Defensive Efficiency Metrics (DEMs): A Paradigm Shift in Defensive Hockey Analysis Based on Per-Possession Measurements.

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1 Introduction

As the age-old adage goes, '*Defense Wins Championships'*. Team defense in all sports, especially hockey, is critical for team success. With and the pace of play being faster than ever before,[1] effective team defense is more important than ever sustained team success.[2]

However, quantitatively evaluating team defensive performance in hockey has proven to be challenging.[3] Existing metrics – such as Goals Against, Corsi Against, and Score-Adjusted Corsi Against – are based solely possession outcomes (i.e., scoring chances or goals) and thus are not accurate predictors of future defensive success.[4] Chris Baker and Stephen Shea, in research for their book '*Hockey Analytics: A Game-Changing Perspective'* (2017), prove that goals and Corsi from the first half of a season are poor predictors of goals against in the second half of a season.[4] Metrics like xG% or High Danger Chances may be decent proxies for offensive evaluation, but they prove to be poor proxies for defensive performance.[5]

Given how integral team defensive performance is to team success, the question is how can assessment of team defensive performance be improved?

The answer, as we demonstrate, is a paradigm shift in the way defensive performance is evaluated. Drawing inspiration from '*Possession Sketches: Mapping NBA Possessions'* (Bornn and Miller, 2017)[6], we leverage event data to create more robust and accurate defensive evaluation metrics by analyzing team efficiencies (a) preventing and (b) defending dangerous types of possessions. This methodology considers all possessions, not just those with a goal or scoring chance. We also explore the concept of per-possession efficiency and how it can be a valuable tool for analyzing team (and eventually player) performance in hockey, as is the case in basketball (NBA)[7] and soccer (Premier League)[8]. Our goal was to create a framework for team defensive performance evaluation using metrics that are (a) a measure of process, and (b) a reliable and accurate predictor of future defensive performance. In this report, we will:

1. Use logistic regression and decision tree models to identify the most impactful events (or sequences of events) that result in a goal or scoring chance.
2. Introduce and test a set of metrics (**Defensive Efficiency Metrics)** to analyze a team's ability to prevent and defend these events on a per-possession-basis.
3. Compare Defensive Efficiency Metrics to current conventional metrics, such as Expected Goals, High Danger Chances Against, and Corsi, as a means of evaluating team defensive performance

2 Team Defensive Efficiency Per-Possession and the TCP Model

In "Hockey Analytics: A Game-Changing Perspective" (Baker & Shea, 2017), Baker and Shea advocate for evaluation of defensive performance by examining efficiency of preventing defensive mistakes on a *per-possession basis*, rather than just metrics that rely on play outcomes (like chances and shot attempts)[5]. Given that there may be only a handful of scoring chances in a certain game, compared to hundreds of possessions for both teams, using possessions as the unit of analysis provides for more observations, and thus much more data, which in turn can be used to create metrics models that are much more accurate and possess much greater predictive power.

Research by Baker and Shea also demonstrated that approximately 75% of goals scored in the NHL occur as a result of three types of defensive mistakes: (1) Odd-Man Rush, (2) Clear-Path Mistakes – when an offensive player is left open in front of the net or in the slot while their team has possession, and (3) Penalties. This influences analysts to evolve the way defensive performance is analyzed and evaluated, shifting from a general 'prevent scoring chances' mindset to a deeper context-dependent breakdown of team performance. For example,

- Does Player X's team give up significantly more transition chances when Player X is on the ice? How effective is he at defending transition chances?
- Does Player Y defend well in the defensive zone? How often does Player Y's pairing get trapped in the defensive zone for more than 10 seconds?

The answers to these questions is essential for coaches and managers when making roster decisions and understanding team strengths and weaknesses. Existing shot-based metrics cannot answer these context-dependent questions, and therefore do not paint the full picture of defenseman value. Our new framework of per-possession efficiency metrics that are much more granular, have much greater statistical significance, and are more reliable proxies for team defensive performance.

