Edited by:
Patrick Lambrix
Mikael Vernblom
Niklas Carlsson
Tim Brecht

Linköping Hockey Analytics Conference
LINHAC 2023

Organizing Committee

Patrick Lambrix, Linköping University, Sweden (chair)
Niklas Carlsson, Linköping University, Sweden (co-chair)
Mikael Vernblom, Linköping Hockey Club, Sweden (co-chair)

Program Committee for the Research Track

Tim Brecht, University of Waterloo, Canada (chair)
Niklas Carlsson, Linköping University, Sweden (chair)
Martin Arlitt, University of Calgary, Canada
David A Clausi, University of Waterloo, Canada
Ulf Johansson, Jönköping University, Sweden
Patrick Lambrix, Linköping University, Sweden
Erik Lignell, Frölunda HC, Sweden
Joshua Pohlkamp-Hartt, Boston Bruins, USA
David Thomas Radke, University of Waterloo, Canada
Michael Schuckers, Statistical Sports Consulting and St. Lawrence University, USA
Oliver Schulte, Simon Fraser University, Canada
Mikael Svarén, Dalarna University, Sweden
Andrew C Thomas, SportsMEDIA Technology, Canada
Sam Ventura, Buffalo Sabres and Carnegie Mellon University, USA
Erik Wilderoth, Färjestad BK, Sweden

In cooperation with

E.H.C. Alliance of European Hockey Clubs

The City of Linköping

In cooperation with

Sportlogiq

Sponsor

The Swedish Research Council for Sport Science

Silver industry collaborator

Hudl

Silver industry collaborator

Stretch On Sense AB

Silver industry collaborator

Sidelinesports

Bronze industry collaborator

49ing

Preface

LINHAC 2023 took place June 7-9, 2023, and was organized by Linköping University (Patrick Lambrix and Niklas Carlsson) and Linköping Hockey Club (Mikael Vernblom). LINHAC brought together professionals and academics with an interest in hockey analytics. It featured the latest research in hockey analytics in academia and companies, discussions with analysts and coaches, industry sessions with the latest hockey analytics products, and an analytics competition for students.

The program included invited research talks by Frans Murto from Wisehockey on possession value models and Andrew C Thomas from SportsMEDIA Technology on puck and player tracking in near-real time. Further, four papers were selected for presentation in the research track of LINHAC. The program chairs for the paper selection committee were Tim Brecht and Niklas Carlsson.

In addition to the research track, Andreas Hofmann from Hudl and Thomas Krauskopf from Lausanne HC and the German national team talked about tailored and visualized feedback. Freddie Sjögren from Malmö Redhawks discussed perfomance analytics, while Johan Andersson talked about his experience with video analytics for the Swedish national team. Finally, Mike Kelly from NHL Network discussed the practical application of data in hockey and differences between regular season and playoff hockey in the NHL.

Further, there were six panel discussions moderated by Mike Helber and Niklas Carlsson. Two panels were made up of analysts, one with members from different SHL teams (Zack Ellentahl from Rögle BK, Erik Lignell from Frölunda Hockey Club, and Erik Wilderoth from Färjestad BK) and one with members from clubs of different leagues (Petter Carnbro from Leksands IF, Thomas Krauskopf from Lausanne HC and the German national team, Jan Morkes from Bílí Tygři Liberec and the Czech national team, Josh Pohlkamp-Hartt from the Boston Bruins, and David Radke from the Chicago Blackhawks). Two industry panels discussed the state of the art and future of hockey analytics where the second panel had an additional focus on data integration (Thorsten Apel from Sportcontract, Meghan Chayka from Stathletes, Miska Kuusisto from Wisehockey, and Morgan Zeba from Spiideo; Lance Du'Lac from Hudl, Andreas Hofmann from Hudl, Albin N Maelum from Stretch on Sense, Sean Tierney from Sportlogiq, and Freddie Sjögren from Malmö Redhawks). Goaltender analytics was discussed in a panel with Thomas Magnusson (Swedish Ice Hockey Federation), William Rahm (SCL Tigers), Maciej Szwoch (Färjestad BK), Sean Tierney (Sportlogiq), and Mikael Vernblom (Linköping Hockey Club). In the final panel, coaches and GMs discussed the use of analytics in their work (Adam Albelin from the Swedish Ice Hockey Federation, Patrik Hall from Växjö Lakers, Jeff Jakobs from Linköping Hockey Club, and Tomas Montén from HV71).

Our industry collaborators presented their products: Hudl, Stretch on Sense, Sideline Sports, and 49ing.

Finally, there was a student competition where the task was to provide insights based on sequences of events in a hockey game. Data was provided by the SHL and Sportlogiq.

LINHAC is the only conference of its kind in Europe, and as far as we know, it is the only hockey analytics conference that covers all aspects related to hockey analytics. This book includes an invited paper, the papers from the research track, contributions from industry, and the student competition papers. Furthermore, we asked contributors to LINHAC to share with us information about their experience with hockey analytics and thoughts about its future.

We thank our moderator Mike Helber, our conference service TM Event, and the members of our local organization team Mina Abd Nikooie Pour, Sijin Cheng, Huanyu Li, Ying Li, Gurjot Sing, Chunyan Wang, Jenny Rydén, Lene Rosell, Anders Cronstierna, and Daniel Jemander, for their excellent support.

Last, but not least, we thank our collaborators the Alliance of European Hockey Clubs, the City of Linköping, Sportlogiq, our sponsor the Swedish Research Council for Sport Science, and our silver (Hudl, Stretch on Sense, Sideline Sports) and bronze (49ing) industry collaborators.

September 2023

Patrick Lambrix (chair),
Niklas Carlsson (co-chair),
Mikael Vernblom (co-chair)

Contents

Invited talk

Towards a real-time possession value framework in ice hockey

Frans Murto

Tampere University
frans.murto@tuni.fi

Abstract. Measuring the individual performance of players is an important task in sports analytics. Traditional statistics-based approaches for evaluating hockey players fail to account for context and long-term impact. Recent advances in data gathering have enabled valuing possessions and actions directly to address these issues. This talk describes the implementation of the first real-time possession value framework for ice hockey.

Keywords: ice hockey · possession value · tracking data

1 Introduction

Being able to objectively quantify performance in ice hockey has important implications for player evaluation and acquisition. Traditional goal- and shot-based statistics are problematic in this regard as they ignore the impact of preceding plays and do not differentiate between situational contexts. Advanced metrics derived from expected goals address the latter issue by incorporating information on how dangerous the shots a team takes or faces, but are unable to directly measure the value of non-shot actions and fail to consider situations where no shot is taken.

With the increasing availability of high-granularity event data streams and tracking data in recent years, various approaches in different team sports have been proposed for directly modeling the value of individual actions or possessions [1, 2, 4]. Related work in ice hockey has been scarce [5, 6], however, owing to a lack of the aforementioned data at least in the public domain. Our work intends to bridge this gap by proposing and implementing the first hockey-specific framework for deriving the total value of any given possession in real time, as well as valuing the risk and reward of individual actions separately.

2 Methodology

Estimating the value of possessions can be framed as a Markov decision process (MDP) where the possible actions a player in possession of the puck can take is represented by the discrete set A for all possible match states S. The actions we consider to be part of this action space are shots, passes, moving with the puck, dump-ins and dump-outs. Each action can be further separated depending on their outcome: whether a shot results in a goal, a pass reaches its intended target, a player maintains possession while moving with the puck, a dump-out is recovered by a teammate or a dump-out successfully exits the zone.

Players can be assumed to perform actions that intend to increase the probability of scoring for their team and decrease the probability of conceding a goal. Some actions that are valuable offensively, however, are inherently more risky despite their greater reward. To represent this trade-off we model the return of an action separately for both outcomes with success states yielding the probability of a team in possession scoring and failure states the probability of a team in possession conceding. We assume that only successful actions have positive returns and unsuccessful actions have negative returns, as even though some failed actions may lead to a positive outcome (e.g. a missed pass is received by another teammate in a relatively good position), from a modeling standpoint we want to consider only the intended target.

A common approach for representing the immediate and future impact of an action has been to use either a time window or a fixed number of future actions to assign positive labels for actions that end up affecting the score and negative labels for actions that do not [3, 4]. We experiment with different approaches and observe in our data that using a fixed window of eight seconds from the start of an action provides the best balance between short- and long-term return. When modeling reward actions we label actions that lead to the team in possession scoring a goal in the next eight seconds as positive, and when modeling risk we label actions that lead to conceding a goal in the next eight seconds as positive.

To formalize this we follow the definition of Fernández et al., where the value of a possession P_t is taken to be the total expectation of all actions in a given state [4]. The probability to take action a and its expected value are learned from $\mathbf{X}_t$, which is the feature vector representation of state s derived from a tracking data snapshot at time t.

$$\mathbb{E}[P_t] = \sum_{a \in A} \Big[\mathbb{E}[A = a | \mathbf{X}_t] \quad \mathbb{P}(A = a | \mathbf{X}_t) \Big] \tag{1}$$

As the outcome of successful and unsuccessful actions is modeled separately for all actions except shots (which we assign a fixed value of zero risk due to lack of a true failure condition), the expectation of an action can be generally decomposed as the difference between its expected reward and risk and how likely it is to succeed or fail. Because we assume a single end location for moves, the expected value of a move action follows this formulation exactly.

$$\begin{aligned}\mathbb{E}[A = \text{Move}|\mathbf{X}_t] = \mathbb{E}[A = \text{Move}_{Success}|\mathbf{X}_t] \quad \mathbb{P}(A = \text{Move}_{Success}|\mathbf{X}_t) \\ - \mathbb{E}[A = \text{Move}_{Failure}|\mathbf{X}_t] \quad \mathbb{P}(A = \text{Move}_{Failure}|\mathbf{X}_t)\end{aligned} \tag{2}$$

Because any teammate excluding goalies can be considered as the possible receiver of a pass, we take the expected value of a pass action to be the total expectation of all possible passes. We define an additional transition probability

$\mathbb{P}(R_t|\mathbf{X}_t)$ for all receivers R_t to represent how likely player r becomes the receiver of a pass.

$$\mathbb{E}[A = \text{Pass}|\mathbf{X}_t] = \sum_{r \in R} \Big[\mathbb{E}[A = \text{Pass}, R_t = r|\mathbf{X}_t] \quad \mathbb{P}(R_t = r|\mathbf{X}_t)\Big] \tag{3}$$

For dump-ins we consider all players except the goalie of the team in possession to be able to recover the puck. As dump-ins do not always have an intended receiver, but a general location instead, we model their success probability as $\mathbb{P}(A, R_t|\mathbf{X}_t)$ to represent how likely player r is to recover the dumped-in puck first. We take the expected value of a dump-in action to be the difference between the total expectation of all teammates T and all opponents O that can recover a dump-in.

$$\begin{aligned}
&\mathbb{E}[A = \text{DumpIn}|\mathbf{X}_t] = \\
&\quad \sum_{r \in T} \Big[\mathbb{E}[A = \text{DumpIn}, R_t = r|\mathbf{X}_t] \quad \mathbb{P}(A = \text{DumpIn}, R_t = r|\mathbf{X}_t)\Big] \\
&\quad - \sum_{r \in O} \Big[\mathbb{E}[A = \text{DumpIn}, R_t = r|\mathbf{X}_t] \quad \mathbb{P}(A = \text{DumpIn}, R_t = r|\mathbf{X}_t)\Big]
\end{aligned} \tag{4}$$

For dump-outs we consider all opponents except the goalie to be able to intercept the puck in the offensive zone. We model $\mathbb{P}(A, I_t|\mathbf{X}_t)$ to represent how likely opponent i is to intercept the dump-out and use the total interception probability to determine the success probability. The expected value of a dump-out action is taken to be the difference between expected reward from successfully exiting the zone and the total expectation of risk for each possible interceptor.

$$\mathbb{P}(A = \text{DumpOut}_{Success}|\mathbf{X}_t) = 1 - \sum_{i \in I} \mathbb{P}(A = \text{DumpOut}, I_t = i|\mathbf{X}_t) \tag{5}$$

$$\begin{aligned}
&\mathbb{E}[A = \text{DumpOut}|\mathbf{X}_t] = \\
&\quad \mathbb{E}[A = \text{DumpOut}_{Success}|\mathbf{X}_t] \quad \mathbb{P}(A = \text{DumpOut}_{Success}|\mathbf{X}_t) \\
&- \sum_{i \in I} \Big[\mathbb{E}[A = \text{DumpOut}, I_t = i|\mathbf{X}_t] \quad \mathbb{P}(A = \text{DumpOut}, I_t = i|\mathbf{X}_t)\Big]
\end{aligned} \tag{6}$$

3 Data & Modeling

We use event and tracking data from the Liiga regular season matches 2020-21 and 2021-22 provided by Wisehockey. The player and puck tracking data is gathered using an indoor positioning system and sampled at a frequency of 20 Hz. The tracking snapshots are automatically synchronized by the system to align with the start timestamps of the events. We split 75% of the 872 matches in our data to train our models and use the remaining 25% as the test set. Events where the team whose scoring probability is being modeled faces an empty net are omitted due to the dynamics of scoring changing significantly in such situations. An overview of the events is presented in Table 1.

Table 1. Event data counts for the Liiga seasons 2020-21 and 2021-22.

Event type	**Success**	**Total**	**Training**	**Test**
Pass	79.87%	535,449	401,583	133,866
Move	95.35%	899,809	674,851	224,958
Shot	5.29%	78,141	58,608	19,533
Dump-in	39.67%	86,579	64,931	21,648
Dump-out	69.88%	48,836	36,630	12,206

Because the system provides situations where players move with the puck as continuous sequences, we split the puck controls into discrete one-second length actions. We assume that moves have one possible end location and set this as the player's position one second into the future based on their velocity at the time of the event. For unsuccessful passes we determine the intended receiver using a nearest-neighbor approach. We take the direction and velocity of the known trajectory of the pass and project it forward from the starting position of the pass at different time steps. The intended receiver is then chosen as the player who is closest to the projected end positions most frequently.

Each model uses positional features engineered from tracking data like location, velocity, direction, distance to goal, angle to goal, distance to puck and angle to puck for the player in possession of the puck and the target of the action (if applicable). To represent the local context of an action these features are calculated for the closest teammate and opponent of the player and the target. We also adapt the pressure model of Andrienko et al. to a hockey context and to consider the velocity of the players [7]. For the global context of an action we derive features using hierarchical clustering with two clusters on the players' locations to represent the tactical structure of both teams.

For the pass and shot expectation models we calculate features relating to the positioning of the goalie and how much of the net the goalie has to cover to make a save against the shooter or pass target. Pass expectation models also include information about the crowdedness and width of the pass lane between the passer and the target. The dump-in models have additional features based on the area where the puck is estimated to be played in for a given target. We use a simple convolutional neural network that takes raw tracking data snapshots as its input to estimate this end location. Finally, we include game and score state features in the action probability model to represent how teams adjust their playing style depending on the overall match situation.

We train our models using XGBoost[8] and optimize hyperparameters for tree depth and various regularization parameters using Bayesian optimization with cross-validation. To prevent overfitting into particular feature combinations we use moderate to high regularization parameter bounds for each model. As many of the learning tasks for our models consist of imbalanced data, we use a low max delta step parameter to ensure well-calibrated posterior probabilities. Based on domain knowledge we enforce monotonicity constraints on some features like distance to goal as this improves predictive performance and helps in dealing with outliers like goals scored from the neutral zone. Model metrics on the test set are presented in Table 2. We summarize the calibration of the models using expected calibration error (ECE), which takes the weighted average of the difference between binned output probabilities and data points.

Table 2. Model performance on the test set.

Model	Log loss	AUC	ECE
Action probability	0.186		
Pass success	0.423	0.803	0.037
Pass receiver	0.422	0.892	0.007
Pass scoring for	0.071	0.823	0.018
Pass scoring against	0.045	0.757	0.008
Move success	0.155	0.856	0.008
Move scoring for	0.053	0.791	0.012
Move scoring against	0.026	0.764	0.005
Dump-in success	0.165	0.873	0.006
Dump-in scoring for	0.029	0.743	0.002
Dump-in scoring against	0.015	0.750	0.003
Dump-out success	0.207	0.858	0.008
Dump-out scoring for	0.019	0.735	0.002
Dump-out scoring against	0.032	0.755	0.005
Shot scoring for	0.174	0.827	0.015

4 Results

As we can determine the total value of any given possession P_t, we can use this to evaluate the impact of each action. The value of an action is then defined by taking the difference between total possession value at the start of the action P_{Start} and the total possession value at end of the action P_{End} for all actions except shots, for which the total value is defined as-is. We define actions that have a positive impact as progressive and divide actions that have a negative impact into three categories: regressive, lost and conceded. Regressive refers to how much value is lost through successful actions that decrease the probability of the team scoring, lost refers to how much value is lost through unsuccessful actions, and conceded refers to the value gained by the opponent through unsuccessful actions. To account for any possible error in the detection of the moment of reception for passes, dump-ins and dump-outs, we take a one-second window after the end timestamp of the action to determine its end value.

The value of move actions is calculated continuously during matches, so we take the cumulative sum of a puck control sequence as the total value of a move action. As the value of move actions is the most sensitive to how other players are positioned, and we do not want to punish the puck carrier for factors outside their control, we limit the amount of regressive and lost value between two consecutive puck controls by the average value of a move action in our data (approximately one goal scored per 100 moves) and divide this limit by the sampling rate used to generate tracking data snapshots.

Because there are no existing ground-truth labels for evaluating the quality of a player's actions, we compare the total estimated possession value of common in-game situations and how often they have led to a goal being scored in the Liiga playoffs 2022-23. A comparison of the best forwards and defencemen that shows how their actions have added and lost value is also presented. We use playoff matches as our out-of-sample prediction because there is a recognized difference in play styles between the regular season and the playoffs, where players are allowed by the referees to play a more physical and disruptive game. This is illustrated by the fact that in our training data the average number of goals scored per match is 5.3, while in the 2022-23 playoffs it was 4.6 goals. We surmise that the features engineered from tracking data provide enough context to help overcome this domain shift.

Table 3 displays the danger level between controlled zone entry types at even-strength. We take the danger of a zone entry to be average of the total possession value in a one-second window following the moment that the offensive blueline has been crossed. We denote a zone entry to have resulted in a goal using the same eight-second window as with our models. Our framework correctly identifies that breakaways and odd-man rushes are likely to result in more dangerous situations than entries where the team in possession has an equal or lower number of players involved compared to the defending team. The estimated danger level generally correlates well with how often the different entry types result in goals, though some types are affected by the natural variance of goal-scoring in relatively small sample sizes. Based on observing individual entries, it is also fairly common for entry types to change a couple seconds after the entry is performed in the favor of the defending team as their forwards hustle to join the backcheck.

Table 3. Even-strength controlled entry danger by type in the Liiga 2022-23 playoffs.

Entry type	Count	Danger	Goal scored
1-on-0	18	12.7%	11.1%
2-on-1	24	7.4%	8.3%
1-on-1	43	5.4%	2.4%
3-on-2	70	4.6%	4.3%
2-on-2	146	4.3%	2.8%
1-on-2	90	3.6%	4.4%
3-on-3	473	3.3%	2.8%
2-on-3	310	3.1%	1.6%
1-on-3	101	2.6%	1.9%

Table 4 displays the danger level of successful even-strength passes by type. We take the danger level of a pass to be its progressive impact as defined above. Passes into the slot, which end in the area between the goal and the first hash marks of the faceoff circle, are intuitively the most dangerous with lateral (east-west) passes and behind-the-net passes inside the offensive zone following suit. We define entry passes as passes that facilitate a zone entry and outlet passes as passes that lead to a zone exit. Low-to-high and high-to-low passes are passes inside the offensive zone that do not cross the center line. It can be seen that the value added by these pass types closely follows the true scoring probabilities.

Table 4. Even-strength pass danger by type in the Liiga 2022-23 playoffs.

Pass type	Count	Danger	Goal scored
Slot	195	9.1%	9.2%
Lateral	994	3.6%	3.4%
Behind the net	226	3.3%	3.1%
Entry	611	2.3%	2.0%
Low-to-high	610	2.1%	1.8%
High-to-low	1142	1.4%	1.8%
Outlet	1631	1.1%	0.9%

Tables 5 and 6 represent the best-performing forwards and defencemen by total value added and lost at even-strength play. Passes, dump-ins and dump-outs have been consolidated together into a single value. The positive impact of an action indicates the progressive value added and the negative impact indicates the sum of regressive, lost and conceded value as defined before. Forwards generate more progressive value on average, but tend to lose more as well through attempting more ambitious and difficult actions. A greater proportion of the negative impact by defencemen is through conceded value, however, as their unsuccessful actions tend to occur closer to their defensive zone.

Table 5. Even-strength forward performance per 60 by possession value type in the Liiga 2022-23 playoffs.

Player	Team	Pass+	Pass−	Move+	Move−	Shot+	Total
Eemeli Suomi	Ilves	0.95	0.53	1.21	0.50	1.00	2.13
Anton Levtchi	Tappara	1.08	0.52	1.16	0.26	0.59	2.05
Joona Ikonen	Ilves	0.88	0.38	0.58	0.15	1.10	2.03
Waltteri Merelä	Tappara	0.48	0.39	0.93	0.34	1.20	1.88
Kristian Tanus	Tappara	0.91	0.49	0.91	0.24	0.73	1.82
Balázs Sebők	Ilves	1.04	0.81	1.31	0.23	0.50	1.81
Santeri Virtanen	Ilves	0.69	0.38	0.66	0.20	0.99	1.76
Matias Mäntykivi	Ilves	1.03	0.45	1.00	0.44	0.59	1.73
Niko Ojamäki	Tappara	0.75	0.35	0.44	0.15	0.97	1.66

Table 6. Even-strength defenceman performance per 60 by possession value type in the Liiga 2022-23 playoffs.

Player	Team	Pass+	Pass−	Move+	Move−	Shot+	Total
Les Lancaster	Ilves	1.06	0.43	0.33	0.10	0.82	1.68
Tarmo Reunanen	Lukko	0.76	0.28	0.68	0.20	0.58	1.54
Colby Sissons	KalPa	0.69	0.31	0.79	0.17	0.40	1.40
Valtteri Kemiläinen	Tappara	0.93	0.22	0.60	0.16	0.22	1.37
Maksim Matushkin	Tappara	0.69	0.20	0.70	0.21	0.33	1.31
Ben Thomas	Tappara	0.58	0.27	0.44	0.09	0.63	1.29
Leo Lööf	Ilves	0.82	0.32	0.62	0.21	0.15	1.06
Casimir Jürgens	Tappara	0.59	0.28	0.42	0.09	0.42	1.06
Thomas Grégoire	Lukko	0.71	0.28	0.43	0.12	0.22	0.96

5 Conclusions

In this talk we have shown that a real-time possession value framework can be implemented in an ice hockey context. The out-of-sample performance of the framework in typical in-game scenarios and events as well as in differentiating the value created by players in different positions matches both domain knowledge and the true underlying scoring probabilities. In the future it would be interesting to extend the framework to model defensive actions and the possibility of shots being indirect passes. Similarly, considering banked and rimmed passes separately would likely improve the performance of pass-related models [9]. Another promising avenue of research would be to use graph-convolutional neural networks with tracking data snapshots, which has been shown to improve model performance over tree-based models and remove the need for advanced feature engineering [10].

References

1. Sicilia, A., Pelechrinis, K., Goldsberry, K: DeepHoops: Evaluating micro-actions in basketball using deep feature representations of spatio-temporal data. In: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 2096–2104. (2019)
2. Burke, B.: DeepQB: Deep learning with player tracking to quantify quarterback decision-making & performance. 2019 MIT Sloan Sports Analytics Conference (2019)
3. Decroos, T., Bransen, L., Van Haaren, J., Davis, J.: Actions speak louder than goals: Valuing player actions in soccer. In: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 1851–1861. (2019)
4. Fernández, J., Bornn, L., Cervone, D.: A framework for the fine-grained evaluation of the instantaneous expected value of soccer possessions. Machine Learning, **110**(6), 1389–1427 (2021)

5. Liu, G., Schulte, O.: Deep reinforcement learning in ice hockey for context-aware player evaluation. In: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, pp. 3442–3448. (2018)
6. Liu, G., Schulte, O., Poupart, P., Rudd, M., Javan, M.: Learning agent representations in ice hockey. In: Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2020 (2020)
7. Andrienko, G., Andrienko, N., Budziak, G: Visual analysis of pressure in football. Data Min Knowl Disc **31**, pp. 1793–1839 (2017)
8. Chen, T., Guestrin, C.: XGBoost: A Scalable Tree Boosting System. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 785–794. (2016)
9. Radke, D., Brecht, T., Radke, D.: Identifying completed pass types and improving passing lane models. In: Proceedings of the Linköping Hockey Analytics Conference LINHAC 2022, pp. 71–86. (2022)
10. Stöckl, M., Seidl, T., Marley, D., Power, P.: Making offensive play predictable - using a graph convolutional neural network to understand defensive performance in soccer. 2021 MIT Sloan Sports Analytics Conference (2021)

Research papers

Professionalism & Leadership Development in Ice Hockey: Understanding Social Emotional Learning Experiences of Coaches in Atlantic Canada

Dr. Lynn LeVatte[1], Dr. Christina Phillips[2],
Dr. Kristin O'Rourke[1], and Shaun Ranni[3]

[1] Education Department, Cape Breton University, Nova Scotia, Canada
(Lynn_levatte@cbu.ca, Kristin_orourke@cbu.ca)
[2] Department of Curriculum, Teaching & Learning University of Toronto, Ontario, Canada (c.phillips@mail.utoronto.ca)
[3] Department of Athletics, Cape Breton University, Nova Scotia, Canada
(Shaun_ranni@cbu.ca)

Abstract. This qualitative research study investigated the Social Emotional Learning training experiences of ice hockey coaches in Atlantic Canada. Social Emotional Learning (SEL) and leadership in sport is an emergent field which has been gaining attention on a national level. The purpose of this study was to examine various aspects of SEL within coaching leadership training of Canadian ice hockey coaches in Atlantic Canada. Minor hockey coaches (n=8) were recruited to participate in semi-structured interviews. Five questions pertaining to hockey coaching background, leadership training, communication, and SEL training experiences were posed to participants. Interviews were offered both in-person or virtually as an option for convenience. Analysis of data suggested that clear expectations and effective communication with players and guardians were valuable aspects for relationship building. Limited professional development opportunities surrounding aspects of SEL were noted by participants, training provided was outdated in certain aspects, and current topics of inclusion, diversity, and culture. Future recommendations for continued study within the field of SEL within ice hockey are offered.

Keywords: Social Emotional Learning, ice hockey, coaching, professional development, leadership in sport, training

1 Introduction

Hockey in Canada has been conceptualized as a cultural truism and a way of life, with a connection so powerful and strong that it has united a vast nation from coast to coast [1]. The sport of hockey is embedded in Canada's national culture. Players, coaches, managers, and officials are key participants for the overall success and sustainability of this popular sport. To compare within a global perspective, there are approximately 1.8 million people who are registered hockey players, of which over one-third, or 631,295, live in Canada. There are 555,935 registered hockey players in the United States, 113,425 in the Czech Republic, 105,059 in Russia, 76,387 in Finland, and 63,901 in Sweden, rounding up the top six ranked countries [2]. The field of sport leadership has also emerged as a notable area of research and covers an increasingly diverse range of topics relevant to success in coaching youth athletes. The sport of ice hockey has grown to include many diverse populations and promotes diversity and inclusivity. While such perceptions of inclusivity have remained prevalent in many sports, recent critical events such as abuse scandals, racism, and bullying have negatively impacted the sport of ice hockey. The sport of ice hockey has witnessed growth within inclusivity and diversity aspects. In Canada, for example, the growth in female hockey has been substantial. Adams and Leavitt [3] reported that "the initiatives of women's sport leaders have led to greater recognition within the local, provincial and national governance structures and increased participation numbers". Exploring the 1980s, Canada saw an expansion of programs across the country to include opportunities for girls and women, and in 1982 a national championship was established [3]. As Hockey Canada [4] posited, within the 2009-2010 season, there were 85,624 girls and women registered as ice hockey participants, an exponential increase from the 8,146 participants reported two decades earlier in 1990.

