^{D}GCR^{EH} - {}^{F}GCR^{EH} $$

When you solve this you get:

$$ {}^{F}GAR^{EH} = (GF^{EH} + \Sigma_{LG}\, {}^{D}T^{EH} \times ({}^{D}GCR^{EH} - {}^{F}GCR^{EH})) / (\Sigma_{LG}\, {}^{F}T^{EH} + \Sigma_{LG}\, {}^{D}T^{EH}) $$
$$ {}^{D}GAR^{EH} = {}^{F}GAR^{EH} + {}^{F}GCR^{EH} - {}^{D}GCR^{EH} $$

So, for even handed situations:

$$ {}^{F}GAR^{EH} = 0.00510 \quad = (4498 + 229440 \times (0.00380 - 0.1079) / 565226 $$
$$ {}^{D}GAR^{EH} = 0.01209 \quad = 0.00510 + 0.01079 - 0.00380 $$

This leads us to the observation that, during even handed play, forwards are 68% offense, 32% defense (0.01079 vs 0.00510) and defensemen are 24% offense, 76% defense (0.00380 vs 0.01209). We know that forwards are responsible for 81% of even-handed offense. The inference is that defensemen are responsible for 62% of even-handed defense. This feels about right.

When it comes to special team play, we use the same general approach.

For the power play we calculate that:

$$ {}^{F}GCR^{PP} = 0.02247 \quad = 1355 / 60596 \quad = {}^{F}GF^{PP} / \Sigma_{LG}\, {}^{F}T^{PP} \text{ (while on the Power Play)} $$
$$ {}^{D}GCR^{PP} = 0.01466 \quad = 431 / 29225 \quad = {}^{D}GF^{PP} / \Sigma_{LG}\, {}^{D}T^{PP} \text{ (while on the Power Play)} $$

And while Short handed

$$ {}^{F}GCR^{SH} = 0.00497 \quad = 176 / 35675 \quad = {}^{F}GF^{SH} / \Sigma_{LG}\, {}^{F}T^{SH} \text{ (while Short Handed)} $$
$$ {}^{D}GCR^{SH} = 0.00149 \quad = 53 / 35477 \quad = {}^{D}GF^{SH} / \Sigma_{LG}\, {}^{D}T^{SH} \text{ (while Short Handed)} $$

But we have to bear in mind that power play and short handed situations are complementary. When Team A is on the power play, Team B is short handed. So here is the slight twist -- **on the power play the value of defense is not equal to the value of offense.** We have to set the value of **power play defense** equal to the value of the **short handed offense**. The same logic holds for short handed situations. The value of short handed defense equals the value of power play offense. So GAR becomes:

$$ {}^{F}GAR^{PP} \times \Sigma_{LG}\, {}^{F}T^{PP} + {}^{D}GAR^{PP} \times \Sigma_{LG}\, {}^{D}T^{PP} = GA^{PP} = GF^{SH} \text{ for the Power Play, and} $$
$$ {}^{F}GAR^{SH} \times \Sigma_{LG}\, {}^{F}T^{SH} + {}^{D}GAR^{SH} \times \Sigma_{LG}\, {}^{D}T^{SH} = GA^{SH} = GF^{PP} \text{ while Short Handed} $$

Completing the arithmetic, you end up with the table below.

Well … not quite. Using this technique I calculate the GAR for forwards on the power play to be a small, negative number. Although the result makes sense algebraically, it makes little sense on the ice. Even a very small GAR or GCR makes little sense and will play havoc with the calculations. As a consequence, I forced the GAR to be a minimum of 0.001 (1 goal allowed per 1000 minutes of playing time).

From this table you can draw certain conclusions about the roles and composition of forwards and defensemen (see table).

Summary of Goal Creation and Allowance Rates 2002-03 by Situation

Situation	Even Handed	Power Play	Short Handed	Total
GCR Forwards	0.01079	0.02247	0.00497	0.01194
GCR Defensemen	0.00380	0.01466	0.00149	0.00460
GAR Forwards	0.00510	0.00100	0.02340	0.00598
GAR Defensemen	0.01209	0.00881	0.02687	0.01332

On the power play, this implies forwards are about 96% offense (0.02247 vs 0.00100) while defensemen are about 62% offense, 38% defense (0.01466 vs 0.00881). While Short handed, this approach implies forwards about 82% defense, 18% offense (0.02340 vs 0.00497) while defensemen are 95% defense, 5% offense (0.02687 vs 0.00149).

Goal Allowance Rates are a very powerful tool. We know a lot about goal creation. If we add some basic assumptions, that the value of offense and the value of defense are equal and that value of defensemen and forwards are equal, we can, by inference, get at average rates at which goals are allowed. This is a pretty big step forward in understanding defense.

Interpretation of Goal Creation and Allowance Rates 2002-03 by Situation

Situation	Even Handed	Power Play	Short Handed	Total
Offense				
% from Forwards	81%	76%	77%	79%
% from Defensemen	19%	24%	23%	21%
Defense				
% from Forwards	38%	26%	46%	40%
% from Defensemen	62%	74%	54%	60%
Forwards				
% Offense	68%	96%	18%	67%
% Defense	32%	4%	82%	33%
Defensemen				
% Offense	24%	62%	5%	26%
% Defense	76%	38%	95%	74%

The next step is to understand goal allowance / prevention at the individual level, situation by situation. We will start with the toughest nut to crack, even handed defense, before moving on to the easier parts, short handed and power play situations and penalties.

Even Handed Situations

So far we have allocated about 16% of the game to goaltending, 42% to offense and 42% to defense. Special team defense accounts for about 13% of the game. Penalties are neutral across the league. That means that even handed defense accounts for about 29%

of the game. This is a significant piece of the game and a key to player contribution is getting this right.

There are several methods to measure defense. They fall into two basic categories: indirect methods and direct methods. The more data you have about defense, the more direct a method you can use. I will go through several methods before getting to the most accurate one. Once you understand the measurement methods for even handed defense, you have the methods to get at special team defense.

Indirect Methods

The Simple Method

The most basic method I can imagine is the allocation of team (even handed) defense to individuals based on their exposure to the defensive situation. So, the Simple Method, is an allocation of even handed team Marginal Goals Defense Even Handed based strictly on ice time and positional factors:

$$PCD^{EH} = PCF \times MGD^{EH} \times (T^{EH} \times GAR^{EH}) / \Sigma_{TEAM} (T^{EH} \times GAR^{EH})$$

I won't show the results of this here. Suffice it to say that this is a pretty crude approach that can be improved upon.

The Fyffe Method

If a player has low offensive contribution but still gets lots of ice time, could it be that it is because of his defense? In fact, there are only two reasonable explanations for the coach playing such a player: he is very hopeful about the offense or he believes in the presence of defensive skills. Hopeful coaches tend not to last long. So … if we can predict ice time based on offensive skills, the difference between this prediction and actual ice time would seem to be an indicator of defensive contribution.

This idea had been rattling around my brain for some time, but I put off any attempt to make it operational in hopes of discovering a more direct method. During the later stages of the development of Player Contribution, I came across Iain Fyffe's Point Allocation Method. In this paper, Iain describes the allocation of defensive points using implied defensive minutes. The Fyffe Method goes something like this: if a forward plays 16 minutes per game but his offense implies that he ought to be playing 18 minutes per game, then his playing time must be comprised of the average of 18 "offensive minutes" and 14 "defensive minutes" (to average 16 minutes). Iain then goes on to credit defense in proportion to defensive minutes as opposed to actual ice time. I think this is a brilliant insight into the game.

Iain's work did not involve the study of special team situations. As a consequence, any player who got a lot of penalty killing duty is gaining credit under the Fyffe method. To be fair, these players are thought to have a high level of defensive skills, they are asked to perform a defensive role and they are unlikely to generate as much offense because of the role. However, an unproductive power play, like New Jersey's just looks like more defense to the Fyffe Method.

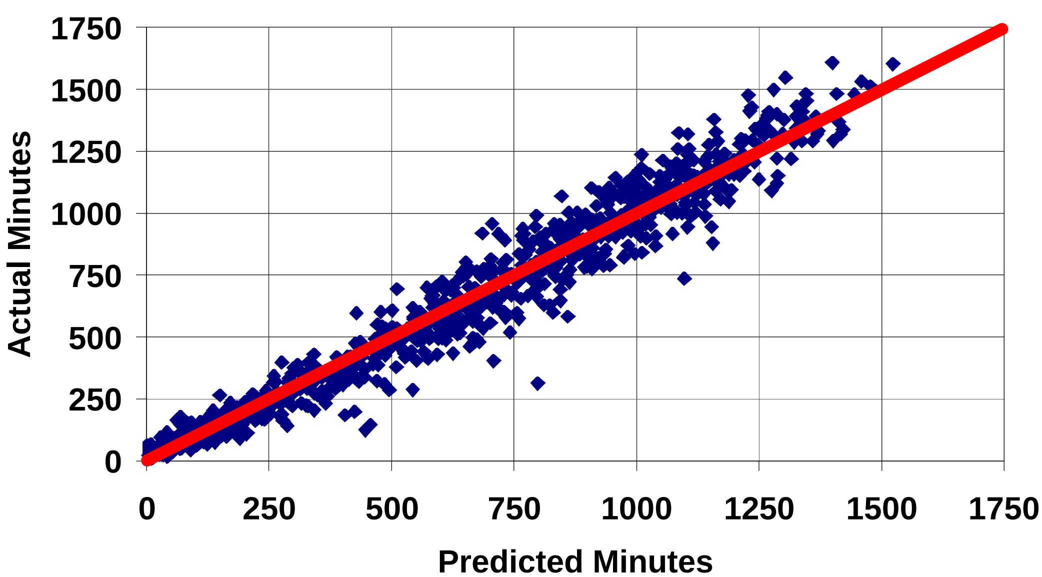
When you try to apply the Fyffe Method to even handed situations it does not work as well. Iain recognized a kind of mean reversion in his ice time forecasting model: a coach has three or four lines and he tends to use them. There is even more of this mean reversion when even handed.

I wanted to apply the Fyffe Method to even handed play. But I used Goal Allowance Rates to make sure that the credit for defense was allocated mainly to defensemen. And I used a different approach, linear regression, to predict ice time. I studied forwards and defensemen separately and, in both cases, it was easily observed that ice time was not a linear function of offense (I used Goals Created as my measure of offense). Good offensive players tend to get disproportionately more ice time than a linear prediction suggested.

Why does this happen? Three explanations come to mind. One possibility is that the coach feels that these players are his best players, playing defense at a similar level to their (observed) offense. Another possibility is that the coach values an offensive effort and is hopeful that these players will produce. The final explanation is that the coach cannot detect good defense as well as he can detect good offense, so he goes with what he knows. This would be an interesting area of further study. The last two explanations suggest that top offensive players may be overworked to the detriment of the team. But that is not the issue of the moment.

Linear regression still works if you can match the curvature of your predictor variable to that of your result variable (see below). This process is more art than science.

