Net Front Presents: A Guide to Getting the Most of your Trip to the Crease

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After taking a look at the OHL data set and putting together a predictive model for deflection success, we discussed if there would be a difference between how men's and women's hockey may differ in what really defines a successful deflection. To do this, we used the 2020 NWHL data from the Big Data Cup and ran the same tests as we did for the OHL data, and found some interesting results. The biggest difference between the data sets was that the NWHL data set drew from a lot fewer games and deflections seemed to be less prevalent in NWHL games compared to the OHL. That being said, there were some minor differences in the results of the few data points we used.

Methodology

While we expected different results compared to the OHL data set, we decided to approach this the same way, defining shots as successful based on goals, shots on net, and second chance opportunities. We then regressed deflection location as well as prior pass and shot location against the deflection ratings. Similarly to the Erie data set, the locations were given "relative" values, with the X value adjusted so the blue line is set to 0 and Y is adjusted so the centre of the net is set to 0 with each increase on Y being considered absolute. A log function was also applied to this data set as it showed better results.

The data we had collected was run through an OLS estimator to determine the ideal locations for deflections, as well as the locations of events preceding deflections. The likelihood of a successful deflection off a shot (D_S) or a pass (D_P) with the location of the deflection (X_1,Y_1) and the location of the preceding event (X_2, Y_2) in the following formulas:

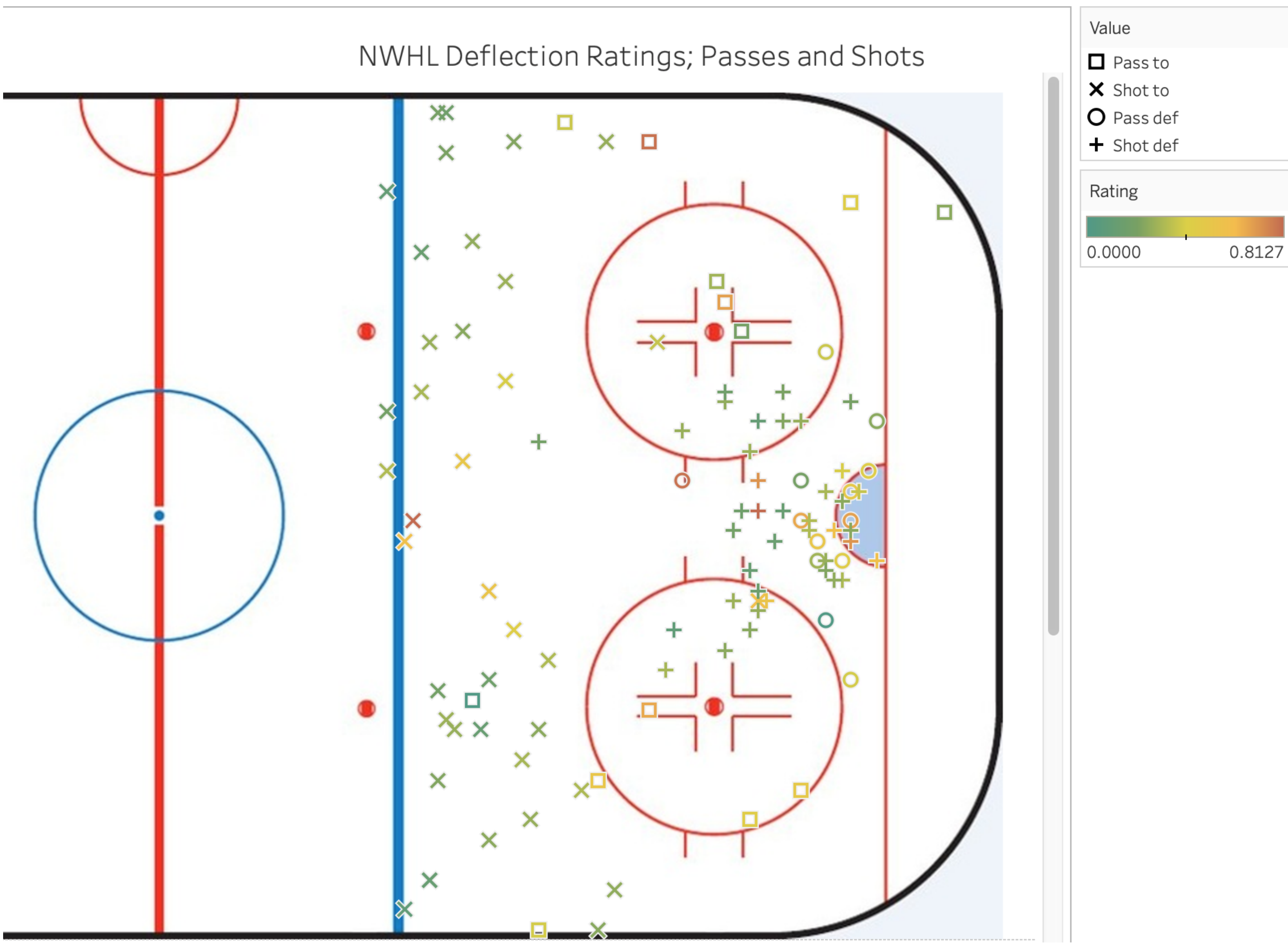
$$D_S=(log_{10}X_1*0.367)+(log_{10}Y_1*0.161)+(log_{10}X_2*0.156)-(log_{10}Y_2 0.473)$$
$$D_P=(log_{10}X_1*-0.812)-(log_{10}Y_1*502)-(log_{10}X_2*0.082)+(log_{10}Y_2*1.567)$$

