How the different gamer personalities affect each other's population.

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1. Introduction

The amount of people who play video games has rapidly increased in the past few years (Lily Juan, 2021). The amount of games has grown alongside them, also increasing in variety. Every gamer plays different games, but also plays them differently.

Over the years there have been many studies regarding the different taxonomies and personalities gamers have. The most known is Bartle's taxonomy of player types (Bartle, 1996), in which he defines four different types of player personalities that affect how they interact in-game with other gamers as well as when playing alone.

In this article we will analyse how each type of player interacts with each other as well as how some types interact more fluently with another while they do not associate well with some of the other types.

To do this we will create an adaptive network model that recreates the scenarios in which these types of players interact.

Literature overview

Bartle’s taxonomy of player types divides players into four different personality types: Killers, Achievers, Socializers and Explorers (Figure 1.1). This classification is based on players’ behaviours, goals and motivations to determine which personality they have (Jacqueline Zenn, 2017). Most players do not fall fully into one category, but instead overlap between two or more of the personalities.

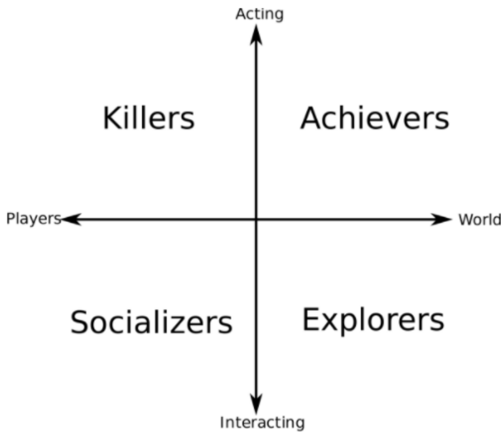

Figure 1.1: Bartle's taxonomy of player types (Jacqueline Zenn, 2017)

Killers care most about being at the top of the hierarchical standings. They do not take other players' experience into consideration very much. Killers tend to try to create chaos, doing things they would not do in real life. They prefer fighting, either players or NPCs. These players see other players as their prey, enjoying the fact that they will get emotional reactions from them. They fall into the category of acting on other players (Figure 1.1).

Achievers want to be the ones at the top of every leaderboard. They want to master the game and get the best possible weapons. Achievers care about their status, they want to be known and respected. To reach these goals, they do not mind spending a lot of time doing quests or other tasks that will increase their status and experience points. They fall into the category of acting within the world.

Socializers are interested in socialising, they enjoy talking to other players and getting to know them, even ending up being friends with some of them. They do not really care about the game or the world in it but the people are what makes a game interesting for them. They fall into the category of interacting with other players.

Explorers want to explore every part of the map, discovering every corner and boundary. They want to be respected for having knowledge about the game other people do not have and enjoy easter eggs within games (Janaki Mythily Kumar et al, 2023). Towards the end of their playing time, explorers will try to discover bugs that have not been discovered yet. They fall into the category of interacting with the world.

These types of players all interact differently with each other, enjoying the existence of some types and loathing the existence of others. This interaction also affects the numbers of the specific types you may see on a game, as the high numbers of some of the types such as killers have a negative effect on the numbers of other types, such as achievers.

After researching those interactions we came to the following conclusion (Bartle, 1996):

- The number of **achievers** in a game can be negatively affected by an increase in the number of killers as they do not work well together, however if controlled, increasing the number of explorers can also increase the number of achievers in a game.

- The number of **explorers** is only increased or decreased by themselves, if there are a lot of explorers, more will come. This type´s numbers are not affected by any of the other types of players.
- The number of **socializers** are affected mostly by the number of killers in the game and by the own number of socializers, as well as by the number of achievers. If there are large numbers of socializers, more will come, however if the number of killers and achievers increase the number of socialicers present would drop.
- The number of **killers** becomes higher when increasing the number of achievers as well as with increasing the number of socializers, but it will be decreased by the increase in the number of explorers.

