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# ANALYSIS OF THE ATTRACTIVENESS OF SOCCER: A GAME REFINEMENT MODEL AND THE SIGNIFICANCE OF "ANTAGONISTIC RATE"

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## ABSTRACT

Soccer (or association football) is now the most popular sports game in the world. Various underlying factors may explain its reasons to be popular. However, there is no underlying explanation as to why the nature of the game processes was appealing to all people of all ages. However, measuring such subjective metric were empirically challenging and costly. In this paper, a mathematical model of a soccer game is established based on the game refinement theory, where the internal processes of a soccer game are explored where interpretation based on the "antagonistic rate" is established. Based on such measures, two stages were identified in the soccer game, and various soccer leagues' data were utilized as the testbed. Further analysis of the soccer game was determined based on physics in mind measure using correspondence of Newtonian law of motions. These measures

provide insights into the game stages' underlying entertainment value, as well as a new perspective on the soccer game attractiveness.

**Keywords:** Soccer, Football, Sport Games, Game Analysis, Game Progress Model, Game Refinement Theory, Antagonistic.

## INTRODUCTION

Sports involves multiple forms of game-like or competitive activities or play that either participated casually or under formal organization, wherein part use, maintain, or improve, in part, the physical ability or skills (fine motor or gross motor movement), broadly followed by the various governing body and largely standardized and known over the globe, and at the same time, entertaining to players and some cases even spectators (Jenny, et al. 2017; Thiel and John, 2018; Parry, 2019).

Other criteria of sports include single to multiple participants, contesting as a team or "free-for-all," either simultaneously or consecutively (e.g., racing), with a single winner or matches between two competing sides, allowing "tie" or "sudden death," arranged in tournament structure or regular sports season with playoffs.

Among the various sports, football (also known as soccer in some countries), part of a family of team sports, is a sport game that involves varying levels of kicking a ball to score a goal. Various forms of football are known as football codes, which include gridiron football (American football or Canadian football), Australian rules football; rugby football (either rugby league or rugby union), and Gaelic football (Reilly & Gilbourne, 2003). This study focuses on the variant that popularly known as soccer (also known as Association Football).

Soccer is highly enjoyable because of its abundant game elements. Soccer is a team game in which 11 players on each side try to score as many times as possible within the time allowed by forcing the ball into the opponent's goal (Lees & Nolan, 1998). The main restrictions on playing the game involve propelling the ball by any part of the body except the arms and hands. Hence, a plethora of strategies and skills have matured and developed to accomplish the objective of scoring goals. This situation is especially true in some high-level leagues, where the two sides often demonstrate incredible spectacles of battles for victory and glory. Fans who support their favorite team or players also feel great satisfaction after spectating the gameplay's progress.

There are variety of factors that makes soccer gameplay have significant appeal to nature of people as a form of entertainment. Among the contributing factors are as follows:

1. ***Low entry barriers*****:** Soccer can be a true sport for people of all ages, and it is easier to participate than other sports. Apart from relatively popular games that require the purchase of professional equipment to participate, like basketball and volleyball, it also requires some skills and experience to play, which makes it is less suitable for pure beginners. However, in soccer games, beginners can find their value in the team by allocating tasks reasonably.

2. ***High playability*****:** The number of players in regular soccer matches is 11, including various roles. Players can play any role according to their technical characteristics or preferences, which gives players many choices.

3. ***Ease of play:*** Soccer is more accessible to play than other traditional sports, and it can be played by anyone who wants to play, which may also be one of the reasons soccer is so attractive and appealing to any players.

These are just a few factors that may contribute to making soccer a popular sport. However, mechanisms that make soccer one of the popular sports games have yet to be investigated. Therefore, this study aims to analyze the game mechanisms through the game refinement theory to quantify the fundamental entertainment aspects of the game. In addition, the scoring model of the soccer game was analyzed where the antagonistic rate of such model was applied to soccer league data to gain new insight.

The structure of the paper starts by outlining and reviewing some of the previous works conducted in analyzing the soccer game from multiple perspectives. Then, the game refinement theory was introduced to analyze the internal processes of soccer. Subsequently, further analysis of the proposed scoring model of soccer is introduced where the measure of the antagonistic rate of soccer was implemented on big soccer league data. In contrast, further analysis was conducted using the law of motions in games. Finally, the conclusion and future work are provided.