Actual vs Predicted Minutes
Even Handed



Here are the regression formulae I derived to predict season total even handed "offensive" ice time (TO^{EH}):

$^{D}TO^{EH} = -51.79 + 13.4 \times GP + 72.1 \times GC^{0.75}$, *for defensemen*
$^{F}TO^{EH} = -36.08 + 7.5 \times GP + 66.0 \times GC^{0.75}$, *for forwards*

There is still some curvature present that a more complex model might have removed. Taking all of the curvature out would imply that the best offensive players are just average defensive players. This denies my first theory of ice time curvature.

The regression formula explains about 95% of the observed variation, which is difficult to improve upon. It also suggests that defense only accounts for, at most, 5% of the allocation of even handed ice time. The multipliers for GP make sense. Those are probably good baseline, even handed playing minutes. The season constants are a little harder to grasp. They say that, over the course of the season, the average defenseman (forward) loses 52 (36) minutes of playing time that the remainder of the formula otherwise predicts. This is just a consequence of the curvature of the data and regression. Regression knows nothing about the process. The result is the result. Some players who only play a few games will have negative predicted minutes. I could have forced the constants to be zero, but that would have decreased the accuracy of the fit among the better players. I tried to forecast average ice time per game, but the results were not as good for players with a lot of ice time. As I would rather err with marginal players, the prediction formula you see is the one I chose.

Once you have these predicted offensive ice times, the defensive ice time is easy:

$TD^{EH} = 2 \times T^{HE} - TO^{EH}$

And you get to my implementation of the Fyffe method this way:

$PCD^{EH} = PCF \times MGD^{EH} \times (TD^{EH} \times GAR^{EH}) / \Sigma_{TEAM} (TD^{EH} \times GAR^{EH})$

What does all that work get you? The answer is a swing of at most 10 PC points versus the Simple Method. I calculated the difference between the Simple and Fyffe Methods and examined the biggest swings. In general, the Fyffe Method seemed to be directionally correct. But the top 10 players from each method had a 90% overlap and the top 20 players had an 85% overlap. This says that the two methods are not very different.

The biggest "winners" by applying the Fyffe method picked up between 3 and 5 PC points. The winners were all defensemen and the leaders were Derrian Hatcher (DAL), Brent Sopel (VAN) and Scott Stevens (NJD). Hatcher' Plus / Minus was +39 and Stevens' was +18, but Sopel was –15 on a good club. Sopel was hardly used to kill penalties (only 41 minutes), so he seemed to pick up extra even handed ice time as a consequence of his apparently poor defensive play. Stevens played little on the power play (71 minutes) and this would have contributed to a little extra time even handed.

The biggest losers were also defensemen. As a group these were marginal players with less than 1000 minutes of ice time, almost all of it even handed, and little offense. They gave up 4 – 10 PC points under the Fyffe method. The major exception to this profile was Andy Delmore (NAS) who logged 470 power play minutes but only 737 even handed minutes and 7, no doubt desperate, short handed minutes. He delivered 14 power play goals and 4 while even handed. Among the leading losers was Scott Ferguson (EDM) who was +11 in under 900 minutes of play on a very average team.

My conclusion is that the Fyffe Method, applied to even handed situations, is not a big improvement over the simple method. I think that it has more application when you want to study data without situational splits. That means that it is extremely useful in historical analysis. But we have the situational data, so let's move on.

Direct Methods

Spreading team defense around in proportion to something is a bit like going to a Penguins game: it is better than nothing, but not as good as the real thing. What is the real thing?

The real thing is a method of debits and credits, like the method used on offense. To do this we need to be able to allocate "blame" for a goal to an individual. But there is no concept of an "error" in hockey. There is no allocation of blame. And I am not sure that we want it. Goals usually happen when the defensive **system** breaks down. There is usually a cascading, domino effect at work: a defensemen out of position, perhaps caused by questionable positioning of the winger, causes the other defensemen to be spread thinly, which causes the center to play a more important back checking role, which he flubs, which results in a high quality shot to the "five hole".

If we don't want "blame", the next best thing would be to know who was on the ice when the goal was scored. With that information, and positional defensive responsibility understood, we could develop a pretty good sense of defensive contribution. Like goals and assists, this data can be used objectively, without judgment.

Where is this data? Although it is public information, published in game logs, it is not summarized for you by the NHL. The NHL seems to think that the Plus Minus statistic is all you need to know about a player's defensive ability. Because of this data gap, I will present below two "direct" methods for measuring even handed defense. The first one, the Ryder Method, assumes that you only have Plus Minus and scoring data. It is therefore only an approximately "direct" method. The second method, which is used in Player Contribution, assumes that you have the all the minus data you want (although it turns out that, for 2002-03, a small amount of the minus data still needs estimation).

The Ryder Method

A good statistic captures a great deal of data without destroying too much information. Goals against averages summarize data nicely. They allow us to compare teams and/or goaltenders with dissimilar numbers of games played. We lose information about variation in goals against from game to game, but because we have a pretty good feel for what that looks like, we don't miss it too much.

A bad statistic destroys a great deal of information without providing much in return. The Plus / Minus statistic is a bad statistic because it destroys information. It is a count of the number of times a player is on the ice when a goal is scored less the number of times a player is on the ice when a goal is allowed. It excludes power play goals, but everything else is fair game. What makes it a bad statistic is the offsetting of pluses and minuses. A player can be +10 because 30 – 20 = 10 or because 70 – 60 = 10. These are two very different players.

Many people try to use the Plus / Minus stat as a measure of defense. They are wrong. It is a statistic that measures both sides of the ledger (hence the "plus" its name). And because it measures both offense and defense it does not seem to be that useful as a pure measure of defense. To make matters worse, the stat includes pluses while penalty killing and minuses while on the power play. So we are left with:

$PM \quad = PL^{EH} + PL^{SH} - MI^{EH} - MI^{PP}$, *Even and Short Handed Pluses less Even Handed and Power Play Minuses*

But, this has the potential to be useful to us. To see that, just rearrange the terms:

$MI^{EH} \quad = PL^{EH} + PL^{SH} - MI^{EH} - PM$

This says that all we need to determine even handed minuses is four pieces of data … of which we have only one. But, if we had the even handed minuses, we would have a road to the "blame" for goals against and we would be (nearly) done. Can it be done? The answer is yes. We have a roadmap to even handed minuses that relies on a fair bit of data which we already have:

- As short handed offense and power play defense account for only about 3% of the game, we are nearly there if we can get at the even handed pluses.

- And the good news is that we know about 55% of the plus information -- scoring points. When an even handed goal is scored, an average of 2.67 points is awarded. These are known, observed pluses. That means that 2.33 pluses are missing per goal (actually a little less due to 4 on 4 play).

Where are the missing pluses? Mainly on defense. The table below sorts that out. We observe that forwards account for 59.3% of ice time. If we assume that there are always 2 defensemen on the ice while even handed, this suggests that there are 2.98 forwards on the ice, on average. That means that the observed and missing pluses add up to 4.98 times the number of even handed goals (4,501). And that means that the missing pluses total 10,436. These are allocated to forwards and defensemen so that the total pluses are in proportion to the observed ice time. There are a few simplifying assumptions embedded in this work, but they will turn out to be immaterial.

2002-03 Even Handed Pluses by Position

	Ice Time		Even Handed Pluses				
Position	**Observed**	**%**	**Observed**	**%**	**Missing**	**Total**	**%**
Forwards	335,928	59.3%	9,479	79.0%	3,829	13,308	59.3%
Defensmen	230,325	40.7%	2,517	21.0%	6,607	9124	40.7%
Total	566,252	100.0%	11,996	100.0%	10,436	22,432	100.0%

The realization that defensemen are short the vast majority of the pluses is a huge step forward from two points of view.

- For defensemen the bad news is that there are a large number of missing pluses. But the good news is the way to allocate them is clear. Most defensemen have, while even handed, relatively even exposure to all of the team's forwards. The forwards are doing most of the offensive work and the defensemen are along for the ride. As a result, the distribution of a team's missing pluses across the defensemen in proportion to their ice time would seem to be a reasonable approach. This might over-allocate pluses to offensive defensemen, but I will deal with that in a moment.

- What this tells us about forwards is that we already know about 70% of their pluses, and by inference close to 70% of their minuses. This is the good news. The bad news is that the missing pluses present more of a challenge to allocate. An offensively challenged winger playing with two scoring machines ought to claim a large number of missing pluses. A line made up of offensively challenged players may generate only a few missing pluses. The team's offensive hero is likely to be participating in a very high percentage of the team's goals, when he is on the ice. It is unlikely that he can claim many missing pluses. But we don't know who is playing with whom. So we will have to settle for an approach that uses the information we do have.

The method I developed to do this allocation is relatively simple. Absent any information at all, one would be inclined, separately for forwards and defensemen, to spread **ALL** pluses around in proportion to ice time. This method might be biased **against** those with lots of scoring points as they generated lots of pluses. A second approach would be, separately for forwards and defensemen, to spread the **MISSING** pluses around in proportion to ice time. This approach might be biased **towards** those with lots of scoring points. Why? Because players who participate in a higher percentage of their team's offense, like Peter Forsberg who had a 41% "participation rate" in Colorado's even handed scoring, may well be on the bench when the rest of the scoring is taking place.

Which method works better? Or is the answer in between? The answer is that the second method is preferred. It produces an even handed minus estimate which is 98% correlated with my better estimate (which I will explain below).

Below is a list of the top even handed pluses (observed and allocated) as estimated by this method. As we would expect, this list is dominated by defensemen from good offensive teams (who get more ice time than do the forwards). The additional pluses put these guys in the ball park with the offensive heroes.

Of course, we still cannot get to even handed minuses unless we address short handed pluses and power play minuses.

For the short handed pluses we use exactly the same approach as was used for even handed pluses. Using the same approach, for example, Nick Lidstrom picks up 7 of Detroit's 19 missing short handed pluses. When combined with his 2 short handed points, he ends up leading the league with 9 short handed pluses.

The approach for individual power play minuses is necessarily different. For the pluses we had scoring points to nudge us in the right direction. For this minus, we have only power play ice time. So we simply estimate team power play minuses as 5 x power play goals against and allocate this result in proportion to power play ice time. Atlanta's Heatley (-10), Tremblay (-9) and Kovalchuk (-9) lead the league in estimated power play minuses because of the Thrashers abysmal power play defense.

With all this in place, we can now estimate even handed minuses. To the tight are the league's biggest estimated totals from 2002-03. I placed my better estimate (MIEH*) beside so that you can see the accuracy of this approach.

