Puck Possessions and Team Success in the NHL

Miles Pitassi, Tim Brecht, and Mingyue Xie

Cheriton School of Computer Science, University of Waterloo

Abstract. This paper investigates the relationship between puck possession and team success in the NHL, focusing on the games played during the 2023-2024 regular season (up to the All-Star break). The analysis first reveals a moderate correlation (r = 0.56) between average team possession percentage and Average Goal Differential (Avg. GoalDiff). Next, we introduce Average Offensive Zone Possession Time Differential (Avg. OZPTD) as a key metric, defined as the difference between a team's offensive zone possession time and that of their opponents. We find a strong correlation (r = 0.77) between Avg. OZPTD and Avg. GoalDiff, thereby highlighting its relevance in assessing team performance. Our analysis confirms OZPTD's stability, discriminatory power, and independence from existing metrics like Shot Attempt Percentage (SAT%), also known as Corsi. Additionally, we detail a comprehensive methodology for processing and cleaning possession data sourced from the NHL. This methodology underpins our findings and facilitates future research involving player and team possession data.

1 Introduction

In the National Hockey League (NHL), where the margin for victory is small, teams are in constant pursuit of advantages to enhance their chance of success (i.e., winning). The unpredictable nature of hockey compounds the difficulty of identifying and quantifying metrics that genuinely influence outcomes. In this paper we analyze puck possession and its use as a potential indicator of success. This work is further motivated by the premise shared across sports that possessing the ball or puck for significantly more time than the opponent increases your chance of winning.

Research in other sports present mixed results regarding the correlation between possession and team success; some studies affirm a strong correlation [19] [16] [13] [5] [3], while others find no significant relationship [4] [6] [7] [9] [12] [10]. In the NHL, prior investigations into puck possession have mainly relied on manual tracking [17] or metrics approximating possession such as Shot Attempt Percentage (SAT%), also known as Corsi [20]. SAT% (Corsi) measures a team's share of the total shot attempts in a game. The rationale behind SAT% (Corsi) is that a higher number of shot attempts, which can only be credited during a possession, indicates superior puck control.

Despite these indirect methods for measuring possession, the strategic importance of puck possession in the NHL has notably increased, particularly during overtime since the introduction of 3-on-3 overtime in 2015. This growing emphasis is underscored by the NHL general managers convening this season to discuss potential regulatory changes, such as implementing a shot clock during overtime [22]. This consideration directly reflects concerns about extended possessions during overtime, highlighting the central role puck control has come to play in modern NHL strategies.

With the recent introduction of puck and player tracking (PPT) technologies in the 2021-22 NHL season and the significance of puck possession, this paper investigates whether teams with more puck possession have greater success. The contributions of this paper are:

- We provide a methodology for cleaning and processing the NHL's player possession data. This is required to support our analyses and also lays the groundwork for future studies.
- We examine correlations between several possession metrics and indicators of team success, providing insights into their predictive value.
- We introduce the Average Offensive Zone Possession Time Differential (Avg. OZPTD) metric, defined as the difference between a team's offensive zone possession time and that of their opponents. Avg. OZPTD is highly correlated ($r = 0.77$) with Average Goal Differential. This highlights its potential for enhancing our understanding of team success in the NHL.
- We show that Avg. OZPTD's is stable across two halves of our dataset (i.e., useful for prediction), is able to differentiate between teams and is independent from existing metrics which demonstrate its potential as a useful new metric.

2 Related Work

Previous studies on the importance of possession across sports provide context for this paper, particularly highlighting the research gap in hockey analytics.

In football (soccer), the relationship between ball possession and team success has been extensively studied using various research methods. Some of these studies find a positive relationship. For instance, researchers studied the 2016 UEFA Euro and found that the average possession time for a leading team was 20.3 minutes with a standard deviation (SD) of 16.0 minutes, compared to 18.2 minutes with a SD of 16.8 minutes for teams when the score was tied, and 13.7 minutes with a SD of 12.3 minutes for a trailing team [5]. The authors explained that the p-value, which assesses the likelihood that these differences occurred by chance, was less than 0.01, indicating a statistically significant difference. Additionally, researchers studying the 2006 FIFA World Cup found that the percentage of ball possession, analyzed using principal component analysis, had the greatest influence on match outcomes with a coefficient with an absolute value of 0.72. This indicates that it is an important variable for discriminating winning teams from those that lose or draw [19]. Another study found that ball possession had a positive effect on winning in the 2014 FIFA World Cup, with an 11% increase in the probability of winning for all matches and a 14% increase for close matches when ball possession increased by two standard deviations [16]. Also, a study covering the 2017-18 and 2018-19 season in the German Bundesliga showed a positive correlation ($r = 0.75$) between team possession and overall points earned [3].