There are a few major differences to consider. The first being that an increase along Y_1 for deflections from shots correlates to a higher probability of success, while an increase on Y_2 for deflections from passes correlates to a higher probability of success; the rest of the variables align with the Erie model. The other significant difference was that the location of the preceding event holds much more significance in this model compared to the Erie model. We believe this could be attributed to a higher variance of shot and pass locations compared to the Erie data set. The variance of locations could be due to the fact that the Erie data set largely draws from a single team, while this data set draws from every NWHL team. After deriving the model, we then applied the formula to every deflection opportunity to find which players tended to generate the best deflections.

Findings

We plotted every deflection, as well as shot and pass preceding the deflection, on figure 1 and colour coated each attempt to visualize the best places on ice to generate and attempt deflections.

Figure 1



There are some major differences here compared to the Erie data set. The most noticeable difference being that most shots preceding deflections from Erie are low quality attempts on the blue line, near the boards, while NWHL players tend to walk in a bit and take higher quality attempts. Another observation was the lack of passes leading to deflections, which were found to be both highly effective in both the Erie and NWHL data sets. We believe this is a potentially under utilized strategy to generate high danger scoring chances.

We then wanted to look at which areas of the ice were the best places to receive deflections, however since the deflection location data mostly mirrored the Erie data, as well as X_2 and Y_2 being much more significant in this model, we decided to instead look at the best places to either pass or shoot into a deflection, as shown in figure 2.