"Hockey needs a good measure of process, and a good measure of process identifies the hockey activities and context that lead to good shot attempts…, and in doing so, sets actionable goals and provides the proper foundation for good coaching strategy" (Baker and Shea, 2017).

3 Building Possessions Database

The data for this competition consists of 40 games of Ontario Hockey League (OHL) play-by-play event data. Building on the foundation created by Luke Bornn and Andrew Miller in "Possession Sketches: Mapping NBA Strategies" (2017),[6] we created a novel **Possessions Database** with the raw event data organized into possessions and possession types. Every possession was assigned a unique ID, and we used feature engineering to create additional features to describe each possession, such as possession starting zone, ending zone, length, number of events, zone entry type, transition (rush) chance, game-state, etc. See Appendix A for Erie's Possession Database and Appendix B for a list of features and definitions.

This allows for in-depth analysis into frequencies of each possession type and the rates at which these possession types typically result in goals or quality shots, as is the norm in basketball and soccer[9]. For example, we can query 'How many D-Zone turnovers did Erie have per game against London?' or 'What was Erie's Team Shooting% on rush chances across all 40 games?'.

In defining whether or not a rush chance occurred, we followed the guidance of Chris Baker and tested how quickly a possession moved through the neutral zone into the attacking zone, measured by the change in distance (feet) over time (seconds) from the moment a team takes possession to the time of the zone entry. Possessions moving faster than 25 feet/ second in the neutral zone were labeled rush chances. We then added transition speed as a feature in our dataset. We also adopted EvolvingHockey's public Expected Goals (xG) model and assigned xG values to Corsi events.[9]

4. Identifying Dangerous Possession Types

We identified the features of defensive possessions (zone entry type, slot pass attempt, transition possession, etc.) that typically result in scoring chances or goals against. We ran a logistic regression and correlation analysis on the 40-game OHL dataset to test which features were the most significant predictors of goals scoring chances occurring (xG values over 0.4). After eliminating insignificant and highly correlated variables, we found that the vast majority (~93%) of all goals and scoring chances develop from only five defensive possession features: See Exhibit 1 for a possession-type breakdown.

1. *Defensive-Zone Start (via Takeaway or Faceoff)*
2. *Controlled Zone Entries (Carried or Played)*
3. *Transition (Rush) Chance*
4. *East-West Slot Pass*
5. *Penalties*

This model had a misclassification rate of 1.2%, and each of the five factors were statistically signficant. In order to better visualize and interpret the relationships between the five factors, we ran a decision tree analysis. Results of both models can be seen in Exhibit 2.