2002-03 (Estimated by Ryder Method) Even Handed Plus Leaders

			Even Handed Pluses	
Player	Team	POS	Observed	Total Estimated
Peter Forsberg	COL	C	73	89
Sergei Gonchar	WAS	D	36	84
Joe Thornton	BOS	C	65	83
Glen Murray	BOS	RW	63	83
Milan Hejduk	COL	RW	63	81
Nicklas Lidstrom	DET	D	30	80
Scott Niedermayer	NJD	D	29	80
Greg de Vries	COL	D	31	80
Derian Hatcher	DAL	D	24	75
Sergei Zubov	DAL	D	27	74
Brian Rafalski	NJD	D	24	72
Al MacInnis	STL	D	29	71
Todd Bertuzzi	VAN	RW	55	71
Pavol Demitra	STL	C	57	71
Scott Stevens	NJD	D	17	70
Adam Foote	COL	D	23	69
Nick Boynton	BOS	D	22	69
Alex Tanguay	COL	LW	52	69
Sergei Fedorov	DET	C	52	69
Zigmund Palffy	LA	RW	55	68

2002-03 (Estimated by Ryder Method) Even Handed Minus Leaders

Player	Team	MIEHe	MIEH*
Jaroslav Spacek	CBJ	77	72
Luke Richardson	CBJ	77	80
Ilya Kovalchuk	ATL	75	77
Frantisek Kaberle	ATL	74	72
Eric Brewer	EDM	72	63
Mario Lemieux	PIT	72	69
Daniel Tjarnqvist	ATL	72	68
Brent Sopel	VAN	72	63
Sergei Gonchar	WAS	69	71
Mike Rathje	SJ	69	65
Glen Murray	BOS	68	70
Greg de Vries	COL	66	63
Joe Thornton	BOS	66	65
Pavol Demitra	STL	66	63
Tom Poti	NYR	66	59
Olli Jokinen	FLA	65	64
Nick Boynton	BOS	65	69
Bryan Berard	BOS	64	60
Ivan Majesky	FLA	64	71
Dany Heatley	ATL	64	67

This method was tough on Eric Brewer (EDM) and Brent Sopel (VAN), each of whom were allocated 9 minuses more than my better estimate and kind to Ivan Majesky (FLA) who was allocated 7 minuses less.

But of course, even handed minus was not the objective. We need some measure of "individual goals against" if we want to apply our standard debits / credits method to even handed defense.

As we did with offense (Goals Created), we need to make a call as to the allocation of responsibility for goals against. We can do this fairly with reference to Goal Allowance Rates:

$${}^{F}GAF^{EH} = ({}^{F}GAR^{EH} \times {}^{F}T^{EH} / G^{EH}) / 2.98$$
$${}^{D}GAF^{EH} = ({}^{D}GAR^{EH} \times {}^{D}T^{EH} / G^{EH}) / 2$$

The Goal Allocation Factor (GAF), which varies by position, is just a way of assigning responsibility for even handed goals against to individual players. Each defensemen takes responsibility for about 31% (${}^{D}GAF^{EH}$) of each goal and each forward for about 13% (${}^{F}GAF^{EH}$) of each goal. The stuff inside the brackets is just the math that got us to the conclusion that defensemen were responsible for about 62% of defense and forwards responsible for about 38%. For forwards we divide by 2.98 because that is the average number of forwards on the ice at any one time during even handed situations.

And finally we can work out PCD^{EH}:

$$PCD^{EH} = PCF \times MGD^{EH}$$
and
$$MGD^{EH} = (1 - G) \times (Credit - Debit)$$
where
$$Credit = (1+DA) \times GA^{EH<} \times (T^{EH} \times GAR^{EH}) / \Sigma_{TEAM} (T^{EH} \times GAR^{EH})$$
and
$$Debit = GA^{EH} \times (MI^{EH} \times GAF^{EH}) / \Sigma_{TEAM} (MI^{EH} \times GAF^{EH})$$

The credit part of the formula gives players an allowance of goals against which is proportionate to ice time (T) and which reflects position. The debit part of the formula allocates the team's even handed goals against in proportion to the player's share of the team's MI^{EH} x GAF. Why would the team total not equal even handed goals against? This happens mainly because not all teams use players in the league average way. This is most evident on the power play, where some teams use four forwards a great deal while others mainly use three. It also happens because of some simplifying assumptions made along the way. This approach paves over these matters. The size of the error is quite small and the math is much simpler.

I won't bother showing the results. The next method is essentially the same only with better data and it therefore produces better results.

Player Contribution Method

The Plus Minus statistic is normally expressed as the number of times a player is on the ice when a goal is scored less the number of times a player is on the ice when a goal is allowed, except for power play goals and short handed goals allowed. This is conventionally expressed as:

$PM = (TGF - PGF) - (TGA - SGA)$

where the following are counts of goals for / against while on the ice:

TGF = *Total Goals For*
PGF = *Power Play Goals For*
TGA = *Total Goals Against*
SGA = *Short Handed Goals Against*

For some time there has been an underground economy collecting TGF, PGF, TGA and SGA from game summaries. So this data is around if you know who to talk to.

Note that my Plus / Minus math is expressed differently:

$PM = PL^{EH} + PL^{SH} - MI^{EH} - MI^{PP}$

To reconcile the two expressions, note that:

$TGF = PL^{EH} + PL^{PP} + PL^{SH}$
$PGF = PL^{PP}$
$TGA = MI^{EH} + MI^{PP} + MI^{SH}$
$SGA = MI^{SH}$

Which means that:

$MI^{EH} = TGA - (MI^{PP} + MI^{SH})$

Unfortunately, this data still leaves us with a small amount of estimation to do: we don't have the power play minuses. The good news here is that this is a very small piece of the puzzle. There were an average of 7.7 power play goals against per team in the NHL in 2002-03. The range was 4 (Detroit, Los Angeles, New Jersey and Washington) to 14 (Atlanta). This means that an average team has 35-40 "fuzzy" minuses to sort out (with a range of about 20 to 70).

To allocate these power play minuses we will use the method described in the previous section:

- Estimate team power play minuses as 5 x power play goals against; and
- Allocate this result in proportion to power play ice time.

To the right are the leaders (all defensemen) in even handed defense together with even handed ice time and (estimated) even handed minuses. Some observations:

2002-03 Player Contribution
Even Handed Defense

Player	Team	MOIEH	MIEH	PCDEH
Eric Desjardins	PHI	1319	30	47
Denis Gauthier	CAL	1175	35	46
Scott Niedermayer	NJD	1480	44	43
Sean Hill	CAR	1278	35	42
Scott Stevens	NJD	1548	50	40
Eric Weinrich	PHI	1381	42	40
Zdeno Chara	OTT	1355	41	40
Derian Hatcher	DAL	1608	49	40
Colin White	NJD	1209	33	38
Kim Johnsson	PHI	1391	44	38
Bob Boughner	CAL	1088	37	37
Brian Rafalski	NJD	1392	45	36
Calle Johansson	WAS	1412	42	35
Wade Redden	OTT	1311	43	35
Sergei Zubov	DAL	1482	48	35
Chris Phillips	OTT	1279	42	35
Darryl Sydor	DAL	1120	26	34
Dan Boyle	TB	1410	48	34
Philippe Boucher	DAL	1291	37	34
Ossi Vaananen	PHO	1058	28	33

- There are only 7 teams represented in this list. Both New Jersey and Dallas placed four players on the leader board.

- Note that many of these players travel in pairs: when two a defensemen play together consistently, they will have to have the same result.

- Eric Desjardins tops the list. He was on the ice for an estimated 30 even handed goals against and racked up a Plus / Minus of + 30. Teammates Weinrich and Johnsson were, defensively, well matched players. They had similar ice time, a similar minus count and, consequently, similar PCDEH scores.

- Both of Calgary's Denis Gauthier and Bob Boughner had Plus / Minus totals of +5. But they get strong PCDEH scores as a result of our conclusion that the Flames had awful goaltending. Because of this, the Player Contribution method steers points away from goaltending and towards defense. They were on the ice for only 35 and 37 goals against respectively while logging around 1100 minutes each (in front of bad goaltending). To put this in context, Tony Lydman, Calgary's best overall defenseman, was on the ice for an estimated 64 goals in about 1400 minutes of play.

- Carolina had the worst offense in the NHL in 2002-03. Every one of the Hurricanes defensemen had Plus / Minus numbers that were under water … except for Sean Hill. He turned in almost 1300 minutes of even handed ice time, was on the ice for only 35 even handed goals and had a Plus / Minus of +5.

- Neidermayer, Stevens, White and Rafalski all had very similar numbers for the Devils. Part of the story of their presence on the list is the fact that New Jersey played more even handed minutes than any other team.

- Hatcher and Zubov also had an incredible amount of even handed ice time to lead the quartet of Dallas Stars onto the leader board. Dallas was second only to Philadelphia in even handed defense.

- Ottawa's Chara, Redden and Phillips had similar numbers and rank, in this list, according to their ice time.

- And then there is 22 year old Ossi Vaananen (PHO) who was on the ice for only 28 even handed goals despite playing 1058 minutes.

The leader board for forwards is a who's who of defensive reputation: Yelle, Alfredsson, White, Madden, Lehtinen and more. I will show it to you soon.

Penalty Killing

The mission of a special team is well understood. On the penalty kill, it is defense. Because the roles and results are clear, an indirect method would get us to a pretty good result. To do that you would just spread the observed defensive success we detect around in proportion to ice time. But we do have the data on penalty killing minuses. So we will use the same method as for even handed defense.

The team formula for MGD^{SHK} is:

$$MGD^{SHK} = (1\text{-}G) \times ((1\text{+}DA) \times SHO \times (1 - PK\text{<}) - GA^{SH})$$

The individual formula is analogous. The credit part is:

$$Credit = (1\text{+}DA) \times SHO \times (1 - PK\text{<}) \times (T^{SH} \times GAR^{SH}) / \Sigma_{TEAM} (T^{SH} \times GAR^{SH})$$

And the debit part is:

$$Debit = [GA^{SH} \times (MI^{SH} \times GAF^{SH}) / \Sigma_{TEAM} (MI^{SH} \times GAF^{PH})$$

And:

$$MGD^{SHK} = PCF \times (Credit - Debit)$$

Let's work through an example for Nicklas Lidstrom:

$$PCD^{SHK} = 21 \quad = 3.74 \times (1 - .34) \times [1.583 \times 377 \times (1\text{-}.836) \times (486 \times .02688) / 64.799 - 55 \times 41 \times .2697 / 54.15$$

The PCF for Detroit is 3.74. This was calculated as 20 / (Marginal Goals / "Wins"), where "wins" is W+T/2. Detroit's goaltending is credited with 34% of goal prevention. That means that 66% of the responsibility for goal prevention lies with skaters.

The Credit is 1.583 (1+DA) times Detroit's Short Handed Opportunities (SHO = 377) times (1 – .836 (league average penalty killing percentage)) times Lidstrom's share of the team's "expected" short handed goals. This last piece is Lidstrom's short handed time on ice (486) times a defenseman's short handed goal allowance rate per minute (.02688) divided by the team total for this calculation.

The charge against this is Lidstrom's share of Detroit's short handed goals against. He was on the ice for 41 short handed goals against. The short handed GAF for defensemen is .2697 (note that this is lower than the even handed GAF for defensemen because forwards have a greater defensive accountability while killing penalties). So we "blame" him for 41 x .2697 goals. Detroit allowed 55 short handed goals. The team total for "blame" is 54.15 goals. Multiplying 41 x .2697 x 55 / 54.15 adjusts for the fact that the "blame" does not quite add up.

