Decision support for Rocket League player improvement

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ABSTRACT

Decision support systems (DSS) are widely used within sports to make decisions about team formations and tactics. Within esports, however, there has only been done limited research on this topic even though the nature of esports shows great potential for the use of DSS. This paper will focus on the possibilities of DSS in the esports title Rocket League. For this paper, interviews with experts were conducted. These interviews provided information about what decisions teams make and what information they base these decisions on. Furthermore, these interviews gave insights into how information can be extracted from the game and what support can actually be delivered. Lastly, a conceptual framework was created and evaluated as the first design of a decision support system in Rocket League. The next step would be to create the system and test its usability.

Keywords

Decision Support Systems, Rocket League, esports

1. INTRODUCTION

In sports, there is wide use of Decision Support Systems (DSS). Initially designed to help business managers in making managerial decisions [3]. DSS interpret given data and present it in an understandable way to the decision maker to aid the decision maker to come to an optimal decision [1, 3]. Within sports these uses include, but are not limited to, tournament scheduling [9]; player performance evaluation [4] and team selection [16] as well as strategic analysis and how DSS can lead to a wrong decision [2]. Despite the potential that DSS shows for business and sports within the field of esports, DSS is used to a little degree. The decision, cognitive and data-driven nature of esports however reveal great potential for DSS in esports.

According to Juho Hamari and Max Sjöblom [6] esports is defined as: "a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams, as well as the output of the esports system, are mediated by human-computer interfaces. In more practical terms, esports commonly refer to competitive (pro and amateur) video gaming that is often coordinated by different leagues, ladders and tournaments, and where players customarily belong to teams or other 'sporting' organizations who are sponsored by various business organizations." In this research, the focus will be on a game called Rocket League. Rocket League is currently the number ten in Newzoo's [15] monthly active users rank on PC and even number six on consoles like the Sony Playstation. It also ranks number 13$^{\text{th}}$ in Newzoo's [15] viewership statistics on Twitch [1]. In 2020 Rocket League started their tenth competitive season which is the biggest so far. The two main regions, North America and Europe, each will play thirteen multi-day tournaments each with a prize pool of \$100.000 [11] and the smaller regions, Oceania and South America, each play thirteen multi-day tournaments each with a prize pool of \$25.000 [11]. In each tournament, there are 20 to 32 participating teams, each consisting of 3 players and possibly a coach or substitute player [11]. Large soccer teams and automobile manufacturer, like FC Barcelona and Renault, even started their own Rocket League teams [10, 12]. In short, Rocket League is soccer with cars. The players control a car that can use boost to fly. With this rocket-powered car, they have to try and hit a ball in their opponents net. In the esports scene, the most dominant variant is a 3v3 setting. Teams play a best of five or best of seven series to determine who wins the matchup.

Decision support in Rocket League could be a real game-changer. Currently, teams have to do hours of replay analysis of themselves and their opponents to see what they did wrong and what weaknesses from their opponents they can exploit. Just like in other esports titles, individual decisions are made within a split second. Everything happens on instinct and it has to happen fast because if a player thinks too long, they get scored on. The ability to make the correct decision in a split second is also what distinguishes pro players from everyday players. However, as a team, many tactics can be applied to counter certain playstyles. A decision support system could help in identifying what tactics work against which playstyles or what tactics have worked against certain teams in the past. Therefore, a DSS is most useful before and after a game. Pre-game a DSS can be used to decide upon a strategy, but also to find a strategy that would work best against their opponents. A DSS can also show mistakes the opponents make to exploit those or show mistakes the team itself makes so those can be fixed. Furthermore, it can give insights into what the team needs to improve on, this can be anything ranging from defensive positioning to accuracy training. Post-game can be interpreted in two ways. First, it can be seen as during a series. In this case, a DSS can be used to adapt the strategy mid-way during a series.

[1]Twitch is one of the largest streaming platforms on the internet

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This means that if the opposing team uses a different strategy than anticipated, the coach could see what would work best against this strategy and in between games advise the team to adapt their current strategy. Second, post-game can be seen as after a complete series. In this case, it can be used to find mistakes in the team's playstyle. A DSS can also show information about individual players so that different strategies can be created to support each player's strengths.

1.1 Problem statement

Currently, the research in DSS in esports is limited. There have only been two studies that have made a start on decision support within the general esports scene [3, 13]. Only one of those two focussed on Rocket League and showed possibilities for their application to be used as a DSS [13]. What both these studies missed, was the input of actual players. Both studies focused on the data side of a DSS. They focused on what data could be extracted and how this data can then be used. In this explorative research, professional players and/or coaches will be interviewed to see what kind of decisions need to be made and what information is needed for that. These decisions will only include pre-series decisions; decisions made during a series and post-series decisions. The actual in-game decisions will be left out as these decisions are made in a split second. Therefore, players cannot evaluate given data in time to make a decision. Furthermore, this paper will dive into the possibilities of retrieving this data. Lastly, using the collected data a theoretical framework for a DSS will be designed for Rocket League.

