Alternative Methods of Evaluating NHL Shooting Capabilities

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A. Introduction:

Created by Mark Broadie in 2011, Strokes Gained Putting (SGP) is a statistic that introduced relative performance evaluation to golf. Prior statistics described singular evaluation, such as total putts, while SGP compares each individual action against the expected result from the competition. By comparing actions against the average results of all PGA Tour members, SGP allows for putting performance comparisons amongst the peer group in the form of a strokes gained or lost. This total value can also be analyzed in greater detail including on a per-shot basis allowing players and coaches to dissect putting performance.

Although a golf metric, the principles that make SGP valuable can be adapted to evaluate relative performance in all sports. Evidence already exists in basketball through Second Spectrum's QSQ and QSI metrics. Quantitative Shot Quality (QSQ) is the average effective field-goal percentage given the shot location, shot type and nearby defenders while Quantified Shooter Impact (QSI) quantifies how well the player shoots relative to the average NBA. Ultimately, QSI allows teams to "differentiate the difference between elite shooters versus guys who get easy shots".

SGP, QSQ and QSI:

Before I discuss the application of these theories to the NHL, I will quickly explain how SGP is calculated. The PGA Tour tracks statistics to compute an expected number of putts for "every putt distance in one-inch increments" as a baseline expected putt distribution. Here is a snapshot of the expected putts distribution presented by PGATOUR.com in 2016:

PUTTING PROBABILITIES				
Distance (feet)	**One-putt %**	**Two-putt**	**Three-putt +**	**Expected putts**
1'	100%	0%	0%	1.001
3'	96%	4%	0%	1.046
5'	76%	24%	0%	1.245
7'	56%	43%	0%	1.440
10'	38%	61%	1%	1.625
12'	31%	68%	1%	1.701
15'	23%	76%	1%	1.784
20'	15%	83%	2%	1.874
25'	10%	87%	3%	1.931
30'	7%	88%	5%	1.977
40'	4%	86%	10%	2.058
50'	3%	81%	16%	2.138
60'	2%	75%	23%	2.214

For every stroke on the green, the result is measured against the expected putts distribution resulting in a value of strokes gained or lost on the competition. Example: Player X takes 1 putt to get the ball in the hole from 7 feet. The expected number of putts from 7 feet is 1.440. Player X would have gained 0.444 strokes on the field, and a two-putt would result in loosing .56 stokes. SGP is then calculated as a running total, so that at the end of every round, each player has a unique value gained or lost on the competition.

Similar to the PGA Tour, Second Spectrum has a distribution of expected effective field-goal percentages for every shot location while taking into consideration the type of shot (catch and shoot / off the dribble) and the distance from defenders. This allows the NBA to have a measurement of shot quality, for the average player, for every given shot. When an individual player's field-goal percentage is subtracted by the corresponding QSQ, we obtain QSI which helps teams determine if they have a sharpshooter or somebody who takes easy shots.

NHL Shot Quality:
There are many articles related to measuring shot quality and scoring potential in the NHL, most notably by Alan Ryder in his article from 2004 on defensive shot quality as well as a more recent series of expect goal articles by Alex Novet featured on Hockey-Graphs. Both authors illustrate the presence of shot quality, especially Novet through the inclusion of pre-shot puck movement. This personal project is an application of SGP, QSQ, and QSI to the NHL to discover metrics that capture relative offensive capabilities with the goal of adding depth to performance evaluations and player research.

B. Acquiring & Cleaning Data

For this project, I used the play-by-play data published on NHL.com. The data features x/y coordinates relative to center-ice for cartesian-plan plotting of shot locations. To collect the data, I used the hockey_scraper python library from Harry Shomer and ran the script to collect data from the last four complete regular seasons (16,17,18,19) and exported the csv into RStudio to begin the project.

The first step in cleaning the data was to remove unnecessary columns as well as manipulate the string variables using the tidyverse. To better evaluate individual events, I also created binomial occurrence columns that will later help with aggregating events based on descriptive measures. In addition, I also filtered to exclude penalty shots, empty net goals as well as created multiple descriptive columns such as power play indicators.

