Analysis of Matchmaking Optimization Systems Potential in Mobile Esports

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Abstract

Matchmaking systems are one of the core features of experience in online gaming. Matchmaking systems influence player satisfaction, engagement, and churn risk. The paper looks into the current state of the theoretical and practical implementation of such systems in the mobile gaming industry. We propose a basic classification of matchmaking systems into random and quasi-random, skill-based, role-based, technical factor-based, and engagement based. We also offer an analysis of matchmaking systems in 16 leading mobile eSport games. The dominant industry solution is skill and rank based systems with a different level of skill depth measurement. In the further part of the paper, we present a theoretical model of engagement and a time-optimized model.

1. Introduction

Online gaming is becoming one of the most common ways to spend time, and one of the most frequently encountered forms of entertainment in the modern society. Esports defined by M.G. Wagner as "an area of sport activities in which people develop and train mental or physical abilities in the use of information and communication technologies" is also getting more and more popular [1]. According to Deloitte analysis, the esports market was worth $325 million in 2015 and is estimated to reach the level of $1 billion in 2018. In 2016 spectators spent more than 5 billion hours watching esport tournaments – it is five times more than in 2010. The largest group of players and spectators comes from China. The biggest league – Electronic eSports League – has more than 6 million members with more than 500 thousands of teams [2].

Academic research on eSports started at the turn of 20. and 21. Century, with the high rate of growth in the number of published articles in the last years. In this article, the esports will be understood similar to Hamari's definition as "a form of sports where the primary aspects of the sport are facilitated by electronic systems" [3]. Human interaction with electronic devices runs all of the input of esports players and the output of games. Both can play esports – professionals as well as by amateurs, individually or in small teams. In this study the authors do not limit esports only to professional gaming, accepting the broader definition which will be important during the next stages of the studies.

With the rise of the mobile gaming industry and the progress in the smartphone hardware development, accompanied by mobile networks technology development (LTE and LTE-R), more mainstream games can be played on smartphones with a similar level of enjoyment in comparison to what is offered by PC or consoles. Mobile games earn more market share regarding the number of players and viability of mainstream games.

One of the most recent developments marking a milestone in the video game industry is the availability of battle royale games in a multi-platform setting, including mobile platforms, where games like Fortnite and PUBG, with 100 concurrent players, are moving beyond another threshold. Another trend fueling the change and further advancement in the video games industry and game design is esports. Nowadays, the most popular mobile esports games – such as Clash Royale or FIFA Mobile – have more than 100 billion downloads according to Google Play app store [4]. The trend is on the rise, and according to the owner and CEO of Critical Force, mobile esports will be much more popular in the future, especially in emerging countries, where more people can afford phones compared to computers [5]. For example, mobile esports is on the rise in Asia, where smartphones are the main means used to consume games. Matchmaking techniques play an important role in large online

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game environments with many players, and are just as important in esports leagues [6]. As for the recent changes in matchmaking methods, we would like to offer another look at different approaches to the matchmaking systems featured in video games, with more focus on the mobile industry.

This paper aims to summarize the current state of knowledge and practice of matchmaking in the mobile game industry. We would also like to offer a general model for matchmaking as a basis for further modeling efforts and building a digital library of the most frequently used and optimized matchmaking methods for public game design platforms.

2. Matchmaking optimization

Matchmaking systems serve a sole purpose of matching players for online gameplay competitively or cooperatively. In essence, such a system pairs or groups of players from the pool of players in a queue. A game designer deciding on the form and role of matchmaking mechanics in a game faces a relatively simple, yet greatly interdependent problem. How to design the matchmaking mechanism to make it fair, appealing, and effective at the same time [7]. Fairness is determined by matching the player with a similar or the same skill level. While effectiveness is the accuracy of the matching algorithm with the function of time as a limitation factor, time is the average time players wait for a completed matching procedure.

The basis for any matchmaking system is the decision on selection of the basic matchmaking type: random or factor based. Random and quasi-random matchmaking systems are one of the most common and dominant solutions in the video computer industry. They simply put the player population into one queue or basket for random assignment to matches. Quasi-random systems divide the population into random subgroups, e.g., by platform, geographical location or language. The biggest disadvantage of random systems is the unpredictability of the paired or grouped composition of players [8]. Beginners can end up facing seasoned players, and in such cases, both sides are not satisfied with such a match [9]. The biggest advantage of such systems is the relatively short time spent in the queue.

