Summary

In an international sports event, a well-planned schedule can ensure fairness, high athletic performance, and environmental sustainability. Our team developed a mathematical model that satisfies all three of these qualities and can be implemented universally. We applied this model to design an international sports event, successfully constructing an initial schedule and extending the model to accommodate various types of sports.

First, our team needed to select the sport most suitable for the Global Sports League (GSL). To quantitatively rank team sports, we developed the Sport Compatibility Score (SCS). The SCS evaluated two key parameters: competitive equity and global popularity. Competitive equity was quantified using the Gini coefficient in sports, while global popularity was measured through Google Trends data. By ranking candidate sports based on their SCS, we selected volleyball as the most suitable option.

Next, our team selected 20 countries to participate in the GSL. To do this quantitatively, we developed the Sport Potential Profile (SPP). SPP first ensured geographic representation by selecting at least two countries from each continent. Then, three parameters were used:

1. Ranking Score, based on FIVB points
2. Social Score, calculated using the percentage of the population under age 15
3. Environmental Sustainability Index, measured using the existing Environmental Performance Index (EPI).

Through this process, we selected the following 20 countries: France, Poland, Slovenia, Germany, Italy, Netherlands, Japan, Iran, Pakistan, United States, Canada, Cuba, Brazil, Argentina, Australia, New Zealand, Cameroon, Egypt, Angola, and Ivory Coast.

For matchmaking, our team developed an entirely new method called the Entropy-Based Interactive Matchmaking Method (E-BIMM). Unlike traditional leagues or tournaments with fixed schedules, E-BIMM updates match pairings round by round using principles from information theory—specifically, Shannon entropy—to maximize the amount of information gained from each game. Matches are chosen to maximize uncertainty and improve ranking accuracy.

To further enhance the schedule, E-BIMM incorporates a Match Compatibility Metric (MCM), which evaluates travel distance and match popularity (Hit Score). When multiple matchups have similar entropy values, MCM is used to prioritize pairings based on cost efficiency, environmental impact, and audience appeal. Travel distances are assessed using a sigmoid-based fatigue model, while the Hit Score is calculated using normalized average Elo ratings and the presence of historic rivalries.

To generate the initial schedule, we used two additional methods. The first was the Arrival Plan (AP), a model that accounts for jet lag to determine appropriate rest periods between matches. The second was the Game Time Calculation Method (GTCM), which determined the specific time each match would take place. GTCM differentiated the time windows available for home and away teams to ensure favorable conditions for both sides.

Using these models, we generated a complete schedule through simulation. We then analyzed the impact of adding four additional teams, examining changes in the number of matches and total travel distance. Finally, we generalized our model to three additional sports, analyzing how the sensitivity of the Elo rating mechanism varies based on historical data.

Keywords: Elo Rating, Shannon Entropy, Optimization

Letter to the Decision Makers

Dear the Directors of IMMC

We're excited to share our proposal for a smarter, fairer, and more sustainable approach to scheduling international sports competitions. Our model, the Entropy-Based Interactive Matchmaking Method (E-BIMM), is designed to make global leagues more balanced, efficient, and engaging for both players and audiences.

We began by selecting the most suitable sport and countries for the pilot version of what we call the Global Sports League (GSL). To choose the sport, we developed a Sport Compatibility Score, which considers competitive balance using the Gini coefficient and global popularity using Google Trends. Volleyball emerged as the strongest candidate.

For country selection, we created the Sport Potential Profile to ensure worldwide representation. This metric considers international rankings, youth population as a sign of future talent, and environmental sustainability based on the Environmental Performance Index. Using this approach, we selected 20 diverse and promising countries.

At the core of our system is E-BIMM, which creates matchups round by round instead of fixing a schedule in advance. Using Shannon entropy, the model prioritizes matches that provide the most valuable information—especially when team rankings are uncertain—leading to more accurate standings as the league progresses.

When multiple matchups offer similar entropy, we apply the Match Compatibility Metric (MCM), which helps choose based on travel distance and match appeal, or "Hit Score." This ensures that scheduling is not only competitive, but also logistically efficient, environmentally conscious, and audience-friendly.

To build the actual schedule, we also introduced two supporting tools: the Arrival Plan, which accounts for jet lag when spacing matches, and the Game Time Calculation Method, which finds fair time slots for both home and away teams.

We further tested our model by simulating the addition of four new teams and applying it to different sports. These results confirmed that E-BIMM is scalable, adaptable, and effective across a range of formats.

We believe this approach offers a fresh and thoughtful way to structure global sports leagues—and we'd be honored to present it in more detail. Thank you very much for your time and consideration.

Sincerely,
On behalf of Team 2025017

Table of Contents

1 Introduction

1.1. Background

In the past, sports were played locally—among friends, families, and small communities. Occasionally, national events sponsored by royalty brought wider attention, but overall, sports remained simple and deeply tied to local traditions. Today, thanks to advances in transportation and communication, sports have become global industries. Major matches feature elite clubs and entire countries, with millions of dollars on the line. Athletes influence culture through media, sponsorships, and social platforms, shaping opinions and inspiring people worldwide.

With this growth, organizing fair and efficient sports events has become a complex task. Every competition has its own goals—some prioritize profit, others focus on entertainment or promoting global unity. Environmental impact and economic sustainability are also growing concerns, especially as international events require significant travel and resource use.

Still, at the heart of sports is the spirit of competition—watching people overcome limits and strive for greatness. This is why we believe smart scheduling is essential. A well-planned schedule ensures fairness, supports athlete performance, and reduces unnecessary strain, cost, and environmental harm. Team 250048 is committed to building a mathematically optimized schedule that not only enhances competition, but also brings lasting, positive impact to both athletes and the world.

1.2. Problem Restatement

The problem requires us to construct a mathematical model for the Global Sports League (GSL), an international sports competition. The model must quantitatively dictate the matchmaking system and the schedule of GSL. Exact requirements are the following.

a. **Firstly**, it is necessary to determine which sports and teams will be included in the Global Sports League (GSL). The league will be limited to team sports in which each team consists of more than four players.
b. **Secondly**, an algorithm must be developed that accounts for multiple relevant factors, such as fairness, travel distance, and rest time.
c. **Thirdly**, using the developed algorithm, an initial schedule for the GSL will be generated.
d. **Finally**, the model will be extended to analyze the impact of adding four additional teams to the league. Furthermore, the applicability of the model to other sports will be examined, along with the modifications required to accommodate varying game structures.

2 Assumptions and Variables

2.1 Assumptions and Justifications

To simplify the problem, we will make and justify the following assumptions. These assumptions will be then used throughout the report paper to simplify the real-world.

- *Assumption 1:* The population of people under 15 represents the number of potential consumers.
- *Justification:* We incorporated the youth population ratio as a proxy for each country's potential consumer base. A higher proportion of young people suggests a more engaged and energetic audience, which can lead to increased local interest, stronger fan communities, and a more vibrant atmosphere for matches. This aligns with the goal of long-term league growth and sustainability through fan engagement.
- *Assumption 2:* Spectators will make use of the country's available infrastructure and public resources.

Justification 2: Because people will visit the stadium live to watch the event, local hospitality will be used and different fans will gather at the stadium. These people will use the infrastructure surrounding the stadium, ultimately influencing the environment and the community of the region.

- *Assumption 3:* The EPI scores from 2024 will remain constant through 2025, allowing for consistent evaluation across all candidate countries.

  Justification 3: EPI scores are measured by factors such as energy, biodiversity, water, habitat and so on. These factors don't change often in cities. And since it is only just a year, let's say that EPI score remains fairly constant.

- *Assumption 4*: Sporting event is hold at the largest city in the country, via population

  Justification 4: A sports event is usually held in a big city due to economic reasons. Since this is a global sports event, it is also fairly reasonable to hold an event in a city accessible by airplanes or trains. We believe that the city that is the most suited to this event would be the largest city in each country, and held GSL at the largest city in the country.

2.2 Definition of Variables

The symbols outlined in Table 3.1. would be commonly used throughout this report. Any other specific symbols will be introduced and explained at the point when it is needed.

Parameter	**Symbol**
Gini Coefficient	GC
Expected Score	E_A
Shannon Entropy	H
Distance Score	S_d
Hit Score	S_H
Arrival Plan	AP

Table 1. Symbols of Used Parameters (Partial)

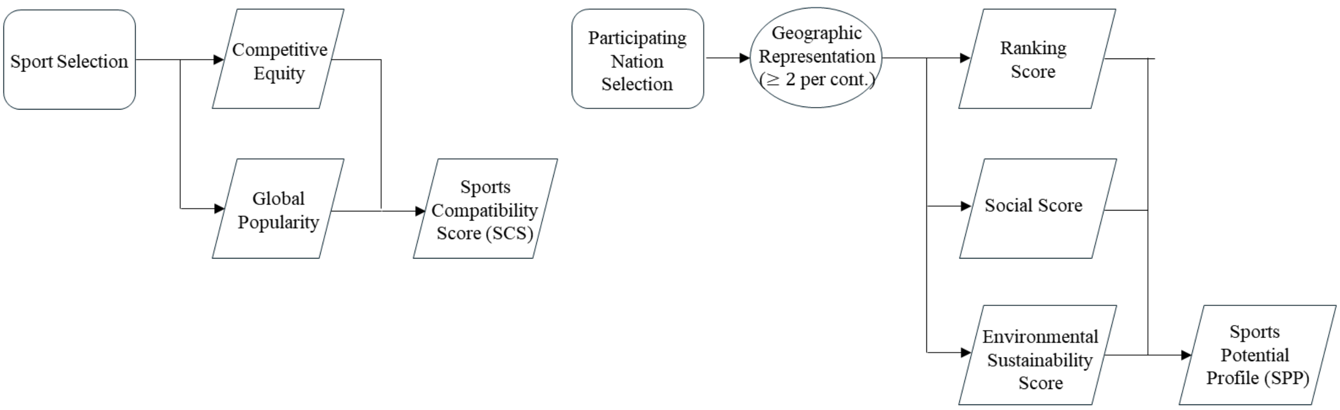


Figure 1. Flow Chart of Determinant Analysis

3 Sport Selection

Before designing a fair and effective schedule as required by the IMMC problem, our team first needed to decide which sport would serve as the foundation for the Global Sports League (GSL). This decision was crucial, as the chosen sport would directly influence the league's feasibility, competitiveness, and global appeal.

3.1 Key Factors Identification

Competitive Equity By establishing a fair degree of competitive balance, it is possible to foster higher engagement across nations, encourage fair competition, lower entry barriers, and ensure long-term sustainability. In particular, a balanced competitive environment incentivizes countries to invest in the sport, thereby spurring the creation of professional leagues and the growth of fan bases in a broader range of regions. Moreover, a sport characterized by minimal inequality is better positioned to promote an inclusive expansion model, ultimately increasing the likelihood of sustainable global development.

Global Popularity We also recognize that fairness alone is not enough. Some sports may have balanced global competitiveness but suffer from low international visibility or lack of an existing fanbase. To address this, we introduced popularity as an additional criterion. However, it is not meaningful to make an additional league to a sport that already has a widely recognized international competition. We excluded these sports from our selection.

Candidate Selection Before selecting the final sports, we first identified a pool of possible sports. According to the minimum condition stated in the problem, each sport must be a team sport with at least five players per team. In addition to this, our team considered it essential that the sport already has a number of active players globally. Therefore, we selected team sports that have been part of the Olympic Games. The resulting list of eight candidate sports are the following: basketball, volleyball, field hockey, handball, football/soccer, water polo, baseball, and softball.

3.2 Sports Compatibility Score (SCS) Index

Competitive Equity Score As previously described, we used the Gini coefficient to evaluate the suitability of each sport for inclusion in the proposed league. To calculate the Gini coefficient in the context of sports, we required win rate data for sports involving teams of five or more players. Since this is a newly proposed international league, we relied on win rate data from the International Olympic Committee for the candidate sports. For each sport, we used country-level win rate data from five recent Summer Olympic Games (2004, 2008, 2012, 2016, and 2020). The detailed data can be found in the Appendix.

Because the Gini coefficient is based on win rates, we excluded data from countries that participated in fewer than three Olympic Games, as their limited data may lead to significant inaccuracies.

The formula used to calculate the Gini coefficient for each sport is provided below.

$$GC = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|x_i - x_j\right|}{2N^2\bar{x}}$$

x_i, x_j *is each team's winning percentage,* $\bar{x}$ *is average winning percentage*

The Gini coefficients calculated for each sport using this method are presented in the table below.