Preparing to meet the coaching needs of diverse populations in the sport and essential training development through leadership is warranted. The International Ice Hockey Federation [2] explained that there are approximately 5,000 outdoor rinks and 3,300 indoor hockey arenas in Canada, and the only other country that has more than one thousand indoor arenas is the United States with 1,535. It can be determined that the sport of hockey has its greatest presence in Canada in terms of diversity growth, places, and facilities designated for ice hockey.

Urquhart et al. [5] explained that many definitions of coaching effectiveness mentioned winning in the professional context, while placing a greater emphasis on coaches developing athletes' confidence, competence, connection, and character. Lara-Bercial and Mallett [6] investigated characteristics of coaches and relationship to leadership. The findings of their study revealed coaches were characterized by a common set of personal characteristics, which included an exceptional work ethic, strong communication skills, a quest for continuous improvement, and effective leadership behaviors that inspired their athletes. This research study will explore the Social Emotional Learning (SEL) training experiences of ice hockey coaches from the Atlantic Hockey Group (AHG). Within the past decade, the attention of SEL has broadened within society. As described by Liew and McTigue [7], educating the "whole child" became more prominent, thus enhancing teaching and coaching skills of professionals who work directly with youth. Within the expansive growth and popularity of diversity in Canadian hockey, leadership and SEL training to address this growth is imperative.

1.1 Impact of Social Emotional Learning (SEL)

Social Emotional Learning (SEL) can be explained as methods in which youth and children tend to learn, recognize, and manage emotions, develop positive relationships, behave ethically and responsibly care about others, make good decisions, and avoid negative behaviors [8]. It involves "teaching children to be self-aware, socially cognizant, able to make responsible decisions, and competent in self-management and relationship skills" [9]. In Figure 1, SEL general competencies are presented. These include self-awareness (e.g., identifying and recognizing emotions), social awareness (e.g., respect for others), responsible decision making (e.g., problem identification and situation analysis), self-management (e.g., self-motivation and discipline), and relationship management (e.g., communication, social engagement). These competencies parallel much of the sport-based research on life skills and psychosocial development of children and youth yet have largely remained isolated from the sport-based life skills development literature. SEL is critical for children and youth long-term success in and out of school [10]. Examining the intrapersonal characteristics for success, in-depth personal reflection, emotional intelligence, and a quest for continuous improvement have been instrumental within SEL research [11].

Furthermore, Elias [12] discussed SEL in sport and athletics, specifically investigating how SEL can be used to promote character development among athletes. The term "Educational Athletics" is used by the Massachusetts Interscholastic Athletic Association to express how athletics and competition can be used as an extension of the classroom and an educational activity within itself to teach life lessons and prepare young people with values for lifelong learning [12].

SEL and behaviour in youth sport was recently investigated in academic literature. Research syntheses, systematic reviews, and meta-analyses support the development of SEL skills for promoting positive youth outcomes and reducing behavioral health challenges [14]. Youth who develop SEL skills can apply the "knowledge, skills, and attitudes necessary to understand and manage emotions, set and achieve positive goals, feel and show empathy for others, establish and maintain positive relationships, and make responsible decisions" [15]. CASEL cites many benefits of SEL skills, including improved attitudes, prosocial behavior, positive relationships, and academic performance [15].

This qualitative research study investigates the SEL training experiences of ice hockey coaches in Atlantic Canada. Professionalism and leadership in sport is an emergent field, which has been gaining attention on a National level [16]. Within the past decade, the attention and importance of SEL has broadened within society. As described by Liew et al. [17], educating the "whole child" became a more prominent approach within education pedagogy, and thus enhanced teaching and coaching skills of individuals who work directly in supporting youth in sport. Framed on the theory based upon Bronfenbrenner's ecological systems theory, which explains that environmental and contextual factors are necessary for understanding human development [18], this research project recognizes the potential and critical role that hockey coaches may play within the lives of youth.

Fig. 1: SEL framework by the Collaborative for Academic, Social, and Emotional Learning [13]

Education research aligns with this theory, as it points to the importance of community, teacher, parent, guardian recreation, schooling, and extra-curricular activities. These are the underpinnings for a holistic approach to education in which the interrelationships at all levels of the educational ecosystem prioritize human development alongside traditional education [19].

Recent research also suggests that ...the synergy between the practice of physical-sport activity together with physical and psychological health is a gradually growing interest area for education researchers [20]. Concepts that are characterized as constructs that are not identified with traditional indicators of cognitive capability or intellectual functioning and are often described under such terms as 21st-century skills, socio-emotional skills, character, or personality. Creating awareness of those skills can be beneficial for youth and coaches alike [20]. Participation in sports has also been related to a variety of social and emotional competencies and related skills that are correlated from extensive research and are essential to general success and well-being in school, work, and relationships [17]. Evidence suggests that youth with strong social and emotional skills are more likely to have positive work and family relationships, enter and graduate college, succeed in their careers, and have better mental and physical health outcomes [21]. Previous research has determined that when enhancing youth social and emotional learning, one important factor is the ability and experiences of educators and coaches to engage and support learners [21]. Anderson-Butcher et al. [14] explained that behavioral and social skill development among youth is a growing concern. Training youth sport workers and community leaders within

SEL has the potential to positively engage youth [14]. Thus, this proposed research project will understand and determine existing levels and types of SEL training minor hockey coaches have received within their coaching training and explore potential need for future specific training.

2 Methodology

Data was collected for this study during the period of November 2022 to March 2023. Participants were recruited via an email sent from the project partner The Atlantic Hockey Group (AHG). The AHG was founded in 1989 by former NHL hockey player Charlie Bourgeois. It has become one of the most successful hockey training programs in Atlantic Canada. Through its many different hockey schools and leagues, the AHG works with over 10,000 hockey players each year. The team of experienced coaches come from the ranks of university, junior, high school, and minor hockey teams. The AHG is based in Moncton, New Brunswick, Canada, with programming offered in three Atlantic Canada provinces (Nova Scotia, Prince Edward Island, and New Brunswick). John Sim, a former NHL player with the Dallas Stars and New York Islanders, is the Director of Operations in Nova Scotia. They provide programming for both male and female hockey players and include speciality programs such as power skating, goaltending, and high-performance player development [22].

The participant sample (n=8) was comprised of minor hockey-level coaches who coach with the AHG and instruct youth aged 4-18 years. The participants were positioned in a head or leading coach role and had main responsibilities to coordinate team rosters, select assistant coaches, schedule practices, book ice times, and coordinate communications with both players and parents/guardians. Within the AHG organization, approximately 95% of head coaches instruct the co-ed and/or male teams, and approximately 75% of male coaches instruct the female teams [23].

This research used purposive sampling, as ice hockey coaches, both male and female, were invited to participate. Recruitment also involved notices through social media and direct email within the AHG organization. This qualitative research study utilized open-ended, semi-structured interview questions to collect data specifically regarding SEL training experiences of hockey coaches. There were small inducements of a coffee card available for participation. Participation was voluntary, and coaches were invited to complete an interview with a member from the research team. The interviews took place in person and/or online via Zoom, depending upon location and availability of each participant. The in-person interviews were conducted primarily within public places. Within the introduction segment of the interview, the researchers read a scripted informed consent, project purpose, and ethics brief from Cape Breton University. This informed the participants of the process and contacts for the CBU research ethics department should they have any questions. Informed consent was obtained prior to the start of each interview. The researchers also explained to participants that they were free to stop the interview at any time should they feel uncomfortable.

Participants were also invited to share their age and number of years coaching. Interview questions were not provided to participants in advance.

Regarding the participant demographic characteristics, 8 (100%) were male participants, and the age range was between 23 and 48 years. The average years of coaching was 9.6 years.

The qualitative interviews were comprised of 5 questions, which were developed to understand the SEL leadership training experiences of hockey coaches in Atlantic Canada.

Interview questions included the following:

1. Can you describe your position with the organization and what are your roles and responsibilities?
2. Can you briefly describe your ice hockey coaching training background? When and what types of training, the length and the content included?
3. Social Emotional Learning includes aspects of enhanced leadership, empathy, understanding, self -regulation, behavior support, trust, honesty, inclusivity, etc. What is your experience with these specific components, were they taught explicitly or included within your coaching training? If yes, what types or when?
4. In your coaching career, how often are you provided with leadership training? What types of training did you receive as Professional Development?
5. When coaching young ice hockey players, what is the most challenging aspect, in terms of connections and relationship building with your players and/or families? Are there other barriers or challenges with your players? What types of training do you feel would be beneficial for coaches?

Field notes were taken by the researchers at the end of sessions to ensure key messages were highlighted, and sessions were also recorded with permission for transcription purposes. Ethics approval was obtained from Cape Breton University. Within the ethics approval, all data was collected and stored within the researchers' personal computers. Raw data was not accessible for public view.

3 Findings

Two main themes emerged from the analysis. Data were organized and analyzed using codes and a thematic approach. The emerging themes were larger and abstract, while the codes were one-word adjectives. Participants referred to a broad range of experiences to describe SEL and coaching training. Inductive content analysis was employed as this project included non-complex research, and the sample size (n=8) was small [24]. As noted by Williams and Moser [25], coding in qualitative research is comprised of processes that enable collected data to be assembled, categorized, and thematically sorted, providing an organized platform for the construction and development of meaning. Interviews were recorded (n=5) and notes were transcribed (n=3) for remaining interviews. The researchers reviewed the collected data which was shared with the team through MS Office Teams. The data analysis was based on word frequency and included verbs and adjectives. As an inductive process, the researchers became familiar with the data, generated initial codes, searched, and developed themes from the data and defined those main categories. Using an Excel spreadsheet, themes and codes were documented by the Primary Investigator. In this article, two main themes will be presented.

3.1 Theme 1: Training Requirements for Coaching Adolescents/Youth

Coaches reported (n=8) that they were head or lead coaches within the AHG organization. Ice hockey coaching training was received through a provincial/national entity. The analysis of data yielded a theme specific to importance of knowledge specific to adolescent behavior and youth development within a coaching context. 75% (6/8) of respondents noted they did not recall receiving training relating to this topic but would find this to be beneficial. Most of the training received was technical based, such as hockey drills and skills relating to shooting or positions. As Participant #4 explained:

> sometimes it can get it can get overwhelming when you're dealing with 17, 14, 15-year-olds that are just going through puberty, just starting to hit that. And then you have other kids that are already there and have hit it. The hormones are just flying.

Participant #2 stated that he utilized youth player development and positive psychology-based training, and it was self-initiated through online research web-based applications. Results also revealed that online training programming was limited or outdated and didn't match the current landscape of hockey players and coaches. Participant #1 explained that "the training is really old, and it really wasn't exciting... it's just online modules and... some old videos, but a lot of the materials are really, really old and really not interesting for anybody that's going to participate".

Table 1 describes codes and themes which were identified during the analysis. Coach training adolescents and youth was one theme which was evident. The need for current and relevant training to meet the needs of coaches who are coaching youth with diverse abilities and needs. 100% of coaches reported they did not receive specific SEL training. It was noted, however, that coaches (n=6) described receiving information about respect in hockey topics, diversity, and inclusive practice. Including SEL within a training and development practice is beneficial for children and youth to understand personal and social responsibility [26]. Engaging hockey coaches who spend countless hours coaching and mentoring children and youth with SEL skills could be a powerful addition to any hockey coaching training regime.

3.2 Theme 2: Effective Communication Practices and Processes

Communication was discussed by 100% of respondents during the interviews. Participants described the impact of coaching children and the importance of

Table 1: Coding and emerging themes

Codes	Emerging Themes
Course Content, Behaviour, Scheduling, Stress Management, Team Building, Children, Delivery of Training, Barriers, Format of Training	Training Coaching Adolescents and Youth
Relationships, Expectations, Comprehension, Listening, Inquiring, Providing Information, Happy, Encouraging, Discussions, Meetings	Effective Communication Practices and Processes

relationship building and expectations as it related to both coaching youth, but also communicating with parents.

Participant #5 explained: You know, they're getting into this teenage age . . . they don't want to listen to adults. They do, but they don't. And they always respect the coaches and love to promote. But finding that that that way to bridge that gap between these preteens that don't want to listen to adults".

Additionally, another response clearly outlined: "Some of the things they say they might make you might make you mad or might just annoy you to shreds" (Participant #4).

Addressing specific communication needs was also highlighted (n=3). Question #5 asked participants to discuss any additional or specific training. Understanding appropriate communication responses for players and parents is important. As an example, the following excerpt defines concerns from a coach: "She [child] did not play center, which then came to I'll call it almost came to blows with the parents getting in my face".

Communicating with guardians or parents is valuable and important. As described by Participant #6:

> setting expectations with the parents.. would be the parents, relationship, you get all, the all the issues with complaints and the blame so that's a huge part of minor hockey, to develop and trying to maintain that relationship... You know having parent meetings up front ongoing discussions with parents through the years and that gets a little bit easier the more you've coached.

The various types of communication were expressed during the interviews. Results indicated coaches utilized team meetings, individual and group emails, social media, and "Coffee with the Coach" panels for a general Q/A period. Open communication was noted as being extremely important to build trust but can also be a challenge without any professional development training. As Participant #7 explained:

> I have to talk to him [player] more than the others, but generally that's probably the biggest challenge how to how to chat and make those relationships without focusing on the game all the time.

The method in which coaches and players exhibit communication can be both verbal and non-verbal. Outbursts of aggression or demonstration of discontent can often result in challenges for the team. Coaches in this study acknowledged that derailing game plans or miscommunication can be difficult at times. Actions and reactions to situations on the ice may impact the team.

In summary, effective practices and processes for communication are an integral part of the coaching role. Guidelines and expectations contribute to this process. The following response identifies this challenge for coaches:

> we have to be prepared ...and parents sometimes are causing a barrier with playing and there's a lot of emotions and you really have to be honest with the kids you know be encouraging and how do you relate to the parents and how do you diffuse a situation... sometimes I'm getting a text in the middle of the night saying my son needs you and you know I'm the coach and trying to understand what does this mean?

4 Discussion

This study highlights the professional development and leadership training experiences of minor ice hockey coaches. Participants were members of the Atlantic Hockey Group organization in Atlantic Canada. Components of Social Emotional Learning (SEL) aspects were identified and explored. The data revealed that hockey training with aspects of SEL were limited and not specific or explicit to Social Emotional Learning. Unlike practitioners in many other fields of teaching or education, coaches in youth sport environments often have limited formal training or financial compensation for their work [27].

Within the analysis, training content for ice hockey coaches was described as primarily focused upon health and physical safety. Concussion protocol, dressing room safety, and physical environment of dressing room areas were reported. Hockey Canada and the Respect in Sport program was noted as an inclusive or diversity training program offered through coach training [28]. When asked about content of this module, participants could not recall specific modules that addressed diversity, inclusion, or communication. Participants did not recall receiving professional development (PD) training relating to SEL practices. Professional development can be defined as:

> Gaining new skills through continuing education and career training after entering the workforce. It can include taking classes or workshops, attending professional or industry conferences, or earning a certificate to expand your knowledge in your chosen field. [29]

As well, PD training was self-initiated and occurred in both online training and in-person formats. In terms of process, the overall findings of this study suggest that additional PD in areas relating to Social Emotional Learning would be beneficial, specifically with aspects of communication, diversity, inclusion, relationship building, and adolescent development. It has been argued that sport organizations do not seem to have systematic programs to teach life and sport skills [30, 31]. This study emphasized the important connections and impact within SEL, sport, and youth development. SEL has become a staple of positive youth development approaches within many educational settings [32]. SEL programming and awareness prepares students to move successfully through life transitions and is an equitable approach to supporting students of diverse backgrounds, including those of minority race or from disadvantaged families [33].

The findings of this study emphasize the importance of current professional development training required for the changing landscape of ice hockey in Canada. Providing youth hockey coaches with specific training relating to SEL may have the power to impact personal growth and leadership. Fostering effective relationships and mentoring youth may be impactful on coaches' abilities to bring additional success to the ice.

This study may align within hockey analytics and coaches' ability to motivate players to become successful leaders both on and off the ice. Building confidence through social skill development, improved communication practice, and leadership may equate in a hockey team's ability to improve upon their drills, scoring, and game planning.

Communication, adolescent development, parent and player expectations, and inclusion were focal points addressed by participants. Our study reported that coaches received technical training in ice hockey skill development, however limited or no training within aspects relating to SEL. Supplementing ice hockey training with PD sessions focused on SEL can not only educate hockey coaches about social skill development, but it can empower them to meet the diverse needs of youth and children whom they support. It is essential to foster relationship skills, self-management, and responsible decision-making in that it will engage managing emotions and exploring possible solutions through equity-focused conversations [13].

Another suggestion for future research involves parent communication and referees. Previous reports have suggested that these aspects can be beneficial in sport coaching [26].

Expanding on this study, the role of parents/guardians in relation to respecting communication with referees was often noted by researchers. Additionally, a future recommendation is for a study that explores the development for coaching various ability levels of players. Team building, social development skills, and using sport to build positive social relationships could be beneficial. Coaches also witnessed the pressure that some players experienced from parents to excel in the sport of hockey and the challenges that are associated with this process. Maintaining an atmosphere where youth could enjoy hockey and enhance social skill development was also highlighted by coaches as being an important area for development.

Limitations noted within the study included sampling of one hockey organization. All participants had coached hockey for the AHG in Atlantic Canada.

In summary, key findings from this study revealed that participant coaches were head or lead coaches within the AHG organization, received ice hockey coaching training from provincial minor hockey organizations, training format delivery included both online and in-person, explicit training specific to SEL was limited, effective communication was stated by all coaches as being an important aspect relating to coaching, and many coaches suggested the need for additional training within SEL, diversity, and inclusion.

5 Conclusion

The current study explored leadership and professional development training experiences of hockey coaches in Atlantic Canada. Results suggest that the majority of coaching training is received through both national and provincial associations. This training is specific to technical drills and skills for hockey development. Limited social skills or leadership training was received. Requirements and additional training that focus on inclusion, diversity, adolescent development, and communication within a hockey realm are noted. Using the tenets and foundations of SEL may provide an important benefit for professional development and leadership training for hockey coaches in Atlantic Canada.

Acknowledgements. We would like to thank the Atlantic Hockey Group for the ongoing support during this study, especially regarding the recruitment of participants

References

1. Cairnie, J.: Truth and reconciliation in postcolonial hockey masculinities. Can. Lit. 237, 103–119 (2019).

2. International Ice Hockey Federation. Survey of players (2018). http://webarchive.iihf.com/iihf-home/the-iihf/survey-of-players/index.html

3. Adams, C., Leavitt, S.: "It's just girls' hockey": troubling progress narratives in girls' and women's sport. Int. Rev. Sociol. Sport. 53, 152–172 (2018). https://doi.org/10.1177/1012690216649207

4. Hockey Canada. Statistics & history (2022). http://www.hockeycanada.ca/en-ca/Hockey-Programs/Female/Statistics-History.aspx

5. Urquhart, D., Bloom, G.A., Loughead, T.M.: The development, articulation, and implementation of a coaching vision of multiple championship-winning university ice hockey coaches. Int. Sport Coaching J. 7, 335–346 (2020). https://doi.org/10.1123/iscj.2019-0096

6. Lara-Bercial, S., Mallett, C.J.: The practices and developmental pathways of professional and Olympic serial winning coaches. Int. Sport Coaching J. 3, 221–239 (2016). https://doi.org/10.1123/iscj.2016-0083

7. Liew, J., McTigue, E. Educating the whole child: the role of social and emotional development in achievement and school success (2010).

8. Gould., D. Martin, E., Walker, L.: A season long investigation of social emotional learning associated with high school basketball participation. J. Appl. Sport Psychol. 34, 1102–1124 (2022). https://doi.org/10.1080/10413200.2021.1955421

9. Zins, J.E., Bloodworth, M.R., Weissberg, R.P., Walberg, H.J.: The scientific base linking social and emotional learning to school success. J. Educ. Psychol. Consult. 17, 191–210 (2007). https://doi.org/10.1080/10474410701413145

10. Weissberg, R.P., Durlak, J.A., Domitrovich, C.E., Gullotta, T.P.: Social and emotional learning: past, present, and future. In: Durlak, J.A., Domitrovich, C.E., Weissberg, R.P., Gullotta, T.P. (eds.) Handbook of Social and Emotional Learning: Research and Practice, pp. 3–19. Guilford Press, New York (2015)

11. Domitrovich, C.E., Durlak, J.A., Staley, K.C., Weissberg, R.P.: Social-emotional competence: an essential factor for promoting positive adjustment and reducing risk in school children. Child Dev. 88, 408–416 (2017). https://doi.org/10.1111/cdev.12739

12. Elias, M.: 4 ways to use athletics to promote social emotional learning and character development (2016). https://www.edutopia.org/blog/4-ways-use-athletics-promote-social-emotional-learning-and-character-development-maurice-elias

13. Collaborative for Academic, Social, and Emotional Learning (CASEL). CASEL's SEL Framework: What Are the Core Competence Areas and Where Are They Promoted? CASEL (2020)

14. Anderson-Butcher, D. et al.: Social-emotional learning interventions in youth sport: what matters in design? Child Adolesc. Social Work J. 38, 367–379 (2021)

15. Collaborative for Academic, Social, and Emotional Learning (CASEL). CASEL guide: effective social and emotional learning programs (2015).

16. Camiré, M.: Benefits, pressures, and challenges of leadership and captaincy in the National Hockey League. J. Clin. Sport Psychol. 10, 118–136 (2016)

17. Liew, J., Cameron, C.E., Lockman, J.J.: Parts of the whole: motor and behavioral skills in self-regulation and schooling outcomes. Early Educ. Devel. 29, 909–913 (2018). https://doi.org/10.1080/10409289.2018.1500513

18. Bronfenbrenner, U.: Developmental ecology through space and time: a future perspective. In: Moen, P., Elder, Jr., G.H., Luscher, K. (eds.) Examining Lives in Context: Perspectives on the Ecology of Human Development, American Psychological Association, Washington, DC (1995)

19. Darling-Hammond, L., Cook-Harvey, C.M.: Educating the Whole Child: Improving School Climate to Support Student Success, Learning Policy Institute, Palo Alto, CA (2018)

20. Luna, P., Guerrero, J., Cejudo, J.: Improving adolescents' subjective well-being, trait emotional intelligence and social anxiety through a programme based on the sport education model. Int. J. Environ. Res. Public Health. 16, 1821–(2019)

21. Jones, S.M., Kahn, J.: The evidence base for how we learn: supporting students' social, emotional, and academic development – consensus statements

of evidence from the Council of Distinguished Scientists. National Commission on Social, Emotional, and Academic Development, The Aspen Institute (2017)

22. Atlantic Hockey Group. About the Atlantic hockey group: our history (2023). https://www.atlantichockeygroup.com/

23. Bourgeois, B.: Personal email, May 24, 2023

24. Vears, Gillam, L.: Inductive content analysis: a guide for beginning qualitative researchers. Focus on Health Professional Education 23, 111–127 (2022). https://doi.org/10.11157/fohpe.v23i1.544

25. Williams, M., Mosher, J.: The art of coding and thematic exploration in qualitative research (2019). http://www.imrjournal.org/uploads/1/4/2/8/14286482/imr-v15n1art4.pdf

26. Shen, Y., Rose, S., Dyson, B.: Social and emotional learning for underserved children through a sports-based youth development program grounded in teaching personal and social responsibility. Phys. Educ. Sport Pedagogy (2022). https://doi.org/10.1080/17408989.2022.2039614

27. Schlechter C.R., Rosenkranz, R.R., Milliken, G.A. et al.: Physical activity levels during youth sport practice: does coach training or experience have an influence? J Sports Sci. 35, 22–28 (2017).

28. Hockey Canada. Respect in sport (2022). https://www.hockeycanada.ca/en-ca/hockey-programs/coaching/essentials/faq/respect-in-sport

29. Parsons, L.: Why is professional development important? (2022). https://professional.dce.harvard.edu/blog/why-is-professional-development-important/

30. Camiré, M., Trudel, P., Bernard, D.: A case study of a high school sport program designed to teach athletes life skills and values. Sport Psychol. 27, 188–200 (2013). https://doi.org/10.1123/tsp.27.2.188

31. Petitpas, A.J., Cornelius, A.E., Van Raalte, J.L. et al.: A framework for planning youth sport programs that foster psychosocial development. Sport Psychol. 19, 63–80 (2005)

32. Elias, M.J., Kranzler, A., Parker, S.J., Kash, V.M., Weissberg, R.P.: The complementary perspectives of social and emotional learning, moral education, and character education. In: Nucci, L., Krettenauer, T., Narvaez, D. (eds.) Handbook of Moral and Character Education, 2nd ed., Routledge, New York (2014)

33. Taylor, R.D., Oberle, E., Durlak, J.A., Weissberg, R.P.: Promoting positive youth development through school-based social and emotional learning interventions: a meta-analysis of follow-up effects. Child Dev. 88, 1156–1171 (2017)

Analyzing Passing Metrics in Ice Hockey using Puck and Player Tracking Data

David Radke, Jaxin Lu, Jackson Woloschuk, Tin Le†,
Daniel Radke, Charlie Liu, and Tim Brecht

Cheriton School of Computer Science, University of Waterloo
University of Calgary†

Abstract. Traditional ice hockey statistics are inherently biased towards offensive events like goals, assists, and shots. However, successful teams in ice hockey require players with skills that may not be captured using traditional measures of performance. The adoption of puck and player tracking systems in the National Hockey League (NHL) has significantly increased the scope of possible metrics that can be obtained. In this paper, we compute recently proposed passing metrics from 1221 NHL games from the 2021-2022 season. We analyze the distributions of values obtained for each player for each metric to understand the variance between, and within, different positions. We find that forwards tend to complete fewer passes with smaller passing lanes, while defensemen pass to forwards significantly more than their defensive partners . Additionally, because these new metrics do not correlate well with traditional metrics (e.g., assists), we believe that they capture aspects of players' abilities that may not appear on the game sheet.

1 Introduction

The idea of using quantitative evidence to understand player tendencies and performance to inform management and strategic decisions has existed in sports for several decades [9]. In sports classified as "striking games", such as baseball, analytics has transformed team operations and strategies [4]. This influence has lagged behind in "invasion games" such as football (soccer), basketball, handball, and ice hockey due to limitations in data collection and the complexities of the sport. Traditional (publicly available) statistics captured in ice hockey revolve around easily measurable offensive events (i.e., goals or shots) leading to the performance of offensive players being disproportionately captured. Successful teams in ice hockey, like all invasion games, require players with diverse abilities that existing offensively biased metrics do not capture, such as passing. This limited information makes constructing teams using quantitative evidence more difficult. The recent implementation of the puck and player tracking (PPT) systems in the National Hockey League (NHL) has led to several new metrics to quantify player behavior [12, 13]. In this paper, we utilize a larger dataset to study how passing metrics can be utilized to understand the variance in behavior among players and players at different positions (metrics with larger variance may provide more opportunities to find under-valued players).

