

An Analysis of NHL Faceoffs
Michael Schuckers, Tom Pasquali and Jim Curro
St. Lawrence University
and
© Statistical Sports Consulting, LLC 2012
schuckers@stlawu.edu

Summary

A faceoff is a potentially pivotal play in a hockey game. As a restart in play, a faceoff gives each team the opportunity to gain possession. In this analysis we looked at the value of winning an NHL faceoff. Faceoffs are a component of evaluating the impact of players on the game as well as looking at strategies for teams. As part of this analysis we analyzed 211,372 faceoffs from the 2008-9, 2009-10, and 2010-11 regular seasons. There are two facets to this analysis. First, we looked at the average faceoff differential required to yield a goal differential. Overall this value is **76.5**. This means that a player must win about 76 more faceoffs than they lose in order to obtain a goal differential for his team. A team that moves from winning 50% of their faceoffs to winning 60% of them gains just over 12 goals per season which is equivalent to two additional wins. Second, we looked at individual player probabilities for winning each of the faceoffs that we analyzed. Our logistic regression model for this novel analysis includes where the faceoff occurred on the ice, whether or not the player was on the home team and if the player's team was shorthanded or on the powerplay. The output from this model is an adjusted faceoff win probability for each player that accounts for the above factors. We find that the correlation between this adjusted faceoff rating and a player's unadjusted faceoff win percentage is very strong, $r > 0.95$, suggesting that evaluation of players should be done simply on their raw faceoff win percentage. Additionally, we find that team strength, either being on the powerplay or being shorthanded, and whether or not a player is at their home rink, significantly impact the probability of winning a faceoff. However, while there is some suggestion that players are more likely to win a faceoff in their offensive or defensive zone relative to neutral ice that effect was not substantial enough for us to consider it significant. Below we provide additional details of these two analyses.

Analysis of the Value of an Individual Faceoff

To assess the value of winning an individual faceoff, we looked at the number of goals gained in 20 seconds after each faceoff. Previously we have found that after 20 seconds the impact of an individual event in the NHL is noise with the exception of penalties (*Curro, Total Hockey Ratings, St. Lawrence University Honors Thesis, 2012*). For this analysis we looked at the goal differential gained by the winning team and added to that the goal differential that would have been obtained had the other team won that faceoff. This was done to ensure that we reward teams not just for the value added by winning but also reward winners for the value that the other team lost as a result of a given faceoff. We did this for all faceoffs and found that, on average, it takes 76.5 faceoff wins to gain an additional goal differential. Note that previous work, by us and others, has found that a goal differential is worth approximately 1/3 of a point in the NHL standings. See, for example, <http://www.hockeyprospectus.com/article.php?articleid=1393>.

We further broke down the number of faceoffs wins needed to gain a goal for a variety of different circumstances. These results are summarized in Table 1. Because of the way that we have defined our metric as goal differential for the winning team as well as the goal differential taken away from the losing team, there are symmetries in our results. That is, the number of faceoff wins it takes to get a goal differential in the offensive zone (Off) is the same as the number of faceoff wins for a goal differential in the defensive zone (Def). Faceoff wins in the Neutral Zone

(Neutral) result in a goal differential after an average of 163.8 faceoff wins, while it take 60.1 faceoff wins, on average, in either Off or Def to result in a goal differential. Similarly there is symmetry for faceoff wins on the power play (PP) or shorthanded (SH). From Table 1 we can see that at even strength it takes just over one hundred faceoff wins (101.6) to produce a goal differential, while it only takes about 40 faceoff wins shorthanded or on the powerplay to yield a goal differential. We also broke our analysis down by combinations of strength and location. Unsurprisingly, the fewest faceoff wins needed to gain a goal occur on special teams, PP or SH, in the Offensive or Defensive Zones at a clip of about 35 goals per goal differential while the most faceoff wins needed come when a faceoff is in the Neutral Zone at Even Strength.

Table 1: Faceoff Wins per Goal Differential (GD) earned.

Scenario		Total number of Faceoffs (Sample Size)	Faceoffs Wins per Goal Differential
All		211372	76.5
Strength			
	EV	164575	101.6
	PP/SH	46797	40.9
Zone			
	Off/Def	139938	60.1
	Neutral	71434	163.8
Zone*Strength			
	Off/Def and EV	101885	80.2
	Off/Def and PP/SH	38053	35.4
	Neutral and EV	62690	170.4
	Neutral and PP/SH	8744	128.6

Adjusted Faceoff Win Percentages

We next analyze the ability of individual players to win faceoffs. As above we analyzed all NHL faceoffs for the past three regular seasons. In this case, due to issues with the recording of the individuals involved in the faceoffs by nhl.com, we had several hundred fewer faceoffs to work with than in the previous analysis. That still left over 210,000 faceoffs for analysis. For all of the faceoffs, we fit a logistic regression model with factors in the model for strength (EV, SH or PP), location on the ice (Offensive Zone, Neutral Zone or Defensive Zone), home team or away team and the players involved in the faceoff. As mentioned above, we found that strength and being the home team was a significant predictor of faceoff wins. While there was some evidence that on-ice location had an effect --- players tend to win more in their defensive end, that effect was not statistically significant. Additionally, there was a very strong correlation, $r > 0.95$, between each player's rating from the logistic model and their actual faceoff win percentage. Consequently we conclude that adjusting for these other factors is unnecessary.