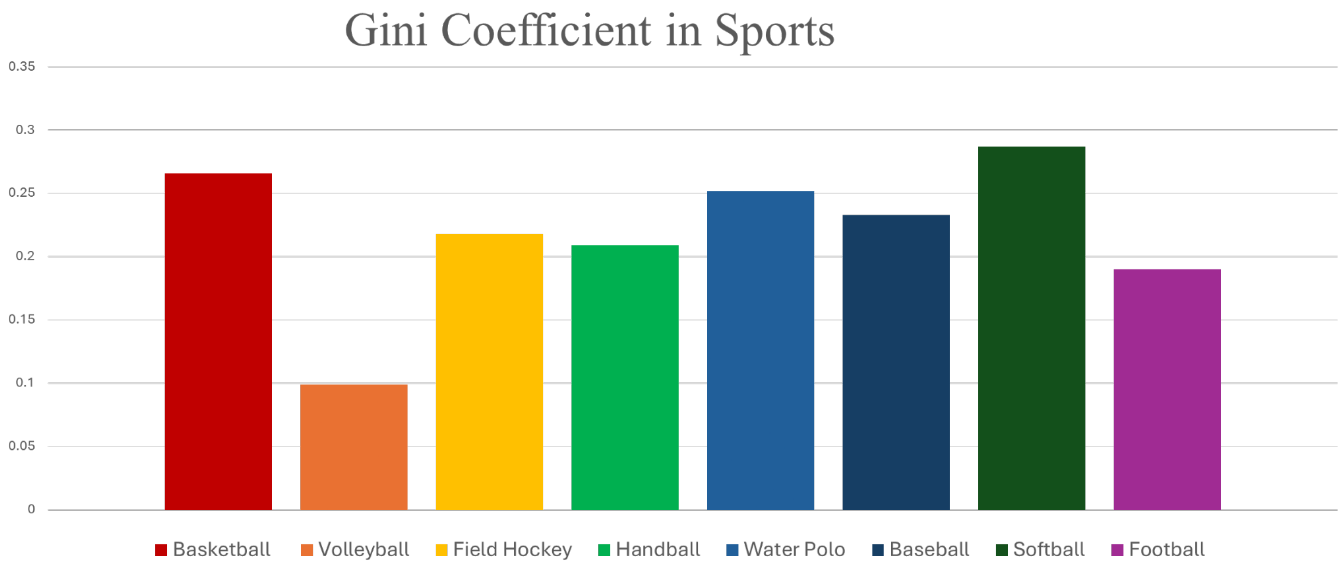


Figure 1. Graph of Gini Coefficient in Sports

A lower Gini coefficient indicates a more desirable outcome, as values closer to 0 imply smaller differences in win rates between participating teams. In the context of sports, the Gini coefficient functions as a measure of inequality; it represents the integral of disparities rather than a simple average. Therefore, it should be interpreted in terms of the variance of pairwise differences, rather than merely comparing average performance levels.

Accordingly, we define the score based on the Gini coefficient as follows:

$$S_{GC} = \frac{1}{GC^2}$$

The results of scoring each sport based on their respective Gini coefficients are as follows.

Sports	S_{GC}	Sports	S_{GC}
Basketball	14.133	Water Polo	15.747
Volleyball	102.030	Baseball	18.420
Field Hockey	21.042	Softball	12.140
Handball	22.893	Football	27.700

Table 2. Competitive Equity Score based on Gini Coefficient

Global Popularity Score In addition to the Gini coefficient as a quantitative indicator, we also assessed the expected popularity of each sport in the proposed league by measuring its Popularity Score using Google Trends. This score is based on the average monthly relative search interest, serving as a proxy for public attention.

The resulting data are presented below.

Sports	S_{GC}	Sports	S_{GC}
Basketball	20.79	Water Polo	0.58
Volleyball	3.94	Baseball	9.28
Field Hockey	0.56	Softball	1.84
Handball	1.68	Football	47.75

Table 3. Global Popularity Score based on Google Trend

Accordingly, we define Sport Suitability Score as the following.

$$Sport\ Suitability\ Score\ (SCS) = \frac{S_p}{GC^2}$$

The final Sport Suitability Score (SCS) values are as follows.

Sports	S_{GC}	**Sports**	S_{GC}
Basketball	293.96	Water Polo	9.11
Volleyball	395.29	Baseball	170.35
Field Hockey	11.78	Softball	22.30
Handball	38.49	Football	1318.69

Table 4. SCS Index by Sports

The results show that football has the highest Sport Suitability Score (SCS). However, since football already has a globally recognized international tournament—the World Cup—volleyball is the most ideal sport for the Global Sports League.

4 Team Selection

4.1 Key Factors Identification

Candidate Identification As the first and most crucial step in selecting participating countries, we prioritized nations with existing stadium infrastructure of sufficient size. This decision was essential to ensure logistical feasibility, cost-effectiveness, and environmental sustainability—core values emphasized by the IMMC. By focusing on countries already equipped to host international matches, we minimized the need for new construction, reduced environmental impact, and ensured realistic implementation of the Global Sports League. This foundational filter allowed us to build a practical and sustainable league structure, after which we further refined our selection using Geographical Representation, Ranking Points, Social Points, and Environmental Sustainability to achieve fairness and global representation.

Geographical Representation The given problem requires us to include at least two countries from each continent. Before ranking the countries, we ensured that at least two countries per continent will participate in GSL.

$$S_{Normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Figure 2. Equation of Minimum-Maximum Normalization
Used in Ranking Score, Social Score, and Sustainability Score

Ranking Score (40%). We used the existing official FIVB men's volleyball world rankings as an objective indicator of each country's current performance level to reflect their proven competitiveness, ensuring a high-quality and engaging league. Because ranking point is directly related to the entertainment effect of the game, we believed that it was a significant factor in maintaining GSL for years to come.

Furthermore, we adjusted the weighting so that this factor accounts for 40% of the overall Sport Potential Profile (SPP) Index. Additionally, we evaluated each country's world ranking using min-max normalization to ensure comparability across different scales.

Social Score (40%). In the context of sports competitions, *social approval* and *social interest* play a critical role, as they are key determinants of profitability. We decided to focus on the potential consumers of GSL. In the long term, the people who would watch GSL would be young people. Thus, to identify potential consumers, we used the population ratio of people under 15. The number of future consumers are detrimental to the existence of a sporting event. This is why social points were also highly weighted.

Environmental Sustainability Score (20%). To evaluate environmental sustainability, we used the 2024 Environmental Performance Index (EPI) as a measure of how green and eco-efficient each country is. According to the International Olympic Committee (IOC), a major source of pollution during global sporting events comes from spectators—through transportation, waste generation, and consumption. All of these categories are considered when constructing EPI. Therefore, countries with higher EPI scores are more likely to have better public transportation systems, green infrastructure, and waste management facilities, making them more suitable for hosting environmentally sustainable sports events. Although environmental sustainability is also important, we believed that it was not a detrimental factor judging the existence of the league itself. Thus, environmental sustainability was weighted lower than its other counterparts.

4.2 Sports Potential Profile (SPP) Index

Ranking Point. Currently. Fédération Internationale de Volleyball (FIVB) is the institution responsible for managing volleyball matches around the world. According to its website, countries are ranked via 'FIVB World Ranking System', which primarily uses win points to decide the ranking. Because volleyball has a very low sport gini coefficient and FIVB ranks countries by win points, we assumed that the distribution of the teams would be relatively linear. Thus, we used minimum-maximum normalization to normalize the data from 0~1. The website only ranks the top 60 teams, so all the other teams that were not in the rank were given 0 points in ranking.

Social Point. To take potential consumers into account, social score was quantified by the population ratio of people under the age of 15. Similar to ranking points, we normalized social points through minimum-maximum normalization and scored each country from 0~1.

Environmental Sustainability. In normalizing EPI scoring, we also used minimum-maximum normalization based on each country's score. All EPI scores were transformed into a scale of 0~1.

The formula for Sport Potential Profile (SPP) is as follows.

$$Sports\ Potential\ Profile\ (SPP)\ =\ 0.4S_{Ranking} + 0.4S_{Social} + 0.2S_{Environmental}$$

Also considering geographical representation, we selected the top 20 countries as follows.

Name	SPP	Name	SPP	Name	SPP	Name	SPP	Name	SPP
France	0.6139	Brazil	0.5177	Cameroon	0.4800	Canada	0.4369	Iran	0.3953
Poland	0.6041	Germany	0.4992	Argentina	0.4760	Ivory Coast	0.4356	Pakistan	0.3927
USA	0.5743	Italy	0.4957	Egypt	0.4664	Netherlands	0.4088	Australia*	0.3328
Slovenia	0.5454	Japan	0.4919	Angola	0.4598	Cuba	0.4086	New Zealand*	0.2130

Table 5. SPP Index by Countries

*Countries with * was not in Top 20 ranked by SPP, but was selected through geographical representation*

5 Entropy-Based Interactive Matchmaking Method (E-BIMM)

This new matchmaking system aims to create a more accurate and efficient meter of a competition than a league or a tournament. Entropy-Based Interactive Matchmaking Method, E-BIMM, uses Shannon entropy to best match the team in a way that the most information is gained from a round. Besides entropy, E-BIMM also utilizes Match Compatibility Metric (MCM) also considering factors like travel distance and audience satisfaction to prioritize countries with similar entropy results.

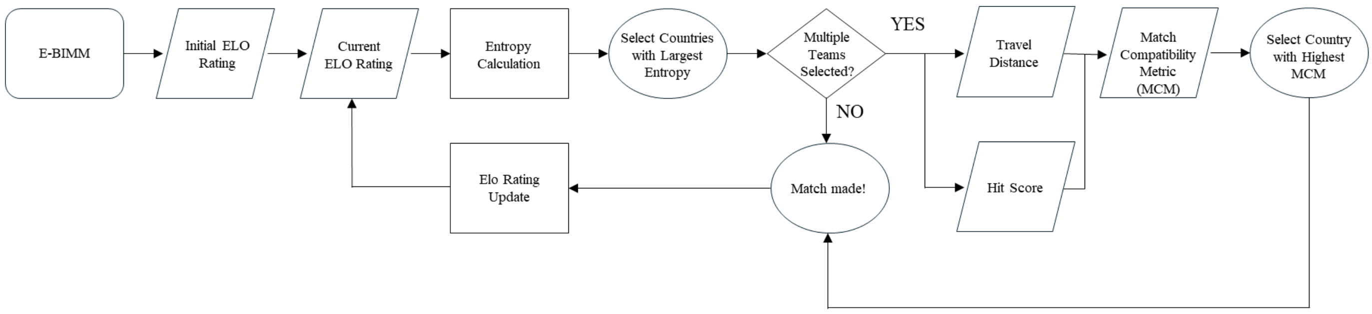


Figure 3. Flow chart of E-BIMM

5.1 Algorithm

E-BIMM is an interactive league based on information entropy analysis. Unlike a league or a tournament, the full schedule is not released from the start. For more efficient matchmaking, matchmaking in Round (n) is designed according to the information gathered up to Round (n-1). Each team is notified about the details of the next match after the previous round ends.

The criteria for optimal matchmaking can be categorized into three key factors: first, the amount of information that can be gained; second, the travel distance required for the teams; and third, the potential for match appeal. To ensure efficient tournament operations, the amount of information to be gained is prioritized. In cases where teams offer the same amount of information, the travel distance and match appeal are considered through a metric known as the Match Compatibility Metric (MCM).

To maximize the amount of information obtained with the fewest number of matches, teams should compete against those that provide the most information. For each team, there are 19 or less options to play games with. However, the information we can gain from a match will vary. For example, if a 1st ranked team plays with a 20th ranked team, the information we gain from learning the result of the match will be very limited. The amount of information gained from matches can be calculated through Shannon entropy. The team with the highest information gain is selected for the next match. After the match, the ranking is updated and based on the information, each team's next round opponent is released.

But what happens if there are more than a single pair with the same entropy? In this case, Match Compatibility Metric (MCM) is used to carry out calculations. Match Compatibility Metric considers travel distance and the popularity of each game, which is quantized as 'hit score'. 'Hit score' serves as an indicator of the popularity of an event. In case of similar entropies, MCM will provide an insightful criterion when judging where to go.

5.2 Priority Mechanism

First, it is necessary to determine the probability that one country will win or lose against another. This can be conveniently estimated based on the Elo ratings of the two countries at the time the probability is calculated. Given two countries, A and B, with different Elo ratings, the probability that country A will win can be expressed using the following formula

$$E_A = \frac{1}{1 + 10^{\left(\frac{R_B - R_A}{200}\right)}}$$

In chess, the denominator in the Elo formula is typically set to 400, which implies that for every 400-point difference in rating, the expected win probability decreases by a factor of 10. However, in the case of volleyball, analysis of historical match data has shown that a 200-point rating difference corresponds to a tenfold change in win probability. Based on this finding, the Elo rating system used in the Global League System (GLS) adopts a denominator of 200.

Using the expected win probability E_A, we compute the Shannon entropy (H) for each potential opponent. Shannon entropy represents the amount of information gained from playing a match against a given team, essentially quantifying the uncertainty of the outcome. After calculating the entropy values for all possible opponents, the team with the highest entropy is selected as the most informative and competitive match.

Shannon entropy is calculated using the following formula

$$H = -\sum_{i} p_i(\log_2 p_i)$$

In the early stages of the Global Sports League (GSL), most teams will have relatively similar Elo ratings. However, as the league progresses, these ratings will begin to diverge and distribute more randomly. Even among teams with comparable Elo ratings, it is necessary to account for additional factors to differentiate between matchups. In such cases, we incorporate other variables and finalize the next round's matchups using a multi-criteria model (MCM).

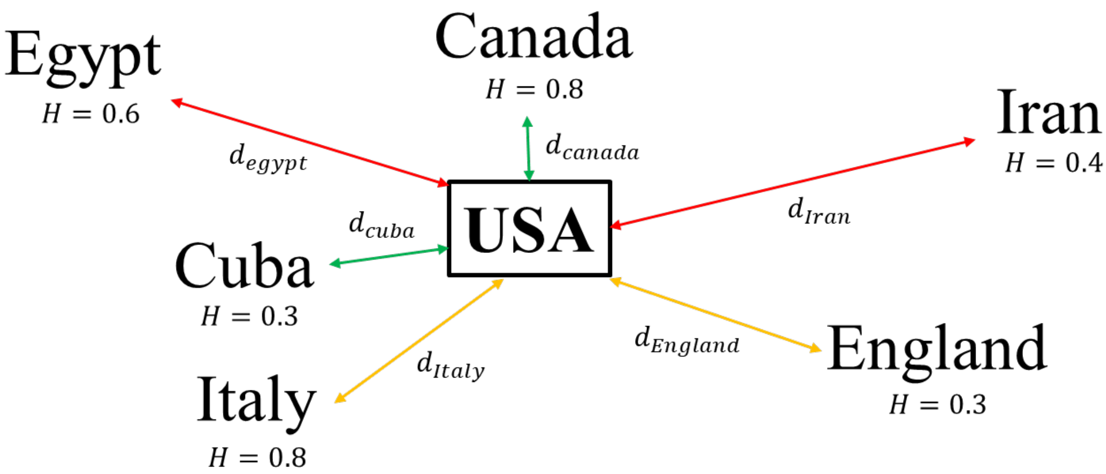


Figure 4. Example of Entropy Calculation.
In this case, the algorithm will compare MCM between Canada and Italy, and finalize the schedule for the consecutive round.