The main motivation behind the development of passing metrics in ice hockey was to capture other player contributions that might not show up on a game sheet [12]. Understanding how players compare to each other within the distribution of passing metrics provides valuable context for team building and management. We perform a deeper analysis into recently proposed ice hockey metrics from NHL puck and player tracking (PPT) data to show how passing metrics can be used to identify diverse behaviors among individuals. The contributions of this work are:

- We perform significant amounts of data cleaning to calculate passing metrics using PPT data from 1221 games in the 2021-2022 NHL season.
- We analyze the distributions of various passing metrics for forwards and defensemen. This provides insights into how much better highly-ranked players are when compared with other players.
- We find that after normalizing for ice time, forwards tend to complete fewer passes than defensemen and have smaller passing lanes, whereas defensemen complete significantly more passes to forwards and overtake more opponents.
- We show that the number of players overtaken with completed passes and the size of the passing lanes for completed passes do not correlate well with traditional offensive-oriented statistics like assists. We believe this demonstrates that some of the our metrics capture aspects of players' abilities that might not show up on the game sheet.

2 Related Work

Understanding how multiple players/agents work together most effectively is a significant area of research in organizational psychology and AI [1, 15]. A general finding is that group diversity, role specialization, and cohesiveness is important for group performance [7, 1, 23, 14]. Similar results have been found in football and sports analytics. Those analytics have focused on the performance of groups of players together [8, 11, 3, 10]. We use football to refer to *association* football (also known as soccer), not American football.

The implementation of passing metrics in football allows the analysis of a player's decision-making and passing ability [20, 19], ability to overtake players with passes [21], impact on scoring probability [5], and ability to act under pressure [2]. In a low-scoring game like football, these models provide insight into players' behaviors independently from offense and enables team building with diverse skills. Similar advancements in ice hockey have analyzed passing lane probabilities [17], as well as passing scenarios and pressure [12, 13].

Despite the development of models that use PPT data in ice hockey, no previous work has analyzed passing models to help understand general distributions, trends, or differences among players in the NHL. In this paper, we calculate various passing metrics from recent work [12, 13] for 1221 games of the 2021-2022 NHL season. We analyze the distributions of each metric among players at different positions and within each position. Furthermore, we cross-reference related metrics to gain insight into how individual players behave with respect to multiple metrics.

3 Puck and Player Tracking Data

In the NHL, hockey is played on an ice surface that is 200 feet long and 85 feet wide. Tracking data is collected by SportsMEDIA Technology [18] (a partner of the NHL). They then derive event-level data (including completed passes) from the location tracking data. These event labels contain information about the time of the event and the identities and locations of the players involved. This paper focuses specifically on completed pass events. We have been granted early access by the NHL to the first full season for which the NHL used the PPT system (2021-2022). The PPT data and our resulting metrics are considered unofficial by the NHL, as the models used for creating event labels continue to be validated and improved. Additionally, the process of making statistical data official requires approval in the collective bargaining agreement, an ongoing process that has not been completed at this time. As a result, we do not provide information about individual player's metrics. Also note that this data may differ from other datasets that contain complete and/or incomplete passes (e.g., a hand labeled dataset). We have processed 1221 of the 1312 regular season NHL games.[1]

Location data is collected through tracking technology that is embedded into pucks and inserted into the sweaters of each player (on the back of the sweater, slightly right of the center of the shoulders). Location information contains x, y, and z-coordinates to record locations in 3-dimensional space. The x and y locations are relative to center ice (which is 0, 0). It is our understanding that when tested, the margin of error for the x and y coordinates is about 3 inches (the diameter of the puck) and very often as little as 1 inch. This is accurate enough for our purposes, as a puck traveling at speeds between 30 and 100 MPH would travel between 8 inches and 28 inches, respectively between readings. Further, our metrics are not overly sensitive to small changes in the puck's location. The z coordinates (not used in this paper) are relative to the surface of the ice. Location data is recorded 60 times per-second for the puck and 12 times per-second for each player on the ice, resulting in a total of about 734,400 location readings of interest in a 60-minute game. Additionally, location data is obtained once per-second for players that are determined to be off of the ice. We interpolate all puck and player locations to 100 readings per-second to more easily identify the positions of all on-ice entities at precisely the same time.

[1] Some games could not be processed due to issues with the data sets and/or some special cases that our code hasn't yet handled.

4 Background of Metrics

We briefly discuss the passing models used to derive the metrics in this paper. We refer the reader to the original paper [12] for further passing model details and to [13] for extensions and improvements to the original passing lane model. To ensure comparisons of different players are fair and are not simply a measure of ice time, we normalize our metrics by time on ice and/or games played, where appropriate (e.g., as is done in Section 6).

4.1 Passing Lane Model

The passing lane model we use in this paper is originally proposed in [12] and enhanced in [13]. The model uses the spatial locations of players in PPT data to estimate the available space between a passer p and any receiver r.

Figure 1 (adapted from [12]) shows the passing lane shape for a direct pass from p to r with three opponents. For each passing event, the model constructs a teardrop-like passing lane shape around the passer p and extending beyond the location of the receiver r (shaded regions). The size of the passing lane is determined by the nearest opponent to the pass and assigns a non-negative real-numbered value γ to be the openness of the pass. Figure 1 shows three passing lanes with respect to each of the three opponents. The γ value of this pass is $\gamma = 0.6$, since o_1 restricts the passing lane the most. We use the enhanced version from [13], where the *expected* locations of the receiver r and all opposing players based on current velocities are used to determine the passing lane. The enhancement also considers indirect passes off the boards. We developed a new constant-time algorithm to directly calculate γ instead of the previous binary search method. Refer to our previous paper [13] for more details.

4.2 Pass Overtaking Model

Previous work proposed and implemented models to understand progressing the puck beyond opponent players with passes [12]. At a high level, this model is represented as a zero-sum game, where a passer p gains a positive value for overtaking opponents with passes, and each opponent overtaken o receives a corresponding negative value. Formally, for a completed pass from p to r, if $\delta(x, y)$ is Euclidean distance between location x and y and $\texttt{NET}$ is the center of the entrance to o's net, o is considered overtaken if $\delta(p, \texttt{NET}) > \delta(o, \texttt{NET})$ and $\delta(o, \texttt{NET}) > \delta(r, \texttt{NET})$.[2] Because defensemen have greater opportunities to overtake more players, the model uses the fraction of players that are possible to be overtaken as the allocated credit. For example, if there are 3 players between p and the net (not counting the goalie) and the pass overtakes 2 opponents, the pass overtake value is 0.67. The passer p receives a positive value of +0.67 and each of the two overtaken players receives a negative value of −0.33 while the remaining non-overtaken player is unchanged.

[2] See Section 8 for variations we plan to consider in future work.

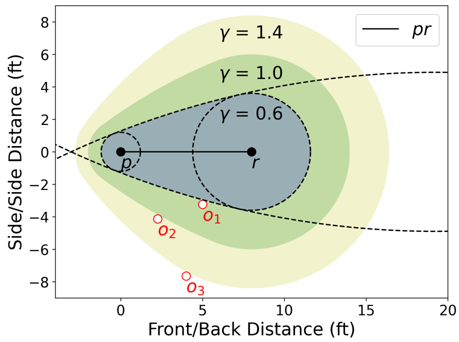


Fig. 1: Passing Lane.

Fig. 2: Adapted from [12]. The passing model for direct passes. The passing lane (shaded regions) surrounds the passer p and receiver r. The size and shape of this lane scales to the nearest opponent o (we show three examples of passing lanes with respect to three opponents). We use an expanded version that incorporates expected movement and indirect passes [13].

These values are aggregated into various metrics, including OVT (overtake total), BTT (beaten total), and PPM (passing plus-minus), calculated as PPM = OVT - BTT. We also calculate OVA, the average fraction of players overtaken with each pass ($\frac{\text{OVT}}{\text{num\_passes}}$). Because there can be significant differences in the number of games played by different players, we use average values per game where appropriate. This ensures a fair comparison when examining and comparing different players.

5 Data Cleaning

When beginning our analysis we found several anomalies that needed to be corrected. Specifically, when using the timestamps associated with a fair number of completed passes, the puck was located at a relatively large distance from the passing player (e.g., significantly outside the reach of the player). To mitigate this issue, we performed a pass timestamp correction phase to better identify and adjust the time at which the event occurred. Adjusting these timestamps is also important to correctly identify the locations of all players on the ice at the time of the event. This is critical to obtain accurate passing metrics. All results in this paper are computed after adjusting the timestamps, which has significantly improved our metrics.

Our adjustment process begins by finding the timestamp for an event t in the PPT data. At a high level, our approach is to find a more accurate timestamp t' where the puck is sufficiently close to the passing player (i.e., within reach of the player).We determined a threshold of $\delta(p, puck) \leq 4$ feet to be a reasonable value, based on discussions with people at the NHL and personal measurements.

Metric	Description
avgOVT_20	The sum of the fraction of opponents overtaken by a player's passes. We scale to 20 minutes of ice time and average per-game.
avgBTT_20	The sum of the fraction a player was overtaken by opponents' passes We scale to 20 minutes of ice time and average per-game.
avgOVA	The average fraction of opponents overtaken by a pass in a game. We average this value per-game.
avgPAA	Average γ (passing lane) value for completed passes. We average this value per-game.

Table 1: Summary of passing metrics discussed in this paper. Additive metrics (totals; end with "T") are averaged over players' games played ("avg") and scaled to 20 minutes per-game if necessary ("_20").

Any passes that could not be corrected using this technique are omitted from our dataset. This was only about 2.6% of the total number of completed passes. There are several possible ways to improve the accuracy of this approach including examining changes in the direction and speed of the puck. However, determining the accuracy of various techniques requires knowing ground truth, as a result this is a topic for future research.

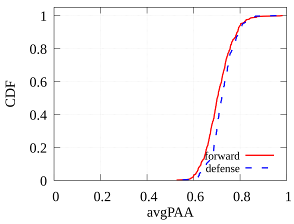
6 Distribution Analysis of Passing Metrics

In the original work where we proposed these passing models we only had access to smaller PPT datasets so we did not conduct a detailed analysis for players [12]. In this paper, we analyze 1221 games and examine whether or not there are differences in passing metrics between forwards and defensemen and study the differences among individual players within the same position. We provide a summary of the metrics we analyze in Table 1. Our dataset includes 1000 players. To ensure that we have a sufficient sample size for various metrics we exclude players that did not play in at least 10 games and average at least 10 minutes of ice time per game. This reduced our dataset to 750 players (478 forwards and 272 defensemen). Because our work in this paper focuses on passing , we do not include goaltenders in any of our metrics or player counts.

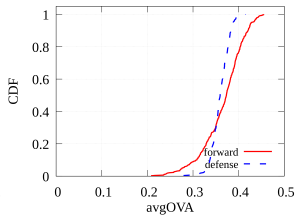
To allow for fair comparisons among players that receive different amounts of ice time (since some metrics correlate with ice time) we normalize metrics (where appropriate) to 20 minutes per game. For each of the metrics in Table 1 we average over a player's games. Thus, a metric such as OVT, the total fraction of opponents a player overtakes with their passes, will be represented as $avgOVT\_20$: averaged over a player's games ("avg") and scaled to 20 minutes of ice time per-game ("_20"), where appropriate.

6.1 Distributions of Metrics Based on Position

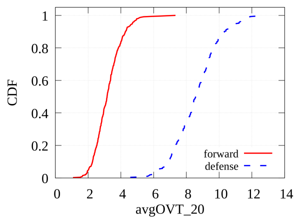
We perform the Welch t-test [22] to analyze how the distributions of metrics vary between forwards and defensemen. When rejecting the null hypothesis for the mean values of a metric being equal between forwards and defensemen at a p-value of 0.05, we find that the mean between forwards and defense for both traditional statistics (e.g., goals, assists, points, shots, and shots blocked) and the new passing metrics in Table 1 are sufficiently different for every metric except for hits (which we do not consider in this paper). As a result, we analyze forwards and defensemen separately and use cumulative distribution functions (CDFs) to analyze the variance of distributions at each position.



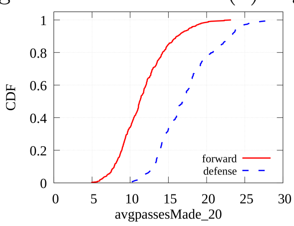
(a) avgPAA.



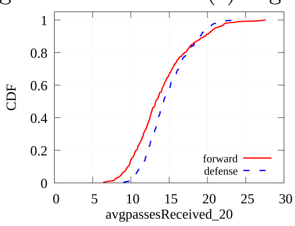
(b) avgOVA.



(c) avgOVT_20.



(d) avgPassesMade_20.



(e) avgPassesReceived_20.

Fig. 3: CDFs plots for passing metrics separated by position, including (a) avgPAA: the average γ value for completed passes (lower indicates smaller passing lanes). (b) avgOVA: the average fraction of opponents overtaken by a pass (larger is better). (c) avgOVT_20: the total fraction of opponents overtaken by a pass (larger is better). Metrics for each player are averaged over the number of games they have played ("avg") and when appropriate scaled to 20 minutes of playing time per-game ("_20"). (d) The average passes made by players per 20 minutes. (e) The average passes received by players per 20 minutes.

Passing Metrics Figure 3a shows the CDF for avgPAA, the per-game average γ value (passing lane size) for completed passes. Our results show that forwards and defensemen have distributions with similar shapes; however, the median defensemen tends to complete passes with slightly larger passing lanes. The forwards with the lowest avgPAA complete passes with about 47% smaller passing lanes than the forwards with the highest avgPAA.

Figure 3b shows the CDF for avgOVA, the average fraction of opponents a player overtakes per-pass, per-game. Higher values of avgOVA suggest the player overtakes a higher fraction of opponents with each pass (i.e., a stretch pass beating four of five players gives $\frac{4}{5} = 0.8$, while beating only the last defender gives $\frac{1}{1} = 1$). The 30th percentile values of each position are similar (about 0.35). Defensemen have lower variance in avgOVA with the range from the 20th percentile to 80th percentile being from 0.34 to 0.37 per-pass (34% to 37%) of the possible players per-pass. Comparatively, forwards have over double the variance than defensemen in avgOVA and the forwards with the highest avgOVA have over double the overtake value per-pass compared to the lowest forwards (0.45 compared to 0.21). The 20th percentile of forwards overtake an average of 33% of the possible players per-pass and the 80th percentile forwards overtake and average of about 40% of the possible players per-pass. The larger variance among forwards is likely caused by forwards typically having fewer opponents to overtake (2 or 3) compared to defensemen (4 or 5). We note that lowest percentile forwards are players that tend to make fewer than five passes per 20 minutes. We acknowledge that there may exist some players within our dataset that circumvent the intent of our filter and if they have a low number of passes, that could skew the distributions of some metrics. Future work could consider filtering techniques to remove players with too few passes.

Figure 3c shows the CDF for the avgOVT_20, the per-game average of the *total* fraction of opponents overtaken with passes normalized for 20 minutes of ice time. Higher values of avgOVT_20 suggest the player overtook a large fraction of opponents with their passes throughout a game. Our results show that the median defenseman achieves 2.8 times higher avgOVT_20 than the median forward (comparing 3 for forwards to 8.5 for defensemen). This difference of 5.5 avgOVT_20 increases to about 6 at the 80th percentile of forwards and defensemen (comparing 3.9 for forwards to 9.5 for defensemen). This change in the differences means the top defensemen for avgOVT_20 overtake more opponents compared to other defensemen than the top forwards compared to the rest of the forward population. Since the median avgOVA value for forwards is 4% higher than the median defensemen (see Figure 3b), we can conclude that higher values of avgOVT_20 for defensemen indicate that they complete more passes than forwards. This is confirmed in Figure 3d which shows the distribution of completed passes per 20 minutes. The shapes of the distributions among each position are almost identical, but defensemen tend to complete about five more passes than forwards at every percentile. The median forward completes about 12 passes per 20 minutes, whereas the median defenseman completes about 17. The forwards that complete the most passes complete up to 23 passes per 20 minutes 92% more than the forward median) and the defensemen that complete the most passes complete up to 27 passes (59% more than the defense median).

On average, despite defensemen completing roughly five more passes each than forwards, both positions tend to receive about the same number of passes

(Figure 3e). Comparing Figures 3d and 3e allows us to draw an interesting conclusion: defensemen complete passes to forwards significantly more often than to their defensive partner.

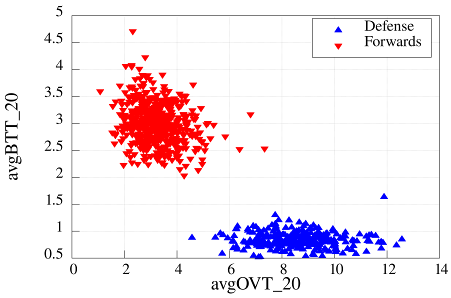
To understand this insight, consider that at even strength, the players that a forward can pass to are the two other forwards and the two defensemen. Assuming each of the other players is equally likely to be chosen (which may not be true), the probability of passing to a forward or defensemen is equal at 0.5. However, for defensemen there are three forwards and one defensemen to choose from. Again assuming the probability of passing to each of the other four players is equally likely (i.e., 0.25), the probability of passing to a forward is 0.75 and their defensive partner is 0.25. For the average pass reception curves for defensemen and forwards to be similar (as seen in Figure 3e) defensemen must complete passes to forwards three times more often. Considering that defensemen typically complete about five *more* passes than forwards (Figures 3d), defensemen must pass to forwards even more. Since these passes are likely up-ice, the higher frequency of passes from defensemen to forwards must be the main reason for high values of avgOVT among defensemen (Figures 3c).

Takeaways: We find that forwards make passes with slightly smaller passing lanes than defensemen. The variance among forwards for overtaking opponents with a pass (avgOVA) is significantly larger than with defensemen; however, the median forwards are only 4% higher than the median defensemen in avgOVA. Despite slightly lower median avgOVA, defensemen accumulate significantly higher *totals* for overtaking opponents (avgOVT_20) and complete about 5 more passes each game compared to forwards. Using Figures 3d and 3e, we find that defensemen pass to forwards significantly more than to their defensive partners.

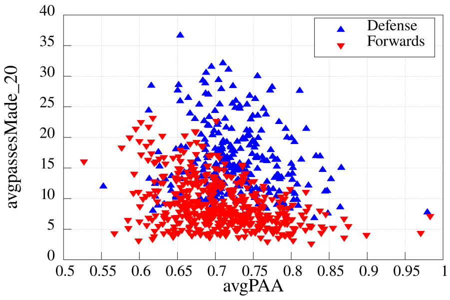
6.2 Analyzing Player Differences

In this section we analyze individual players across a variety of metrics to gain insights into differences among players. One of the main passing metrics derived in our previous work [12] and discussed in Section 4 is passing plus-minus (PPM), defined as PPM = OVT - BTT. PPM gives insight into if a player overtakes more opponents than they are overtaken themselves; however, the metric removes additional context that may be important when understanding player behaviors. For example, a player that rarely overtakes opponents while also never being overtaken could have the same PPM value as a player that overtakes many opponents but often gets overtaken.

Figure 4a compares the two components of PPM to analyze the distribution of players along these two dimensions. The x-axis shows avgOVT_20, the total fraction of opponents that a player overtakes with their passes (per-game average, higher is better) and the y-axis shows avgBTT_20, their total fraction of being overtaken by opponents (per-game average, lower is better). Red triangles represent forwards and blue triangles represent defensemen. Players in the lower right corner overtake more opponents while not being overtaken by many opposing team passes. Analyzing where players are in these distributions may be important when constructing forward lines or defensive pairings as a coach, or a roster as a manager.



(a) avgOVT_20 vs. avgBTT_20.



(b) avgPAA vs. avgPassesMade_20.

Fig. 4: (a) The two components of passing plus-minus (PPM; presented in Section 4.2). The avgOVT_20 metric (overtake total; x-axis), the total (per-game average) fraction of opponents a player overtakes with their passes and avgBTT_20 (beaten total; y-axis), the total (per-game average) fraction that players are overtaken by opponents. (b) The average γ value (passing lane) for a player's completed passes (avgPAA; x-axis) compared to players' average completed passes per 20 minutes.

Figure 4a shows that there is diversity (or variation) among forwards with respect to both avgOVT_20 or avgBTT_20. Table 2 shows the avgOVT_20 and avgBTT_20 values with 95% confidence intervals for the forwards and defensemen with the highest, median, and lowest values for each metric. None of the confidence intervals for the three forwards intersect for either metric; thus, we can confirm that there exist forwards with differences that are statistically significant. In comparison, Figure 4a shows that defensemen mostly vary along the dimension of how they overtake opponents with passes (avgOVT_20). Table 2 confirms that the confidence intervals for defensemen do not intersect for avgOVT_20 but do intersect for avgBTT_20. Therefore, we conclude that defensemen mostly distinguish themselves from their peers by overtaking more opponents with their passes (avgOVT_20).

Figure 4b compares the per-game average value of γ (passing lane size) for a player's completed passes (avgPAA_20; x-axis) and the average number of passes made by that player (avgPassesMade_20; y-axis). For both forwards and defensemen, players that complete the most passes (higher on the y-axis) tend not to have the lowest or highest values of avgPAA (x-axis) compared to the other players within their position. This implies that the players who complete a large number of passes do so in situations that are not anomalous (i.e., they are not mostly passing in easier situations).

Takeaways: There exists diversity among forwards with respect to overtaking opponents with passes and being overtaken by opponent passes. Defense-

Player	avgOVT_20	95% CI	avgBTT_20	95% CI
Fwd. Highest	7.28	±1.84	4.66	±1.09
Fwd. Median	3.16	±0.42	3.00	±0.19
Fwd. Lowest	1.05	±0.43	2.05	±0.17
Def. Highest	12.46	±1.91	1.58	±0.73
Def. Median	8.57	±0.60	0.83	±0.24
Def. Lowest	4.55	±0.52	0.51	±0.10

Table 2: Analyzing the mean and 95% confidence intervals for the highest, median, and lowest values for forwards and defensemen for avgOVT_20 and avgBTT_20. Our results show diversity among forwards with respect to both metrics while the highest defensemen tend to mostly separate themselves from their peers with respect to avgOVT_20.

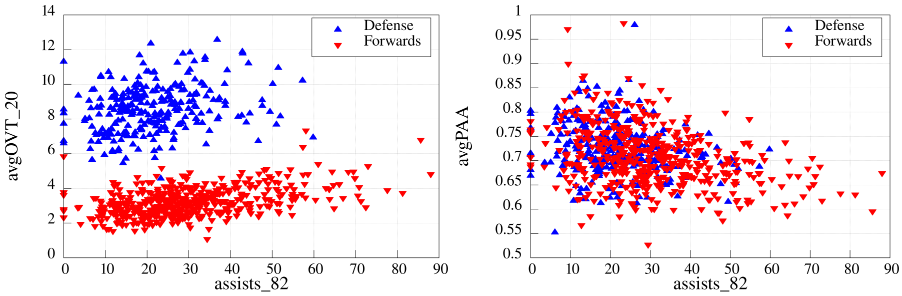
men mainly separate themselves from their peers by overtaking more opponents, while there is less distinction with how defensemen are overtaken by opponents. At both positions, players that complete the most passes tend to do so with an average passing lane size instead of completing a disproportionate amount of easier passes with bigger passing lanes.

7 Comparative Analysis

Inspired by the work on "Meta-Analytics" (to examine stability, discrimination and independence of metrics) proposed by Franks *et al.* [6], we present a simple analysis of some of our metrics to show that avgOVT_20 and avgPAA do not correlate well with assists (i.e., to provide some indication of independence from a traditional offensive oriented statistic). We also compare the avgOVA, avgOVT_20, and avgPAA metrics obtained from the first 50% of the games with the same metrics computed across the last 50% of the games we have processed (to examine the stability of those two metrics). We divide games using the unique value assigned to each game (game id) which are typically ordered by scheduled date. Note that because a small number of games were postponed due to COVID-19, the split may not be precisely by the date games were played. In the future we plan to conduct an in depth analysis of all of our metrics (and other existing statistics) using the "Meta-Analytics" framework.

7.1 Comparison with Traditional Statistics

Figure 5a compares assists_82 (normalized to 82 games with 20 minutes per-game) and avgOVT_20 (the sum of the fraction of opponents overtaken by a player's passes normalized to 20 minutes). Advancing the puck and overtaking opponents is a valuable aspect in invasion games like ice hockey [16]. Figure 5a shows there exists many players at both positions who overtake a significant number of opponents with completed passes who do not record a large number of assists. These players with high avgOVT_20 values may not always show up on a game sheet; however, they may be playing important roles on their team.



(a) assists_82 vs. avgOVT_20

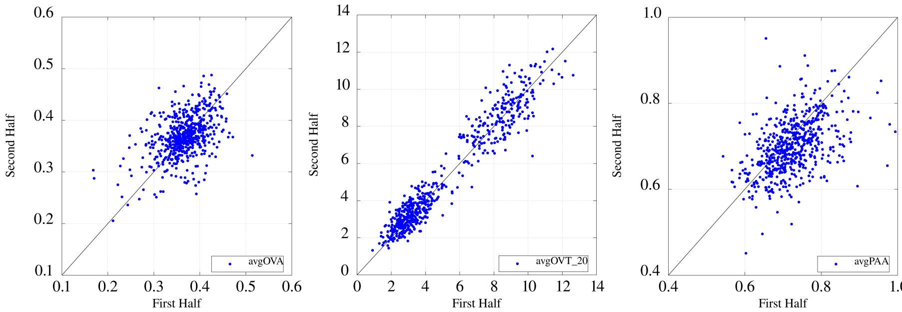
(b) assists_82 vs. avgPAA

Fig. 5: (a) Assists projected to 82 games and 20 minutes per-game (assists_82) versus the total fraction of opponents overtaken by passes (avgOVT_20; per-game average; higher is better). (b) Projected assists (assists_82) versus the average value of γ for completed passes (avgPAA; per-game average; lower means smaller lanes).

Figure 5b compares assists_82 with avgPAA for players' completed passes in a game (avgPAA is the average γ value, or passing lane size; lower indicates smaller lanes). Note that there are no players with both high avgPAA and high assists_82 (i.e., no players in the top right of Figure 5b). However, many players with the highest assists_82 values have relatively low avgPAA (between 0.59 and 0.70). This may suggest a connection between recording many assists and being able to complete passes with smaller lanes. In future work we plan to examine this question more closely by separating, studying and comparing passing lanes for completed passes that result in assists. Again, we believe that considering traditional offensively-oriented statistics for a player could reduce one's ability to see other potentially important skills.

7.2 Evaluating Stability

Figure 6 compares metrics computed over the first 610 games with the same metric computed over the last 611 games. If the metrics obtained for each player during the first half of the games were able to perfectly predict the metric computed over the second half of the games, all data points would fall exactly on the diagonal line. These graphs indicate that the avgOVA and avgPAA metrics are well correlated across the two halves of the season (their correlation coefficients, r, are 0.87 and 0.89, respectively). The avgOVT_20 metric is strongly correlated with $r = 0.99$. For comparison we found (details and graphs have been excluded for brevity) that the correlation coefficient for players' points is $r = 0.80$ and for goals is $r = 0.72$. This indicates that our new metrics are more stable (i.e., future values may be more predictable) than points and goals.



(a) avgOVA (b) avgOVT_20 (c) avgPAA

Fig. 6: Comparing different metrics from the first half of the games with the same metric computed over the second half of the games. Points on the diagonal line are perfectly correlated.

8 Discussion

While we perform an extensive analysis of several metrics and their distributions across players, our work has several limitations. One limitation is that we do not consider different factors such as coaching style (or team systems), manpower (e.g., even strength or not), goal differential, time of the game, and play location that may provide further insights. Future work may consider analyzing these scenarios separately.

Another limitation is the aggregation of metrics while including players with few samples. We filter our dataset by excluding players that don't receive a minimum average amount of ice time per game or have not played a minimum number of games. However, among the unfiltered players, some players recorded relatively few completed passes . Future work could apply additional filters (e.g., filtering players by a minimum number of samples).

