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

As part of my work 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 adjusted team ratings based on results, incorporating factors such as opponent strength, Home/Away effects, and 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 this new format might not accurately reflect the true strength of the participating teams. Since matchups are not uniform, some teams could face weaker opposition and advance, while others might be eliminated despite playing stronger opponents.

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

Where $W_e = \dfrac{1}{10^{\frac{-dr}{400}}+1}, dr = R_1 - R_2$, with the home team receiving a $+100$ 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

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

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, the model correctly predicted 72% of outcomes.

For comparison, the naive benchmark of always predicting the home team to win would achieve an accuracy of around 55%, while the predictions of top analysts from CBS Sports were only 61% accurate.[2] My model significantly outperformed both of these baselines, demonstrating its effectiveness in capturing underlying team strength.

This Elo model will ultimately serve as the foundation for a predictive system 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 both pre-match betting strategies and team performance assessments.

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