

Branch and Bound Optimization for Entropy-Maximized Esports League Scheduling

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Abstract—Scheduling an esports league is a complex process which involves deep combinatorial optimization, this problem affects many factors, mainly fairness and viewer engagement. This paper aims to explore and proposes a Branch and Bound-based algorithm which maximizes the distribution of match excitement across a season. Excitement is quantified using team popularity scores based on real-world information, while entropy is used to calculate the uniformity of excitement distribution among scheduling periods. An upper bound based on entropy is developed to help with pruning efficiency. Experiments on leagues with a variety of schedules demonstrate the capability of the algorithm to produce schedules with higher entropy compared to random and greedy baselines with a significant improvement in search space.

Index Terms—Branch and Bound, Esports Scheduling, Information Entropy, Combinatorial Optimization, Tournament Scheduling.

I. INTRODUCTION

A. Esports and League Scheduling

Esports, or Electronic Sports is a form of competition using video games as a medium. Esports can take many forms, a team versus team matchup, a massive free-for-all battle, or the classic duel format. The most common form of tournaments mostly consists of a player pool. The players would then in turns, play against each other using a predetermined format. For each turn, a predetermined amount of participants are then eliminated.

Games such as Mobile Legends: Bang Bang, League of Legends, and Counter-Strike reaching millions of peak concurrent viewers [1], Esports is growing and showing no signs of stopping. The growth of Esports brings out a new issue in managing tournaments and matches. Unlike regular sports, Esports are more flexible of its scheduling, having a lower barrier of entry to play and less requirement to schedule a match. This flexibility issues a new problem on how to create the most optimal schedule for a tournament, whilst accounting for many factors. Factors such as viewership and match fairness are a part of the many factors of creating a schedule. Viewer engagement is needed to fulfill the financial side of running a tournament, and match fairness ensures both participants and viewers have an enjoyable experience while playing or watching.

Riot Games, the developer of one of the biggest competitive first person shooter, VALORANT, also runs the highest

level of its competition. This league is split into 4 major regions: VALORANT Championship Tour (VCT) Pacific (Asia Pacific), VCT EMEA (Europe, Middle East, and North Africa), VCT Americas (North and South America), and VCT China. The Tour consists of 3 seasons per year, Kickoff, Split 1, and Split 2. Kickoff consists of a triple elimination bracket where teams are seeded based on their last year performance. Split 1 and Split 2 consists of 2 stages, a group stage where teams are split into 2 groups based on their previous stage performance. There is also 3 international tournaments which consists of 2 Masters and a Champions. Masters participants consists of the top 2 teams and the top 3 teams for Kickoff and Stage 1, respectively. There are 2 ways of qualifying for Champions, performing at least second place on Stage 2, or by performing well enough throughout the year that they accumulate enough Champions Points to qualify, the 2 teams with the most points per region qualifies to champions, with their spot given to the next team in line if they achieve at least second place.

B. Scheduling Challenges

A simple approach to scheduling may result in a problematic schedule. Some matches that consists of popular participants can be clustered together, resulting in spikes and valleys of engagement, instead of being smooth and distributed throughout the season, which can lead into an "unsuccessful" event from the viewpoint of the organizers.

Other than viewerships, schedules must also take into account fairness. Unfairness can take on many forms, such as a team having a clustered playing schedule, instead of being spread out. Another example of an unfair schedule might be where a team played all their matches significantly before or after other teams.

The complexity of running a league as big as the VALORANT Championship Tour allows solutions such as using an Entropy-Maximized Branch and Bound algorithm to solve a seemingly simple scheduling problem.

II. THEORETICAL BASIS

A. Tournament Scheduling

Define tournament scheduling as a process of arranging matches to a specific time slots while satisfying certain constraints. Given a set of teams T and a set of matches M , the organizer need to be able to determine when and by

whom each matches will be played. As the amount of teams and matches increase, the possible amount of combinations increases exponentially.

For example, let there be m matches and w weeks, each match can be assigned to one of w weeks, then the amount of possible schedules is

$$w^m$$

Let there be a tournament with $T = 5$ and each team go against each other teams once per week. The matches can be calculated as

$$\begin{aligned} m &= \frac{T(T-1)}{2} \\ &= \frac{5(5-1)}{2} \\ &= 10 \end{aligned}$$

Let a season is a month long, we can say that $w = 4$, which will results amounting to $4^{10} = 1048576$ possible schedules. Before even accounting for more complex schedules with multiple matches per week or formats such as Swiss or Double Round-Robin, the exponential growth makes scheduling an optimization problem, even for simple approaches.