Figure 2

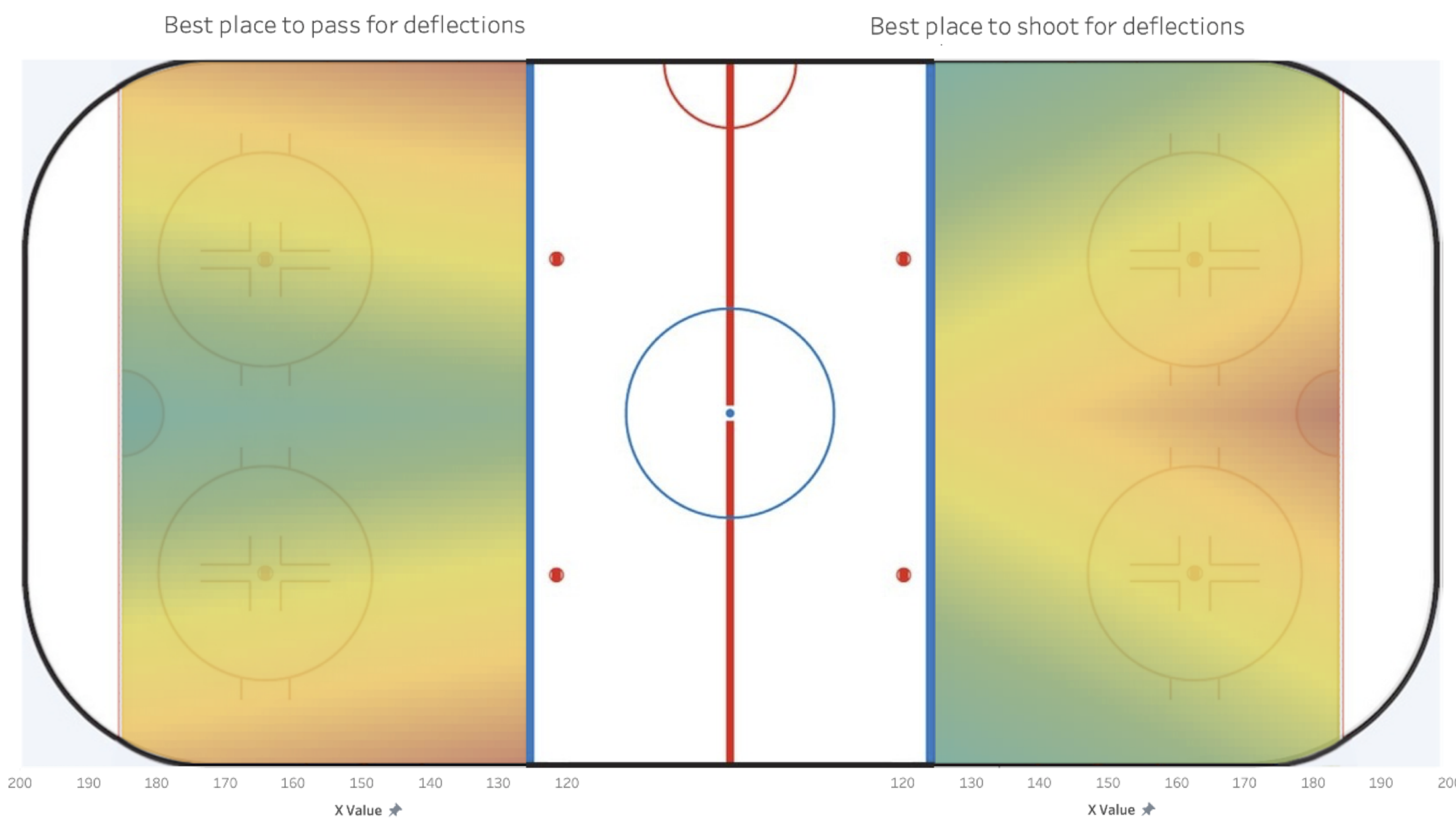


Figure 2 largely mirrors the Erie data set, however places much more importance on the X_2. Also as noted previously, NWHL players tend to take an additional few steps into the zone before shooting, showing that shot attempts in the high slot are more likely to result in high quality scoring attempts. Similar to the Erie data set, the passing model shows pass attempts from further out result in higher quality scoring attempts, likely due to the "Royal Road" effect. The next step was to apply the model to each player in the NWHL to find which players had the most success deflecting pucks and which were the most successful at generating deflections.

Key Action Points

One of the most powerful uses for micro stats is finding which players are most effective at being “specialists”. While finding players who are truly elite is one of the most important parts of constructing a championship roster, sometimes these specialty players are useful for filling out a roster and patching up weaknesses. With the current scouting landscape being largely affected by COVID, micro stat scouting is more important than ever in unearthing talent.

The table below is divided into four sections (Player Info, Raw Stats, Deflecting, and Deflection Creation), and are highlighted with the strengths and weaknesses of specific players in this field. While the previous section focuses on a general overview from all teams, this section specifically keys in on individuals. We calculated the average quality of deflections/deflections created, and then gave a rating (the total sum of deflection quality) of said shot type to show which players are the most successful at using deflections. Success, as previously mentioned, relates to either scoring a goal, creating a second chance, or landing a deflection on net. While there was only a limited amount of data per player, we can still determine which players may tend to get into these high danger areas and which may tend to create these chances the best.