In 2002-03, Lidstrom's PCD^{SHK} was second in the NHL. He played for a team that had very ordinary penalty killing (PK% = 85.4%). His penalty killing skills were better than the team's (his personal PK% is estimated at 87.3%). But Lidstrom lead the league with 486 penalty killing minutes and, with this level of performance, he contributed a win to the team through his efforts.

Power Play Situations

Our approach to defense on the power play will be identical to that used in short handed situations. The team formula for power play defense is:

$$MGD^{PP} = (1 - G) \times ((GA^{PP<} \times (1 + DA)) - GA^{PP})$$

The individual PC formula is therefore:

$$PCD^{PP} = PCF \times (1 - G) \times (Credit - Debit)$$

Where:

$$Credit = (1+DA) \times GA^{PP<} \times (T^{PP} \times GAR^{PP}) / \Sigma_{TEAM} (T^{PP} \times GAR^{PP})$$

And:

$$Debit = GA^{PP} \times (MI^{PP} \times GAF^{PP}) / \Sigma_{TEAM} (MI^{PP} \times GAF^{PH})$$

It is pretty clear what are the expectations for the power play unit. Although an occasional goal is allowed, the job is to score goals. Forwards are almost completely focused on this. It shows up in the Goal Allowance Rates (0.00100 for forwards vs 0.00869 for defensemen) and therefore the Goal Allocation Factors (0.08 for forwards vs 0.46 for defensemen).

Note that power play minuses had to be estimated. But, as discussed above, there are very few of them so it is hard to get this very wrong.

Let's look again at Nicklas Lidstrom (who had an estimated MI^{PP} of 3):

$$PCD^{PP} = 8 = 3.74 \times (1 - .34) \times [7.7 \times (407 \times .00869) / 8.8314 - 4 \times (3 \times (407 \times .461) / 3.7964)]$$

In 2002-03, Lidstrom tied for third for PCD^{PP}. Detroit tied three other teams for the fewest power play goals against. He ranked 6th amongst defensemen in power play ice time.

When you put short handed and power play situations together you see that Lidstrom contributed more to special team defense (PC = 29) than any other player.

Penalties

In order to allocate responsibility for the creation of short handed situations, we must translate individual penalty data to short handed opportunities (SHO). As the league does not publish this statistic, we can only estimate this. Misconducts don't created short handed situations and it takes two to fight. So we are left to conclude that penalty minutes are a poor predictor of SHO. Minor penalties are (mainly) what we need. Here is the formula for individual (estimated) SHO:

PSHO = Minor Penalties +Major Penalties – Fighting Majors,
(penalties potentially generating short handed situations)

$$SHO = SHO_{TEAM} \times PSHO / \Sigma_{TEAM}\, PSHO$$

Offsetting minors and bench penalties are complications. Offsetting penalties do not create short handed opportunities. Bench penalties do not show up in player statistics. $PSHO / \Sigma_{TEAM}$ PSHO is a simple way of adjusting for both of these problems.

So the formula for PCD^{SHO} is:

$$PCD^{SHO} = PCF \times MGD^{SHO}$$
$$= PCF \times (1\text{-}G) \times (1+DA) \times (GA^{SH}< \times T / \Sigma_{TEAM}\, T - (1 - PK<) \times SHO_{TEAM} \times PSHO / \Sigma_{TEAM}\, PSHO)$$

In this formula, the basic individual moving parts are the penalties. The other factors are basically league or team based. The credit part of the formula ($GA^{SH}<$) is allocated across the team in proportion to individual ice time. Why not reflect position in this allocation? I studied this individual SHO estimate by position and discovered that forwards and defensemen generate short handed opportunities at about the same rate per minute of ice time. This result surprised me until I reminded myself that individual defensemen get more ice time than individual forwards.

Recall that MGD^{SHO} was constructed to be neutral across the league. An individual player can get a positive PCD^{SHO} by avoiding penalties or a negative PCD^{SHO} by taking them. Below are a couple of sample calculations for Sami Salo and Todd Bertuzzi of Vancouver. This says that Salo won 3/4 of a game by staying out of the penalty box. Bertuzzi cost Vancouver a win with his penalty taking.

Salo:

$$PCD^{SHO} = 15 \quad = 3.76 \times (1 - .24) \times 1.58 \times (59.6 \times (1591 / 24094) - (1 - .836) \times 390 \times 5 / 440)$$

Bertuzzi

PCD^{SHO} = - 22 = 3.76 x (1 - .24) x 1.58 x (59.6 x (1687 / 24094) – (1 – .836) x 390 x 62 / 440)

Below is a listing of the top "penalty avoiders" as ranked by PCD^{SHO}:

2002-03 Defensive Player Contribution
Penalty Avoidance

Forwards				Defensemen		
Player	**Team**	**PCDSHO**		**Player**	**Team**	**PCDSHO**
Brad Richards	TB	13		Toni Lydman	CAL	19
Mike York	EDM	13		Brian Rafalski	NJD	18
Jozef Stumpel	BOS	13		Sami Salo	VAN	15
Tony Hrkac	ATL	12		Sergei Zubov	DAL	14
Steve Rucchin	ANA	12		Scott Stevens	NJD	14
Patrik Stefan	ATL	12		Brent Sopel	VAN	14
Mario Lemieux	PIT	12		Jordan Leopold	CAL	13
Miroslav Satan	BUF	12		Nicklas Lidstrom	DET	13
Alexander Mogilny	TOR	11		Daniel Tjarnqvist	ATL	13
Martin Straka	PIT	10		Jonathan Girard	BOS	12

Brian Rafalski took only 7 minor penalties in 1829 minutes, but Toni Lydman edged him out to be the league's PCD^{SHO} leader. This is quite an accomplishment for a young defenseman. He played 2088 minutes and collected only 14 minor penalties.

Lydman's score was helped a bit by Calgary's low MG/W of 4.9 and by Calgary's awful goaltending. There are 3 Thrashers on this list. They got there by the confluence of (a) the league's lowest MG/W of 4.6, (b) weak goaltending and (c) generally avoiding penalties. The way to translate this into English is that these players were very successful at avoiding penalties **in a situation where it really mattered** -- a team with poor goaltending and a propensity to squeeze victories out of close games. Remember that Player Contribution is about the contribution to winning. On teams like Atlanta and Calgary, penalty avoidance counts for much more than it does on a team like New Jersey.

In every other "situation", looking at the bottom end of the list would not have told us much. You end up at the bottom of those lists by not playing much or not playing well or both. Because penalties are neutral across the league, we can learn something from looking at the lowest scores. Below is a listing of the top penalty taking impact as ranked by PCD^{SHO}:

2002-03 Defensive Player Contribution Penalty Taking

Forwards				Defensemen		
Player	**Team**	**PCDSHO**		**Player**	**Team**	**PCDSHO**
Chris Simon	CHI/WAS	-23		Andy Sutton	ATL	-24
Todd Bertuzzi	VAN	-22		Sean Hill	CAR	-17
Donald Brashear	PHI	-21		Wade Belak	TOR	-17
Darren Langdon	VAN/CAR	-21		Cale Hulse	NAS	-13
Chris Clark	CAL	-20		Todd Simpson	PHO	-12
Scott Mellanby	STL	-18		Bryan McCabe	TOR	-12
Nik Antropov	TOR	-18		Chris Tamer	ATL	-12
Sean Avery	DET/LA	-18		Shane Hnidy	OTT	-12
Matt Johnson	MIN	-17		Barret Jackman	STL	-12
Tyson Nash	STL	-16		Denis Gauthier	CAL	-12

Although Sean Hill lead the league with 63 minor penalties, notice that Andy Sutton (53 minor penalties) is way out "in front" on the defenseman's list. Again we see Atlanta's circumstances magnifying the impact of penalties. Although there are some "tough guys" on this list, most of these players I would call undisciplined.

Results

Defensive Player Contribution leaders are shown below for forwards and defensemen, for even handed and short handed situations and overall (you already have the penalty avoidance leaders).

2002-03 Defensive Player Contribution by Situation and Position

Forwards										
Even Handed				**Short Handed**				**Overall**		
Player	**Team**	**PCDEH**		**Player**	**Team**	**PCDSHK**		**Player**	**Team**	**PCD**
Stephane Yelle	CAL	18		Todd Marchant	EDM	18		Jere Lehtinen	DAL	38
Daniel Alfredsson	OTT	15		Kris Draper	DET	16		Patrik Elias	NJD	35
Todd White	OTT	15		Kent Manderville	PIT	15		Todd Marchant	EDM	34
John Madden	NJD	14		Jere Lehtinen	DAL	14		John Madden	NJD	34
Jere Lehtinen	DAL	14		Kirk Maltby	DET	14		Mike York	EDM	30
Daymond Langkow	PHO	14		Artem Chubarov	VAN	13		Richard Park	MIN	29
Michal Handzus	PHI	14		Blake Sloan	CAL	13		Tony Hrkac	ATL	29
Mike Modano	DAL	14		Patrik Elias	NJD	13		Brad Richards	TB	28
Jeremy Roenick	PHI	13		Mike York	EDM	12		Artem Chubarov	VAN	28
Keith Primeau	PHI	13		Patric Kjellberg	ANA	12		Jozef Stumpel	BOS	28

Defensemen										
Even Handed				Short Handed				Overall		
Player	Team	PCDEH		Player	Team	PCDSHK		Player	Team	PCD
Eric Desjardins	PHI	47		Toni Lydman	CAL	23		Toni Lydman	CAL	73
Denis Gauthier	CAL	46		Nicklas Lidstrom	DET	21		Eric Desjardins	PHI	73
Scott Niedermayer	NJD	43		Chris Chelios	DET	20		Scott Niedermayer	NJD	72
Sean Hill	CAR	42		Scott Niedermayer	NJD	19		Nicklas Lidstrom	DET	71
Scott Stevens	NJD	40		Zdeno Chara	OTT	18		Brian Rafalski	NJD	68
Eric Weinrich	PHI	40		Robyn Regehr	CAL	18		Kim Johnsson	PHI	67
Zdeno Chara	OTT	40		Luke Richardson	CBJ	18		Scott Stevens	NJD	66
Derian Hatcher	DAL	40		Adrian Aucoin	NYI	18		Sergei Zubov	DAL	66
Colin White	NJD	38		Todd Marchant	EDM	18		Eric Weinrich	PHI	63
Kim Johnsson	PHI	38		Bryan McCabe	TOR	18		Wade Redden	OTT	63

These lists are "who's who" of defense. Lydman is probably the most surprising name amongst defensemen. Let's compare his PCD scores to the other in the top five:

Player	Team	PCDEH	PCDPP	PCDSHK	PCDSHO	PCD
Toni Lydman	CAL	27	3	23	19	73
Eric Desjardins	PHI	47	3	12	10	73
Scott Niedermayer	NJD	43	7	19	2	72
Nicklas Lidstrom	DET	28	8	21	13	71
Brian Rafalski	NJD	36	8	6	18	68

You can see that these five players got to the top of this list in different ways. Compared to Desjardins, Niedermeyer and Rafalski, Lydman lagged even handed. But he made up for it by avoided penalties (vs Desjardins and Niedermeyer), and killing penalties (vs Desjardins and Rafalski). The most similar profile to Lydman was Lidstrom's. Neither player had exceptional even handed performance. But both contributed a lot on the penalty kill, ranking one and two. Lidstom played 486 minutes short handed while Lydman played 325 minutes. Lidstrom was on the ice for 41 short handed goals against (Lydman 30) with a personal PK% of 87.3% (Lydman 85.8% in front of weak goaltending). Both players were adept at avoiding penalties. Both players were among the top 10 in ice time (Lidstom 2406 minutes, Lydman 2088).