2. Network Model for the player types

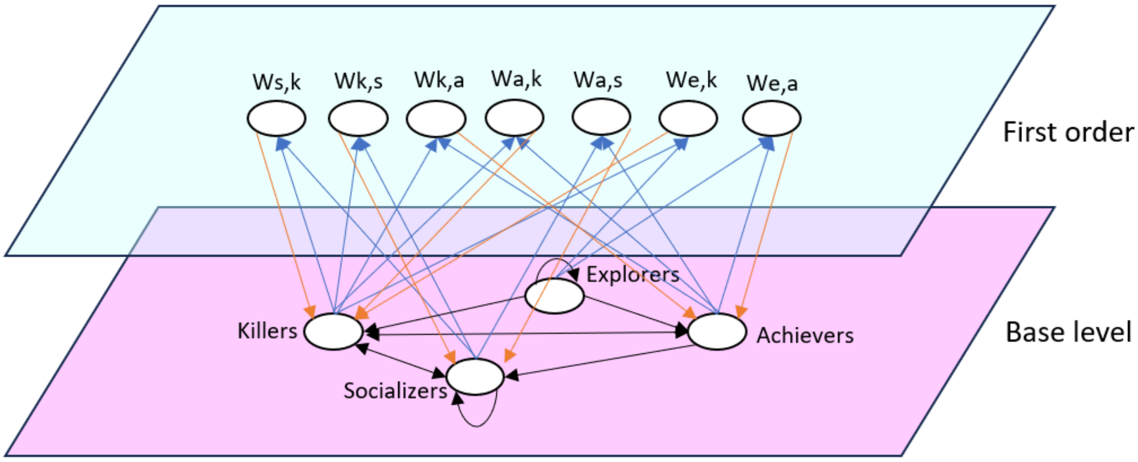

Figure 2.1: Network Model

State nr	State name	Explanation	Level
X_1	Killers	Bartle personality type killer	Base level
X_2	Explorers	Bartle personality type explorer	
X_3	Socialisers	Bartle personality type socialiser	
X_4	Achievers	Bartle personality type achiever	
X_5	$W_{S,K}$	Affect of having more socialisers on the amount of killers	First order
X_6	$W_{K,S}$	Affect of having more killers on the amount of socialisers	
X_7	$W_{K,A}$	Affect of having more killers on the amount of achievers	
X_8	$W_{A,K}$	Affect of having more achievers on the amount of killers	
X_9	$W_{A,S}$	Affect of having more achievers on the amount of socialisers	
X_{10}	$W_{E,K}$	Affect of having more explorers on the amount of killers	
X_{11}	$W_{E,A}$	Affect of having more explorers on the amount of achievers	

Figure 2.2: Table containing state names and an explanation

Using the research that was done, we created an adaptive network model. The network model (Figure 2.1) describes the influence of certain player types on the population of the other player types within a game. Some player types increase or decrease the amount of players from another type. In the network model, we have two layers, one for the base level and one for the first order adaptations.

On the base level, we have four states representing the four types of gamer personalities. Between these states, we also added all links between them that impact another state. For example, the amount of socialisers impacts how many killers there are. Two of these links are from a state to themselves. This is because these types of players like being surrounded by other players of their type, thus leading to a positive link to itself.

On the first order level, there are adaptive connections for every connection there is on the base level. Every one of the connections takes into account both of the states in the base level and influences the state of which the link is pointing towards. The states on the first order level are adaptive, changing with the changes of the states it relies on.

3. Design and simulation experiments with the model

3.1 Non-adaptive model

We started the project by creating a non adaptive model, in which we only used the base level in the network model (Figure 2.1) to see how the values reacted when the simulation was not adaptive. This was used in order to transform it into the adaptive model more easily.