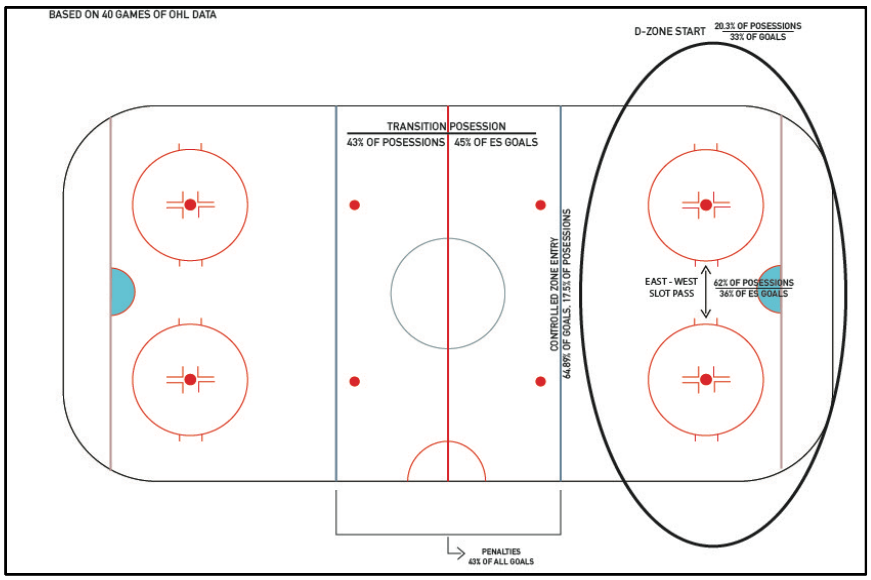

Exhibit 1: Breakdown Of The 5 Dangerous Possession-Types

```
Coefficients:
                                    Estimate Std. Error z value Pr(>|z|)
(Intercept)                          -6.2439     0.2153 -29.002  < 2e-16 ***
Possession_Zone_Entry_Control_Success 2.1984     0.2111  10.414  < 2e-16 ***
Possession_Zone_Entry_Played_Success  2.4459     0.3320   7.368 1.73e-13 ***
Successful_O_Zone_RR_Direct_Pass      0.7888     0.1157   6.815 9.42e-12 ***
ES_Possessions_TestingTakeaway        0.3902     0.2335   1.671 0.094695 .
ES_Possessions_TestingOzone           1.9374     0.2427   7.983 1.43e-15 ***
ES_Possessions_TestingTRUE            0.7427     0.2144   3.463 0.000534 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1635.1  on 11852  degrees of freedom
Residual deviance: 1347.8  on 11846  degrees of freedom
AIC: 1361.8

Number of Fisher Scoring iterations: 8
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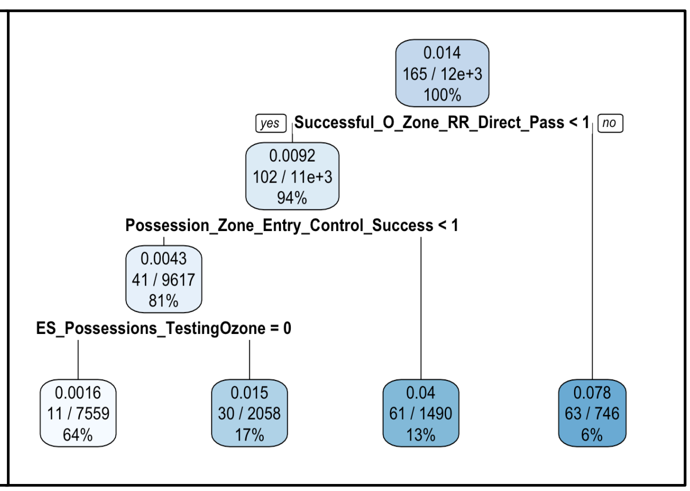

Exhibit 2: Logistic Regression Model & Decision Tree Model Results

These models prove that each of these five possession-types are significant predictors of goal scoring, and that 93% of all goals are scored as a result of at least one of these possession types (and/ or often a combination of possession-types). Therefore, we can conclude that efficiency preventing (and defending against) these possession-types is crucial to defensive success. As such, analyzing efficiencies preventing and defending these possession types will provide detailed insight into team defensive performance.

In contrast to typical xG or Corsi-adjusted metrics, which are based solely on play outcomes[9], the variables and datasets we use in this model is based on play development types; a measure of process as opposed to outcome. While xG and Corsi can be valuable when used in the right context, these aggregate summary metrics can't be used to dig deeper into specific game-contexts. There is definite value in a more granular analysis, as demonstrated in the NBA and Premier League[9].

5. Defensive Efficiency Metrics (DEMs)

In answering our initial question of finding metrics that teams can use to better analyze team-level defensive performance, we present a set of efficiency metrics that paint a more comprehensive picture of team performance. These metrics, called **Defensive Efficiency Metrics (DEMs),** indicate how efficient a given team is at (a) preventing and (b) defending the five dangerous possession-types identified in Section 4. For example, if a team allows 20 transition chances in 100 possessions, they would have an 80% transition prevention score. If they allowed 5 goals on those 20 possessions, they would have a 25% transition defense score. Exhibit 3 shows the relationship between Transition Chance Defense, Controlled Zone Entry Defense, and Goals.

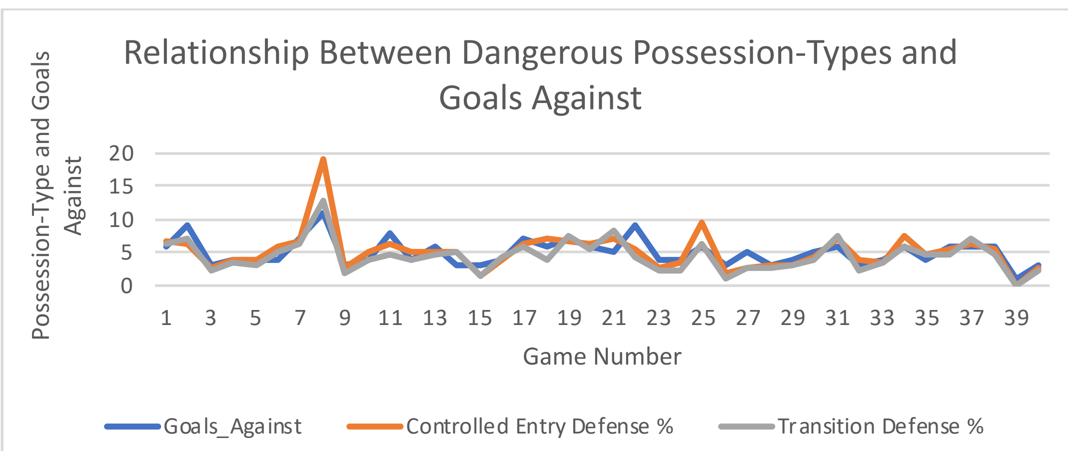

Exhibit 3: Relationship Between Controlled Zone Entries, Transition Chance, and Even Strength Goals Against