Niedermeyer would have been the league's top defensive defenseman but for his penalty taking. Ironically, he might have been the league's top defensive defenseman but for his team's lack of penalty taking. The Devils took fewer penalties than any other team. Niedermeyer played short handed for 185 minutes and was on the ice for **only 6 goals against** (personal PK% of 94.7%)!

The even handed defense leader board for forwards is actually populated by competent offensive players. With one exception, the top 10 all collected 19 or more goals. Yelle had only 10 goals and 15 assists. He was also -10. So how did he get to the top of the list? Yelle played 1069 even handed minutes. This was a very typical figure for this group. He was on the ice for an estimated 32 even handed goals against. This is also typical of this list (Lehtinen led the list with an estimated 25 even handed minuses). But the analysis gives Yelle a break for playing in front of incompetent goaltending.

The Frank Selke Jr. Trophy goes to the top defensive forward. Jere Lehtinen (DAL) won the award and the other finalists were John Madden (NJD) and Wes Walz (MIN). This is a trophy the voters usually get wrong, voting on reputation. But this year they (sort of) got it right. Lehtinen and Madden did distance themselves from the pack. But not only did Walz not belong on the ballot, he was not even his team's best defensive forward. Here is the profile of the real top five, plus, for completeness, Walz and teammate Richard Park:

2002-03 Frank Selke Jr. Trophy

Player	Team	PCDEH	PCDPP	PCDSHK	PCDSHO	PCD
Jere Lehtinen	DAL	14	0	14	9	38
Patrik Elias	NJD	12	0	13	10	35
Todd Marchant	EDM	11	0	18	6	34
John Madden	NJD	14	0	11	9	34
Mike York	EDM	4	0	12	13	30
Richard Park	MIN	10	0	10	9	29
Wes Walz	MIN	10	0	8	-1	17

Lehtinen and Madden look pretty similar. These guys both stay out of the penalty box, play an important part of a successful penalty kill and get a lot of even handed ice time on good defensive teams. Lehtinen wins the comparison based on penalty killing. I estimate his personal penalty killing percentage at 87.8% (vs Madden at 83.7%).

Elias is one of my favourite players. You have got to like him for 28 goals and 29 assists. But you have you like him even more when you notice how competent a defensive player he is. In particular, Elias was outstanding on the penalty kill. He spent 142 minutes killing penalties and was on the ice for **only 5 goals against** (a personal PK% of 94.3%). What are they eating in New Jersey? Madden has a Selke already and, for this trophy, reputations rule. Elias won't win the trophy with Madden on his team.

Step 8: Allocate Marginal Goals Goaltending to Individual Goaltenders

Allocating MGG, is simple. As all of the factors are available at the individual level, we are just going to use the team formula on individual players:

MGG = (SOG – ENG) x (1 – SPT) – (SOG x (1 – SQNSV) – ENG)

MGG =(SOG – ENG) x (1- SPT) – (GA – ENG)

As there are no empty net goals or shots allocated to individual goaltenders, this becomes:

MGG = SOG x (1 – SPT) – SOG x (1 – SQNSV)
and
PCG = PCF x MGG

Goaltenders also contribute occasionally to offense. This part is also simple. For Goaltenders we give credits for Goals Created and apply no debits (ie the threshold level of performance is no offense). Goaltenders take penalties. We give no credits for this, just debits. These two approaches are not faitheful to the rest of Player Contribution, but the distortion is very small

Below is a list of the top goaltenders as ranked by their Player Contribution. The offensive and defensive parts of this don't add up to much. PCO is basically a few assists. PCD is from penalty taking. The MGG formula is basically "opportunities" x "performance". All of these goaltenders played a lot of games, faced a lot of shots and had pretty good shot quality neutral save percentages.

2002-03 Top 10 Goaltenders

Player	Team	GP	Min	GAA	SV%	SQNSV%	MGG	MGG/G	PCG	PCO	PCD	PC
Roberto Luongo	FLA	65	3,628	2.71	0.918	0.924	**63**	1.04	244	0	-1	**243**
Marty Turco	DAL	55	3,203	1.72	0.932	0.930	**51**	0.95	184	3	-5	**183**
Ed Belfour	TOR	62	3,738	2.26	0.922	0.922	**49**	0.79	180	2	-4	**178**
Olaf Kolzig	WAS	66	3,894	2.40	0.919	0.919	**47**	0.72	175	0	0	**175**
Jean-Sebastien Giguere	ANA	65	3,775	2.30	0.920	0.918	**45**	0.72	177	0	-2	**175**
Patrick Roy	COL	63	3,769	2.18	0.920	0.917	**45**	0.72	174	0	-2	**172**
Mike Dunham	NAS/NYR	58	3,286	2.50	0.916	0.920	**43**	0.78	161	1	0	**162**
Dwayne Roloson	MIN	50	2,945	2.00	0.927	0.918	**43**	0.88	154	1	-1	**154**
Tomas Vokoun	NAS	69	3,974	2.20	0.918	0.922	**39**	0.59	148	1	-5	**144**
Roman Cechmanek	PHI	58	3,350	1.83	0.925	0.920	**37**	0.66	145	0	-3	**142**

As we would expect after completing our assessment of team goaltending, there is Luongo sitting at the top of the list. This analysis demonstrates the uselessness of Goals Against Average in assessing a goaltender. Luongo had the highest GAA on the list. But when you back out the team effects (shots on goal and shot quality) you find that he is an awfully good goaltender. Notice that Turco had a higher SQNSV%. If he had played as much as Luongo and faced the same number of shots, he would have had a higher PC score. So he looks like the more "talented" goaltender. But remember that Player Contribution sets out to measure contribution. Luongo contributed way more.

Where is Vezina Trophy winner Martin Brodeur? He ranks 23rd with a PC of 82. As Brodeur played more than any other NHL goalie, you might think that he ought to rank higher. But he played behind excellent team defense. New Jersey allowed the fewest shots on goal in the league and Brodeur faced only 1706 shots. New Jersey allowed the lowest shot quality in the league (SQA of .915). In his defense, he was not given the same opportunity to contribute that was given to Luongo. Still, his raw save percentage (.914) was lower than any of the top 10 goalies. His SQNSV% of .906 was uninspiring. Sorry trophy voters. You got this one wrong.

Are Goaltenders Really That Valuable?

The top 12 PC leaders are all goaltenders and 17 of the top 25 PC scores are from goaltenders. Do goaltenders really contribute that much to team success? Would St. Louis have been 9 wins better off with Belfour between the pipes? My answers are yes and no.

Every year you hear about how much goaltending means to a team during the playoffs. They gave the Conn Smythe trophy to Giguerre and they keep giving it to goalies (9 of 39 winners). Goaltending is no more important in the playoffs than during the regular season. I know goaltenders tend not to win the Hart Trophy. But they should, most of the time, as the "most valuable player to his team".

The answer to the Belfour question is complex. Below is a snapshot of the Blues' goaltending. It is clear from this picture that St. Louis did not have much goaltending. The crease clearly had the appearance of a revolving door. Over the course of the season, Johnson was statistically the main man. However, the team seemed to feel that he wasn't good enough. In November St, Louis gave Barasso a shot, but he was released in December. Brathwaite got 23 starts but the Blues released him in March after acquiring Chris Osgood. Osgood's record with the Blues was similar to his record with the Islanders, but he was no better than Brathwaite. Along the way, a number of minor leaguers were given a shot, but none of them impressed enough to stay with the team.

	GP	GS	MIN	W	L	T	GA	GAA	SOG	SV	SV%	MGG	PCG
Tom Barrasso	6	6	293	1	4	0	16	3.28	132	116	0.879	-0.6	-2
Fred Brathwaite	30	23	1615	12	9	4	74	2.75	631	557	0.883	-0.7	-3
Reinhard Divis	2	2	83	2	0	0	1	0.72	34	33	0.971	2.7	10
Brent Johnson	38	35	2042	16	13	5	84	2.47	844	760	0.900	29.9	48
Chris Osgood	9	9	532	4	3	2	27	3.05	241	214	0.888	0.9	3
Cody Rudkowsky	1	0	30	1	0	0	0	0.00	10	10	1.000	1.1	4
Curtis Sanford	8	7	397	5	1	0	13	1.96	148	135	0.912	3.8	14

To figure the impact of signing Belfour as a free agent, you have to recast Belfour's numbers in the St. Louis context. You also need to recast the contribution of other St. Louis goaltenders. Let's just keep Johnson and have him play 20 games. That would give him a PC score of 29. Let's have Belfour play 62 games. He brings his SQNSV%

of .922 from Toronto, but you have to project his shots in a St. Louis context. The Blues averaged 15.5% fewer shots per game than did the Maple Leafs. Adjusting for the differences in PCF between the two teams, minutes played and shots faced, Belfour's PC score becomes about 147. That would give St, Louis a hypothetical PC from goaltenders of 176, 102 points more than were produced in reality. This translates to about 5 extra wins.

Before closing the chapter on goaltenders, we should take note of the bottom end of the goaltender list as well. There were 23 goalies with negative PC, 8 had PC scores less than –15 and 2 goalies with PC of –40 or less. Most of this crowd played fewer than a dozen games. There were 6 goalies from this list that played in more than 20 games. Brian Boucher (PHO) played in 45 games (PC = -4), Fred Braithwaite (STL) played 30 games (PC = -3) and Ron Tugnett (DAL) played 31 games (PC = -1). Calgary's Jamie McLennan (PC = -16) and the Sharks' Miikka Kiprusoff (PC = -21) both played 22 games. But the two worst performances came from Carolina's Arturs Irbe (–40 PC in 34 games) and Atlanta's Byron Dafoe (17 games, PC = – 51).

Goaltending is the one place where we expect to find a large negative Player Contribution. Because there are so few goalies, there is little perceived depth at the position. An injury or a perceived lack of options can compel a coach to stick with a veteran who is having a bad year.