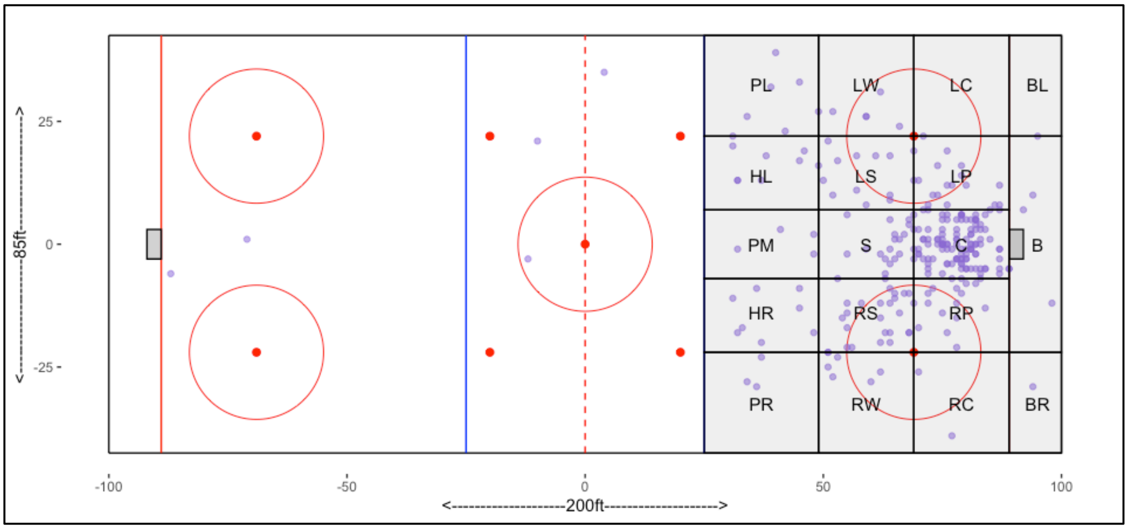
```
# 5) Creating binomial values for easy aggregation of events and calculations
Shot_Types$BL <- if_else(Shot_Types$Event == "BLOCK",1,0) #Indicates if a shot is blocked
Shot_Types$SA <- if_else(Shot_Types$Event %in% c("SHOT","MISS","GOAL","BLOCK"),1,0)#Indicates all shot attempt
Shot_Types$OnT <- if_else(Shot_Types$Event %in% c("SHOT","GOAL"),1,0) #Indicates if Shot hits target
Shot_Types$G <- if_else(Shot_Types$Event == "GOAL",1,0)

# 6) Extracting shot distances (only X values are provided for NHL public data 2019-2020)
Shot_Types$Distance <- ifelse(Shot_Types$Event %in% c("SHOT","MISS"),
                              str_sub(Shot_Types$Description,-7,-4),"" )
```

```
# 9) Entering data in order to determine The strength (Even,PK,PP)
PP <- Rates_Data %>%
  filter(Strength %in% c("5x4","5x3","6x5","6x4",
                         "4x5","3x5","5X6","4x6") )
PP <- PP %>%
  mutate(PP_team = ifelse(Strength %in% c("5x4","5x3","6x5","6x4"), Home_Team, Away_Team))%>%
  select(X1,PP_team)
Rates_Data <- left_join(Rates_Data, PP, by = 'X1')
```

C. Shot Charts:

To calculate expected results in the NHL, the x/y shot coordinates are grouped using a grid layout inspired by NBA shot charts used in post-game and scouting reports. This helps build average result distributions relative to zones on the ice. To do so, I created a scale rink background using ggplot and annotations, inverted the negative x and y coordinates so that the offense is moving from left to right, and created an overlay for shot chart zones:



<u>Shot Chart Categories:</u>

PL: *Point Left (xmin = 25, xmax = 49, ymin = 22, ymax = 42.5)*
HL: *High Left (xmin = 25, xmax = 49, ymin = 7, ymax = 22)*
PM: *Point Middle (xmin = 25, xmax = 49, ymin = -7, ymax = 7)*
HR: *High Right (xmin = 25, xmax = 49, ymin = -7, ymax = -22)*
PR: *Point Right (xmin = 25, xmax = 49, ymin = -22, ymax = -42.5)*