3.1.1 Matrix elicitation

Mb	base connectivity	1	2	3
X_1	Killers	X_2	X_3	X_4
X_2	Explorers	X_2		
X_3	Socialisers	X_1	X_4	X_3
X_4	Achievers	X_1	X_2	

mcw	connection weights	1	2	3
X_1	Killers	-0,1	1	1
X_2	Explorers	1		
X_3	Socialisers	-1	-0,1	1
X_4	Achievers	-1	-0,1	

mcfw	combination function weights	1 alogistic
X_1	Killers	1
X_2	Explorers	1
X_3	Socialisers	1
X_4	Achievers	1
X_5	Ws,k	1

mcfp	combination function parameters	1 alogistic	
		1	2
X_1	Killers	5	0.6
X_2	Explorers	5	0.2
X_3	Socialisers	5	-0,1
X_4	Achievers	5	-0,6

ms	speed factors	1
X_1	Killers	0.4
X_2	Explorers	0.4
X_3	Socialisers	0.4
X_4	Achievers	0.4

iv	Initial values	1
X_1	Killers	0.01
X_2	Explorers	0.1
X_3	Socialisers	0.8
X_4	Achievers	0.1

Figure 3.1.1: Matrices used in the simulation

We first created the matrices necessary to run a simulation (Figure 3.1.1). The first one (top left) shows all incoming connections for each state. The second one (top right) shows the weight of each of these connections. The combination function weights (middle left) shows which functions are used to calculate the values of each state. In this case, they all use the alogistic function. The combination function parameters matrix (middle right) describes the parameters that are used within the function. In the case of the alogistic function, the first parameter is the steepness and the second is the threshold. The second to last matrix (bottom left) controls how fast the states react to the changes they undergo. The last matrix (bottom right) shows the initial values of each of the states, before the simulation is run.

The base connectivity matrix was created with the use of the base level from the network model. The connection weights are all at 1 except for the ones that are influenced negatively by the other variables. Some connections only have a small effect on another state, which is why their value is lower.

For the simulation, we used the alogistic combination function. We will use the same function for the base levels in the adaptive model as those variables will always be non-adaptive while the rest of the variables will need other functions. A steepness of 5 was used for all states using this function. The thresholds differ, with the state for the Killers having the highest. This is because it has two large positive incoming connections and only one small negative incoming connection. The explorer's state has the second highest threshold, since the only connection it has is a positive connection to itself. The state for the socialisers has a small negative threshold, as its weights end up giving negative numbers as a result. Lastly, for the achievers state, the threshold is a relatively large negative, because it only has negative incoming connections.

All the variables will have the same speed factor as they need to work at the same speed during the simulation. For the initial values, we used the percentages of the number of players of each personality type we found in the documents from Bartle´s research. 1% of the players are of the type killer, while this is 10% for both explorer and achiever. Most gamers are of the personality type socialisers, at around 80%.

3.1.2 Expectations

In the simulation, we expect the amount of killers to go up, since it is positively influenced by the socialisers. The socialisers already start at a high value, so we expect this to result in an increase in the number of killers. The explorers should also go up to a high amount, they are only positively influenced by themselves and do not receive any negative connection. This increase of explorers should lead to a decrease of killers, since they are negatively affected by the explorers. The socialisers should remain somewhere near the top at the start, since they have a positive link to themselves, which is stronger than the negative effect of the achievers. The negative influence of the killers should keep the socializers numbers from increasing drastically, and it will end up causing the decrease in the number of socializers. We expect the number of achievers to decrease, given it only receives negative input from killers and explorers.

