Game theory in Valorant

P S Abhiram
University of Ottawa
Ottawa, Canada
spand086@uottawa.ca

ABSTRACT

Modern tactical shooters have evolved more from CS:GO into a format that requires more communication and planning of strategies based on the utility or actions a certain agent can perform in the game. One such game is Valorant, which a 5v5 First person shooter game. In such a game, we often see patterns and a team's strategist often takes into consideration many factors before laying out a strategy. In this paper, we go over the different concepts of Game Theory that can be applied in this game. Using datasets from Valorant tracker and Liquipedia, we prove by using game theory why a team chose the agents they did and the strategies they did.

KEYWORDS

Legends, Myths, Folktales

ACM Reference Format:
P S Abhiram. 2023. Game theory in Valorant. In *Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), London, United Kingdom, May 29 – June 2, 2023*, IFAAMAS, 7 pages.

1 INTRODUCTION

Valorant is a 5v5 tactical shooter First person shooter(FPS) game. There are currently 8 maps present in the game, with 20 agents a person gets to choose from. The allocation of which map the game is played is completely random. The game theory part comes into play in two stages here.

- Stage 1: Selection of agent: There are currently 4 classes of agents.
  - Sentinels: Defence oriented agents
  - Initiators: Reveal information as to where opponents are located.
  - Controllers: Probably the most important set of agents. These agents have the ability to deploy smokes for the team blocking lines of sight.
  - Duelists: Their kit is designed to enter into a site first with the prior knowledge given to them by the initiator.
- Stage 2: Which strategy should a team choose? This part can be solved by Q-learning and implementations of extensive form game. Ultimately, the actions chosen by a team throughout the game defines the end result.

In this paper, we consider the latest Valorant Professional tournament - Valorant Champions 2022 (VCT 22'). My justification on some of the common questions are as follows:

- Why on pro play? Professional play is extremely organized and almost every action is planned or reharsed by the teams. Additionally, professional players can all be considered on the sae skill cap. Yes, some are definitely better than others, but, the difference is marginal. For the sake of simplicity we ignore the possibility of an extremely good player in a team. Finally, data for professional play is available in detail. In regular games, there is not detailed data except the pick rate and win rate of agents present in the game.
- Why VCT 22'? The teams present in this tournament go through several filtering tournaments and end up here. Furthermore, the teams present here come from several regions, which gives rise to different strategies and pool of selection of agents on a certain map. Finally, we assume that the difference in skill cap between the weak and strong teams is marginal. The main difference here presents in strategies chosen by teams, which is exactly what we are trying to solve.
- Why Valorant? There are several team games present in the current scenario similar to Valorant. Apex Legends, Fortnite, Overwatch 2, etc. are some examples. Valorant poses a rather simple sample space in the sense that there are lesser number of factors to consider. The fact that this is a 5v5 tactical shooter game enables us to decode the data and present it.

2 RELATED WORK

Counter Strike: Golabal Offensive (CS:GO) is a game that has the most simlarities with Valorant. This is in the sense that the game also is a 5v5 tactical shooter game and the winners in Valorant are judged in the exact same way as CS:GO. Applications of CS:GO have been studied extensively and one such study has been conducted by [3]. In this paper, thea authors observe that communication and leadership are crucial for teamwork and enable the other competencies. A Creative Technology approach is taken to create a tool that uses quantitative data analysis to analyse speech data. This analysis uses Bales Interaction Process Analysis (IPA) model to identify group processes and uses research by Butler et al. to interpret Bales' IPA model for leadership styles. The tool uses manual transcription, since available automatic tools are qualitatively not good enough or are outside the scope of this study. The information that is retrieved from the analysis is outputted on a dashboard to give an insight in how communication and leadership are reflected when people play CS:GO. To verify the tool, communication data during a CS:GO game is used from two sessions. One session with an experienced team and the other with an inexperienced team. The tool is expected to show different communication patterns between the two teams. These different patterns show in the results, indicating that the model can discriminate between teams. To conclude, the tool can give insight in communication and leadership in CS:GO, outputting information on a dashboard that can be used for training purposes. A validation of the tool needs to be done to assess the correctness

Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), A. Ricci, W. Yeoh, N. Agmon, B. An (eds.), May 29 – June 2, 2023, London, United Kingdom.

of the output. Next to this, there needs to be further research into how the manual transcription of the data can be solved if the tool is to be used in training scenarios. The results of the study show the existence of different communication patterns and leadership styles.