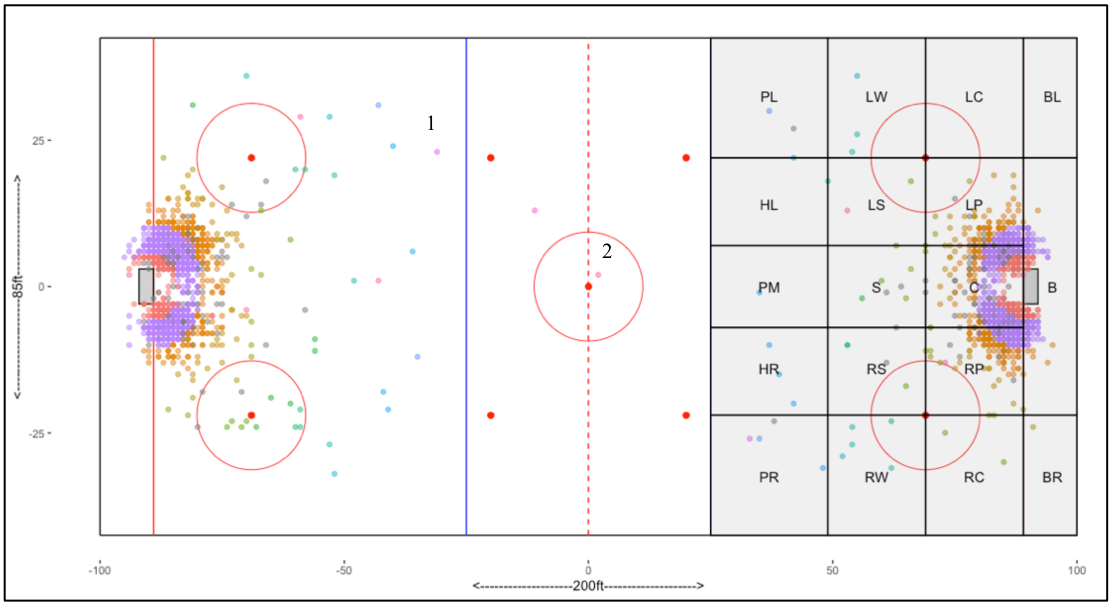
LW: *Left Wing (xmin = 49, xmax = 69, ymin = 22, ymax = 42.5)*
LS: *Left Slot (xmin = 49, xmax = 69, ymin = 7, ymax = 22)*
S: *Slot (xmin = 49, xmax = 69, ymin = -7, ymax = 7)*
RS: *Right Slot (xmin = 49, xmax = 69, ymin = -7, ymax = -22)*
RW: *Right Wing (xmin = 49, xmax = 69, ymin = -22, ymax = -42.5)*

LC: *Left Corner (xmin = 69, xmax = 89, ymin = 22, ymax = 42.5)*
LP: *Left Post (xmin = 69, xmax = 89, ymin = 7, ymax = 22)*
C: *Crease (xmin = 69, xmax = 89, ymin = -7, ymax = 7)*
RP: *Right Post (xmin = 69, xmax = 89, ymin = -7, ymax = -22)*
RC: *Right Corner (xmin = 69, xmax = 89, ymin = -22, ymax = -42.5)*

LB: *Left Behind (xmin = 89, xmax = 100, ymin = 22, ymax = 42.5)*
B: *Behind (xmin = 89, xmax = 100, ymin = -22, ymax = 22)*
RB: *Right Behind (xmin = 89, xmax = 100, ymin = -22, ymax = -42.5)*

Data Quality Warning:

Before I discuss data aggregation and creating metrics, it is important to note an important data quality issue. The shot type variable is important to build accurate offensive metrics; however, the plot below illustrates some potential issues within the variable. The plot is visualizing "wrap-around" shot types in the data set. Although most of the data points are localized appropriately, it is abnormal to have "wrap-around" shot types at the point[1] and even at centre ice[2].