Once the matches in the next round are completed, the outcomes are incorporated into the Elo ratings using the following formula

$$R_{new} = R_{old} + 20(S - E_A)$$

Subsequent rounds are then conducted based on the updated Elo ratings. Because the problem states that a season is 8~9 months long, we will conduct 9 rounds, 1 round per month. Through simulation, we will prove that 9 rounds are reasonable to accurately rank the countries.

5.3 Match Compatibility Metric (MCM)

After improving rating accuracy and efficiency based on the priority mechanism, we next developed a **Match Compatibility Metric (MCM)** to determine priorities when entropy values of multiple countries are identical, allowing us to match countries more effectively. The first evaluation factor we considered was *travel distance* between countries. To ensure that all teams could perform in optimal condition and minimize financial and environmental waste, we aimed to select matchups with the shortest possible travel distances. Additionally, to maintain fairness in the competition, we decided to alternate between home and away games.

The second evaluation factor was the *Hit Score*, which estimates the expected popularity of a match. Since more popular games tend to be more profitable, we introduced this metric to reflect potential revenue. The Hit Score was measured based on the average Elo ratings of the two countries and whether a rivalry existed between them. Matches between higher-ranked teams and those involving rival nations are generally more appealing to audiences, as people tend to show greater interest in games featuring top-performing teams or traditional rivals. We assumed that these factors would significantly influence viewer engagement and overall popularity.

$$\text{Match Compatibility Metric (MCM)} = 0.7S_d + 0.3S_H$$

In the overall metric, we assigned a higher weight to travel distance(S_d) than to Hit Score(S_H), as travel considerations were deemed more important in terms of cost-efficiency, player condition, and overall operational effectiveness.

5.3.1 Travel Distance Modelling

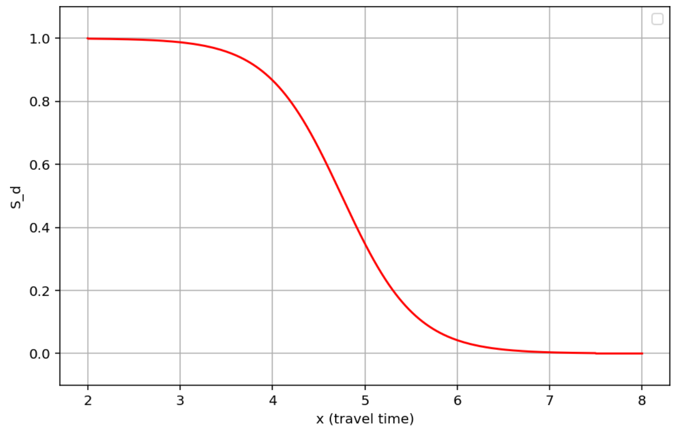


Figure 5. Graph and equation of S_d function

$$S_d = \begin{cases} 1 \ (x = 2) \\ \dfrac{1}{1 + e^{2.5(x-4.75)}} \ (2 < x < 7.5) \\ 0 \ (x \geq 7.5) \end{cases}$$

In the above formula, the x-value represents travel time. The distances between countries, when divided by the cruising speed of a Boeing 737, results in travel times ranging from approximately 2 to 7.5 hours. Therefore, we defined the domain of the function as [2, 7.5]. We assigned a score of 1 to the minimum travel time (2 hours) and a score of 0 to the maximum travel time (7.5 hours). For values within the range $2 < x < 7.5$, we adjusted the sigmoid function to be symmetric about x=4.75 (which is the middle value of the range) and smoothly connected to the endpoints, forming an "S"-shaped curve.

We chose a sigmoid function because it captures how fatigue and performance degradation tend to increase non-linearly with longer travel durations. Initially, small increases in flight time may not drastically affect players' condition, but beyond a certain threshold, fatigue rises sharply. The S-shape of the sigmoid curve models this trend effectively, penalizing excessively long travel times while preserving fairness for shorter distances.

5.3.2 Hit Score Modelling

People tend to be more engaged with matches between high-performing countries or between rival nations. Therefore, the Hit Score was determined by two factors: the average Elo rating of the two teams and whether the two countries have a rivalry. Among these, we assumed that the combined skill level of the teams would have a greater influence on audience interest than rivalry alone, and thus assigned a higher weight to the average Elo rating in the Hit Score calculation.

Elo Average Elo rating can be expressed as following

$$\overline{Elo(i,j)} = \frac{Elo(i) + Elo(j)}{2}$$

$$\overline{Elo}_{Norm} = \frac{\overline{Elo} - Elo_{min}}{Elo_{max} - Elo_{min}}$$

$\overline{Elo}_{Norm}$ represents the normalized value of the average Elo rating, scaled between 0 and 1.

Rivalry Rivalry status is represented as either 0 or 1, depending on whether a rivalry exists between the two countries. The list of all rivalries in volleyball is included in the appendix. Rivalry function R(i, j) can be represented as following

$$R(i,j) = \begin{cases} 1 \text{ (if i and j has a rivalry)} \\ 0 \text{ (else)} \end{cases}$$

Total Hit Score is calculated as the following.

$$S_H(i,j) = 0.8 \cdot \overline{Elo}_{Norm} + 0.2 \cdot R(i,j)$$

6 Game Scheduling

6.1 Arrival Plan

When athletes travel across time zones, they experience jet lag, a physiological condition caused by the disruption of the body's internal circadian rhythm. Research shows that the human body typically requires about one day to adjust to each time zone crossed, particularly when the time difference is significant (usually more than 6 hours).

To minimize the negative effects of jet lag—such as fatigue, impaired cognitive function, and reduced physical performance—we introduce an Arrival Plan (AP) that includes rest days based on time zone differences.

$$AP = \frac{T_{travel}}{24} + 1 + max(Jetlag - 6,\ 0)$$

In this model, a baseline rest period of one day is provided upon arrival to allow for basic recovery from travel fatigue. Also the travel time is calculated by dividing the distance between two countries by the average cruising speed. However, if the time difference between the departure and arrival locations exceeds 6 hours, the body's internal clock experiences greater disruption.

Therefore, for every hour beyond the 6-hour threshold, we assign one additional AP day. This reflects the body's increased need for adjustment time to restore optimal performance levels, ensuring fairness and athlete well-being in international competitions.

We applied this arrival plan to every round when running the simulation.

6.2 Game Time Calculation Method (GTCM)

The scheduling of game times based on the time difference between the home and away countries is modeled as follows. Let Country A be the home team where the match is played, and Country B be the away team, where the match is not held but broadcasted live. A volleyball match lasts for 3 hours.

6.2.1 Modeling Game Time Schedule

T_A be the start time of the match in A-country time. Δt would be the time difference between the two countries. If B is 3 hours ahead of A, then Δt would be +3. If B is 5 hours behind the time of A, then Δt would be -5. T_B is going to be the start time of the match in B-country time, while T_A would be the start of the match in A country time. We can simplify these variables into an equation.

$$T_B = T_A + \Delta t$$

Viewership Window From the perspective of the home team, it would be the most ideal if the match was held between 10 a.m. and 10.p.m. When a match is held too late, there will be less live spectators in the stadium. There will also be a shortage in staff members and workers on the field. Thus, the people in the home team would want the game to be held at day.

On the other hand, for the people of Away team, the most ideal match schedule would be from 5 p.m. to 2 a.m. Spectators in the away team would most likely be people watching the game through TV. For them, staying up late at night is acceptable. However, when a game is scheduled during the day, they would most likely have to go to work. Thus, the people in the away team would want the game to be held at night.

The two conditions can be expressed as follows. However, when there is a conflict of interest, our team would prioritize the needs of the home team, because the requirements from the home team is mostly out of necessity while conditions from team B is more out of preference.

$$10 \leq T_A \leq 22$$

$$17 \leq T_B \leq 26$$

Watch Conditions Generally, when people watch a sports match from the beginning, they won't bother watching if they can only see the first 30 minutes, because they couldn't watch the key matches and know the result. However, if they can watch the latter part of the game, even just the final 30 minutes, they would likely watch the game because they can know the results. Therefore, if people in Country B watch from the beginning, they must be able to watch at least the first 2 hours of the match. If they start watching from the middle, they must begin at least 30 minutes before the match ends.

Viewability conditions can be classified into either of the following.

Full Watch Condition

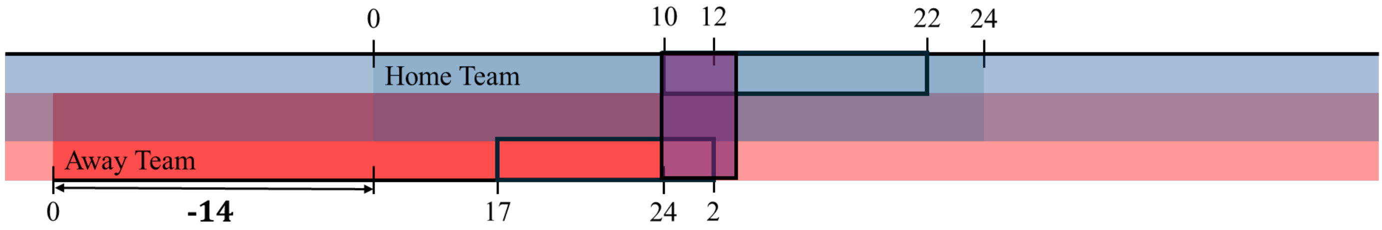


Figure 6. Scheduling Diagram (Full Watch)

People in Country B can watch from the beginning if:

$$T_B = T_A + \Delta t \geq 17 \quad \text{(5:00 p.m. B-time)}$$

$$T_B + 2 = T_A + \Delta t + 2 \geq 26 \quad \text{(2:00 a.m. B-time)}$$

So,

$$17 - \Delta t \leq T_A \leq 24 - \Delta t \quad \text{(Condition 1)}$$

Late Join Condition

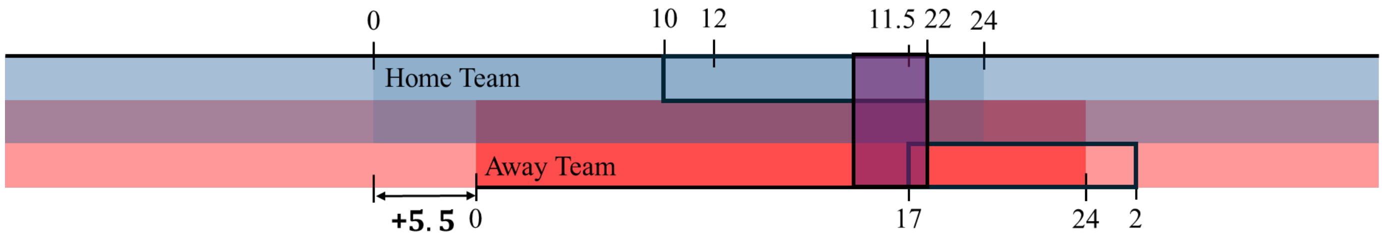


Figure 7. Scheduling Diagram (Late Join)

People in Country B can watch from the middle if they begin at least **30 minutes before the end**, meaning:

$$T_A + 2.5 + \Delta t \leq 26 \Rightarrow T_A \leq 23.5 - \Delta t \quad \text{(Condition 2)}$$

Considering both A-country game time condition ($10 \leq T_A \leq 22$) and viewability condition 1 or 2,

we get the final game time:

$$T_A \in [max(10, 17 - \Delta t),\ min(22, 24 - \Delta t, 23.5 - \Delta t)]$$

6.2.2 Generalized Form

If you put the conditions for the possible time of play in country A as

$$T_A \in [T_{A\cdot start}, T_{A\cdot end}]$$

and the conditions for the game viewing time of country B as

$$T_B \in [T_{B\cdot min}, T_{B\cdot max}]$$

the final generalized formula for game time is

$$T_A \in \ [max(T_{A\cdot start}, T_{B\cdot min} - \Delta t),\ min(T_{A\cdot end}, T_{B\cdot max} - 2.5 - \Delta t)]$$

7 Simulation

7.1 Methodology

7.1.1. Geography and AP (Arrival Plan) Calculation

The distance between each pair of countries was calculated using the Haversine formula, based on the latitude and longitude of their capital cities. Flight time was estimated using the average cruising speed of a Boeing 737. The Arrival Plan (AP) was then determined by factoring in both the calculated flight time and the time zone difference between countries to ensure fair competition by allowing athletes adequate rest.

By default, one rest day was added upon arrival. Additionally, if the time zone difference exceeded 6 hours, extra AP days were granted—one additional day for each hour beyond the 6-hour threshold—reflecting the time required for the human body to recover from jet lag and restore peak performance.

7.1.2. Elo Rating and Match Simulation

The Elo rating updates and Shannon Entropy were calculated using the E-BIMM method previously described. When two countries are matched using E-BIMM, their Shannon Entropy is close to 1, meaning their win probabilities are roughly equal (~50%), and the outcome appears random.

However, this does not accurately reflect each country's actual volleyball skill. To address this, we defined a new metric: Skill Level.

The Skill Level is an updated Elo rating for 2024, inferred from each country's Elo in 2018 and match outcomes between 2018 and 2024. Elo ratings were calculated using match data from the FIVB Men's Volleyball Nations League (2018–2024) and the Summer Olympics (2016–2024), with Olympic results weighted 6/5 relative to Nations League results based on FIVB's performance evaluation criteria.