Conclusions

What we have done is slice team performance into 9 component parts and then allocate the team performance to individuals. Breaking performance up in this fashion allows us to see the game in smaller, more homogeneous bits. At the individual level we have observed or estimated individual performance so that the team is the sum of the players. Individual performance has been measured against thresholds that reflect the circumstances, position and situation. These circumstantial thresholds are fair across position and situation. Now we are ready to add up the pieces and assess the results.

But before we bring this all together, I need to comment on three issues – key assumptions, trades and negative Player Contribution.

Key Assumptions

The most critical assumption I made was that DA = 7/12 (58%). This is really two assumptions joined together: that goaltending represents 1/6th of the game and that skaters play offense half the time and defense half the time.

Using Bill James' criteria, does DA = 58% fit the data well? Not really. The "data" would be people's **impressions** of player performance over the years. It is very clear, historically, that forwards have been perceived as being more valuable that other players. Goaltending has not attracted 1/6th of payrolls. They don't win the Hart trophy every year. If goaltenders should not win the Hart, then defensemen don't win their proportionate share of Hart Trophies. And defensemen don't get paid like forwards. I have heard the argument that defense is a passive, reaction skill and must therefore be less impactful than offense. My response to this is to watch the All-Star game and note the impact of an absence of defense.

I decided not to make Player Contribution "fit the data" because impressions are not data. I don't believe that goaltending and defense have ever been properly measured. We are impressed by goal scoring and playmaking because we can directly attribute these critical events to individuals. Yet we struggle with goaltending. We don't have a metric for "brilliant saves". We can't give credit for cutting the angle down. We don't know how to compare goaltenders to forwards. And we struggle even more with defense where we have no metrics at all.

If you accept my two basic assumptions, I think you will find that the results of the analysis make sense even if they surprise you. Player Contribution gives us a metric for defense. It puts offense, defense and goaltending in the same currency. If you wish, the Player Contribution method is robust enough to use different basic assumptions.

The obvious consequences of these two assumptions are:

- The best goaltenders ought to have much higher Player Contribution than the best skaters. I believe that this makes sense. If I were building a team, I would start in goal.

- Defensemen can be as valuable as forwards. This is especially true of offensive defensmen. These guys have always had the short end of the stick at trophy and salary times. Now that we have a measure of defense, maybe they can get the credit they deserve.

Traded Players

Traded players cause some headaches because of the tendency to publish data at the individual level, rather than for players within teams. As you have already seen, situational play and ice time are key to the method. But all I had to work with for traded players was the combined detail for all games and a limited amount of summary information for each team. I was forced to assume that players had the same ice time profile for each of their teams. I also had to distribute situational goals, assists and penalties between the player's teams. Although I made attempts to reconcile these splits to team data, some distortions certainly crept in.

Negative Player Contribution

What to do with negative PC? Bill James zeroed out negative Win Shares, effectively spreading the negative contribution of individuals across the team. I have let negative Player Contribution stand. It is not Dany Heatley's fault that the coach played Byron Dafoe in goal. The way the method is set up, a player with any amount of playing time generally ends up with positive PC. I think that it is totally reasonable to have parts of the game come up negative. If a player has terrible defense but makes up for it with great offense, the coach will have a role for him. Can a player have a negative contribution overall? Sure. The player should have been sitting on the bench, but the coach played him. Maybe a good measure of coaching is the sum of the team's negative PC points?

The biggest source of negatives is from penalties. Since we set up PCD^{SHO} to be neutral across the league, a number of skaters with large penalty totals had large negative PCD. Todd Bertuzzi (VAN) had PCO = 91 and PCD = -13. Seven skaters have PC of –10 or lower. All of them had PCD^{SHO} worse than –8. I can't tell you how much I agonized over the right treatment for penalty taking. The big negatives bother me, but I thought that my approach was the best solution.

The only other way you get to negative Player Contribution is to play a lot at a sub-marginal level. Although this is mainly a goaltender phenomenon, some skaters managed to do this as well. If you take penalty taking out of the analysis, Chicago's Burke Henry was the most sub-marginal player in the NHL with a PC of –6 (PCO of –1 and PCDEH of –5). He played only 16 games, averaged 18 minutes of ice time and had a +/- of – 13. Peter Worrell (FLA) patrolled left wing for 63 games, collected 5 scoring points and had a +/- of –14. He averaged 9 minutes of ice time per game. His PC points were –7 offensively and +2 defensively, before he contributed –14 by taking penalties.

Results

Below is a list of the PC leaders, other than goaltenders, from 2002-03:

2002-03 Player Contribution Leaders (excluding Goaltenders)

				Offense (PCO)					Defense (PCD)				
Player	Team	Pos	PC	EH	PPP	PPO	SH	PCO	EH	PP	SHK	SHO	PCD
Nicklas Lidstrom	DET	D	124	28	23	-2	3	53	28	8	21	13	71
Al MacInnis	STL	D	114	24	29	1	3	56	31	8	8	11	58
Markus Naslund	VAN	LW	110	46	51	1	0	98	9	0	1	1	11
Milan Hejduk	COL	RW	109	61	31	0	-1	91	11	0	2	5	18
Sergei Zubov	DAL	D	106	19	22	-1	-1	40	35	5	12	14	66
Sergei Gonchar	WAS	D	103	34	22	-1	3	59	22	11	5	6	44
Scott Niedermayer	NJD	D	99	27	3	-2	-1	27	43	7	19	2	72
Dany Heatley	ATL	RW	98	53	40	0	1	94	3	-1	2	0	4
Marian Hossa	OTT	RW	98	50	28	1	-1	78	11	0	2	6	19
Dan Boyle	TB	D	98	21	21	1	0	43	34	9	4	7	55
Eric Desjardins	PHI	D	96	22	1	-1	1	24	47	3	12	10	73
Peter Forsberg	COL	C	96	66	21	0	0	87	8	0	1	0	9
Kim Johnsson	PHI	D	96	17	12	-1	1	28	38	4	16	9	67
Wade Redden	OTT	D	96	18	15	1	-1	33	35	4	17	6	63
Zigmund Palffy	LA	RW	95	51	15	0	4	70	11	1	7	7	25
Glen Murray	BOS	RW	94	61	21	-1	1	82	7	0	5	0	12
Joe Thornton	BOS	C	94	59	27	-1	3	88	6	0	6	-5	6
Alexander Mogilny	TOR	RW	93	48	15	0	8	71	2	0	8	11	22
Pavol Demitra	STL	C	92	53	27	1	0	81	4	0	-1	9	12
Zdeno Chara	OTT	D	92	16	12	1	2	31	40	3	18	0	61

MVP

Lidstrom is way out in front on the strength of 71 defensive points (impressive when you note that Detroit was a very average defensive team). Lidstrom was a workhorse. He lead the league with 2406 minutes. After spending over 900 minutes on special teams, he still ranked 6th in even handed minutes (1514). Remember that Player Contribution is roughly “opportunity” x “performance”. Although none of his defensive stats were spectacular, they were all solid. And the ice time was certainly there. On offense he excelled as well. He delivered 18 goals (8 power play and 1 short handed) and 44 assists (22 on the power play).

MacInnis had a profile that looked much like Lidstrom. Their biggest divergence was in penalty killing. MacInnis got only 61% of Lidstom’s ice time, but he also was less effective (personal PK% of 82.7%).

What about Forsberg, who won the Hart, or Naslund, who won the Pearson? Between the two I like Naslund better. Forsberg lead the league in scoring points and was the league’s top offensive player even handed, 19 PC points ahead of Naslund. But Naslund is a sniper (48 goals) and was the league’s dominant power play personality. The Player Contribution method gives more credit to goals than assists. But it also knows that power play offense is “easier” and “taxes” it more heavily. In spite of this, Naslund was 30 PC points ahead of Forsberg on the power play.

Unless you rely on Player Contribution, it is nearly impossible to compare forwards and defensemen. The way I look at it, MacInnis and Lidstom contributed as much defensively as a top forward does offensively. Lidstrom's PCD of 71 was like the offensive contribution of Alexander Mogilny or Zigmund Palffy. MacInnis' PCD of 58 was like the offensive contribution of Martin St. Louis or Jerome Iginla. Then these two players added more than 50 PC points on offense, something that no forward can match on defense. This demonstrates the value of the offensive defenseman. These guys can play both ways and have impact. Only exceptional forwards have a chance of being as valuable as a top offensive defenseman.

Defensemen:

Gonchar kept pace with Lidstroms offensively (he excelled even handed), but his defense held him back. Zubov's season looked a lot like that of Lidstrom, less some even handed offense and penalty killing. Johnsson looked like Zubov with less power play contribution. Boyle looked like MacInnis with a little less offense.

If Niedermeyer could have delivered on the power play (he had only 3 goals and 7 assists in 319 minutes), he could have been MVP. Although he also had his chances, Desjardins did not do much on the power play. He was, however, an exceptional even handed player. Ottawa's Redden and Chara looked like bookends, except in stature.

Forwards:

Naslund was the top forward, by a nose over Hejduk, by being the league's most dangerous player on the power play. Hejduk got to second a different way. He was very strong even handed and contributed more defensively. Hossa's profile looked a lot like Hejduk's. Heatley was in between the two offensively, but was a marginal defensive performer (PCD = 4). Demitra stayed out of the penalty box, but was otherwise lame defensively. Thorton, Forsberg and Murray all excelled at even handed offense but did not play much defense. Palffy was the best defensive forward on the leader board. He combined this with a great even handed offensive performance. Finally, Mogilny collected 16 PC points on the penalty kill and stayed out of the penalty box better than any of the other top forwards.

Trophy Winners

Here are the Player Contribution Leaders for selected NHL trophies:

2002-03 Player Contribution Trophy Winners

Trophy	Given To	Recipient	PC	Comments
Hart	Most Valuable Player	Nicklas Lidstrom (DET)	124	Traditionally goaltenders need to walk on water to win this, so I excluded them.
Vezina	Top Goaltender	Roberto Luongo (FLA)	243	Played more and faced more adversity than Turco. Otherwise Turco would have won it.
	Top Forward	Markus Naslund (VAN)	110	It speaks volumes that the Hart Trophy is the proxy for the top forward award
Norris	Top Defenseman	Nicklas Lidstrom (DET)	124	Lidstrom said that he thought MacInnis would win it.
Calder	Top Rookie	Henrik Zetterberg (DET)	52	Barret Jackman, next best at 41, gave up 22 points to Zetterberg by taking more penalties.
Selke	Top Defensive Forward	Jere Lehtinen (DAL)	76	Lehtinen had 31 goals and 17 assists. But PCD = 38 means that Lehtinen was still 50% defense.
Lady Byng	Combining Skill with Gentlemanly Play	Alexander Mogilny (TOR)	93	See below …

Here is my rationale on the Lady Byng Memorial Trophy. It goes to the player "adjudged to have exhibited the best type of sportsmanship and gentlemanly conduct combined with a high standard of playing ability". The word "combined" suggests an "AND" condition rather than an "OR" condition. Player Contribution was built on "OR" conditions. You get points for being good at offense, or defense, or penalty killing, etc. With "OR" conditions you add. With "AND" conditions you multiply. You need both factors to be strong to get a good "AND" rating. I took Player Contribution to be the measure of skill and (50 – PIM) to be a measure of gentlemanly play. 50 minutes was pretty arbitrary, but Hull was not going to beat Mogilny no matter what. When you put this all together, you get the following Lady Byng finalists. Notice that neither of Lidstrom or Modano, the other finalists, made it to my list. Also note that there are two defensemen on my list. Yet this trophy never goes to a defenseman.

