Analysis of Optimization Approaches for the Game-Theoretic Matchmaking Queue Model in League of Legends

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ABSTRACT

This study takes the League of Legends matchmaking queuing system as an example. Using game theory frameworks, it constructs a basic queuing game model, analyzes non-cooperative game theory and Nash equilibrium, and incorporates mechanism design theory to model player decision-making behavior. It systematically analyzes the equilibrium characteristics of existing matchmaking rules and the conflict between queue waiting time and fairness. Based on this, it proposes a reputation- and priority-based dynamic matchmaking mechanism, a multi-agent game optimization model, and load balancing and cross-server matchmaking strategies. The aim is to alleviate player churn and toxicity issues through incentive-compatible design, thereby improving system efficiency and the competitive experience. This research provides theoretical support and practical pathways for online game matchmaking optimization and has significant reference value for the healthy development of the esports ecosystem.

Keywords: Queuing Game Model, Matching Mechanism Optimization, Nash Equilibrium Analysis, Player Behavior Modeling, Load Balancing Strategy.

1. INTRODUCTION

1.1 Research Background

With the rapid expansion of the global esports industry, League of Legends has become one of the most influential multiplayer online tactical competitive games. Its daily active player base is huge. As the core mechanism, the matchmaking queue system directly determines the fairness, competitiveness and player retention of the game. The matchmaking process relies on the hidden MMR (Matchmaking Rating) system, which aims to assign players with similar skill levels to opposing teams in order to achieve a balanced game with an expected win rate of close to 50%. However, there are significant challenges in actual operation: the queue waiting time fluctuates with the differences in player rank, server region and character selection, especially in high ranks or off-peak hours; at the same time, players' subjective perception of the game balance often deviates from objective data. Empirical user research by Claypool et al. shows that although the average rank difference between the two teams is less than 1 level in more than 80% of the games, nearly 80% of the losing players perceive the opponent as stronger, which leads to a significant decrease in game enjoyment, while the winning team is more likely to accept the balance [1]. From the perspective of game theory, players' queuing timing, character preference and queue avoidance behavior constitute a typical non-cooperative game situation, affecting the overall efficiency and stability of the system [2]. In addition, perceived unfairness in matchmaking or long waiting times can easily induce toxic behaviors, including verbal attacks and passive resistance. Kou's research systematically summarized the classification framework of toxic behaviors in team competitive games and their situational causes [3]. Recently, Chen et al. proposed the EOMM framework, which provides a new path for optimizing the participation of matchmaking strategies by modeling the dynamic impact of win-loss results on player participation [4]. The above-mentioned real-world problems highlight the academic and practical urgency of systematically analyzing and optimizing the LoL matchmaking queuing model from the perspective of game theory and mechanism design.

1.2 Significance of the Research

This study has significant value in both theoretical deepening and practical guidance. Theoretically, integrating the core concepts of game theory, non-cooperative equilibrium analysis and queuing theory and applying them to team matching and resource allocation problems in large-scale online games can enrich the theoretical framework of mechanism design in multi-agent systems and provide analytical tools for fairness-efficiency trade-offs in complex dynamic environments [2][4]. In practice, the proposed optimization ideas are expected to help game developers shorten effective queue time, improve objective and perceived fairness, enhance the fun of the game, thereby reducing player churn, suppressing the frequency of toxic behavior, and improving the overall community ecology [1][3]. In society, this kind of research helps to promote the evolution of the e-sports industry towards a healthier and more sustainable direction, reduce frustration and negative interactions caused by system defects, and meet the current global expectations for the responsible governance of digital entertainment platforms. In the context of the continuous evolution of highly commercialized MOBA games such as LoL, the relevant optimization strategies have broad reference value for the system design of similar online e-sports platforms and are expected to provide empirical reference and methodological inspiration for interdisciplinary human-computer interaction and online platform optimization.

2. MODELING THE MATCHING QUEUING PROBLEM WITHIN THE FRAMEWORK OF GAME THEORY

2.1 Basic Model of Queuing Game

Queue game theory shows how the matching between players happens, just like strategy games. In League of Legends, players need to consider the waiting time to join the queue and the benefits of pairing according to their own level. The basic model uses the M/M/1 queue framework to describe how the system works, and the average waiting time formula of its steady state is as follows:

$$W = \frac{1}{\mu - \lambda} \tag{1}$$

In the formula, W represents the average waiting time, λ is the player arrival rate, and μ is the matching service rate. When λ approaches μ, the waiting time increases rapidly, revealing the congestion effect under high load. The player utility function is further defined as:

$$u_i = v - c \cdot W_i \tag{2}$$

Where v is the expected value of successful matching, c is the unit waiting cost coefficient, and W_i is the single waiting time. System equilibrium requires players to choose a strategy that makes marginal revenue equal to marginal cost. Thirdly, the fluid approximate equation of queue length can be expressed as:

$$\frac{dL}{dt} = \lambda - \mu \cdot \min\left(1, \frac{L}{K}\right) \tag{3}$$

L represents the current queue length, and K represents the number of players required for a single match. This model provides a quantitative basis for analyzing strategic behavior in LoL queuing, emphasizing the impact of decisions on system stability.