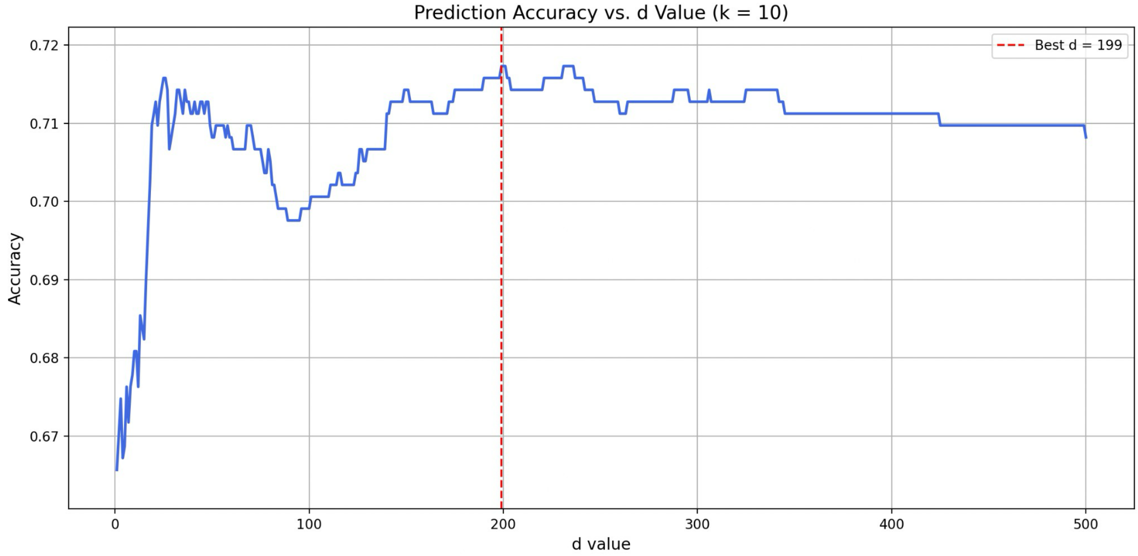


Figure 8. d value prediction accuracy in volleyball

The expected win probability E_A for Country A, based on Elo ratings, is given by:

$$E_A = \frac{1}{1 + 10^{\left(\frac{R_B - R_A}{200}\right)}}$$

Using this formula, we recalculated the win probability between each pair of teams. The match outcome was then simulated based on this probability.

Note: Elo rating changes during the Global Sports League (GSL) have no effect on Skill Level; Skill Levels remain constant throughout the season.

Each round consists of both home and away matches, resulting in 20 games per round. To ensure fairness, Elo point changes are symmetric for home and away games. Once two countries have competed, their Shannon Entropy is set to 0 to prevent future rematches. After simulating N rounds, we calculated the average Shannon Entropy across all matchups.

a. Scheduling

Each round begins on the 1st of the month. Team A first uses its assigned AP days for travel and rest, then plays an away match against Team B under fair conditions. After the match, both teams travel to Team A's country and again use their respective AP days.

On the following day, a home match is held in Team A's country, completing one round of competition between Teams A and B. This scheduling method is applied to all other team pairs in the same round.

b. Visualization Method

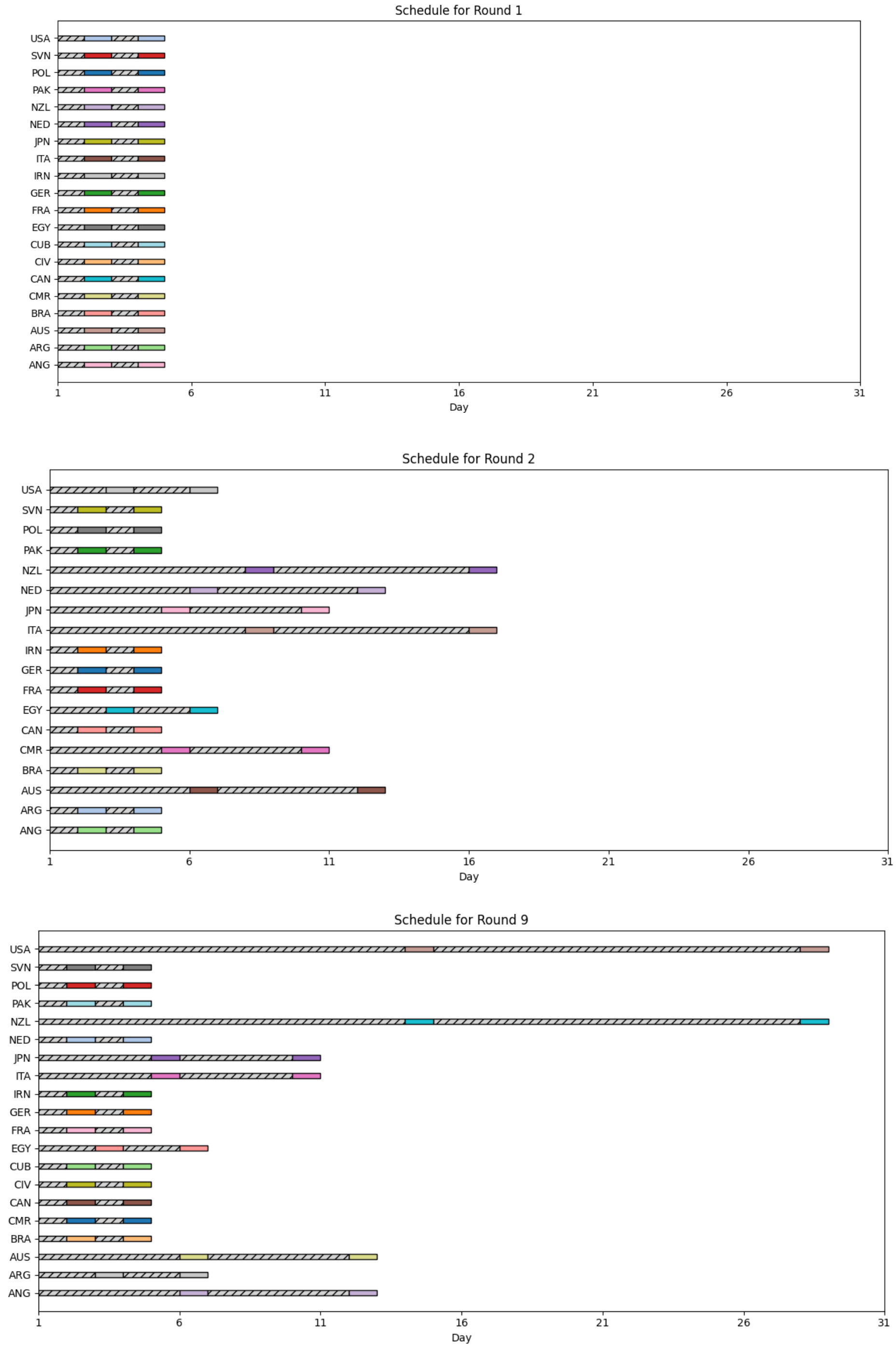
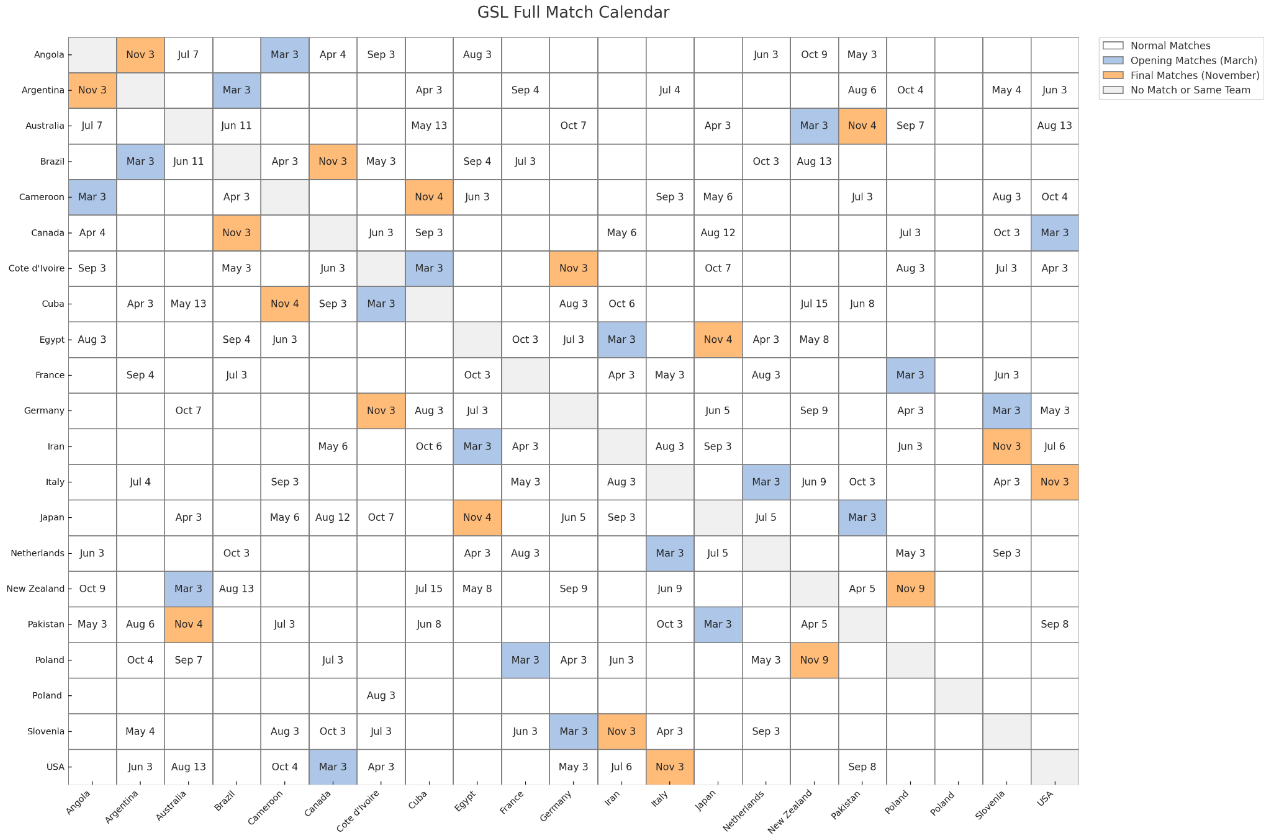


Figure 9. Gantt Chart Example of Schedule for Round 1, 2, 9

Schedules for each round were visualized using a Gantt chart format. The x-axis represents a fixed monthly timeline (from the 1st to the 31st), and the y-axis lists the names of participating countries.

Schedules are shown as horizontal bars. Each of the 20 countries is represented by a unique color, and AP (Arrival Plan) days are marked with diagonal hatching to distinguish rest and travel periods.



	Angola	Argentina	Australia	Brazil	Cameroon	Canada	Cote d'Ivoire	Cuba	Egypt	France	Germany	Iran	Italy	Japan	Netherlands	New Zealand	Pakistan	Poland	Poland	Slovenia	USA
Angola		Nov 3	Jul 7		Mar 3	Apr 4	Sep 3		Aug 3						Jun 3	Oct 9	May 3				
Argentina	Nov 3			Mar 3				Apr 3		Sep 4			Jul 4				Aug 6	Oct 4		May 4	Jun 3
Australia	Jul 7			Jun 11				May 13			Oct 7			Apr 3		Mar 3	Nov 4	Sep 7			Aug 13
Brazil		Mar 3	Jun 11		Apr 3	Nov 3	May 3		Sep 4	Jul 3					Oct 3	Aug 13					
Cameroon	Mar 3			Apr 3				Nov 4	Jun 3				Sep 3	May 6			Jul 3			Aug 3	Oct 4
Canada	Apr 4			Nov 3			Jun 3	Sep 3				May 6		Aug 12				Jul 3		Oct 3	Mar 3
Cote d'Ivoire	Sep 3			May 3		Jun 3		Mar 3			Nov 3			Oct 7				Aug 3		Jul 3	Apr 3
Cuba		Apr 3	May 13		Nov 4	Sep 3	Mar 3				Aug 3	Oct 6				Jul 15	Jun 8				
Egypt	Aug 3			Sep 4	Jun 3					Oct 3	Jul 3	Mar 3		Nov 4	Apr 3	May 8					
France		Sep 4		Jul 3					Oct 3			Apr 3	May 3		Aug 3			Mar 3		Jun 3	
Germany			Oct 7				Nov 3	Aug 3	Jul 3					Jun 5		Sep 9		Apr 3		Mar 3	May 3
Iran						May 6		Oct 6	Mar 3	Apr 3			Aug 3	Sep 3				Jun 3		Nov 3	Jul 6
Italy		Jul 4			Sep 3					May 3		Aug 3			Mar 3	Jun 9	Oct 3			Apr 3	Nov 3
Japan			Apr 3		May 6	Aug 12	Oct 7		Nov 4		Jun 5	Sep 3			Jul 5		Mar 3				
Netherlands	Jun 3			Oct 3					Apr 3	Aug 3			Mar 3	Jul 5				May 3		Sep 3	
New Zealand	Oct 9		Mar 3	Aug 13				Jul 15	May 8		Sep 9		Jun 9				Apr 5	Nov 9			
Pakistan	May 3	Aug 6	Nov 4		Jul 3			Jun 8					Oct 3	Mar 3		Apr 5					Sep 8
Poland		Oct 4	Sep 7			Jul 3				Mar 3	Apr 3	Jun 3			May 3	Nov 9					
Poland							Aug 3														
Slovenia		May 4			Aug 3	Oct 3	Jul 3			Jun 3	Mar 3	Nov 3	Apr 3		Sep 3						
USA		Jun 3	Aug 13		Oct 4	Mar 3	Apr 3				May 3	Jul 6	Nov 3				Sep 8				

Figure 10. World Map Marked With GSL Travel Paths of Round 1

To make it easier to notice the matchups of each country, we made a time table that shows the DSL full matchup schedules. Regarding the 8-9 month season, we set the whole season from March to November. (One round at a month)