Similar to the limitations with previous work [12, 13], we are only able to analyze completed passes. In the future we hope to discern or obtain information about unsuccessful passes. Additionally, our model for overtaking opponents does not consider potentially valuable passes such as those from close to (or behind) the net to the slot area, or east-to-west passes on odd-man-rushes, as overtaking opponents. Future work may adapt our model to include these types of passes.

9 Conclusions

Traditional ice hockey statistics disproportionately capture the offensive perspective of players. Understanding other characteristics of players' behaviors is important for constructing forward lines, defensive pairings, or entire teams. In this paper, we analyze several recently proposed passing metrics using PPT data from 1221 games of the NHL 2021-2022 season. We find that forwards tend to complete passes with slightly smaller passing lanes compared to defensemen; however, defensemen complete more passes and overtake more opponents. Examining players by comparing their scores on the basis of two metrics reveals the diversity of behavior among players with regards to pass overtaking and being overtaken by passes. Finally, because these new metrics do not correlate well with traditional metrics, we believe they capture aspects of players' abilities that may not appear on a traditional game sheet. This analysis may be of significant interest to coaches and managers as they attempt to construct successful teams.

Acknowledgments

We thank Rogers Communications for providing funding for this project. In addition, this research is partially funded by the Natural Sciences and Engineering Research Council of Canada (NSERC), two University of Waterloo Math Undergraduate Research Awards and a University of Waterloo Undergraduate Research Fellowship. We thank the members of the National Hockey League's Information Technology Team and the Stats and Information Team for their participation in fruitful discussions and their insights related to this work. From AWS, we thank Candi Jeronimo for providing us with credits and Varad Ram for technical assistance that enabled us to process the games using AWS. We thank Neel Dayal and Jonah Eisen from Rogers Communications for making this project possible. We thank Robby Brecht for his feedback on an earlier draft of this paper. Finally, we thank the anonymous reviewers for their constructive and helpful feedback.

References

1. Andrejczuk, E., Rodriguez-Aguilar, J.A., Sierra, C.: A concise review on multiagent teams: contributions and research opportunities. Multi-Agent Systems and Agreement Technologies (2016)
2. Andrienko, G., Andrienko, N., Budziak, G., Dykes, J., Fuchs, G., Landesberger, T.V., Weber, H.: Visual analysis of pressure in football. Data Mining and Knowledge Discovery **31**, 1793–1839 (2017)
3. Bransen, L., Van Haaren, J.: Player chemistry: Striving for a perfectly balanced soccer team. arXiv preprint arXiv:2003.01712 (2020)
4. Elitzur, R.: Data analytics effects in major league baseball. Omega **90**, 102001 (2020)

5. Fernández, J., Bornn, L., Cervone, D.: Decomposing the immeasurable sport: A deep learning expected possession value framework for soccer. In: 13th MIT Sloan Sports Analytics Conference (2019)
6. Franks, A., D'Amour, A., Cervone, D., Bornn, L.: Meta-Analytics: Tools for understanding the statistical properties of sports metrics. Journal of Quantitative Analysis in Sports **12**(4), 151–165 (2016)
7. Hong, L., Page, S.E.: Groups of diverse problem solvers can outperform groups of high-ability problem solvers. Proceedings of the National Academy of Sciences **101**(46), 16385–16389 (2004)
8. Ingersoll, K., Malesky, E., Saiegh, S.M.: Heterogeneity and team performance: Evaluating the effect of cultural diversity in the world's top soccer league. Journal of Sports Analytics **3**(2), 67–92 (2017)
9. Lewis, M.: Moneyball: The art of winning an unfair game. WW Norton & Company (2004)
10. Ljung, D., Carlsson, N., Lambrix, P.: Player pairs valuation in ice hockey. In: MLSA@PKDD/ECML (2018)
11. Nsolo, E., Lambrix, P., Carlsson, N.: Player valuation in european football. In: Machine Learning and Data Mining for Sports Analytics: 5th International Workshop, MLSA 2018, Co-located with ECML/PKDD 2018, Dublin, Ireland, September 10, 2018, Proceedings 5. pp. 42–54. Springer (2019)
12. Radke, D.T., Radke, D.L., Brecht, T., Pawelczyk, A.: Passing and pressure metrics in ice hockey. Workshop of AI for Sports Analytics (2021)
13. Radke, D., Brecht, T., Radke, D.: Identifying completed pass types and improving passing lane models. In: Linköping Hockey Analytics Conference. pp. 71–86 (2022)
14. Radke, D., Larson, K., Brecht, T.: Exploring the benefits of teams in multiagent learning. In: IJCAI (2022)
15. Radke, D., Larson, K., Brecht, T.: The importance of credo in multiagent learning. ALA Workshop at AAMAS (2022)
16. Radke, D., Orchard, A.: Presenting multiagent challenges in team sports analytics. In: AAMAS (2023)
17. Ritchie, R., Harell, A., Shreeves, P.: Pass evaluation in women's olympic ice hockey. In: Proceedings of the 5th International ACM Workshop on Multimedia Content Analysis in Sports. pp. 65–73 (2022)
18. SMT: SportsMEDIA technology. `https://www.smt.com` (2021), accessed: 2023-03-19
19. Spearman, W.: Beyond expected goals. In: Proceedings of the 12th MIT sloan sports analytics conference. pp. 1–17 (2018)
20. Spearman, W., Basye, A., Dick, G., Hotovy, R., Pop, P.: Physics-based modeling of pass probabilities in soccer. In: Proceeding of the 11th MIT Sloan Sports Analytics Conference (2017)
21. Steiner, S., Rauh, S., Rumo, M., Sonderegger, K., Seiler, R.: Outplaying opponents—a differential perspective on passes using position data. German Journal of Exercise and Sport Research **49**, 140–149 (2019)
22. West, R.M.: Best practice in statistics: Use the welch t-test when testing the difference between two groups. Annals of Clinical Biochemistry **58**(4), 267–269 (2021)
23. Zaccaro, S.J., Dubrow, S., Torres, E.M., Campbell, L.N.: Multiteam systems: An integrated review and comparison of different forms. Annual Review of Organizational Psychology and Organizational Behavior **7**(1), 479–503 (2020)

Simple and Practical Goal Importance Metrics for Ice Hockey

Rasmus Säfvenberg, Niklas Carlsson, and Patrick Lambrix

Linköping University, Sweden
firstname.lastname@liu.se

Abstract. To capture that not all goals are of the same importance, a new performance metric called the Game Points Importance Value (GPIV) was recently proposed. While this metric takes into account the expected impact that a goal has on the outcome of a game based on the context when the goal was scored, it relies on a relatively fine-grained state space. To address this problem, this paper presents simplified and more practical variations of the GPIV metric. Motivated by our analysis of the relative importance of different dimensions of the state space, we present two metrics that capture the most important component(s) of GPIV. Our evaluation shows that the metrics are relatively stable and capture most of the relative differences between GPIV and traditional metrics (e.g., goals, assist, points, and +/-). These results suggest that these simple and practical metrics are intuitive, capture most of the desirable variations that GPIV captures, and that the value of a goal can be well estimated using GPIV data based on historic data.

1 Introduction

In ice hockey, not all goals are of equal importance or have the same impact on the outcome of a game. For example, a game-tying goal in the final minute of regulation has a greater impact on the game outcome than a goal scored while leading by seven goals, as in the latter case the outcome is all but decided. In recent work [7, 8], we proposed a metric to quantify the importance of a goal on the game outcome in the National Hockey League (NHL). This metric, referred to as Game Points Importance Value (GPIV), accounts for the current goal difference (GD), manpower difference (MD), and the time of the game when the goal was scored. For each such (goal) state, we then compute a GPIV value, quantifying the goal importance, as the estimated change in the weighted probabilities (before vs. after the goal) for winning, losing in overtime, and losing in regulation. As an example, a game-tying goal in the final minute of regulation will increase the probability of winning and losing in overtime while simultaneously reducing the probability of losing. Such goal will therefore obtain a relatively large GPIV. In contrast, a goal scored when leading by a large margin will have negligible impact on the expected outcome, resulting in a small GPIV.

One downside of GPIV and other complex metrics is that they rely on a relatively fine-grained state space. To address this problem, this paper presents and evaluates two simplified and more easy-to-use variations of the GPIV metric. To derive and motivate these metrics, we make use of a decision tree and estimates of the variations that each of the state parameters are responsible for when using the original GPIV metric, and then define approximate metrics based on the insights provided. The resulting approximations capture the most important component(s) of GPIV and provide practitioners with an easy and straightforward application of the metric to real-time situations.

Like the pure GPIV metric, instead of attributing each goal an equal value, the approximations assign each goal a value based on the current state. However, by using a much smaller set of states, the approximations provide a more intuitive description of which goals have the highest importance within a game. These simplified valuations of player performance can therefore provide fans, teams, and media with an easy-to-apply metric for evaluating and comparing players that account for goal importance. Our evaluation of the approximations also shows that the metrics are relatively stable, allowing past seasons (or past games played) to be used to estimate and apply the metrics on current and future games. As desired, the metrics also have stronger correlations with GPIV than with the corresponding traditional metrics, and the relative player ranking variations (compared to traditional metrics) capture most of the explainable variations that have been observed using GPIV. These results suggest that these simple metrics are practical, intuitive, and capture most of the desirable goal importance variations captured by GPIV.

Throughout the remainder of this paper, data from the 2013-2014 NHL regular season is used to illustrate the approach.

2 Two simplified GPIV metrics

The original GPIV metric is based on each goal being its own state, where a state is represented by a time (in seconds), GD, and MD. However, not all these components are of equal importance for the computation of the GPIV value.

To evaluate the importance of each variable (i.e., time, GD, and MD), a decision tree was fitted with GPIV as the outcome and time, GD, and MD as variables. These results are shown in Figure 1. From this decision tree, we observe that GD is the variable with the most splits, followed by time, while MD had no splits. This relative ranking is also echoed by the variable importance (summarized in the same figure): GD (216.177) being the most important variable, time (76.586) being the second most important variable, and MD (0.398) being the least important variable. The variable importance is computed by summing the contribution of each variable (either as a primary or surrogate splitter) with a higher value corresponding to a higher contribution.

Looking closer at the decision tree, we also note that the least important goals were scored while already in the lead (GD ≥ 1) within the first two periods, while the most important goals were goals in the final five minutes of regulation while trailing by one goal.

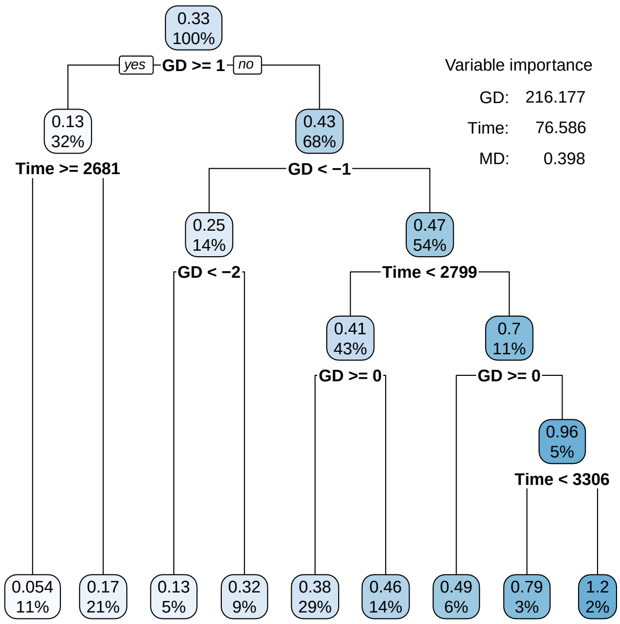


Fig. 1: Decision tree with GPIV as the outcome and GD, MD, and time as variables. Darker colors represent higher GPIV values, with the percentage describing the number of goals in each node.

These findings suggest that simplified metrics can be created by grouping some subsets of GD cases and time cases into a smaller set of categories, and that MD can be ignored as its importance is far smaller than the other factors.

First, for the GD dimension, we identified the following primary classes: reducing the deficit (GD ≤ -2), tying the game (GD $= -1$), taking the lead (GD $= 0$), and extending the lead (GD ≥ 1). For completeness, we also include the special case of an overtime (OT) winning goal, which exclusively occurs in overtime. Table 1 summarizes the average GPIV scores for each of these goal types (i.e., when considering GD only). Here, we note that the relatively big differences in the average GPIV of tying the game (0.594) and extending the lead (0.125), highlighting the value of such differentiating metric.

Second, for the time dimension, we selected to group goals according to the period a goal was scored but always considered them in combination with the above GD categories. The average GPIV values for each of these combined categories are shown in Table 2.

Based on the above categorizations, we can then define the two simplified GPIV metrics: *GD only* and *GD+Period*. For our notation, we let $\text{GPIV}^*_{\text{GD only}}$ be the approximated GPIV using GD only, and $\text{GPIV}^*_{\text{GD+Period}}$ be the approximated GPIV using both GD and period. In both cases, we simply assign each goal in a category the average GPIV value of all goals of that type. In the case

Table 1: Average GPIV per goal type when considering GD only.

Situation	Average GPIV	Goals
Reducing the deficit	0.249	887
Tying the game	0.594	1,263
Taking the lead	0.396	2,184
Extending the lead	0.125	2,102
OT winner	0.500	129

Table 2: Average GPIV per goal type when considering both GD and period. An OT winner has an average GPIV of 0.5.

	First period		**Second period**		**Third period**	
Situation	Average GPIV	Goals	Average GPIV	Goals	Average GPIV	Goals
Reducing the deficit	0.241	83	0.294	368	0.212	436
Tying the game	0.424	317	0.451	493	0.868	453
Taking the lead	0.370	1099	0.392	646	0.465	439
Extending the lead	0.180	397	0.162	789	0.070	916

that such GPIV values are based on prior games or seasons, these approximate GPIV values can therefore quickly be calculated at the time that a goal is scored.

When only considering GD, we note that tying the game is the most important goal, followed by OT winner, taking the lead, and reducing the deficit. Extending the lead is the least valuable goal. Similar conclusions can be drawn when also considering the period of the goal, although goals that tie the game or take the lead have an increased value as the game progresses. On the contrary, goals that reduce the deficit are most important in the second period while goals that extend the lead are most important in the first period, with the least important goals occurring in the third period for both situations. Another observation is that both simplifications lead to all goals having a positive value, which need not be the case in the full GPIV implementation [7, 8].

3 Stability of metrics

For previous estimations of the weights given to each goal to be useful, the metric should not change too drastically. Figures 2 and 3 visualize how the GPIV weights vary over time (on a season-per-season basis) for the approximate GPIV metrics based on GD only and GPIV based on GD+Period, respectively. When only considering GD, the GPIV weights exhibit low variability with stable weights over time. We also observe a strict order of the relative importance of the type of goals (matching the importance order from Table 1): goals that tie the game are the most important, followed by goals taking the lead, goals reducing the deficit, and goals extending the lead.

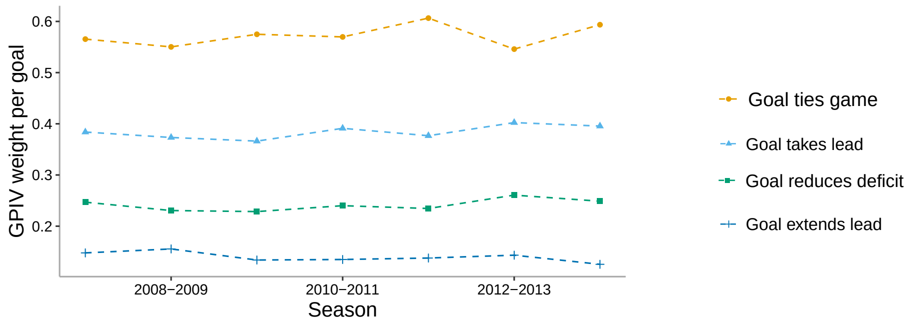


Fig. 2: GPIV weights by season when considering GD only.

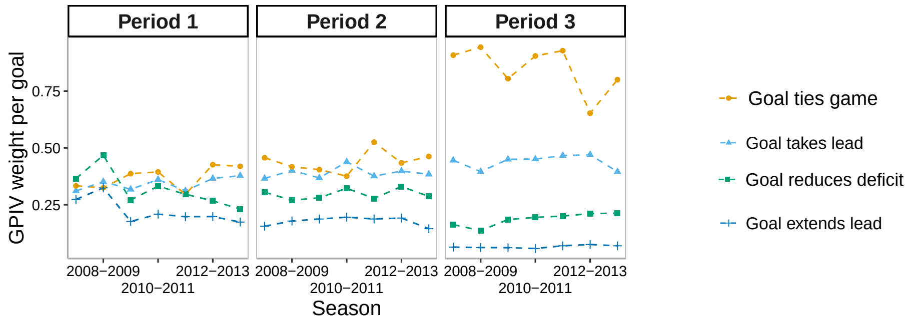


Fig. 3: GPIV weights by season when considering GD+Period.

If we also account for the period in which the goal occurs additional insights can be found. In general, regardless of the period, the least important goals are the goals that extend the lead, where the importance decreases with time. Although goals that reduce the deficit are the third most important goal in both the second and third periods as well as most seasons, they had the highest importance in the first period in both the 2007-2008 and 2008-2009 seasons. The importance of these goals also decreases in the third period. Another overall trend present is that goals taking the lead are the second most important goal type, with a mainly stable weight across all periods. The most important goals are found when tying the game in the third period, with the importance of a game-tying goal increasing as the game progresses.

4 Evaluation

Ideally, we would like the approximate metrics to capture most of the performance variations observed with GPIV. To determine if the metrics behave in a similar way as GPIV, we performed correlations comparisons and a rank-based analysis in which we compare with both GPIV and the corresponding traditional metrics. Some of these results are presented next.

Table 3: Spearman correlation between GPIV, simplified GPIV, and traditional metrics. Blank cells indicate a correlation between the same metric.

			Simplified GPIV metrics	
Class	Prior metric	Full GPIV	GD only	GD+Period
Goals	Traditional	0.971	0.979	0.975
Goals	Full GPIV		0.989	0.993
Assists	Traditional	0.979	0.986	0.983
Assists	Full GPIV		0.993	0.996
Points	Traditional	0.988	0.992	0.990
Points	Full GPIV		0.996	0.998
+/-	Traditional	0.775	0.843	0.802
+/-	Full GPIV		0.924	0.962

4.1 Correlation comparisons

As a point of comparison, we compute the Spearman rank correlation between the GPIV-based and the traditional metrics of goals, assists, points, and +/-. The correlations can be found in Table 3. Here, the class indicate what type of action the metric is calculated (i.e., the goals scored by a player, the assists made by the player, the sum of the first two, and whether a player was on the ice or not when a goal was scored during even strength). For each class we then present the correlation between the traditional metrics of that class and the three corresponding GPIV metrics (first row of each class), as well as between the full GPIV metric and the two approximations (second row of each class). As an example, we compute the correlations between Traditional Goals and Full GPIV by considering the total seasonal values for all players (Goals and GPIV-G).

First and most importantly, we note that the correlations between the full GPIV and the simplified GPIV metrics (second row for each class) are higher than the correlation with the traditional metrics (first rows). This suggests that the simplified metrics capture the most important variations of the full GPIV.

The table also highlights that GPIV has the lowest correlation of the considered methods, with both approximate methods having a higher correlation for all metrics. In particular, the simplified GPIV based on GD only was observed to have the highest correlation of all methods. This can be explained by GPIV considering a larger number of possible states, where some goals receive little to no value, which in turn lowers the correlation as the contrast between a goal of value one and close to zero is far larger than the approximate methods where the lowest value is 0.125 (simplified GPIV based on GD only) and 0.07 (simplified GPIV based on GD+Period).

Similarly, Figure 4 depicts the correlation for each pair of metrics across the analyzed seasons. We observe that goals, assists, and points all exhibit similar patterns over time, while +/- differs from the rest, particularly in the 2012-2013

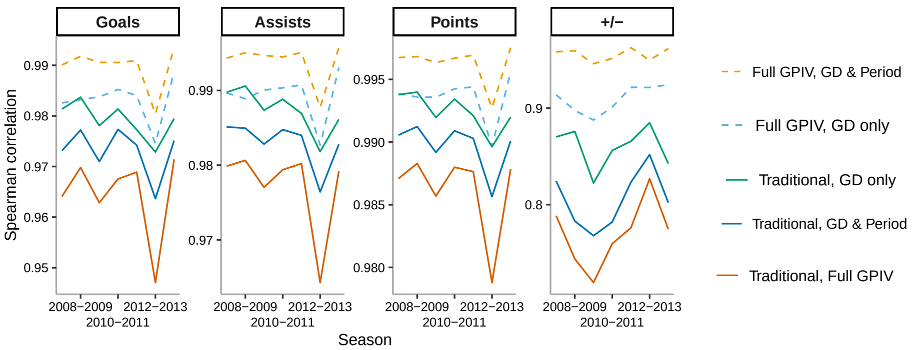


Fig. 4: Spearman correlation for each pair of metrics by season.

Table 4: Top-10 players for GPIV-P for the 2013-2014 season. Change is the difference in rankings for traditional and GPIV.

Rank							
P	GPIV-P	Change	Player	Position	P	GPIV-P	GPIV-P/P
1	1	0	Sidney Crosby	C	104	36.360	0.351
8-11	2	6	Alex Ovechkin	R	79	30.415	0.385
8-11	3	5	Nicklas Bäckström	C	79	29.199	0.370
19-22	4	15	Blake Wheeler	R	69	29.114	0.422
8-11	5	3	Joe Pavelski	C	79	27.995	0.354
4	6	-2	Tyler Seguin	C	84	27.614	0.329
3	7	-4	Claude Giroux	C	86	27.440	0.319
19-22	8	11	Kyle Okposo	R	69	26.951	0.391
16-18	9	7	Anze Kopitar	C	70	26.327	0.376
6-7	10	-4	Phil Kessel	R	80	26.225	0.328

season, which can be attributed to the lockout. Moreover, the correlations for +/- have a larger range, between 0.72 and 0.96, while goals, assists, and points all have values between 0.94 and 0.99. As desired, the strongest correlation was consistently observed between the full GPIV metric and its approximations. Among the five pairs, the correlation between the traditional and full GPIV metrics was the lowest, although the correlation is still high.

4.2 Player rankings

GPIV can also be used in the context of player valuation. In this section, we provide the top-ten rankings for GPIV points (P) for each of the three methods for comparison. The top-ten players according to the GPIV method can be found in Table 4, while Tables 5 and 6 contain the results for the simplified GPIV based on GD only and (simplified GPIV based on GD+Period), respectively. Overall, eight players are present in all three tables: Sidney Crosby, Alex Ovechkin, Nick-

Table 5: Top-10 players for simplified GPIV*-P based on GD only for the 2013-2014 season. Change is the difference in rankings for traditional and GPIV*.

Rank								
P	GPIV*-P	GPIV-P	Change	Player	Position	P	GPIV*-P	GPIV*-P/P
1	1	1	0	Sidney Crosby	C	104	36.520	0.351
8-11	2	5	6	Joe Pavelski	C	79	28.546	0.361
19-22	3	4	16	Blake Wheeler	R	69	28.514	0.413
8-11	4	2	4	Alex Ovechkin	R	79	27.742	0.351
2	5	11	-3	Ryan Getzlaf	C	87	27.406	0.315
4	6	6	-2	Tyler Seguin	C	84	27.300	0.325
8-11	7	3	1	Nicklas Bäckström	C	79	27.254	0.345
6-7	8	10	-2	Phil Kessel	R	80	27.185	0.340
3	9	7	-6	Claude Giroux	C	86	26.643	0.310
6-7	10	13	-4	Taylor Hall	L	80	26.399	0.330

Table 6: Top-10 players for simplified GPIV*-P based on GD+Period for the 2013-2014 season. Change is the difference in rankings for traditional and GPIV*.

Rank								
P	GPIV*-P	GPIV-P	Change	Player	Position	P	GPIV*-P	GPIV*-P/P
1	1	1	0	Sidney Crosby	C	104	36.485	0.351
8-11	2	2	6	Alex Ovechkin	R	79	28.877	0.366
8-11	3	5	5	Joe Pavelski	C	79	28.129	0.356
19-22	4	4	15	Blake Wheeler	R	69	28.072	0.407
8-11	5	3	3	Nicklas Bäckström	C	79	27.985	0.354
6-7	6	10	0	Phil Kessel	R	80	26.787	0.335
4	7	6	-3	Tyler Seguin	C	84	26.751	0.318
13	8	12	5	Joe Thornton	C	76	26.749	0.352
3	9	7	-6	Claude Giroux	C	86	26.687	0.310
2	10	11	-8	Ryan Getzlaf	C	87	26.264	0.302

las Bäckström, Blake Wheeler, Joe Pavelski, Tyler Seguin, Claude Giroux, and Phil Kessel. Although the rankings of players differ between the tables, Sidney Crosby remains atop all three tables with similar GPIV values. A possible explanation is the large difference in points between him and the lower-ranked players. If we consider the simplified GPIV based on GD only, simplified GPIV based on GD+Period, and GPIV in order of complexity, we can also see that both Alex Ovechkin and Nicklas Bäckström gain ranks with increased GPIV complexity. Their ascent is likely a result of the number of goals scored in close games, losing by one or tied, at the end of the game or in overtime with Ovechkin as the likely goalscorer and Bäckström with the assist. Similarly, Blake Wheeler also gains ranks in all cases while also having the highest average importance per point. On the contrary, Ryan Getzlaf, who ranked second in total points, loses ranks as he is ranked fifth for the simplified GPIV based on GD only, tenth for the GD

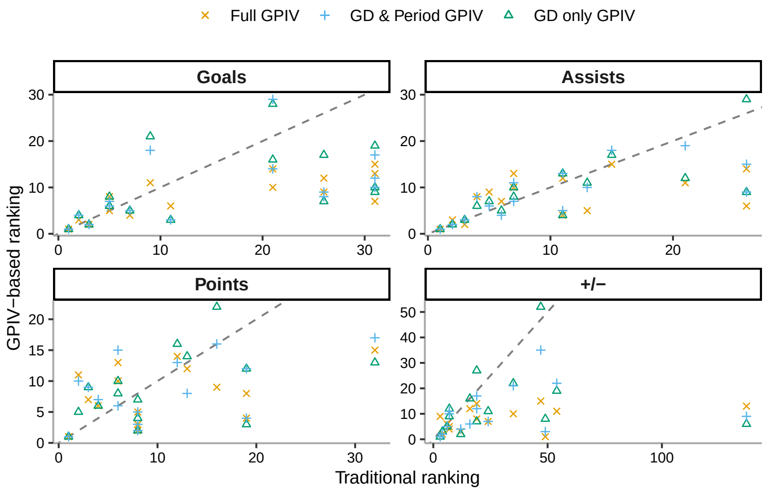


Fig. 5: Top-15 ranked players per full GPIV metric. Note that some players share the same rank on the x-axis.

and Period simplification, and eleventh for the full GPIV. These observations are consistent with the correlation results.