In the face of the rising tide of esports, games have to be more precise regarding matching players. Thus, factor-based matchmaking systems have appeared in response to the said demand, and they can be divided using the following criteria.

2.1. Skill-based systems

Skill in video gaming is the relative power or progress of the player in the game world [10]. Skill measurement in the form of rating has been first introduced by Elo [11], and it analyzes the relative skill rating of player versus their opponents in the form of probabilistic distribution based on Gaussian function. The Elo system is based on the Bradley-Terry model [12], updated later by Elo [13]. In this system, the optimal rating for online chess matches are matches between players with the closest rating, and such systems are featured in many computer games. If, however, the same logic would be applied to online games with live service, it could be hard to find equally skilled players each time in the queue, thus the waiting times could vary to extremity. The problem of matching players with equal skills versus time has been known for quite some time now [14]. Different solution have been presented in the source literature, with the first Bayesian model introduced as the Glicko model [15], which was also applicable to group play [12]. The TrueskillTM proposal has been the most sophisticated Bayesian-based system introduced and tested on live servers [16].

2.2. Role-based systems

In many online mobile games, the type of the class played or the role performed in the game is much tied to the in-game player performance. Games like World of Warcraft, League of Legends or DOTA 2 rely strongly on class systems, and the skill gained in one class might be hard to compare to another class [17][29], so allowing players to group based on the preferred role in the team can be beneficial to both in-game performance and player satisfaction [18]. Such systems are very vulnerable to in-game class popularity, and players tend to abuse such systems on purpose by, e.g. choosing less popular classes even without knowing how to play them – just to skip the waiting time.

2.3. Technical factors-based systems

In the wake of the cross-platform online gaming and mobile gaming development, device and latency optimized matchmaking systems have also been analyzed and taken into account [19]. Such systems aim to match players with the matching latency ranges, meaning that the game behaves in a similar way to the opponent or the co-player [20]. The rise of the cross-platform gaming and mobile gaming puts more pressure on the technological side of the matchmaking in pursuit of creating even playing field for the players. Matching players from different technological platforms or who are on the move can be increasingly important in the future. This is especially important for mobile eSports as the players can be located in different mobile network coverage conditions.

2.4. Engagement-based systems

Engagement and churn optimized systems: one of the most recent takes on the matchmaking logic and systems is the engagement approach to the matchmaking logic and systems design [21]. Engagement is defined as the probability that the player will keep playing in the same game session and the near future, e.g., for one week [22]. Matchmaking is a really important factor influencing the level of engagement and the study concerning this subject has been already conducted by the authors [23]. At the same time, the more players are engaged, the more interesting is the gameplay. Then, the game has more spectators and is more profitable for the company which developed it.

The basic assumption is that the best conditions for a match is to pair or group players with equal – or closest to equal – skill levels. Recent papers on the subject have questioned the basic assumption, arguing that the goal of matchmaking is not to match players based on the skill level, but rather based on their win-loss track record and the prediction of churn risk [24]. Churn in the video game industry is the probability that a player will leave the game and stop playing for a certain period, e.g., a week, or quit the game permanently [25]. Such matchmaking mechanisms are optimized to match players with skill modified by their churn risk rate and create specific conditions for the players, e.g., too long winning or losing streak.

3. Mobile games matchmaking analysis

In order to conduct an in-depth analysis of existing matchmaking systems in mobile esports at present, we have analyzed 16 highly popular mobile esports games and in particular the existing approaches in these games to match the players. The games have been chosen based on the popularity of each game measured by the number of downloads from the most popular online stores. As the number of mobile esports is still limited, our purpose was to cover the majority of mobile game types in the research. Taking popularity as the only factor applied when choosing the games to be included in the analysis, we have ended up with a quite differentiated sample of games.