2.2 Application of Non-cooperative Game Theory and Nash Equilibrium in Matching

Non-cooperative game theory holds that players are completely reasonable and selfish agents, and they make their own decisions in the matching process in order to win as many victories as possible. Strategy selection includes the time to enter the queue, role selection, and the behavior of avoiding the queue. The gain function looks at the expected winning rate, waiting time and penalty risk of violating the rules. In the pairing of League of Legends, players don’t always know what their team will look like, which leads to complex and diverse strategic interactions. Nash equilibrium means that when all players’ strategies are combined, if a player changes his strategy alone, he will not get more. When we use this idea in matching, we can predict the best decision for advanced players to wait or leave in a long queue. This explains why the system remains stable as a whole, but there may be problems in some places. Equilibrium analysis helps to understand the risks of coordination problems, such as pairing delay or resource waste due to collective strategy.

2.3 Mechanism Design Theory and Matching Optimization

Mechanism design theory discusses how the rulemakers design matching mechanisms to achieve system goals, such as maximizing fairness, efficiency and participation. In the pairing optimization of League of Legends, designers can encourage players to express their true preferences and reduce strategic manipulation by changing MMR update rules, setting dynamic priority queues and avoiding the penalty mechanism of queues. The main principle is compatibility incentive to ensure that each player's best strategy is consistent with the system goals. The optimization model usually uses the social welfare maximization framework to balance the conflict between queue waiting time and matching quality. This theory provides systematic suggestions for creating adaptive matching algorithms, thus reducing the number of players who leave, preventing toxic behaviors and improving the overall competitive experience.

3. GAME THEORY ANALYSIS OF THE MATCHMAKING QUEUE SYSTEM IN LEAGUE OF LEGENDS

3.1 Game Theory Modeling of Player Decision-Making Behavior

The behavior of players in the queue can be regarded as a game, and you don't know everything. Players, who are smart, decide whether to join the team, choose a role, or avoid playing, and use personal information (such as their mood, how they think to play, and their past results). They make decisions to get the best results, considering waiting time, game quality and system punishment. In League of Legends, this game usually has Bayesian update function, and players can change their plans by looking at teammates' information. Aeschbach and others' research shows that players are easily influenced by their own ideas and think they are better than the actual situation (their ELO level) [5]. This makes them continue to play or avoid long queues or bad games, even if it is illogical. This model adds a term to the thinking error in the decision function, which helps to understand how the player's choice affects the system. Besides, choosing a role is like a coordination game: people prefer popular posts, which will cause traffic jams and reduce the efficiency of the game.

3.2 Balance Analysis of Existing Matching Rules

The current pairing rules in League of Legends are based on MMR. Besides automatic filling, position priority and behavior system, it also tries to play a balanced and fast game. When observing the balance, these rules usually lead players to form a Nash equilibrium strategy, in which the player's best choice (such as playing games during peak hours or choosing special characters) does not meet the overall goal of the system. When players think that the match is unfair, they often do something to avoid or play passively, which will lead to the restart of the queue and waste of resources. The analysis of Agri and others shows that under the current rules, toxic behavior becomes a balanced result in a highly competitive environment, and players express their dissatisfaction by insulting or doing AFK to reduce their own costs [6]. This analysis shows that even if the rules seek a 50% chance of winning, they don't really consider the strategic response of players, which leads to the continued existence of inefficient balance. In order to improve, it is necessary to increase incentives and constraints to break this stable but bad state.

3.3 Conflict between queue waiting time and fairness

There is a trade-off between the waiting time in the queue and the fairness of matching. Shortening the waiting time will expand the scope of MMR, which will lead to a larger level gap and lead to game imbalance. On the contrary, if we want a very strict fairness, then players with high-level or unusual roles will wait longer, which will make them feel depressed and let them leave. In League of Legends, this problem is very serious: on a server with a small number of players, the waiting time during peak hours may be as long as several minutes, and players' views on fairness will affect whether they stay. Kang et al.' s research shows that pairing experience (fairness and fun) helps to keep players interested, while unfair or long-term bad experiences make them leave faster [7]. This can be improved by mechanisms such as dynamic priority or region matching, but Pareto improvement can only be achieved by balancing multiple objectives. The trade-off between efficiency and fairness in the current system often leads to bad experience, which indicates the need to optimize the model.