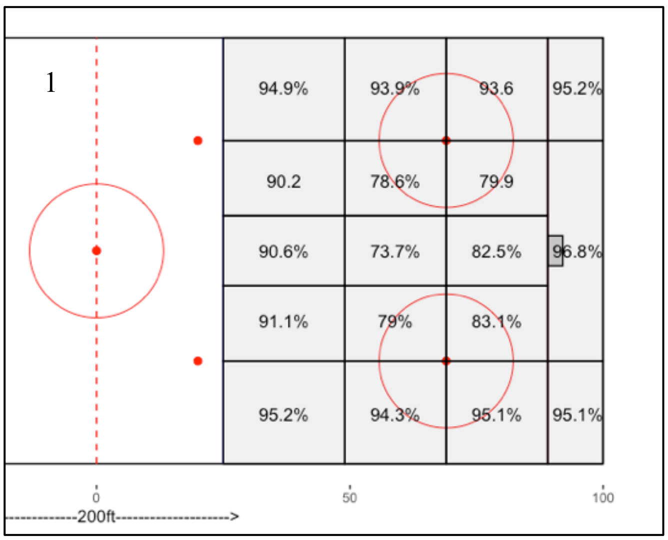


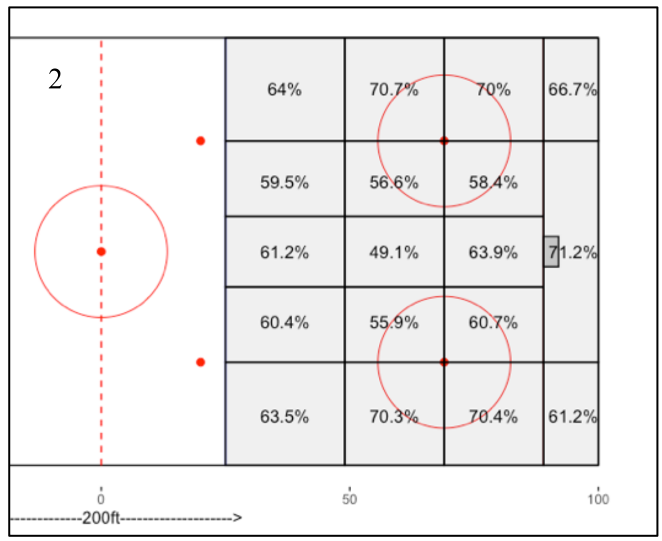
To combat the inaccuracies, I created two versions of distributions. First, I produced a generalized distribution that only accounted for the season and shot location which neglected data quality issues in the shot type variable. The second version considered season, player, shot location, shot type and play situation (PP vs PK). Both outcomes delivered comparable results, and ultimately the concept of relative performance comparison remained true. For the purpose of the article, I will focus on the detailed version as it is more beneficial in understanding the benefits of evaluating performance through this concept.

