The Art of Penalty Killing

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Abstract

This report explores the dynamics of penalty killing at the NHL level. Using team data from the past three NHL seasons, the study aims to identify trends contributing to a successful penalty kill. Using parameters such as Shorthanded Goals Scored, and Skating Distance Penalty Killing as a high-level indicator for assertiveness, the analysis focuses on whether teams with an aggressive penalty kill find more success. The study reveals a positive correlation between the skating distance and PK%, but a surprising lack of correlation between shorthanded goals and penalty killing, or shorthanded goals and skating distance. This indicates that it is important for penalty killers not to over-extend themselves and that scoring shorthanded goals is not necessarily reflective of good penalty killing. The analysis also underscores the importance of solid defensive structure and good goaltending as evidenced by the emergence of Shots Against per Game Player (SA/GP) and Save % as strong predictors for a team's PK%. The study suggests that on top of good goaltending, having a unit that can kill penalties aggressively, without sacrificing defensive structure, will lead to the most success. The report ends with recommendations for future work, including incorporating additional parameters and conducting a deeper analysis of team-specific and player-specific tendencies and strategies.

Introduction

Special teams are a crucial part of the game of hockey. Whether it's capitalizing on the man advantage, or a momentum boost from a timely penalty kill, a team's special teams' success, or lack thereof, can have a major impact on the outcome of a game, and ultimately the season. During the 2023-2024 NHL season, all but 3 playoff teams ranked in the top half of the league in combined power play percentage (PP%) and penalty kill percentage (PK%). Looking more specifically at PK%, 11 of the 16 playoff-bound teams ranked in the top half of the league, and of the 5 remaining teams, only 1 made it past the first round.

But what separates the bad from the good, and the good from the great when it comes to playing short-handed? The analysis contained herein looks to identify underlying trends in a team's penalty-killing success, particularly when it comes to the "aggressiveness" of the penalty kill.

Data

The following parameters were collected for each NHL team from the last three NHL seasons:

- Penalty Kill (PK) %
- Save %
- Shorthanded Goals (SHG)
- Net Penalty Kill %
- Goals Against (GA)
- Power Play (PP) %
- Penalty Minutes (PIM)
- Goals Against per Game (GA/GP)
- Skating Distance Penalty Killing
- Shots Against per Game (SA/GP)

Additional fields such as 'Skating Distance Penalty Killing per PIM'[1] and 'PK% vs. Net PK% Difference' were derived from these values.

The data used in this report was retrieved from the official NHL website [1] and ESPN's website [2]. Missing values[2] in the data were collected from Yahoo Sports' website [3], known values were cross-referenced across the three sites to ensure consistency and accuracy of the data. The full set of data is accessible in the utah-summer-analytics-challeng Git repository.

Methodology and Analysis

To better understand and identify trends in the data, we calculate the mean, standard deviation, and variance. These values for some of the key parameters of interest are summarized in Figure 1 below.

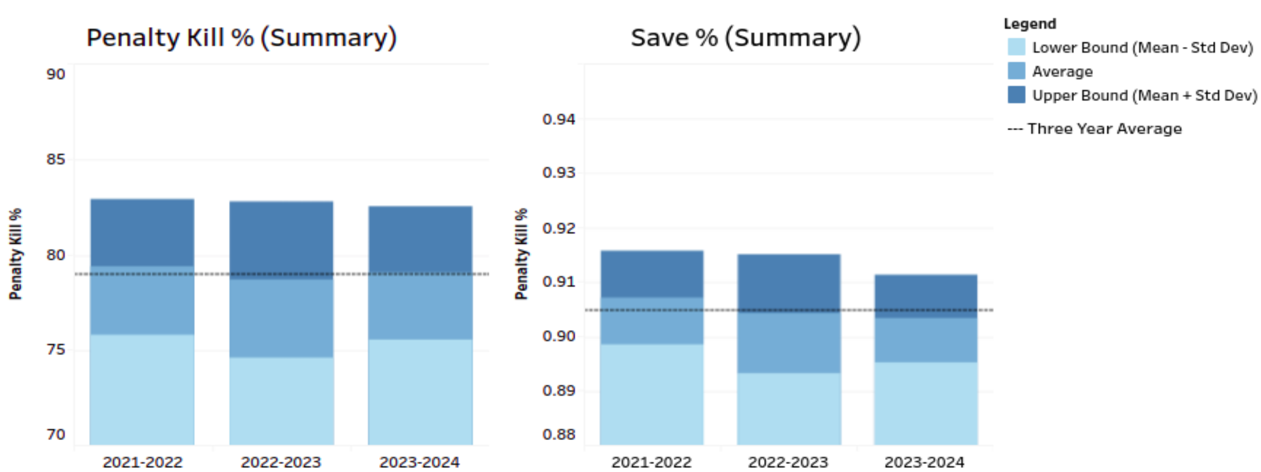
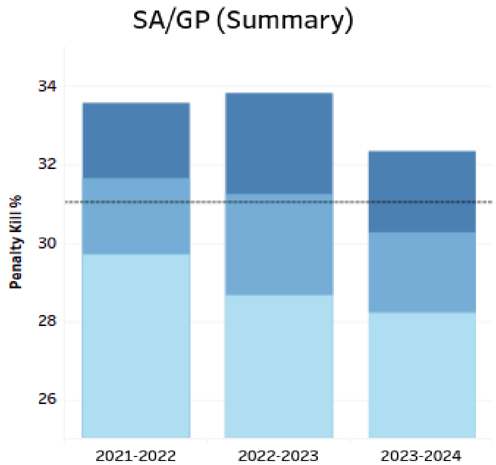
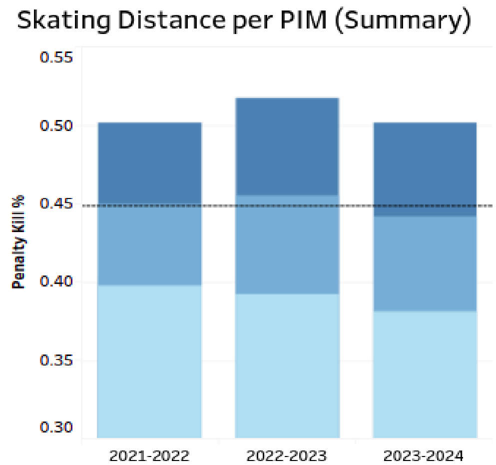