To investigate the impact that each GPIV-based method has on play ranking, Figure 5 shows ranking using each GPIV-based metric (y-axis) vs. the traditional ranking (x-axis) for the top-15 ranked players using the full GPIV metric. For both GPIV-Goals and GPIV-Assists it appears that the top-ranked players are mainly unaffected by the different methods as their ranks remain stable. The variability in ranking becomes more prevalent for somewhat lower traditional rankings, as the highest climbing players may have higher variability in ranking across the GPIV-based methods. As an example, Anze Kopitar was ranked 28th and 29th when considering the GPIV-based approximations based on GD only and GD+Period, respectively, but for the full GPIV he was ranked 14th. For GPIV-Points some players also manage to maintain a stable rank, for instance, the top-ranked player Sidney Crosby. The GPIV-based ranking for points also had the lowest range, between 1 and 22. On the contrary, +/- had the highest range, between 1 and 52, while also having the largest spread for traditional ranking with Matt Duchene climbing from 137th in the traditional +/- to top 15 in GPIV-+/-. The variability of rankings for the GPIV-based +/- metrics is also the highest, as some players have a larger discrepancy between their rankings of the different methods. For instance, Sidney Crosby had rankings of 15th (full GPIV), 35th (GPIV based on GD+Period), and 52nd (GD only).

Another way to illustrate the difference in ranking between the traditional ranking and the GPIV ranking can be found in Figure 6, where the top-15 players, for each full GPIV metric, are visualized. Here we note that the largest rank increases are found for +/-, with Matt Duchene gaining over 100 ranks

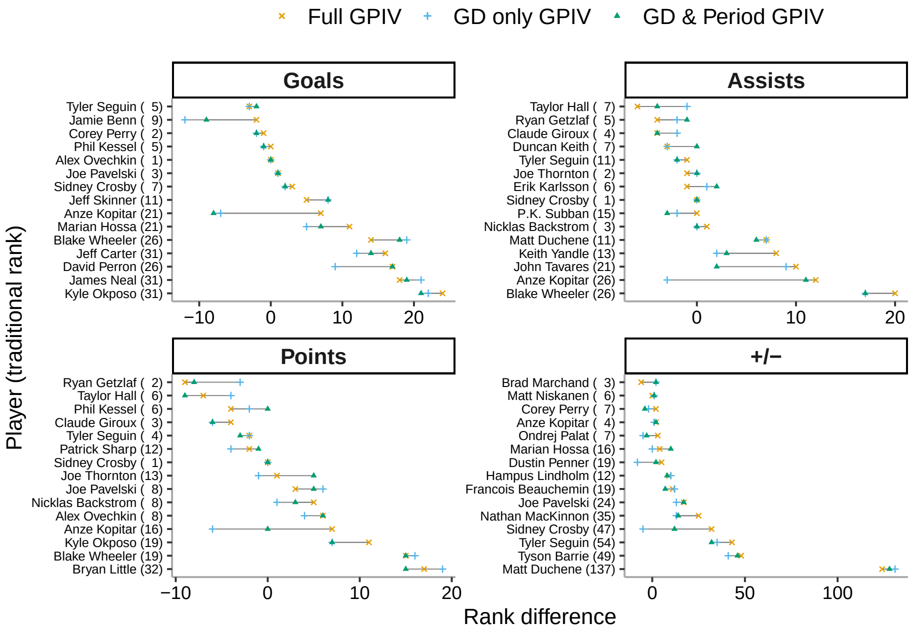


Fig. 6: Rank difference between the traditional and GPIV-based ranking for the top-15 per full GPIV metric.

while e.g., Tyler Seguin and Tyson Barrie also gain approximately 50 ranks. Another thing to note is that for GPIV-+/-, few players lose ranks compared to the traditional +/-. As for goals, assists, and points, players losing ranks is more prevalent. For GPIV-Goals we also observe that the different GPIV-based methods result in mostly similar rankings, although Jamie Benn and Anze Kopitar have a larger difference between the full GPIV and the approximations. In addition, for the simplified GPIV-based methods, Anze Kopitar loses ranks for GPIV-Goals while he gains ranks for the full GPIV. The same results can also be seen for Anze Kopitar in GPIV-Assists and GPIV-Points. In general, GPIV-Assists and GPIV-Points also have a higher difference in rankings when comparing the GPIV methods than goals. We also note some of the big climbers, e.g. Bryan Little (Points) and Blake Wheeler (Assists and Points), while players who lose ranks, e.g., Ryan Getzlaf (Assists and Points) and Taylor Hall (Assists and Points), also have variability between the different GPIV-based methods, with the full GPIV tending to assign them the lowest ranking.

5 Related work

The most used performance metrics in ice hockey are the total number of goals, assist, and points accumulated over a season or some other time period or set of games. Like these metrics, the GPIV metric and the GPIV-based approximations presented here are calculated as the sum of all goals. The main difference is in the weight given to each goal and that these traditional metrics do not account for the potential impact a goal may have on the game outcome.

Some extensions to these traditional metrics have been proposed (e.g., for the +/- metric [11, 4]) and combined metrics have been proposed (e.g., based on principal component analysis [5]). Others have proposed player performance metrics take game context into account (e.g., the probability that an event leads to a goal in the subsequent 20 seconds [15]) or that incorporate the game models using Markov games where two opposing sides (i.e., the home team and the away team) try to reach states in which they are rewarded (e.g., scoring a goal) [18, 6, 13, 16, 17, 9, 14, 10]. One critique of these more advanced metrics is that they are not easily understandable by or explainable to practitioners such as coaches, players, and GMs. In this work, we aim to present such simpler and more practical metrics that still differentiate between the potential impact that a goal may have on the game outcome.

Prior works have also considered the importance of scoring the first goal [1], a two-goal lead [2], and late-game reversals [3]. For example, it was found that teams that take a two-goal lead win in 83% of games, while having the lead after two periods leads to a win in 84% and 80% of games for the home and away team, respectively.

Except our prior work defining the original GPIV metric, the only other work that considers the importance of goals is the added goal value (AGV) metric presented by Pettigrew [12]. The importance of a goal is based on GD and time and is defined using win probabilities for that context and neighboring contexts (with GD one higher and one lower). The AGV is then defined for a player by comparing the importance of the player's goals to the importance of all other players' goals.

Some players can have a positive (or negative) impact even when they are not the player scoring the goal or assisting to the goal. Perhaps the most used metric to estimate the value a player brings to team performance (during 5-on-5 play) is the +/- metric. While the metric has been criticized due to its disregard of contextual information [18], alternative approaches typically also ignore the importance of individual goals. Interesting examples falling in this category include works based on hazards models [18], regularized logistic regression for predicting player impact on scoring [4], or models that sum over all actions performed by a player [13] or set of players [10] when on the ice at the same time.

6 Conclusions

This paper has presented two approximate GPIV metrics: GD only and GD+Period. The design of the metrics was motivated by our analysis of the relative importance of different dimensions of the state space, and our evaluation demonstrated that the metrics are relatively stable and capture most of the relative differences between GPIV and traditional metrics (e.g., goals, assist, points, and +/-). The presented metrics are practical, intuitive, capture most of the desirable variations that GPIV captures, and show that the value of a goal can be well-estimated using GPIV data based on historic data. These properties should make it desirable for fans, teams, and media that want an easy-to-apply metric for evaluating and comparing players that account for goal importance.

References

1. Brimberg, J., Hurley, W.: A note on the importance of the first goal in a National Hockey League game. International Journal of Operational Research **6**(2), 282–287 (2009)
2. Brimberg, J., Hurley, W.: Do professional hockey teams with a two-goal lead lose more often than they should? International Journal of Operational Research **15**(2), 226–233 (2012)
3. Gill, P.S.: Late-game reversals in professional basketball, football, and hockey. The American Statistician **54**(2), 94–99 (2000)
4. Gramacy, R.B., Jensen, S.T., Taddy, M.: Estimating player contribution in hockey with regularized logistic regression. Journal of Quantitative Analysis in Sports **9**(1), 97–111 (2013)
5. Gu, W., Foster, K., Shang, J., Wei, L.: A game-predicting expert system using big data and machine learning. Expert Systems with Applications **130**, 293–305 (2019)
6. Kaplan, E.H., Mongeon, K., Ryan, J.T.: A Markov Model for Hockey: Manpower Differential and Win Probability Added. INFOR Information Systems and Operational Research **52**(2), 39–50 (2014)
7. Lambrix, P., Carlsson, N.: Performance metrics for ice hockey accounting for goal importance. In: Linköping Hockey Analytics Conference. pp. 11–25 (2022)
8. Lambrix, P., Carlsson, N., Säfvenberg, R.: Goal-based performance metrics for ice hockey accounting for goal importance (2023), submitted
9. Liu, G., Schulte, O.: Deep reinforcement learning in ice hockey for context-aware player evaluation. In: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence. pp. 3442–3448 (2018)
10. Ljung, D., Carlsson, N., Lambrix, P.: Player pairs valuation in ice hockey. In: Machine Learning and Data Mining for Sports Analytics. MLSA 2018. pp. 82–92 (2019)
11. Macdonald, B.: A Regression-Based Adjusted Plus-Minus Statistic for NHL Players. Journal of Quantitative Analysis in Sports **7**(3) (2011)
12. Pettigrew, S.: Assessing the offensive productivity of NHL players using in-game win probabilities. In: MIT Sloan Sports Analytics Conference (2015)
13. Routley, K., Schulte, O.: A Markov Game Model for Valuing Player Actions in Ice Hockey. In: Uncertainty in Artificial Intelligence. pp. 782–791 (2015)
14. Sans Fuentes, C., Carlsson, N., Lambrix, P.: Player impact measures for scoring in ice hockey. In: MathSport International 2019 Conference. pp. 307–317 (2019)
15. Schuckers, M., Curro, J.: Total Hockey Rating (THoR): A comprehensive statistical rating of National Hockey League forwards and defensemen based upon all on-ice events. In: MIT Sloan Sports Analytics Conference (2013)
16. Schulte, O., Khademi, M., Gholami, S., Zhao, Z., Javan, M., Desaulniers, P.: A Markov Game model for valuing actions, locations, and team performance in ice hockey. Data Mining and Knowledge Discovery **31**(6), 1735–1757 (2017)

17. Schulte, O., Zhao, Z., Javan, M., Desaulniers, P.: Apples-to-apples: Clustering and Ranking NHL Players Using Location Information and Scoring Impact. In: MIT Sloan Sports Analytics Conference (2017)
18. Thomas, A., Ventura, S.L., Jensen, S., Ma, S.: Competing Process Hazard Function Models for Player Ratings in Ice Hockey. The Annals of Applied Statistics **7**(3), 1497–1524 (2013)

The Importance of Special Teams in Ice Hockey

Rasmus Säfvenberg[1], Mikael Svarén[2], Niklas Carlsson[1], and Patrick Lambrix[1]

[1] Linköping University, Sweden
[2] Dalarna University, Sweden

Abstract. This paper explores the significance of special teams, particularly powerplay, in ice hockey. Despite the commonly held perception of their importance, little research has examined the impact of powerplay and penalty kill performance on overall team success. The paper uses several seasons of NHL data to characterize goal-scoring and manpower opportunities, and perform analysis from several perspectives. The results indicate that individual even strength goals and powerplay goals have similar value, but the larger share of even strength goals scored over a season makes even strength play a more important contributor to team success. The paper also finds a high correlation between teams that perform above/below average during even strength and powerplay. This study provides insights into the dynamics of ice hockey gameplay and the role of special teams in determining team success.

1 Introduction

Like most games, ice hockey is played according to a set of rules, and if a player violates a rule during the game, the team responsible for the violation is given a penalty. Furthermore, the player who committed the violation is then sent to the penalty box, and as a result, the opposing team is typically given a temporary manpower advantage to play against the penalized team.

A penalty in ice hockey can significantly alter the game's dynamic by disrupting the offensive and defensive strategies of both teams. The non-penalized team gains a numerical manpower advantage, which typically leads to increased possession of the puck closer to the opposing team's net, providing them with a boost in offensive capabilities [9]. On the other hand, the penalized team is often forced to play more defensively to prevent the non-penalized team from scoring while the player is in the penalty box.

Whenever a penalty occurs in ice hockey, both teams field their "special teams"; i.e. their powerplay unit or their penalty killers. The team who receives a numerical advantage from the penalty goes on the powerplay and typically play their strongest offensive players in an attempt to maximize their scoring chances, while the penalized team play their best defensive players in an attempt to prevent the other team from scoring during the penalty [1].

Due to the increased scoring opportunities that come with powerplay opportunities, both teams and fans often put great weight on the powerplay. However, the perceived importance must also be put in perspective of the full game and the impact that powerplay goals have on the outcome of the games. Here, it should be noted that NHL games (studied here) span 60 minutes and there is no guarantee that a given team will be on the powerplay. Instead, the vast majority of the game is played in even strength.

Although commonly perceived to be a vital part of team success, the importance of special teams, in particular powerplay, has not been extensively studied. Research by [10] has reported that gaining a powerplay opportunity can drastically increase the conditional probability of scoring a goal. Similarly, a higher goal scoring probability while having a numerical advantage was described in [6]. Another area that has not been thoroughly explored is the relationship between team success in special teams and overall team success, in particular, the exact dynamics of how performance in powerplay and penalty kill influence even strength performance and vice versa.

This paper studies and quantifies the importance of special teams in ice hockey from several perspectives, considers its contribution to team success, and compares the importance to the importance of even strength team success. After describing our dataset (Section 2) and characterizing the goal scoring and manpower opportunities in a typical game (Section 3), we perform our analysis from several perspectives. In particular, we use the recent GPIV metric to analyze the importance of individuals goals (Section 4), use correlations (Section 5) and model-based evaluations (Section 6) to consider how much powerplay goals contribute to the outcome of individual games, and finally we study correlations between team success on a per season basis and perform above/below average at even strength and on the powerplay (Section 7).

Our results show that individual even strength goals and powerplay goals have similar value (when scored at similar times of the game and when the goal differential is the same), but that the larger share of even strength goals (compared to powerplay goals) scored over a season makes even strength play a more important contributor to team success. However, it should also be noted that we have found high correlation between teams that are above/below average during even strength and during powerplay, suggesting that in many cases the teams that have above/below average players for even strength also have above/below average players for powerplay.

2 Dataset

This paper uses data from `https://www.NHL.com` and their public API. We use the information regarding penalty and goal statistics. More specifically, the duration of various manpower situations and whether one or more goals were scored during these situations. The seasons included in the data are the regular seasons from 2010-2011 to 2021-2022 where overtime periods were excluded. Here, we note that the 2012-2013 season consisted of only 48 games due to a lock-out, while the 2019-2020 and 2020-2021 seasons were shortened due to COVID-19.

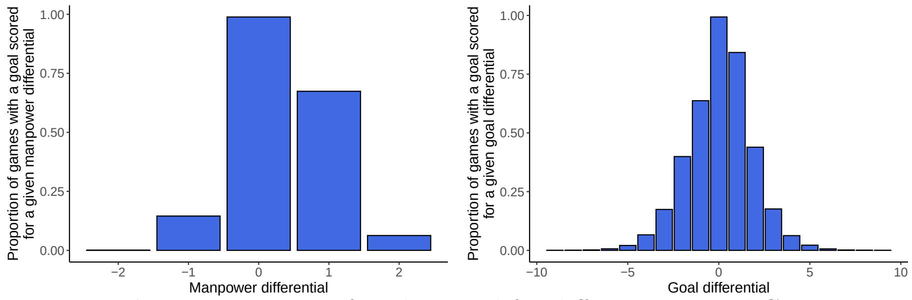


Fig. 1: Frequency of goals scored for different MD and GD.

3 Goal scoring and manpower opportunities

3.1 Goal scoring

While almost all games include even strength goals, less than 75% of games include at least one powerplay goal. This is illustrated in Figure 1, where we show the proportion of games with at least one goal scored with different manpower differentials (MD) from the scoring team's point of view. For completeness, we also include the same statistics for the goal differential (GD) i.e., the goals scored by the scoring team minus the goals scored by the other team. We note that in 99% of cases, a goal is scored for GD = 0 in games with a goal scored in regulation and/or overtime, while a similar value can also be observed for MD = 0. For GD, there is also a slightly higher prevalence for scoring when leading by one goal, compared to trailing by one. Empty net goals may be a factor here. Otherwise, there is a balance between goal scoring in the case of a positive and negative GD of the same absolute quantity. When considering MD, we note that many games have goals scored while having a numerical advantage, particularly when playing 5v4 or 4v3. It is also noteworthy that scoring goals in 5v3 (i.e., MD = 2) is less common than scoring while shorthanded (e.g., MD = -1).

3.2 Frequency of manpower scenarios

Figure 2 shows the proportion of each manpower scenario, and how it has changed over time. We note that most of the game is played in 5v5 (approx. 75% to 80% of the total game time), while either team having a one-man advantage occurs between 15% to 19% of the game. Moreover, around 1-2% of the total time is played 4v4, with the remaining time distributed for a two-man advantage and 3v3. We note a slight increase in the fraction of time spent in 5v5 from 2010-2011 to 2021-2022.

3.3 Powerplay scoring in different manpower scenarios

Naturally, the more opportunities a team obtains on the powerplay, the greater chance there is that a team scores at least one powerplay goal. Here, we quantify

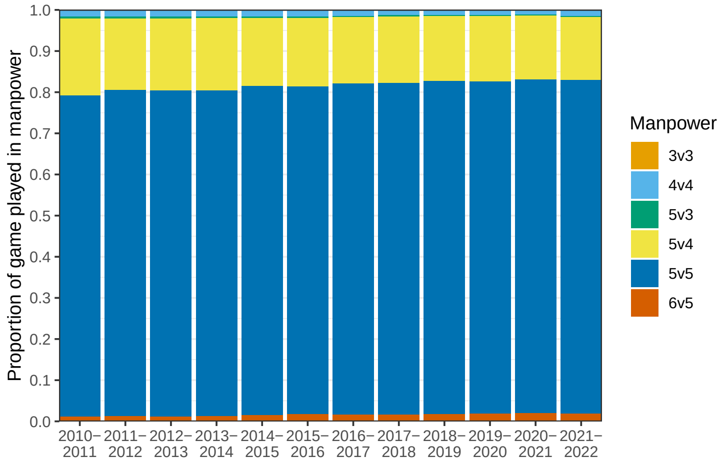


Fig. 2: Proportion of each manpower situation over time.

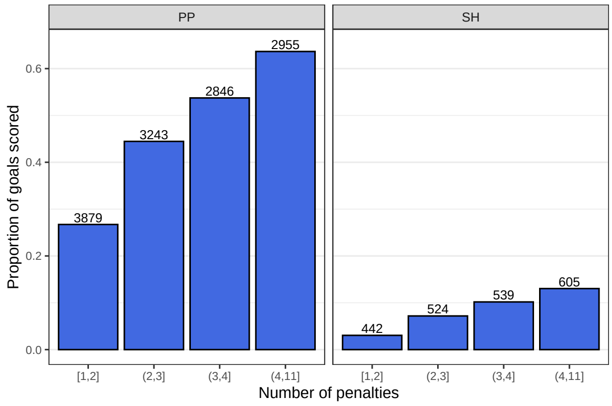


Fig. 3: Proportion of goals scored by number of penalties. The number on the bar shows the total number of goals.

the fraction of a game when a team scored at least one powerplay (or shorthanded) goal as a function of the number of powerplay (or shorthanded) opportunities they obtain in a game. These results are shown in Figure 3. For completeness, we include the number of games associated with each case. We note that the fraction of games that at least one powerplay goal was scored goes up from 25% when only having one or two powerplay opportunities during a game to approximately 44% when having three penalty opportunities, 54% when four penalties, and 64% when five or more penalties.

3.4 Goal scoring during double-minors and major penalties

Although the two-minute minor penalty is the most common type of penalty, double-minors and majors (including match penalties) may still occur and affect the state of the game. A double-minor (2+2 minutes) lasts four minutes at most,

Table 1: Long penalties scoring rate.

	Double-minor		Major	
Goals scored	Occurrences	Proportion	Occurrences	Proportion
0	790	0.688	383	0.670
1	307	0.267	142	0.248
2	51	0.044	37	0.065
3 or 4			9+1	0.018

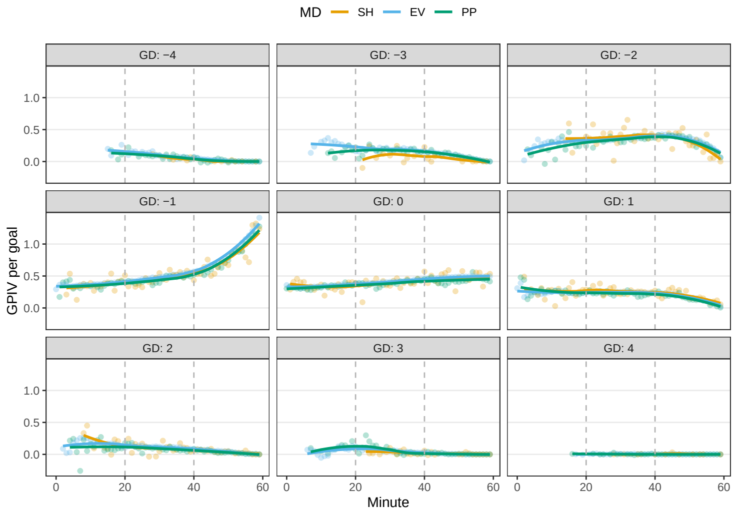


Fig. 4: GPIV per goal and minute.

although a goal will remove up to two minutes of penalty time and two goals will nullify it completely. In contrast, there is no upper limit for how many goals can be scored during a major penalty. A major penalty lasts five minutes and is not ended if a goal is scored. For the investigated seasons, there was a total of 1,148 double-minors and 572 majors that caused a manpower change. Coincidental penalties that cancel each other out are not included in this count. This way we exclude the case when two players from opposing teams draw a major penalty each for fighting. The observed outcomes and scoring rates for double-minors and majors can be found in Table 1. We note that 68.8% and 67% of double-minors and major penalties, respectively, end without a goal being scored. However, a few double-minors have two goals (4.4% of cases). Similarly, of the major penalties, only 8.2% result in two or more goals being scored.

4 The relative value of individual goals

For this analysis, we use the GPIV metric [4,5] to assign every goal an importance value that take into account the goal state, defined by the time, GD, and MD at the time that the goal was scored. Intuitively, the GPIV can be seen as a

Fig. 5: GPIV per goal. The numbers above bars indicate the total number of goals.

weighted metric that captures the change in the probabilities (before vs. after the goal) for winning, losing in overtime, and losing in regulation, as well as the number of points that a team obtains if one of those game outcomes take place.

In Figure 4 we illustrate how the average goal is valued for different GD and MD scenarios per minute. A general observation is that MD does not seem to affect goal importance, rather it is more reliant on GD and elapsed time. For instance, the highest average goal importance can be seen near the end of regulation when trailing by one goal, as these goals tie the game and result in a higher probability of attaining game points. Similarly, we note that a larger absolute GD (e.g., -4, -3, 3, and 4) tends to have negligible importance on the outcome of the game. However, the manpower curves suggest that there is no clear distinction between shorthanded, even strength, and powerplay.

Another aspect worth considering is the average GPIV per goal for different GD and MD and whether there are any noticeable differences between them. These comparisons are shown in Figure 5. Here it can be noted that the importance of a goal is the highest when trailing by one, and higher absolute GD are seldom important. When contrasting the different manpower scenarios we note that, in general, the goals scored in even strength have a higher average GPIV for a given GD despite a far larger sample size than shorthanded and powerplay goals. Interestingly, powerplay goals are typically the least important for a given GD, although the differences are somewhat small.

5 Impact on winning a game

To examine the importance of special teams scoring within a single game, we next consider the correlation of the scoring rates in each state with each game

Table 2: Spearman correlations.

Manpower	Game points	Win
EV For	0.524	0.507
EV Against	-0.559	-0.507
PP For	0.222	0.212
PP Against	-0.127	-0.112
SH For	0.115	0.112
SH Against	-0.235	-0.212

Table 3: Average goals for and against per game, by game points.

	Goals for				**Goals against**			
Game points	Total	EV	PP	SH	Total	EV	PP	SH
0	1.64	1.21	0.38	0.04	4.07	3.12	0.13	0.82
1	2.38	1.79	0.53	0.07	2.38	1.80	0.06	0.52
2	3.68	2.81	0.76	0.11	1.81	1.35	0.05	0.42

outcome. Naturally, the team with the most goals at the end of the game wins. However, does the amount of goals per manpower scenario have equal importance for this? To answer this, the Spearman correlation between winning a game (1 if win, 0 otherwise) and obtaining game points (2 if win, 1 if overtime loss, and 0 if loss) and the number of goals scored and allowed per game was investigated. The results are shown in Table 2.

We note that the strongest relationship between both winning and obtaining game points was found with even strength scoring, while powerplay goals for/shorthanded goals against ranked second, although with a weaker correlation. This result could be expected, as a majority of the game is played in even strength and we may therefore expect that most goals are scored during this manpower scenario.

These correlations can also be explained from the point of view of average scoring and conceding rates. These results are shown in Table 3. Here we note that, from both perspectives, most goals occur during even strength play while the average number of goals scored increases when the game points increase, while goals against decrease when game points increase. The same pattern can also be discerned for powerplay and shorthanded situations, as the scoring rates also increase with game points while goals against decrease with increased game points. Interestingly, if powerplay goals were to be excluded, most games would still have the same outcome.

6 Relationship between game points and manpower

With the inherent randomness in ice hockey, the goal importance in a given game may have larger variability than if considering the entire season. As an example, the powerplay efficiency in one game may be 100%, with the team scoring a goal in one powerplay opportunity, but this is not expected to be true for the entire season. Instead, the team success in powerplay typically ranges between 10% and 30%, where the best scoring teams average higher numbers than the worst scoring teams. Yet, only considering a team's powerplay efficiency without accounting for their skill in even strength and while shorthanded fails to fully contextualize the performance of a team. Therefore, to fully account for all of these situations, we implement several generalized additive models (GAMs)[3] models to investigate the relationship between game points and efficiency in various manpower situations. Table 4 summarizes these results. The choice of a GAM model is suitable as it allows for flexible modeling of the relationship between an outcome and a set of variables [11]. Here, each model has the same outcome, points accrued after a full season,[4] while the variables differ. To evaluate the out-of-sample quality of each model, data from 2010-2011 until 2020-2021 were used as training data while 2021-2022 was used as the test set. The variables in each model are:

- SH: Shorthanded goal differential per game.
- SH_{te}: Interaction between shorthanded goals for and against per game.
- PP: Powerplay goal differential per game.
- PP_{te}: Interaction between powerplay goals for and against per game.
- SP: Powerplay and shorthanded goal differential per game.
- SP_{te}: Interactions between powerplay goals for and against per game, and shorthanded goals for and against per game.
- EV: Even strength goal differential per game.
- EV_{te}: Interaction between even strength goals for and against per game.
- All: Interactions between even strength and powerplay goal differential per game, and even strength and shorthanded goal differential per game.
- All_{te}: Interactions between even strength and powerplay goals for per game, and even strength and shorthanded goals allowed per game.

From the set of models, we note that the deviance explained (where a value of 0 indicates no explanation of the outcome while 1 provides a perfect explanation) varies by model, with specific manpower situations, i.e. shorthanded and powerplay, having the lowest value, while the model using all scenarios obtained the highest scores. These results indicate that merely considering a team's strength in, e.g., shorthanded or powerplay, is insufficient to explain the total team points they will accumulate over the season. By considering both shorthanded and powerplay situations in a model, we find increased deviance explained at 40-42%. In contrast, by only accounting for the quality of play in even strength situations we can explain approximately 85% of the deviance, and by including the other two scenarios this increases to 90%. Similarly, when evaluating the out-of-sample performance of the models, the even strength and all-inclusive model has

[3] With restricted maximum likelihood estimation and thin plate splines.

[4] For the non-82 game seasons, the accrued game points after their last game was generalized to an equivalent of 82 games.

Table 4: Model evaluation metrics.

