Relating NHL Shift Times with Scoring Rates

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Abstract

Optimizing substitution strategy in hockey can be a key to utilizing players efficiently and improving overall team performance. Statisticians have published plenty of research analyzing hockey using a Poisson process to analyze team success, but they have not analyzed how a team's substitutions could be related to their success. This study investigates the relationship between NHL teams' average shift time with their scoring and defensive rates at different manpower levels. We created an algorithm that parses through NHL shift charts to calculate the number of players on the ice at any moment in any game during the season in order to calculate the average shift time for each team at each manpower. The average shift times are then compared with the team's scoring and defensive rates using Poisson regression. Our analysis found that in multiple manpower scenarios, how often teams scored or allowed goals was strongly associated with how long their players were on the ice. With these findings, NHL organizations can adjust their substitution strategies accordingly in order to improve their goal differential over the course of a season. As well, our model can be expanded upon in further studies to better understand the relationship between substitutions and team performance.

Keywords: Hockey, Poisson Regression, Substitution, Analytics

Introduction

How long is too long? This is a question that hockey coaches, players, and fans have been asking about shifts since the game's inception. A "shift" in hockey is the period of time when a player is on the ice and active in the game, and the length of a shift is critical to a team's strategy due to the fast-paced nature of the game, and the fact that substitutions occur without a stoppage of play. In recent years, as NHL franchises have begun to expand their use of analytics, shifts have gotten shorter to increase puck possession and save the energy of their players over the course of a game and the season. However, not all shifts are created equal. It is important to analyze the context of shifts, to see if shorter shifts may be more conducive for preventing goals or scoring goals depending on how many skaters are on the ice. With this information, in-game player management strategy can improve for teams to cycle through their shifts depending on whether they are trying to focus on scoring or defending, and the game's current manpower situation, and improve the performance of hockey prediction models.

A lot of research has been conducted about modeling hockey games and season performance using Poisson processes, due to goals being counted over time as a rate, that results with the team with the higher Poisson random variable (number of goals scored) winning the game. Buttrey et. al. (2011) analyzed the 2008-2009 season with a Poisson process to develop a model to predict teams' performance over the course of a season using their offensive and defensive scoring rates, home ice advantage and manpower situations. This project uses Buttrey et. al. as its groundwork and attempts to expand their findings to find more specific variables, specifically skaters' average shift time that may have a more specific impact on a team's performance within a game. With this it was found that at certain strengths, when viewing goals as a Poisson random variable, teams' average shift time had an association with their scoring rates or defensive rates during the 2019-2020 NHL regular season.

Using Poisson random variables to represent goals to analyze NHL performance dates back to the 1970's (Mullet, 1977), where general models were very similar to Buttrey et. al., but not quite as advanced in terms of factoring in specific in-game variables, or using the specific team's schedule for prediction. Though this model was very general, it provided the framework and theory behind general NHL prediction models, especially with such limited technological availability of that time for processing large amounts of data.

As well, similar research in Poisson model prediction has been done in different goal-scoring sports, specifically soccer, which has provided the means to improve the results of hockey models (Everson and Goldsmith-Pinkham, 2008). Generally, hockey and soccer are both low scoring, which makes each goal important in determining the outcome of a game. This makes it more difficult to analyze and find relationships between scoring rates, as opposed to higher scoring sports like basketball or American football. With the saturation of soccer in sports research in Europe, more complex models have been developed to predict team's performance over the course of their seasons, including analyzing games with more complex bivariate Poisson distributions (Marek et al., 2014). The complexity of soccer Poisson models with many soccer specific variables, such as team formations, provides insight that though Poisson hockey models have been used for decades, they can still be developed further by looking at specific attributes of the game.

Thomas (2007) looks more in depth into the context of when goals are scored in NHL games, specifically at the score and time remaining scenario of goals, while analyzing them separately at different manpower strengths. This research focused on modeling the events within a game rather than the performance of a team in a season, and shows that goals may not be as randomly scored over the course of a game, as it may be assumed in many NHL Poisson models. With this research in mind, it is important to look at specific aspects and trends within NHL games to accurately create models for teams to improve their in game strategies.

