UCL Elo Ratings & Predictive Modeling (2024/25 Season)

As part of my interest in quantitative finance and sports analytics, I developed an Elo rating system to evaluate team performance throughout the 2024/25 UEFA Champions League (UCL) season. Using match-by-match updates, this system dynamically adjusts team ratings based on results and incorporates factors such as opponent strength, Home/Away effects, and the final goal difference.

Background and Methodology:

The Elo ranking system was created by Arpad Elo as a method for calculating the relative skill levels of players in zero-sum games, i.e. games where one person's gain is equal to another person's loss. Given the two Elo rankings of two competing players X and Y to be R_x and R_y, the probability of player X winning—P_x—is as follows:

$$P_x = \frac{1}{1 + 10^{\frac{R_y - R_x}{400}}}$$

This year, UEFA introduced a new format for the Champions League group stage. Instead of dividing teams into eight groups of four—where the top two from each group advanced after playing two matches against each opponent—the tournament now features a single 36-team league. Each team plays eight matches against different opponents, with the top eight teams advancing directly to the Round of 16. The next 16 teams compete in a one-off playoff to secure the remaining eight spots.

I was concerned that the new format might distort true team strength: with each team playing only 8 of the 36 participants, some could face exclusively strong opponents and suffer early elimination or lower rankings, while others might advance by playing only weaker teams.

To address this concern, I sought to determine the Elo rankings of each team. By using an objective rating system that adjusts based on match outcomes and opponent strength, I aimed to develop a more accurate measure of team performance throughout the competition. I adapted the Elo system to be applied to the Champions League using the modifications proposed by Bob Runyan[1] as outlined below.

$$R_n = R_0 + P$$

$$P = KG(W - W_e)$$

R_n = the new rating

R_0 = the old rating

P = the point change

K = the weight of each game, set at 40

W_e = the expected result of the match

$$G = \begin{cases} 1, \text{ if a draw or the goal difference } = 1 \\ \frac{3}{2}, \text{ if the goal difference } = 2 \\ \frac{11 + N}{8}, \text{ if the goal difference } \geq 3 \end{cases}$$

W = the result of the match: 1 if a win, 0.5 if a draw, 0 if a loss

1 Lyons, Keith. "What are the World Football Elo Ratings?". The Conversation. Retrieved 28 January, 2025

And $W_e = \frac{1}{10^{\frac{-dr}{400}}+1}$, $dr = R_1 - R_2$, with the home team receiving a $+200$ Elo boost

I used a simple Python script and data sourced from https://www.football-data.org/ to calculate the individual Elo rankings of each of the 36 teams in the 2024/2025 UCL League system. Thus, the final rankings provide an accurate and objective representation of a team's underlying strength based off its opponent's strength, Home/Away effects, and final goal difference. As I suspected, the league format does not accurately portray the underlying strength of most of the teams: the results are below.

Performance Classification:

To provide additional insight, I also implemented a performance coding system that categorizes teams based on the quality of opposition they earned points against:

Team	ELO	Position (League)	Overrated?
FC Barcelona	2029.19	2	Underperforming
Arsenal FC	2023.39	3	Underperforming
FC Internazionale Milano	2010.25	4	Underperforming
Liverpool FC	1990.43	1	Overperforming
Lille OSC	1987.04	7	Underperforming
Club Atlético de Madrid	1983.09	5	Mildly Overperforming
Bayer 04 Leverkusen	1981.85	6	Mildly Overperforming
Real Madrid CF	1969.16	11	Underperforming
PSV	1969.15	14	Underperforming
Atalanta BC	1966.38	9	Mildly Overperforming
Borussia Dortmund	1963.29	10	Mildly Overperforming
Aston Villa FC	1943.2	8	Overperforming
FC Bayern München	1935.74	12	Mildly Overperforming
Sport Lisboa e Benfica	1930.15	16	Underperforming
Paris Saint-Germain FC	1926.18	15	Performing as Expected
Juventus FC	1920.01	20	Underperforming
AC Milan	1915.88	13	Overperforming
Stade Brestois 29	1905.08	18	Performing as Expected
GNK Dinamo Zagreb	1902.41	25	Underperforming
Club Brugge KV	1900.2	24	Underperforming
Manchester City FC	1898.49	22	Underperforming
Celtic FC	1893.87	21	Mildly Overperforming
Feyenoord Rotterdam	1892.51	19	Overperforming
AS Monaco FC	1880.42	17	Overperforming
Sporting Clube de Portugal	1869.76	23	Overperforming
VfB Stuttgart	1869.15	26	Performing as Expected
Bologna FC 1909	1865.4	28	Underperforming
FK Shakhtar Donetsk	1838.62	27	Mildly Overperforming
SK Sturm Graz	1836.5	30	Underperforming
FK Crvena Zvezda	1815.85	29	Mildly Overperforming
RB Leipzig	1809.56	32	Underperforming
Girona FC	1794.22	33	Underperforming
AC Sparta Praha	1789.02	31	Overperforming
FC Red Bull Salzburg	1749.2	34	Performing as Expected
ŠK Slovan Bratislava	1743.63	35	Performing as Expected
BSC Young Boys	1701.75	36	Performing as Expected

Underperforming – A team that earned most of its points against tough opposition but sits lower in the league than expected.