Figure 1 – Summary of key parameters (continued on next page).

[1] It is acknowledged that 'per Time Short Handed' would be a more accurate representation, but such data was not readily available.
[2] ESPN was missing values for the Arizona Coyotes (now Utah Hockey Club).





Additional visualizations are available in the Utah Hockey Club Summer Data Analytics Challenge Tableau dashboard.

A combination of correlation analysis and regression analysis was used to evaluate the impact of the various parameters on a team's Penalty Killing %.

The regression analysis was performed in Python making use of the *pandas*, *scikit-learn*, and *statsmodels* libraries. Multicollinearity[3] problems reduced the regression model to four predictors:

1. Save %
2. Skating Distance Penalty Killing (per PIM)
3. SA/GP
4. Power Play %

Highly correlated variables were identified by calculating the Variance Inflation Factors[4], parameters with a Variance Inflation Factor greater than 10 were removed from the model. Key values from the multiple regression analysis are summarized in Table 1 below.

Table 1 – Summary of multiple regression analysis.

Dataset	Metric	Value
Full	Adjusted R^2	0.476
	F-statistic	22.53
	P-value [F-statistic]	5.91e-13
	Save %	159.689 ($p < 0.001$)
	Skating Distance Penalty Killing (per PIM)	12.4481 ($p = 0.017$)
	SA/GP	-0.6226 ($p < 0.001$)

Simple regression analysis was also performed for each of the individual predictors in the model above. Key values from the simple regression analyses are highlighted in Table 2 below.

Table 2 – Summary of simple regression analysis performed on key parameters.

Predictor	Metric	Value
Save %	Adjusted R^2	0.252

[3] Multicollinearity occurs when independent variables in a model are highly correlated. This undermines the significance of the independent variables and results in less reliable statistical determinations.
[4] Variance Inflation Factors quantify the amount of multicollinearity in a regression analysis. Values greater than 10 indicate very high multicollinearity.

	F-statistic	32.95
	P-value [F-statistic]	1.15e-07
	Coefficient	201.5734 ($p < 0.001$)
Skating Distance Penalty Killing (per PIM)	Adjusted R^2	0.165
	F-statistic	19.79
	P-value [F-statistic]	2.37e-05
	Coefficient	26.5237 ($p < 0.001$)
SA/GP	Adjusted R^2	0.262
	F-statistic	34.76
	P-value [F-statistic]	5.81e-08
	Coefficient	-0.8500 ($p < 0.001$)

The full Python notebooks of the regression analysis are available in the utah-summer-analytics-challeng Git repository.

The correlation analysis was done within Microsoft Excel, making use of the built-in CORREL function and a custom formula sheet to calculate the Pearson and Spearman Rank Correlation Coefficients respectively. The results of the correlation analysis are summarized in Table 3 and Figure 2 below.

Table 3 – Summary of correlation values between key parameters.

Correlation	Pearson	Spearman
Save % vs. PK%	0.5095	0.5094
Skating Distance (per PIM) vs. PK%	0.4170	0.3738
SHG vs. PK%	0.1004	0.1654
SA/GP vs. PK%	-0.5196	-0.4937
SHG vs. Skating Distance (per PIM)	0.2115	0.2031