2002-03 Lady Byng Trophy – Player Contribution Finalists

Player	Team	Player Contribution	PIM	Lady Byng Points
Alexander Mogilny	TOR	93	12	3,550
Brian Rafalski	NJD	89	14	3,221
Sami Salo	VAN	79	10	3,174
Mike York	EDM	65	10	2,612
Brett Hull	DET	91	22	2,543

All Star Teams

Below are all star teams, both overall and by situation, as chosen by Player Contribution.

2002-03 Player Contribution All Star Teams

Overall

	First Team				Second Team		
	Player	**Team**	**PC**		**Player**	**Team**	**PC**
LW	Markus Naslund	VAN	110		Patrik Elias	NJD	83
C	Peter Forsberg	COL	96		Joe Thornton	BOS	94
RW	Milan Hejduk	COL	109		Dany Heatley	ATL	98
D	Nicklas Lidstrom	DET	124		Sergei Zubov	DAL	106
D	Al MacInnis	STL	114		Sergei Gonchar	WAS	103
G	Roberto Luongo	FLA	243		Marty Turco	DAL	183

The West dominates the first team with 5 of 6 players. The NHL's lack of depth at left wing shows up as Elias has the lowest score on the team. Remember, when looking at the, that Player Contribution amounts to "opportunity" x "performance". Turco may have been the "better" goaltender, but he did not play enough to make beat Luongo.

East

	First Team				Second Team		
	Player	**Team**	**PC**		**Player**	**Team**	**PC**
LW	Patrik Elias	NJD	83		Vaclav Prospal	TB	77
C	Joe Thornton	BOS	94		Mario Lemieux	PIT	88
RW	Dany Heatley	ATL	98		Marian Hossa	OTT	98
D	Sergei Gonchar	WAS	103		Dan Boyle	TB	98
D	Scott Niedermayer	NJD	99		Eric Desjardins	PHI	96
G	Roberto Luongo	FLA	243		Ed Belfour	TOR	178

West

	First Team				Second Team		
	Player	**Team**	**PC**		**Player**	**Team**	**PC**
LW	Markus Naslund	VAN	110		Geoff Sanderson	CBJ	73
C	Peter Forsberg	COL	96		Pavol Demitra	STL	92
RW	Milan Hejduk	COL	109		Zigmund Palffy	LA	95
D	Nicklas Lidstrom	DET	124		Sergei Zubov	DAL	106
D	Al MacInnis	STL	114		Tony Lydman	CAL	84
G	Marty Turco	DAL	183		J.S. Giguerre	ANA	175

Tampa Bay places two on the second team in the East. Hossa is the only player from the exceptionally strong Senators to make the all-stat team. Desjardins is a worthy all-star as is Belfour. Lemieux doesn't play defense, but he sure can score.

With the exception of Zubov, the second team presents the new faces in the west. Lydman gets a well deserved spot on defense. Giguerre belongs in goal. Up front Palffy and Demitra are joined by Geoff Sanderson (who was 1 PC point ahead of team mate Ray Whitney)..

Honourable mention goes to Kim Johnsson (PHI), Wade Redden (OTT), Glen Murray (BOS), Alexander Mogilny (TOR), Zdeno Chara (OTT), Thomas Kaberle (TOR), Mike Modano (DAL), and Brett Hull (DET) who all collected 90 points or more, but failed to make the cut.

Green (25 & Under)

	First Team				Second Team		
	Player (Age)	Team	PC		Player (Age)	Team	PC
LW	Ilya Kovalchuk (19)	ATL	64		Martin Havlat (21)	OTT	63
C	Joe Thornton (23)	BOS	94		Vincent Lecavalier (22)	TB	83
RW	Dany Heatley (21)	ATL	108		Marian Hossa (23)	OTT	98
D	Wade Redden (25)	OTT	96		Thomas Kaberle (24)	TOR	92
D	Zdeno Chara (25)	OTT	92		Tony Lydman (25)	CAL	84
G	Roberto Luongo	FLA	243		J.S. Giguerre	ANA	175

Grey (35 & Over)

	First Team				Second Team		
	Player (Age)	Team	PC		Player (Age)	Team	PC
LW	Cliff Ronning (37)	MIN	40		Ulf Dahlen (35)	DAL	40
C	Mario Lemieux (37)	PIT	88		Vincent Damphousse (35)	SJ	44
RW	Brett Hull (38)	DET	91		Scott Young (35)	DAL	50
D	Al MacInnis (39)	STL	114		Eric Weinrich (36)	PHI	72
D	Scott Stevens (38)	NJD	75		Calle Johansson (35)	WAS	62
G	Ed Belfour (37)	TOR	178		Patrick Roy (37)	COL	172

(Age) =2002 - Calendar Year of Birth

Ottawa had the best team in the league and one of the youngest. Redden and Chara give Ottawa a very strong defensive foundation over the mid-term. Up front Hossa and Havlat are awesome. Atlanta has a promising future with Heatley (the only Green All Star Team member who made the overall All Star Team) and Kovalchuk. They just need to teach these guys to play defense, and some goaltending, and a supporting cast, and …

The only Grey All Star Team member to make the Overall All Star Team was MacInnis. He is still at the top of his game. Of course, Belfour and Roy would seem to be still at the top of their game. Other outstanding "grey" performances came from Lemieux and Hull. Dallas was the only team with two players on the Grey team -- Dahlen and Young.

Offense

	First Team				Second Team		
	Player	Team	PCO		Player	Team	PCO
LW	Markus Naslund	VAN	98		Ilya Kovalchuk	ATL	64
C	Joe Thornton	BOS	88		Peter Forsberg	COL	87
RW	Dany Heatley	ATL	94		Milan Hejduk	COL	91
D	Sergei Gonchar	WAS	59		Nicklas Lidstrom	DET	53
D	Al MacInnis	STL	56		Dan Boyle	TB	43

Defense

	First Team				Second Team		
	Player	**Team**	**PCD**		**Player**	**Team**	**PCD**
LW	Patrik Elias	NJD	35		Radovan Somik	PHI	28
C	Todd Marchant	EDM	34		John Madden	NJD	34
RW	Jere Lehtinen	DAL	38		Mike York	EDM	30
D	Tony Lydman	CAL	73		Scott Niedermeyer	NJD	72
D	Eric Desjardins	PHI	73		Nicklas Lidstrom	DET	71

Lidstrom makes both teams. That, by itself, tells me that he belongs on the top of the PC leader board. Do you wonder why New Jersey is such a tough team to beat? Elias, Madden and Niedermeyer are evidence of the hard work, discipline and talent on that team. Rafalski, Stevens and Pandolfo were also not far from the All-Defense team.

Even Handed

	First Team				Second Team		
	Player	**Team**	**PCEH**		**Player**	**Team**	**PCEH**
LW	Markus Naslund	VAN	55		Alex Tanguay	COL	53
C	Peter Forsberg	COL	74		Joe Thorton	BOS	65
RW	Milan Hejduk	COL	72		Glen Murray	BOS	68
D	Scott Niedermeyer	NJD	70		Derian Hatcher	DAL	67
D	Eric Desjardins	PHI	70		Nicklas Lidstrom	DET	67

PCEH = PCOEH + PCDEH

Naslund is still the top even handed left winger notwithstanding his prowess on the power play. Desjardins made the first team on defense. Hatcher shows up too. How would you like to have Tanguay, Forsberg and Hejduk as your number one line?

Power Play

	First Team				Second Team		
	Player	**Team**	**PCPP**		**Player**	**Team**	**PCPP**
LW	Markus Naslund	VAN	51		Dave Andreychuk	TB	28
C	Mario Lemieux	PIT	40		Vincent Damphousse	SJ	28
RW	Todd Bertuzzi	VAN	40		Dany Heatley	ATL	49
D	Al MacInnis	STL	37		Mathieu Schneider	LA / DET	33
D	Sergei Gonchar	WAS	34		Nicklas Lidstrom	DET	32

PCPP = PCOPPP + PCDPP

It is interesting to me how only two players, Naslund and Lidstrom, are on both the even handed and power play teams. I would have guessed at much more overlap. The rest of the power play team reminds me of sharks – they know what to do when there is blood in the water. And what's with Dave Andreychuk? His PCO^{PPP} is 28, but his PCO^{EH} is -7!

Short Handed

	First Team				Second Team		
	Player	Team	PCDSH		Player	Team	PCSH
F	Todd Marchant	EDM	22		Chris Draper	DET	20
F	Kirk Maltby	DET	21		Shawn Bates	NYI	17
D	Nicklas Lidstrom	DET	24		Chris Chelios	DET	24
D	Tony Lydman	CAL	24		Bryan McCabe	TOR	23

PCSH = PCOSH + PCDSHK

Here is Lidstrom again! Offense on the penalty kill is a bit of a lottery and could have an effect on the leader board. If you look at penalty killing defense only Niedermeyer takes McCabe's place on defense and Kent Manderville and Jere Lehtinen bump Maltby and Bates.

Final Remarks

Does player contribution do what I claim it does? There are several ways to try to answer the question.

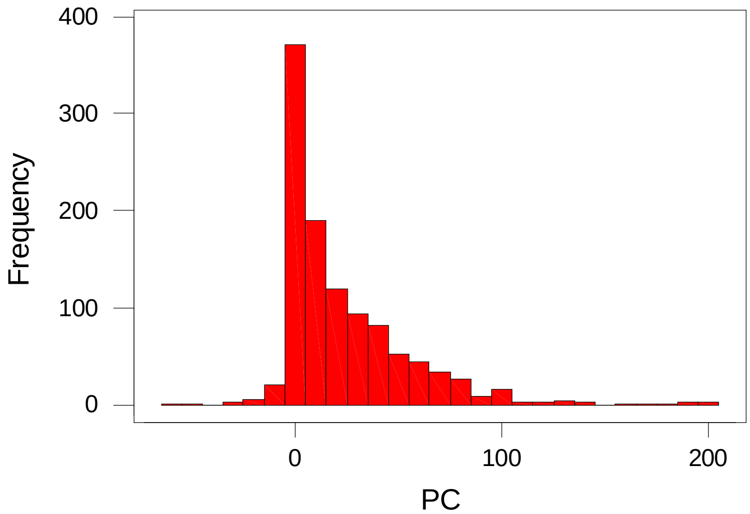
First, let's have a look at the distribution of PC points between defensemen and forwards. In any group of 20 players, we would expect to find 8 defensemen since defensemen account for about 40% of ice time. So here is a look at the top 100 players, stratified into groups of 20:

2002-03 Player Contribution Stratified Counts

Ranking	Number of Forwards	Number of Defensemen
1-20	10	10
21-40	12	8
41-60	13	7
61-80	12	8
81-100	14	6

Of the top 100 players, 39 are defensemen. We would expect about 41 defensemen based on ice time, maybe fewer if you take headcount into consideration. There is a bit of bias towards defensemen in the results at the very top, but it is not statistically significant. Overall, this analysis suggests that Player Contribution is fair to all skaters and that we are getting a fair measure of defensive contribution.