However, other studies have found that possession may not correlate with or may even negatively impact team success. For example, researchers for the FIFA Training centre studied the 2022 FIFA World Cup and found that, for the men's tournament, teams with less possession than their opponents won slightly more games (26 wins versus 23) [10]. Additionally, a study of the 2010-11 season in the Portuguese Premier

League found that the amount of ball possession had a very weak negative correlation (r = -0.192) with the match result [12]. In a study analyzing elite leagues in Europe, researchers found that a significant difference in ball possession percentages between winning and losing teams only occurred in matches with wide result margins (3 or more goals). In the other, closely contested matches, the difference in possession between winning teams (51.48% with a SD of 13.05%) and losing teams (48.52% with a SD of 13.05%) was not statistically significant [9]. Similarly, researchers studying the World Cups of 2002, 2006 and 2010 found that ball possession was slightly higher for winning teams (51.6% with a SD of 6.8%) compared to those that drew (49.9% with a SD of 5.8%) or lost (48.5% with a SD of 6.8%), though the differences were not statistically significant [6]. In another study using data from five European leagues, UEFA, and FIFA tournaments, researchers found that possession time was a poor predictor of team success once team quality and home advantage were accounted for [7].

In basketball, intuition might lead one to believe that possession is less important due to the shot clock, which mandates a field goal attempt within 24 seconds in the NBA and most European leagues. Previous studies have shown a positive but insignificant correlation between longer possessions and success. Research on the Spanish Basketball Playoffs from the 2004-05 season investigated the possession durations of winning and losing teams against various defensive systems. They found that, when averaged across all defenses, winning teams had an average possession duration of 13.1 seconds with a SD of 6 seconds, compared to 12.32 seconds with a SD of 5.88 seconds for losing teams [13]. Although significant differences were observed depending on the defensive system faced, these differences did not translate into statistically significant overall differences in possession durations between winning and losing teams.

In American football, significant value is placed on time of possession, notably because it allows the defense to rest, enhancing both offensive and defensive performance. Time of possession refers to the amount of game time an NFL offense has the ball. Researchers studied the 2003-04, 2004-05, and 2005-06 NFL seasons and found that 67% of teams with greater time of possession than their opponents won their games [4]. However, the research recognized potential biases; leading teams often prolong their possessions near the end of the game to conserve their lead. To avoid this bias, the analysis was confined to first-half data. In this analysis, a logisitic regression model was applied to predict the halftime score. The model revealed a negative coefficient for time of possession (β = -0.126), indicating that for each additional minute of possession in the first half, the log-odds of winning at halftime decrease by 0.126. This indicates that more possession, with biases removed, does not contribute positively to winning.

Hockey's analysis of puck possession has comparatively been less robust as it relies on manual tracking [17] or metrics approximating possession such as SAT% (Corsi) [20]. Some studies using manual tracking or SAT% (Corsi) have found a positive correlation between possession and team success. For instance, a study of 243 NHL overtime periods from 2015 to 2021 in which possessions were manually tracked revealed that victorious teams in 3-on-3 overtime generally have a higher count of individual possessions (53 percent of the total number of individual possessions of both teams), a higher duration of individual possession (54 percent of the total duration of individual possession of both teams), and more offensive zone time (57 percent of the total offensive zone time of both teams) compared to teams that lost [17]. Additionally, a study of the 2007-08, 2008-09, and 2009-10 NHL regular seasons revealed that SAT% (Corsi) Tied (even strength SAT% (Corsi) with the score tied) is more predictive of how well a team will perform (r = 0.47) than goal ratio (r = 0.35) or winning percentage (r = 0.34) [20]. This correlation is relatively low compared to our findings, where higher correlations emerge from utilizing PPT data to measure various metrics of puck possession, most notably for Average Offensive Zone Possession Time Differential (Avg. OZPTD).

Although previous hockey analytics research shows a positive correlation between possession and team success, there are challenges to manually tracking possession. As well, SAT% (Corsi) has its limitations, as it does not account for possession in the defensive or neutral zones and may not reflect the strategy of teams that prioritize high-quality shots over quantity.

In recent years, expected goal (xG) models have gained popularity. Originating in football (soccer), xG represents the probability that a scoring opportunity will result in a goal. It addresses some issues with SAT% (Corsi) as it includes weighting shot attempts based on quality, recognizing that certain shots have a higher probability of resulting in a goal. In hockey, efforts to evaluate shot quality began in 2004 [23] [14] [15]. This foundational work led to the first explicit mention of xG in hockey in a 2012 study, which used ordinary least squares (OLS) regression and ridge regression to predict goals, incorporating variables such as goals, shots, missed shots, blocked shots, faceoffs, hits, turnovers, and zone starts [18]. Since 2012, numerous xG models have emerged, each aiming to capture the best set of predictive variables, often including more than ten variables weighted during model training [8] [24] [26] [25]. These models generally outperform SAT% (Corsi) and other metrics in predictive accuracy [8] [25].