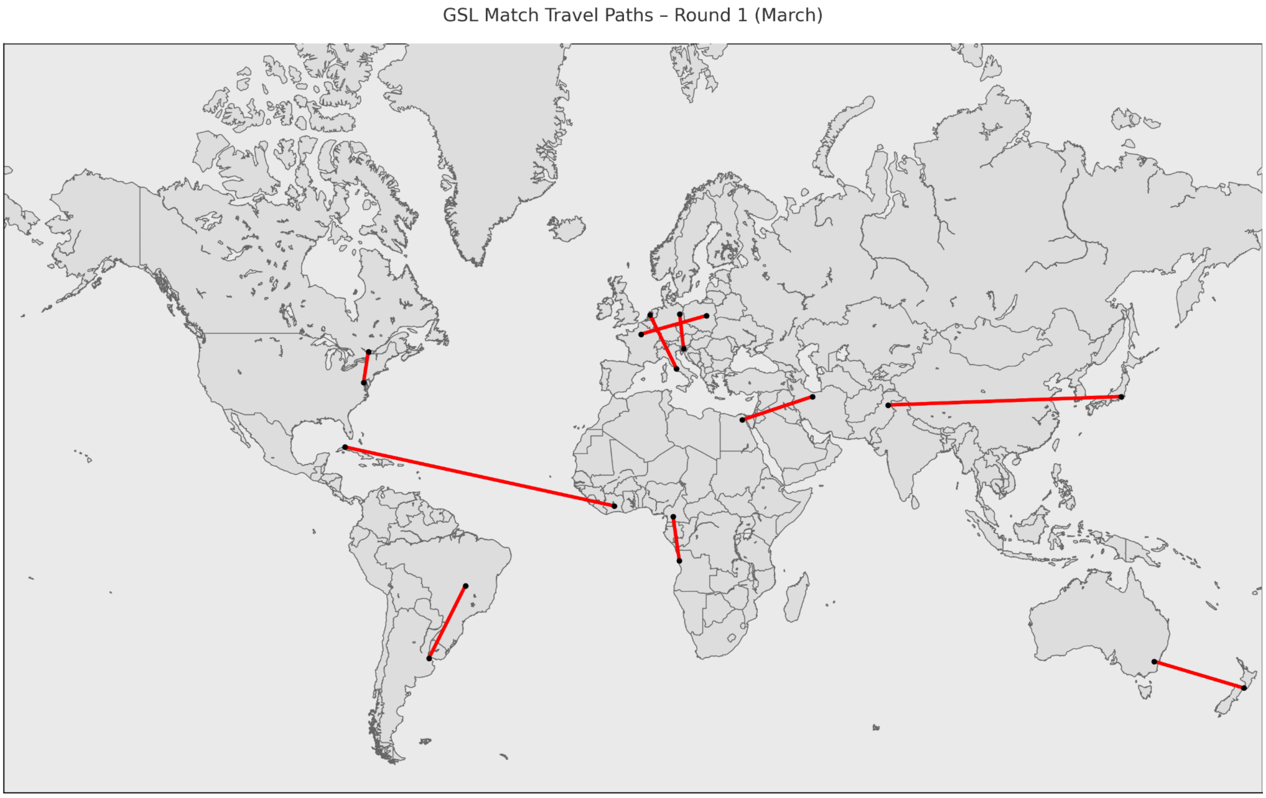


Figure 10. World Map Marked With GSL Travel Paths of Round 1

7.2 Result

The IMMC specified that the GSL season should span either 8 or 9 months. Based on this, our team assumed one round per month and ran multiple simulations for two cases: N = 8 and N = 9.

- For N = 8, the average Shannon Entropy was 0.5812.
- For N = 9, the average Shannon Entropy decreased to 0.5121.

As previously discussed, lower Shannon Entropy indicates a more predictable outcome and a more reliable league ranking. An entropy value of 0.5121 implies that about 88% of match outcomes are biased toward the stronger team. Therefore, with 9 rounds, the GSL can yield reliable team rankings without needing a full round-robin schedule.

Each round involves 10 matchups, with each pair playing both home and away games, resulting in 20 games per round. Thus, with 9 rounds, the league consists of 180 total games, and each team plays 18 matches.

By contrast, a traditional round-robin league requires

$$\binom{20}{2} \times 2 = 380 \text{ matches.}$$

The GSL structure reduces this to 180 matches, saving 200 games while still providing a valid and efficient method for determining the league winner.

7.3 Sensitivity Analysis

As Shannon Entropy decreases, the probability of one-sided outcomes increases—but at a diminishing rate. Even when the entropy value fluctuates slightly around 0.5121, the win probabilities remain relatively stable, suggesting that the system is robust and reliable near the optimal range.

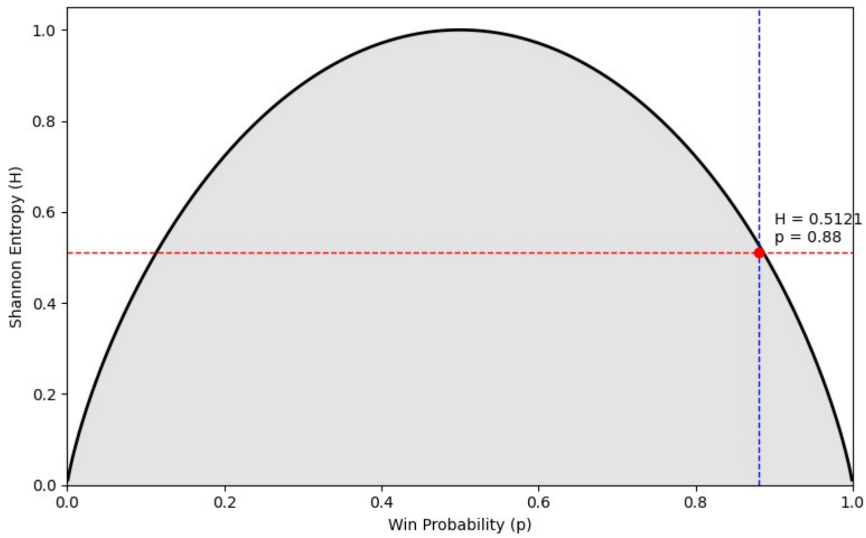


Figure 11. Shannon Entropy versus Win Probability

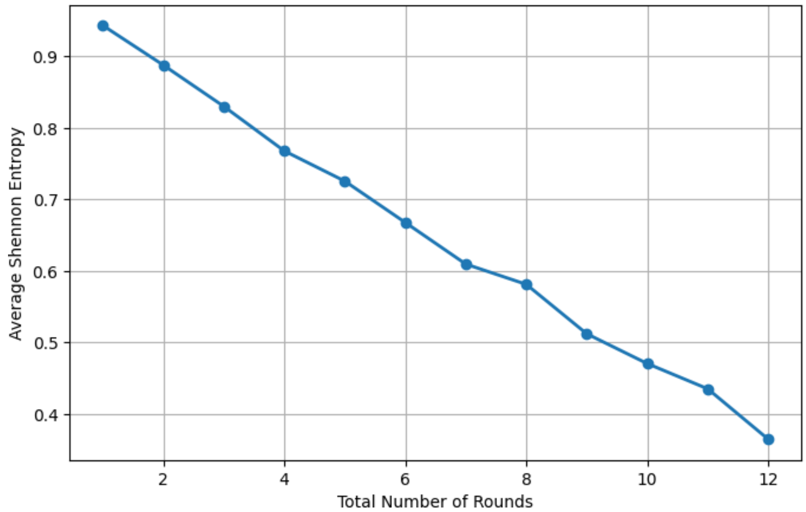


Figure 12. Number of Rounds versus Average Shannon Entropy

When simulating with N increasing from 1 to 12, the graph of the average Shannon Entropy values with respect to N appears as a linear function. As mentioned earlier, since beyond a certain level the change in Shannon Entropy results in only a negligible delta win rate, there is no logical flaw in choosing N=9.

9 Model Generalization

9.1. Team Addition

9.1.1. Team Selection Criteria

To add 4 more teams, our team used the SPP index which we initially used to select 20 teams. Because each continent already had 2 teams, we didn't consider geographical representation. Four teams were selected from the top of the SPP ranking.

The following are the four teams and their SPP score.

Country Name	SPP	Country Name	SPP
Belgium	0.3927654358	Serbia	0.3837546938
Dominican Republic	0.3916871997	Czech Republic	0.3765871263

Table 6. SPP Index of Belgium, Serbia, Czech Republic, and Dominican Republic

9.1.2. Expansion's Impacts

After increasing the number of teams to 24 and running the simulation, we observed a notable difference from the previous case with 20 teams. Even after 9 rounds, the average Shannon Entropy remained around 0.6. To find an appropriate number of rounds N, we incremented N from 9 upward and found that the average Shannon Entropy reached 0.5 at N=11. This corresponds to a total of 264 matches—24 matches per round over 11 rounds—which means each team plays 22 matches. Although this is 84 more matches than required in the 20-team case, it still represents a significant reduction from the 552 matches that would be needed in a full round-robin league format.

The scheduling algorithm ensures that each team plays a different opponent in every round and does not face the same team more than once throughout the league. With 24 teams, each round contains 12 pairings. The model also balances the number of matches each team plays across the rounds.

Additionally, the model dynamically allocates travel and rest periods (AP) by accounting for flight durations and jet lag effects. This guarantees a fair distribution of long-distance travel burdens among teams. The inclusion of new teams does not introduce excessive travel demands, thus preserving the model's emphasis on sustainability.

9.2. Sports Generalization

The E-BIMM model is an enhanced framework built upon the Elo rating system, incorporating entropy to improve predictive efficiency. When adapting the model to different sports, the most significant variation lies in the mechanism by which Elo ratings are calculated.

The Elo rating system utilizes two key constants which can be found below. Both of them govern the relationship between Elo ratings and win probability. The first constant, k, determines the magnitude of rating changes based on match outcomes (wins or losses). The second constant, d, reflects the sensitivity of predicted win probability to differences in Elo ratings.

$$E_A = \frac{1}{1 + 10^{\left(\frac{R_B - R_A}{200}\right)}}$$

$$R_{new} = R_{old} + k(S - E_A)$$

Variations in sport-specific rules, game duration, and team dynamics are all captured through adjustments to these constants. In the context of volleyball, as applied in the Global Sports League (GSL) model, the values k=20 and d=200 have been employed. To evaluate the scalability of the proposed model, we designed a generalized framework applicable to three globally popular sports: football (soccer), basketball, and baseball (see Appendix).

9.2.1 Football

For the football model, we utilized data from the FIFA World Cup spanning 2010 to 2022. Matches from the quarterfinal stage onward were assigned a weight of 1.2, reflecting FIFA's official point allocation system, in contrast to group stage and early tournament matches.

All teams were initialized with an Elo rating of 1000, and the constant k was fixed at 10. We then searched for the optimal scaling factor d within the integer range of 1 to 500, aiming to maximize prediction accuracy. As a result, the model achieved a highest prediction accuracy of 64.65% (excluding draws) when d=121, indicating strong predictive performance.

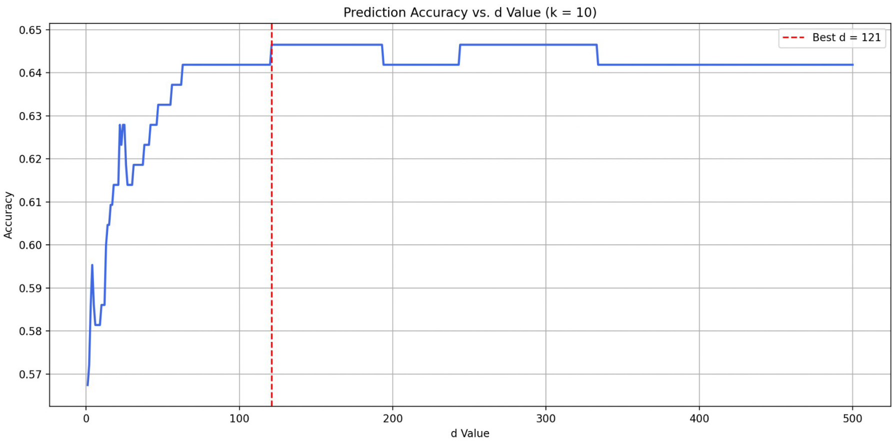


Figure 13. d value prediction accuracy in football

9.2.2 Basketball

For the basketball model, data were drawn from Basketball at the Summer Olympics (2016–2024) and the FIBA World Championship (2006–2023). To calculate Elo ratings, the FIBA World Championship matches were weighted 1.25 times higher than Olympic matches, following FIBA's official point system.

As in the football model, all teams were initialized with an Elo rating of 1000, and the constant KKK was fixed at 10. The optimal value of the scaling factor d was then determined by searching the integer range from 1 to 500 to maximize prediction accuracy. This process yielded an optimal d value of 52, corresponding to a highest prediction accuracy of 72.12%.

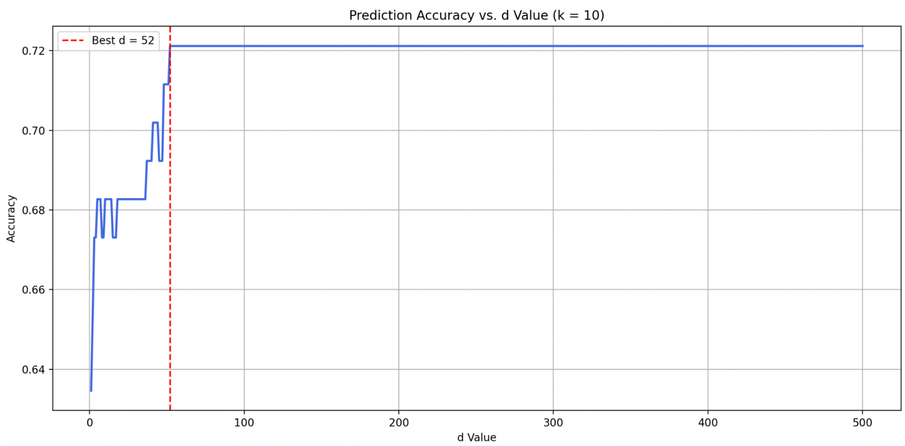


Figure 14. d value prediction accuracy in basketball

9.2.3. Baseball

To generalize the baseball prediction model, historical Olympic match data from the period 2000 to 2020 was utilized. A parameter sensitivity analysis was conducted with respect to the Elo scaling factor dd, while maintaining a fixed initial rating of 1000 and a constant K-factor of 10. The analysis revealed that the model achieved its highest predictive accuracy of 85.09% when d=11.

