Effect of Different Looting Systems on the Behavior of Players in a MMOG: Simulation with Real Data

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Abstract. Massively Multi-player Online Games (MMOGs) are complex and persistent video games developed for a large public of players. The complex relations and dynamics among players represent an interesting research topic not only for developers, but also for experts in social relations and psychologists. Looting Systems (LSs), i.e. the procedure applied to allocate goods or items to a group of players after a successful collaborative activity, can have an important role in the overall satisfaction of a player towards the game and the other players in her group, leading even to the decision to abandon the virtual world. In this work we analyze different types of LSs, and we try to simulate the behavior of different type of players using real data from World of Warcraft, in order to understand which LS can be the more appropriate to maintain a high level of satisfaction and engagement in the players.

Keywords: Videogames · Massively multiplayer online games · Agent base model simulation · Looting system

1 Introduction

Massively Multi-player Online Role-Playing Games (MMORPGs) and Massively Multi-player Online Games (MMOGs) are games where players interact in an online, persistent, and shared virtual world. This game category has gained success and diffusion thanks to Blizzard's World of Warcraft (WoW) [1]: in 2014, WOW could count on 10 million worldwide subscribers [2,3]. The high number of players, and the need of a large scale cooperation, interaction and competition among players have led to a relevant interest not only from the gaming research community, but also from experts in social sciences and psychologists. As a matter of fact, in literature it has been proposed that satisfaction or frustration in video game can modify short-term emotions: "games are generally more or less appealing, and have a greater or lesser influence on player well-being, as a function of the extent to which the in-game experiences they provide fulfill fundamental psychological needs" [18]. In this paper, we aim to investigate

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the role of the Looting System (LS) [5], i.e. the procedure applied to allocate the resources/items won by a group of players after a successful collaborative activity in a MMOG.

Dungeons and *Raids* are two common structures used by almost all MMOs. Usually, *Dungeons* are instanced confined areas designed for a limited number of players at a time. *Raids* are similar to the *Dungeons* but designed for a larger number of players that devote a relevant amount of time in order to accomplish the mission and to obtain, usually, items or objects of higher level than in the Dungeons. In almost all MMOs, there is a *guild* (also named *clan*) system. It unifies different classes of players under the same name and rules, and consequently these players regularly play together creating a bond that allows a better game performance. Once the guild has successfully concluded a Raid, the items obtained during the mission have to be allocated among the players. If this situation is mismanaged, the satisfaction of the players (and their will to continue to participate and play to the game with that guild) can be affected.

Valid LS can contribute to the overall success of a MMOG, by maintaining an appropriate level of satisfaction in the players, by allocating fairly the obtained items, on the basis of well-described and explained rules.

Unfortunately, only a few studies have been conducted on this topic [6,8,11]. In the present work, we try to understand which approach could guarantee an adequate level of satisfaction in the players. To this aim, we show the results of a simulation based on real data from WoW, applied to several LSs described in literature.

2 Types of Looting System

Different approaches to LS are present in literature (for a detailed description and overview see [8–10]).

In this paper, we consider the following methods:

- *Rolling*: this system tries to reproduce the most random action possible. Each player rolls a "dice" for each object (from 1 to 100), and the player with the highest result gets the item.
- *Dragon Kill Points (DKP)*: During various events players can obtain points (called DKP) that are later used as a currency to bid on available items. In the paper, we consider the following variants of the original DKP approach:
  - *DKP fixed*: the item has a fixed price in DKP. Players interested in the loot bid the points. The item is then assigned randomly among them or following a predetermined priority list.
  - *DKP auction*: the item is put up for auction. Different types of auction can be used.
  - *DKP zero-sum*: the points spent on the item are redistributed amongst other participants in the group.
- *Dual Token*: a pair of Tokens is assigned to every player (Need and Greed). Players interested in the item use their Need token: the object is then assigned

randomly among those who used their tokens. In case no Need tokens were used, Greed tokens placement takes place, to assign the item for speculative goals or for a secondary use on the character.
- *Dual Token ordered (hybrid)*: a hybrid looting system proposed in [8]. It combines ideas from both Dual Token and *DKP relational* (where the order in which players are listed is based on the relationship between acquired and spent DKP). The use of tokens is the same as in the Dual Token system, but the priority list on which the item is assigned is based on the relationship between number of missions whose the player has taken part and the value of the items she has already received. In this case, a player with a high number of missions but without many powerful items will have priority on a player with many powerful items already assigned.

3 Looting System Effect Analysis

In the work by *Maggiorini et al.* [8], a preliminary evaluation of different LSs has been presented, and in this paper we expand their approach, basing our analysis on a simulation based on real data regarding WoW players characteristics and classification.

3.1 Players Classification and Data

The analysis is based on a classification of players: the parameters used for the classification are Bartle-Type, Game-Time, and Class.

Bartle classification [4] tries to describe how the players interact with each other. He identifies four main types of players:

- *Killers*: focus on winning, rank up and competition
- *Achievers*: focus on attaining status and achieving pre-set goals quickly
- *Socializers*: focus on socializing and aim at developing a network of friends
- *Explorers*: focus on exploring and aim at discovering the unknown.

