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"What are the Odds?" Improving In-Game Win Probability Models in Football

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ABSTRACT

This paper investigates football win-probability models to understand how they can be made more accurate and helpful for analysts, clubs, and fans. Since football is a low scoring and unpredictable game, probability models help us interpret uncertain outcomes and support strategies and decisions. The paper looks into Sam Green's expected goals model and how it laid the foundation for future forecasting. It also evaluates how Fivethirtyeight's and Herbinet's models have expanded on this by integrating simulations, team strength ratings, and machine learning. By assessing the strengths and weaknesses of these three models, this paper identifies the most accurate approach for forecast match results.

Keywords: *Win-probability models, football analytics, expected goals, machine learning, spatio-temporal, sports betting, Fivethirtyeight.*

1. INTRODUCTION

Probability is the measure of how likely an event is to occur, ranging from 0 (impossible) to 1 (certain). The values between 0 and 1 represent different chances of events occurring, and the closer the number is to 1, the more likely the event is. For example, the probability of getting tails when flipping a fair coin is 0.5, or 50%. While a coin flip is a basic example, probability also plays a key role in understanding and predicting outcomes in various routine yet complex situations. In our everyday life, probability appears in weather forecasts, card games, making informed decisions in business strategy, as well as medicine. It also adds excitement and strategy to entertainment, from betting in sports and fantasy leagues to casino games like roulette and blackjack. Even video games often rely on probability to determine random events, like loot drops, game events, and opponent selection. Rather than being just abstract numbers, probability has an influence in our entertainment and decisions too. This influence is made more accurate by the probability models that work behind the scenes.

Probability models are statistical tools that mathematically represent and quantify the various outcomes of different events. They help us understand, analyze and predict the likelihood of different possibilities, and are used in fields like finance, engineering, biology and social sciences. A few common probability models are: discrete and continuous probability models, and binomial, normal, and Poisson distributions. Their ability to predict uncertain outcomes makes probability models extremely useful. A key example is win-probability models being used to predict game outcomes in sports.

In today's sports culture, probability does more than just predict outcomes, it also powers multi-billion dollar industries. The global sports betting market, estimated to be worth $244 billion, relies on probability to set odds, assess risk, and draw more users (Beal et al. 2). Betting companies use Poisson and Bayesian models to estimate match results, score predictions, and even the next players to score (Egidi et al. 5). These probabilities set the odds offered to millions of bettors all over the world, who make their decisions and strategies based on the likeliness of each outcome.

Probability also plays a key role in fantasy sports and sponsorships. In fantasy leagues, users create their teams based on expected performances of players, often based on statistics that estimate the likelihood of a player scoring or providing assists.
Fans that understand these odds create better teams, increasing their winning chances. The same logic applies on a larger scale, where major sponsors and advertisers invest in players and clubs based on performance forecasts. A player who is more likely to score a lot of goals or provide many assists would attract more sponsors. This shows how probability influences not just game strategies and coaching, but contracts and partnerships. Win-probability models are an application of probability models, and can predict the outcome of a game based on a few factors: team strengths, historical data and in-game features (score differential, possession, time remaining, etc.). In sports like basketball, cricket and football where outcomes are unpredictable, such models have had a significant impact. They have changed the way games are analyzed and strategies are developed, and helped optimize player training and performance. Whether it's predicting the winner of a match, calculating a team's chances to qualify or making decisions during games, win-probability models bring clarity to these seemingly random outcomes.

Football, one of the most watched sports in the world, is driven by chance and uncertainty. Due to the relatively low scoring nature of the game, with an average of 2-3 goals per match, each goal is of utmost importance. A single defensive mistake or a good scoring opportunity can turn the game around. In contrast, basketball games often exceed 100 points per team, so missing a shot or conceding a basket would have a much smaller impact on the final outcome. Since each goal is crucial in a football match, chance can play a major role in determining the outcome of the game.