## RELATED WORKS

Earlier work on soccer analysis focused on making the computerized soccer analysis viable, especially in automating such a process. For instance, Taki et al. (1996) developed image motion analysis of soccer games using minimum moving patterns and dominant regions to quantify significant factors that characterize teamwork. Then, video-based analysis becomes prominent as technological advancements and high-performance computing become increasingly ubiquitous. Since then, video-based analysis has been focused on determining the underlying factors that effects goal scoring (Armatas et al., 2007), performance outcome (Cavalera et al., 2015), and movement quality (Soniawan et al., 2021) (cf. Fischer et al. (2019) for a detailed survey on video-based analysis of soccer categorized based on levels of complexity, automation, video support, visual techniques, and usability). Such works provide visual or tacit insights for coaches to understand their team's strengths and performance better

Another school of work focuses on identifying the semantic motivation of the underlying information collected from videos or statistics of soccer play. Such works have been adopting inference engines based on a Bayesian network to collect low-level evidence from a recorded soccer video (Huang et al., 2006), interactive performance analysis based on user's geospatial data (Benito et al., 2018), and generate a highlight time curve (HTC) by fusing factors that composed the affection arousal to determine the excitement value of the game (Wang, 2021). Such studies captured many expert workflows of the soccer match analysis, while others focused on producing end-to-end solutions for automated soccer analysis via powerful parallelism such as the deep neural networks (Sheng et al., 2020; Marchiori and de Vecchi, 2020). These studies make quantitative statistics more meaningful and provide visual information delivery; thus, more practical for coaches to make critical judgments, determine the favorable outcome, and establish optimum field control strategies.

Some studies provided critical information, data abstraction, and some form of visualization that were helpful in training, tactics, and strategy development in soccer matches. Such study typically focuses on movement trajectories and interactions among them (individually or the whole team) (Kang et al., 2006), play positions (Modric et al., 2019), outcomes of soccer games prediction, and factors that influence it (Eryarsoy and Delen, 2019), team formation and pattern extraction (Narizuka and Yamazaki, 2019), potential passes (Fernández and Bornn, 2020), and their combinations (Pereira et al., 2021). The findings of these studies provide essential indicators to establish an effective training regiment, ensure players' tactical responsibility, evaluate passing risk and options, and provide insights into the game dynamics and players' behaviors.

Theoretical analysis of soccer games based on the dynamics of information was also conducted, which involves using some mathematical representation or model to determine the underlying play pattern relative to some considered factors (or features). The relationship between such factors would help coaches design the appropriate control that optimizes such information dynamics. For instance, Lopes and Tenreiro Machado (2019) adopted fractional calculus theories for studying the evolution of a national soccer league season and possible patterns in successive seasons, where a soccer league is treated as a complex system with a state observable at discrete time instants. Furthermore, the kinetics and full-body kinematics of elite goalkeepers performing a complex motor task of a diving save in soccer were investigated by Ibrahim et al. (2019), where practical assessment and training were highlighted. Also, Falces-Prieto et al. (2021) investigated the influence of role rotation (offensive, defensive, and wildcard) in a small-sided soccer game relative to physical demand, technical performance, and the internal load of young soccer players.

However, entertainment aspects of the soccer game have been scarcely investigated; instead, quantitative measures of such aspects. To the best of our knowledge, the work by Ben-Naim et al. (2007) that extensively employed statistical analysis to compare results of major sports competitions and quantify the predictability of games based on the likelihood of the frequency of upsets ($q$) is the first quantitative measures for determining soccer game competitiveness. Although in comparison, recent works did consider quantitative measures in their study (Benito et al., 2018; Wang, 2021; Fernández and Bornn, 2020; Pereira et al., 2021), their intended application was motivated by tactical and some specific strategic interests of the coach and the soccer team. Consequently, such works neglect the spectators' perspective of the game and the underlying strategy that makes the soccer match attractive and entertaining. Therefore, this study proposed utilizing the game refinement theory as a measure of entertainment and attractiveness of soccer and determining the potential mechanisms that make soccer one of the popular games worldwide.