A simpler analysis of the CS:GO is studied in [2]. This paper explores the nature of multiplayer first-person shooter video games, which have been very popular. We have chosen Counter-Strike: Global Offensive (CS:GO) as the benchmark in this study. Many data from official CS:GO tournaments and public match are collected for the analysis, whereas game refinement measure is employed for the assessment with a focus on two aspects: gameplay and rounds system. The results show that the gameplay aspect has lower game refinement, i.e., the game is highly skillful, whereas the rounds system aspect has higher game refinement, i.e., the game is highly stochastic. The combination of the two aspects successfully balances the skillfulness and chance, which results in their popularity. In addition, since their release, CS: GO has sold more than 40 million game copies, awarded as "Best eSports Game of The Year" and updated maps and successfully maintain the game balance of the maps, as measured by game refinement.

In order to prove that skill cap is not the issue, the authors in [1] examine the experiences of nine young CS:GO players and their coach enrolled in an esports program at a sports college in the greater Copenhagen area. Through observation and group interviews we try to identify the pedagogical goals of the coach and how these are understood and experienced by the players. Based on Gee's notion of affinity space and Dialogical Self Theory, they explore how the players position themselves in relation to their esports activities as well as their perception of what it takes to be a competent player. The preliminary findings show that both the players and their coach emphasize healthy culture as a key aspect of the esports activities. Thus, players believe that being able to communicate well and in a respectful tone is a core competency on par with technical skills and understanding of the game. In summary, players report that their experience of better communication skills is an ongoing concern both inside and outside of the game. In addition, the players describe how their 'people skills' transfer to friends, family and school work as a result of esports training.

Most related work in this domain correspond to CS:GO due to the high popularity and prevalence of the game throughout the decade. Since Valorant is gaining traction and is now almost as popular as CS:GO, I could not find any papers going through the game theory concepts of the game. Hence, this paper lays out the template for any coach or strategies out there to develop.

3 GOALS AND CONTRIBUTIONS

The goals of this paper are as follows:

- Gather competitive play data over a span of a tournament
- Analyze which agents a team of 5 has to choose to have the best possibility to win a game.
- Why is it that these agents are chosen? Is this the Nash equilibrium based on data?
- Which strategy should a team choose to play for a particular round without being "repetitive"? What is repetitive in this case and why is this not good? How is strategy evolving over a set of rounds in a game?
- Analyze the most picked agent in a particular class, and see if the game devs made a right decision in making their "balance changes". Did they do this change because this agent is part of the Nash equilibrium?

4 DATA

In this section, we look at how we are going to use the data and where we can get this data from. The primary source of data for this project is obtained from Valorant tracker and Liquipedia.

Valorant tracker is used to to obtain data of agent selections of each team throughout the tournament. However, we do not get the information what type of composition won or lost. This data can then be obtained with Liquipedia. Hence, these two websites go hand in hand.

When it comes to noting down the strategies used by a team in the game, I had to watch the games manually and keep track of the actions withing the game. The video of every game is present in YouTube and the link can be found in Liquipedia.

5 BACKGROUND AND CONSIDERATIONS

In this paper, we will go through two maps - Bind and Ascent. There is no main reason why these two maps are chosen except for the fact these two are the maps that are played the most in the tournament. There are currently 20 agents in the game. Each team picks 5 agents to play a game. The sample space we are looking at 20 choose 5 for both teams. This is a large number, so can we reduce this using domain knowledge? Yes. Most maps do not actually require a 20 choose 5. For instance, in Ascent, we come across a certain combination. More on this in the section 5.

Valorant comprises of agents with their utilities. For the sake of simplicity, the paper considers components like Operator investment and splits present in a game.

5.1 Agent Selection

Agent selection is an important part of Valorant which lays out the strategies you choose in a game. In professional play, it is observed that teams like to pick more initiators than other class of duelists, and there is always atleast one agent who can deploy smokes i.e. Controllers. Why is this the case? Professional players do not like to take an action without complete information. This is also an advantage to us in analyzing games because it causes teams to act in a methodical manner. Thus, from here on, we will act under the assumption that teams have information and it is a perfect information game.