With so much importance in today's NHL stressed upon the power play, in order to improve predictive hockey models it is important to not just include the manpower situation within the game, but the underlying trends that influence the effectiveness of a power play. A team enters a 'power play' when its opposition commits a penalty where the penalized player must leave the game for a certain amount of time without substitution, which forces the penalized team to play with less players during that time. Little public research has been done analyzing what makes NHL power plays (along with penalty kills) effective, or about how a team's average skater shift time affects performance. Therefore, the following sections of the paper will analyze how shift length tendencies are associated with NHL scoring rates at different manpower strengths.

Methodology

Gathering Data

The necessary data was gathered to compute the amount of time that each team played at each manpower situation during the course of the 2019-2020 regular season. This season was suspended on March 12th, 2020 due to the COVID-19 pandemic with teams playing in between 68 and 71 games, as opposed to the scheduled 82 games, so the representative data only comprised these regular season games.

The shift data was gathered from the NHL API's shift charts for each game, which can be found at the website:

https://api.nhle.com/stats/rest/en/shiftcharts?cayenneExp=gameId=2019020001

The 'gameId' portion of the link represents the Game ID that the NHL applies to each game, where the first 4 digits represent the year that the season started in, the next 2 represent the category of game that season (02 represents regular season), and the last 4 digits represent the number of chronological regular season game of the season. The shift charts include information for when each player on the ice started and ended their shift over the course of a game.

Each game's shift data was read from the API and processed using R software (R Core Team, 2019). All of the code and data files used for this project can be found in a Github repository located at: https://github.com/SamGasell/NHL-Shift-Project. From there, for each second a player entered or exited the ice and the number of players on the ice for each team was calculated, as well as a running total for how long the certain manpower situation in the game had been maintained. Then the amount of game time, total shift time by the players, and number of shifts for each manpower situation for each team were summed up for each game. Shifts were assigned to a certain strength based on when they began. Since the shift charts do not account for a player's position, in order to avoid the goalie's lengthy shifts skewing data, all shifts less than 5 minutes were not included in the game sums. As well, the manpower situations recorded were 6 players on the first team vs. 6 players on the second team, 5 vs. 5, 4 vs. 4, 6 vs. 5, 5 vs. 4, 6 vs. 4, 5 vs. 6, 4 vs. 5, and 4 vs. 6. It is typical for these strengths to be referred to excluding the goalie (i.e. 5 vs. 5 would be full strength for both teams), but since the shift charts do not specify a player's position, this research gathered the total number of players on the ice for each team. These data points were gathered for each game, organized for each team, and the average shift time for each team at each strength was computed, obtained by dividing the total shift time by the total number of shifts at that strength.

To ensure that the algorithm to compute the number of players on ice for each team was working correctly, 5 games from the 2019-2020 season were haphazardly selected to manually compare the algorithm's output to the actual number of players on the ice for each team in a game. Official NHL play-by-play reports were used in comparison to the algorithm, found here , where the last number in the link represents the Game ID, which is the same one used in the shift chart link. The play-by-play reports include penalties and their length, which dictate when a team will have less players on the ice, and for how long. After analyzing all 5 of the randomly selected games, there were 26 seconds of time in which the algorithm's output did not match that of the play-by-play's number of players on the ice. This amounted to only 26 seconds of error in 18,327 seconds of game time, 0.142% of the time. When analyzing the error, the moments of error occurred because the shift of the player coming onto the ice would be slightly delayed in comparison to the player they were replacing on the shift chart. With so little error, and the error due to the shift reports, we concluded that the algorithm and its shift time calculations are reliable.

The NHL also collects data for the number of goals that each team allowed and scored at each strength during a season, the data for the 2019-2020 can be found here for Goals Against by Strength, and: here for Goals for by Strength. The NHL records this data based on the number of skaters (non-goalies) on the ice, not total players as our research used, so a player (the goalie) will be added to each team for the strengths represented in this data to align with the research's shift data. This results in the 5 vs. 5 goals for or against representing 6 players vs. 6 players, and so on. The goals for or against by strength data also includes sections when a team has 6 skaters, meaning a skater substituted into the game for a goalie, but this research does not analyze that event, because the shift data cannot decipher this scenario from when a team has 5 skaters and 1 goalie. The goals for or against by strength data is paired with the regular season's total shift data to compute the scoring rates for each team at each strength, dividing the number of goals by the amount of time at each strength. The gathering data process is visualized in a flow chart format in Figure 1.