Figure 3

Player Info	Stats					Deflecting					Deflection Creation				
Player	Total Shots	Total Def	Def on Net	Def Goals	2nd Chance %	Shot Def Average	Shot Def Rating	Pass Def Average	Pass Def Rating	Deflecting Rating	Deflection Creation	Shot Def Rating	Pass Def Average	Pass Def Rating	Creation Rating
Taytum Clairmont	7	1	0	1	0%	36%	0.36	68%	0.68	1.04	0%	0.00	66%	0.66	0.66
Janine Weber	17	5	1	0	20%	24%	0.95	51%	0.51	1.46	0%	0.00	0%	0.00	0.00
Amy Curlew	5	1	1	1	0%	69%	1.39	0%	0.00	1.39	0%	0.00	0%	0.00	0.00
McKenna Brand	23	1	0	1	0%	0%	0.00	52%	1.04	1.04	0%	0.00	29%	0.29	0.29
Kelly Babstock	9	1	0	0	0%	51%	0.51	0%	0.00	0.51	71%	0.71	0%	0.00	0.71
Breanne Wilson-Bennett	16	2	1	1	0%	39%	1.16	0%	0.00	1.16	0%	0.00	0%	0.00	0.00
Shiann Darkangelo	22	1	0	0	0%	0%	0.00	44%	0.44	0.44	0%	0.00	68%	0.68	0.68
Christina Putigna	21	0	0	0	0%	0%	0.00	0%	0.00	0.00	24%	0.24	80%	0.80	1.03
Mikyla Grant-Mentis	26	1	1	0	0%	0%	0.00	66%	0.66	0.66	36%	0.36	0%	0.00	0.36
Taylor Turnquist	8	0	0	0	0%	0%	0.00	0%	0.00	0.00	29%	0.58	44%	0.44	1.02
Sarah-Eve Coutu Godbout	26	2	1	0	0%	16%	0.32	0%	0.00	0.32	58%	0.58	0%	0.00	0.58
Samantha Davis	19	3	2	0	0%	24%	0.48	39%	0.39	0.87	0%	0.00	0%	0.00	0.00
Shannon Doyle	4	0	0	0	0%	0%	0.00	0%	0.00	0.00	21%	0.85	0%	0.00	0.85
Taylor Woods	10	0	0	0	0%	0%	0.00	0%	0.00	0.00	81%	0.81	0%	0.00	0.81
Hanna Beattie	4	0	0	0	0%	0%	0.00	0%	0.00	0.00	30%	0.30	51%	0.51	0.81
Alyson Matteau	8	0	0	0	0%	0%	0.00	0%	0.00	0.00	40%	0.79	0%	0.00	0.79
Rebecca Russo	4	0	0	1	0%	71%	0.71	0%	0.00	0.71	0%	0.00	0%	0.00	0.00
Katelynn Russ	20	1	0	1	0%	35%	0.70	0%	0.00	0.70	0%	0.00	0%	0.00	0.00
Alyssa Wohlfeiler	12	1	0	0	0%	24%	0.24	0%	0.00	0.24	43%	0.43	0%	0.00	0.43
Mary Parker	5	1	1	0	0%	0%	0.00	37%	0.37	0.37	28%	0.28	0%	0.00	0.28
Allie Thunstrom	12	2	1	0	0%	10%	0.10	49%	0.49	0.59	0%	0.00	0%	0.00	0.00
Lindsay Eastwood	8	0	0	0	0%	0%	0.00	0%	0.00	0.00	20%	0.60	-2%	-0.02	0.58
Sarah Steele	5	0	0	0	0%	0%	0.00	0%	0.00	0.00	57%	0.57	0%	0.00	0.57
Kristin Lewicki	10	1	0	0	0%	53%	0.53	0%	0.00	0.53	0%	0.00	0%	0.00	0.00
Jillian Dempsey	13	2	1	0	0%	24%	0.24	29%	0.29	0.52	0%	0.00	0%	0.00	0.00
Kiira Dosdall	12	0	0	0	0%	0%	0.00	0%	0.00	0.00	51%	0.51	0%	0.00	0.51
Lauren Kelly	12	0	0	0	0%	0%	0.00	0%	0.00	0.00	27%	0.27	24%	0.24	0.51
Meghan Lorence	14	2	2	0	0%	30%	0.30	19%	0.19	0.49	0%	0.00	0%	0.00	0.00
Tori Howran	5	0	0	0	0%	0%	0.00	0%	0.00	0.00	25%	0.49	0%	0.00	0.49
Jonna Curtis	15	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	49%	0.49	0.49
Mallory Souliotis	14	0	0	0	0%	0%	0.00	0%	0.00	0.00	24%	0.48	0%	0.00	0.48
Taylor Wenczkowski	17	2	0	0	50%	24%	0.47	0%	0.00	0.47	0%	0.00	0%	0.00	0.00
Jordan Juron	17	2	2	0	0%	22%	0.45	0%	0.00	0.45	0%	0.00	0%	0.00	0.00
Emma Woods	16	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	44%	0.44	0.44
Tereza Vanisova	14	1	1	0	0%	0%	0.00	44%	0.44	0.44	0%	0.00	0%	0.00	0.00
Taylor Wasylk	10	1	1	0	0%	14%	0.14	0%	0.00	0.14	25%	0.25	0%	0.00	0.25
Paige Capistran	7	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	39%	0.39	0.39
Marie-Jo Pelletier	4	0	0	0	0%	0%	0.00	0%	0.00	0.00	19%	0.38	0%	0.00	0.38
Kaleigh Fratkin	9	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	37%	0.37	0.37
Elena Orlando	2	0	0	0	0%	0%	0.00	0%	0.00	0.00	18%	0.36	0%	0.00	0.36
Mackenzie MacNeil	16	0	0	0	0%	0%	0.00	0%	0.00	0.00	31%	0.31	0%	0.00	0.31
Sara Bustad	3	0	0	0	0%	0%	0.00	0%	0.00	0.00	30%	0.30	0%	0.00	0.30
Amanda Conway	5	1	0	0	0%	30%	0.30	0%	0.00	0.30	0%	0.00	0%	0.00	0.00
Meaghan Rickard	8	1	1	0	0%	28%	0.28	0%	0.00	0.28	0%	0.00	0%	0.00	0.00
Carlee Turner	13	1	0	0	0%	27%	0.27	0%	0.00	0.27	0%	0.00	0%	0.00	0.00
Lexie Laing	12	1	1	0	0%	26%	0.26	0%	0.00	0.26	0%	0.00	0%	0.00	0.00
Lenka Curmova	5	1	0	0	100%	25%	0.25	0%	0.00	0.25	0%	0.00	0%	0.00	0.00
Emily Janiga	4	1	0	0	0%	25%	0.25	0%	0.00	0.25	0%	0.00	0%	0.00	0.00
Mallory Rushton	6	0	0	0	0%	0%	0.00	0%	0.00	0.00	25%	0.25	0%	0.00	0.25