So to narrow down our agent combinations, we will separate each class of agents and then apply our model on the selections made. This allows us to not only pick from a significantly lower sample space but also provides better information to the teams

5.2 In-game Strategies

The in-game strategies is the next stage in which teams need to consider once agent selection is done. The strategies are formed based on the type of agents and the map the teams are playing

Figure 1: Ascent Map

in. For example, a team with Chamber and Jett is likely to use the Operator more than the teams without them. This is mainly because of the utility kit available to the agents.
Figure 1 showcases the map of Ascent. Before the start of the round, the attackers can choose to start anywhere in the red section, the defenders in the green section and the blue-grey section is up for competition. Attackers have to plant the spike in either A-site or B-site. What is winning for attacker:

- Plant spike and defend post plant
- Eliminate all defenders

Any of the two outcomes result in a win for attackers, whereas for defenders it is:

- Prevent planting of spike in either of A-site or B-site.
- Eliminate all attackers
- Allow planting of spike at either A-site or B-site, but play a post plant scenario, and defuse the planted spike.

The defenders are generally at an advantage in the game since the onus is on the attackers to make their moves. Hence, defending teams usually play passive in general cases. In most professional plays, you see teams competing aggressively for blue-grey areas.

Based on the above information, the strategies available are as follows, for attackers:

- Execute into A, if successful, plant spike, defend post plant.
- Execute into A, if not successful, retreat.
- Execute into B, if successful, plant spike, defend post plant.
- Execute into B, if not successful, retreat.

Some important actions teams take while defending or attacking is the investments in weapons. One such weapon is the operator.This weapon has 2 zoom-in scopes - one for short range and one for long. The advantage to buying this gun is that, it is effective in stopping pushes and taking space aggressively. Why? The gun has the capability to eliminate an opposition based on a single shot anywhere from and above waist level. Challenging this gun with a normal assault rifle, is doable but the chances you will come out on top is less likely. This is mainly because the assault rifles do not have zoom-in scopes, and to eliminate an opponent using an assault rifle, it takes a headshot. So, challenging long range/short range with this gun against the operator is not fruitful.
Is this gun an advantage for attackers? The nature of the operator is to stay stationery and hold an angle. Attackers however need to be on the move because they are the ones challenging to plant the spike. Thus, the gun is more effective for defenders and in a

scenario where an individual holds the angles.
The rules of the game:

- Played for a minimum of 13 rounds, where the teams switch attackers and defenders after round 12.
- The team to win 13 rounds first wins. However, if the score is 12-12, the game is not played to 14 i.e. team to reach 14 rounds wins.

Now that we have defined the basic strategies present in a 13 round game, we will now go over the rules, costs associated to the game and a Q-learning model in the next section.

6 MODEL AND METHODOLOGY

6.1 Agent Selection

As discussed previously, selection of agents happens blindly in Valorant, in the sense that one team is not aware of the selection of the other team. Hence, in this case we can classify this model/behaviour into a Normal Form game. Although there is prior information based on past decisions, this part of the game is done independently by each team. Using this information, we can now reduce this game to a simple Normal Form Game. In this normal form game, the row players and column players will be for both teams respectively and a table represents a certain class of agents.
Why are we only looking at a class of agents while agent selection? This comes down to domain knowledge. In a game, for attack, the duelist, initiator, controller and depending on the situation, either controller or the sentinel's utility kit help in attack. For example if we look at Chamber, there is not much he can do in helping the team taking control of a site. His strengths can be used elsewhere like lurking and watching flanks. Another example is controllers - they are the most crucial agent in a game. Yes teams always pick more than on initiator, but execution onto a site is near impossible when threat of present from multiple angles. In order to attack or defend, teams need to block lines of sight for oppositions so that there is "lesser area to worry about". Therefore, a controller is bound to take much lesser risk than a duelist. It is simply down to the fact that a duelist's utility kit helps them duel. Therefore, we separately each class and then perform this normal form game.