B. Information Entropy

Information entropy is a concept introduced by Claude Shannon [5] to measure the uncertainty or diversity of a probability distribution.

Let a probability distribution $P = \{p_1, p_2, p_3, \dots, p_n\}$, p_i represents probability of event i , and the following must hold

$$\sum_{i=1}^n p_i = 1$$

and H is defined as

$$H = - \sum_{i=1}^n (p_i \times \ln p_i)$$

To illustrate, we can use a simple coin flip with the following probability distribution

$$\begin{aligned} P_{normal} &= \{0.5, 0.5\} \\ P_{weighted} &= \{0.9, 0.1\} \end{aligned}$$

The entropy can be calculated as

$$\begin{aligned} H_{normal} &= - \sum_{i=1}^2 (p_i \times \ln p_i) \\ &= -(0.5 \times \ln 0.5 + 0.5 \times \ln 0.5) \\ &\approx 0.69317 \end{aligned}$$

$$\begin{aligned} H_{weighted} &= - \sum_{i=1}^2 (p_i \times \ln p_i) \\ &= -(0.9 \times \ln 0.9 + 0.1 \times \ln 0.1) \\ &\approx 0.32508 \end{aligned}$$

Compare both entropy and the weighted coin has a lower entropy, which reflects the weighted coin tendency to be more predictable, compared to the regular coin. For scheduling, entropy can be used to arrange a set of matches such that throughout a season, there is less predictability, and therefore more engagement, since viewers would keep going back to watch the latest matches.

C. Branch and Bound Algorithm

Branch and bound algorithm is a algorithm optimization technique that can be used to solve combinatorial optimization problems. It systematically explores a search space—the set that consists of all possible combination, usually represented as a tree—and eliminates spaces that mathematically cannot contain an optimal solution. Compared to brute-force, which explores the entire search space, branch and bound attempts to reduce the computation needed by exploiting bounds on the objective function.

To illustrate the Branch and Bound algorithm [6], consider a tournament with 3 teams $\{A, B, C\}$. The possible matches are AB , AC , and BC . With a season of 3 weeks and a constraint of exactly 1 match per week, scheduling reduces to assigning each match to a distinct week. This creates $3! = 6$ possible schedules. The search tree below visualizes all possible schedules, where each node represents a scheduling decision.

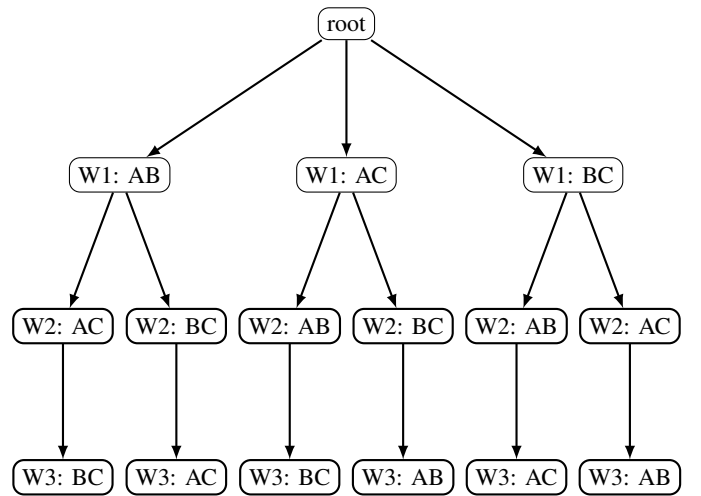


Fig. 1. Search tree for all possible schedules of a 3-team tournament over 3 weeks (1 match per week).

A brute-force algorithm would go through all the possible leaves, while branch and bound could prune a specific leaf and its children by using upper bounds on the objective function.

Using the search tree in Figure 1. Let $H = 0.65$ after computing one possible schedule (e.g., W1: AB, W2: AC, W3: BC). This becomes our current best (lower bound). For each node, we compute an upper bound $UB(n)$ representing the maximum entropy achievable from that partial schedule onward. For example:

$$\begin{aligned} UB(W1 - AB) &= 0.85 \\ UB(W1 - AC) &= 0.70 \\ UB(W1 - BC) &= 0.60 \end{aligned}$$

Since the current best (lower bound) is $LB = 0.65$, we can prune branches where $UB(n) < LB$. The pruning decision for each branch is:

- $UB(W1 - AB) = 0.85 > 0.65$
 \Rightarrow **Continue** (Branch not pruned)
- $UB(W1 - AC) = 0.70 > 0.65$
 \Rightarrow **Continue** (Branch not pruned)
- $UB(W1 - BC) = 0.60 < 0.65$
 \Rightarrow **Prune** (Branch eliminated)

By pruning the $W1 - BC$ branch, we eliminate exploring all 2 complete schedules beneath it (W3: AC and W3: AB combinations). Instead of evaluating all 6 possible schedules, the algorithm needs to evaluate only 4, reducing the search space by approximately 33%. As problem complexity increases (more teams, more weeks), the pruning efficiency only becomes for significant, and therefore saves more compute.