When looking at skilled puck deflectors, we wanted to highlight 2020 first overall pick Samantha Davis of the Boston Pride. While only having played her first seven games in the NWHL this season, she trails only Janine Weber, who has five deflections. Davis has shown through a smaller sample that she has a great ability to get to the front of the net and battle to win her space. This shows development and adaptability in her game. The next step that she will need to take when in front of the net is improving the quality of her defections. Right now, the average deflection Samantha is creating is on net, but lacks the danger needed to either score or create a second chance in front of the goaltender. This can be achieved better if she were to stand closer to the net.
However, taking a look at deflection creation, we only had a few instances of a player generating more than one deflection, either off a shot or a pass. Although, there was one player who very clearly stood out: Shannon Doyle. While we only had 4 recorded shots from her, all 4 resulted in deflection opportunities. This was the most of any player we had recorded, which is especially impressive considering how few games she had played and how few shots she had recorded. A reason for this might be that because she is a more veteran player, she has a much more effective ability to read the ice and identify potential deflection opportunities, which is a key talent for play driving defensemen to possess. While a larger data set might be able to find more identifiable trends, this data may give us a small insight into identifying players who excel in the crease area.

Summary, Limitations, and Future Considerations

The main limitation with this data set was simply lack of appropriate sample size. While we also cited a small sample in the Erie data set causing some limitations, this data set was much smaller, included more players, and higher variance of event locations. For example, we tracked 47 total deflections and only 13 off of passes, with only 6 goals total, meaning that the criteria for how “success” was defined was most likely skewed to a couple especially high danger chances.
However, we felt this experiment was successful coinciding with the larger Erie data set as we can see some of the subtle differences between how NWHL and OHL teams and players may approach deflections. We originally approached this topic because we felt that deflections were both under utilized and under researched, with the primary source we found that really analyzed deflections being written over 15 years over. After analyzing two very different leagues and data sets, we still don’t feel we’ve truly even scratched the surface of maximizing deflection efficiency.