6.1.1 Building a Normal Form Game for Agent Selection. In this paper, we will be looking at Ascent Map of the game between OPTIC vs LOUD in the VCT 22' Finals. We choose this game to further negate the skill cap and to also prove that both teams are well structured.
How are the payoffs assigned? The payoffs are calculated by the number of times a team picked a certain agent and won. For example, if OPTIC picked the agent - Chamber, their payoff in this case would be like this - Every time OPTIC picks chamber and won whilst the opposition played an agent x. This agent x is now cross validated based on the class of agents. As discussed previously, we will only compare a class of agents against another. So in our example the x here would be - Chamber, Cypher, Killjoy, Sage. This gives OPTIC an insight into which agents to pick based on the scope of their chance of winning. A detailed example is as follows - Let's say OPTIC picked Chamber 4 times and in these 4 instances, when they picked Chamber, the Opposition picked Killjoy. In this scenario, if OPTIC won 3 times, their payoff is 3 in the cell which is Chamber x Killjoy for OPTIC. We represent the row players are OPTIC and column players as LOUD throughout the paper.

6.2 In-game Strategies

Based on the background information in section 5, we can now switch this game into an extended form game. However, it is not as straightforward as we think. Recall that teams can retreat and re-hit a site A or B. Hence, we will use the concepts from Q-Learning. The algorithm is described in Figure 2. The way we go about to describe the algorithm for nodes labelled attackers is as follows:

```
Require: a <- 100 all nodes

if (one player eliminated at site x)
      a <- a - 2 # At node x
if (Invested in Operator)
      a <- a + 2
if (Planted Spike)
      a <- a + 5 # At node x
if (Lost post plant)
      a <- a -5 # At post plant node
if (Lost game)
      a <- a - 10 # At all nodes in game where the team visited
if (Lost game with an invested operator)
      a <- a - 12 # At all nodes in game where the team visited
if (Won Game)
      a <- a + 10 # At all nodes in game where the team visited
```

Figure 3: Algorithm to compute the payoffs at each node for attackers

The way we go about to describe the algorithm for nodes labelled defenders is as follows:

```
Require: b <- 100 all nodes

if (one player eliminated at site x)
      b <- b - 3 # At node x
if (Invested in Operator)
      b <- b + 3
if (Planted Spike)
      b <- b + 5 # At node x
if (Won post plant)
      b <- b + 10 # At post plant node
if (Lost Post plant)
      b <- b - 10 # At post plant node
if (Lost game)
      b <- b - 5 # At node x
if (Lost game with an invested operator)
      b <- b - 6 # At all nodes in game where the team visited
if (Won Game)
      b <- b + 10 # At all nodes included in split and desense
```

Figure 4: Algorithm to compute the payoffs at each node for defenders

7 RESULTS

7.1 Agent Selection - Results

Based on the classes of agents we have, and the selection of agents, as discussed previously, we now represent the tables for this map:

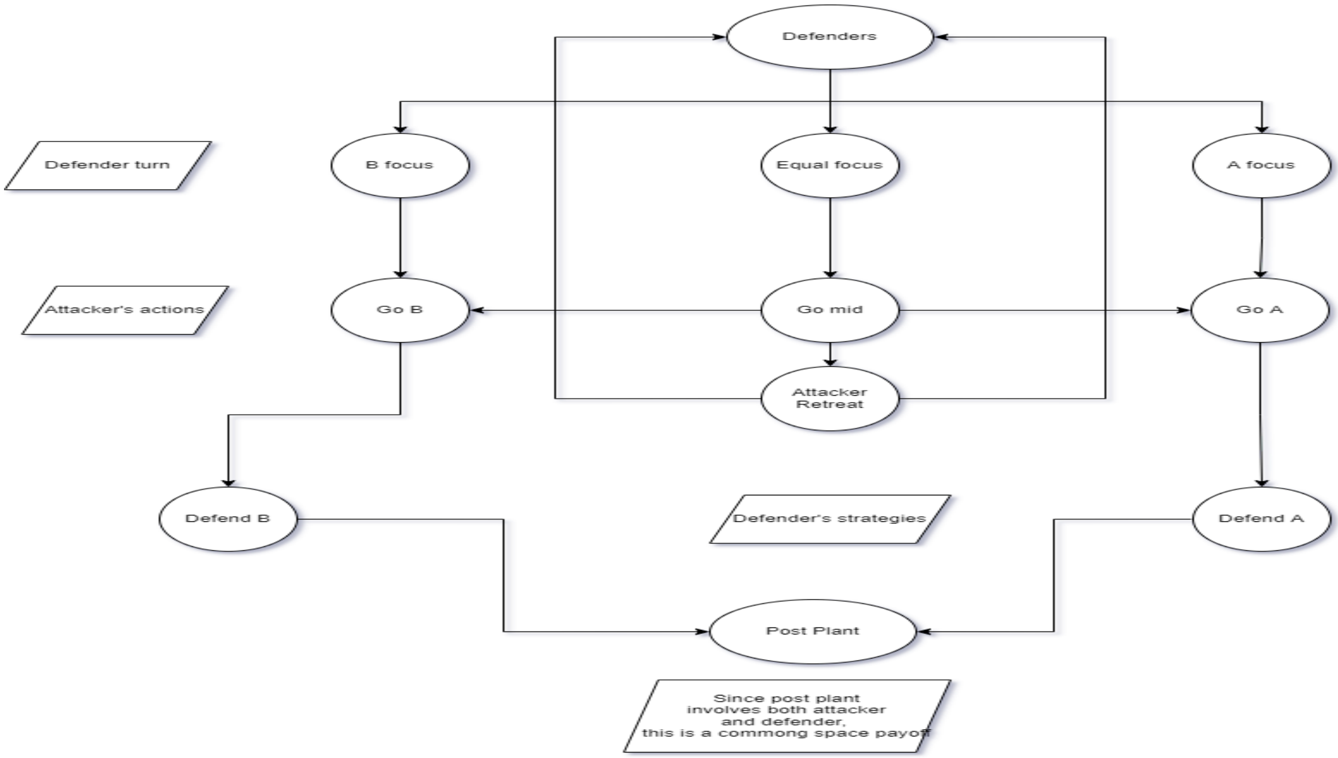

Figure 2: Diagram representing the actions for in-game strategies

- Duelists: The role of duelists in Valorant is to enter first into the site of execution, and either get traded (i.e. if the enemy kills you, one of your teammate trades by) by your teammates or win the duel. Thus, most teams find this risky. OPTIC is from North America and LOUD is from South America. Therefore, from the table below, we can directly see the differences in strategies between the two teams. While OPTIC prefers to run a composition with no duelist, LOUD always picked a certain duelist - Jett in this case. The normal form game for this class of agents in the tournament is as follows:

Duelists	Jett	Phoenix	Raze
Jett	(1,5)	(0,0)	(0,0)
Phoenix	(0,0)	(0,0)	(0,0)
Raze	(0,0)	(0,0)	(0,0)

As discussed above, OPTIC are the row players and LOUD the column players.
Computing Nash Equilibrium: By picking Jett, a team cannot do better by switching because:
– They have not tried that agent
– They do not have the strategy laid out by using that agent
Dominant Strategy for OPTIC: OPTIC played Jett less frequently, and when they did they only won once. Hence, although the table suggests that Jett is dominant strategy, once we look at other tables, we can form our opinions a little differently.
Dominant Strategy for LOUD: LOUD always picked Jett throughout the tournament. Obviously the team did not feel the need to experiment a different composition. So the dominant strategy would be to pick Jett.

- Initiators: The case for initiators was an interesting factor to consider. This class is arguably the most picked agents in terms of number of slots assigned in the 5 man team. In Ascent, most teams ran a minimum of 2 initiators, and teams like OPTIC often picked triple initiators. Hence, simply comparing a single agent with the others is not ideal as we are not actually comparing a composition against another but instead, a single agent with another which is often not the case. Hence, in the table we see more than one initiator per strategy. Here, we are comparing a composition of initiators against another. I believe this gives a much informative strategy to the strategist.