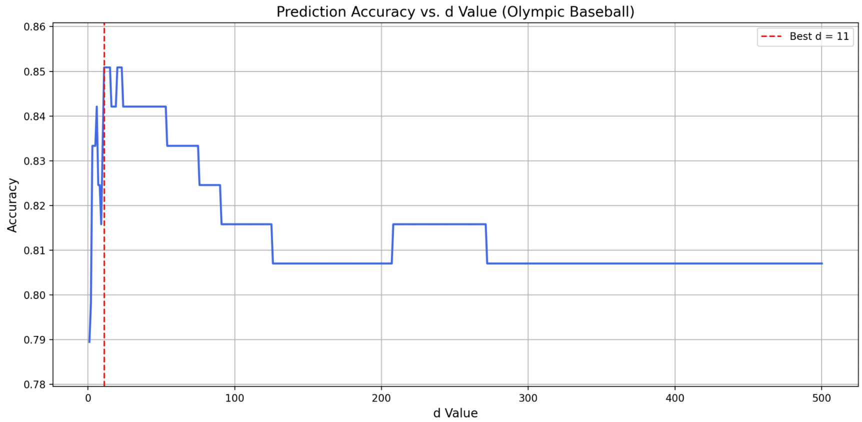


Figure 15. d value prediction accuracy in Baseball

10 Conclusion

10.1. Strengths & Weaknesses

10.1.1 Strengths

- Innovative Matchmaking Model:
  Developed the Entropy-Based Interactive Matchmaking Method (E-BIMM) to dynamically generate fair and information-rich matches using Shannon Entropy and Elo ratings.

- Comprehensive Metric Integration:
  Incorporated travel time (fatigue model) and match popularity (Hit Score) through a Match Compatibility Metric (MCM) for sustainable and engaging scheduling.

- Holistic Sport & Country Selection:
  Chose volleyball using a custom-built Sport Compatibility Score (SCS) based on competitiveness and popularity. Country selection used the Sport Potential Profile (SPP) considering performance, youth demographics, and environmental sustainability.

- Realistic Scheduling Components:
  Introduced the Arrival Plan (AP) to account for jet lag and Game Time Calculation Method (GTCM) to optimize match times across time zones for both in-person and remote viewers.

- Scalability & Adaptability:
  Successfully generalized the model to other sports (e.g., football, basketball, baseball) by adjusting Elo sensitivity constants (k and d).
  Also simulated expansion from 20 to 24 teams and validated its robustness.

- Simulation & Visualization:
  Backed claims with simulations, entropy tracking, Elo updates, and Gantt charts and world maps to illustrate schedule flow and travel impact.

10.1.2 Weaknesses

- Complexity in Implementation:
  Real-time entropy and Elo-based scheduling may be logistically difficult to apply in real leagues that require fixed schedules in advance.

- Dependence on Assumptions:
  Relies on several simplifying assumptions (e.g., constant EPI scores, largest city hosting matches), which may not reflect real-world variability.

- Limited Validation of Viewer Interest:
  The Hit Score model assumes audience engagement is driven mainly by Elo and rivalries, without empirical validation from actual viewership data.

- Lack of Stakeholder Perspective:
  The model does not explicitly consider players' unions, broadcasters, or tournament organizers, whose constraints might alter the feasibility of adaptive scheduling.

- Static Skill Assumption in Simulation:
  Assumes fixed skill levels throughout the season, which may not reflect real-time team performance evolution due to injuries, form, or roster changes.

References

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[3] Jet Lag Recovery Time, Available: https://doi.org/10.4103/jfmpc.jfmpc_220_17

[4] EPI(Environmental Performance Index), Available: https://worldpopulationreview.com/country-rankings/greenest-countries

[5] Google Trend, Available: https://trends.google.com/trends/explore?q=volleyball&hl=ko

AI Usage Report

1. OpenAI *ChatGPT* (Nov 5, 2023 version, ChatGPT-4)

   Query 1: *"Europe: France, Poland, Slovenia, Germany, Italy, Netherlands (6 countries)... Please sort it into the country name comma here and translate it into English"*

   Output: *Europe: France, Poland, Slovenia, Germany, Italy, Netherlands Asia:*

   Japan, Iran, Pakistan

   North America: United States, Canada, Cuba

   South America: Brazil, Argentina

   Oceania: Australia, New Zealand

   Africa: Cameroon, Egypt, Angola, Ivory Coast

2. OpenAI *ChatGPT* (Nov 5, 2023 version, ChatGPT-4)

   Query3: *"after what hours is jet lag start to effect you?"*

   Output: *Jet lag typically starts to affect you when you cross two or more time zones, and its effects become noticeable within the first 24–48 hours after arrival...*

Appendix

(1) Gini Coefficients of Sports

Sports	Gini Coefficient	Sports	Gini Coefficient
Basketball	0.266	Water Polo	0.252
Volleyball	0.099	Baseball	0.233
Field Hockey	0.218	Softball	0.287
Handball	0.209	Football	0.190

(2) SPP Ranking of all Candidate Countries

Countries	SPP	Ranking Point	Ranking Points Normalized	Youth Population Percentage	Social Score Normalized	EPI Normalized
France*	0.6138983936	378.07	0.9389753958	0.17	0.1764705882	0.8386
Poland*	0.6041388235	401.31	1	0.15	0.1176470588	0.7854
United States*	0.574268983	365.87	0.9069401045	0.18	0.2058823529	0.6457
Slovenia*	0.545391854	352.5	0.8718325762	0.15	0.1176470588	0.748
Brazil*	0.5176781495	305.87	0.7493894914	0.2	0.2647058824	0.5602
Germany*	0.4992147888	274.38	0.6667016779	0.14	0.08823529412	0.9862
Italy*	0.4956521207	346.23	0.8553685371	0.12	0.02941176471	0.7087
Japan*	0.4918538843	338.12	0.8340729459	0.12	0.02941176471	0.7323
Cameroon	0.4799952193	79.27	0.1543733424	0.42	0.9117647059	0.2677
Argentina*	0.4759979255	266.94	0.6471654019	0.22	0.3235294118	0.4386
Egypt	0.466367868	156.94	0.3583226111	0.32	0.6176470588	0.3799

Angola	0.45984	0	0	0.45	1	0.2992
Canada*	0.4369167733	254.46	0.6143948744	0.15	0.1176470588	0.7205
Ivory Coast	0.4355658824	0	0	0.42	0.9117647059	0.3543
Netherlands*	0.4087875203	204.81	0.484021742	0.15	0.1176470588	0.8406
Cuba*	0.4086437516	249.34	0.6009505554	0.16	0.1470588235	0.5472
Iran*	0.3953715067	185.07	0.4321875903	0.23	0.3529411765	0.4066
Pakistan	0.	80.71	0.1581545572	0.37	0.7647058824	0.1182
Belgium	0.3927654358	180.24	0.4195047659	0.16	0.1470588235	0.8307
Dominican Republic	0.3916871997	125.41	0.2755297639	0.27	0.4705882353	0.4662
Serbia*	0.3837546938	259.28	0.6270514403	0.14	0.08823529412	0.4882
Czech Republic	0.3765871263	168.95	0.3898589922	0.16	0.1470588235	0.8091
Finland	0.3733534195	146.72	0.33148649	0.15	0.1176470588	0.9685
Estonia	0.353711012	110.82	0.2372187065	0.16	0.1470588235	1
Kazakhstan	0.3533760583	57.96	0.09841661634	0.3	0.5588235294	0.4524
Israel	0.3439108615	68.97	0.1273271538	0.28	0.5	0.4649
Turkey*	0.3435839975	175.28	0.4064805819	0.22	0.3235294118	0.2579
Mexico	0.3412455499	112.85	0.2425491689	0.25	0.4117647059	0.3976

Ukraine	0.3380693418	196	0.4608880603	0.14	0.08823529412	0.5921
Austrailia*	0.3328012026	114.61	0.2471706536	0.18	0.2058823529	0.7579
Iraq	0.3291023529	0	0	0.37	0.7647058824	0.1161
Jordan	0.3257741176	0	0	0.31	0.5882352941	0.4524
Bulgaria*	0.3197552582	161.06	0.3691410866	0.15	0.1176470588	0.6252
Romania	0.3163243938	143.07	0.3219021611	0.16	0.1470588235	0.6437
Tuinisia	0.3148468514	95.09	0.1959141874	0.24	0.3823529412	0.4177
Slovakia	0.3095023142	107.27	0.2278969619	0.16	0.1470588235	0.7976
Switzerland	0.3090889834	106.9	0.2269253998	0.15	0.1176470588	0.8563
Greece	0.3075368165	118.87	0.2583567471	0.14	0.08823529412	0.8445
Algeria	0.306892613	23.43	0.007746238479	0.31	0.5882352941	0.3425
Croatia	0.3068492315	136.4	0.3043877846	0.14	0.08823529412	0.749
Denmark	0.3061691004	93.3	0.1912139275	0.16	0.1470588235	0.8543
Portugal*	0.3050061562	147.16	0.3326418612	0.13	0.05882352941	0.7421
Norway	0.3029593358	71.16	0.1330777512	0.17	0.1764705882	0.8957
Chile	0.2956012737	139.14	0.3115825959	0.17	0.1764705882	0.5019
Latvia	0.2942568866	111.93	0.2401333929	0.16	0.1470588235	0.6969

Venezuela	0.2889105882	0	0	0.26	0.4411764706	0.5622
Sweden	0.2864649073	53.59	0.08694168001	0.17	0.1764705882	0.9055
Libya	0.2839546365	41.63	0.05553659113	0.28	0.5	0.3087
Colombia	0.2827826133	84.36	0.1677388861	0.21	0.2941176471	0.4902
Guatemala	0.2813125861	22.74	0.005934406428	0.32	0.6176470588	0.1594
Spain	0.2792228419	115.11	0.2484835753	0.13	0.05882352941	0.7815
Panama	0.2763658824	0	0	0.25	0.4117647059	0.5583
Austria	0.2762032267	83.04	0.1642727726	0.14	0.08823529412	0.876
Qatar	0.2737520189	151.46	0.3439329885	0.15	0.1176470588	0.4456
Phillipines	0.2688140497	46.69	0.0688233595	0.29	0.5294117647	0.1476
Luxembourg	0.2669285122	29.32	0.023212457	0.16	0.1470588235	0.9941
Puerto rico	0.2614309249	135.23	0.3013155476	0.12	0.02941176471	0.6457
England	0.2603482353	0	0	0.17	0.1764705882	0.9488
Peru	0.2570721798	36.79	0.04282750834	0.24	0.3823529412	0.435
North Macedonia	0.2550057323	100.49	0.2100937426	0.17	0.1764705882	0.5019
Lebanon	0.2495752941	0	0	0.27	0.4705882353	0.3067
Montenegro	0.2482700533	91.94	0.1876427802	0.18	0.2058823529	0.4543

Kosovo	0.2469652354	50.64	0.07919544154	0.21	0.2941176471	0.4882
China*	0.2434669203	144.02	0.3243967124	0.17	0.1764705882	0.2156
Iceland	0.2423825108	23.65	0.008323924061	0.18	0.2058823529	0.7835
Indonesia	0.2420894777	59.29	0.1019089883	0.25	0.4117647059	0.1831
Morocco	0.2363105882	20.48	0	0.26	0.4411764706	0.2992
Hungary	0.2333802264	75.63	0.1448152719	0.14	0.08823529412	0.7008
El Salvador	0.2316258824	0	0	0.25	0.4117647059	0.3346
South Korea*	0.2282798157	138.48	0.3098495392	0.11	0	0.5217
Saudi Arabia	0.2242011765	0	0	0.24	0.3823529412	0.3563
Georgia	0.2173837907	31.54	0.02904182969	0.21	0.2941176471	0.4406
New Zealand	0.2130529412	0	0	0.18	0.2058823529	0.6535
Albania	0.2130078261	0	0	0.17	0.2608695652	0.5433
Lithuania	0.2021788235	0	0	0.15	0.1176470588	0.7756
Malaysia	0.1951517647	0	0	0.22	0.3235294118	0.3287
Azerbijan	0.1938538822	22.31	0.004805293701	0.22	0.3235294118	0.3126
Vietnam	0.1933056436	58.91	0.1009111677	0.24	0.3823529412	0
Monaco	0.1912494118	0	0	0.13	0.05882352941	0.8386

Chinese Taipei	0.1889069067	81.22	0.1594937374	0.13	0.05882352941	0.5079
Barbados	0.1830282353	0	0	0.17	0.1764705882	0.5622
India	0.1769058824	0	0	0.25	0.4117647059	0.061
Cyprus	0.1749635294	0	0	0.16	0.1470588235	0.5807
Taiwan	0.1721682353	0	0	0.17	0.1764705882	0.5079
Russia*	0.1689729412	0	0	0.18	0.2058823529	0.4331
Andorra	0.1680647059	0	0	0.12	0.02941176471	0.7815
United Arab Emirates	0.1670835294	0	0	0.16	0.1470588235	0.5413
Bahrain	0.1627772863	43.12	0.05944909802	0.19	0.2352941176	0.2244
Thailand	0.1566750796	46.43	0.06814064018	0.15	0.1176470588	0.4118
Singapore	0.1271247059	0	0	0.12	0.02941176471	0.5768