## Game Refinement Theory

The outcome of a game is usually the sum of countless games between two (or more) sides (Hammond, 2004). According to the game refinement theory (Iida et al., 2003), the game can be thought of as consisting of two critical information (Sutiono et al., (2014); Panumate et al., (2015)). One is the in-game processes determined by the in-game factors, while the other is the game progress constructed based on the results after the game is over.

## Game Information Progress

A game information progress has complete information of the overall game progress based on the result of the game, that is, after the end of the game. So, the game process $x(t)$ can be regarded as a linear function of time $t$, given by (1), where $0 < t < T$ and $0 \leq x(t) \leq 1$. It implies that the rate of game progress $x'(t)$ is proportional to $x(t)$ and inverse proportional to $t$. In such a context, $x(T)$ represents the overall progress of the game, $\frac{n}{t}$ is regarded as the speed to push the game information forward, and $t$ is regarded as the number of attempts to achieve the goal during the game.

$$x'(t) = \frac{n}{t} \cdot x(t) \qquad (1)$$

However, in the process of the game, a lot of information is unknown, and the exact value is uncertain until the end of the game. Hence, (1) is modified to fit the actual game-playing situation, given by (2). Here $n$ represents a constant parameter (Xiong et al., 2017) based on the game observer point-of-view. Only in a boring (or dull) game will the game progress become linear. In most cases, the progress of the game is complex and dynamic, so it is reasonable to assume the value of $n$ is based on the conjecture of the progress of the game. If the game information is a state that was fully known (*n=1*), the game progresses become a straight line. Assuming the solved information *x(t)* is twice derivable at *t* between *[0,T]*, solving *t=T*, the second derivative of (2) indicates the accelerated velocity of the game progress, which is given by (3). The acceleration of velocity implies the difference of the rate of acquired information during game progress.

$$x(t) = \left(\frac{t}{T}\right)^n \tag{2}$$

$$x''(t) = \frac{n(n-1)}{T^n} t^{n-1}|_{t=T} = \frac{n(n-1)}{T^2} \tag{3}$$

According to Newton's classical mechanics, the force in physics comes from the mass of an object and its acceleration. This study assumes that the progress of game information is accomplished in the brain (Agarwal et al., 2016). Although the physical properties and principles in the brain is not yet known, but it is likely that the acceleration of game information progress is related to the forces in our brain (Khalid and Iida, 2020). Based on the previous study by Sutiono et al., (2014) and Sutiono et al., (2015), the measure of game refinement (*GR*) is obtained as the root square of the second derivative of (3), where the term $\sqrt{n(n-1)}$ is approximated by the average number of successful shoots (*G*), while the *T* is average number of total shoots. Then, the *GR* value, given by (4), can be determined for a number of fans mainstream sports games (see Table 1).

$$GR = \frac{\sqrt{n(n-1)}}{T} \approx \frac{\sqrt{G}}{T} \tag{4}$$

**Table 1**

*The GR value of current mainstream ball games (Sutiono et al., 2014; 2015).*

| Game | G | T | GR | Fan Size (Millions) |
|---|---|---|---|---|
| Soccer | 2.64 | 22.00 | 0.073 | 2700 |
| Volleyball | 25.00 | 44.00 | 0.114 | 260 |
| Table tennis | 54.86 | 96.47 | 0.077 | 249 |
| Basketball | 36.38 | 82.01 | 0.073 | 182 |
| Badminton | 46.34 | 79.34 | 0.086 | 133 |
| Baseball | 4.73 | 33.67 | 0.065 | 100 |

### Game Information Progress

In real games, there is also internal game progress driven by the speed generated by both sides of the players (or team) in the game. The "game speed" may be composed of two factors (Iida, 2008): (1) the final score obtained in the game according to the game rules, and (2) the number of attempts to gain such points in the game.