Model	Res. Df	Res. Dev	Dev. Expl.	Training MSE	Test MSE
SH	330.9	58900.3	0.187	176.35	329.20
SH_{te}	328.5	58164.2	0.197	174.14	327.77
PP	331.5	55210.6	0.238	165.30	182.49
PP_{te}	330.0	54829.0	0.243	164.16	179.98
SP	331.0	43085.2	0.405	129.00	157.03
SP_{te}	324.2	41573.3	0.426	124.47	151.92
EV	331.7	11167.5	0.846	33.44	48.51
EV_{te}	327.5	10891.6	0.850	32.61	49.40
All	322.0	7212.0	0.900	21.59	30.17
All_{te}	324.7	7113.6	0.902	21.30	32.72

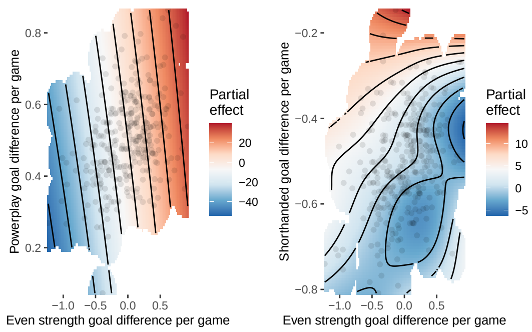


Fig. 6: Effect of manpower scenario goal differential on earning game points from the 'All' model. Partial effect of 0 means average, while red indicate more points and blue less points

the best performance, while the shorthanded and powerplay models have higher test MSE.

Thus, it becomes evident that the main component in explaining team success, measured in team points, lies in the quality of their even strength play. This stands in unison with the fact that a vast majority of an ice hockey game is being played in even strength, in particular during 5-on-5. A visualization of the best performing model, with respect to deviance explained and test MSE, can be seen in Figure 6. The figure shows the joint impact of two sets of variables: GD per game in EV and PP (left) and GD per game in EV and SH (right).

Overall, the model highlights results that are expected. In particular, a higher even strength goal differential typically leads to more game points, while higher goal differentials for powerplay and shorthanded also increase the expected number of game points.

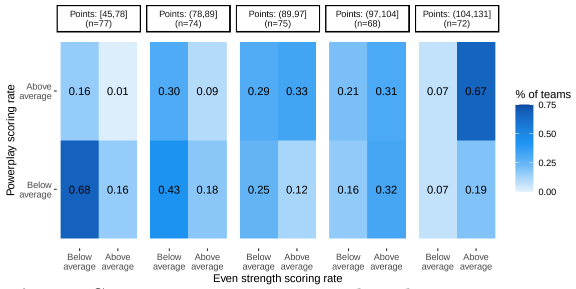


Fig. 7: Scoring rates compared to league average in PP and EV.

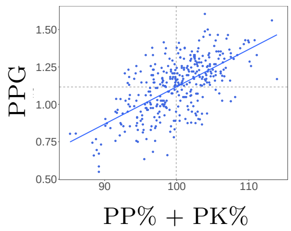


Fig. 8: Special teams (PP% + PK%) vs. points per game (all seasons).

7 Team-based per season analysis

7.1 Correlations

Even though even strength (as per the above results) explains most of the team success, it is clear that many good teams have a strong powerplay and many bad teams have weak powerplay. We expect that this is due to good teams having good players to put on the powerplay and bad teams often having to put weaker players on the powerplay. This is illustrated by the high concentration of the top teams (e.g., with more than 104 points in a season) having both above average even strength scoring rate and above average powerplay scoring rate (last cell in Figure 7) and the high concentration of the bottom teams (e.g., with less than 76 points in a season) having both below average even strength scoring rate and below average power-play scoring rate (first cell in Figure 7).

These observations can also be extended to special teams in general, where teams that can ice a strong 5v5 team often can ice a strong unit or two for both powerplay and shorthanded situations. For example, we have observed a strong correlation between the sum of the (PK% + SH%) and team success (Figure 8). We note that a team with (PK% + SH%) above 100% typically sees a net gain from special teams situations (assuming a similar number of powerplays and shorthanded situations) and teams with values below 100% generally are outperformed in special teams situations. When discussing penalty killing, it can also be noted that the goaltenders, who make up an important part of a strong penalty killing unit often also play a big part in a team's 5v5 success.

7.2 Longitudinal analysis

While there are exceptions (especially some teams becoming weaker), we have observed a relatively larger increase in the fraction of even strength (EV) goals compared to special teams goals (PP and SH). These statistics are shown on a team basis in Figure 9. The increase in goal-scoring in the figure aligns with an overall increase in scoring from 2010-2016 (2.71-2.79 goals per game) and 2017-2023 (2.94-3.18 goals per game).

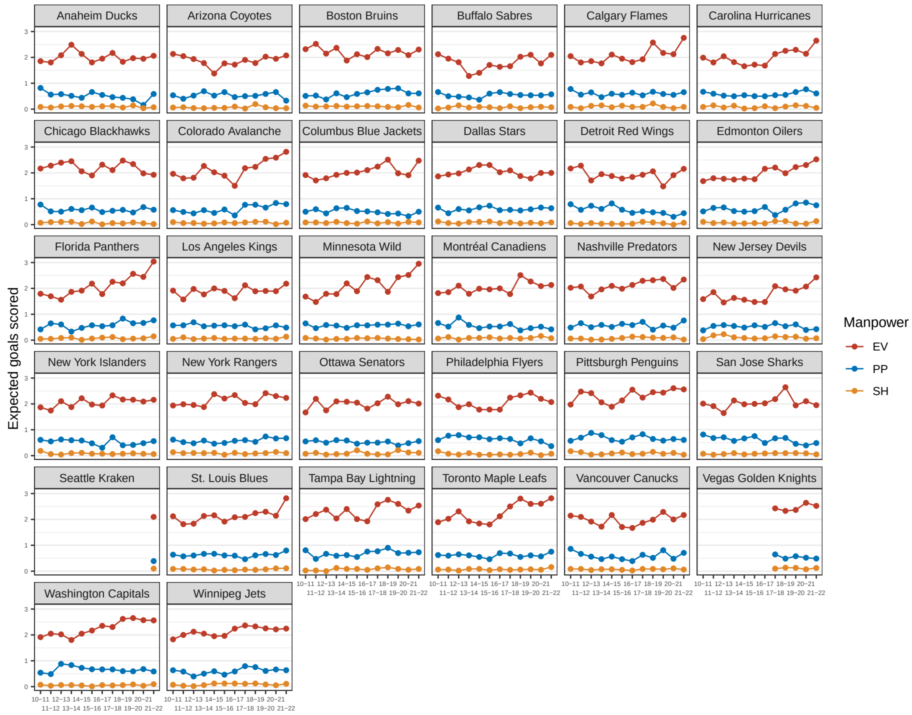


Fig. 9: Expected goals scored per team, season and manpower.

8 Discussion in a wider context

An important aspect is the impact the importance of special teams may have on player development among younger athletes [3]. What is viewed as important may be reflected in how the coach of a youth team chooses to coach, e.g. having a "win-first" mentality [12]. For instance, if powerplay is seen as a vital component of the game, it may affect teams at the youth level, where the focus is placed on specialized situations, e.g. powerplay and penalty killing, instead of focusing on fundamental individual skills, e.g. skating, passing, and stick-handling, and team skills, e.g. puck support and knowledge of tactical situations. A large proportion of practice may be dedicated to these specialized situations despite the majority of a hockey game being played in even strength [7]. Who gets to play in these specialized settings may also vary, as some coaches only select the best players while others allow most, if not all, players to participate. However, this typically changes when the stakes are higher, e.g. in playoffs or tournaments, where most coaches lean toward only choosing the players who they believe will maximize their winning chances [3]. This type of specialization may hamper individual development and affect both the preferred and non-preferred players negatively [8,2]. While our study cannot provide a clear answer to how much time kids should practice powerplay skills, it highlights that even strength play may have a greater impact on team success at the NHL level than powerplay.

9 Conclusion

In conclusion, our analysis of individual goal scoring, game outcomes, and team success across multiple seasons provides insight into the significance of powerplays and penalty kills in the NHL. We found that powerplay goals and even strength goals have similar values when scored at similar times of the game and when the goal differential is the same. However, even strength play is a more important contributor to team success due to the larger share of even strength goals scored over a season. Our results also show a high correlation between teams that perform well during even strength and powerplay, indicating that team success is closely linked to the overall skill level of the team's players.

Overall, our study highlights the importance of a team's ability to perform effectively on special teams, but also the importance of maintaining a strong even strength performance. The findings of this study may inform coaches and players on the relative importance of special teams versus even strength play and provide guidance for optimizing team strategies for success. Our study also suggests potential avenues for further research into the dynamics between special teams performance and overall team success in ice hockey.

References

1. von Allmen, P., Leeds, M., Malakorn, J.: Victims or Beneficiaries?: Wage Premia and National Origin in the National Hockey League. Journal of Sport Management **29**(6), 633–641 (2015)
2. Donnelly, P., Petherick, L.: Workers' playtime? child labour at the extremes of the sporting spectrum. Sport in Society **7**(3), 301–321 (2004)
3. Gilbert, W.D., Trudel, P.: Role of the coach: How model youth team sport coaches frame their roles. The Sport Psychologist **18**(1), 21–43 (2004)
4. Lambrix, P., Carlsson, N.: Performance metrics for ice hockey accounting for goal importance. In: Lambrix, P., Carlsson, N., Vernblom, M. (eds.) Linköping Hockey Analytics Conference. pp. 11–25 (2022)
5. Lambrix, P., Carlsson, N., Säfvenberg, R.: Goal-based performance metrics for ice hockey accounting for goal importance (2023), submitted
6. Pettigrew, S.: Assessing the offensive productivity of nhl players using in-game win probabilities. In: MIT Sloan Sports Analytics Conference (2015)
7. Preston, C., Allan, V., Fraser-Thomas, J.: Facilitating positive youth development in elite youth hockey: Exploring coaches' capabilities, opportunities, and motivations. Journal of Applied Sport Psychology **33**(3), 302–320 (2021)
8. Preston, C., Fraser-Thomas, J.: Problematizing the pursuit of personal development and performance success: An autoethnography of a canadian elite youth ice hockey coach. The Sport Psychologist **32**(2), 102–113 (2018)
9. Schuckers, M., Brozowskia, L.: Referee analytics: An analysis of penalty rates by national hockey league officials. In: MIT Sloan Sports Analytics Conference (2012)

10. Schulte, O., Khademi, M., Gholami, S., Zhao, Z., Javan, M., Desaulniers, P.: A markov game model for valuing actions, locations, and team performance in ice hockey. Data Mining and Knowledge Discovery **31**, 1735–1757 (2017)
11. Wood, S.N.: Thin plate regression splines. Journal of the Royal Statistical Society: Series B (Statistical Methodology) **65**(1), 95–114 (2003)
12. Wright, T., Trudel, P., Culver, D.: Learning how to coach: the different learning situations reported by youth ice hockey coaches. Physical Education and Sport Pedagogy **12**(2), 127–144 (2007)

Industry papers

Achieve excellent performance

Sideline Sports was founded in 2001. We started out with three people, and today we're a company of more than 30. Our main offices are in Iceland and Sweden with most of us working remotely so you will find us spread out around the world.

For two decades we've been helping our customers become more organized and effective, by improving communication and providing access to the key data that drives decision-making.

Our main product is the XPS Network coaching platform and we've earned the repeat business of thousands of customers including some of the world's largest - and smallest - sport clubs and organizations.

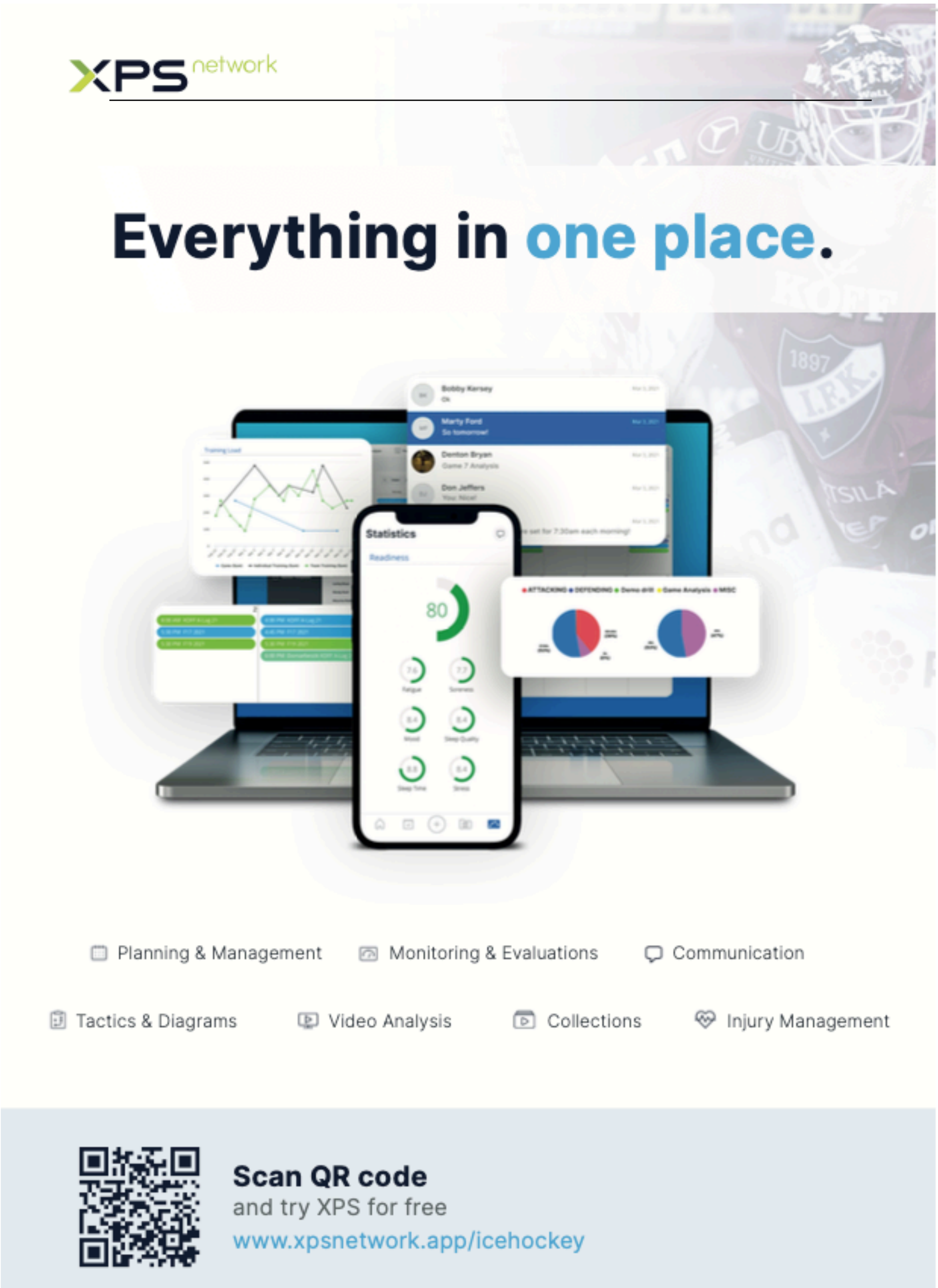
We're proud of our success and we will continue to raise the bar, providing cutting-edge software solutions for coaches in all sports, around the world. We feel we're just getting started!

Keep in simple

"We are big believers in keeping it simple. In the power of data in sports, and how much coaches can do with the right information at your fingertips. Our priorities have always been the same: Provide great service, build the best data-driven products in the business, and have fun! For our coaches and sports teams across the world, XPS Network is like a lighthouse - it helps them navigate."

In the decades to come, we'll continue to focus on clarity and ease-of-use in our products, always with the same core goal in mind: Supporting coaches in the development of teams and athletes.

sidelinesports.com


XPS network
Everything in one place.
Planning & Management
Monitoring & Evaluations
Communication
Tactics & Diagrams
Video Analysis
Collections
Injury Management
Scan QR code
and try XPS for free
www.xpsnetwork.app/icehockey

Hat-TriQ

by Stretch On Sense

The magic of Hat-TriQ

Hat-TriQ is a unique analysis platform assisting elite teams with detailed player analysis. How the players practice, how the players play the game, and the player's well-being, all gathered on one platform. Focused on empowering decision-makers with data, Hat-TriQ gives you detailed player and team analysis for your organization to make decisions based on true facts. As we combine all systems into one, you will reach your full potential for your entire organization. **With Hat-TriQ, there are no silos. IT's one platform.**

Hat-TriQ – The sports analytics' Spotify

Before Spotify, iTunes, and even Napster, we listened to music on a CD player.

If you wanted to listen to Bruce Springsteen's Born To Run, the song, not the whole album, you needed to buy that CD. If you wanted to listen to Glory Days from the album Born in the U.S.A., you needed to buy a second album from Bruce Springsteen. In that case, you now have 20 songs, but you only wanted to listen to 2 songs. You have too much music for your appetite and desire, which you also can compare to too much-unfiltered data.

With Spotify, you have one platform with all artists, bands, and songs from the past, and what's fresh today and what will be cool and fresh tomorrow. You can choose one song from one album and quickly switch to a new artist and song. You can access all the music in the world and easily filter and listen to what you like.

With Hat-TriQ, you have the same option. We offer you all the systems on the market into one platform, and we can easily be the filter of your choice. We customized Hat-TriQ for you as Spotify creates your playlists.

HAT-TRIQ

STRETCH ON SENSE | Qlik

49ing

Founded in 2016 by the Hänni brothers Andreas and Michael, 49ing is a sports data and analytics platform dedicated to ice hockey. In Switzerland, 49ing is the official data provider to the National League and Swiss League and its video analytics software powers hockey development at all levels, professional and amateur, from the national teams to youth programs. For the 2023/24 season, 49ing will launch automated computer vision based game tracking from broadcast video to scale statistical collection and analysis so coaches, players and fans across all levels can benefit from the data.

Our business began after Andreas, a professional hockey player for nearly twenty years, retired from the game and Michael, an ETH computer science graduate, built ten years of accomplished industry experience as software engineer. The two have always been close and had discussed technology topics for some time: when will the digital revolution happening in other industries reach hockey and what could be the impact? Democratization of hockey with data-based decisions, video-based tools for player development and scalable technology solutions for clubs and leagues were all among our objectives as we launched 49ing with a mission to grow the game of hockey.

In the early years the company provided data analysis and consulting to customers like the Swiss National Team and single teams, but in 2020 the professional leagues in Switzerland as well as the Federation entrusted 49ing to develop a software platform that encompass all sporting needs of professional hockey in one solution: Analytics, Scouting, Player Development, Video Analysis, Officiating, Player Safety, Game Operations as well as real-time Coaches' Challenge to name some key components. The result is the Data Cockpit, 49ing's state-of-the-art hockey platform.

49ing continues to grow rapidly and with the launch of broadcast computer vision tracking, plans to scale its team and technology solution globally. Hockey is a fast-moving, complex sport that requires a dedicated technology partner to process the data and translate analysis into insights and engagement to grow the game.

Some questions to hockey analytics experts

Johan Andersson, Swedish National Team

How do you use hockey analytics in your job?

For pre scout reports on other teams, scouting of players to the team and looking at how lines and players are doing individually.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

I like to simplify as much as possible and make it very easy to understand. I think a lot of interesting information gets lost because of difficult presentations and diagrams.

What hockey question would you like hockey analytics to answer next?

How good is a player's game sense?

Which hockey analytics method/notion is the most important/influential in your job?

Using the good tools and platforms available for hockey teams. but also going through video clips myself to check the stats. I think it is important to quality proof the stats and check the videos as well.

Where is the hockey analytics field going? What do you envision for the next 10 years?

I hope that the ”number analytics” goes more and more together with the ”video and coaching analytics”. At the moment I think it is in many places two different areas. Just in a few years all the SHL teams will have a analytics staff.

Petter Carnbro, Leksands IF

Who are you and what is your connection to hockey analytics?

Petter Carnbro, scout and analyst for Leksands IF of the SHL.

How do you use hockey analytics in your job?

Scouting, player projections, pre and post-game reports, meetings, roster construction, to name but a few.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

Reports and meetings, a lot of visualizations and a lot of casual conversations. It's an everyday thing.

What hockey question would you like hockey analytics to answer next?

The importance of space.

Which hockey analytics method/notion is the most important/influential in your job?

Methods pertaining to regularization and adjustments of on ice events.

Where is the hockey analytics field going? What do you envision for the next 10 years?

Wider (more high end national leagues will invest, women's hockey as well) and deeper (junior and youth hockey).

Zach Ellenthal, Rögle BK

Who are you and what is your connection to hockey analytics?

I am a hockey analyst and scout with Rögle BK of the Swedish Hockey League, where I work closely with the organization's management and coaching staff on a variety of projects across the club. Hockey analytics, and sports analytics in general, starting coming to prominence when I was a teenager. Reading that early research had a large influence on how I watched and thought about hockey, both on the ice tactically and from a management perspective strategically. Analytics ended up providing a path for me to go from being a hockey fan to pursuing hockey more seriously professionally.

How do you use hockey analytics in your job?

In all areas – thinking about a game or a player or a roster or a league analytically is central to my job. I use both proprietary data and data provided by league partners/third-party platforms to help us make more informed decisions on things like free agent signings, simply to increase awareness on things like player development or team trends, or conduct bigger picture research on something like broader league trends.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

It's a moving target and depends on the situation. Over the course of a season, several one-off ideas and questions come about that might only warrant a quick conversation or text. For larger projects and more evergreen analysis (e.g. pregame scouting), ideally we will have built out a standardized reporting template that makes for efficient communication in all directions. For me, I care much more about management and coaches receiving the information in a way that makes sense for them to see and hear it than the specific way it gets communicated.

What hockey question would you like hockey analytics to answer next?

I hope to see continued efforts to use analytics for unlocking improved player development outcomes. If I look at a sport like baseball, there has been an enormous player development revolution in the last 10 years, with analytics helping players improve very specific aspects of their games – things like swing paths, swing decisions, pitch grips, and pitch usage. It's part of a natural progression across sports from analytics initially identifying what is most important to success and how to measure it toward using analytics to help players improve and get the most out of their abilities.

Which hockey analytics method/notion is the most important/influential in your job?

"The magic of analytics is in recording all of the small things lost to memory that add up to something significant." – Eric Tulsky, Assistant GM of the Carolina Hurricanes

Where is the hockey analytics field going? What do you envision for the next 10 years?

I agree with the area that was stated repeatedly at the LINHAC conference – effectively harnessing more sophisticated tracking data. Collectively, the hockey analytics community will likely evolve its understanding of more advanced concepts such as better isolating an individual skater's impact or how to better measure defense.

Andreas Hänni, 49ing

Who are you and what is your connection to hockey analytics?

Andreas Hänni, former pro player of nearly 20 years in Switzerland. In my playing days, I was often questioning the assessments on teams, player selection and player combos in hockey. After my player career, I founded 49ing, aspiring to use my hockey knowledge and combine it with today's data and computing power.

How do you use hockey analytics in your job?

Our platform breaks down video to deliver data and analytics to the hockey world.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

Communication, the transmission of findings, is in fact a crucial element. In the context of hockey personnel, the first key is to stay within the jargon, hockey people trust hockey people easily, if they feel they know what they are talking about. With players, video is by far the most used channel - get your findings from the data and communicate via video example. In our mandates in broadcasting, findings need to be communicated to a crowd with little hockey knowledge as well. Here it's get your findings from the data, then communicate in simple and clear terms, most of the time with some visualization, graphs or video, or the two combined.

What hockey question would you like hockey analytics to answer next?

More than specific unsolved questions, I see a very big potential from unused synergies within organizations, their data and their processes. E.g.: for every game played, a player works on his game habit in 2-3 practices. If we train to improve how we perform in the games, then we should combine the two and measure practice performance and measures its effect on game performance.

Which hockey analytics method/notion is the most important/influential in your job?

We all love the great game of hockey for many reasons. Certainly one of the most fetching is the emotional component of the game. While we all want to keep that, we know best analysis are made ice cold - without any emotions.

Where is the hockey analytics field going? What do you envision for the next 10 years?

Hockey is still way too egocentric, a quasi clerical structure. Coaches are not as important as the framework and the culture set up by the organizations. Similarly, I see clear limits in value and scalability potential with today's role of analysts in a somewhat compartmented role, trying to solve specific questions. Instead, I see a disruptive potential by sports entities picking up what has already been standard for some time in business: engineering processes that use data, computing power and AI. Define a strategy, implement, measure and monitor. I'm convinced that's where we're headed for in sports as well.

Mike Kelly, Sportlogiq and NHL Network

Who are you and what is your connection to hockey analytics?

Mike Kelly, hockey analyst specializing in analytics with Sportlogiq and NHL Network.

How do you use hockey analytics in your job?

Analytics and data-driven analysis play a major role in my work at Sportlogiq and NHL NETWORK. While it is a piece of the overall analysis, data informs a great deal of how I evaluate the game.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

ABC - accuracy, brevity, clarity. Regardless of the value of the insights you are able to provide, if not communicated effectively it will be difficult for your audience to gain value from what you produce. I start with the end point and work my way backwards as much as required to articulate my findings.

What hockey question would you like hockey analytics to answer next?

Quantifying ‘hockey IQ’ is something that interests me.

Which hockey analytics method/notion is the most important/influential in your job?

Know what you don’t know. Blindspots exist regardless of your background and experience evaluating hockey. The better understanding you have of what you don’t know, the better you can fill in those gaps to produce the best and most holistic analysis possible.

Where is the hockey analytics field going? What do you envision for the next 10 years?

Puck and player tracking data, in addition to event data and real time data is going to revolutionise the industry and provide many answers to questions we currently do not have answers to. Technology will continue to improve and push the limits of what can be quantified. Predictive analysis is still in its infancy in this sport and I anticipate there will be significant gains made in the ability to produce predictive models of higher quality in the coming years.

Albin N Maelum, Stretch On Sense

Who are you and what is your connection to hockey analytics?

My name is Albin Nordstrand Maelum, I'm the CEO at Stretch On Sense, a SportsTech company working in the field of sports analytics. We have built a cloud-based platform on Qlik technology, for a detailed team- and player analysis. We break down the silos and gather all the market systems of your choice to the platform Hat-TriQ.

How do you use hockey analytics in your job?

Hockey analytics is what we do!

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

We are working closely with clients, partners, and experts on the market. In that way, we can stay ahead and always develop and be quick-footed.

What hockey question would you like hockey analytics to answer next?

Detailed real-time analysis. How can advanced player tracking data be used to optimize team strategies and player performance in real-time during games.

Which hockey analytics method/notion is the most important/influential in your job?

We do detailed team and player analysis for the whole organization and scouting analysis. We crack the numbers and assist elite teams with detailed hockey analytics.

Where is the hockey analytics field going? What do you envision for the next 10 years?

The field of hockey analytics are in the start, and the business will continue developing and adapting. We will have more data to analyze, and all the systems will be even better with higher accurate and detailed measurements. In 10 years, we will be working in a whole new environment. We have an exciting future ahead of us.

Jan Morkes, Bílí Tygři Liberec

Who are you and what is your connection to hockey analytics?

My position is data analyst/scout and together with my brother David, who specialises in analytics/skill development, we form one of the largest analytics departments in European hockey, working for Bílí Tygři Liberec in the Czech Extraliga:)

How do you use hockey analytics in your job?

I don't make a big contrast between "analytics" and traditional knowledge. In every part of our work, we're trying to combine the best possible information and come up with coherent answers. And because European organisations are less crowded than US ones, you usually find yourself in the middle of discussions about everything. Scouting, game performance, internal player development, tactics, general trends in hockey. A complex knowledge of "analytics" underpins it all.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

The key is to do your homework and communicate the conclusions of your research to managers/coaches/players. Explain what it means in hockey terms and how they can use the information in a practical way. Use the data if you have to, but only to illustrate the point. Nobody "cares" about complex statistical analysis.

