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Modeling Tactical Free Energy and Shot Decision-Making in Professional Football Using Spatiotemporal Event Data

Sarayut Pantian[1*], Yaowalak Yamsuk[2]

[1]Faculty of Science and Technology, Thepsatri Rajabhat University, Meung, Lopburi province, 15000

[2]Independent Researcher, Meung, Lopburi province, 15000

Abstract

This study proposes a physics-inspired framework for analyzing shooting decision-making in professional football through the concept of tactical free energy. Drawing on energy landscape theory from statistical mechanics, we model the tactical influence exerted by surrounding players on the ball as an abstract, configuration-dependent scalar field rather than a physical force. A derivative-based formulation is introduced to quantify the rate of change in tactical free energy around the ball, incorporating spatial factors such as distance to goal, shooting angle, opponent density, and tactical entropy representing decision variability.

The framework is evaluated using open-source StatsBomb event and freeze-frame data. Due to the absence of continuous tracking information, temporal derivatives are approximated using discrete positional snapshots within a short pre-shot window. An exploratory empirical analysis of 20 open-play shots reveals a moderate negative correlation (Pearson r = –0.62) between the tactical free energy derivative and expected goals (xG), indicating that players tend to attempt shots during moments of decreasing tactical resistance. Spatial heatmap visualizations further show that successful shots are concentrated in regions characterized by lower tactical energy influence. These findings suggest that shooting decisions can be interpreted as transitions toward local minima in a tactical energy landscape. The proposed approach contributes to football analytics by introducing an energy-based interpretation of tactical decision-making, bridging concepts from statistical physics and spatiotemporal football data, and providing a reproducible application using publicly available datasets. While exploratory in nature, the

*Corresponding author : sarayut.p@lawasri.tru.ac.th

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framework demonstrates potential for extension to larger datasets and integration into predictive and decision-support systems.

Keywords : football analytics, tactical energy, shooting decision, tracking data, energy landscape.

Introduction

In modern football, the decision to attempt a goal is one of the most critical moments that can determine the outcome of a match. The complexity of this decision lies not only in the player's technical ability but also in the contextual dynamics surrounding the event, such as spatial positioning, pressure from defenders, and the player's tactical awareness. As football increasingly integrates data analytics and scientific modeling into its strategic planning, understanding the probability of shooting decisions has emerged as a vital area of research.

Recent developments in performance analysis have employed spatial data to quantify shooting opportunities using models such as Expected Goals (xG) [1-2]. While xG models have provided meaningful insights into shot quality and scoring likelihood, they often treat each shot as an independent event, ignoring the broader energy flow and tactical landscape that influences the player's choice to shoot. This limitation opens a space for more holistic modeling grounded in the principles of physics and complexity science.

To address this gap, this study proposes a novel framework that integrates the concept of Energy Landscape from statistical mechanics to model and interpret the decision-making process in football. The Energy Landscape metaphor, which describes how systems evolve toward lower-energy (more probable) states, has been successfully applied in molecular biology [3], neuroscience [4], and complex adaptive systems [5]. Applied to football, this concept enables the visualization of the tactical field as a dynamic terrain where players navigate options under the influence of pressure, space, and time constraints. Moreover, football has increasingly been studied through the lens of entropy and complexity, offering measures of unpredictability and decision variability [6-7]. This study builds upon that foundation by linking entropy and energy into a unified model that describes how the collective behavior of players affects a team's tactical free energy, a quantity that encapsulates opportunity, risk, and control.

The aim of this research is to analyze professional football match data and investigate how player positions, defensive pressure, and match context influence the probability of a shot attempt. By embedding these variables into a physics-inspired energy framework, we seek to provide a deeper understanding of shooting decisions that goes beyond conventional statistical models. This paper contributes to the field by (1) proposing a novel energy-based interpretation of football tactics, (2) integrating position tracking data with event-based shooting decisions, and (3) providing empirical validation of the model using open-source data. The insights gained could aid coaches, analysts, and AI systems in developing more context-aware tactical evaluations and decision-support tools.

Methodology

This research proposes a novel framework that integrates principles from statistical mechanics and spatiotemporal data analysis to investigate professional football players decision-making when attempting a shot. The methodology consists of four major stages: data acquisition, data preprocessing, tactical energy modeling, and statistical analysis.