In scoring sports (e.g., football and basketball), this process can be regarded as the "game speed'" is the quotient of the final goals scored and total shots taken, that is, the "goal rate" as the "game speed" of a game, given by (5).

$$Game\ Speed = \frac{Number\ of\ Goals}{Number\ of\ Shoots} \tag{5}$$

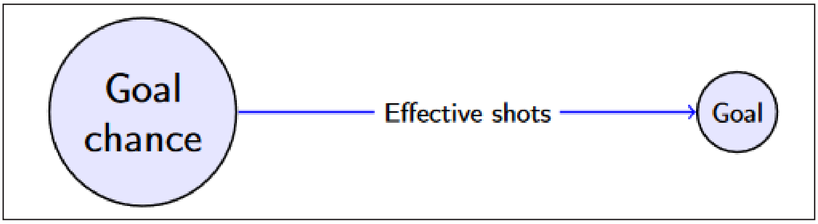
## ANALYSIS OF SOCCER GAME

### Soccer Scoring Model

A previous study regarded the performance of the team-based scoring game based on their capability to achieve a score over the total scoring tries (Sutiono et al., 2015). For this study, team games (such as soccer and basketball) are regarded as a game between two sides (similar to two-player games). By doing so, the complexity of the game processes can also be reduced into two stages. Such stages can be depicted as a brief model of a soccer game (Figure 1).

**Figure 1**

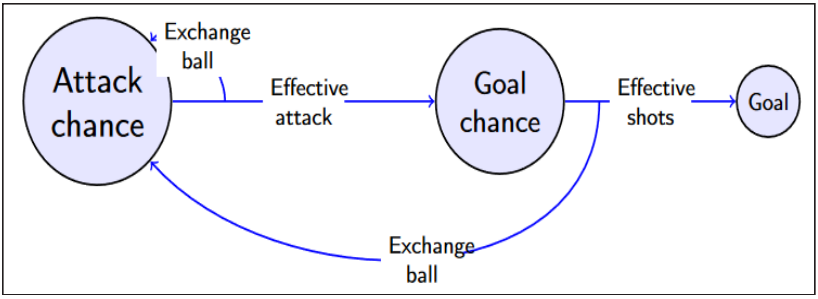
*A Brief Model of A Soccer Scoring*




In an ideal game situation, based on the soccer scoring model, both sides would repeat this process until the end of the game. However, this situation is not always true where some attacks may eventually land a shot, while others may revert to exchanging ball between team members due to unsuccessful tries. Hence, the soccer scoring model is optimized according to an actual competition setting, given by Figure 2. This model also aligned, in part, with the work on trajectory interactions between objects in a soccer game by Kang et al. (2006), and the qualitative study conducted by Cavalera et al. (2015) on linking primary, secondary, and tertiary performance outcomes of soccer matches.

**Figure 2**

*Realistic Model of A Soccer Scoring*




Most of the time in soccer games, either side would indulge with a lot passing in the first phase, where most of the shots were blocked. For this research, it is assumed that the ball exchange between the two teams happened at the beginning of the other team's attack. In particular, the ball is exchanged in a soccer match when:

1. ***Interception:*** when a player on one side is intercepted while passing a ball to a teammate.

2. ***Tackle*:** A loss of possession by a player on one side who is defended by another player while carrying the ball.

3. ***Foul:*** Refers to a player from one side who violates the rules of the game or makes dangerous moves during the game and is suspended by the referee, and the ball is given to the other side (set pieces).

4. ***Out of Bounds:*** When a player from one side makes a mistake in holding the ball and it crosses the boundary of the court, the referee hands the ball to the player on the other side.

5. ***Missed Shots:*** When a player from one side shoots but the ball is confiscated by the opposing goalkeeper, the defender gains the ball; When a player on one side shoots but the ball goes out of bounds, exchange the ball.