However, there are drawbacks to xG models. First, there are many different xG models, which can have varying parameters, potentially leading to inconsistencies when advising a team on how to improve their xG to win more games. Additionally, to our knowledge, there has been limited work on testing the stability of these models, meaning the parameters and weights might not remain consistent from one season to the next. Lastly, because these models have several parameters, determining the specific actions a team can take to improve their xG may not be straightforward.

In this paper, we utilize PPT data to conduct a detailed investigation into measures of puck possession and their correlation with NHL team success. Our findings indicate that a single metric of possession can be as effective, if not more so, than existing, publicly available xG models in predicting team success.

3 Background

3.1 Definitions of Individual and Team Puck Possession

Before we delve into the dataset and analysis, we define the concepts of individual and team puck possessions as utilized in our study.

According to the NHL definition for the model that produces the individual possession data we employ, a player is considered to have possession and control of the puck, and thus in individual possession, when they make two or more consecutive touches with the puck. The start of the individual possession is marked by the first touch, which is confirmed upon a second touch. Individual possessions also includes brief moments during one-touch actions, like shots, passes, or area plays (e.g., dump-ins). An individual possession ends when the player is separated from the puck or when another player gains possession. We delineate these episodes to identify windows of time with "no individual possession", representing segments of active gameplay where the puck is not under direct control by any player. This includes scenarios ranging from face-offs, puck battles, and loose pucks to passes, shots, and "area plays" (e.g., dump-ins and dump-outs). The top line in Figure 1 shows examples of individual possessions by members of different teams (red and blue lines) and "no possession" (orange dotted lines).

We define team puck possession as the aggregate of individual possessions with continuous possession by members of the same team, interrupted only by game stoppages or a change in possession to the opposing team. Consequently, "no team possession" intervals are distinct from "no individual possession" intervals. The bottom line in Figure 1 shows examples of team possession (red and blue lines) and "no team possession" (green dashed lines). As shown in the figure, team possessions end when the puck is last touched by one team, prior to the opposing team gaining possession. Our use of team possession differs slightly from the official NHL definition as the details required to implement the NHL's definition aren't available in the current dataset.

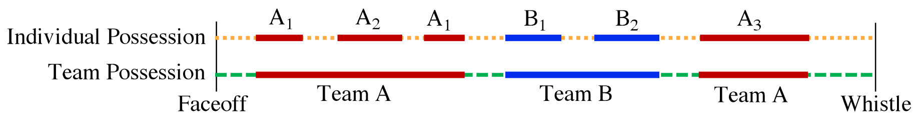

Fig. 1. Differentiating individual and team possessions

3.2 Dataset Overview

This paper utilizes the proprietary PPT dataset provided to us by the NHL. The PPT data, captured through devices in players' sweaters and the puck, records x, y, and z coordinates at high frequencies: 60 times per second for the puck and 12 times per second for each player on the ice. An additional update is provided once per second for players on the bench, resulting in around 734,400 location points in a typical 60-minute game. Due to the varied frequencies of data collection across players and the puck, and the lack of synchronization between devices, all player and puck positions are interpolated to uniform timestamps every hundredth of a second.

In March 2023, a significant advancement was made with the introduction of an individual player possession model into the "DISH" data stream, which features Delayed, Interpolated, Smoothed and Hundred-Hertz enhancements. This dataset is considered unofficial by the NHL and may differ from other datasets that track possession information (e.g., a hand-labeled dataset). Our study uses the DISH data to compute team possessions, which form the basis of our analysis. Since this data only became available in March 2023, the dataset for the 2022-2023 season is limited. Consequently, our analysis focuses on the 2023-2024 NHL season, using data from 780 games played up to January 31, 2024 (the All-Star break). After excluding games with significant data issues, as detailed in Section 4.3, or those with no tracking data, such as the Heritage Classic and the games played in Europe, 708 games remained for analysis.

4 Dataset Cleaning and Filtering

The player possession data provided in the NHL's DISH data stream, indicating who held the puck and for how long, lacks broader game context such as powerplay situations and player locations. To address this, we merge it with data from a detailed game information file, enriching player possessions with relevant game context, and then compute team possessions based on this integrated data. Through this process, we encounter challenges that necessitate extensive cleaning and preprocessing to ensure data integrity. Cleaning refers to the process of correcting or removing inaccuracies within the data that can be rectified, such as adjusting timestamps or eliminating duplicates. Conversely, filtering is our strategy for dealing with more complex issues that cannot be directly corrected; it involves the exclusion of entire games from our dataset.

4.1 Dataset Cleaning

Possessions Occurring During Stoppages: One issue with the data is that some possessions occur either entirely during stoppages or span active and stopped intervals. These erroneous possessions are identified after merging the player possession file with the game information file and computing active gameplay intervals. To resolve this issue, we eliminate portions of the possession that occurred during stoppages, ensuring accuracy in active play representation.