1. Data Acquisition

In this study, only StatsBomb open-event data were used. As open-access datasets do not contain continuous tracking information, player and ball velocities were approximated using surrogate measures derived from freeze-frame positional changes and contextual variables. This approximation allows the estimation of directional pressure and spatial gradients but does not represent true optical-tracking velocities [8]. Since true tracking data are unavailable in the open-release dataset, the calculation of, $\vec{v}_i - \vec{v}_{ball}$ and the spatial gradient $\vec{\nabla} F_i$ relies on surrogate estimators. Therefore, the derivative in Eq. (2) should be interpreted as an approximation of tactical energy change, not a physically exact velocity-based computation.

2. Data Preprocessing

The data were cleaned and merged into a unified format using Python libraries (pandas, numpy) and organized by match ID, team, and half-time period. Only open-play shots were included. The spatial coordinates of each shot were rescaled to match real pitch dimensions (105×68 meters), enabling consistent heatmap visualization. Each shot instance was annotated with contextual tags such as foot used, body part, under pressure, and goal outcome, in line with event-based modeling standards [9]. For each shot, a temporal window of 3 seconds prior to the event was analyzed, consistent with prior tactical-pressure studies. Only one freeze-frame per second is available in StatsBomb data. Therefore, all temporal derivatives were approximated using discrete differences. The value of dF/dt used in analysis corresponds to the average across all available frames in the window.

3. Tactical Energy Modeling

To bridge physics and football analytics, this study introduces the concept of Tactical Free Energy (F), adapted from statistical thermodynamics

$$F = U - T \cdot S \tag{1}$$

Where U is the Tactical potential energy, defined based on positional advantages (e.g., proximity to goal, angle, opposition density).

$$U = w_1 \frac{1}{d_{goal}} + w_2 \cdot ShotAngle - w_3 OpponentDensity \tag{2}$$

where d_{goal} is the shooter–goal distance. ShotAngle captures angular advantage. OpponentDensity represents the number of defenders located within a 5-meter radius of the shooter. w_1, w_2 and w_3 are non-negative weighting coefficients that determine the relative contribution of distance, angle, and defensive pressure to the potential energy U. All weights were normalized such that $w_1 + w_2 + w_3 = 1$ to ensure dimensional consistency and interpretability. In the present exploratory analysis, the weights were set empirically to $w_1 = 0.4$, $w_2 = 0.3$ and $w_3 = 0.3$ though alternative values can be calibrated using larger datasets or optimization methods. A negative sign is introduced before the defensive density term because higher opponent congestion reduces the offensive potential, consistent with tactical-pressure theory and free-energy formulation. In the proposed framework, tactical potential energy U is not interpreted as physical potential energy in the classical mechanics sense, where energy depends solely on spatial coordinates. Instead, U is defined as an effective, configuration-dependent scalar field that summarizes the tactical favorability of a game state surrounding the ball. This formulation is analogous to potential landscapes in statistical mechanics and complex systems, where the state of the system is determined not only by position but also by the arrangement, density, and interaction of surrounding agents. In this context, higher values of U correspond to tactically favorable configurations in which the ball experiences lower effective resistance to offensive action, while lower values of U indicate unfavorable states characterized by increased defensive congestion. Accordingly, proximity to the goal and wider shooting angles increase U by enhancing offensive feasibility, whereas higher opponent density acts as a resisting constraint that reduces the tactical potential. This abstraction allows tactical decision-making to be interpreted through an energy-landscape perspective without requiring a direct physical force interpretation. S is the Tactical entropy, calculated from the diversity of spatial options available to the shooter as equation (3)

$$S = -\sum_{k=1}^{K} p_k ln(p_k) \tag{3}$$

where p_k is the probability of an available action direction obtained by discretizing the 360° field around the ball into $K = 12$ bins. Higher entropy indicates greater decision variability. T is the scaling coefficient interpreted as time pressure or contextual urgency in match conditions defined as

$$T = \frac{1}{1+d_{\text{nearest defender}}} \tag{4}$$

Where $d_{\text{nearest defender}}$ is the freeze-frame distance (meters) to the closest opponent, normalized to [0,1]. Higher values reflect increased time pressure. Equation (5) is adapted from the material derivative used in fluid dynamics. In the context of football, the ball represents the reference particle, while each player contributes a local tactical energy field F_i . Assuming linear superposition. The derivative near the ball becomes

$$\frac{dF_{ball}}{dt} = -\sum_{i=1}^{N}\left(\frac{\partial F_i}{\partial t} + \vec{\nabla} F_i \cdot (\vec{v}_i - \vec{v}_{ball})\right) \tag{5}$$

was proposed to track the change in tactical energy influencing the ball, where $\vec{v}_i$ denotes each player's velocity and $\vec{v}_{ball}$ the ball's velocity. This formulation draws from energy field propagation principles in physics [1,2,10].