3.1.3 Simulation

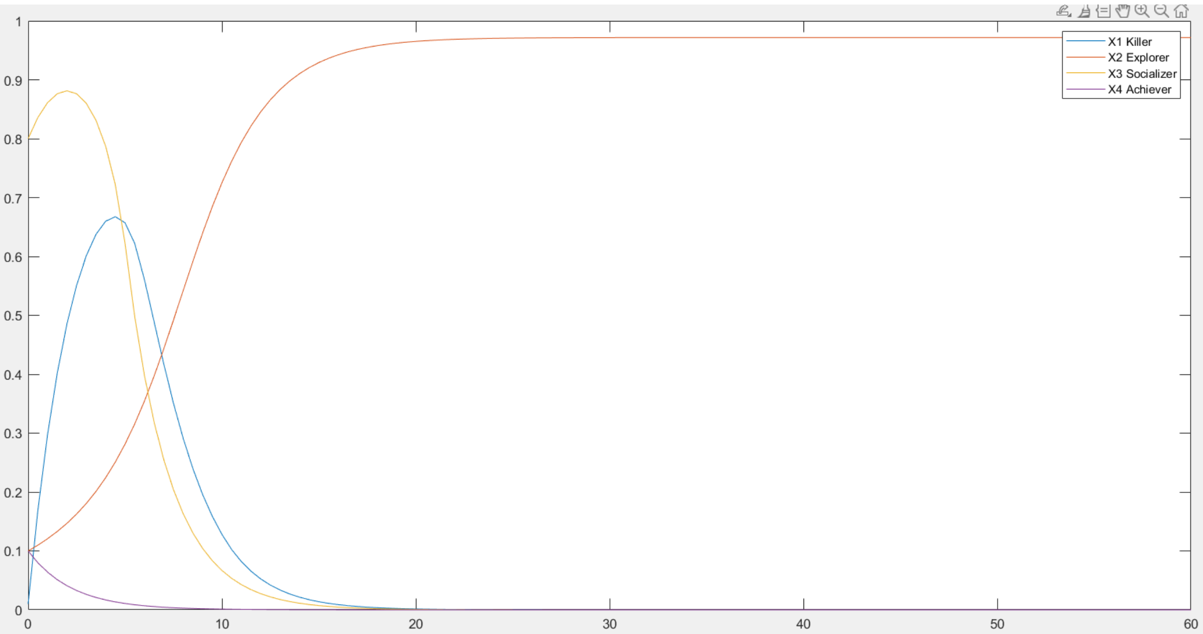

Figure 3.1.2: Graph obtained after running the simulation

When running the simulation for the non-adaptive model, we obtained the graph shown above (Figure 3.1.2). In this graph we can appreciate the expected high numbers for the explorers as well as the initial increment in numbers from the killers and socialicers that then are affected by the other variables and their numbers drop. While the number of achievers go down from the start, being negatively influenced by the number of killers.

3.2 Adaptive model

3.2.1 Matrix elicitation

Mb	connectivity	1	2	3
X_1	Killers	X_2	X_3	X_4
X_2	Explorers	X_2		
X_3	Socialisers	X_1	X_4	X_3
X_4	Achievers	X_1	X_2	
X_5	Ws,k	X_3	X_1	X_5
X_6	Wk,s	X_1	X_3	X_6
X_7	Wk,a	X_1	X_4	X_7
X_8	Wa,k	X_4	X_1	X_8
X_9	Wa,s	X_4	X_3	X_9
X_{10}	We,k	X_2	X_1	X_{10}
X_{11}	We,a	X_2	X_4	X_{11}

mcw	connection weights	1	2	3
X_1	Killers	X_{10}	X_5	X_8
X_2	Explorers	1		
X_3	Socialisers	X_6	X_9	1
X_4	Achievers	X_7	X_{11}	
X_5	Ws,k	1	1	1
X_6	Wk,s	1	1	1
X_7	Wk,a	1	1	1
X_8	Wa,k	1	1	1
X_9	Wa,s	1	1	1
X_{10}	We,k	1	1	1
X_{11}	We,a	1	1	1

mcfw	combination function weights	1	2	3
		alogistic	hebb	heebneg
X_1	Killers	1		
X_2	Explorers	1		
X_3	Socialisers	1		
X_4	Achievers	1		
X_5	Ws,k		1	
X_6	Wk,s			1
X_7	Wk,a			1
X_8	Wa,k		1	
X_9	Wa,s			1
X_{10}	We,k			1
X_{11}	We,a			1