D. Entropy-Maximized Scheduling

The primary objective of achieving a schedule that distributes audience interests as evenly throughout the duration of the season, we can model a function that calculates the probability distribution such as

$$p_k = \frac{W_k}{\sum_i W_i}$$

Where W_k represents the total excitement or hype for week k . Finding the most uniformly distributed hype across the whole season means we are looking for the maximum amount of H across all possible schedules.

Consider 2 schedules, schedule A

- Week 1 - $p = 0.7$
- Week 2 - $p = 0.2$
- Week 3 - $p = 0.1$

and schedule B

- Week 1 - $p = 0.4$
- Week 2 - $p = 0.3$
- Week 3 - $p = 0.3$

As calculated before, a more uniformly distributed probability results in a higher entropy, and could lead to more consistent viewer engagement.

III. IMPLEMENTATION

A. Data Collection and Processing

This paper uses real-world data from the VALORANT Champions Tour (VCT) Pacific. The objective of the data collection process is to construct a Team Viewership Index (TVI) that serves as a representation for audience interest in individual teams.

Viewership statistics were collected from publicly available esports analytics platforms, primarily Esports Charts [2], which provides historical records of peak viewers, average viewers, and watch hours for professional VALORANT events. Other sources such as tournament analysis and published viewership reports [3], [4] are also used.

The study focuses on eight teams participating in the VCT Pacific league:

- Paper Rex (PRX)
- RRQ
- Gen.G
- T1
- DRX
- ZETA DIVISION
- Detonation FocusMe (DFM)
- Team Secret (TS)

For each team, a Team Viewership Index (TVI) is assigned based on its historical contribution to highly viewed matches and regional audience engagement. The resulting values are normalized to a scale between 0 and 100, where larger values indicate greater audience interest.

Let TVI be composed of three factors:

$$TVI_i = 0.5M_i + 0.3R_i + 0.3P_i$$

where:

- M_i = Match Popularity Score
- R_i = Regional Audience Strength
- C_i = Competitive Performance Score

All components are normalized to $[0, 100]$.

1) *Match Popularity Score*: Using multiple sources from tracking websites such as Esports Insider [4] and Esports Charts [2], the following MPS are assigned

Team	Raw Score
PRX	100
RRQ	95
Gen.G	90
DFM	85
ZETA	80
T1	75
DRX	70
TS	60

2) *Regional Audience Strength*: Multiple regions have difference strength in audience, we can use Esports Chart data to split audience strength into multiple regions:

- Japan
- Indonesia
- Korea

- Other (SEA-Mixed)

With Japanese and Indonesian audience having the most strength.

Region	Audience Strength
Japan	100
Indonesia	95
Korea	85
SEA Mixed	80

We can then assign audience strength to each respective team:

Team	Region	R_i
PRX	SEA	80
RRQ	Indonesia	95
Gen.G	Korea	85
T1	Korea	85
DRX	Korea	85
ZETA	Japan	100
DFM	Japan	100
TS	SEA	80

3) *Competitive Performance*: We also factor in a team's performance into their TVI , since better teams usually attracts more audiences. Using the Stage 1 2025 Pacific data, we rank the teams as follow

Team	P
RRQ	100
Gen.G	100
DRX	100
PRX	85
T1	70
ZETA	50
TS	30
DFM	10

After taking account all these factors, a final value TVI for each team can be found.

Team	TVI
RRQ	96
PRX	91
Gen.G	88
DFM	83
ZETA	80
DRX	78
T1	75
TS	60

B. Match Excitement Modeling

To be able to calculate audience excitement, each match must be assigned an excitement score based on the TVI values of participating teams.

Let TVI_i represents the Team Viewership Index for team i , and the excitement score of a match consisting of team i and j is

$$E(i, j) = \sqrt{TVI_i \times TVI_j}$$

Where TVI_i is the popularity score of team i , and TVI_j is the popularity score of team j . The geometric mean is used to rewards matches with 2 popular teams, and not have a lopsided match where a single popular team dominates the score.