## The First Stage and Effective Attack Measure

The process of getting the ball until a team starts shooting is identified as the first stage. When a shooting occurs, it means that one side has completed the first stage. If there is no shooting and the opponent has the ball, the other side starts the first stage. By calculating the number of exchanging balls between the two sides, the starting number of the first stage in the match between the two sides can be determined. The number of the exchange of the ball is identified as the *E* value, as shown in (6). Based on the formulation, the *E* values have been calculated and collected for the five most popular leagues in the world over the past five years (https://www.fifa.com/), given in Table 2.

$$E = Tackles + Interceptions + Fouls + Outside + (Shots - Goals) \quad (6)$$

**Table 2**

*E Value of the World's Five Major Leagues*

| **League Name** | ***E* value** |
|---|---|
| English premier league | 111.59 |
| Spain La Liga | 121.61 |
| Serie A | 118.57 |
| La liga | 119.22 |
| Bundesliga | 124.32 |
| **Average** | **118.63** |

Effective attacks are those that start the first phase and eventually turn into shooting behavior. Thus, "effective attack rate" can be regarded as the speed for driving the first stage processes, called $p_1$, as given by (7). The *T* here is the total number of shots taken by the two sides in the match. Therefore, by collecting relevant game data (https://www.whoscored.com/), the average speed of the five major leagues in the first stage can be determined, which is given in Table 3.

$$Effective\ Attack = p_1 = \frac{E}{T} \quad (7)$$

**Table 3**

*The Average Number of Shots Scored and the Speed of the First Stage in the Five Major Leagues (Past Five Years)*

| League Name | $E$ | $T$ | $p_1$ |
|---|---|---|---|
| English premier league | 111.59 | 25.43 | 0.228 |
| Spain La Liga | 121.61 | 24.02 | 0.198 |
| Serie A | 118.57 | 26.51 | 0.224 |
| La liga | 119.22 | 23.93 | 0.201 |
| Bundesliga | 124.32 | 25.82 | 0.208 |
| **Average** | **118.63** | **25.14** | **0.212** |
| *E:* ball exchange rate; *T:* total number of shots taken by both sides; $p_1$: effective attack rate; | | | |

## The Second Stage and Effective Shooting Measure

The second stage is identified as the process of starting the shooting until the goal is scored. However, if the scoring attempt failed and the ball is exchanged, the team that has the ball will start a new round of attack. The effective shooting at this time is essential in promoting the smooth progress of the second stage of the game. Therefore, "goal rate" is regarded as the speed in the second stage of the soccer match ($p_2$), given by (8).

$$Effective\ Shot = p_2 = \frac{G}{T} \tag{8}$$

In the current context, the total number of goals scored by both sides in the match is $G$. Consequently, by collecting relevant game-playing data (https://www.whoscored.com/), the average speed of the five major leagues in the second stage can be calculated (see Table 4).

**Table 4**

*The Average Number of Goals Scored in the Five Major Leagues in the Past Five Years and the Speed of the Second Stage*

| League Name | $G$ | $T$ | $p_2$ |
|---|---|---|---|
| English premier league | 2.714 | 25.43 | 0.107 |
| Spain La Liga | 2.736 | 24.02 | 0.114 |
| Serie A | 2.724 | 26.51 | 0.103 |

(continued)

| League Name | $G$ | $T$ | $p_2$ |
|---|---|---|---|
| La liga | 2.584 | 23.93 | 0.108 |
| Bundesliga | 2.888 | 25.82 | 0.119 |
| **Average** | **2.729** | **25.14** | **0.110** |
| *G:* total number of goals scored by both sides; *T:* total number of shots taken by both sides; $p_2$: goal rate; | | | |

## ANTAGONISTIC RATE OF SOCCER

### Rate of Antagonism

Winning in almost all ball games requires a higher score than the opponent, and depending on the game, the method and difficulty of earning points vary. Regardless of the rules, the probability of earning points in the game is often represented as the game "score rate." The higher the score, the easier the game is to score, while the lower the score, the harder the game is to score. The game's "score rate" corresponds to the "game speed" (denoted as $p$) that drives the game progression.

For example, the aforementioned "game speed" of soccer can be represented by the "score rate" (denoted as $p_2$) of the second stage. On the contrary, if a game is more difficult to score, it means that every attempt to score is more likely to be defended, making a mistake, or caused by some other off-field factors. This situation is defined the "antagonistic rate" (denoted as $m$) of the game, given by (9).

$$m = 1 - p \tag{9}$$

Based on the collected data, analysis and calculation of both the "game speed" ($p$) and the "antagonistic rate" ($m$) of the current mainstream ball games can be conducted, which is given in Table 5. It can be observed from the table that the "antagonistic rate" of soccer is higher than that of any other mainstream ball game. This situation suggests that a soccer game is more difficult to score and may have more randomness in trying to score. Such randomness can be caused by shot misses by the striker or a successful block by an opponent's defender, or it could be something else that causes the shot to fail.