Abnormal Timestamps and Non-chronological Data Entries: The game information file contains updates every hundredth of a second, but some of these updates display additional digits of precision and are out of sequence. These extraneous updates, found to be non-essential, are removed to maintain dataset integrity. After their removal, the data is re-sequenced to reflect the actual gameplay order.

Clock Resets: Another issue encountered in the dataset are unexpected time jumps, with the time remaining on the scoreboard clock suddenly increasing, leading to duplicated timestamps. These time jumps primarily occur after video reviews where time is added back to the clock, such as when a play is subsequently ruled as offside. Smaller adjustments may also result from false face-offs or if the clock inadvertantly continues running briefly after a whistle. The NHL addresses these situations by eliminating all recorded statistics and events that transpired during the time that is later nullified. Our approach mirrors this; upon identification of such a clock reset, we disregard stats and possessions recorded during the time frame subject to the reset.

Overlapping and Duplicate Player Possessions: The last challenge rectified through cleaning is the presence of duplicate or overlapping possessions. Duplicates are resolved by retaining a single entry. For overlapping possessions, we evenly distribute the overlapping time (i.e., the period during which the data indicates two players simultaneously possess the puck) among the involved players.

4.2 Dataset Filtering

There are cases where the above cleaning methods are insufficient to repair the data and preserve the integrity of the dataset. Consequently, we establish exclusion criteria based on the severity of data corruption: if the data is compromised for either more than 4% of a game's duration or more than 4% of a team's possession time, we exclude the game from our analysis. This filtering process results in the exclusion of 68 games, leaving 91% of the games for which we have data available for use in our analysis. The distribution of team appearances in the excluded games varied, with an average of 4.5 games per team, a standard deviation of 2.2 games, a minimum of 1 game for the Tampa Bay Lightning (TBL), and a maximum of 11 games for the Vancouver Canucks (VAN), constituting 22.4% of their total games. In Section 6.1, we show that robust analysis can be achieved with just 20% of a team's games in our dataset, as the correlation between early game data and the rest of the season stabilizes after this. Table 1 shows the number and percentage of games impacted by each filter; note that the sum of games exceeds 67 and the sum of percentages exceeds 9% since 20 games were subject to more than one filter criterion.

Filter Criteria	Games Impacted	Percent Impacted
Irregular Possession Lengths	34	4.4%
Clock Gaps	30	3.8%
Irregular Period Lengths	26	3.3%
Possessions with Missing Data	5	0.6%
Excessive Distance Between Puck and Possessor	2	0.3%

Table 1. Impact of various filters on game dataset

Irregular Possession Lengths: Games are flagged for exclusion when the duration without any possession or the length of specific possessions significantly exceeds normal expectations. For total "no possession" time, we apply the statistical outlier definition of mean plus three standard deviations. Given the mean of 62.8% and the standard deviation of 4.8%, this led to the exclusion of any game exceeding 77.2%. Additionally, games with a no possession duration longer than 144 seconds, or any individual possession lasting more than 48 seconds, are excluded, impacting 4.4% of the total games. The limit of 144 seconds corresponds to 4% of a 60-minute game and 48 seconds represents 4% of the average of the per game sums of individual possession times (20 minutes).

Clock Gaps: We identify games with significant windows of time missing in scoreboard data timestamps, indicating lost data segments affecting puck locations, player locations, or possession details. We set a 144-second threshold for these gaps, equivalent to 4% of a 60-minute game. Games exceeding this limit due to missing data are excluded, affecting 3.8% of the dataset.

Irregular Period Lengths: We identify games with periods deviating significantly from the standard 20-minute length in order to filter games with extensive data loss or situations where our data cleaning techniques may be ineffective. We exclude games with periods exceeding or falling short of the expected duration by more than 48 seconds, equivalent to 4% of a 20-minute period, impacting 3.3% of the total games.

Possessions with Missing Data: Games are flagged when they contain missing player data, or missing possession start or end times. This is likely due to tracking failures in the puck or jerseys, or instances where a player does not have a tracking device in their jersey. Games with more than two instances of missing data related to possessions are removed from the dataset; impacting 0.6% of our games.

Excessive Distance Between the Puck and Possessor: We considered possessions where the distance between the puck and its possessor is too large. We focus on possessions where the puck is over 16 feet from the possessor continuously for more than 2 seconds, indicating potential data inaccuracies. Games with a total “excessive distance duration” exceeding 48 seconds, equivalent to 4% of a team’s average possession time of 20 minutes, are excluded, affecting 0.3% of the total games. In previous work, we adjusted the timestamps for events like shots and passes to try to more accurately capture the point of release [21]. We considered a similar approach in this work but the problem proved more difficult because we found instances where the distance between the puck and possessor is large in the middle of the possession. Adjusting such possessions would amount to building a new model, which is currently the domain of the NHL.