Table 1 showcases the normal form game computed for initiators.
Computing Nash Equilibrium: OPTIC plays a mixed strategy with Kay O + Sova and Kay O + Sova + Fade. This gives them the opportunity to create a mixed equilibrium. The Nash equilibrium can be { Kay O + Sova + Fade, Kay O + Sova + Fade } purely off the fact the OPTIC won more by running this compositions and LOUD had similar success levels running the triple initiator composition. Furthermore, the OPTIC have experimented on other combinations in the

Initiators	Kay O + Sova	Kay O + Fade	Kay O + Sova + Fade
Kay O + Sova	(0,0)	(0,0)	(1,3)
Fade + Kay O	(0,0)	(0,0)	(0,0)
Kay O + Sova + Fade	(1,0)	(1,0)	(0,0)

Table 1: Normal Form game for initiators

tournament, but LOUD have stuck to their triple initiator composition throughout.
Dominant Strategy for OPTIC: Although OPTIC tried other combinations, their dominant strategy is to play the combination they won with the most, which is Kay O + Sova + Fade.
Dominant Strategy for LOUD: LOUD always picked the triple agent composition and never felt the need to change since it worked. Hence their dominant strategy is clearly Kay O + Sova + Fade throughout the tournament.

- Controllers: These are arguably the class of agents who are picked regardless of the map, the reasons are discussed in the previous sections. In this map, the teams did not run more than one controller at a time, hence, there is no need to club different agents together like we did for initiators. The normal form game when computed is as follows:

Controllers	Omen	Astra	Viper
Omen	(1,5)	(0,0)	(0,0)
Astra	(2,1)	(0,0)	(0,0)
Viper	(0,0)	(0,0)	(0,0)

  Computing Nash Equilibrium: { Astra, Omen } is the Nash equilibrium. Why?
  – OPTIC would choose Astra regardless of what oppostion is doing.
  – LOUD would choose Omen regardless of what opposition is doing.

  Dominant strategy for OPTIC: The team has experimented with Omen and Astra, however they have had more success with Astra. Hence, the dominant strategy for OPTIC is to pick Astra.
  Dominant Strategy for LOUD: This team has always picked Omen and had great success. Hence, they do not need to deviate from what is working. Thus, Omen is the dominant strategy for LOUD.
- Sentinels: In this map, all teams felt the need to run a sentinel. The roles were discussed in the previous sections. Some teams run Killjoy whilst other prefer Chamber. Based on the number of wins against each class, the table for sentinels is as follows:

Sentinels	Killjoy	Chamber	Sage
Killjoy	(1,5)	(0,0)	(0,0)
Chamber	(1,1)	(1,0)	(0,0)
Sage	(0,0)	(0,0)	(0,0)

  Computing Nash Equilibrum: { Chamber, Killjoy } is the Nash equilibrium for this scenario since Optic had more wins (2) by choosing Chamber but they only had 1 win when playing Killjoy.
  Dominant Strategy for Optic: Playing Chamber is the dominant strategy for OPTIC. This is because the won twice by picking the agent when compared with Killjoy. Dominant Strategy for LOUD: Playing Killjoy is the dominant strategy for LOUD since they always picked this agent and had the most success rate.

7.1.1 Observations- Agent Selections. Based on the above computations, we can now discuss on what the final picks of the agents must look like.
OPTIC: Optic never had success playing a duelist, hence their 5 man team should look like this: { Kay O, Sova, Fade, Chamber, Astra }. Why? Optic's best success rate arrived when playing a triple initiator combination. Furthermore, the number of games they won by doing this is 2 in comparison with running a duelist in Jett. the rest of the composition is based off the diminant strategy computed for each class.
LOUD: Throughout the tournament, LOUD always played the same composition. This means that there is less wiggle room in terms of randomization. Even if LOUD were to change their composition for the finals, it would be a risk because - Why fix what is already working? Hence the best composition for LOUD would be: { Jett, Kay O, Sova, Omen, Killjoy }.
What actually happened in the finals? In the finals, the compositions of the teams were:

- LOUD: { Jett, Kay O, Sova, Omen, Killjoy }
- OPTIC: { Jett, Kay O, Sova, Omen, Killjoy }

The result of the finals was: LOUD won and OPTIC lost. This proves my analysis that if teams stuck to their dominant strategies, they ,might have a better chance to win. As we can seem LOUD stuck to their dominant strategy, whilst OPTIC switched and lost the game. This gives us an interesting question to answer - Why did OPTIC choose a strategy that is not their dominant strategy? This question is not answered in this paper, but it would be interesting to see why this particular decision was made.