Performing as Expected – A team whose league position accurately reflects its quality.

Mildly Overperforming – A team that earned some points against weaker opposition, placing slightly higher than expected.

Overperforming – A team that earned most of its points against weaker opposition, ultimately ranking higher in the league table than it should.

Key Insights from the Final Matchday 8 Rankings

The final Elo rankings following the League Phase revealed several notable trends. Liverpool, with an Elo rating of 1990.43, emerged as an overperforming team, benefiting from favorable matchups against weaker opponents that inflated their final league standing. Conversely, FC Barcelona (2029.19 Elo) and Arsenal (2023.39 Elo) fell into the underperforming category. Despite their strong underlying ratings, both teams struggled in crucial fixtures, suggesting they may be more formidable than their final rankings indicate—something to watch for in the knockout rounds. Meanwhile, Manchester City (1898.49 Elo) and Real Madrid (1969.16 Elo) performed largely as expected, consistently securing results in line with their opposition's strength, typically beating weaker teams while drawing or losing against stronger ones.

Flaws & Limitations

While Elo ratings provide a useful framework for evaluating team strength, the model has inherent limitations. One major drawback is the use of arbitrary starting values, as every team began the season with a default Elo rating of 1500 rather than one derived from prior seasons' performance. As a result, early-season rankings may not fully capture true team strength. Additionally, the model does not account for key injuries, tactical adjustments, or squad rotations, all of which can significantly impact match outcomes. Another limitation is the simplified approach to match context; while the system adjusts for win/loss margins, it does not incorporate advanced metrics such as expected goals (xG) or possession statistics, which could enhance predictive accuracy. Lastly, the model does not separately account for home-field advantage, treating all matches as neutral contests, which may overlook a critical factor in determining match outcomes.

Applications & Future Work

Using the formula[2]

$$P_{\mathrm{H}} = \frac{1}{1 + 10^{\frac{R_{\mathrm{A}} - R_H - \sigma}{400}}}$$

Where

$P_{\mathrm{H}} =$ the probability of the home team winning

$R_{\mathrm{A}} =$ the Elo of the away team

$R_H =$ the Elo of the home team

$\sigma =$ the home advantage parameter, set at 200

and the Elo ratings calculated through Matchday 7 of the league phase, I back-tested my model by comparing its predicted match outcomes with actual results. **Out of 16 matches, my model correctly predicted 67% of outcomes.**

For comparison, the naive benchmark of always predicting the home team to win would achieve an accuracy of around 55%, while **CBS Sports analysts achieved an accuracy of only 61%** in their predictions.[3] My model significantly outperformed both of these baselines, demonstrating its

[2] This formula assumes only two possible match outcomes: a home win or a home loss. While draws can occur in the league phase (e.g., two occurred on Matchday 8), my focus is on predicting knockout-stage matches, where a decisive winner is always determined. Therefore, I maintain this binary framework.

[3] CBS Sports, "Champions League expert picks, predictions, best bets on Matchday 8". CBS Sports. Retrieved 7 February, 2025

effectiveness in capturing underlying team strength. Specifically, my model correctly predicted that GNK Dinamo Zagred would beat AC Milan (5.71 odds) and that Sturm Graz would beat RB Leipzig (3.95 odds), two outcomes that were not expected by many.

To further evaluate the effectiveness of my Elo-based prediction model, I simulated a betting strategy where I placed a hypothetical $100 wager on each match based on the model's predicted outcomes. Using historical pre-match odds[4], this strategy yielded **a total return of $2,525** from an initial betting outlay of **$1,800** (18 bets of $100 each), resulting in a **profit of $722**.

This corresponds to an overall **return on investment (ROI) of 28.71%**, demonstrating that the model not only achieved strong predictive accuracy (67%) but also showed profitability in betting markets. The positive return suggests that my Elo-based approach successfully identified value in the odds, outperforming random or naive betting strategies.

This Elo-based model will ultimately serve as the foundation for a predictive system that I am currently developing that is aimed at forecasting knockout-stage outcomes. Additionally, I plan to expand this project to generate machine learning-based predictions for the English Premier League, leveraging a larger dataset to improve accuracy. By integrating advanced statistical techniques, I aim to refine the model's predictive power for team performance assessments and match outcome prediction.

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[4] OddsPortal, "Champions League Results," OddsPortal. Retrieved 7 February, 2025.