(3) Volleyball Rivalry List of Countries

Brazil vs. Russia

Italy vs. Brazil

USA vs. Brazil

Poland vs. Brazil

Brazil vs. Argentina

USA vs. Canada

Italy vs. Poland

Serbia vs. Italy

Russia vs. Poland

France vs. Poland

Japan vs. South Korea

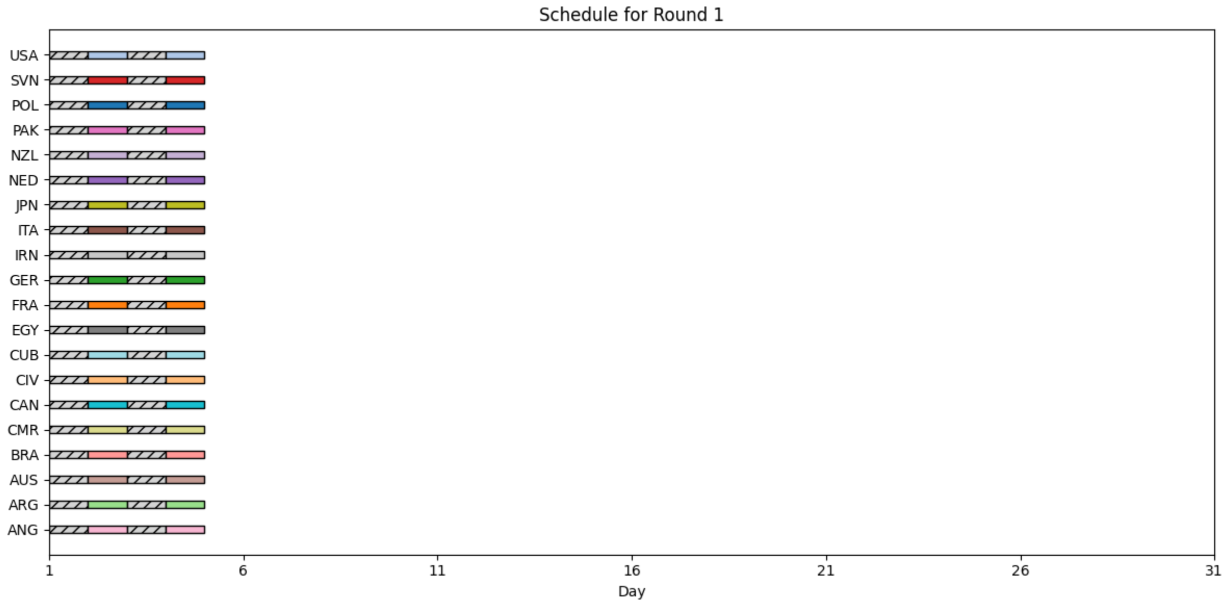
Iran vs. Japan

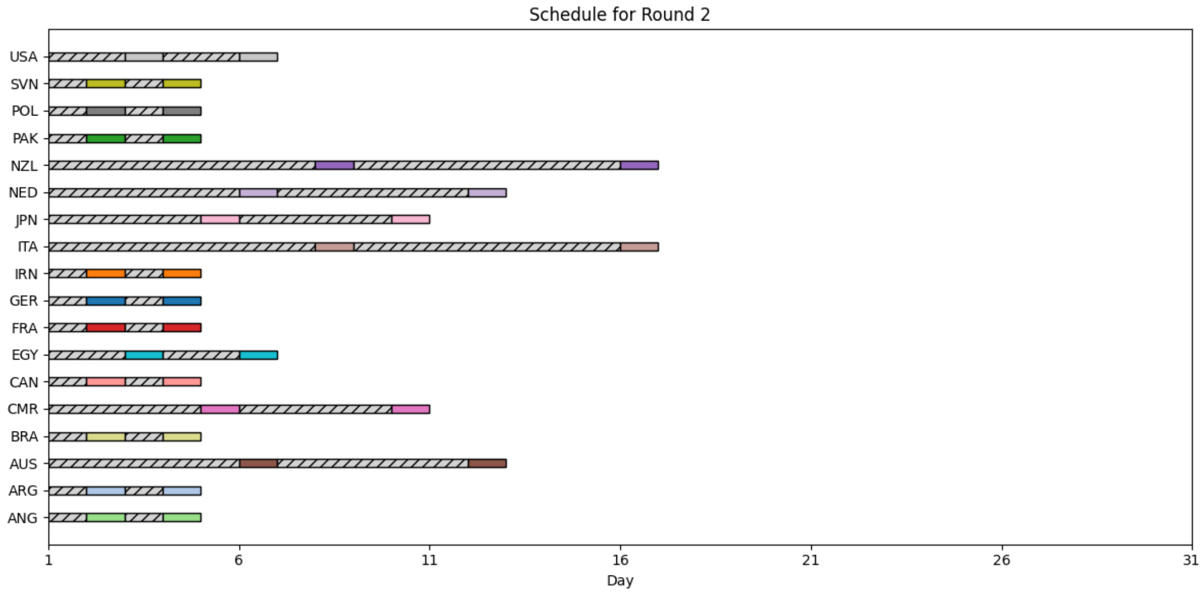
Iran vs. South Korea

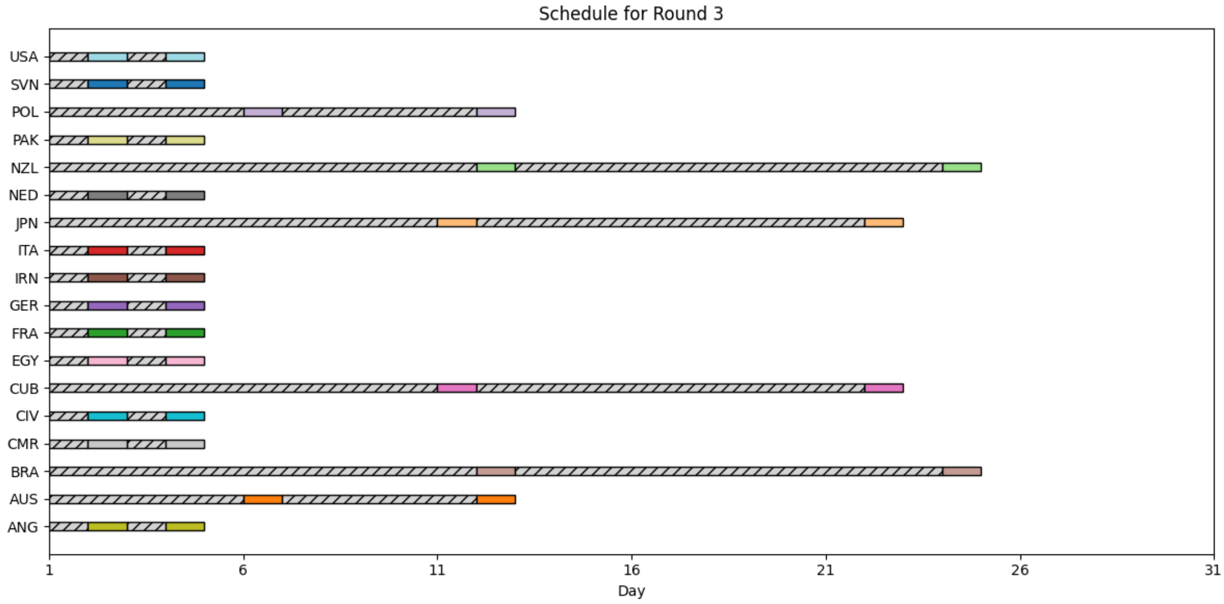
Egypt vs. Tunisia

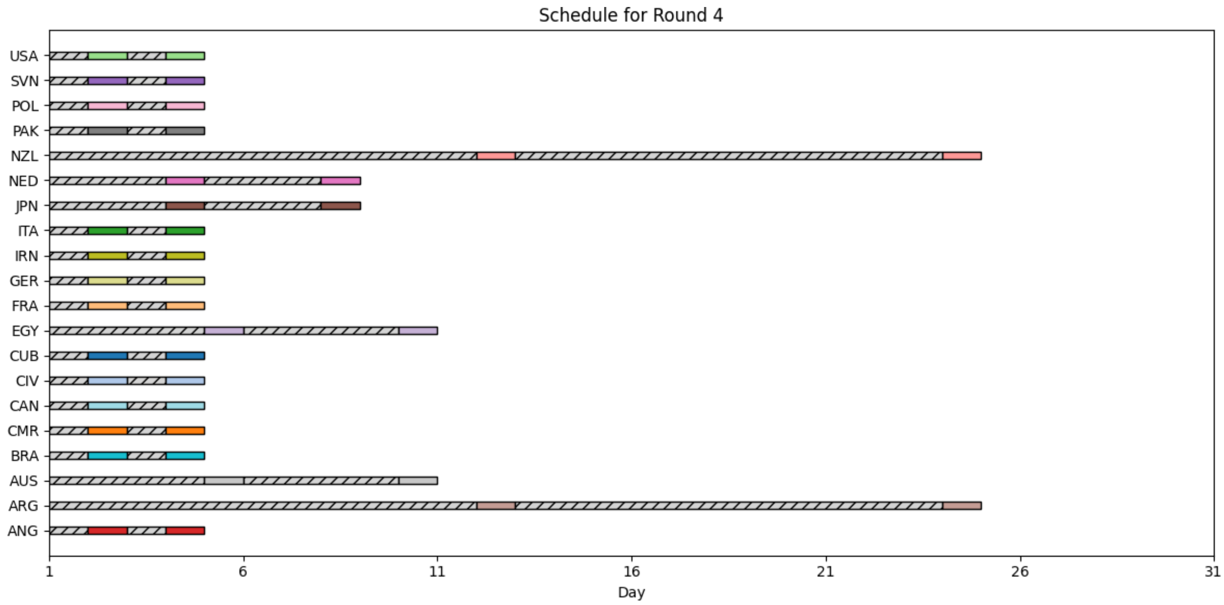
Australia vs. New Zealand

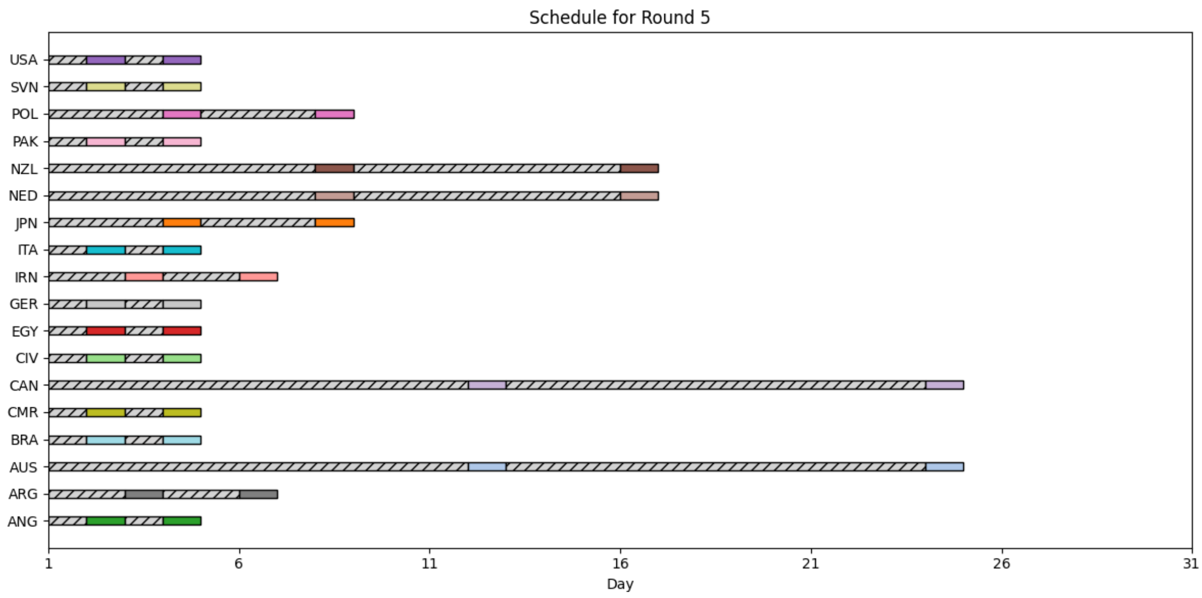
(4) d calculation code
(5) simulation code
(6) Gantt Chart of the Schedule