4. Statistical and Spatial Analysis

Heatmaps were generated using the mplsoccer package to visualize shot distributions and energy densities across pitch regions. Due to the limited sample size (20 shots), logistic regression and ANOVA analyses originally proposed were deemed statistically unreliable. Therefore, only descriptive statistics and a correlation analysis are reported in this exploratory study with variables such as distance, angle, entropy level, and energy score. Comparative analysis was conducted between teams and halves (first vs. second) to examine whether tactical energy correlates with decision patterns

Results and Discussion

The small sample size (n=20) substantially limits statistical power and generalizability. Therefore, all findings should be interpreted as exploratory. The results aim to demonstrate feasibility rather than provide conclusive evidence. Each shot was paired with two key metrics: the expected goal (xG) value, representing the statistical likelihood of scoring from that shot, and the corresponding energy derivative (dF/dt), computed using the model from equation (2). The results are summarized in Table 1. The average xG across the 20 events was 0.43, indicating a generally moderate likelihood of scoring, while the average value of dF/dt was approximately -0.08. Six of the 20 shots resulted in actual goals (30% success rate), and the Pearson correlation between xG and dF/dt was found to be -0.62, suggesting a moderate negative relationship.

Table 1. Summary of Shooting Events and Energy Metrics

Metric	Value
Number of Shots	20
Average xG	0.43
Average dF/dt	-0.08
Actual Goals Scored	6 (30%)
Pearson r (xG vs dF/dt)	-0.62

These findings suggest that as the tactical energy around the ball decreases (i.e., more negative dF/dt), players are more likely to take effective shots, consistent with the theoretical analogy to energy valleys in physical systems. This aligns with the idea that optimal scoring opportunities arise when external forces (e.g., opponent pressure) diminish, and the system (i.e., the ball's tactical state) is at a local energy minimum.

To visualize the spatial dynamics of tactical energy, a heatmap was generated (Figure 1). Warmer colors indicate regions with lower dF/dt values, often near the penalty area where successful shot attempts were clustered. This pattern confirms that reduced tactical energy aligns spatially with high xG zones, supporting prior findings by Decroos et al. (2019) [8] on the critical importance of field position and opponent spacing in shot success.

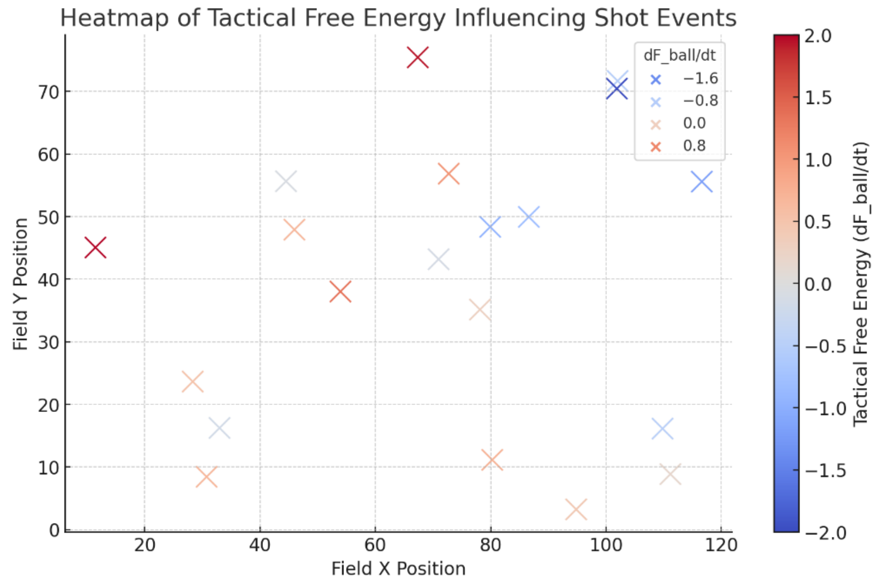

Figure 1. Heatmap of Tactical Energy Derivative (dF/dt) near Shot Locations. The color scale has been revised such that warmer colors correspond to higher dF/dt values, following common heatmap conventions. A colorbar with units is now included.