The model that we chose to utilize here was a logistic one that is appropriate for binary outcomes. The response is the probability that player A wins a faceoff against player B. The model had terms to account for the effects of players A and B as well as the effect of being in either Off or Def relative to the neutral zone, the effect of being on the power play, the effect of player A being at home or on the road. Given the large number of players involved in this analysis, we adjusted our level of significance to account for the multiplicity of comparisons. The effect of being on the power play relative to even strength is to increase the probability of winning by 5.7% ($p < 10^{-100}$) while being at home increase the win percentage by 1.5% ($p < 10^{-39}$). The top players based upon faceoff win percentage from the 2010-11 regular season are given below in Table 2.

Looking at Table 2, we can see that David Steckel had the highest rating and the highest faceoff win percentage. Manny Malhotra earned more goals (4.34) for his team than Steckel did due to the sheer number of faceoffs in which he was involved. The last column in our table gives the goals gained assuming the same number of faceoffs per player. This allows for a straightforward comparison between players. On average a player that takes 1200 faceoffs and wins 60% of them should earn their team a goal differential of 3.13 three goals or one point per season. The number of goals gained is dependent upon the situations in which a player was used. We note here that Jerred Smithson has a lower than expected number of goals gained due to the fact that he was rarely used on the powerplay by the Predators. A player who had the same number of faceoffs (1006) as Smithson but with a more typical distribution would have earned his team approximately 1.9 goals. As we noted above, several analysts have concluded that a goal differential of three goals in the NHL is worth approximately one point in the standings and is also worth \$1 million. Smithson made just under \$800K in 2010-11 according to capgeek.com and he his faceoff performance alone was sufficient to earn that paycheck. The logistic model rating given here is based upon comparing the effect of a given player relative to a replacement player. For example, the probability that Manny Malhotra would win an even strength neutral zone faceoff against a replacement player would be $e^{0.815} / (e^{0.815} + 1) = 0.69$ or 69%, while Steckel would have a 57% chance of beating Toews, from $e^{0.885-0.605} / (1 + e^{0.885-0.605})$ under the same circumstances. Here we considered a replacement faceoff player one that took less than 20 faceoffs over the course of the three years for which we had data. For numerical stability we aggregated these players into a single replacement player in our analysis.

Table 2: Top Faceoff Performers for 2010-11

Team	Player	Logistic Model Rating	Faceoff Count	Actual Win%	Goals Gained	Goals Gained per 1000 face-offs
Capitals/Devils	Steckel	0.885	820	0.623	2.68	4.10
Canucks	Malhotra	0.815	1261	0.616	4.34	3.44
Sabres	Gaustad	0.724	1157	0.597	3.38	2.92
Predators	Smithson	0.661	1006	0.574	1.32	1.31
Islanders	Konopka	0.659	1062	0.578	2.26	2.13
Capitals	Gordon	0.648	719	0.579	1.78	2.48
Canucks	Kesler	0.629	1496	0.574	3.72	2.49
Kings	Stoll	0.627	1310	0.574	3.13	2.39
Stars	Ott	0.608	1082	0.565	2.40	2.22
Blackhawks	Toews	0.605	1653	0.566	3.81	2.30

An analysis at the team level revealed that some teams have enjoyed greater success in winning faceoffs than others. In particular, for the seasons that we studied San Jose as a team gained approximately 6.1 goals per season as a result of their prowess winning faceoffs while Vancouver and Detroit gained approximately 4.4 and 4.1 goals per season, respectively. At the other end of the spectrum, Edmonton lost an average of 5.3 goals per season as a result of faceoffs. Note that this means that San Jose has earned approximately one additional win per season via winning faceoffs while Edmonton has lost a win per season because of their faceoff performance.

Note that conversations with one NHL team analyst who has compared video of faceoffs with nhl.com's RTSS reports concludes that approximately 5% of all faceoffs are recorded incorrectly. This individual further indicates that Nassau Coliseum is especially egregious in this regard. (As an aside this suggests that New York City is a statistical hockey Bermuda Triangle given the issues with shot location at Madison Square Garden and the recording of faceoffs at Nassau Coliseum.) This knowledge suggests that our conclusions should be tempered somewhat.

However, given the highly significant nature of our results, we're confident that they are robust to these measurement errors.

In this paper we have reported results from two analyses. In the first of these analyses we found that, in terms of goal differential, not all faceoffs are equal. Faceoff wins in the offensive and defensive zone as well as those won on special yield a goal differential more quickly. From the second analysis we conclude that faceoff win percent is a metric that does not currently need adjusting since raw faceoff win percentage is very highly correlated with adjusted faceoff win. However, it is conceivable that as teams start to utilize players in more specialized manners (cf Cody Hodgson and Manny Malhotra) that an adjusted faceoff percentage would be warranted. At this time, it is not necessary. The results here suggest that there are strategic advantages to be gained by having the best faceoff players take faceoffs outside the neutral zone and on special teams. While special teams is an unlikely place to insert a player, having the best faceoff winners take more of their faceoffs outside the neutral zone has the potential to play dividends. For a player that wins 60% of their 1200 faceoffs, taking 20% more faceoffs outside the neutral zone can add an additional 3 goals or one win per season.

This article summarizes work done by Tom Pasquali (now a graduate student in Statistics at Villanova University) and Jim Curro (now a graduate student in Statistics at Iowa State University) as part of their undergraduate honors theses and builds on the work done by previous St. Lawrence University undergraduate students Matt Generous (currently playing for Lukko Rauma in Finland) and Dennis Lock (now a PhD student in Statistics at Iowa State University).