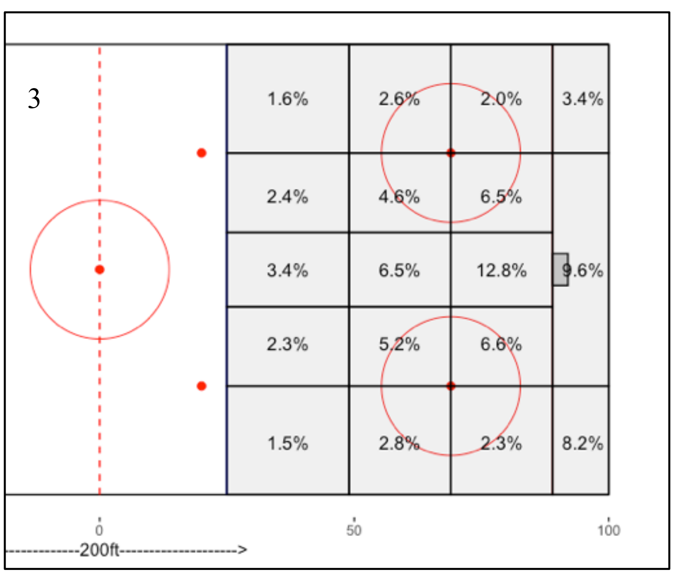
D. Event Distributions

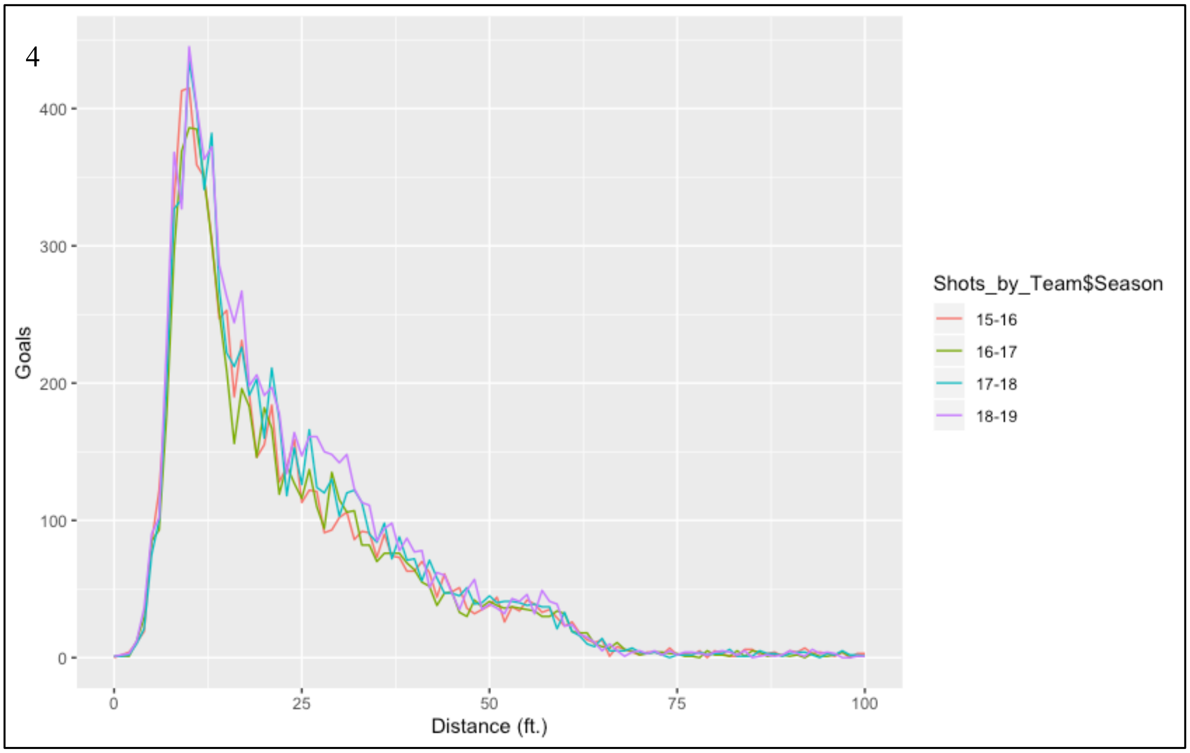
Now that we have proper criteria for placing and categorizing shot attempts on the ice, I generated event distributions to serve as the expected performance for the average NHL player. For each zone in the shot chart, we obtain the rate of shots not getting blocked[1], of the shots hitting the net[2], and goals scored[3] from the last four complete regular seasons. Below, the visualizations represent general distributions, however the three rates are calculated for every combination of shot type, shot location, and play situation.

We can notice that the probability of shots going in, hitting the target as well as getting past defending players varies significantly throughout the offensive zone. The visualization of the distributions proves there is evidence of shot quality variation. This is even more clear when we plot goals scored over the distance of the shot from the goal[4].









E. Evaluation Metrics:

To calculate individual performance metrics, I returned to the binomial occurrence columns built during the data cleaning. By aggregating the 1's and 0's for each player, I obtained individual success rates for getting shots through, for hitting the net, as well as scoring for every attempted combination of season, shot type, shot location and play situation. I then used SQL commands as part of the dplyr package in to join the detailed average league distribution to the individual obtained results table.