Table 1. Mobile games and matchmaking systems (MM)*

#	Title	# of downloads	Publisher	Year of release	Type of game	Type of MM	Included in MM	Not included in MM	Level of MM transparency
1	Clash Royale	> 100 M	Supercell	2016	collectible card, multiplayer online battle arena (MOBA)	ranked	trophies, losing streak	levels, levels of cards	High
2	FIFA Mobile	> 100 M	EA Sports, Electronic Arts	2016	Sport, Player versus player (PVP)	ranked	number of fans, division tier	squad OVR	High
3	World of Tanks Blitz	>50 M	Wargaming. net	2010	Massively multiplayer online game (MMO)	ranked	tank hardware, balance weight (vehicle overall efficiency); formation of teams with equal number of vehicles with the same tier	Personal Rating Tank progress; Nation and class of the vehicle configuration; Crew mastery level	High
4	Hearthstone	> 10 M	Blizzard Entertainment	2015	Collectible card game, single/multiplayer	ranked/ arena	rank or win/loss record	deck, class, playing history	High
5	Critical Ops	> 10 M	Critical Force Entertainment	2015	Multiplayer first person shooter	ranked	n/a	n/a	Low
6	Knives out	> 10 M	NetEase Games	2017	Adventure	ranked	leagues	n/a	Medium
7	Mortal Kombat X	> 10 M	Warner Bros. Interactive Entertainment	2015	fighting	random	n/a	n/a	Low
8	PUBG Mobile	>10 M	Tencent Games/Bluehole	2018	Battle Royale	Random/ ranked	n/a	n/a	Low
9	Rules of Survival	> 10 M	NetEase Games	2017	battle	ranked	leagues	n/a	Medium
10	War Robots	> 10 M	Pixonic	2014	third-person shooter, MOBA	ranked	leagues	n/a	Medium
11	Chess - Play & Learn	> 5 M	Chess.com	2010	logical	ranked	rank, win/loss ratio	n/a	Medium
12	Injustice 2	> 5 M	Warner Bros. Interactive Entertainment	2017	fighting	random/ ranked	n/a	n/a	Low
13	Tekken Mobile	>5 M	Bandai Namco Entertainment	2017	fighting game	Random/ ranked	n/a	n/a	Low
14	Vainglory	> 5 M	Super Evil Megacorp	2014	MOBA	ranked	rank based on wins and losses	Karma system	High
15	WarFriends	> 1 M	Electronic Arts, Chillingo	2017	real-time PvP multiplayer third-person shooter	ranked	strength of the portfolio, strongest owned units and weapons	currently equipped units	High
16	World of Warships Blitz	> 1 M	Wargaming Group	2018	action MMO	ranked	leagues	n/a	Medium

Source: Authors' own work based on data collected on 14.04.2018, only from official sources (ex. https://www.clashroyalepedia.com, http://clashroyale.wikia.com, http://www.fifplay.com/fifa-mobile-17-vs-attack-matchmaking-system/, www.reddit.com, https://hearthstone.gamepedia.com/Matchmaking, https://superevil.zendesk.com, http://wiki.wargaming.net.

The data has been collected from the official producer sources, through gameplay as well as from gamers' forums. The methodology had to be adjusted to each of the games, as the most reliable information comes from the developers. However, most of them do not want to share too much information about the matchmaking systems. Some companies like Wargaming.net are very open about the systems used for matchmaking, and ready to explain the model's parameters and how it operates in general. However, many companies disclose their models for neither matchmaking nor skill-rating composition directly. In the direct games analysis (see table 1), we have included how much information on matchmaking mechanics is shared with the players. In cases of medium or low transparency, we have analyzed both games themselves and the most popular sources of player feedback – like official forums and Reddit pages and threads for particular games. We have reviewed player feedback on the matchmaking systems used in the games, their concerns, and answers to these concerns provided by game developers through official statements and comments. We have also observed that in the majority of games with low transparency players try to reverse engineer the matchmaking system by observation. Also, that exiting matchmaking systems are one of the main sources for the frustration of the players.