4. MATCHING QUEUE OPTIMIZATION IDEAS AND STRATEGIES

4.1 Dynamic matching mechanism based on reputation and priority

The dynamic matching mechanism based on reputation and priority uses real-time player data and feedback to adjust the matching parameters (Figure 1). In League of Legends, the reputation system will be updated according to performance, teammates' scores and monitoring results. Players with good reputation have higher priority or greater MMR weight in the queue, which reduces their waiting time and improves the matching quality. This mechanism increases the reputation of utility function, and urges players to avoid toxic behaviors and adopt cooperative strategies to keep a good record. Priority queues use ranking rules so that players with lower reputation can also play, while players with higher reputation have a more stable experience. The dynamic adjustment algorithm changes the matching threshold in real time according to the queue length and reputation distribution, which is helpful to solve the conflict between waiting time and fairness. Through the mechanism theory, the system realizes the incentive balance, guides the player's decision-making towards the system goal, and improves the health of the competitive environment and user loyalty.

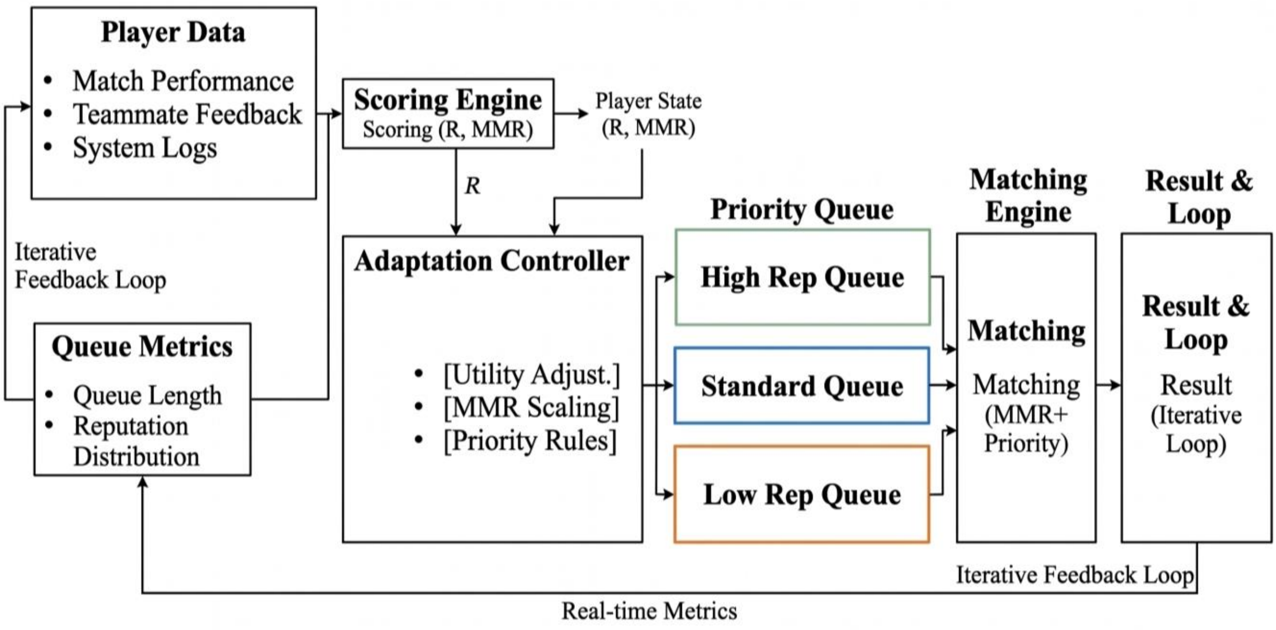

Figure 1. Dynamic matching mechanism based on reputation and priority.

4.2 Multi-agent game optimization model

The multi-agent game optimization model models the matching process as an interactive game environment between players and systems. Each player, as an independent agent, chooses strategies according to private information and observed state to maximize personal gains. This model uses a multi-agent reinforcement learning framework (Figure 2), in which agents dynamically optimize the matching allocation through continuous interactive learning of Nash equilibrium strategies or related equilibrium strategies to maximize the social welfare function. The model integrates the player's decision-making deviation and balance analysis described in Chapter 3 into the state space, and the system agent guides the player's behavior to Pareto optimality by adjusting the parameters of the matching rules. In League of Legends applications, this model can simulate the strategy evolution under different skill levels and role combinations in real time, and predict and prevent inefficient balance such as collective avoidance or popular character crowding. Through iterative optimization, the model can minimize the average waiting time while ensuring the fairness of matching, provide computable theoretical support for dynamic matching algorithm, and effectively improve the system efficiency and the satisfaction of large-scale online game players.