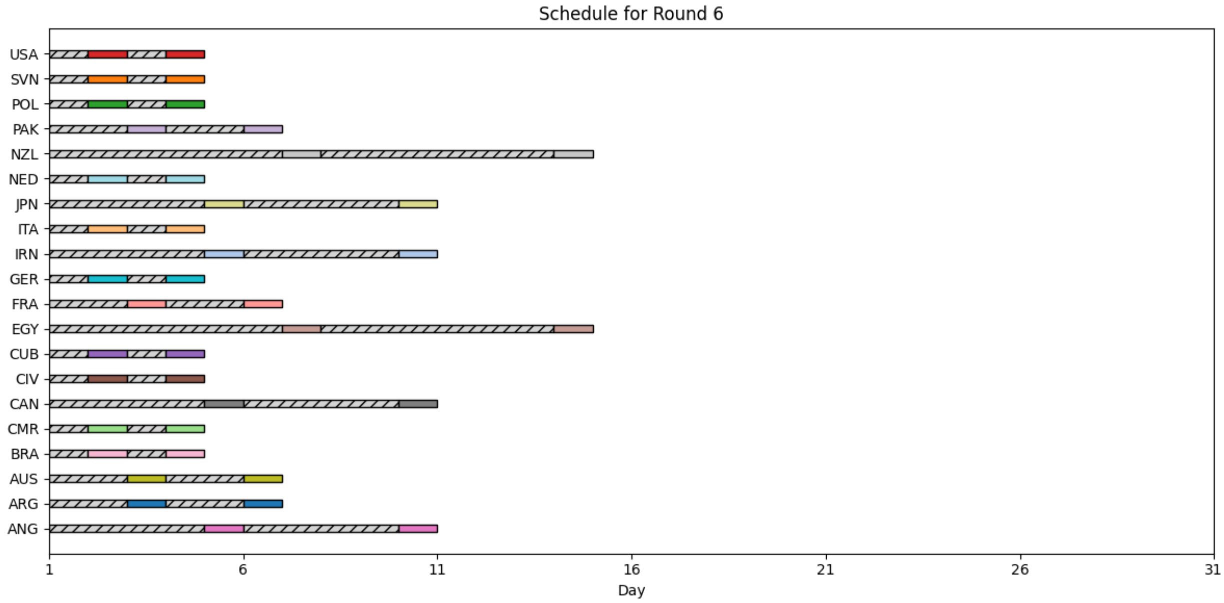


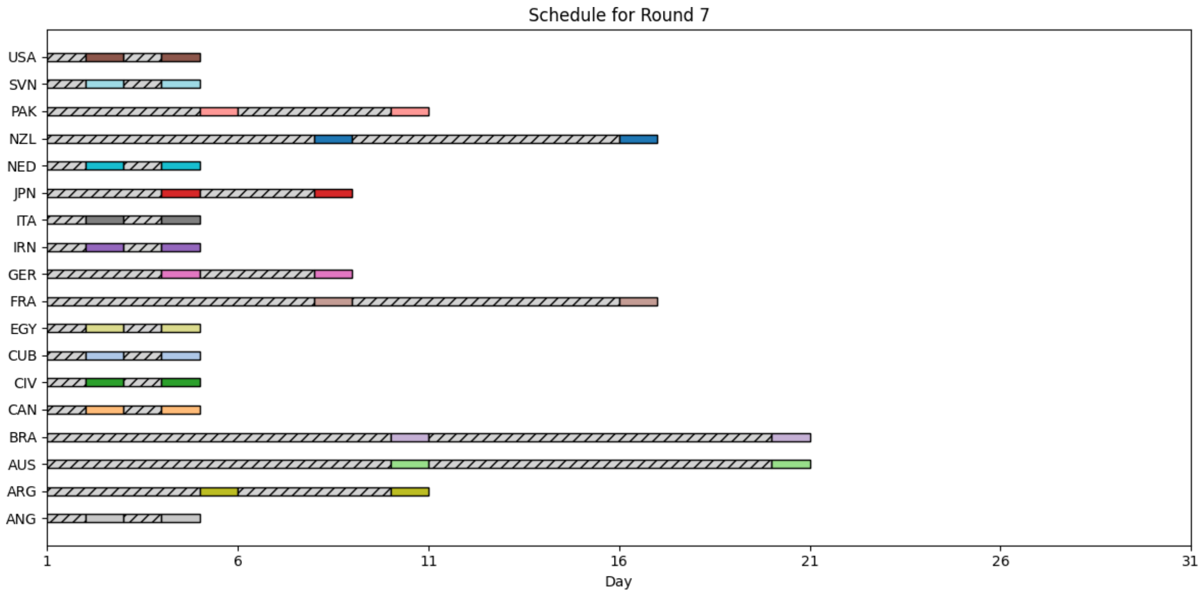


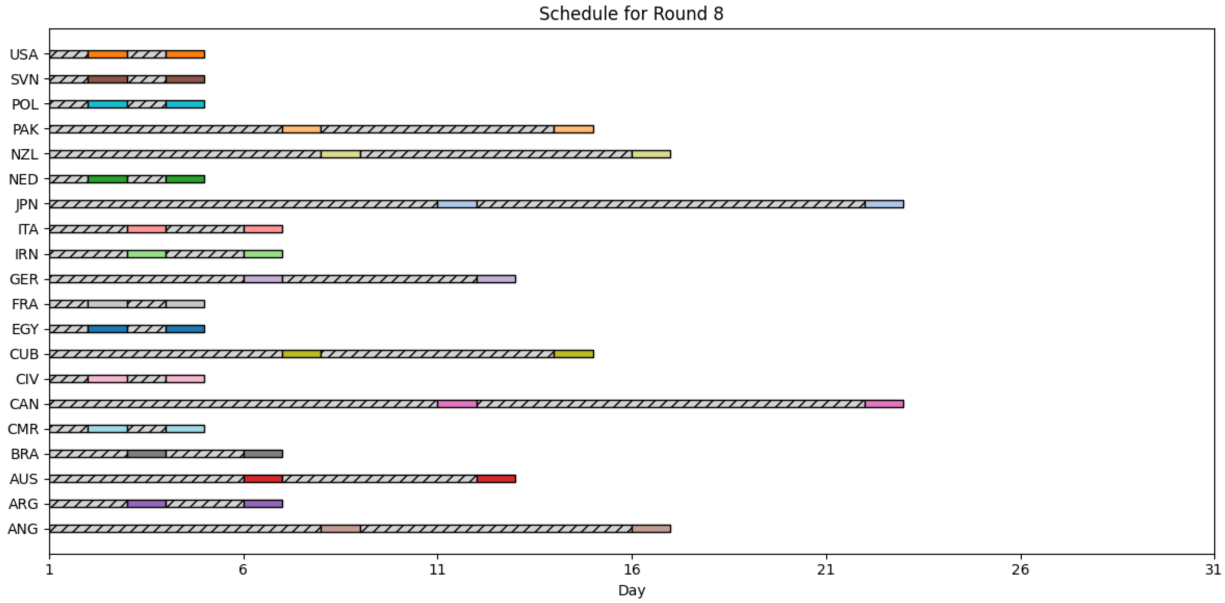

Schedule for Round 3
USA
SVN
POL
PAK
NZL
NED
JPN
ITA
IRN
GER
FRA
EGY
CUB
CIV
CMR
BRA
AUS
ANG
1
6
11
16
21
26
31
Day

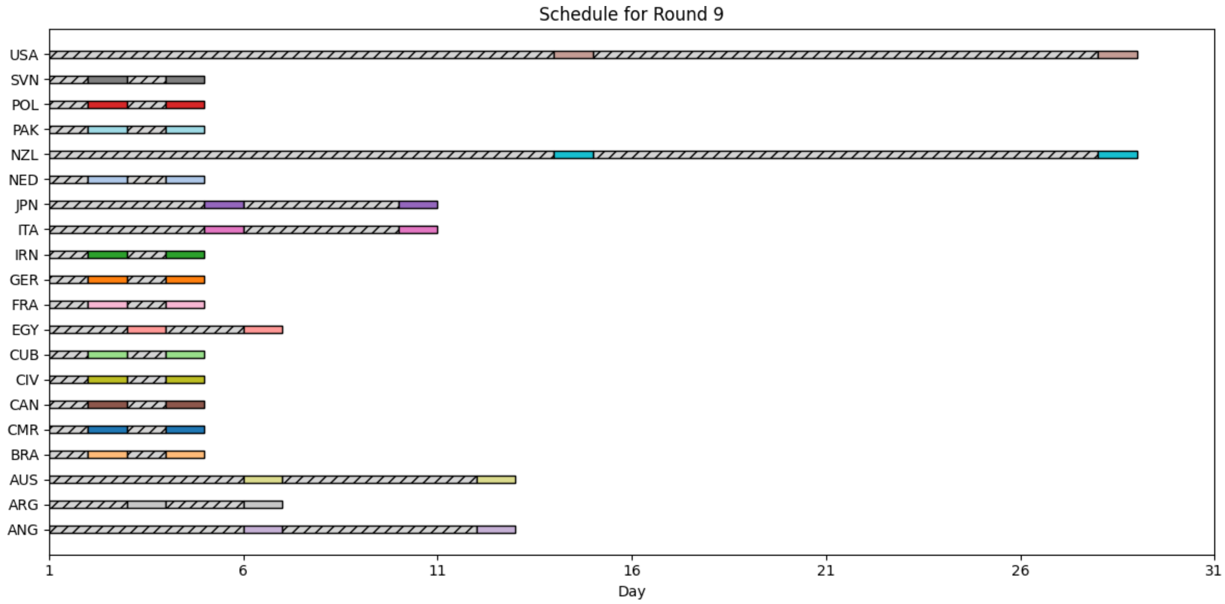

Schedule for Round 4
USA
SVN
POL
PAK
NZL
NED
JPN
ITA
IRN
GER
FRA
EGY
CUB
CIV
CAN
CMR
BRA
AUS
ARG
ANG
1
6
11
16
21
26
31
Day


Schedule for Round 5
USA
SVN
POL
PAK
NZL
NED
JPN
ITA
IRN
GER
EGY
CIV
CAN
CMR
BRA
AUS
ARG
ANG
1
6
11
16
21
26
31
Day


Schedule for Round 6
USA
SVN
POL
PAK
NZL
NED
JPN
ITA
IRN
GER
FRA
EGY
CUB
CIV
CAN
CMR
BRA
AUS
ARG
ANG
1
6
11
16
21
26
31
Day


Schedule for Round 7
USA
SVN
PAK
NZL
NED
JPN
ITA
IRN
GER
FRA
EGY
CUB
CIV
CAN
BRA
AUS
ARG
ANG
1
6
11
16
21
26
31
Day





Poland: #ff7f0e/Slovenia: #2ca02c/Germany: #d62728/Italy: #9467bd/Netherlands: #8c564b/Japan: #e377c2/Iran: #7f7f7f/Pakistan: #bcbd22/USA: #17becf/Canada:/#aec7e8/Cuba:/#ffbb78/Brazil:/#98df8a/Argentina: #ff9896/Australia: #c5b0d5/New Zealand: #c49c94/Cameroon: #f7b6d2/Egypt: #c7c7c7/Angola: #dbdb8d/Cote d'Ivoire: #9edae5

***The color of the bar represent the country that are matched with. For example, USA's bar color is #c49c94 indicating that USA is being matched with New Zealand in Round 9.*

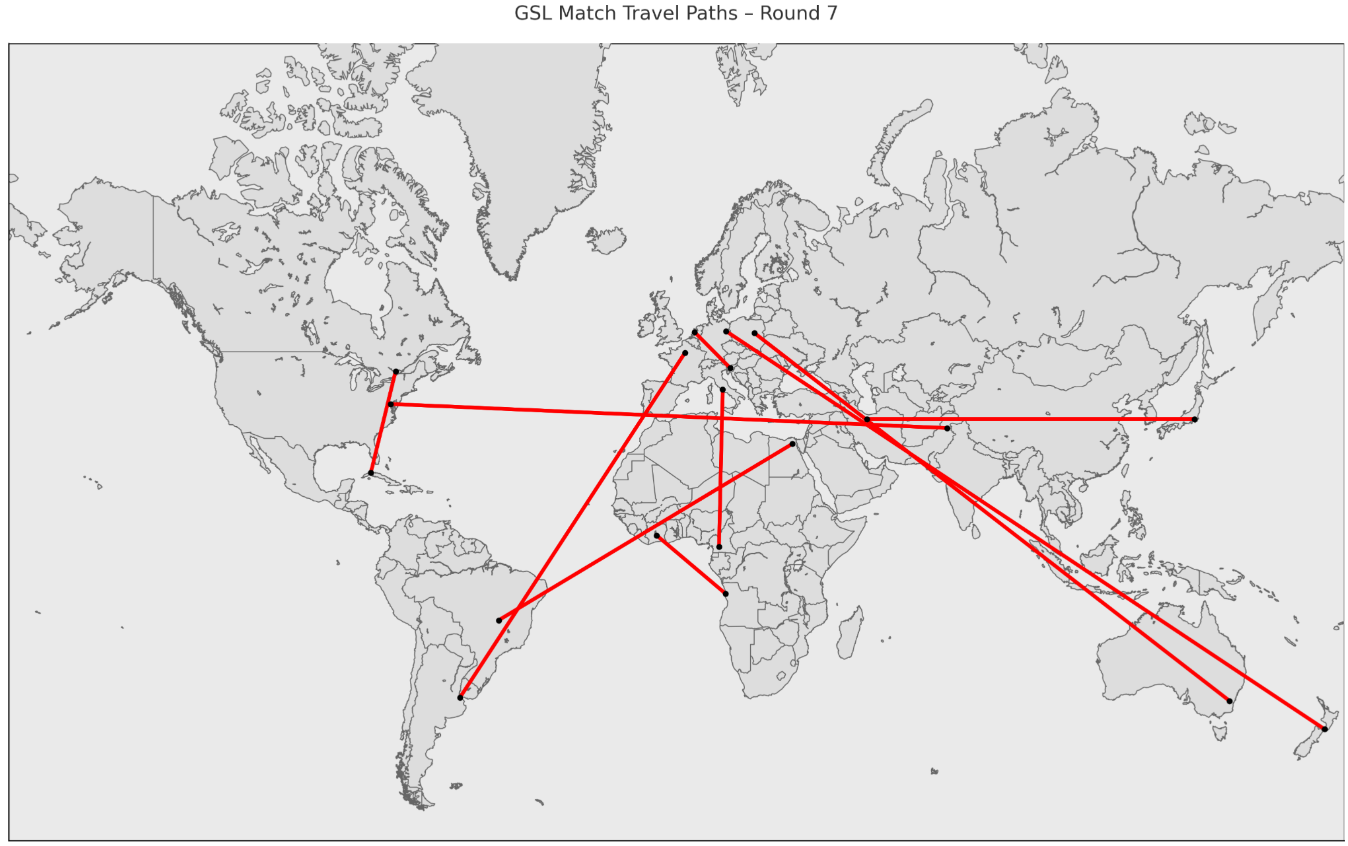
GSL Match Travel Paths – Round 2

GSL Match Travel Paths – Round 3

GSL Match Travel Paths – Round 4

GSL Match Travel Paths – Round 5

GSL Match Travel Paths – Round 6


GSL Match Travel Paths – Round 7


GSL Match Travel Paths – Round 8

GSL Match Travel Paths – Round 9