mcfp	combination function parameter	1		2		3	
		alogistic		hebb		heebneg	
		1	2	1	2	1	2
X_1	Killers	5	0.6				
X_2	Explorers	5	0.2				
X_3	Socialisers	5	-0,1				
X_4	Achievers	5	-0,6				
X_5	Ws,k			0.999			
X_6	Wk,s					0.999	
X_7	Wk,a						
X_8	Wa,k			0.9			
X_9	Wa,s					0.1	
X_{10}	We,k					0.1	
X_{11}	We,a					0.1	

ms	speed factors	1
X_1	Killers	0.4
X_2	Explorers	0.4
X_3	Socialisers	0.4
X_4	Achievers	0.4
X_5	Ws,k	1
X_6	Wk,s	1
X_7	Wk,a	1
X_8	Wa,k	1
X_9	Wa,s	0.4
X_{10}	We,k	0.4
X_{11}	We,a	0.4

iv	Initial values	1
X_1	Killers	0.01
X_2	Explorers	0.1
X_3	Socialisers	0.8
X_4	Achievers	0.1
X_5	Ws,k	0.5
X_6	Wk,s	-0,1
X_7	Wk,a	-0,1
X_8	Wa,k	0.5
X_9	Wa,s	-0,1
X_{10}	We,k	-0,1
X_{11}	We,a	-0,1

Figure 3.2.1: Matrices used in the simulation

The base connectivity matrix (Figure 3.2.1) was created with the use of the network model. All links were added to this matrix, including a link to itself for all the adaptive states for persistence. The connection weights are all at 1 except for the ones that are influenced by the adaptive states. The values of the connection weights for these states are the adaptive states that they are influenced by. For example, for the connection from X3 to X1, the value of state X5 is the connection weight.

For the simulation, we used three combination functions: alogistic, hebb and hebbneg. Logistic was used for all the states in the base level, since these are non-adaptive. Since some of the adaptive relations are positive and some are negative, we divided these over the hebb and hebbneg respectively. This can also be seen in Figure 3.1.

For the alogistic function, the same steepness and thresholds were used as in the non-adaptive model.
For the hebbian function (hebb), the persistence factor of the link from the socialisers to the killers is very high, since the amount of socialisers has a big impact on the number of killers. The connection from the achievers state to the killer state is also quite high, but has a little less impact than the socialisers. For the negative hebbian function (hebbneg), the link from killers to socialisers is a large negative, since a large number of killers drastically decreases the amount of socialisers. For the other three negative connections, the effects are a lot smaller.

The speed factors for all the base level connections are 0.4, since all these should work at the same speed. The first order states with large impacts also have large speed factors. The ones with little impact have the same speed factor as the states in the base level.

The initial values for the base states are the same as in the non-adaptive mode. All negative adaptive connections start at a negative value, while the positives start at a positive value.

3.2.2 Expectations

In the simulation, we expect the amount of killers to go up by quite a lot, since it is positively influenced by the socialisers. The socialisers are already at a high value, so we expect this to increase the amount of killers heavily. The explorers should also go up to a high amount, since it is positively influenced by itself and not negatively influenced by any others. The socialisers should remain somewhere near the top, since they have a positive link to themselves, which is stronger than the negative effect of the achievers. The negative influence of the killers should keep them from going up a lot, but since the amount of killers should never get super high, this effect won't cause the amount of socialisers to decrease. The achievers should decrease, since it only has a negative impact from killers and explorers.