Although we can see that the vast majority of the games featured in the analysis use ranked systems, companies use a lot of different techniques to influence game performance and player satisfaction [22]. In the case of many games, skill is measured by rank or skill-rating. In order to let equally-ranked players avoid long waiting times, companies have created different modes of gameplay, including causal (skirmish), ranked, and arena-style type of gameplay. The difference between such types of encounters is predominantly about the way the matchmaking mechanism operates, from complete randomness to very specific rank or skill matching. Another type of technique involves creating in-game brackets, often called leagues. Leagues divide players into separate matching groups and only very rarely make it possible to match players from different leagues, e.g., beginners are matched only with other beginners – to avoid frustration caused by many matches lost in a row.

Games like Hearthstone or War Robots use skill equalizing mechanics for unequally matched players or for arena mode, in which players' strengths and weaknesses are equalized to some extent, e.g., a weaker player gets a boost while a stronger player is 'handicapped.'

The case of PlayerUnknown's Battlegrounds (PUBG) mobile is very special. This game is a battle royalé game for 100 players with the time-optimized matchmaking system, i.e., you always wait around 1 minute for the match. Although Bluehole Studio Inc. originally developed PUBG, the mobile version was developed and offered by Tencent. This Chinese company is currently one of the biggest mobile game developers worldwide, but most of its products is sold mainly in China. Tencent is quite known for using so-called bots to create opponents in their mobile games, and it is suspicious that PUBG mobile takes advantage of this technology to optimize both time and players' experience – especially at early stages of the in-game progress. However, it has not been officially confirmed by the company. Using bots and time optimization would be a unique and innovative way to use AI technologies on such a wide scale.

4. Modelling an engagement model for mobile online games

None of the games presented above use any other system then rank- or skill- based or random matchmaking mechanics. So we have decided to attempt to model an engagement-optimized matchmaking system for a mobile game.

We have applied the following mathematical model to find optimal matches for each player. We have built this model based on our research and experience with different action games as well as card games, where matches do not last on average more than 10 minutes. We plan to implement this model as a generalized model for a mobile game creation platform. The model itself is universal in the sense that it does not distinguish between different types of games, but we assume that the specific features used for the evaluation of players' skills are encoded into random variables, and they vary from game to game. We shall come back to this issue in subsequent papers where we analyze the possible skill parameters.

We define the set of players at a given moment by $P = \{p\_1,..., p\_N\}$. We determine their respective skills by

$\{\mu_1,...,\mu_N\}$, where μ_i is a random variable (modeled, for example, by TrueSkill, etc.)

Let $c_{i,j}$ be a churn rate, which is the probability that player p_i will keep on playing after playing with player p_j. We have $c_{i,j} = 0$ if player p_i stops playing after a game with p_j, and $c_{i,j} = 1$ if p_i continues playing after a game with p_j (no matter what the result of the game is).

In general, we want to model $c_{i,j}$, which should depend on $o_{i,j}$ – the probability that player p_i will dominate player p_j

The record of recent games played by p_i and their win/loss ratio (which models the fun they have) when playing in particular with $c_{i,j}$ does not have to equal $c_{j,i}$.

In our simplest model, we have $o_{i,j} = \mu_i / (\mu_i + \mu_j)$, so the win depends directly on the skill of player p_i relative to the skill of player p_j. We assume here that a better skill makes μ_i larger.

We introduce two arbitrary parameters: $\alpha = a$, a real number larger than 0, and $m = a$, a natural number (larger than 0). Let l_i be the number of losses of player p_i in the last m games divided by m. Thus, l_i belongs to interval [0,1].

In our model, churn $c_{i,j}$ depends directly on l_i and $o_{i,j}$, which we normalize with α to avoid l_i being 0. We set:

$c_{i,j} = [(l_i + \alpha) o_{i,j}] / [1 + \alpha]$

(which belongs to interval [0,1], that's why we normalize it)

This model assumes that the more player p_i has won in the last m games, the less they care about winning in the next game, and there is a larger chance that they keep playing.

For good matchmaking, we want to maximize

$\sum_{i,j} c_{i,j}$

where the sum runs over indexes i,j, whenever players p_i and p_j play each other. We choose matchmaking which maximizes this sum and defines it by M_N. This is our good matchmaking model in a given time.

The major disadvantage of the model presented above is the matter of time, of course. In such a model without time restrictions, the waiting time for an optimal match can be long, especially when the number of available players is limited. Therefore, we have added the time parameter to the modeling of the optimized engagement model for mobile online games.