1.1.1 Research question

The above problem statement leads to the following research question: *What are the possibilities within Rocket League for a decision support system aimed at player improvement?* This question can be answered by answering the following sub-questions:

1. What decisions need to be made as a team before, during and after a series?
2. What information is needed to make those decisions?
3. How can this information be retrieved from the game?
4. How useful is the proposed Rocket League DSS framework?

The structure of the paper is as follows. In section 2, the related work and background information of this research will be discussed. In section 3, the methods used to answer the research questions will be laid out. In section 4, the results of the research will be presented. Furthermore, a framework will be described together with its evaluation. In sections 5 the overall conclusion will be given. In section 6, some improvements and notes will be given on this research as well as suggestions for future research.

2. BACKGROUND

In this section, related work in the domain of DSS and esports will be discussed. To find related research, Scopus, ACM digital library, Google Scholar and IEEE were used. On these platforms search terms like 'Decision support systems', 'esports' and 'Rocket League' were used, either separately or a combination of two of those.

In both decision support systems as well as in esports in general, research has already been done. The results from the literature study show that the focus of DSS is mostly on business decisions. When it comes to DSS in sports, the focus is on decisions like player evaluations [1, 2, 4, 9, 16]. These researches show the versatility of DSS. In esports the research ranges from business models [22, 24]; to looking for opportunities in combining physical sports with esports [17, 23] and looking into mental retardation [7].

There has also been some more data-driven research on specific esport titles. For example, there have been studies into ranking algorithms [18], as well as a beginning of a decision support system in some sense. Namely, research has been conducted in which the movement of players within the esports title Counter Strike Global Offensive was tracked and analyzed [21]. Results only showed two pieces of research within the field of DSS and esports combined. One research looked at the development of a commentator support system as well as a player evaluation system for StarCraft 2: Wings of Liberty [3]. Only one study discussed a DSS concerning Rocket League.

Lastly, results show a total of five pieces of research which either are about Rocket League or use Rocket League as a test platform. Firstly, there has been a social study on the impact of agency in cooperative multiplayer games [19] where Rocket League was one of the test platforms. Other studies where Rocket League was used as a test platform were a study on challenges for casting esport titles [8] as well as a study on training and performance of several esports titles [14]. More specific research has also been done on Rocket League regarding artificial intelligence and the possibilities of a complete AI team or a team consisting of both humans as well as AI to compete in Rocket League [20].

The last research on Rocket League is closest related to the research described in the paper. This research looks at mining behavioural patterns to model player skills [13]. In this research, an identifier for certain skills was developed and tested on replays. This identifier could see when an advanced mechanics was pulled off and resulted in a goal. The conclusion of this study showed that the data that can be obtained with this identifier is perfect for player profiling and thus for analyzing your opponents. It can therefore be a great fit for a decision support system to see what are the strengths and weaknesses of certain teams and adapt the teams own strategy accordingly.

3. METHODOLOGY & APPROACH

To answer the research questions different methodologies were applied in the current research. In the next section, these research methods and their proposed outcomes will be discussed

3.1 Decisions within Rocket League

The first research question concerns gathering information about the decisions that need to be made in Rocket League. The second research question concerns knowing how these decisions are made. To find out this information, an interview with the Rocket League coach of Esports Team Twente (ETT) was held. He is not only a coach for this team, but also for several other teams which play in international high-level tournaments. During the interview, a player of one of these teams was also present to get more insight into what decisions are made by players and what decisions are made by coaches. During the interview, the following topics were discussed. Firstly, the preparation of the match was discussed. This included their preparation cycle, where the focus lies in replay analysis and how the strategy is determined for the next series. Secondly, the process during a series was discussed. This part was about changes made during a series and how effective certain plays are. Thirdly, their analyses after a series were discussed. Lastly, the team composition was discussed and how the team composition alters the strategy of a team. The interview was recorded to be able to analyze the answers that were given afterwards. How the answers were analysed is described in 3.3.1.

3.2 Available data from the game

The third research question concerns retrieving relevant data from the game. Therefore, an interview was conducted with a data analyst from ETT who specializes in Rocket League analysis. He developed his own library in Python to work with the data obtained from replays and has already done multiple analysis projects on Rocket League including on positioning. During the interview, the following topics were discussed. Firstly, some of his earlier work was discussed to get an idea of what he already accomplished. Next, different possible parts of the DSS, like for example positional mistakes on offence and defence and whether or not it was the right decision to challenge the ball, were discussed to find out whether or not this could be extracted from the game. Furthermore, the type of data that could be used for all possible parts was also discussed throughout the interview. Lastly, some examples of his work were shown and discussed to see how everything comes together in visual form. The interview was recorded to be able to analyze the answers that were given afterwards. How the answers were analysed is described in 3.3.1.

3.3 Creation and evaluation of the conceptual framework

3.3.1 Framework development

After the interviews, the results from research questions one, two and three were used to create the framework. First, all interviews were transcribed. Next, categories were distinguished in the results from research questions one and two. Then, the results from research question three were also categorised in the same categories. Finally, this categorisation led to three different parts to be included in the framework. A statistical overview of players and team, positional mistakes and challenges. For creating the first part, the statistical website ballchasing.com [5] was used. For the description of parts two and three, the answers from the data analyst were used.