Model

As described in the introduction, there is a well documented and successful history of modeling scoring in hockey as a Poisson random variable, as it represents the counting of events. It is of interest in this project to see if there is an association with the average shift time of a team and their offensive and defensive scoring rates, and how that may vary at different strengths. Based on this information, a team could adjust the average shift time of their skaters in order to improve their offense or defense at certain strengths. With the distribution of the response variable in mind, it is logical to perform a Poisson regression on goals for or against a team. With different teams varying the amount of time they spend at different strengths, and with a varying number of games played due to a COVID shortened season, it is paramount to offset the goals scored response variable by the logarithm of the time the team spent at that strength. This offset is set in order to correspond to the exponential nature of Poisson regression, so the logarithm of the goal rates can be interpreted linearly with respect to the average shift time. This prompts us to analyze the goals scored data as a rate.

Therefore, let μ_{ijk} represent the mean number of goals for or against ($k = F, A$), for the i^{th} team at the j^{th} manpower situation. Let t_{ij} be the total time the i^{th} team spent at the j^{th} situation measured in 60 minute intervals. Let x_{ij} represent the average shift time for the i^{th} team at the j^{th} manpower, and β_0 be the intercept and β_1 be the regression coefficient for x_{ij}. Then the general Poisson regression model for average number of goals scored in a season will be $\mu_{ijk} = t_{ij} e^{\beta_0 + \beta_1 x_{ij}}$, so $\frac{\mu_{ijk}}{t_{ij}}$ represents goals scored or allowed per 60 minutes during the season.

After analyzing the number of shifts, total game time, and total shift time for each team at certain strengths it was evident that situations when one team had 5 players on the ice and the other only had 4 were fairly rare over the whole season. In fact, some teams had as little as 2 shifts that started in 5-on-4 conditions. With this in mind, these situations were combined with their 6-on-5 and 5-on-6 counterparts to analyze situations when a team had a 1 skater advantage or deficit. This is a reasonable assumption to make given the small amount of 5-on-4 and 4-on-5 shifts, and the similar on-ice strategy will be used between those conditions, and 6-on-5 and 5-on-6 conditions, respectively.

The Poisson regression model was then applied to each manpower category for both goals for and goals against, using R software, and the glm() function, with “family = ‘poisson’”, the goals for or against at that strength as the response, the logarithm of the game time spent at that strength as the offset, and the average shift time at the strength as the predictor. As well, scatter plots were created for each model to visually represent the linear representation (or lack thereof) between the average shift time and the logarithm of the scoring rate, with a line of best fit, if there was a goal rate of zero in that category for a team, those teams were not included in the line of best fit calculation. The results of each model will be displayed, and discussed in the following section.

Results

Under this model, each coefficient β_1 can be interpreted as for each increase in average shift time by 1 second is associated with an increase of β_1 in the logarithm of the scoring rate at the specified manpower. For goals scored, a positive coefficient reflects that for longer average shifts, the goals scored at a higher rate on average, and a negative coefficient is associated with goals scored at a higher rate on average for shorter average shifts. Conversely, for goals allowed, a positive coefficient represents less goals allowed on average for longer average shifts, and a negative coefficient is associated with less goals allowed on average for shorter average shifts. Tables 1 and 2 present the Poisson regression coefficients and significance of each of those coefficients. Each coefficient was generated in a separate Poisson regression model at each strength to model either scoring rates or defensive rates. We determine the significance of the coefficients using the p-value generated by the model. These p-values represent the probability of observing a coefficient as extreme or more extreme than what was observed, if there is truly no effect. Strengths with an average shift time significance level of less than 0.1 are highlighted, and visuals are provided in the form of scatter plots with regression lines in Figures 2-5.

Goals Scored		
Strength	Coefficient for Average Shift Time	Significance of Average Shift Time (p-value)
6-on-6	0.019388	0.0205
5-on-5	0.009549	0.773
4-on-4	0.005614	0.784
1 Up	0.01259	0.209
6-on-4	0.02610	0.235
1 Down	-0.07467	0.026041
4-on-6	-0.1311	0.370

Table 1: Output of Poisson glm() regression model for goals scored with coefficients for average shift time for each manpower situation, and their significance level, with significance level < .1 highlighted.