3.2.3 Simulations

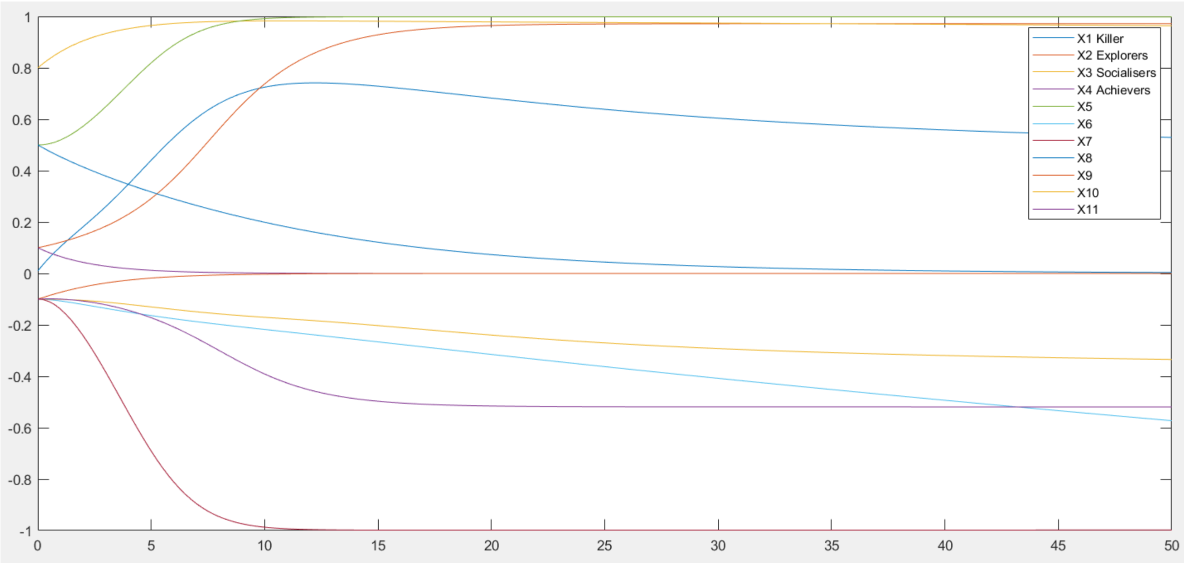

Figure 3.2.2: Graph obtained after running the simulation

After running different simulations and tuning the values used in the matrixes, we reached the result shown in the picture above (Figure 3.2.2). The results ended up being what we were expecting, The explorers (X_2) increased in numbers until staying constant, the same happened with the numbers of socialicers (X_3) that stayed high throughout the simulation. The amount of killers increases at the start of the simulation, until they decrease due to the increased number of explorers. And lastly, having an increased number of killers (X_1) as well as explorers causes the number of achievers (X_4) to decrease during the simulation, reaching low numbers.

The simulation for the adaptive model shows the progression of the different personality types throughout a certain time period. Our goal was to see how the different personality types impact the amount of players of all the personality types. An easy way to see this is in percentages, detailing the portion of each player type in regards to the total number of players.