By subtracting the obtained individual rates by the league average for the corresponding variables, I obtained three metrics that depict how much better or worse a player is at three offensive skills from the league average:

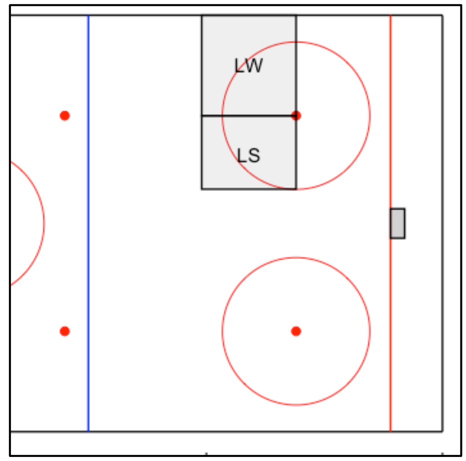
1. Shot Attempt Index (*SaTHRU*)
2. Shooting Index (*ONTARGET*)
3. Goal Index (*GOALS*)

At a high-level, we can aggregate all the variables by season and player in order to obtain an overall picture of the three offensive metrics →

	event_player	Season	SA	G	SaTHRU	ONTARGET	GOALS
1	A.J. GREER	16-17	11	0	0.1900	0.0770	-0.4401
2	A.J. GREER	17-18	17	0	0.2904	0.9000	-0.4194
3	A.J. GREER	18-19	11	1	-0.0943	0.1216	-0.1381
4	AARON EKBLAD	15-16	271	15	-0.3704	0.3580	0.2651
5	AARON EKBLAD	16-17	343	9	-0.5255	0.5107	-0.2082
6	AARON EKBLAD	17-18	321	16	-0.5888	-0.9876	0.1414
7	AARON EKBLAD	18-19	262	13	-0.4840	1.1968	0.5786
8	AARON NESS	15-16	16	0	-1.8311	-1.6782	-0.4522
9	AARON NESS	16-17	1	0	0.0569	-0.7031	-0.0281
0	AARON NESS	17-18	2	0	0.2198	0.7533	-0.0822
1	ADAM CLENDENING	15-16	66	1	-1.4475	-0.8345	-0.5225
2	ADAM CLENDENING	16-17	67	2	-2.7561	-2.7014	-0.1618
3	ADAM CLENDENING	17-18	11	0	-0.7985	-1.5348	-0.2179
4	ADAM CLENDENING	18-19	7	0	-3.1471	-1.2291	-0.2552
5	ADAM CRACKNELL	15-16	106	5	0.4522	-1.1677	-0.2669

Shot Attempt Index describes how much better or worse the player takes shot attempts that do not get blocked compared to the average. Shooting Index describes how much better or worse the individual hits the net for a given shot attempt. Finally, Goal Index is how much better or worse the player is able to convert a shot attempt into a goal.

At a more detailed level, we can aggregate the results within each variable for player research. With the appropriate filters, the data can help us determine lists of best and worst players relative to the NHL average for each of the three offensive skills in a given situation. For example, if we want to do player research in order to acquire a player who can play on the powerplay and take one-timers from the left slot and left wing. We can filter the data to gather a list of players, then sort by the relative capability for all three metrics as a part of the evaluation process.




```
Player_Reseach <- Player_Detailed_Season %>%
  filter(Shot_Loc == 'LW' |
         Shot_Loc == 'LS'
           )%>%
  filter(Type == 'SLAP SHOT')%>%
  filter(Season == '18-19'|
         Season == '17-18') %>%
  group_by(event_player,Type)%>%
  summarise(SA = sum(SA),
            G = sum(G),
            SaTHRU = sum(SaTHRU),
            ONTARGET = sum(ONTARGET),
            GOALS = sum(GOALS),
            OFF = SaTHRU+ONTARGET+GOALS)%>%
  filter(SA >=10)
```

event_player	Type	SA	G	SaTHRU	ONTARGET	GOALS	OFF
SHEA WEBER	SLAP SHOT	28	6	0.5810	0.2295	1.9785	2.7890
LOGAN COUTURE	SLAP SHOT	12	3	0.2572	0.3979	1.8653	2.5204
MARK SCHEIFELE	SLAP SHOT	15	3	1.2572	2.0646	1.4986	4.8204
NATHAN MACKINNON	SLAP SHOT	49	6	1.3190	0.1517	1.0071	2.4778
NICK SCHMALTZ	SLAP SHOT	12	2	1.2219	0.0056	0.9573	2.1848
MATT BENNING	SLAP SHOT	12	2	-3.6023	-1.7470	0.9394	-4.4099
ALEX OVECHKIN	SLAP SHOT	185	25	1.3309	0.6800	0.8940	2.9049
JOE THORNTON	SLAP SHOT	20	4	0.2937	1.9636	0.8717	3.1290
MATT DUMBA	SLAP SHOT	36	5	0.5023	1.2069	0.8296	2.5388