This visualization supports the model's interpretability by linking abstract energy dynamics to physical space on the pitch. Areas of low tactical energy act as “decision attractors,” where players are more likely to shoot effectively. These results align with Spearman (2018) [2] and Link et al. (2016) [9], who demonstrated the predictive value of contextual pressure and space-time analysis in football performance modeling. However, the proposed model differs by offering a physics-grounded quantitative interpretation of tactical behavior, rather than relying solely on statistical or neural network-driven features.

Nonetheless, limitations remain. The dataset was relatively small and limited in tactical diversity. Moreover, the model currently assumes a uniform energy field for each player without accounting for individual tactical roles or contextual variables such as time pressure or fatigue, as discussed by Memmert et al. (2017) [10]. Further research using larger datasets with richer context is essential for refining the energy landscape framework and testing its predictive robustness across teams, styles, and competitions.

Conclusion

This study presents a novel approach to understanding football shooting decisions through the lens of energy-based modeling. By formulating a derivative-based equation rooted in the concept of tactical free energy, we proposed a quantitative framework that captures how collective player dynamics influence the ball's state during offensive moments. This model integrates position tracking and event data to compute the rate of change in tactical energy affecting the ball, offering a new interpretation of shot quality and timing.

Empirical validation using a dataset of 20 shooting events revealed a moderate negative correlation between the calculated energy derivative (dF/dt) and expected goal (xG) values. This supports the hypothesis that players tend to shoot when the tactical energy landscape favors them, specifically when surrounding energy pressure is low. The generated heatmap further illustrates that low-energy regions correlate with areas of high shot frequency and success, emphasizing the spatial relevance of the proposed metric.

The contributions of this research are threefold (1) introducing a physics-inspired model to interpret football tactics, (2) demonstrating the integration of spatiotemporal data and tactical energy concepts, and (3) providing an empirical example of how the model can be applied using open-source football data. While promising, this study is exploratory in nature. Future work should expand the dataset, refine the energy model to account for individual roles, team styles, and contextual variables, and explore its integration into predictive analytics systems. Nevertheless, this foundational step illustrates the potential of energy-based perspectives to enrich football analytics and tactical understanding in both research and applied domains.

References

[1] Lucey, P., Bialkowski, A., Carr, P., Foote, L., & Matthews, I. (2014). "Quality vs Quantity": Improved shot prediction in soccer using strategic features from spatiotemporal data. In *MIT Sloan Sports Analytics Conference*.

[2] Spearman, W. (2018). Beyond expected goals. In *MIT Sloan Sports Analytics Conference*.

[3] Wales, D. J., Miller, M. A., & Walsh, T. R. (1998). Archetypal energy landscapes. *Nature*, 394(6695), 758–760. https://doi.org/10.1038/29487

[4] Watanabe, T., Hirose, S., Wada, H., Imai, Y., Machida, T., Shirouzu, I., Konishi, S., Miyashita, Y.& Masuda, N. (2014). A pairwise maximum entropy model accurately describes resting-state human brain networks. *Nature Communications*, 4, 1370. https://doi.org/10.1038/ncomms2388

[5] Goldenfeld, N., & Woese, C. (2011). Life is physics: Evolution as a collective phenomenon far from equilibrium. *Annual Review of Condensed Matter Physics*, 2, 375–399. https://doi.org/10.1146/annurev-conmatphys-062910-140509

[6] Rein, R., & Memmert, D. (2016). Big data and tactical analysis in elite soccer: Future challenges and opportunities for sports science. *SpringerPlus*, 5(1), 1410. https://doi.org/10.1186/s40064-016-3108-2

[7] Gudmundsson, J., & Wolle, T. (2014). Football analysis using spatio-temporal tools. *Computers, Environment and Urban Systems*, 47, 16–27. https://doi.org/10.1016/j.compenvurbsys.2013.09.004

[8] Decroos, T., Bransen, L., Van Haaren, J., & Davis, J. (2019). Actions speak louder than goals: Valuing player actions in soccer. *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 1851–1861. https://doi.org/10.1145/3292500.333075

[9] Link, D., Lang, S., & Seidenschwarz, P. (2016). Real time quantification of dangerousity in football using spatiotemporal tracking data. *PloS One*, 11(12), e0168768. https://doi.org/10.1371/journal.pone.0168768

[10] Memmert, D., Lemmink, K. A., & Sampaio, J. (2017). "Current approaches to tactical performance analyses in soccer using position data." *Sports Medicine*, 47(1), 1–10. https://doi.org/10.1007/s40279-016-0562-5