5 Analysis of Team Possessions

In this paper, we explore the relationship between team success and possession metrics, focusing on team possession percentage, aggregate individiual possession count differential, and offensive zone team possession time differential. Team success is measured primarily by goal differential because it is adaptable across game situations, unlike points per game, which is less flexible. Additionally, for the games in our dataset, average goal differential exhibits a strong correlation with average points per game (r = 0.95). Note that, unless stated otherwise, the analysis includes all strengths (i.e., even-strength and powerplays) and pertains exclusively to regulation time. This means that for our analysis, each team is awarded one point if a game goes to overtime.

5.1 Team Possession Percentage Versus Team Success

Team possession percentage is calculated by dividing the total duration of team A’s possession by the combined possession duration of team A and the opposing team. Team possession percentage is calculated for each team in every game and subsequently averaged across all games played. We compute the correlation between average team possession percentage and average goal differential (Avg. GoalDiff), as well as average goals for (Avg. GF) and average goals against (Avg. GA), aiming to delineate the correlations of possession with offensive and defensive metrics.

As shown in Table 2, average team possession percentage is moderately correlated with Avg. GF, suggesting that teams with higher possession tend to score more goals. In contrast, the correlation between average team possession percentage and Avg. GA is weaker, implying that while possession might play a role in limiting opposition goals, its effect is not as strong.

Possession Metric	Success Metric	*r*-value
Avg. Team Possession Percentage	Avg. GF	0.56
Avg. Team Possession Percentage	Avg. GA	-0.38
Avg. Team Possession Percentage	Avg. GoalDiff	0.56

Table 2. Correlations between average team possession percentage and team success metrics

Furthermore, our analysis reveals a nonlinear relationship among the correlations of average team possession percentage with Avg. GF, Avg. GA, and Avg. GoalDiff. Intuition might lead one to expect these correlations to sum linearly; for example, given the correlation between average team possession percentage and Avg. GF is +0.56, and between average team possession percentage and Avg. GA is -0.38, one might anticipate the correlation between average team possession percentage and Avg. GoalDiff to be the difference, equating to +0.94. This is not true and can be explained by understanding the correlation formula's normalization process. The Pearson correlation coefficient is:

$$r = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where $\text{cov}(X,Y)$ is the covariance between X and Y, and σ_X and σ_Y are the standard deviations of X and Y, respectively. The denominator normalizes the covariance by dividing it by the product of the standard deviations of X and Y, ensuring the correlation values fall within the range of -1 to +1. Given the distinct standard deviations for Avg. GF (0.44), Avg. GA (0.39), and Avg. GoalDiff (0.70), this normalization introduces nonlinearity to the relationships.

5.2 Possession Count Differential Versus Team Success

Shifting our analysis from the percentage of team possession to the aggregate quantity of individual possession instances can potentially offer new insights by capturing both the totality of possessions gained through turnovers or puck battles and the extent of puck movement within team possessions. To assess which teams excel in managing aggregate individual possession quantity, we introduce a metric called average possession count differential.

For team A, the possession count differential is defined as the count of team A's individual possessions, minus the count of the opposing team's individual possessions. We compute this metric for each game and subsequently determine the average across all games played by each team. Utilizing this metric reveals a slightly enhanced correlation with Avg. GoalDiff (r = 0.63) compared to the correlation between average team possession percentage and Avg. GoalDiff (r = 0.56). This improved correlation may indicate the potential impact of frequent and dynamic possession changes to outscoring opponents, suggesting a strategy centered on maximizing possession instances correlates positively with achieving a better goal differential.

5.3 Offensive Zone Possession Time Differential Versus Team Success

We now examine the significance of possession within the offensive zone. The rationale for this approach is that possessions in the defensive or neutral zones can serve to facilitate transitions, whereas offensive zone possessions might contribute more directly to scoring goals and outscoring the opponent. In this refined analysis, we introduce a new metric, Offensive Zone Possession Time Differential (OZPTD), which is defined as the sum of the duration of team A's individual possessions in the offensive zone, minus the sum of the duration of the opposing team's individual possessions in their offensive zone (team A's defensive zone). For possessions that span multiple zones, the duration is allocated proportionally based on the time spent in each zone. Similar to the previously examined metrics, OZPTD is computed for each game and subsequently averaged across all games played by each team.