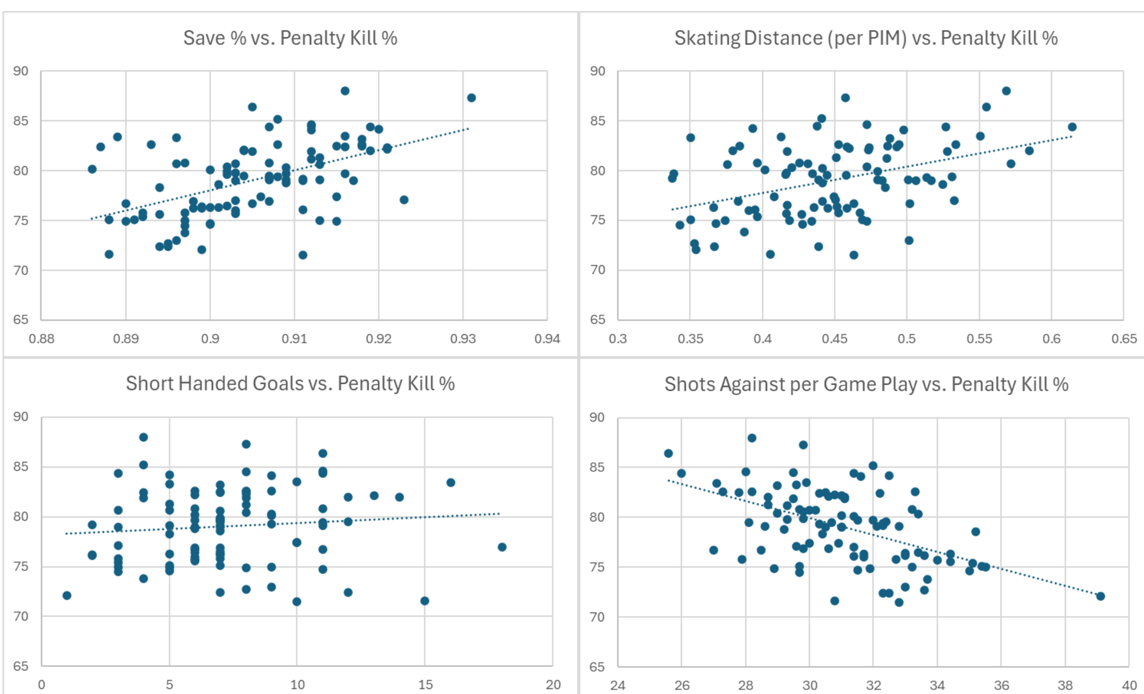


Figure 2 – Scatter plots for key values produced during the correlation analysis.

Results and Discussion

While not significant enough to make any definite conclusions, the results of the regression and correlation analysis do point to a positive correlation between Skating Distance Penalty Killing and PK%. Assuming skating distance can be used as an indicator of a team's tenacity on the penalty kill, this suggests that teams that are more aggressive on the penalty kill will have more success.

The analysis also revealed Save % and SA/GP as slightly stronger predictors for a team's penalty-killing success. The positive relationship between Save % and PK% re-enforces the famous Dave Allison quote "Your best penalty killer is your goalie". Meanwhile, the negative coefficient (regression analysis) and correlation between SA/GP and PK% suggest that teams with better defensive structure and who are more adept at getting in shooting lanes (thus allowing fewer shots against) are more proficient on the penalty kill.

Finally, the analysis revealed some interesting discoveries such as the weak correlation between PK% vs. SHG, and SHG vs. Skating Distance Penalty Killing (per PIM). It is noted that the data does not consider a team's ability to capitalize while shorthanded (i.e., Expected goals or shooting percentage), regardless, the results do contradict initial predictions of a stronger penalty kill, or even a more aggressive penalty kill[5], would lead to more shorthanded goals.

While the study would benefit from a more in-depth analysis, see Next Steps and Recommendations, the data points to a structured yet aggressive penalty-killing unit in front of a reliable goalie, to increase the odds of escaping the penalty unscathed.

Next Steps and Recommendations

Several key areas of the analysis warrant additional investigation. First, additional variables such as time shorthanded, shots against/penalty kill, and pressure metrics (such as forced turnovers or disruptions) could be used to better model aggressiveness and provide deeper insights into penalty-killing success.

Second, a deeper analysis of individual teams to discover any trends or patterns as a team's penalty-killing % fluctuates year over year. Some inferences can already be made from the Utah Hockey Club Summer Data Analytics Challenge dashboard, such as Linus Ullmark's Vezina winning season propelling Boston to the league's best penalty kill in 2022-2023, or Anaheim allowing nearly 6 more shots per game to coincide with a near 9% drop in their penalty kill from the 2021-2022 to the 2022-2023 season.

Finally, data concerning power play and penalty-killing lineups and strategies would further enhance the analysis. Potentially identifying what penalty-killing structure (e.g., box vs. diamond) works best against which power play structure (e.g., 1-3-1 vs. umbrella), or even the success of lineups or players based on their position on the ice and the handedness of their shot.

References

[1] NHL, "Team Stats," NHL.com. [Online]. Available: https://www.nhl.com/stats/teams. [Accessed: 16-Aug-2024].

[2] ESPN, "NHL Player Stat Leaders," ESPN. [Online]. Available: https://www.espn.com/nhl/stats. [Accessed: 16-Aug-2024].

[3] Yahoo Sports, "NHL Stats & Leaders," Yahoo Sports. [Online]. Available: https://sports.yahoo.com/nhl/stats/. [Accessed: 16-Aug-2024].

[5] It is acknowledged that Skating Distance is not the sole indicator of aggressiveness on the penalty kill.