**Table 5**

*p and m Values of some Mainstream Ball Games (p: game speed; m: antagonistic rate;)*

| Game | *p* | *m* |
|---|---|---|
| Soccer | 0.120 | 0.880 |
| Baseball | 0.141 | 0.859 |
| Basketball | 0.444 | 0.556 |
| Volleyball | 0.568 | 0.432 |
| Table tennis | 0.569 | 0.431 |
| Badminton | 0.584 | 0.416 |

## Analysis of Antagonistic Rate in Soccer

The size of the *m* may be an important factor in making soccer so popular, because scoring is so difficult that the audience is likely to be more excited about it. To test this idea, the data of the average number of shots for goal (*T*) and the average number of goals scored (*G*) in several national soccer leagues (https://www.jleague.jp/) over the past five years, as well as the international soccer leagues (https://www.whoscored.com/), given in Table 6.

**Table 6**

*The Average Number of Goals Scored and Shots Taken in Some National Leagues Over the Last Five Years, as Well as Their m Values.*

| Year | English Premier League | | Spain La Liga | | Major League Soccer | | France Le Championed | | Japan J Alliance | | China Super League | | Germany Bundesliga | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | G | T | G | T | G | T | G | T | G | T | G | T | G | T |
| **2019** | 2.82 | 25.36 | 2.60 | 24.35 | 3.04 | 27.26 | 2.56 | 24.74 | 2.58 | 21.94 | 3.08 | 25.74 | 3.18 | 26.98 |
| **2018** | 2.68 | 24.44 | 2.70 | 24.10 | 3.14 | 26.60 | 2.70 | 24.82 | 2.66 | 22.84 | 3.18 | 25.26 | 2.82 | 25.30 |
| **2017** | 2.80 | 25.62 | 2.96 | 24.06 | 2.90 | 25.50 | 2.64 | 24.12 | 2.60 | 22.18 | 3.02 | 25.58 | 2.86 | 24.96 |
| **2016** | 2.71 | 25.74 | 2.76 | 23.82 | 2.84 | 25.66 | 2.52 | 23.10 | 2.54 | 22.24 | 2.65 | 23.76 | 2.84 | 25.74 |
| **2015** | 2.56 | 26.00 | 2.66 | 23.74 | 2.76 | 24.40 | 2.50 | 22.80 | 2.70 | 22.10 | 2.70 | 24.06 | 2.74 | 26.12 |
| **Ave. *G*** | 2.714 ±0.104 | | 2.736 ±0.138 | | 2.936 ±0.153 | | 2.584 ±0.084 | | 2.616 ±0.064 | | 2.926 ±0.237 | | 2.888 ±0.170 | |
| **Ave. *T*** | 25.432 ±0.600 | | 24.022 ±0.247 | | 25.888 ±1.094 | | 23.932 ±0.905 | | 22.260 ±0.343 | | 24.880 ±0.908 | | 25.821 ±0.170 | |
| ***m*** | 0.893 | | 0.887 | | 0.886 | | 0.892 | | 0.882 | | 0.881 | | 0.889 | |

*G:* average number of goals scored; *T:* average number of shots for goal; *m:* antagonistic rate;

According to the table, the "antagonistic rate" corresponds to the national leagues' ranking of the past five years. The leagues' "antagonistic rate" is then compared with the actual rankings based on the world popularity rankings, obtained through the survey (http://www.teamform.com/cn), summarized in Table 7. It can be observed that the ranking is given by the "antagonistic rate" (*m*) is roughly similar to the popularity ranking of the soccer league (the difference in the 2nd, 3rd, and 4th ranks due to small differences of the averaged data), which may indicate that *m* is an essential factor affecting the popularity of soccer.