As shown in Figure 2, our analysis reveals a significant positive correlation of 0.77 between Avg. OZPTD and Avg. GoalDiff. This finding highlights the importance of not just possessing the puck more than the opponent, but doing so in the offensive zone where it more strongly correlates with outscoring the opponent. Teams such as the Colorado Avalanche (COL) and Florida Panthers (FLA) who, on average, maintain offensive zone possession longer than their opponents, typically see positive goal differentials. Interestingly, the Winnipeg Jets (WPG), Boston Bruins (BOS) and Vancouver Canucks (VAN) achieved the highest Avg. GoalDiff values despite having values of Avg. OZPTD near the league average of 0. In contrast, the San Jose Sharks (SJS) and Chicago Blackhawks (CHI) exhibit negative Avg. OZPTD values and, correspondingly, negative Avg. GoalDiff values. Recognizing that SJS and CHI may contribute significantly to the strong correlation, we compute the correlation coefficient without those two teams and observe an r-value of 0.63. In future work we plan to examine if offensive zone possession counts and differential are also correlated with success.

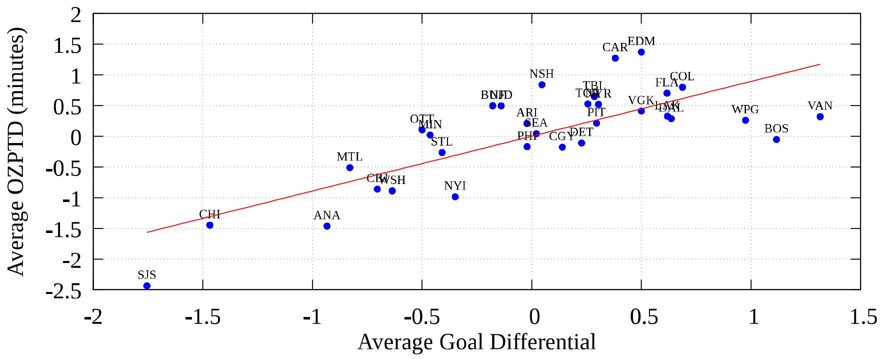

Fig. 2. Avg. OZPTD versus Avg. GoalDiff (r = 0.77)

As Avg. GoalDiff is highly correlated (r = 0.95) with average points per game for the games in our dataset, Figure 2, which arranges teams from left to right based on Avg. GoalDiff, provides a useful reference for readers to assess team standings, offering a more accurate perspective than actual standings that include games outside our analysis.

Recognizing the significance of the correlation, we conduct a deeper examination of its components, focusing exclusively on even-strength play. The correlation remains high at 0.73, indicating that the initial correlation is not simply a byproduct of power plays but is also prevalent during even-strength play, reinforcing the importance of offensive zone control throughout the game.

Given Avg. OZPTD's strong correlation with Avg. GoalDiff, we also analyzed it on a per-game basis, as depicted in Figure 3. This per-game analysis shows an r-value of 0.00, indicating no correlation. This finding suggests that, despite the correlation between Avg. OZPTD and Avg. GoalDiff across many games, individual games show high variability. Thus, while superior offensive zone possession doesn't guarantee game victories, teams with consistently higher offensive zone time may outscore their opponents over the course of a season.

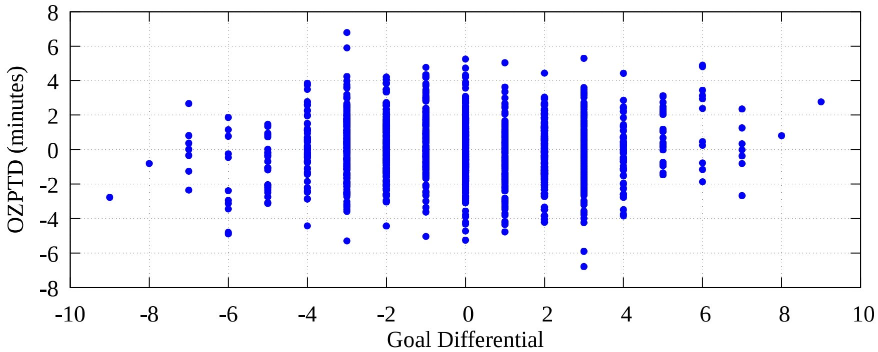

Fig. 3. OZPTD versus GoalDiff for all games (r = 0.00)

5.4 Possession Across Different Strengths

Building on our earlier findings, this section delves deeper into possession metrics across different strength scenarios, as shown in Figure 4. We observe that at even strength, possession is typically balanced between teams. However, with a plus-1 strength advantage, teams dominate possession. In contrast, a minus-1 strength differential leads to a substantial decrease in possession percentage for the disadvantaged team.

The variance in average team possession percentages is notably higher in even strength scenarios than in situations of plus-1 or minus-1. Specifically, the Chicago Blackhawks (CHI) and San Jose Sharks (SJS) show lower possession percentages at even strength, yet they are near the league average in plus-1 and minus-1 situations.