Goals Allowed		
Strength	Coefficient for Average Shift Time	Significance of Average Shift Time (p-value)
6-on-6	0.005113	0.541
5-on-5	-0.02164	0.515363
4-on-4	0.005862	0.774
1 Up	0.05466	0.0145
6-on-4	0.11108	0.149370
1 Down	-0.007043	0.628
4-on-6	-0.07452	0.0214

Table 2: Output of Poisson glm() regression model for goals allowed with coefficients for average shift time for each manpower situation, and their significance level, with significance level < .1 highlighted.

These β_1 coefficients can be interpreted as the associated increase in the goals per 60 minutes by a factor of e^{β_1} for that team for an increase of one second in average shift time, at a certain manpower. For goal scoring, in 6-on-6 situations, longer shifts were associated with a higher scoring rate, a 1 second increase in average shift time is associated with an increase in the goals scored per 60 minutes by a factor of $e^{0.019388} = 1.0196$ on average. A similar but weaker relationship was found when a team was at a 1 or 2 player advantage. Conversely, when a team was at a 1 skater disadvantage, shorter shifts were related to a higher scoring rate, a 1 second decrease in average shift time is associated with an increase in the goals scored per 60 minutes by a factor of $e^{0.07467} = 1.0775$ on average.

On the other hand, when looking at goals allowed, shorter shifts were associated with less goals allowed when a team had a 1 player advantage, as a 1 second increase in average shift time was related with a increase in the rate of goals allowed per 60 minutes by a factor of $e^{0.05466} = 1.0562$. A similar but weaker relationship when a team had a 2 player advantage. Lastly, a team with a 2 player disadvantage, longer shifts were accompanied with less goals, as a 1 second decrease in average shift time corresponds to an increase by a factor of $e^{0.07452} = 1.0774$in the goals allowed rate per 60 minutes of game time.

Discussion

Overall, this model was able to find that in some manpower situations, there are relationships between player shift time and scoring/defensive rates. Depending on the in-game situation, teams can apply strategy to adjust how long their skaters are staying on the ice to improve their chance of scoring, or stopping their opponent from scoring. As well, if the appropriate strategy is optimized over the course of a season, teams can improve their overall performance, increase their goal differential over time, and ultimately win more games.

What could be the most impactful finding is that when both teams have all of their skaters on the ice -- a 6-on-6 situation -- longer shifts were associated with higher scoring rates. It could be hypothesized that this association could be due to more cohesion of the offense during longer shifts, resulting in more time in the offensive zone, and potentially leading to more goals. However, it would take a more in-depth analysis of these shifts to confirm a true reason behind this correlation. The majority of game time is spent at this manpower, so optimizing shift time at this manpower could lead to many more goals over the course of a season. Being adherent to the data in these power play situations, as well as those with not quite as significant relationships can help teams optimize their advantage, or limit their disadvantage when there are an uneven number of players on the ice.

All of the other significant relationships were where the manpower situation in the game was not even. Specifically, when teams are looking to score goals, teams could look to shorten their shifts when they have one less player than their opponent. When trying to prevent goals, teams could look to shorten their shifts when they have one more player on the ice than their opponents, and lengthen their shifts when they are at a two player disadvantage.

As well, it is notable that in situations where teams were at uneven strengths, average shift time had the same effect on the goal rate regardless if there was a two player or one player difference between the teams. Though the strength in these relationships vary, it is encouraging to see that the effect of shift time on goal rates did not change in sign between one player difference and two player difference, showing that those relationships are consistent.

Though this study found some interesting trends, there is plenty of room for further analysis on hockey shifting strategies. Simply applying this model to data from different seasons to see if these trends are consistent would be impactful. Going forward, it would be interesting to factor in position into this model to see how shift length affects the performance of offensive players, defensive players, and even goalies over the course of a game. With this, we could analyze whether varying offensive player shift times, or defensive player shift times have a stronger relationship with scoring rates. In addition, factoring in position will allow one to see if there is any impact of pulling the goalie to come back in the game, and if shift time varies in that situation.

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