This raises the question of whether the final result reflects skill or is significantly influenced by luck. However, in the long run it's skill that separates the best teams from the rest. To accurately calculate the performance of a team without factoring in luck, instead of goal-based metrics, shot-based metrics became more common (since shots don't involve as much luck as goals, they are better predictors) (Noordman 1).

A commonly used metric in football is expected-goals (xG), first introduced in the premier league in 2012. Expected-goals calculates the probability of a certain goal-scoring opportunity to be converted into a goal, based on the circumstances. It first appeared in 2004, when Pollard, Ensum and Taylor estimated the probability of a shot going into the goal. They used a logistic regression model with three variables: the distance to the goal, the angle to the goalpost and the distance to the nearest opponent (Noordman 5). Later, in 2012 Sam Green published a blog about his xG model. His model had the same principles as the one created by Pollard et al., breaking the factors down to the quality of the chance (location, context), the quality of the shot (trajectory, placement), and the impact of the goalkeeper (Keogh). Soon, similar but improved models started surfacing. For example, in 2015 Lucey, Bialkowski, Monfort, Carr & Matthews presented a model based on spatio-temporal data of every player on the field to acquire accurate data about defender proximity, interaction of surrounding players, speed of play and location of the shot (Lucey et al. 2). William Spearman developed a similar model in 2018, but to analyze off-ball scoring opportunities and player positioning using spatio-temporal data (Spearman 2). Expected-goals has had a huge impact on football, helping coaches and analysts to evaluate player and team performances. For example, a team or player with a high xG but fewer goals may indicate that they will have to improve their finishing. However, while all these models can be used to predict match outcomes, they do have limitations as their primary function is to assess the performance of players and teams.

Recognizing these limitations, analysts and mathematicians have developed in-game win-probability models specifically for forecasting match outcomes. D. Page shows that just relying on the summed up values of expected-goals only shows "half of the story," as it overlooks variance and can lead to misleading conclusions (Noordman 6). The first in-game win-probability models made solely for predicting the outcome of a match were published by Google and FiveThirtyEight in the 2018 World Cup. Google didn't give any details on how they overcame the challenges they faced, however Fivethirtyeight published an article about how their model works. Fivethirtyeight had published predictions in the 2014 world cup as well, but those were just based on Soccer Power Index (SPI). Their predictions in 2018 involved new features such as probability of teams making knockout-round matches, likely opponents in the knockout matches and in-game win probabilities that update in real time. The newer model applies SPI in many ways, using it to predict pre-match outcomes, tournament outcomes, and live in-game predictions.

The pre-match forecasts follow 3 steps: first. calculating the expected goals for each team; second, applying Poisson distribution to estimate the probability of each team scoring 0, 1, 2, 3, etc. goals; and third, combining the two distributions into a "matrix" of possible match scores to forecast the likelihood of a win, loss, or a draw for each team. These pre-match predictions form the foundation for Fivethirtyeight's tournament simulations. Their tournament predictions are based on thousands of simulations of the world cup, each one based on the pre-match forecasts. The probability that a team wins the world cup represents the amount of simulations in which they win. When the world cup starts, their in-game win-probability forecasts contribute to the tournament predictions, updating in real time to predict the winner (Boice).

Despite the development in win-probability models and their increasing reliance in football analysis, challenges still remain in improving their accuracy. Making these models more precise is essential, as it can lead to better performance evaluation and smarter in-game plays. Therefore, this research focuses on the question: How can in-game win-probability models be improved to more accurately reflect match outcomes and provide better insights for analysts, teams, and the rest of the football community?

History of Probability in Sports

The use of probability in sports has come a long way, evolving from simple betting odds based on instinct or past experiences, to advanced models and real-time predictions. This seemingly speculative exercise is driven by our desire to know the outcome before the event occurs, more so in adrenaline filled activities. Betting on sports and games dates back to Ancient Greece, where the parimutuel, or mutual betting system was used. This system was invented by Joseph Oller 1867, where "all the stakes bet by the bettors were pooled into a common pool before being redistributed to the winners in proportion to their stake." Since then, betting systems have advanced, the most popular one being the fixed odds betting system. In this system, bookmakers set odds based on the estimated probability of events, based on statistics and historical data. These odds are fixed once a bettor places a bet, and the payout multiplier is determined. However, bookmakers also include a profit margin in the odds to manage financial risk (Steffen 1–2).