**Table 7**

*World Average Ranking in the Last Five Years as Well as the Real Ranking and the Antagonistic Rate Ranking in the Sample*

| League Name | $Rank_a$ | $Rank_b$ | $Rank_m$ | $m$ |
|---|---|---|---|---|
| English premier league | 1.4 ± 0.5477 | 1 | 1 | 0.893 |
| Spain La Liga | 1.6 ± 0.5477 | 2 | 4 | 0.887 |
| Germany Bundesliga | 3.4 ± 0.5477 | 3 | 3 | 0.889 |
| France Le Chanpionnat | 5.4 ± 0.5477 | 4 | 2 | 0.892 |
| Major League Soccer | 55.2 ± 2.1679 | 5 | 5 | 0.886 |
| Japan J Alliance | 57.6 ± 3.2094 | 6 | 6 | 0.882 |
| China Super League | 63.6 ± 1.5166 | 7 | 7 | 0.881 |

$Rank_a$: last five years average world ranking; $Rank_b$: ranking in popularity in based on data sample; $Rank_m$: ranking based on antagonistic rate; $m$: antagonistic rate;

## Physical Significance of "Antagonistic Rate"

The "antagonistic rate" indicates the hardness or difficulty of scoring in the game. Such a condition can be reasonably assumed as the quality of the game itself. Concerning the Newtonian laws of motion, such a measure can be linked to mass in the game. In physic, motion is described by its mass, where larger mass is more difficult to assert motion upon, and vice versa. Hence, the "antagonistic rate" translates as the mass in mind or difficulty to make a move in our mind.

However, as the scoring model of the soccer game involves two stages, defining what constitutes a "motion" in the game is essential. In the context of soccer, since the first stage involves achieving a smaller probability of the scoring outcome (towards the second stage), while the second stage involves achieving the best possible scoring outcome (making a goal), then those situations can be mapped as reduction of state space of scoring possibilities. Therefore, motion in the game can be defined as the reduction of state space of all possible scoring, where the stages defined in this study is the speed of such reduction.

Based on the game refinement theory, if $t$ is the total length of the game, and $y(t)$ is the function of time ($t$), then the "antagonistic rate" refers to the velocity ($v$) of the game, given by (10). Then, the acceleration ($a$) of the game is given by (11).

$$y(t) = vt \tag{10}$$

$$y(t) = \frac{1}{2}at^2 \tag{11}$$

## The Measure of "Power" in Soccer Game

Given the quality of the game, analogous to the laws of physics, the forces ($F$) generated in the game of soccer can be calculated, given by (12). Solving (10) and (11) at $t=T$, then the acceleration ($a$) can be derived as (13), where $v = p$ that corresponds to the "game speed" (velocity), and $T$ is the total number of attempts to achieve the goal in each stage. As previously defined, the first stage is the number of attacks, and the second stage is the number of shots. Then, the two forces in a football match for those two stages is given in Table 8.

$$F = ma \tag{12}$$

$$a = \frac{2v}{T} \tag{13}$$

**Table 8**

*The Force Generated in Two Stages of the Five World's Major Soccer Leagues*

| League Name | First Stage ($F_1$) | Second Stage ($F_2$) |
|---|---|---|
| FA premier league | 0.0031 | 0.0085 |
| Spain La Liga | 0.0026 | 0.0084 |
| Serie A | 0.0029 | 0.0070 |
| Ligue 1 | 0.0027 | 0.0081 |

(continued)

| League Name | First Stage ($F_1$) | Second Stage ($F_2$) |
|---|---|---|
| Bundesliga | 0.0027 | 0.0081 |
| **Average** | **0.0028** | **0.0078** |

### The Measure of "Momentum" in Soccer Game

If the process of football is regarded as a closed system, then the momentum can be calculated for the soccer games, based on (14). Since $p = v$ (velocity), then the momenta can be calculated for both stages according to (15), as given in Table 9. Based on the game refinement interpretation, momentum value corresponds to the magnitude of difficulty in gaining an advantage or successful for players within the team and against opponent's team players. Also, applying (13), the peak value of momentum was found at $\vec{p} = \frac{1}{4}$ and $m = \frac{1}{2}$. This situation implies the interactions (or movements) among team members between the two opposing teams are balanced.