C. Schedule Representation

This paper assumes a single round-robin structure. Let $T = \{t_1, t_2, \dots, t_n\}$ is the set of participating teams. The complete set of matches is defined as $M = \{m_1, m_2, \dots, m_k\}$. For this scenario, there are 8 and therefore $\frac{8 \times (8-1)}{2} = 28$ matches.

With the schedule represented as seven weeks $S = \{w_1, w_2, \dots, w_7\}$. And each week has 4 matches exactly $W_k = \{m_1, m_2, m_3, m_4\}$.

Each team only appears once per week, only one unique match per season, and each pair of teams meets exactly once. These constraints is used to reduce the computational power needed for simulations.

D. Entropy-Based Objective Function

The excitement of a week is defined as the sum of excitement scores of all matches assigned to that week.

$$S_k = \sum_{m \in w_k} E(m)$$

Where $E(m)$ is the excitement score of match m .

The excitement distribution is transformed into a probability distribution:

$$p_k = \frac{S_k}{\sum_{i=1}^s S_i}$$

where

$$\sum_{k=1}^s p_k = 1$$

The entropy of a schedule is then computed as

$$H = - \sum_{i=1}^n (p_i \times \ln p_i)$$

The objective of the optimization process is $max(H)$

E. Branch and Bound State Representation

The scheduling process is modeled as a state-space search tree. Each node represents a partially completed schedule and is defined as

$$N = (W, U, S, H, UB)$$

where:

- W is the completed weeks,
- U is the set of unused matches,
- S is the weekly excitement totals,
- H is the current entropy estimate,
- UB is the entropy upper bound.

The root node contains no assigned matches, while all matches remain available for scheduling.

F. Branching Strategy

At each iteration, a valid weekly matching is generated, and it is added as the next week matches.

Each child node corresponds to one possible weekly match. The process continues recursively until all matches have been assigned. A leaf node at the bottom of tree therefore represents a complete schedule.

G. Upper Bound Estimation

The efficiency of Branch and Bound depends on the quality of the upper bound function. Let R_e denote the total excitement score of all remaining unscheduled matches. Given a partial schedule, an optimistic upper bound is defined by assigning an excitement score that maximizes balance.

The procedure is as follows:

- Compute current weekly excitement values.
- Compute total remaining excitement.
- Construct the most balanced possible excitement distribution.
- Compute the entropy of the resulting hypothetical schedule.

The resulting entropy value is used as the node's upper bound $UB(N)$. Since the computation assumes ideal future assignments, no descendant node can exceed this entropy value.

H. Pruning Strategy

Let H_{best} represent the highest entropy value found during the search. For every generated node, an upper bound value is computed.

If $UB(N) < H_{best}$, then the node cannot produce a schedule better than the current best solution. Therefore, the node and all of its descendants are discarded. This pruning strategy significantly reduces the number of explored states compared to exhaustive search while preserving optimality.

I. Implemented Algorithm

The proposed algorithm can be represented as follows:

Input:

- Team set T
- Week set W
- Team Viewership Index values

Output:

- Schedule with maximum entropy

Generate all matches

Initialize root node

while nodes remain:

 select node with highest UB

 if schedule complete:

 evaluate entropy

 else:

 generate candidate weeks

 for each candidate:

 compute UB

if UB > Hbest:

 insert into queue

return best schedule

IV. SIMULATION AND EXPERIMENTATION

A. Experiment Setup

The proposed scheduling algorithm was evaluated using teams from the VALORANT Champions Tour (VCT) Pacific. Team popularity is represented using the Team Viewership Index (TVI) as follows

Team	TVI
RRQ	96
PRX	91
Gen.G	88
DFM	83
ZETA	80
DRX	78
T1	75
TS	60

A single round-robin tournament format was assumed, resulting in $\frac{8(8-1)}{2} = 24$ matches. The season was divided into seven weeks, with four matches scheduled per week. The excitement score of a match was calculated using $E(i, j) = \sqrt{TVI_i \times TVI_j}$ and schedule quality was measured using entropy. The season consists of 7 weeks. Each week contains 4 matches, ensuring that all 8 teams compete exactly once per week.

B. Simulations

The simulation can be split into 4 stages.

1) *Match Generation*: All possible team pairings is first generated, for 8 teams, 24 unique matches is generated

2) *Match Excitement Calculation*: The excitement value is calculated using the predetermined formula.

3) *Weekly Schedule Construction*: For each week, all feasible match combinations satisfying the determined constrained is generated.

4) *Entropy Evaluation*: The entropy value for a complete schedule is then calculated.