The increasing availability of data and growth of sports analytics have transformed how probabilities are calculated and applied. The use of sabermetrics, popularized by the movie "Moneyball", showed how data-driven player scouting could outperform traditional scouting methods. In heavily bet-on sports, like football, basketball, and tennis, bettors have access to hundreds of possible wagers. However, the most important prediction remains the outcome of the match. To estimate this accurately, analysts rely on probability models based on large amounts of data and in-game variables, making forecasts more reliable and precise than ever. These developments reflect how far probability modelling in sports has evolved over hundreds of years (Steffen 2–3).

2. LITERATURE REVIEW

This section analyzes the evolution of expected goals models, starting with Sam Green's original model and then moving on to an advanced adaptation of it using spatio-temporal data. By evaluating their approaches, strengths, and limitations, we can improve our understanding of how xG contributes to predicting match outcomes and where it falls short.

Sam Green introduced his expected goals model through a blog post in 2012, explaining the model he built to assess the performances of strikers. He aimed to quantify shot quality, laying the foundation for performance analytics. Green's model was built upon earlier research by Pollard et al., who also used logistic regression to estimate the probability of a shot being converted into a goal (Noordman 5). His model expanded on the 3 basic variables used before, adding factors like the impact of the goalkeeper, the type of shot, the body part used, and the context of the shot (set piece, through ball, counter-attack, open play) (Keogh).

The model calculates the xG of a shot by comparing it to similar shots in the past - the percentage of similar shots that have resulted in a goal will be the xG value. These values have also been used as win-predictors by summing up all the expected goals values from a match and comparing them between the 2 teams. Obviously, the team with the higher total xG would be expected to win.

The model's key strength was its ability to standardize player and team performance evaluation. His model allowed teams and analysts to compare players and create better strategies to improve team performances. Another strong suit of his model was its shift in focus from outcomes to processes. Before Green's xG model, most evaluations relied on goals, assists, or coach judgement. Instead, his model allowed coaches and the media to additionally analyze the quality of the chances, laying the foundation for more advanced football analytics. However, Green's model also has its limitations.

It doesn't factor in the team structure, speed of play, and off ball movement beyond the immediate circumstances of the shot. These limitations also reduce the accuracy of predicting match outcomes using xG values: just summing up expected goals values fails to account for variance. An example used by Noordman to explain this is, "if a home team creates no chances during a game except for one very big chance and the away team gets a lot of small chances which is summed up the same amount of expected goals over a game. The probability that the home team scores one goal is very big, but the probability of the home team scoring two goals is zero. On the other hand, the possible amount of goals the away team scored is very big, since it is possible that every little chance they got went in." (Noordman 2). Thus, while Green's model was foundational and influential, it lacks accuracy in predicting full match outcomes.

While adaptations of Sam Green's expected goals model have improved the accuracy of predicting whether a shot will result in a goal, they are still limited in predicting full match outcomes. Simply summing of xG values fails to account for important game features like variance, off-ball positioning, and time-dependent variables. To better estimate a team's chances of winning, Fivethirtyeight win-probability model uses simulations and pre-game strengths, the focus of the next section.
Fivethirtyeight's win probability model developed by Jay Boice for the 2018 world cup was the first in-game win-probability model in football. They used pre-game team strengths (SPI), simulations and in-game forecasting to predict match outcomes as well as the tournament winner. SPI is calculated from 2 systems: an offensive rating (how many teams they are expected to score against an average opponent) and a defensive rating (how many goals they are expected to concede against an average opponent). These ratings are based on historical data all the way from matches in 1905, adjusted for red cards, game state (time and score), and expected goals. Together, these components produce an SPI rating for the team to represent the percentage of points a team would receive if they played the same match repeatedly (3 points for a win, 1 point for a draw, 0 for a loss). For world cup ratings, a team's SPI combines 75% match based performances and 25% roster strength based on the players' clubs and playing time. Given these ratings, Fivethirtyeight runs thousands of simulations of the world cup, giving a win percentage to each team depending on the number of simulations in which they win. During the world cup, they use in-game forecasts to predict match outcomes and calculate various factors, all contributing to the world cup winner probability.