6 Meta Metrics: Evaluating Average OZPTD

Due to Avg. OZPTD's significant correlation with Avg. GoalDiff, and thus its potential to offer insights, it is imperative to evaluate this new metric. We utilize the notions introduced by Franks et al. [11], which emphasizes three key properties: stability, discrimination, and independence. While some of our tests of these properties differ slightly from those suggested in their paper, we maintain the spirit of each property. Stability measures the consistency of a metric across seasons or portions of a season (e.g., the

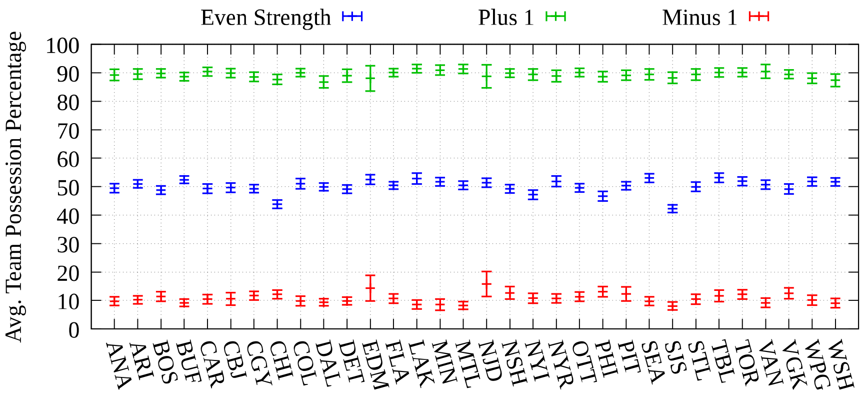

Fig. 4. Average team possession percentage: even strength, +1 and -1 (95% confidence intervals)

value of using the metrics in predictions), discrimination measures its ability to distinguish between players or teams, and independence assesses whether it provides unique insights when compared with existing metrics.

6.1 Stability

To assess the stability of Avg. OZPTD and determine its potential for predictive use, we calculate Avg. OZPTD separately for the first and second halves of the dataset. The observed strong correlation (r = 0.84) between Avg. OZPTD in the two halves, depicted in Figure 5, validates the metric's consistency. To further our understanding of the metric's stability, we conduct a rolling correlation analysis where the Avg. OZPTD is calculated for each team across incremental segments of the dataset, ranging from 5% to 50% and then these values are compared with Avg. OZPTD for the remaining games. The correlation starts at 0.68 when using the first 5% of the games to predict the Avg. OZPTD of the remaining 95% of the games and stabilizes above 0.80 when using the first 20% of the games to predict the remaining 80% of the games.

Predictive Power: To evaluate the predictive accuracy of Avg. OZPTD, we divided our dataset into two halves. Using data from the first half of our dataset, we built a linear regression model to establish the relationship between Avg. OZPTD and Avg. GoalDiff. We then tested this model with data from the second half of our dataset, using measured Avg. OZPTD to predict Avg. GoalDiff for each team. Our predictions were compared to the actual outcomes, resulting in an R^2 value of 0.49, and a correlation coefficient of 0.73. This correlation indicates a relatively strong correlation between the predicted and actual values.

To compare results obtained when using other metrics for predicting team success, we find that the 2012 study by Macdonald yield a correlation between actual and predicted goals of 0.69 using his ridge regression model [18]. Next, we found that a 2022 study, described on the Hockey-Statistics website [25], that reports that using their xG model and the xG model from Evolving-Hockey [1] to predict the expected goals for

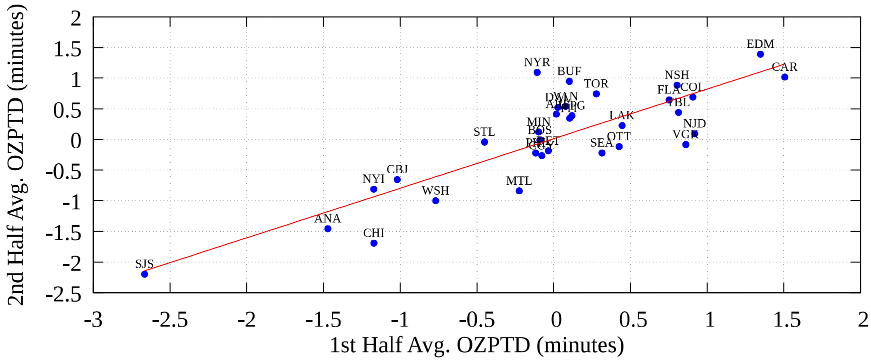

Fig. 5. Average OZPTD across dataset halves (r = 0.84)

percentage (xGF%) yielded an R^2 value of 0.49 in both cases. This prediction was based on the xGF% from the first 41 games of a season for each team to forecast the xGF% for the last 41 games. Note that xGF% is the ratio of a team's expected goals for compared to their opposition. Another study from 2015 considers a different expected goals model, and found that when using their model built using the first 40 games to predict GF for each team at the end of the season, they obtained an R^2 value of 0.51 [8].