Another criterion by which players can be classified is how much time they spend playing every week. We can identify three groups: Casual (<20 h), Medium (20–40 h), and Hardcore (>40 h) players.

Finally, we classified players on the basis of their main Class in WoW: tank, healer, melee DPS, and ranged DPS. We limited the classification to 4 classes because the actual class structure in WoW is too complex and redundant to be handled by the simulation.

After a review of the literature [15–17], we determined a set of data related to real players in Wow. The results are summarized, in percentage, in Table 1, and they represents the basis for the overall simulation on LSs effect.

Table 1. Resuming empirical data in percentage [15–17].

Bartle-type	Percentage	Game-time	Percentage	Class	Percentage
Explorer	30%	Casual	50%	Tank	15%
ocializer	25%	Medium	35%	Melee DPS	25%
Achiever	25%	Hardcore	15%	Ranged DPS	40%
Killer	20%			Healer	20%

3.2 Simulation

The simulation model considered is an expansion of the model used by *Maggiorini et al.* [8]. A detailed description of the original model is beyond the scope of this paper. We recall the overall principles of the model, and we describe the extensions and differences introduced to deal with the set of data regarding actual WoW players.

Overall Approach. While the previous method [8] was focused more on the simulation of the possible choice made by a guild to change the adopted LS (the players of a guild use a specific LS, then after each raid vote the effectiveness of the LS and choose if change or keep it), the current approach is focused instead on the possible decision to change the guild, made by a single player, because of dissatisfaction of the current LS. Other differences with the previous model are mainly due to the adoption of real data to set Bartle type and the time spent playing (in the previous model they were calculated in a separate simulation), and in the consideration of a higher number of players (ten times more than in [8]) inserted in a dynamic flow of players composed by newbies and players that abandoned the game.

The presented simulation is based mainly on the mathematical model presented in [8].

In the original model, the players judged the adopted LS, and evaluated if to change or keep it. This decision calculating with the following formula:

$$Change_D = diss(item, player) + change(Ls, tot\_items) \tag{1}$$

Where *diss* is measure of dissatisfaction of the player for the item dropped by the mission, and $change(Ls, tot_items)$ measures the desire to change the current situation (using LS and the number of objects collected by the player).

In the original model, contribution of each player of a guild to the $Change_D$ parameter is compared with a random number (<100): if the value is bigger, the simulation would force a new LS for the guild, otherwise the current LS is used again for the next mission, and a counter connected to the current LS is increased. The simulation described in [8] would end here, looping for a fixed amount of missions and showing the results, printing the LSs counters and showing which one was kept the longest and voted to be changed the last times.

In the proposed approach, this is not adequate since we are adding guilds and players movements between different guilds instead of a static environment, and as a consequence LS cannot be changed in the same way. Therefore, in our approach a guild never changes its LS: on the contrary, a specific and unchangeable LS is randomly assigned to every guild. In the new model, the evaluation of single $Change_D$ parameter determines whether a player of the guild is more inclined to stay or to change guild. When players are searching for a guild, they will be less interested in guilds with a high number of members because the chance to participate in raids carried out by that guild will be much lower than with a smaller one [12].

Simulation Setup and Parameters. The simulation is initialized with 250 guilds with an average of 16.8 players each [14]. The initial population consists of 5000 players. During the simulation the number of players may fluctuate because there is a process of introduction of newbie players and the elimination of players abandoning the game. The players are simulated through *agents* using [7]: i.e., a software simulation about an entity with its personal goals and behaviors, which adapts and modifies its behaviors according to the environment. Following [13], we set in the simulation a random number between 3 and 6 of players linked to other players, in order to simulate friendship bonds from the real life between players.

During the simulation, the probability that a player attends at one raid is calculated using the amount of time spent playing alone and by his guild, if the guild has enough members. A hardcore player has a higher chance to participate (95%) than medium (70%) and casual (50%). Raids give higher rewards (medium-high power items) and the assigned LS of the guild is used after the mission. Then, a fixed number of dungeons, depending on the total number of players, are simulated: groups of 5 players are randomly created without checking guild membership. However, the simulation tries to have a balanced group with at least one tank, one healer, and one DPS. There is also a 50% probability to choose a hardcore player, 30% a medium, and 20% a casual. Items, of low-medium power, are assigned using a *rolling* LS.

A general loot generated by a dungeon or a raid can fall in 5 groups. The items in the first 4 groups regard only one of the four classes: tank, healer, melee DPS, and ranged DPS (e.g. a special bow usable only by a ranged DPS). In this case the item will interest only players in the same item class. In addition to this, the item can be a no-class item that can be taken by any player (e.g. consumables, recipes, crafting requirements). Every player that plays in the raid group generates a preference value very similar to the model described in [8].

For every simulated day, the simulation checks if a player is unsatisfied with his guild and its LS. The overall behavior of an agent is controlled by 3 parameters: the *guild-satisfaction*, *move-changes*, and *overall-satisfaction*.