Fivethirtyeight's main strength lies in their application of past models and concepts, for instance expected goals. It incorporates xG and off-ball xG to accurately quantify a team's performance during matches. Fivethirtyeight's prediction model has also incorporated elements like red cards, time-dependent variables, and home advantage, allowing for a more precise evaluation of team performances. These approaches allow the in-game win-probability model to respond to such features, something that is lacking in most xG based models. This also enables the model's simulations to respond to game state and red cards, enhancing the accuracy of its win predictions. Therefore, while the model contributes significantly to future predictive modelling, its predictions are limited by the assumptions they are based on (Garnica-Caparrós et al. 576).

In contrast to Fivethirtyeight's simulation based approach, Herbinet's model focuses more on match data and machine learning to predict match results.

Herbinet uses a regression model to predict football match outcomes by combining expected goals, team strength ratings, and machine learning. The model calculates each team's xG based on shot quality and match stats, then uses an ELO rating system to evaluate each team's offensive and defensive performance over time. Machine learning helps the model find patterns in the data and make accurate predictions. These features are used to predict match outcomes (win, draw, or loss) and expected scores (Herbinet 3, 5, 7–22).

This model stands out not just for calculating expected goals, but combining it with ELO ratings and machine learning for more accurate predictions. Herbinet uses both event-based and statistical data, and finds patterns through machine learning techniques that most other models would miss. This makes the model more adaptable and data-based, enhancing its predictions and allowing it to adjust as new information becomes available.

Regardless of its strengths, Herbinet's model was limited in some key aspects. The expected goals values that are calculated do not consider the position of the opposing team's players at the time of the shot, something that could determine whether the shot goes into the goal or not. It also doesn't account for other spatio-temporal data like crosses, tackles, or dribbles that could have resulted in a goal. Another limitation for the model is its lack of team and player data, which could improve xG accuracy and add to the ELO ratings (Herbinet 57–59).

3. CONCLUSION

The goal of this research paper was to explore how current win-probability models can be made more accurate and useful for analysts, teams, and the football community. By evaluating existing models, we can identify which approach offers accurate results and would be best suited for predicting match outcomes.While all three models that we assessed (Sam Green's xG, Fivethirtyeight's, and Herbinet's) have contributed significantly to developing models, they fall behind on few elements. Green laid the foundation for future models by introducing expected goals to football. Fivethirtyeight's model built upon it, using simulations based on pre-game ratings and in-game predictions. Herbinet combined expected goals with ELO ratings and machine learning to enhance prediction accuracy. The use of machine learning allows the model to unravel complex patterns and in-game features that other models might miss, improving its ability to adjust to team form, playing styles, and other performance factors. Among the three, Herbinet's model offers the most accurate and adaptive predictions, making it the most promising option.However, as discussed in the previous sections, all of these models lack spatio-temporal data.

Without it, important data such as real-time player movement, positioning, interactions on the field, and off ball scoring opportunities aren't taken into account. Integrating spatio-temporal data into win-probability models would significantly improve their ability to better evaluate chance quality, identify missed opportunities, and understand match context beyond basic match and player statistics (Spearman 16). A model that combines spatio-temporal data with the strengths of existing models such as ELO ratings, simulations, and machine learning would provide the most accurate, adaptable and realistic predictive tool for football analysts, clubs, and the wider community.

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