7.2 In-game strategies Results

Based on the algorithms computed for a half where OPTIC is defending and LOUD is attacking, in figure 2, we have the following payoffs at each node, for defenders is as follows:

- B focus ⟵ 100
- Equal focus ⟵ 116
- A focus ⟵ 115
- Defend B ⟵ 108
- Defend A ⟵ 104
- Post Plant ⟵ 154

Similarly, the nodes for attackers is affected as follows:

- Go B ⟵ 54

- Go mid ⟵ 86
- Go A ⟵ 103
- Post plant ⟵ 216.75

7.2.1 Observations on results from In-game strategies. In the finals, the score was 12-12. So, the game now has to be played till 14 where OPTIC is defending and LOUD is attacking. We have the above reference for payoffs when OPTIC is defending and LOUD was attacking. According to game theory, OPTIC must give up the site and play post plant and try to win the post plant because their highest payoff is in the post plant. Similarly, according to the numbers, LOUD had the highest success when they executed site A and tried to split between A and mid (meaning, send 2 players mid and 3 players directly to A).

Interestingly, this is exactly what happened in the game. On round 25, LOUD went for an A-split and OPTIC chose to play post plant. Since payoff for LOUD is higher in the post plant scenario, they eventually won the game. However, we can see from game theory that the numbers don't lie and we can use such approaches to develop strategies in Valorant. In the next section, we will go over the shortcomings of the paper and some discussions.

8 CONCLUSION

In this paper, a brief introduction to Valorant was made and using the concepts from Mutliagent Systems, we setup an algorithm to give us an insight on the different approaches that can be made whilst selection of agents and picking the strategy of execution for attackers and defenders. However, there are some drawbacks that this paper has. Firstly, we do not consider a larger dataset. Unfortunately, the dataset taken only restricts to the tournament. However, the playoffs for each region is also a factor to consider while building tables and picking strategies. One of the main reason why the playoffs were not considered was, balance changes. The developers of the game frequently push in balance changes, add new agents and maps that would change the strategies to pick. But, when we scope in to a single tournament, the game is a constant and all decisions made are based off the constant state of the game. In the future, this can be rectified by assigning weights to each agent. If the agent's abilities were buffed in the balance changes, then the weight of the agent increases, and vice-versa. Furthermore, in the in-game strategies section, we do not consider which agent was eliminated at a site. For any team, the loss of a controller is arguably the biggest loss. Another example to this scenario is that in an eco-round, i.e. a round in which the teams do not have enough money to buy a gun, some agents in the game have their ultimate that serves them with an extremely powerful weapon. Some examples are Jett's knives and Chamber's operator. Elimination of such agents during a round is vital since these weapons are powerful and could change the tide against the opposition team instantly. Another feature that is yet to be incorporated into the model is that we do not consider the utility of the agents ad their duration. In Valorant, each agent has a duration and number of units of utility to deploy. For example, Brimstone - a controller class agent, can only deploy 3 smokes per round. Where to deploy these smokes and how much effect they have is not calculated in this paper. There are plenty of other examples for each class of agents where we do not keep track of the utilities used. Finally, the economy aspect of the game is not considered. How much money should the team spend in their save rounds? Do you force yourself into buying good weapons by sacrificing armour? One of the main reasons why some of the aforementioned points are left unanswered is mainly due to the fact that they are a completely different sub problem, which a future researcher can answer with better gathering of data.

To conclude, in this paper we prove by using concepts of Game theory the actions taken in the game represent the team's dominant strategy. It is clear to why LOUD won in the finals - they played to their strengths i.e. their dominant strategies all the time.

ACKNOWLEDGMENTS

I would like to thank my professor Koon-Ho Alan Tsang for assisting me trough out the semester in working on this project. His valuable feedbacks and pointers have helped me achieve good results from the project. Finally, I would like to thank my peers for providing feed back regarding my project and providing insightful ideas.

REFERENCES

[1] Rune Kristian Lundedal Nielsen and Thorkild Hanghøj. 2019. Esports skills are people skills. In *Proceedings of the 13th European Conference on Game-Based Learning*. 535–542.

[2] M. Nazhif Rizani and Hiroyuki Iida. 2018. Analysis of Counter-Strike: Global Offensive. In *2018 International Conference on Electrical Engineering and Computer Science (ICECOS)*. 373–378. https://doi.org/10.1109/ICECOS.2018.8605213

[3] TWA Zandt. 2021. *CS: GO as a Serious Game for the Navy*. B.S. thesis. University of Twente.