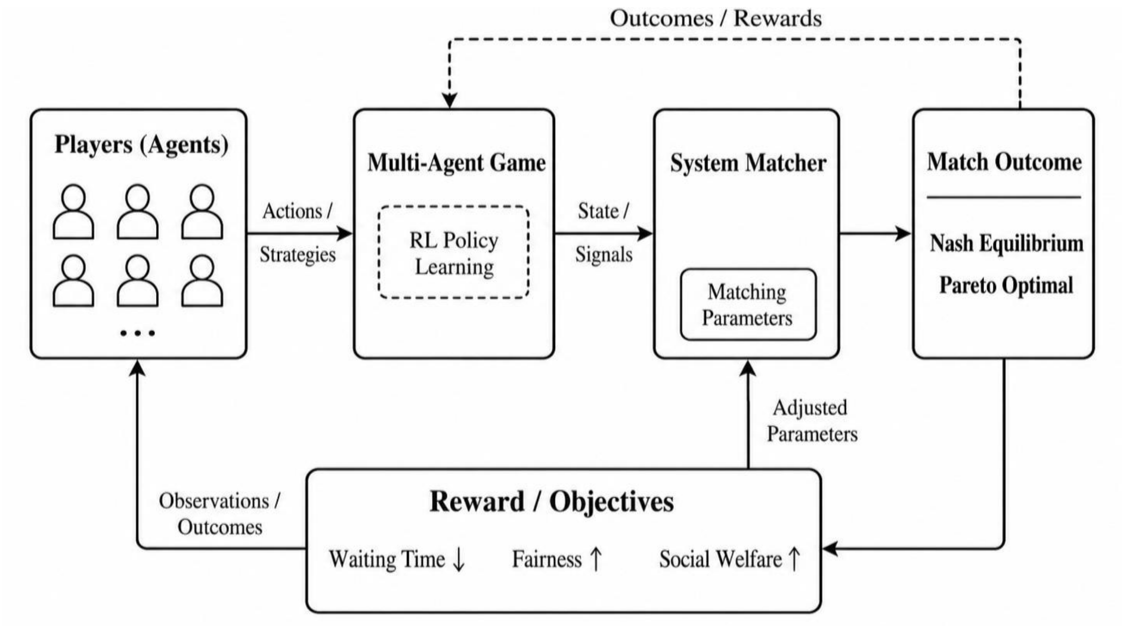

Figure 2. Multi-agent game optimization model.

4.3 Load Balancing and Cross-Server Matching Strategies

Load balancing and cross-server matching strategies are helpful to solve the imbalance between high-load servers and low-player servers by using dynamic allocation of server resources and cross-regional matching mechanisms. In League of Legends, the system will check the queue length and the distribution of players on each server in real time. When the waiting time of an area exceeds a critical value, cross-server matching will be automatically started, and a delay compensation factor will be added, so that the matching quality will not change much; This strategy puts the load balancing goal in a multi-objective optimization framework, and uses the reputation priority mechanism to first provide low-latency cross-server options for players with good reputation. In this way, while reducing the total waiting time, the sense of fairness is maintained. Cross-server algorithm uses matching rules considering delay to prevent players from feeling unfairly treated due to network differences. This helps to reduce the conflict between waiting time and fairness. Through the balanced analysis of game theory, this strategy reduces the negative players’ decisions caused by long-time waiting, and increases the desire of players from different regions to participate. Finally, the combination of load balancing and cross-server matching provides scalable system architecture support for large-scale MOBA games.

5. CONCLUSION

This research focuses on how to improve the game theory model of League of Legends matching system. By making simple queue Game model, non-cooperative games and Nash equilibrium framework, and mechanism design theory, we can see how players make decisions and why the current matching rules have balance problems. This shows the conflict between waiting time and fairness. The new dynamic matching system based on reputation and priority, multi-agent game optimization model, load balancing and cross-server matching strategy are helpful to combine theory with practical problems. It provides a solution to prevent players from leaving, reduce bad behavior and make pairing faster. These insights help to better understand how to use game theory in online games, and provide guidance for game operators, so that the matching system can adjust itself and make players behave well.

Although the research has made progress in modeling and strategy analysis, there are still limitations, such as insufficient simulation verification and limited access to data from different platforms. In the future, researchers may combine real data with reinforcement learning algorithm to better verify the model and understand whether multi-objective dynamic optimization is applicable to other MOBA games. This research brings a multi-disciplinary way of thinking to help the healthy development of e-sports world and the design of large online platforms. This is very important for both theory and practice.

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