$$\vec{p} = mv \tag{14}$$

$$\vec{p}_{total} = \sum_{i} m_i v_i \; where \; i = stages \tag{15}$$

**Table 9**

*The Force Generated in Two Stages of the Five World's Major Soccer Leagues*

| League Name | $\vec{p}_1$ | $\vec{p}_2$ | $\vec{p}_{total}$ |
|---|---|---|---|
| FA premier league | 0.176 | 0.096 | 0.272 |
| Spain La Liga | 0.159 | 0.101 | 0.260 |
| Serie A | 0.174 | 0.092 | 0.266 |
| Ligue 1 | 0.161 | 0.096 | 0.257 |
| Bundesliga | 0.165 | 0.105 | 0.270 |
| **Average** | **0.167** | **0.098** | **0.265** |

$\vec{p}_1$ :momentum in the first stage; $\vec{p}_2$ :momentum in the second stage; $\vec{p}_{total}$ : total momenta based on (15);

## GENERAL DISCUSSION

Based on the result analysis (see Table 3 and Table 4), it can be observed that the speed (or velocity) of soccer game in the first stage was higher than the speed in the second stage. Similar pattern was also observed for the momentum (see Table 9), while the opposite was observed for the force (see Table 8). Hence, such results were consistent with the realistic scoring model of the soccer (see Figure 2).

Such observations can induce several insights. The game speed should be higher in the first stage to quickly traverse the possible state space of scoring, which explains the many effective attack actions needed for such a stage. Additionally, higher momentum that acted upon the motion of the game corresponds to the magnitude of players' gaining advantage during this stage. Therefore, actions in this stage require an equivalent level of effort to overcome the difficulty of scoring, which can be translated to low ability requirements (low force). From the perspective of the observer, this stage is less engaging but more comfortable to follow.

Meanwhile, the second stage is achieved, when possible, state space of scoring is successfully reduced. In such a situation, players were limited to potential goal tries, which may be impeded by opponents or become a successful goal. In this stage, lower momentum acted upon the motion of the game, which translates to less magnitude of players' gaining advantage during this stage. Also, a higher force is analogous to a more significant effort requirement in scoring and higher ability demands. This situation corresponds to the informational acceleration in our mind, where the possibility of scoring is ``felt'' as a risky motion in the game (chance-based). From the perspective of the observer, this stage is engaging and thrilling.

Such findings is also consistent with the work by Armatas et al. (2007) and Cavalera et al. (2015) where players in the later stage of the game (i.e., second half) were showed to induce higher scoring opportunity compared to the initial stage of the game (i.e., first half). In addition, it was observed that all the soccer leagues average is about $\vec{p}_{total} = 0.265$, which reaches the peaked momentum ($\vec{p}_1 \geq 0.25$). This situation implies that soccer games have the greatest magnitude of gaining advantages in a match while at the same time being among the most difficult to score. These findings showed that soccer is the most competitive game among other popular sports (i.e. baseball, basketball, hockey) (Ben-Naim et al., 2007), which also explained the attractiveness of soccer from the perspective of its audience.

## CONCLUSION

In this study, the analysis based on the soccer scoring model and application of game refinement theory identified two distinct stages in football games. This situation implies that football can be an attractive game to its audience based on two perspectives. Viewers who enjoy the tactical setup, team offensive operations, and team defensive operations are likely to be attracted to the first stage. Such a situation was relatively associated with the works conducted by Armatas et al. (2007), Cavalera et al. (2015), and Soniawan et al. (2021) on video-based analysis where higher-order cognition was essential. In contrast, spectators who enjoyed the kick's randomness and the goal's excitement were more likely to be drawn to the second stage, which was the essence of the works by Modric et al. (2019) and Fernández and Bornn (2020). Besides, this study found that the "antagonistic rate" in soccer games may also be an essential factor in soccer's popularity. The resulting physical quantification may also measure other games' attractiveness.

Future works could investigate the potential of such scoring model and antagonistic rate to measure not only the attractiveness of the sports game but also other video games, such as action games and VR-based games or games with multi-modal inputs (or games with a high number of actions and multi-stages). In addition, the proposed model could provide an exciting take on simulation games and non-game decision-making (e.g., business model or educational pedagogy).

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