These metrics provide critical insight into team defensive performance, strengths and weaknesses. Exhibit 4 provides a breakdown of Erie's 40-game DEM scores, alongside traditional Goals and Corsi Against. Exhibit 5 provides a one-game summary report for the game on December 29th, 2019 between Kitchener and Erie. In analyzing the DEMs we identify critical trends and themes in game-to-game possession data. For example, in Exhibit 5 it is clear that Erie defended zone entries effectively but struggled defending east-west slot passes. We present a comprehensive breakdown of potential insights for coaches managers in Section 8. We can also account for game-state, creating DEM-close metrics that only include possessions when the score is within 1.

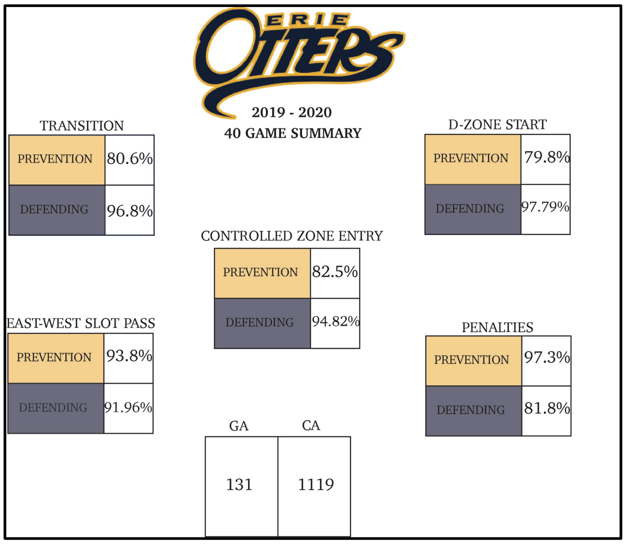

Exhibit 4: ***Erie 40-Game DEM Results***

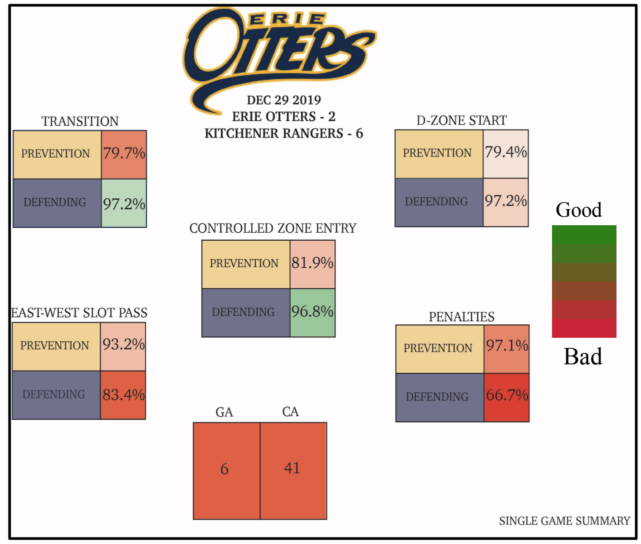

Exhibit 5: ***Mock Erie DEM Game Report Card***

The value of using per-possession metrics to generate more observations (i.e., ~200 possessions per game vs. ~28 shots) is critical. With even 20 games of data (~4,000 possessions) we can create per-possession models with much more certainty compared to models based on the ~500 shots or ~80 goals in that time. We can accurately study team consistency by analyzing game-to-game variations in DEMs, and evaluate performance against specific teams. With samples from multiple teams we can test how long it takes for teams to reach their long-run-efficiency-average in each DEM (as is the case with batting average in baseball).[10]

7. Results

Assessing defensive performance using the DEMs has three primary benefits:

1. Using possessions as the unit of analysis, DEMs are calculated from a large sample of observations including all types of possessions (not only the rare possessions with a shot/ goal).
2. Given the larger set of observations, DEMs demonstrate less game-to-game variation compared to scoring chances or (especially) goals (34.5% vs 56% vs 89%). This is important because less variation indicates less randomness, meaning these metrics can be more accurate (less random) variables for predictive modelling.
3. Resting the urge to create aggregate summary metrics to value overall performance (like xG%, CF%, or RAPM), each DEM considers one of the five key 'components' of goal prevention. By analyzing these metrics both individually and as a collective we can identify critical trends and themes in team performance. Unlike xG% or xThreat models, we don't face the obstacle of assigning subjective values to events. Given the random and continuous-flow nature of hockey, we chose to avoid subjective valuations in favor of a more objective methodology.

It is clear that preventing and defending the five dangerous possession-types is highly correlated with team goal prevention (see Exhibit 3), and thus that we can leverage efficiencies in these possession-types to create accurate proxy metrics for defensive performance. Although there's no exact blueprint of efficiencies that leads to optimal results (i.e., limiting or rush chances or controlled zone entries), we uncover insightful context-specific rates and trends.