Guild-satisfaction defines how much an agent is satisfied by his/her guild and the connected LS. It is formulated using the $Change_D$ value, the threshold of objects satisfaction (*Item won*) described in [8], and data in *Patil et al.* [19].

Table 2. Guild satisfaction changes. For more information on *Item won* see [8]

Event	Guild-satisfaction change
Not raiding	−days since last raid * 0.1%
Guild size > 80	−0.10%
Guild size > 120	Additional −0.10%
Item won	$+item\ satisfaction\ ratio * (\frac{No.\ found\ obj.}{No.\ players\ in\ the\ mission})$
$Change_D$ check passes	−50

The calculation of *guild-satisfaction* is described in Table 2. It generally increases on successful acquisition of items and lowers vice-versa.

When "*guild-satisfaction*" goes under 50, a random check is done to see if the player leaves the guild.

Players that leave a guild, or never had a guild, will try to find a new guild. Every player checks for one guild chosen by one of his friends every day. The simulation calculated an index called "*move-chance*" in order to determine the inclination of the player to join a guild.

It is calculated using different properties:

- if Player game-time == hardcore then *move chance* += 30,
- if Player game-time == medium then *move chance* += 25,
- if Player game-time == casual then *move chance* += 20,
- if Player Bartle == guild Bartle then
  - if Player game-time == hardcore then *move chance* += 50,
  - if Player game-time == medium then *move chance* += 40,
  - if Player game-time == casual then *move chance* += 30,
- if Player game-time == guild game-time then *move chance* += 40,
- if Guild size > 30 then *move chance* += (100 - guild size),
- if Guild size > 70 then *move chance* −= (guild size - 30).

The *move-chance* value is then compared to a random value (<100): if it is bigger, than the player joins the guild adopting its LS.

Finally, "*overall-satisfaction*" checks if a player is playing or being passive. This value is affected by Bartle type and time spent playing. It decreases if the agent does not participate to a raid for several days. In particular, the "*overall satisfaction*" value is changed as:

- if casual: $-0.1\% * day\_since\_last\_raid$,
- if medium: $-0.2\% * days\_since\_last\_raid$,
- if hardcore: $-0.3\% * ticks\_since\_last\_raid$.

At the same time participating in a raid will give following bonus:

- if casual: +3,
- if medium: +6,
- if hardcore: +9,

- if killer: +2,
- if achiever: +4,
- if explorer: +7,
- if socializer: +9.

Reaching a very low value in this field (<25) will make the player leave the game.

4 Results and Discussion

The simulation process described in the previous section runs for 300 times, to simulate an average video game year (300 days). At the end, every LS is assigned a value, corresponding to the average number of people that left guilds using that LS during raids. Every single simulation has been executed 50 times and the average for every LS calculated and compared with the others.

Figure 1 shows the data related to guild abandoning between various *game-time* types of agents. Analyzing the results of the simulation, the Dual Token ordered hybrid LS seems to be the LS with potential lower dissatisfaction for every type of *game-time* players. This result is in line with the results presented in [8].

Therefore, we can identify three major LSs groups, depending on their success rate. The first one is made up of LSs that clearly fail to make the player satisfied. We can consider not successful all LSs that base their core decision on a random value (rolling, dual token). The second group contains LSs that, at cost of some extra time needed to set up and use the model, give the players a fairer chance to obtain the loot wanted. This is generally the DKP system in its various applications. Lastly, the third group contains the LSs that are the most successful, as, in the case of the presented simulation, Dual Token ordered hybrid LS.

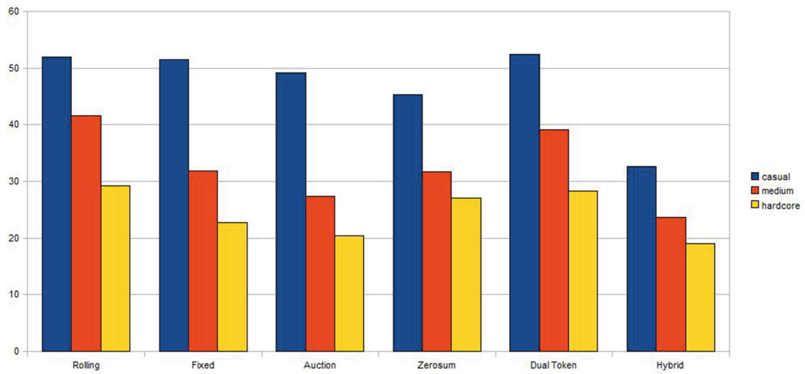

Fig. 1. Game-time type preferences population. The y axes define the average of players that leave a guild.

Generally we can say that a relational system (like the hybrid system), that takes into consideration both the loot already acquired and the time spent in the guild/game, could obtain a high general satisfaction from the average MMOG player. However it comes with the cost of harder and more complex implementation and maintenance.

The presented approach can be easily integrated with future proposed LSs and supplementary real data, and adapted to changes in general WoW settings. Moreover, the presented approach can contribute to influence the overall player well-being, by providing a fair and clear feedback to the time and efforts put in the game by the player, and, as a consequence, by maintaining a high level of engagement, and the will to continue to participate in the virtual world.

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