We can similarly define M_k, where k is an even number smaller than or equal to N. We define M_k as the maximum of the sum

$\sum_{i,j} c_{i,j}$

with an additional assumption that in our matchmaking, only k players play in the next round, and $(N-k)$ wait for their game (because, for example, we cannot find a good opponent for them). For each k, we have an inequality

$M_N >= M_k + M_{(N-k)}$

This way of splitting N players into two groups – one of k players who play in the next game, and $(N-k)$ players who wait – can improve the matchmaking. If we are not content with the matchmaking results at any given moment, we can choose to engage only some players and let others wait, counting on the fact that in a moment there will be more players who could be more appropriate opponents, and our matchmaking will become more effective. This kind of reasoning applies to games with a large number of players who keep joining the game all the time.

5. Limitations of the study

The conducted study has been extensive, however, did not lack some of the limitations. Choice of the games to the study is very wide, as it is aligned with understanding esport as competitive gameplay in video games. On the other hand, we would look at the matchmaking as universal on-line games functionality. An additional constraint of the study, which need to be mentioned is the fact that many developers do not share detailed information about their matchmaking systems. In order to discover the type of matchmaking that is used in some esports games, the reverse-engineering analysis needed to be done as well as some game forums (ex. Reddit) analysis. It means that in some of the cases, the authors of this article cannot be convinced about the type of the matchmaking system.

The mathematical model that has been constructed during the study also faces some limitations. Firstly, it is devoted only to single-player games. In the future the model can be expanded and also adapted for multiplayer games. Secondly, it is just the theoretical model which needs to be validated against real data[28]. During the next stages of the project, two different esports games will be developed to enable testing the model against the data from the gameplay. In this case, the authors of the research will have access to all of the information about the game mechanics and skill measurements and then different types of matchmaking can be tested and compared.

6. Discussion and summary

The mobile gaming industry is currently experiencing another revolution. The missing element of the next step in the advancement was the ability to connect players online and enable them to engage in a large-scale competitive play. Games like World of Tanks: Blitz, PUBG mobile and Fortnite are reshaping the industry. Matchmaking is the essential part of the core experience of the players in such games. Unfortunately, in most of the analyzed cases, the matchmaking mechanics becomes one of the frustrating elements of gaming. The mobile market is very sensitive to time. Fast pace, hop-in/hop-off game systems seem to be most effective in this environment [20].

However, the analysis of the current publication trends shows an inclination towards new models of matchmaking, like engagement modeling, time, and technical factors such as latency. Yet, practice shows that the systems currently in use are quite uniform. The presently applied matchmaking systems are based on skill-rating systems or progress, with more or less sophistication to skill calculation or matchmaking itself. Usually, ranks, levels or ratings are built around the win/loss ratio or the number of experience points earned collectively in a given game season or historically. Such a solution is relatively simple to develop and implement, but it can have more disadvantages than advantages if the number of the available players in the matchmaking pool is low [26].

Such a disparity between the theoretical level and the practical application is certainly not new, but it can have an impact on the ability of players in a game to survive the game in the long run [25]. Our modeling attempt takes into consideration the possibility of changing some parts of matchmaking algorithms and adding the engagement factor to the equation with a restriction of the timeframe and an increase in the probability of the game success in the long run [27]. The basic assumption behind this reasoning is the need to use more sophisticated multifactor matchmaking algorithms to create a successful online experience. Including more factors like engagement, platform, churn probability, expected latency, into future matchmaking equations, beyond players skill or rank, will create challenges in research and modeling. We think that such a hybrid solution can be beneficial for the industry in the future.

Of course, this model needs to be confronted with the existing models and be subject to a comparison study in the future. The model will be tested on a few mobile esports games, where the level of player engagement will be measured. The model will be easy to introduce in all kinds of esports mobile games, not only in one type as it has been used so far. Creating an optimal matchmaking model can have a great impact on player engagement, enjoyment from playing the game, the sense of immersion, and flow. At the same time, it could impact the practice of developers and a number of people watching esports as it can become more popular and more spectacular.

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