Of course, the list above is at a league level and most of those players would not be readily available. However, in a player research scenario, we can compare players with each other to know the best choice relative to the average for a given situation. To gain a better appreciation of how the metrics rank players, here is the top ten players for each of the three metrics from 2018-2019:

Shot Attempt Index

event_player	Season	SA	SaTHRU
MARK SCHEIFELE	18-19	313	8.6685
JUSTIN WILLIAMS	18-19	335	7.9883
GABRIEL LANDESKOG	18-19	336	7.9724
BROCK NELSON	18-19	272	7.8129
BRAYDEN SCHENN	18-19	248	7.3903
VINCENT TROCHECK	18-19	254	7.3676
ALEKSANDER BARKOV	18-19	307	7.3398
TYLER TOFFOLI	18-19	338	7.2446
YANNI GOURDE	18-19	185	6.9387
JONATHAN TOEWS	18-19	322	6.8990

Shooting Index

event_player	Season	SA	ONTARGET
YANNI GOURDE	18-19	185	13.0298
GABRIEL LANDESKOG	18-19	336	12.3177
JONATHAN TOEWS	18-19	322	11.7006
ZACH PARISE	18-19	327	11.4804
TYLER SEGUIN	18-19	494	10.4828
JUSTIN WILLIAMS	18-19	335	10.2180
BRAYDEN POINT	18-19	299	9.6750
MATT CALVERT	18-19	177	9.4241
FRANK VATRANO	18-19	285	9.4097
JACK ROSLOVIC	18-19	110	9.3543

Goal Index

event_player	Season	SA	GOALS
MIKE HOFFMAN	18-19	391	7.8901
STEVEN STAMKOS	18-19	406	5.7956
JOE PAVELSKI	18-19	292	5.2718
ELIAS PETTERSSON	18-19	256	5.2649
LEON DRAISAITL	18-19	394	5.2016
ANTHONY MANTHA	18-19	285	5.1114
NIKOLAJ EHLERS	18-19	215	4.6901
WILLIAM KARLSSON	18-19	275	4.6286
BRAYDEN POINT	18-19	299	4.5881
BRENDAN LEMIEUX	18-19	92	4.3156

F. Future Applications:

All three of the metrics successfully measure relative offensive capability and can be extremely useful in various scenarios including:

1. Tracking player development progression: Teams can track each of the three metrics over time for a given set of variables to better understand effectiveness of player development programs.
2. Tracking player fit: Coaches who want to place players in the best scenario for team and individual success can apply these three metrics to learn more about line combinations, strategy, and ice time opportunity.
3. Internal and external player research: GM's can better evaluate players on a standardized scale for easier, relative comparison of offensive capabilities. Furthermore, developing the same metric for the AHL would allow teams to make better decisions when calling up players from the minors.

There is no such thing as a perfect metric, and to evaluate player performance, these three statistics would need to be a small piece of a larger puzzle. This raises the question of how many different relative performance metrics can we create in order to find players who are experts at specific skills. For example, it would be interesting to know puck retrieval success rates given how many opposing players, and side of the ice. A team would then be able to rank players compared to the league average to find the best puck retrievers to play alongside more skilled players. Other skills such as breakout passing, and crease box-outs could also be measured in a similar way expanding our ability to measure and build successful teams.

G. Conclusion:

To wrap things up, the theories that make Strokes Gained Putting, Quantified Shot Quality and Quantified Shot Index are useful in developing metrics for relative comparison in the NHL. Although applied to individual offense to capture a Shot Attempt Index, Shooting Index, and Goal Index, the concept can work for many other offensive and defensive skills. I hope to use this is a foundation for creating new metrics, as well as applying them in predictive models that will allow managers to build better teams and for coaches to make optimal decisions.

For any questions, recommendations or collaborations on future projects, feel free to reach out at
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