While a more in-depth evaluation needs to be done using larger sample sizes with a direct comparison between metrics, this preliminary investigation indicates that our fairly simple Avg. OZPTD metric performs on par with existing, relatively complex models (because they typically use a large number of parameters that appear to require tuning) for predicting team success.

6.2 Discrimination

Our evaluation of Avg. OZPTD's discriminatory power, depicted in Figure 6, shows the Avg. OZPTD for each team, including 95% confidence intervals. There are statistically significant differences between some teams, however the overlap in confidence intervals for many teams indicates that the metric might have moderate discriminatory power.

6.3 Independence

In assessing the independence of Avg. OZPTD, we revisit SAT% (Corsi) and expected goals (xG). SAT% (Corsi) has traditionally been used to approximate possession by measuring the ratio of a team's shot attempts (goals, shots on net, shots that miss the net, and blocked shots) to the total shot attempts in the game. xG models attempt to improve on the predictive power of SAT% (Corsi) by including several variables related to the shot to better describe the context around the shot. To analyze the independence of Avg. OZPTD from these two metrics, we show the correlation between them, as well as each metric's correlation with team success (Avg. GoalDiff) as shown in Table 3. Note that the data used for the xGF% model is from Natural Stat Trick [2].

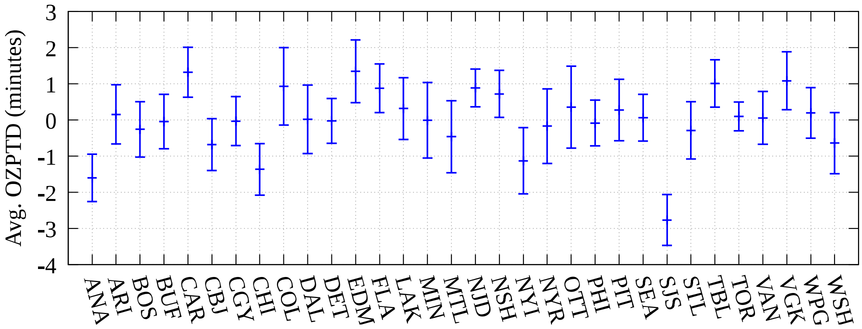

Fig. 6. Average team OZPTD, with 95% confidence intervals

The results indicate that Avg. OZPTD is strongly correlated to SAT% (Corsi) but shows a stronger correlation to Avg. GoalDiff compared to the correlation between SAT% (Corsi) and Avg. GoalDiff. This stronger correlation for Avg. OZPTD implies it provides additional insights beyond SAT% (Corsi), especially in relation to game outcomes. The results also indicate that Avg. OZPTD is strongly correlated to xGF%, with both metrics having the same correlation to Avg. GoalDiff. However, as mentioned previously, there are potential drawbacks to xG models, such as possible inconsistencies in parameters across different models and the complexity of determining specific actions to improve xG.

Metric	**Correlation with Avg. OZPTD**	**Correlation with Avg. GoalDiff**
Avg. OZPTD	1.00	0.77
SAT% (Corsi)	0.83	0.62
xGF%	0.88	0.77

Table 3. Correlation of Metrics with Avg. OZPTD and Avg. GoalDiff

In terms of evaluating established metrics, the work by Franks et al. [11] does evaluate some NHL metrics for individual players but does not include team metrics. As described in Section 6.1, some previous studies have examined the predictive power of various expected goal (xG) models. However, there is a lack of work in evaluating those metrics in terms of stability, discrimination and independence. In the future, we hope to evaluate established team performance metrics alongside our metrics.

7 Conclusions

In this paper we examine team possession metrics and whether they correlate with team success. Interestingly, we find that average team possession percentages are only weakly correlated with team success metrics like, average goals for ($r = 0.56$) and average goal differential (also $r = 0.56$). We introduce a new metric called the average offensive zone possession time differential (Avg. OZPTD) which measures the difference between the time that team A has possession of the puck while in their offensive zone and the time that the opposing team has possession of the puck while in their offensive zone (i.e., team A's defensive zone). We find that there is a strong correlation between Avg. OZPTD and Avg. GoalDiff (r = 0.77). Furthermore, we show Avg. OZPTD to be stable, capable of discriminating between teams, and providing new information over other metrics like SAT% (Corsi). The strong correlation and these attributes underscore its potential to provide deeper insights into team success.

The existence of the NHL's possession data paves the way for more detailed and exciting analysis. With our methodology for preparing, cleaning, and filtering possession data, we are poised to further investigate possessions in future work. On the team-level, it would be interesting to determine if time spent in the offensive zone correlates with team success or if puck possession is a key component. We would also like to examine chains (or sequences) of individual possessions. Metrics of interest would be the length of the chain and the number of different players in the chain. We would also like to study individual player possessions and correlations with player and team success.

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