C. Scenarios

To evaluate the effectiveness of entropy maximization, three scheduling approaches were compared.

- Scenario 1: Random Scheduling, matches assigned randomly while maintaining constraints. (Baseline)
- Scenario 2: Monte-Carlo Greedy Scheduling, schedules generated through Monte Carlo simulation.
- Scenario 3: Entropy-Oriented Scheduling, proposed strategy used to distribute excitement as evenly as possible.

V. RESULTS AND ANALYSIS

Three scheduling approaches were evaluated and compared: Monte-Carlo Simulation, Branch and Bound Optimization, and Random Scheduling. The results are presented in Tables below. After simulations, there doesn't seem to be any significant difference with the entropy of each schedules produced by each algorithm. This is most likely due to the "small" sample size. Despite the large search space, the similar TVI values of each teams and the tiny amount of teams in the first place results in the Branch and Bound algorithm not producing results that are significantly better than other algorithms. Despite that, the Branch and Bound algorithm advantage of being exhaustive can shine, especially with larger datasets.

Score	Match 1	Match 2	Match 3	Match 4
323.89	RRQ vs T1	DFM vs PRX	TS vs ZETA	DRX vs Gen.G
324.02	DRX vs ZETA	DFM vs T1	PRX vs RRQ	Gen.G vs TS
323.69	DRX vs PRX	RRQ vs ZETA	DFM vs TS	Gen.G vs T1
323.73	DFM vs DRX	T1 vs ZETA	PRX vs TS	Gen.G vs RRQ
323.35	DRX vs T1	RRQ vs TS	DFM vs ZETA	Gen.G vs PRX
324.4	DFM vs Gen.G	PRX vs ZETA	DRX vs RRQ	T1 vs TS
324.19	PRX vs T1	DRX vs TS	Gen.G vs ZETA	DFM vs RRQ

TABLE I

MONTE-CARLO SIMULATION SCHEDULING (ENTROPY 1.94591)

Score	Match 1	Match 2	Match 3	Match 4
324.01	TS vs ZETA	DFM vs RRQ	PRX vs T1	DRX vs Gen.G
324.08	DFM vs PRX	RRQ vs T1	DRX vs TS	Gen.G vs ZETA
323.73	T1 vs ZETA	PRX vs TS	Gen.G vs RRQ	DFM vs DRX
324.4	DRX vs RRQ	PRX vs ZETA	T1 vs TS	DFM vs Gen.G
323.69	RRQ vs ZETA	Gen.G vs T1	DFM vs TS	DRX vs PRX
324.02	Gen.G vs TS	PRX vs RRQ	DRX vs ZETA	DFM vs T1
323.35	RRQ vs TS	DFM vs ZETA	Gen.G vs PRX	DRX vs T1

TABLE II

BRANCH AND BOUND OPTIMIZED SCHEDULING (ENTROPY: 1.94591)

Score	Match 1	Match 2	Match 3	Match 4
324.70	PRX vs RRQ	DFM vs Gen.G	TS vs ZETA	DRX vs T1
324.69	DFM vs PRX	DRX vs TS	Gen.G vs RRQ	T1 vs ZETA
322.95	Gen.G vs ZETA	DFM vs T1	DRX vs PRX	RRQ vs TS
323.90	DFM vs TS	RRQ vs T1	Gen.G vs PRX	DRX vs ZETA
323.23	DFM vs DRX	RRQ vs ZETA	Gen.G vs T1	PRX vs TS
323.30	Gen.G vs TS	DRX vs RRQ	DFM vs ZETA	PRX vs T1
324.52	T1 vs TS	DRX vs Gen.G	DFM vs RRQ	PRX vs ZETA

TABLE III

RANDOM SCHEDULING (ENTROPY: 1.94591)

VI. CONCLUSION

Entropy-based scheduling model may have some merit, but the current esports scene may not need a novel way of scheduling. This algorithm would work better for larger tournaments, such as a Pokemon International or another open-format tournament, where the player count is in the thousands.

The purpose of this paper is to propose a computational approach of tournament scheduling. Despite the "failure" of the algorithm, mathematics is a wide field of study, and hopefully, there would be some use for this approach.

VII. APPENDIX

The code for the simulation can be found on <https://gist.github.com/PikaProgram/6906442ae88ecf89ffe710223b26ddbfb>

PERNYATAAN

Dengan ini saya menyatakan bahwa makalah yang saya tulis ini adalah tulisan saya sendiri, bukan saduran, atau terjemahan dari makalah orang lain, dan bukan plagiasi.

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