8. Applications

Team On-Ice Strategy : Defensive Tendencies, Strengths and Weaknesses:

The DEMs can easily be leveraged to analyze team performance, strengths and weaknesses. We can conduct a thorough analysis of defensive performance, compare rankings for each DEM, and illuminate trends that call for crutial strategic adjustments. We can identify that, if Team X gives up a high proportion of rush chances, they should (a) adjust forecheck or neutral zone strategies, (b) make roster changes that improve team rush defense, or (c) adjust lines or matchup decisions.

Team Off-Ice Strategy : Impact on Personnel Decisions, Scouting and Player Acquisition

Managers and coaches can visualize and analyze the specific defensive contexts their team is struggling with and draw detailed, team-specific insights. Perhaps Erie struggles against one team with a strong forecheck but excels against a higher-ranked team that employs a neutral-zone trap. Decision-makers can use DEMs to inform key personnel decisions by identifying which situations a team struggles in defending and draft or acquire players that thrive in those contexts.

9. Conclusion

This paper proposes a novel framework to evaluate team defensive performance in hockey. Building on concepts presented by Baker and Shea[5], we propose a set of Defensive Efficiency Metrics to be used for more detailed, accurate, and context-specific analysis. The DEMs indicate team efficiencies preventing and defending the dangerous possession-types outlined in Section 4.

Given that hockey, like soccer, is a low-scoring sport[11], outcome-based metrics don't consider the vast majority of possessions that don't result in a shot, or the many events that led up to a shot. DEMs consider all possessions, resulting in larger samples of observations. Therefore, barring tests on a larger dataset, this method is a *reliable measure of process* to complement existing measures of outcome that are prone to randomness. See Appendix C for a comprehensive list of limitations and recommendations for future direction.

10. Discussion & Future Work: Player Evaluation & On-Ice Systems Analyses

This method of defensive analysis will provide a valuable foundation for player-level analysis once spatial tracking data is available. We could analyze player efficiency rates across each possession-type, and build on the work by Chu, Wu, Reyers, and Thomson (2019)[12] to map and assign player routes to possession-types. This allows in-depth analysis into context-specific player performance.