For us, it's not just about going to analytics conferences like LINHAC, it's also about visiting hockey coaches' conferences, listening to players and coaches, knowing how they think and what their problems are. My brother David's role is focused on understanding the deepest details of skill development so that he can discuss all the issues directly with the players.

What hockey question would you like hockey analytics to answer next?

I don't have a specific wish, but I think it would be immensely helpful if analytics could come up with a clear and intuitive way to distinguish player roles. Something more sophisticated than shooter/playmaker/offensive D/defensive D. It's nothing spectacular, but I think improvements like that could make analytics more ingrained in the minds of coaches, players and even casual fans. And I envy basketball and other sports that have been able to invent these categories and back them up with data.

Which hockey analytics method/notion is the most important/influential in your job?

Probably the basic scientific idea that you can measure a lot of things, but you have to conceptualise and operationalise them properly before.

Where is the hockey analytics field going? What do you envision for the next 10 years?

I think we're moving from the era of limited data to the era of abundant data. There will be a lot of companies offering interesting services and sports organisations will need people who can navigate through all these sources and help teams find their comparative advantage.

Inside the organisation, I hope that the use of data analytics will become as casual and boring as the use of video. Everyone will do it and understand the benefits.

Frans Murto, Wisehockey

Who are you and what is your connection to hockey analytics?

I work in a research & development role at the analytics department of Wisehockey.

How do you use hockey analytics in your job?

I design and implement models and algorithms that combine event and tracking data. Some of the projects I've worked on include a possession value framework for ice hockey, automated event detection and various machine-learning models for player evaluation.

What hockey question would you like hockey analytics to answer next?

As the majority of advanced metrics in hockey have so far focused on offensive play (perhaps understandably due to lack of data), I'd like to see more work on evaluating defensive positioning and decision-making. In a similar vein, evaluating the effectiveness of different breakout and forechecking schemes and how they match up would be an interesting avenue of research.

Which hockey analytics method/notion is the most important/influential in your job?

This comes more from a machine-learning perspective, but I've found that forming a set of events that cover both typical hockey scenarios as well as various edge cases has been the most helpful way to evaluate our models. Computational metrics are of course important, but taking the time to dive into the data and seeing how the model behaves in real situations has usually been the deciding factor between prospective model candidates.

Where is the hockey analytics field going? What do you envision for the next 10 years?

While a bit late to the tracking data party that other major team sports have been enjoying, the increasing availability of such data means that hockey analytics is at a similar position as soccer was five years ago. Though not a silver bullet by any means, tracking data will likely open up new areas of research and help improve on existing methods.

Josh Pohlkamp-Hartt, Boston Bruins

Who are you and what is your connection to hockey analytics?

Josh Pohlkamp-Hartt, Data Scientist with the Boston Bruins.

How do you use hockey analytics in your job?

I am the primary quantitative analyst for the Bruins and in that role I build and communicate hockey analytics to our hockey operations staff. We have data, models and analysis for most areas of hockey operations, from pro-level trades and signings to areas like amateur scouting and player development.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

We use a variety of technologies, including presentations, technical reports and dashboards. The method of communication is dependent on the audience. For some it is as simple as a quick email or text with a keen insight while others are large scale interactive web applications.

What hockey question would you like hockey analytics to answer next?

The two most exciting areas where analytics can start to shine some light are: player development from Junior to Professional hockey and attribution of defensive impact.

Which hockey analytics method/notion is the most important/influential in your job?

Do not be average. If you follow established wisdom and play to be consistent with other teams; you do not have an underlying advantage. With no differentiation from your opponents, your success is driven by luck. Find what you believe creates an advantage in your league and be consistent in following it. Analytics can help you find advantages and measure your progress in acting on them. The other very important notion is the 80/20 rule. We rarely need the perfect analytical solution in hockey, having a very good solution that takes much less time and allows you to tackle another problem provides more value to your team.

Where is the hockey analytics field going? What do you envision for the next 10 years?

With an overwhelming amount of data becoming available, data engineering and management will be paramount over the next few years. In conjunction to that we will start to see exciting spatial analysis of decision making with the increases in tracking data. As our sport matures, we will begin to look more like soccer in terms of analytical offerings and non-shot related metrics will become more common in public evaluations.

David Radke, Chicago Blackhawks

Who are you and what is your connection to hockey analytics?

David Radke, Sr. Research Scientist, Hockey Systems and Analytics Group, Chicago Blackhawks.

How do you use hockey analytics in your job?

My job revolves around trying to develop and evaluate new analytics and performance models. I read analytics papers and aim to measure value for management, coaches, and players.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

In my academic background I have written research papers and given talks at conferences and seminars. At work, I continue to communicate my models and findings through text-based mediums and make myself available for questions from any stakeholders.

What hockey question would you like hockey analytics to answer next?

I would like hockey analytics to better capture the passing abilities of players across different contexts. This includes different areas of the playing surface, manpower scenarios, and opponent/gameplay situations players find themselves in.

Which hockey analytics method/notion is the most important/influential in your job?

My background being in artificial intelligence and multiagent systems, I mostly rely on methods from the field of reinforcement learning (RL) in my job. I try to combine this with my playing experience to solve challenging problems with real in-game data.

Where is the hockey analytics field going? What do you envision for the next 10 years?

I would like the analytics field of all "invasion game" sports to adapt more multiagent perspectives to problems. I recently co-authored a conceptual position paper paper titled "Presenting Multiagent Challenges in Team Sports Analytics" with Alexi Orchard at the International Conference on Autonomous Agents and Multiagent Systems (AAMAS) 2023. There are many great researchers in the multiagent community working on similar problems to those that exist across invasion game sports analytics. More progress at the intersection of these two fields would be particularly exciting.

Freddie Sjögren, Malmö Redhawks

Who are you and what is your connection to hockey analytics?

I am workig as Performance Director for an SHL club in Sweden. Working daily with some kind of analytics.

How do you use hockey analytics in your job?

Using it to try go get different silos in hockey to get closer cooperation. Tactic - Technical - Physical - Psychological.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

Through weekly meetings and better visualization.

What hockey question would you like hockey analytics to answer next?

Better holistic profiling of a player when it comes Tactic - Technical - Physical - Psychological.

Which hockey analytics method/notion is the most important/influential in your job?

Can't pin point one method.

Where is the hockey analytics field going? What do you envision for the next 10 years?

Better visualization to get everyone onboard.

Maciej Szwoch, Färjestad BK

Who are you and what is your connection to hockey analytics?

I have been working as an analyst for my club and was a part of building our very first analytics department.

How do you use hockey analytics in your job?

I use it daily, to check on KPI´s, look for answers to why our performance is the way it is. I use it for scouting and pre scouting purposes as well. In short, I use analytics to either verify or question what my hockey experience tells me.

How do you communicate hockey analytics findings to your customers/viewers/players/coaches?

We have daily coaches meetings where we discuss findings and elaborate why. Players are included on a need-to-know basis. If it can help them, we will include them but usually we tend to present short info to streamline the message.

What hockey question would you like hockey analytics to answer next?

I would like to see more context in the Goaltending evaluation field. We do not have enough to truly tell which goalie is the best or even answer strengths and weaknesses.

Which hockey analytics method/notion is the most important/influential in your job?

There are so many! On a yearly basis we are fueled with new information and insights, so a straight answer is very hard to give. But it all started with Rob Wollman and his Hockey Abstract

Where is the hockey analytics field going? What do you envision for the next 10 years?

The field has had a MASSIVE explosion the last 5 years and I can't see why the evolution will start. Teams will broaden their staffs with analysts and data engineers. The merge between Video and Analytics will become tighter but I also believe that teams will build their own analytics solution using 3rd party data to fit their needs.

Student competition papers

Comparing Defensive Pressures Using Possession Retention Probability and Expected Goals

David Awosoga[1], Justin Cui[2], Aujin Li[2], Jaden Majumdar[2], and Junhao Wang[2]

[1] University of Waterloo, Waterloo ON N2L 3G1, CAN
[2] University of Toronto, Toronto ON M5S 1A1, CAN

Abstract. Hockey places a high value on possession time and efficiency as a way to generate offensive success and improve win probability. Under this guiding principle, this work will employ a possession-based framework to evaluate events in terms of their impact on a teams' possession retention probability. Finally, a metric will be introduced to evaluate player actions by their resulting offensive potential in different situations. A case study investigating puck protection strategies on offence and defensive pressure techniques such as bodychecking will illustrate the application of this metric and lead into areas of future analysis.

Keywords: hockey analytics · spatiotemporal analysis · sports statistics

1 Introduction

Puck possessions play an important role in dictating the outcome of hockey games. Metrics such as CORSI and FENWICK [1] have demonstrated that the more frequent and higher possession quality that a team has, the better their opportunities to generate scoring chances. Conversely, defensive actions that force a change in possession should be similarly valued by teams and analyzed accordingly. In this paper, defensive pressure techniques will be assessed for effectiveness by examining resulting offensive opportunities.

An extension of this work will focus on physicality (in the form of checking) and its statistically observable impact on offensive output. Gone are the days of the fourth line goon, crushing hits and heavyweight bouts unfolding on the ice. In hockey today, speed and skill are paramount. Hits per game are on the decline, and with it, strategies are evolving. Body checks and stick checks are two principle methods of forcing a change in possession, though due to a decline in physicality, the former is seemingly being phased out of the game. In our literature review of previous studies conducted in hockey analytics, the projects that have utilized similar data sets have overwhelming focused on passing related metrics [2–4]. Additionally, competitions such as the 2021 Big Data Cup worked with women's hockey datasets, a league in which body checking is prohibited. Thus, applying our possession-based event valuation framework to bodychecking and puck protections delves into a relatively understudied and potentially valuable area in the hockey analytics space.

2 Background

The analysis was conducted using event data provided by Sportlogiq from twenty games played during the 2020-2021 season in the Swedish Hockey League (SHL). Table 1 displays the different types of recorded events, broken down into three categories: **Possession-Continuing**, **Possession-Terminating**, and **Other**. Possession-continuing events take place while one team attempts to advance an offensive possession, and can be disrupted by actions performed by the defending team, causing a live change in possession. They differ from possession-terminating events, which result in an automatic play stoppage, such as a penalty or offside, or a voluntary relinquishing of possession, such as a dump in or shot on goal. Events that didn't fit in the previous two categories were place in the "Other" category and served as event descriptors (such as an assist describing a pass) or an event where no team is in possession, such as a faceoff.

Table 1. Categorization of Event Types

Possession-Continuing	Possession-Terminating	Other
carry	shot	save
pass	dump in	rebound
puck protection	dump out	controlled entry
loose puck retrieval	offside	controlled exit
check	icing	faceoff
reception	penalty	shootout events
controlled entry against	penalty drawn	goal
block		assist

The most pertinent events to this project were player interactions, primarily checks and puck protections. Although basic familiarity with hockey is assumed, a brief explanation about such interactions will be given. An offensive player can attempt to protect the puck by either shielding it with their body or performing a "deke", where they use their stick to maneuver the puck around their defender. In the flow of a game, checking occurs via the defender's body or stick and serves to disrupt a play in the hopes that the ensuing loose puck can be retrieved by the defending team. Body checking is used to take an opposing player out of the play by physically knocking them off the puck. This can take the form of open ice hits and checks along the boards, though as Figure 1 shows, the majority happen in the defensive zone (shown on the left) along the boards. While body checking takes the opposing player off the puck, it can also take the defending player making the check out of the play, which has strategic ramifications requiring the need for coverage from supporting teammates. Stick checking takes advantage of the hockey stick as an extension of the player's body, allowing them to knock the puck off of or lift an opponent's stick. Positioning of defending players remains an important factor in this form of checking, though infractions such as tripping, high sticking or slashing are more likely to occur in the use of stick checking.

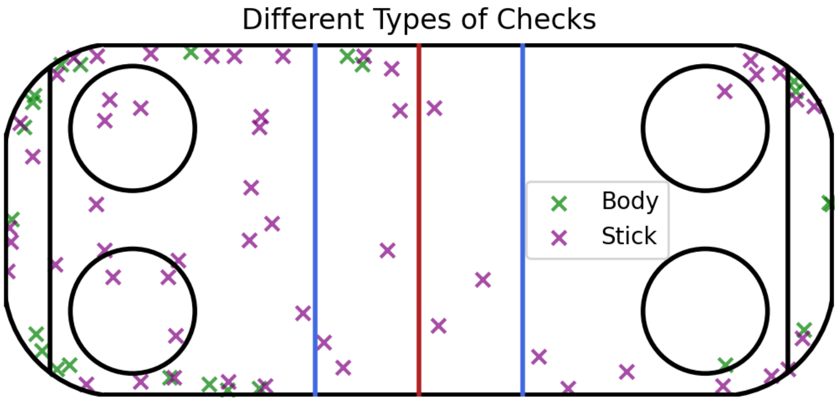


Fig. 1. Spatial Distribution Example of Stick Checks and Body Checks From a Game

3 Methods and Algorithms

With the event categories established, a model was developed to predict possession retention probability within the next two plays of a possession-continuing event. Offensive and defensive actions within this set were assumed to be disjoint, with the few overlaps in the data removed. Eleven features mirroring those used in similar outcome probability models were selected: the period, time remaining in it, amount of skaters on ice for both teams, whether the player in possession is on the home team, the score differential, the (x,y) coordinates for the event, the name and type of event, and the position of the player (Forward/Defense). An xgboost model was created and tuned using a random search strategy over 10 iterations. It had a test AUC of 0.795, an overall accuracy of 84.73% on the withheld test set and a balanced accuracy of 72.16%. From its predictions, checks had the highest average expected turnover probability of any defensive pressure technique, at 59.8% for body checks and 57.5% for stick checks.

Inspired by VICE [5], a metric was created to quantify the change in expected goals (`xG`) that each event gave to the team in possession. For every event, the next 45 seconds (average hockey shift length [6]) was observed and the xG of each shot within that time frame was summed. This quantity was multiplied by the proportions of shots that came from that region of the ice as an estimate of shot probability, and also multiplied by the predicted possession-retention probability of the play in question. The difference (or sum in the case of a change in possession) in this quantity before and after each event was then calculated. We denote the resulting value as `Offensive Relative Event Contribution` (O-REC), and it represents how important a play was in generating resulting xG, contrasting the "risk" involved in committing the action with the "reward" in terms of generating a shot from the location of the event. A larger value when comparing play types indicates a higher value in terms of generating offense.

4 Overview and Discussion of Findings

The average O-REC for puck protections and checks were compared by type (stick/body for checks, deke/body for puck protection) and in the aggregate with 95% confidence intervals superimposed on each bar. Addition comparisons were made by their magnitudes (Figures 2 & 3) and raw values (Figures 4 & 5). Outliers on the lower end of magnitude were filtered to de-noise the impact of significant plays, and events that did and did not result in a change in possession were compared independently due to their large differences in O-REC.

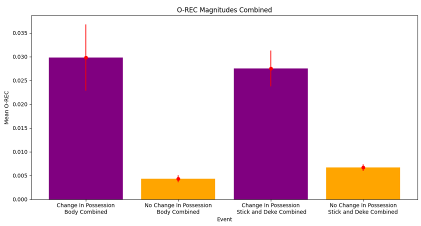


Fig. 2. Aggregate Magnitude Comparison of Checks and Puck Protections.

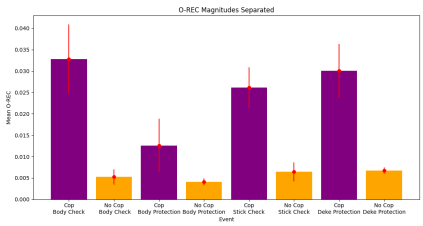


Fig. 3. Separated Magnitude Comparison of Checks and Puck Protections.

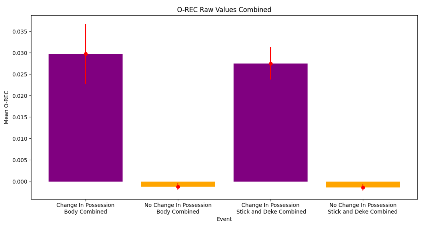


Fig. 4. Aggregate Raw Value Comparison of Checks and Puck Protections.

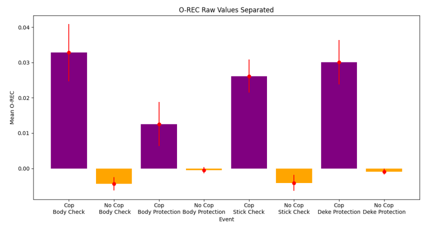


Fig. 5. Separated Raw Value Comparison of Checks and Puck Protections.

From Figure 2 we see that the magnitude of O-REC of stick checks is larger than that of body checks when there is no change in possession. This could be because using one's body takes oneself out of the play, while a successful deke could take the defender out of the play and increase the chance of an odd man rush which comes with a higher chance of generating xG. This difference is not observed when raw values are used, which suggests that the magnitudes are higher in both directions on deke attempts and lead to bigger changes in xG for both teams during a game. When looking at the difference in magnitudes with puck protections and checks separated, a change in possession on a body puck protection offers significantly less offense than the other type of forced turnover. This could be because a body check takes both players out of a play, so if the puck is not knocked loose (a check event), then the player with the puck is already being marked by the player they just took the puck from, limiting their ability to generate offence. This result is echoed in Figure 5, further suggesting that a body check generates less resulting offense after a change in possession. When there is no change in possession on a body puck protection, there is less of a change in offence generated by the team in possession than if the same situation occurs with a stick protection instead. The reasoning is that retaining possession after a body check does not guarantee the ability to create separation from the defensive player. In summary, these results suggest that there is a statistically significant difference between using one's body and one's stick on both puck protections and checks, and that eliminating body checks may have negative effects on available strategies. For example, if body checks generate less offence, a coach may opt to send out their players to hit more in order to slow the game down when things are getting out of hand for the team.

5 Conclusion and Future Steps

With our possession-based event valuation framework, we found that while body checks have a higher turnover probability than stick checks, they generate less resultant offence than stick checks on changes in possession. Additionally, when there are no changes in possession, body checks have less impact on O-REC than stick checks. This suggests that body checks and stick checks have important but distinct use cases, with their exact impacts necessitating further analysis. If more data was available, one could look at checks and puck protections by zones of the hockey rink to see whether certain types are more effective in certain areas, such as along the boards verses at center ice. More intricate tracking data could also analyze decision making of these defensive pressures by considering the location of other teammates on the ice at the time of an event.

6 Code Access Links

The code for this project is linked here: `https://github.com/awosoga/linhac2023`

References

1. Herman, J.: Better Know a Statistic: Corsi & Fenwick. The Hockey Writers. https://thehockeywriters.com/corsi-fenwick-stats-what-are-they/
2. Morse, D.: Quantifying Offensive Passing Ability with Expected Primary Assists. https://github.com/danmorse314/Expected-Primary-Assists
3. Howell, B.: How Do We Get There: Quantifying Pass Types and Their Value. http://benhowell71.com/big-data-cup-submission/?ref=theicegarden.com
4. Treisman, D.: A Framework for Assesing Shooting and Passing Skill in the NWHL. https://github.com/dtreisman/BigDataCup2021
5. Douglas, E., Clement, S., Wan, N., Greengross, I.: Valuing Individual Contributing Events (V-ICE) in Hockey. https://www.statsportsconsulting.com/wp-content/uploads/Valuing-Individual-Contributing-Events-V-ICE-in-Hockey.pdf
6. Jones, W. How long do hockey players stay on the ice? A guide to shift lengths. Hockey Answered. https://hockeyanswered.com/how-long-do-hockey-players-stay-on-the-ice-a-guide-to-shift-lengths/

Where did they get out? Evaluating zone exits using expected threat in hockey

Tim Keller

Student Computer Science, University of Basel, Basel, Switzerland
tim.keller@unibas.ch

Abstract. Analyzing the effect of zone exits in hockey through different lanes one the ice. The paper introduces an implementation of the soccer metric expected threat adjusted for hockey. Additionally to offensive expected threat, the metric also quantify defensive danger. The metric is used to analyze the xT for sequences of passes and carries leading up to a zone exit and compares the different lanes.

Keywords: zone exit · expected threat · entry/exit lanes

1 Introduction

1.1 Zone Exits

Good defense in hockey is mostly determined by minimizing the scoring chances of the opponent by keeping them away from dangerous areas and suppressing shots from these areas. Successful zone exits at the same time decrease the danger of the opponent scoring and require a zone entry to get into the scoring position. But are all zone exits the same? Do exits in different locations have different impacts on the danger of the opponent? Personal observations would lead to the thesis that zone exits over the sides is more effective and danger-reducing but is that really true?
Looking at the controlled exits in the dataset and the events leading up to it is what we are trying to answer in this project. We are using the concept of offensive zone entry lanes introduced by Daniel Weinberger [1] and re-introduced by Nick Czuzoj-Shulman in his 2022 SEAHAC presentation [2] to apply it to the zone exits locations.

1.2 Expected Threat (xT)

The concept is based on Sarah Rudd's work on evaluating actions in soccer using Markov chains [5] that was further developed into the concept of expected Threat by Karun Singh [6]. The concept gives a value to every section of a field to show the probability of scoring a goal in a certain amount of action from that place on the field. Through the difference between the beginning and ending coordinates of an action that moves the ball, the difference in the values is the expected Threat (xT) added through that action. In a presentation at a Football Analytics seminar [7] Hugo Fabrègues presented his new approach to Expected Threat by defining expected Threat with absorption state 1 for a scored goal and -1 for a conceded goal. After application of the markov chain simulation, the resulting matrix is a symmetric shape of xT values that includes the danger of scoring a goal but also the danger of not scoring a goal.

2 Implementation

2.1 Implementation of Expected Threat (xT)

The implementation of expected threat in hockey is largely based on the implementation of expected threat in soccer by David Sumpter and Aleksander Andrzejewski [8]. The start was made by dividing the hockey rink into a 16 $\times$

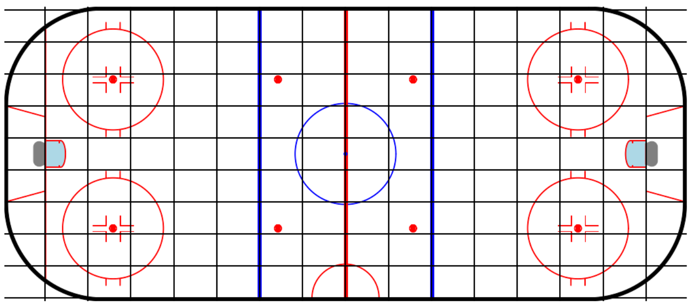


Fig. 1. Dividing the ice into a grid 16 sections (length) and 9 sections (width) for the implementation of expected Threat.

9 matrix (length $\times$ width) to have the zones aligned with all the important sections of the ice (fig. 1). Only passes and carries were defined as move actions to make ensure consistency. First, we calculate the probabilities of the puck being moved from a specific tile or if there is a shot taken from that tile, the so-called move probability. The goal probability is simply taken by the expected goals of all shots in the Sportlogiq dataset. Following the algorithm for transition matrices in the tutorial [8] is used to calculate the probability to go from to a specific tile from a given tile for every tile on the ice. Using the transition matrices, goal probability, and moving probability we now use the Markov chain technique to create the transition matrices after a certain amount of steps until it converges after 8 moves. Now the matrix has all the values for the offensive expected threat. To get the defensive expected threat we flip the matrix and multiply the values with -1. This way we get the expected Threat against the matrix. Finally summing up the both matrices element-wise results in the net xT matrix (fig. 1) that is used in the analysis. The model is agnostic of the team in possession

at the moment and only depends on the position on the field. Although we did not calculate it with the same absorption states as Fabrègues [7] we get a result with a similar basic idea.

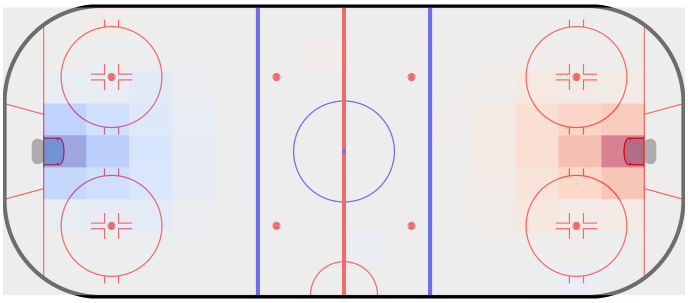


Fig. 2. Values of each zone for the xT net graphic where red are positive values and blue negative values.

2.2 Exit Sequences

In the analysis, we want to use multiple moving actions leading up to an exit. Utilizing the way David Sumpter and Aleksander Andrzejewski isolated possession chains [9] we implemented an algorithm that creates sequences breaking off at game stoppages, definite possession changes as well as a controlled exit. Later analysis was possible this way by getting the 3 moving actions (passes and carries) leading up to a controlled exit. The last action is usually the action fulfilling the zone exit.

2.3 Exit Lanes

Similar to Weinberger [2] and Czuzoj-Shulman [2] for zone entries the idea was to create zones along the width of the ice for the zone exits, resulting in 5 bins. The first idea was to take the coordinates of the controlled exits in the data set and bin the coordinates along the y-axis. Because the coordinate is not necessarily the coordinate where the puck crosses the blue line but where the action fulfilling the controlled exit ends. By calculating the intersection of the action leading to the zone exit we projected the crossing coordinate. Now the exit lanes for the controlled exits especially towards the middle of the ice are a different because for example common breakout passes break the lines we created [10]. For that reason, the intersection exit lanes were used for the analysis.

3 Results

Exit sequences were used to filter the last 3 moving actions before successfully exiting the zone. The passes and carries may not directly follow each other, but

they are related to the same sequence leading up to a zone exit. Typically, the last action is the one fulfilling the zone exit.
As the exit sequences are mixed, we did not differentiate between carries and passes. In the results, we found that the peak values for the left and right lanes were quite high, but the middle lane was also able to compete for the highest net xT in a sequence (fig. 3). Surprisingly, the left lane also had the lowest values in a sequence, which was not the case for the right lane. The graph shows that the higher average values for the left, right, and middle lines come from a view of very high net xT events. Most of the values for all lanes are in a similar range.
Overall, it is evident that the right and left lanes have the most zone exit

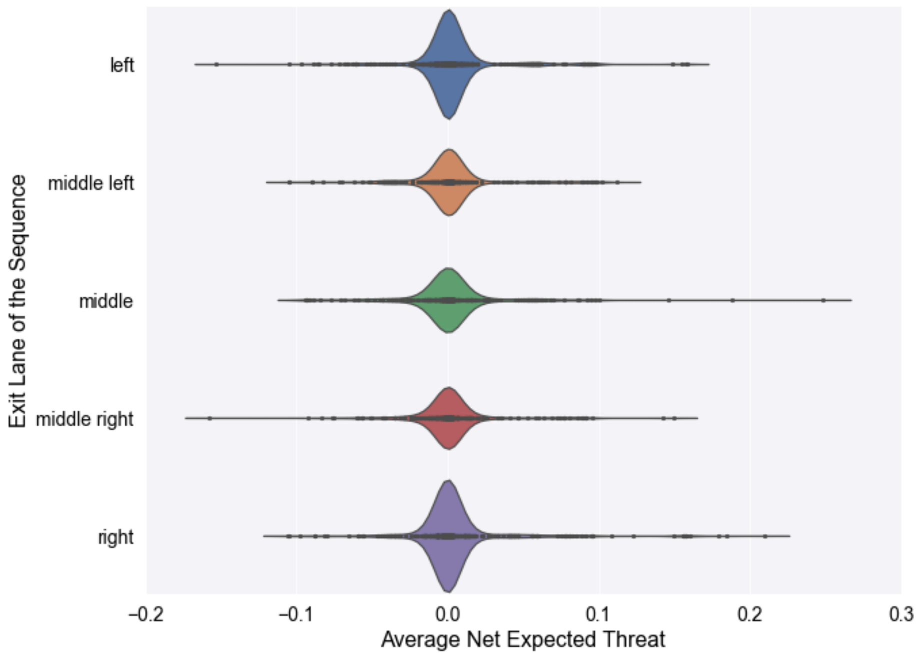


Fig. 3. A violin plot displaying the xT net values for exit sequences group according to their exit lanes.

sequences and therefore have the potential for the most extreme values. A very good play outside the middle could also have high net xT values. This could be due to xT against, which reduces the danger of conceding a goal, or high xT for value that describes the increased possibility of ending up in a good scoring position. All in all, the results show that most zone exits occur over the outside lanes, but the expected threat values are not conclusive enough to show that there is more danger created or prevented by exiting the defensive zone via one of the outside lanes.