Now, let's have a look at a frequency chart for Player Contribution. This graph (see below) looks just like what I promised you at the beginning of Step 6 … the "tail" of a distribution. The fact that there are very few players with PC much less than zero is an endorsement of the level of the Defensive Attribution (58%).



More formally, there are two basic ways to assess the reliability of the Player Contribution model.

Reproducibility

The first way to evaluate the method is to look at "reproducibility". Does the method give the "same" player (roughly) the same score under varying circumstances?

Does a "good" player on a "bad" team get the same score as if he had played on a "good" team? One way of looking at this is the distribution of the top players amongst teams. Every team placed at least one player in the top 100. Vancouver placed 7, Ottawa, Detroit, Dallas and Tampa Bay each placed 6. Colorado, New Jersey, Philadelphia and Toronto each placed 5. As the method allocates wins to players, top teams have more wins to go around. And this in turn means that the best teams will tend to place more players on the leader board. As I eyeball the results, it looks to me like good players on "bad" teams can score well. Roberto Luongo (FLA) really stands out. So does Mario Lemieux, although his scoring did not need Player Contribution to help us see this. Columbus placed 4 players in the top 100. Geoff Sanderson, Ray Whitney and Andrew Cassels each had a big year. Calgary placed Toni Lydman and Jerome Iginla in the top 100.

The "varying circumstances" are, for most players, season to season. The tough part about that is that teams tend not to change much from season to season while there is an element of variation in player performance. Even then, the reproducibility test can only get you so far. Remember that this method sets out to measure the **contribution** of a player. The coach gets to decide this. If a good penalty killer, for some reason, does not get the chance to kill penalties, he won't get any PC points for penalty killing. And team context may well change. In 2002-03, Atlanta won a lot of close games. Dany Heatley's

PC score was high because his offense mattered more in this context. If, as I suspect, the Thrashers were just plain lucky in close games last season, Heatley's PC score will probably drop next season.

The best way to assess reproducibility might be by following traded players and free agents where the team context for players changes considerably. I am not yet in a position to do this analysis as I have not applied this method backwards. In any case, that analysis would be full of "noise". A big part of a player's contribution is determined by the coach and a given player will be used differently by two coaches. Even the same coach will adjust roles from season to season. Furthermore, a player's performance naturally varies from season to season. Considering these issues, the "noise" may be overwhelm the data.

Validation

The second way to look at this is "validation". Does the method give you answers you would expect? You can only go so far with this. If Player Contribution always gives you the answers you expect, then it does not expand our understanding of the game. But let's see …

Lehtinen won the Selke, Mogilny won the Lady Byng and Lidstrom won the Norris. These awards validate the method. But Forsberg won the Hart, Naslund won the Pearson, Jackman won the Calder and Brodeur won the Vezina. This contradicts the method. So I don't know if we have validation or not. Part of the problem is that we don't know if the voters are smart or not.

In Brodeur's case, I think the voters are dead wrong. He did not face that many shots and he did not have an impressive save percentage. The voters seem to think that a save percentage of .914 is similar to .924 (Roberto Luongo). It's not. It says that, over 2000 shots on goal, Luongo stops 20 goals that Brodeur lets in. And let's not forget that the Devils had the lowest shot quality allowed in the NHL whereas Florida ranked 29^{th}. Luongo was the most valuable goaltender to his team by a long distance. He and Turco were the top talents in the league.

In the case of the Calder, voters are not well equipped to compare forwards, defensemen and goaltenders. Generally this award goes to a forward and it should have in 2003. Jackman had a pretty solid looking year. But he took a lot of penalties and was carried by MacInnis. Zetterberg had good looking offensive stats (22 goals, 22 assists) and played pretty good defense for a rookie.

As to the Hart / Pearson, there is an historic bias towards forwards in this voting. I have long felt that a goalie should win this almost every year. But they don't. I got over it. Over the years defensemen, with one notable exception, have been downtrodden. I am not over this! This is just evidence that we have not been able to measure defense. Player Contribution finally gives us a way to do that. If a forward should win this award, my vote would go to Hejduk. His PC score is just a bit better than Nasland's, whose raw offensive numbers were fattened up on the power play (he spent 90 more minutes on the power play than did Hejduk). Hejduk was better defensively, or, at least, such an offensive threat that he never had to play much defense. Player Contribution sorts these differences out for you. But I think that it was very close between Naslund, Forsberg and Hejduk. The two trophy winners were good choices.

Another validation test is to identify players with similar PC numbers during 2002-03 and then ask yourself if you believe that these players had similar performance. To do this (for skaters only), I assessed the similarity of all players to a benchmark player's performance by calculating the difference between the 8 benchmark PC scores (offense and defense, by situation) and the 8 scores of the other players. Then I squared the difference, added up the results and finally added the square of the difference in ages between the player under consideration and the benchmark player. Using this approach to "similarity scores", lower scores are a better match (a score of zero is a perfect match across age and all 8 dimensions of PC).

I chose some higher profile players with a PC of 50 or more as benchmarks and then determined the 5 most similar performances from last season. Generally similarity scores of less than 100 are a pretty good fit. As beauty is in the eye of the beholder, you need to judge the accuracy of these comparisons for yourself:

Martin St. Louis				Offense				Defense					
Player	Team	Pos	Age	EH	PPP	PPO	SH	EH	PP	SHK	SHO	PC	Sim
Martin St. Louis	TB	RW	27	40	14	1	6	6	1	9	8	84	0
Jarome Iginla	CAL	RW	25	41	12	1	5	5	0	2	9	75	67
Patrik Elias	NJD	LW	26	37	8	-1	3	12	0	13	10	83	103
Mike Johnson	PHO	RW	28	35	12	1	-2	9	0	7	4	65	129
Geoff Sanderson	CBJ	LW	30	33	20	1	4	6	0	4	5	73	136
Alexander Mogilny	TOR	RW	33	48	15	0	8	2	0	8	11	93	139

Iginla is an excellent fit for this versatile and rapidly developing player. I think they had similar impact in 2002-03. People won't easily see this as these two players had opposite trend lines -- Iginla dropping off an MVP year and St. Louis had a breakthrough year. I would not trade Iginla for St. Louis, but I think they had similar years.

Darryl Sydor				Offense				Defense					
Player	Team	Pos	Age	EH	PPP	PPO	SH	EH	PP	SHK	SHO	PC	Sim
Darryl Sydor	DAL	D	30	11	13	-1	0	34	4	8	6	74	0
Alex Khavanov	STL	D	30	8	10	1	6	31	3	12	6	77	83
Niclas Havelid	ANA	D	29	13	9	0	1	26	5	6	8	69	99
Karel Rachunek	OTT	D	23	10	10	1	1	28	2	6	5	62	114
Rob Blake	COL	D	33	16	14	0	4	26	4	11	4	79	137
Kim Johnsson	PHI	D	26	17	12	-1	1	38	4	16	9	96	147

Sydor is strong defensively. His numbers on that side of the ledger compare well against the others. He developed over half of his offense on the power play. This is a bit unsual for a defenseman, but Khavanov did it too and Rachunek and Blake were close.

Steve Sullivan				Offense				Defense					
Player	**Team**	**Pos**	**Age**	**EH**	**PPP**	**PPO**	**SH**	**EH**	**PP**	**SHK**	**SHO**	**PC**	**Sim**
Steve Sullivan	CHI	RW	28	42	0	-1	5	7	0	7	4	64	0
J. Langenbrunner	NJD	RW	27	37	4	-1	1	9	0	8	3	61	61
Jason Blake	NYI	LW	29	42	4	0	3	8	0	9	-3	64	65
Jeff Friesen	NJD	RW	26	40	1	-1	0	12	0	1	6	59	91
Alex Tanguay	COL	LW	23	44	4	0	0	9	0	1	3	61	106
Eric Boguniecki	STL	RW	27	35	1	0	2	11	0	1	2	51	115

Sullivan presents the profile of good, two way player (even handed). He contributed both ways on the penalty kill but demonstrated a power play outage (he had his chances). Blake and Langenbrunner are good fits. Sullivan chipped in a bit more short handed offense than the peer group.

Adrian Aucoin				Offense				Defense					
Player	**Team**	**Pos**	**Age**	**EH**	**PPP**	**PPO**	**SH**	**EH**	**PP**	**SHK**	**SHO**	**PC**	**Sim**
Adrian Aucoin	NYI	D	29	6	11	1	2	8	5	18	1	52	0
Rod Brind'Amour	CAR	C	32	5	15	1	1	6	0	11	3	41	121
Jaroslav Spacek	CBJ	D	28	13	15	1	2	9	4	11	0	56	121
Curtis Brown	BUF	C	26	4	6	0	4	11	0	11	1	37	129
Alex Karpovtsev	CHI	D	32	2	6	-1	2	9	1	9	6	35	156
Dallas Drake	STL	LW	33	12	8	0	1	9	0	10	3	43	165

A tricky one, with no similarity scores under 100 and some forwards showing up on the list. Aucoin had odd offensive stats, performing, like Sydor, much better on the power play. On defense, a very strong penalty killer and unusual power play defensive points, but weak even handed.

Mark Recchi				Offense				Defense					
Player	**Team**	**Pos**	**Age**	**EH**	**PPP**	**PPO**	**SH**	**EH**	**PP**	**SHK**	**SHO**	**PC**	**Sim**
Mark Recchi	PHI	RW	34	15	17	-1	1	12	0	1	7	52	0
Ulf Dahlen	DAL	LW	35	13	14	0	0	8	0	0	5	40	37
Doug Weight	STL	C	31	15	22	1	1	10	0	1	4	54	49
Andrew Brunette	MIN	LW	29	12	18	0	0	6	0	0	3	40	84
Cliff Ronning	MIN	LW	37	13	9	0	2	7	1	0	7	40	99
Radek Bonk	OTT	C	26	18	21	1	0	11	0	1	3	54	106

Offensively, Recchi stands out on the power play but contributes less even handed. It happens, but is unusual for PCO^{PPP} to exceed PCO^{EH}. Four other examples of this make the Recchi similarity list. None of these players seem to get to kill penalties.

Enough. A great deal more validation work can and should be done, but I am comfortable that the method validates as well as it is going to. You cannot expect too much from validation tests. If Player Contribution always validates your pre-conceived notions, it must have added little to your understanding of the game. Player Contribution attempts to materially expand our understanding of the game and it will bring along some surprises. It is easy to dismiss Player Contribution analysis. It is harder to embrace.