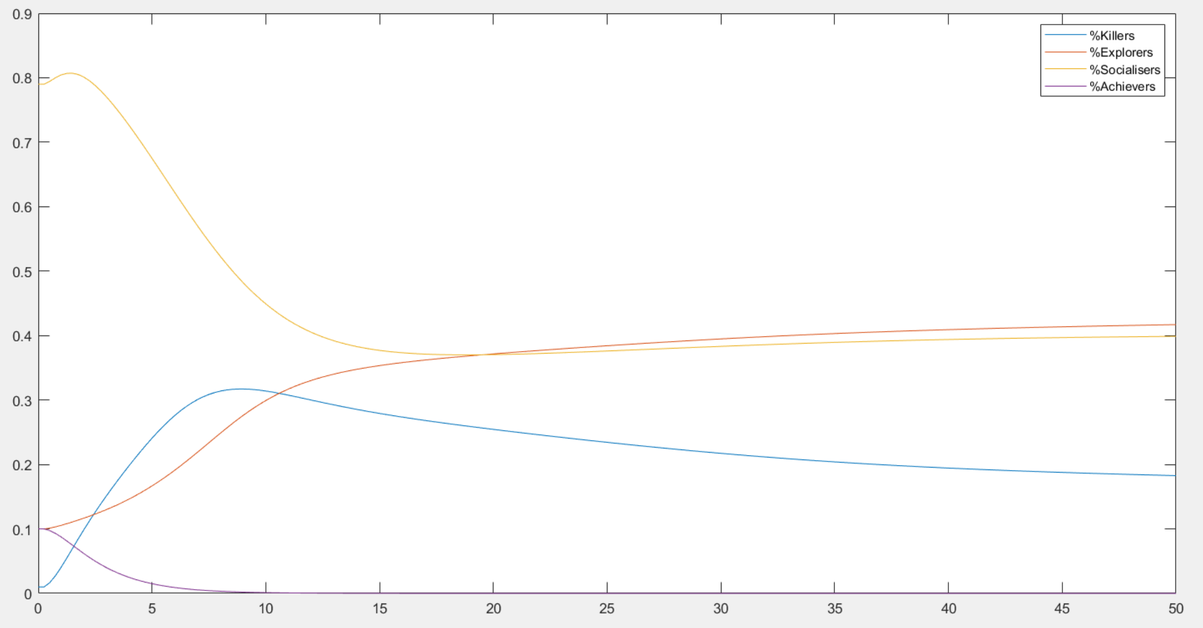

Figure 3.2.3: Percentages of total players for each personality type

In the first simulation we ran (Figure 3.2.3), every player is equally as likely to be every one of the gamer personalities. The initial values of the percentages are the same as in Figure 3.2.1, decreasing the socialisers to 79% for the total to equal 100%. As you can see after some time, the amount of explorers catches up to the amount of socialisers, both being around 0.4. The killers increase a lot at the start, but decrease towards the end and end up at around 0.18. The number of achievers decreases to close to 0. If there were the same amount of each gamer personality in the world, the game would end up with around 40% socialisers, 42% explorers, 18% killers and close to 0% achievers.