We can study *Zones of Control* (Fernandez and Bornn, Premier League, 2018)[13], which involves using velocity and positional data to assign players 'zones of control' that indicate how well they prevents space generation from attackers. We can analyze zones of control within each possession-type to assess situation-specific efficiencies. This will provide meaningful insight into player tendencies and effects of teammates or competition. Finally, and perhaps most excitingly, we can use the DEMs to study team strategy (i.e., 1-2-2 forecheck, collapsing DZ coverage), how efficient strategies are against other strategies, and even player effectiveness in defined roles within the system (i.e., first forechecker, strong-side D-zone winger). These are just a few of the possible as a result of this DEM evaluation framework, helping elevate hockey defensive analytics to the level of other pro sports with more in-depth and granular tools for analysis.

References:

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Appendix A: Possessions Database

	Possession_Game	Goals_Against	Possessions_Against	Possession_Mean_Length	O_Zone_Start_Goal	Transition_Possession_Slot_Goal
1	2019-09-20	2	215	4.532407	0	1
2	2019-09-21	4	150	5.740000	3	0
3	2019-09-26	2	197	6.269036	0	0
4	2019-10-04	4	186	5.435484	0	0
5	2019-10-11	3	211	4.042654	0	1

Appendix B : Possession Features and Definitions

Feature	Definition
Possession Start Event	Faceoff, Takeaway, Puck Recovery, Rebound
Possession End Event	Faceoff, Goal, Turnover, Event Prior to Puck Recovery by New Team, Penalty
Controlled Zone Entry	Carried or Played Successful Zone Entry
East-West (RR) Slot Pass	Successful Direct Passes in the Offensive-Zone Slot that Move Across the Centre Line.
Successful O-Zone Pass	Pass Attempts in the Offensive Zone that are Direct or Indirect and Successful
Corsi Event	Blocked or Unblocked Shot
Slot Shot	Shot in the Home Plate Region of the Offensive Zone
Number of Events	How Many Events A Possession Consists Of
O-Zone Possession Start	Possession that Starts in the Offensive Zone of the Team With the Puck.
Possession-Length	Time (Seconds) that a Team Maintains Puck Possession
Transition (Rush) Chance	Possessions When the Offensive Team Moves the Puck Through The Neutral Zone at a Rate Faster than 25 Feet/Second.
Transition-Length	Time (Seconds) of Puck Moving Through Neutral Zone
Possession Start Zone	Left O-Zone, Center O-Zone, Right O-Zone, Left Neutral-Zone, Center N-Zone, Right N-Zone, Left D-Zone, Center D-Zone, Right D-Zone,
Possession Start Zone	Left O-Zone, Center O-Zone, Right O-Zone, Left Neutral-Zone, Center N-Zone, Right N-Zone, Left D-Zone, Center D-Zone, Right D-Zone,

Appendix C: Limitations & Future Recommandations

The primary limitation of this model is the predictive validity of the DEMs due to the limited sample size of available data. As larger datasets become available we can test and validate the DEMs as proxies for longer-term defensive success. Another limitation we faced was attempting to consider player-level metrics (like how many takeaways a given defender had per-possession), but with only a handful of takeaways for most players every game this did not provide nearly a large enough sample of observations to draw accurate conclusions. Lastly, in order to adopt this method for analysis in other hockey leagues it would be prudent to re-run the logistic regression and confirm the significance of each possession-type, as each league may have different rates.