4 Discussion

Over the project, there are for sure some more statistical adjustments possible. For example with the expected goals values or use a distribution instead of line intersections to model the locations of the zone exit. Further work might also include looking at different pass types and carry types instead of categorizing them all as a whole. Another idea would be to look at the effects of the moving actions after a zone exit to look at how the exit lane affects possibilities in the neutral zone and the transition into the offensive zone. Some great work was already done on that by Daniel Weinberger [1] and Jen LC [4].

5 Acknowledgements

The Author thanks David Sumpter and Aleksander Andrzejewski for making their code of the soccer implementation of expected threat and possession chains publicly available. I do not take any credit for the code part that belongs to their copyright and is clearly marked in my published notebook, which I adjusted for a hockey context. Another Thank you is extended to Vincent Karpick for the hockey_rink package.

The code is availabe on GitHub: https://github.com/TK5-Tim/linhac/tree/main/2023

References

1. Daniel Weinberger, Lateral Puck Movement in the neutral zone, Article, https://hockey-graphs.com/2019/10/24/lateral-puck-movement-in-the-nz/, last acessed: 22.04.2023 (2019)
2. Nick Czuzoj-Shulman, SEAHAC 2022 - OZ Entry Lanes, Presentation, https://www.flipsnack.com/75B8FBBBDC9/seahac-2022-oz-entry-lanes.html, last acessed: 22.04.2023 (2022)
3. Alex Novet, Why Possession is the Key to Zone Exits, Article, https://hockey-graphs.com/2019/07/30/why-possession-is-the-key-to-zone-exits/, last acessed: 22.04.2023 (2019)
4. Jen LC, Clearing the Defensive Zone: The Dangers of Dumping the Puck Out, Article, https://jenlc13.wordpress.com/2015/05/19/clearing-the-defensive-zone-the-dangers-of-dumping-the-puck-out/, last acessed: 22.04.2023 (2015)
5. Sarah Rudd, A Framework for Tactical Analysis and Individual Offensive Production Assessment in Soccer Using Markov Chains, Presentation, https://docplayer.net/27070167-A-framework-for-tactical-analysis-and-individual-offensive-production-assessment-in-soccer-using-markov-chains.html, last acessed: 22.04.2023 (2011)
6. Karun Singh, Introducing Expected Threat (xT), Website, https://karun.in/blog/expected-threat.html, last acessed: 22.04.2023
7. Hugo Fabrègues, A new Expected Threat (xT) Model, not publicly availabe (2023)
8. David Sumpter and Aleksander Andrzejewski, Calculating xT (position-based), Website, https://soccermatics.readthedocs.io/en/latest/gallery/lesson4/plot_ExpectedThreat.html, last acessed: 22.04.2023

9. David Sumpter and Aleksander Andrzejewski, Possesion Chains, Website, https://soccermatics.readthedocs.io/en/latest/gallery/lesson4/plot_PossesionChain.html, last acessed: 22.04.2023
10. Daniel Weinberger, Passing clusters: A Framework to Evaluate a Team's Breakout, Article, https://hockey-graphs.com/2019/10/22/passing-clusters-a-framework-to-evaluate-a-teams-breakout/, last acessed: 22.04.2023 (2019)

On the Attack: Using Analytics to Unlock the Secrets of Successful Zone Entries in Hockey*

Anton Olivestam[1], Axel Rosendahl[1], Hampus Svens[1], and Lukas Hellberg[1]

Linköping University liu.se

Abstract. In this paper, we use machine learning methods to see what types of offensive zone entries and their upcoming play sequence lead to shots with high xG values in hockey. Our results showed a clear difference in sequence characteristics regarding the length of the sequence, the type of zone entries, the number of events, and in what zones those events took place for good goal-scoring opportunities compared to worse ones.

Keywords: Zone entries · Neural Networks · xG · Play sequence

1 Introduction

In this paper, we represent an analysis of different offensive zone entries and the upcoming play sequence to see which type of sequences that leads to shots with high expected goal value (xG). This we will do by creating a neural network model to analyze the sequences and then gather statistics to see which zone entries lead sequences resulting in a high xG value.

An offensive zone entry is defined as the act of a team carrying, passing, or dumping the puck across the opposing team's blue line, i.e. entering the offensive zone. Wilderoth *et al.* found that no goals during SHL seasons 2018/19, 2019/20, and 2020/21 were scored without being in the offensive zone given that both teams were at full strength and that the goalkeeper has not been pulled [1]. This makes entry into the offensive zone crucial in the game of hockey.

Similar work has been done by Chatel [2]. Chatel divided the game into sequences where each sequence started from every possession change. The post looked at what particular outcome a type of zone entry would lead to frequently. It did this by looking at how the expected goal (xG) value changed. Chatel captured this into a decision tree that shows the risk and reward for each action in different zones.

2 Background

Offensive zone entries can be divided into three types. (1) a dump-in, (2) a carry-in, and (3) a pass. However, a further division of these zone entries was made in this study. A carry-in was split into two versions: wideCarry and middleCarry.

* Supported by Linköping University.

These different versions describe where along the blue line the player skated into the offensive zone with the puck. A pass entry was split into two different versions: widePass which meant that the puck moved more than half of the rink size in the sideways direction and shortPass which means that the puck moved less than half the rink size in the sideways direction.

Table 1. Statistics for the different offensive zone entries.

Entry	Percentage of total entries	Average xG on shots	Shots	Goals
wideCarry	37%	0.05	44.5%	3.3%
middleCarry	16%	0.07	47.4%	5.2%
widePass	4%	0.05	64.7%	4.7%
shortPass	6%	0.07	48.7%	9%
dumpIn	37%	0.06	17.4%	1%

In Table 1 we have displayed some statistics gathered from our dataset, which is based on 20 SHL games, to give a hint of what to expect from our analysis. Here we could see that a WidePass most often leads to a shot on net. However, a shortPass is the entry that most often leads to a goal and also has the highest average xG. Further, we can also see that a middleCarry more often leads to a goal and has a higher average xG than a wideCarry.

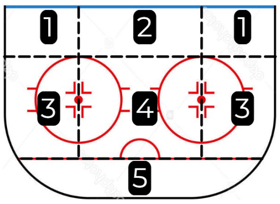


Fig. 1. Zone split.

Further, the offensive zone was divided into five different sub-zones in order to make it easier to analyze the data. In Figure 1 a visualization of the zones is made. The two zones 1 is called upperWide, zone 2 is called upperMiddle, zones 3 is called middleWide, zone 4 is called slot, and zone 5 is called behindGoalCrease.

3 Algorithms

In this paper, we present one model created in order to analyze the entry types and the sequences after. This model is an LSTM model created to predict xG based on a certain entry type and the sequence after.

3.1 Recurrent Neural Network

Recurrent Neural Networks (RNN) have been used in a huge variety of different areas due to their ability to predict the next event in a sequence [4]. However, a traditional RNN struggle to capture long-term dependencies due to the vanishing gradient problem [3]. To tackle this, LSTM (Long short-term memory) a more complex architecture that was specifically designed to overcome these issues, was introduced. Since our data consists of sequenced events and our goal is to predict the next event, or more specifically predict the xG after our sequence, LSMTs, and RNNs were a highly suitable tool [4].

4 Results

4.1 Predict xG

In Figure 2 we can see the performance of our LSTM model. The scatter plot suggests that our neural network has a decent level of predictive capability for xG.

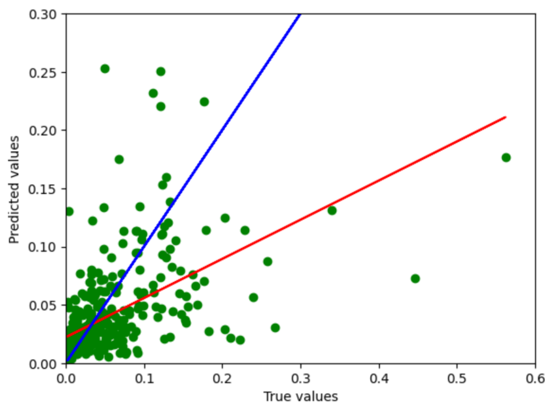


Fig. 2. The plot shows the predicted xG in relation to the true xG in the data. The red line is the regression line for all of the predicted xGs and the blue line is the optimal regression line that we strive to get the points to be close to.

Table 2. Average number of occurrences for five events for the 100 sequences with highest predicted xG and the 100 sequences with lowest predicted xG values.

Event name	High xG sequences	Low xG sequences
pass	28%	22%
reception	24%	15%
lpr, (loose puck recovery)	18%	24%
shot	5%	3%
puckprotection	4%	7%
average sequence length	23.52	9.66

In Table 2 we have extracted the sequences where our model predicted best xG values versus the sequences where our model predicted worst xG values and displayed how often five different events on average occurred in the two types of sequences. From Table 2 we can see that the biggest difference between the two types of sequences is that for those leading to a higher xG the number of receptions is higher whilst the number of passes is slightly higher. This means that the number of successful passes is a lot higher for high xG sequences. Another big difference is that the number of lpr's are more frequent for the low xG sequences which probably means that there are fewer direct passes and more lost pucks from the offensive team in those sequences.

Table 3. Average percentage of events in each zone of the offensive zone split.

Zone	High xG sequences	Low xG sequences
middleWide	26%	19%
slot	21%	13%
behindGoalCrease	20%	22%
upperWide	18%	32%
upperMiddle	15%	14%

In Table 3 we can see the average percentage of events happening in each zone from Figure 1 in the two different sets of sequences. What we can see in this table is that high xG sequences have more events in the slot and middleWide zones than low xG sequences. More events happening in the slot for high xG are expected since shots from this area are a good scoring opportunity. More events in the middleWide zone probably give a higher xG since a player controlling the puck in this zone has a lot of options, the player can shoot, pass to the slot, or pass over the central line to a player in the same zone but on the opposite side which all could create a great scoring opportunity. Also as expected low xG sequences have a lot of events in the upperWide zone which is furthest from the goal and a zone that is hard to create a scoring opportunity from.

4.2 Zone Entries

Table 4. Statistics for frequent patterns of zone entries.

Entry	Sequences	Slot shots	Receptions in middleWide	Ratio A	Ratio B
wideCarry	527	209	219	0.4	0.42
middleCarry	255	66	25	0.26	0.098
widePass	55	17	23	0.3	0.42
shortPass	87	27	152	0.31	1.7
dumpIn	37	0	123	0	0.59

In Table 4 we have calculated statistics for each zone entry based on the best zones and events to have in a sequence according to our results from the LSTM model. These zones were middleWide and slot and we added the reception event to the middleWide zone and the shot event to the slot zone. The ratio A and ratio B in the table are calculated as follows:

$$Ratio\ A = \frac{Shots\ in\ slot}{Total\ sequences} \ , \ Ratio\ B = \frac{Receptions\ in\ middleWide}{Total\ sequences} \tag{1}$$

The sequences used in Table 4 are the same sequences that were used in our LSTM model which means that these are all the sequences that included a shot. From Table 4 we can see that the wideCarry most often leads to a slot shot amongst these sequences. The biggest difference between the zone entries are the number of receptions in the middleWide zone which on an average happens 1.7 times for a shortPass entry while the second most frequent is only 0.59 times. This makes shortPass a great entry since we could see from Table 2 and 3 that having more reception events and more play in the middleWide zone relates to a high xG value. This we can also relate back to Table 1 were we could see that a shortPass entry most often ended up in a goal and had the highest average xG out of all entries.

4.3 Summary

In this paper we have analyzed different offensive zone entries and with the help of a neural network gained further insights into sequences of play in ice hockey. We found clear differences in characteristics for sequences with a high predicted xG value compared to their counterpart sequences with low xG values. We found that the most significant difference between the sets of sequences where that more events of receptions meaning more successful passes, more events in the middleWide zone, and more events in the slot zone lead to a higher xG value. We then found that the entry that most often had receptions in the middleWide zone was shortPass entry which we also could clarify led to most goals our of the entries in our dataset. Further, we found that a wideCarry entry most often lead to a shot in the slot zone amongst the sequences that included a shot.

4.4 Future ideas and improvements

To further analyze zone entries it would be interesting to look at sequences before the zone entry as well and see how that affects the performance of a offensive zone entry. Another thing that could be improved in this paper is the size of the dataset used since our only included 2550 zone entries and 961 zone entry sequences including a shot which was used for the LSTM model. This could be reason to why we "under-predict" the high xG values since they are not that common in out small dataset.

5 Code appendix

The code for the LSMT model and scripts for calculating staistics used in this paper can be found in the following GitHub link:
https://github.com/Olivestam/linhac_zone_entries

References

1. Wilderoth, Erik, Ulf Johansson, and Arsalan Sattari. "Where not to lose the puck." Linköping Hockey Analytics Conference. 2022.
2. Chatel, T. (2020, March 26). Introducing offensive sequences and the Hockey Decision Tree. Hockey Graphs. https://hockey-graphs.com/2020/03/26/introducing-offensive-sequences-and-the-hockey-decision-tree/ . Last accessed 10 Apr 2023
3. Hochreiter, Sepp. "The vanishing gradient problem during learning recurrent neural nets and problem solutions." International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 6.02 (1998): 107-116.
4. Sherstinsky, Alex. "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network." Physica D: Nonlinear Phenomena 404 (2020): 132306.

Defensive Zone Puck Battles and Breakout Success

Ethan Parliament

Queens University, Kingston ON, Canada

1 Introduction

Ice hockey is a sport that has embraced analytics to better understand the game and gain a competitive edge. As such, this paper aims to delve into two important aspects of hockey analytics: the importance of puck possession and winning battles in the defensive zone, and the relationship between puck battles and successful breakouts, using breakout success rates, expected goals (xg), and possession time. With a focus on understanding the factors that contribute to success in the defensive zone and successful transitions to offense, this paper provides valuable insights for teams and analysts looking to gain an edge in the modern game of hockey.

2 Background Information

Breaking out of the defensive zone is a critical aspect of hockey, as it sets up the team for offensive opportunities while minimizing the risk of conceding a goal. Strong breakouts can lead to quick counter-attacks and more sustained possession in the offensive zone, resulting in increased scoring chances and ultimately, higher goal-scoring. In contrast, poor breakouts can lead to turnovers in the defensive zone, putting the team at a disadvantage and increasing the likelihood of conceding a goal. Therefore, understanding which puck battles lead to successful breakouts and how to effectively win those battles is essential in improving a team's performance on both ends of the ice.

The quality of a breakout can be measured in a few ways. The simplest and most important way of evaluating breakout quality is whether or not the breakout succeeded. This is measured by recording if the breaking out team successfully moves the puck out of the defensive zone while maintaining possession of the puck. Another way to measure the quality of a breakout is through the use of expected goals (xg). By tracking breakout attempts, we can score them based on the cumulative xg that they generate during that possession. Finally, a third way we can evaluate a breakout is by tracking time of possession. Time of possession can serve as a reliable indicator of which team is in control, and thus can also provide valuable insight into the strength of a team's breakout strategy.

3 Algorithms and Methods

3.1 The Dataset

The data provided for this competition by Sportlogiq included data from 20 games of the 2020-21 SHL season. Each row represents a single event that occurred during the game, and includes data such as the team and player, event name and type, success/failure, and the time and location of the event. The dataset also includes the xg for all shot attempts. The most important features of the dataset for this research was the event name, and the location of the event. Two key event names are 'lpr' (loose puck recovery) and 'controlledexit'. These events were crucial for the continuation of this research.

3.2 Method

Before getting into the analysis, some pre-processing had to be done to put the data into a form that was easier to work with for these purposes. Using an array of Pandas DataFrames, the dataset was broken up into individual possessions. Once each individual possession was accessible, further analysis could be done.

Firstly, an analysis of loose puck recoveries (lpr) was conducted to get a general understanding of the problem and the dataset. Each possession that included an lpr event had its location record as X and Y coordinates, as well as other pieces of information, such as shots taken, cumulative xg, and total time of possession. These features that were extracted from the dataset can now be plotted to visualize the impact that they have on the game. This research only considered possessions that began in the defensive zone, in order to get a deeper understanding of the success of breakouts.

After looking at lprs, different breakout strategies can be considered. Three different metrics were used to evaluate the quality of a breakout. For each metric, the data was grouped using a 2d histogram to capture the spatial data of each metric using the X and Y coordinates recorded during the pre-processing phase. The first metric, breakout success utilized a net breakout success rate. A successful breakout was given the score of +1, and a failed breakout was given a -1. Each bin in the histogram records the net number of successful breakout attempts.

The second metric considered when evaluating breakouts is the cumulative xg that comes from the possession after the breakout. This was tracked using play sequencing techniques to track shot attempts and their respective xg for each possession. Then each possession is given a total xg equal to the sum of all xg during that possession.

The third and final metric used is time of possession. This metric followed a similar approach to the first 2, using a 2d histogram to bin the data with respect to the starting locations of the data. This time, the weights used for the bins of the histogram was the time of possession, taken from the 'compiledgametime' field of the dataset.

3.3 Visualizing the Data

The locations used in the data and all plots shown are based on a grid centered at center ice. The bounds of the defensive zone is shown in Fig. 1.

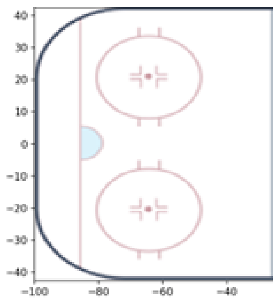


Fig. 1. The scale use for coordinates in the defensive zone

The end boards are located along the Y = -100 line, and the blue line is located at the Y = -25 line. All figures shown in this report work with respect to the coordinates shown.

4 Results

4.1 Breakout Success

For the simple net breakout success metric, there is are a few clear locations to start the breakout from (Fig. 2). The most obvious are the two zones from the hashmarks to just before the blueline; the closer you are to the neutral zone, the easier it is to get the puck out. More interestingly are the other large zones directly behind the net and in the slot. These zones also have a very high chance of a successful breakout after winning an lpr in these locations.

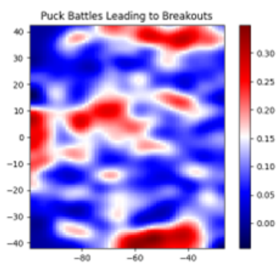


Fig. 2. The locations of highest (red) and lowest (blue) breakout success

4.2 Expected Goals

In the scenario when you are losing and need to score, maximizing your xg will lead to your greatest chance of success (Fig. 3). Compared to the breakout success metric above, maximizing your xg off of a breakout should come from different areas of the ice. Once again, starting your breakout from behind the ice is a good idea, but winning lprs from the high slot does not provide the same results as before. Instead, look to move the puck and breakout from closer to the blueline in the center of the ice. This will provide your team with a higher chance of scoring, but with a higher degree of difficulty and risk associated with it.

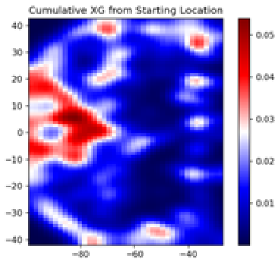


Fig. 3. The locations of the highest (red) and lowest (blue) xg based on starting location

4.3 Time of Possession

In the case you want to play a strong puck possession game, breakouts along the boards are your best bet (Fig. 4). When looking at time of possession for breakout locations, along the boards has a strong advantage compared to moving the puck through the middle of the ice. Both expected goals and breakout success metrics consider the middle of the ice strong areas to breakout through, but in terms of puck possession, the boards are a much safer choice.

5 Summary of Results and Next Steps

Like any game, hockey requires a changing strategy depending on what the current game situation is. Using the results above, different defensive strategies can be used depending on the situation. If you are currently in a winning situation and want to play defensively, forcing the puck to behind the net and, and towards the hashmarks is the most effective strategy, as well as keeping the puck away from the corners. However, if you are losing and need to generate some offensive opportunities, allowing the puck to enter the middle of the defensive zone can be a risky, but rewarding strategy that allows your team to create high quality scoring opportunities from the defensive zone. Finally, if you need to control the

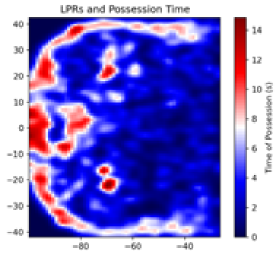


Fig. 4. The highest (red) and lowest (blue) time of possessions based on starting location

pace of play of the game and hold the puck as long as possible, breaking out from along the boards can make your possessions last two to three times longer on average.

Moving forward, there are several areas of research that could build upon this study's findings. One potential avenue would be to incorporate additional variables into the analysis, such as player position and handedness, to better understand how these factors impact successful breakouts. Another possibility would be to compare breakout success rates between different game situations, such as even strength versus power play scenarios. Additionally, this study could be expanded to include a larger sample size of games to increase the statistical power and generalizability of the findings. Overall, there is much potential for future research to build upon the insights gained from this study and further advance our understanding of the importance of breaking out of the defensive zone in hockey.

6 Link to Code

`https://github.com/eparly/Linhac2023`

The Impact of Winning Faceoffs on Expected Goals (xG) in Power plays: An Analysis of 2020-2021 SHL Season Data

Elias Stihl

KTH Royal Institute of Technology, Stockholm, Sweden

1 Introduction

Over the last decade, the overall efficiency of Power plays in ice hockey has been on the rise, suggesting an increasing importance placed on this aspect of the game. Every power play starts with a faceoff, making it a crucial play as it provides a chance to gain possesion of the puck. Teams that can effectively take advantage of their power play opportunities are more likely to score goals and ultimately win games. As a result, teams are constantly seeking ways to improve their power play.

In this context, analyzing the impact of winning faceoffs during power play situations can provide valuable insights for teams seeking to enhance their power play performance. By understanding the effect that winning faceoffs has on a team's expected goals (xG) during power plays, teams can make more informed decisions about their approach to power play situations, potentially leading to improved overall performance.

2 Research question

– How does winning a faceoff impact the expected goals during power plays in ice hockey?

3 Background

A previous study on faceoffs in the NHL has shown that faceoffs can have a notable impact on a teams success over a full season (Schuckers, Tom Pasquali and Jim Curro 2012). Increasing the faceoff win rate from 50% to 60% is equivalent to 12 goals and two more wins over a season according to their results. They also found that it takes 40.9 faceoff wins in the power play to gain a goal differential and 76.5 faceoff wins during even strength, suggesting it is more important to win a faceoff during a power play.

To analyze the effect of the faceoff result, it must be defined what events should be attributed as a result of the faceoff. Compared to the previous study by Schuckers, Pasquali and Curro, this study do not limit the impact of the faceoff to 20 seconds since puck possesion is switching far less often during power plays compared to when teams play with equal strength. In this report, a simplistic approach has been chosen where all events in a game sequence are attributed as a result of the faceoff. A game sequence has been defined as all power play events that happen between the current faceoff and the next power play faceoff. If the faceoff is the last faceoff during the power play, all events until the teams play with equal strength are included in the game sequence.

The event data used in this research was acquired from Sportlogiq, as provided by LINHAC. The dataset covers 20 games from the 2020-2021 SHL season and contains over 76,000 rows, each representing a distinct game event. Although the dataset captured 22 attributes for each event, only a subset of these attributes were deemed relevant to the research question and were therefore analyzed.

4 Method

The provided dataset was loaded into Python using the Pandas library. The dataset was then divided into power play game seqeunces according to the definition in the background of the report. All game sequences were then filtered so that only the expected goals of the power play team were included in the game sequences. The game sequences were then divided into two groups based on the result of the faceoff.

Data from these two groups were then collected, which included the sum of all goals, expected goals and total time. This allowed for calculation of the expected goals per 60 minutes (xG/60).

5 Results

A total of 244 faceoffs were analyzed during 135 penalties. Of these, 148 faceoffs were won and 96 were lost by the power play team. When the power play team won the faceoff, 24 goals were scored with an expected goals (xG) of 16.44, resulting in an expected goals per 60 minutes (xg/60) of 8.17. In contrast, when the power play team lost the faceoff, 8 goals were scored with an expected goals (xG) of 8.31, resulting in 5.90 xG/60.

Table 1. Impact on goal scoring and expected goals during power play based on faceoff result

	Faceoffs	Goals	total xG	xG/60
Won	146	24	16.44	8.17
Lost	96	8	8.31	5.90

The results indicate a significant difference in the xG per 60 minutes when comparing faceoff wins and losses. Winning a faceoff during a power play situation led to an increase in xG per 60 minutes by 38% compared to losing the faceoff (8.17 xG/60 vs. 5.90 xG/60). Noticeably, approximately 46% more goals were scored compared to expected goals after winning a faceoff.

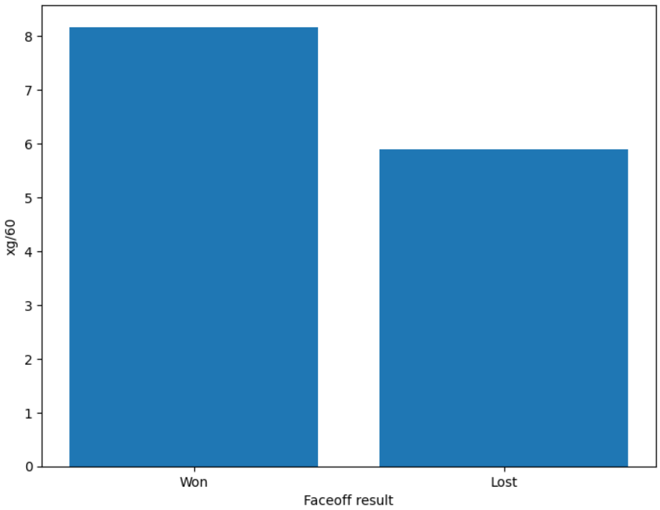


Fig. 1. Expected goals per 60 minutes based on faceoff result

6 Discussion

The findings of this report further supports the importance of winning faceoffs during power play situations. With a 38% increase in xG/60, it is evident that winning a faceoff during a power play leads to a significant increase of the expected goals. Thus, having a great faceoff player on the ice during a power play is highly important.

This study suggests that teams having weak faceoff statistics in their power play should potentially prioritize improving their faceoff strategies rather than other components of their power play game.

It is important to acknowledge that the dataset used in this study covers a relatively small sample size of only 20 games. Therefore, the findings should be interpreted with caution. Future research with a larger dataset over several seasons could help to confirm or refute the findings of the report. The definition of game sequences used in this study is also very simplistic, and more advanced methods could be used to define which events should be attributed as a result of a faceoff more accurately. For example, if the puck switches possesion between teams or if the puck leaves the offensive zone, then the result of the faceoff might not matter that much anymore.

Despite these limitations, the findings of this report provide valuable insights into the impact of winning faceoffs that can be used by teams to improve their power play efficiency and ultimately win games.

GitHub link

https://github.com/EliasStihl/LINHAC-2023

References

1. Schuckers, M., Pasquali, T., Curro, J. : An Analysis of NHL Faceoffs. (2012)