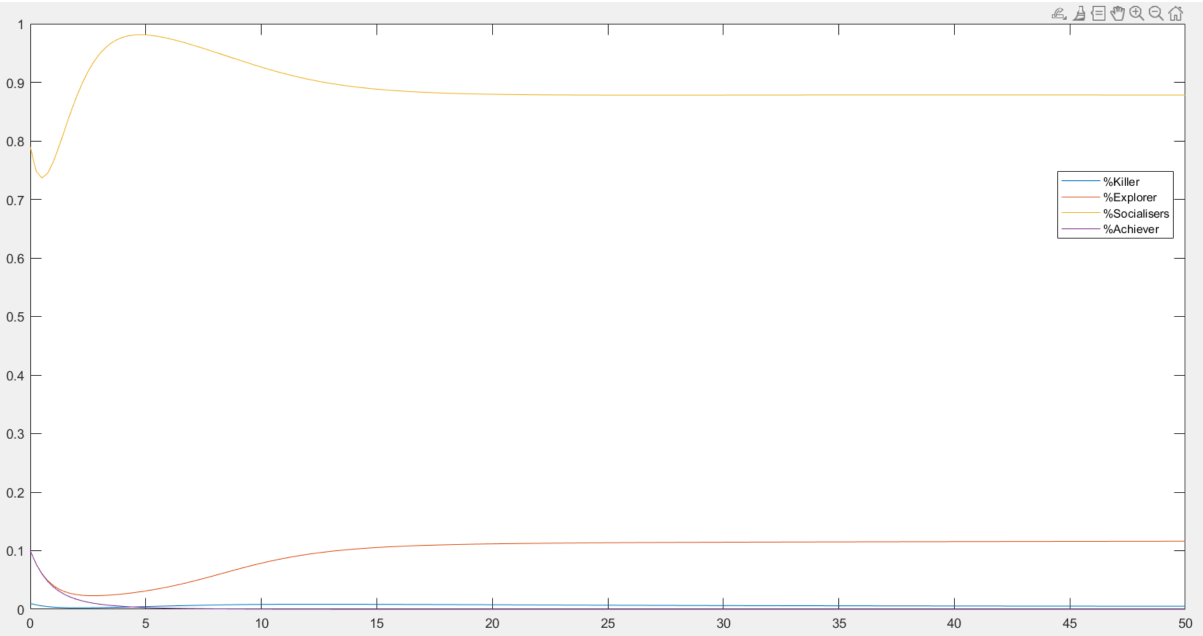

Figure 3.2.4: Percentages of player types, adjusted to real life

According to Bartle, there are not the same amount of each personality type. There are around 79% socialisers, 10% of both explorers and achievers and 1% killers. To make our model more realistic, we also ran a simulation to decipher the percentages of players taking into account some types are more likely than others (Figure 3.2.4). This simulation shows that most of the players in the game will be socialisers, at around 88%. The number of explorers will be around 12% of the player base. A small number of killers will be playing the game, around 0.5%. Almost none of the players will be achievers.

4. Discussion

4.1 Conclusion

This article describes the research done to determine how the different gaming personalities affect each other's population. This was done by initial literature research, reading up on Bartle's taxonomy of player types. Every player type and their impact on each other was researched more thoroughly. With this, a network model was created. The model has the four gamer personalities on the base level: Killers, Explorers. Socialisers and Achievers. These personalities are connected for every impact one type has on another. On the first-order level, there are adaptive connections for each of the links between the gaming personalities, making the impact they have on each other change according to the changes the states themselves make.

The model was used to create matrices for the simulation that were run. These matrices were carefully crafted by thorough experimentation to get the best values and use the best functions. The first matrices were made for a simulation that would be non-adaptive, only containing the states in the base level and the connections between them. In this simulation, the socialisers and killers start rising at the start, along with the explorers. Eventually the rise of the amount of killers starts to decrease the amount of socialisers. The explorers remain increasing, since nothing negatively influences them. This, along with the decrease of the socialisers, eventually leads the killers to decrease as well. After some time, both the socialisers and the killers reach a low value, joining the achievers which don't have any incoming positive values. The explorers stay high.

After this, the entire network model was simulated, with the adaptive connections as well. This way, the model adapts to the changes the base states make throughout the simulation. This simulation shows the amount of explorers increasing thoroughly, while the achievers fell close to zero. The number of killers also rose a lot, not getting as high as the explorers though. The socialisers remained at a high point, having an equilibrium at around the same point as the explorers.

To show a clearer picture of the percentages of each player type, two more simulations were run. The first one having an equal chance of every personality type. This showed a high percentage of socialisers and explorers, both being at around 40%. The number of killers was at around 18%, while the achievers dropped close to zero. In the second simulation, the overall percentages of the player types was taken into consideration. In total, around 79% of gamers are socialisers, both explorers and achievers are around 10% and only 1% of players are killers. When taking this into consideration, the game consists of around 88% socialisers, 12% explorers, 0.1% killers and almost no achievers.

All of these numbers are near our expectations, except for the fact that the achievers dropped so far down. We did not expect this number to drop so drastically, and this would not happen in a real life situation.

4.1 Improvements

The current model does not take everything into consideration. There were some interactions between the player types that were not modelled. For example, to increase the number of achievers, the number of explorers should be increased only if the number of killers is high. This kind of relation is hard to model, so the decision was made not to include this within our model. Another unmodelled part is suddenly massively increasing one of the player types. This would lead to changes in some other player types. This is also hard to model and not something included within the model.

These changes could, for example, lead to less of a decrease of the amount of achievers. Including these parts in the model would make it more similar to the actual simulation and would make the simulation more realistic. The results of our current model are fairly accurate, but incorporating these changes would make the model even better and give a more accurate picture of how the actual situation would be.

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