3.3.2 Evaluation

For the evaluation of the framework, the coach of ETT was asked once again, as well as the captain and a player of the Rocket League team from Delft Student Esports Association (DSEA). The latter two have been playing together for a long time and are also playing in high-level tournaments just like the teams coached by the coach of ETT. During the evaluation, the three different parts of the framework were discussed. These different parts are a statistical overview of players and team, positional mistakes and challenges. For each topic, the goal was to find out whether it would be useful to have this in a system and what could be improved. Lastly, they were asked if anything was missing from the proposed solution.

4. RESULTS

In this section, the results obtained from the different parts of my research will be discussed. In the first part, the results for research question 1 and 2 will be discussed as they were obtained from the same interview. In the second part, the results for research question 3 will be discussed based on the interview with the data analyst. The third part covers the explanation of the framework based upon the results from the first two parts. The last part will be about the evaluation of the framework.

4.1 Decisions within Rocket League

4.1.1 Preparation

In preparation for a match, the team watches replays and plays practice matches against other teams. During replay analysis, the coach will focus on the positions of his team and on the decisions that they make during the game. For example, if a player goes towards the ball while they should not have, the coach will tell them. Furthermore, if a player is too far forward or too far to one side, the coach will also mention this. If a goal is scored against the team, the coach tries to point out what went wrong and how this could have been prevented. Players focus more on their own decision. Their decisions are based on two main things, instinct and what is going on on the field. The players look at where all the players are on the field and where the ball is and instinctively decide where to move their car. Even the slightest change in position from a single player can change this decision. When they watch a replay, they look at their own decisions that they made and look for any flaws and wrongdoings. The players try to remember why something did not work to try something different in a similar situation next time. For example, if a player notices he is always late to the ball on the left wall because he does not take the optimal path, he can adjust his decision in the next game by either taking a better path or by rotating back. The replays that are analysed are often from recent matches, as these can give the players a lot of insights into what is going wrong at the moment, but sometimes these are also some older replays if they lost their previous match against this opponent to see why they lost last time. When watching these older replays, the coach will look also look for weaknesses in the opponents playstyle to exploit. For example, using the website ballchasing.com [5], the amount of boost used per second of each player can be seen. When this is higher than average, it means that this team uses a lot of boost. Therefore, it can be useful to actively try to steal more boost to make it more difficult for the opponent. It can be concluded that for preparation, teams mainly focus on their own mistakes which are identified by looking at replays, but they can also focus on weaknesses from other players.

4.1.2 During the series

During a series of games against a team, the coach again focuses on positional mistakes and decisions from players to go for the ball similarly as is done during the preparation. The players are not as much involved in the process during the series, as they need to focus more on playing the game itself. Next to positional mistakes, the coach tries to look for weaknesses in the opponent's playstyle to exploit. During the series itself, there is no statistical information that the coach uses to find these mistakes and weaknesses. The coach watches along with the match and tells the players what he notices. A coach often has a lot of his own experience and can therefore point out these weaknesses. For example, the only resource to manage in the game is boost, some teams use more boost than others. Therefore, if the coach notices that a team uses a lot of boost, he will tell the players to steal the opponents boost more often to slow them down. The players will then adapt their decisions by looking for more opportunities to steal the boost from their opponent. Another example could be that the coach notices that the opponent is very aggressive and moves up very far. The coach will then instruct his players to look out for this. If a player now notices this, he might decide to hit the ball downfield immediately instead of passing or dribbling to catch the opponent off guard. It can be concluded that during a series, the coach again looks for mistakes that are being made and, if necessary, adjust their strategy according to how their opponent plays.

4.1.3 *After the series*

After a series is done, the cycle already starts over. They analyse the replays of this series to prepare for the next one. The focus is again on the positional mistakes that were made and the decisions to challenge the ball. The most common mistake, and reason a goal is scored against a team, is that all three players move up the pitch too far. This is caused by the last player deciding to move up as well, while he should have stayed further back. The ball is thrown over his head and the goal is wide open. Another common mistake is that players decide to go for the ball while they have no chance of getting to it on time or they come from the wrong angle. Both scenarios will most likely result in the ball flying towards their side of the field or even towards the goal.

4.1.4 *Team composition*

Usually, a team has a certain playstyle that they try to play in every match. Sometimes this playstyle is adjusted accordingly depending on which team they play or it is adjusted halfway through the series. This initial strategy is all based on the players that are part of the team. Some players are more defensive while others are more offensive-oriented. A team consisting of three offensive players who leave the backfield completely open will not work. Therefore, there needs to be a proper variety in players. During the interview, the coach mentioned that the team from the player who was present was actually built around him. He stated that usually when he is building a team, he first looks for a player who is capable of easily transitioning from defence to offence and who is capable of creating scoring chances, as this is an important part of the game. He continued that the rest of the team would play a more supportive role for this so-called star player. For the players, this means that they have to adjust their decision making accordingly. They know that this one player is their key to transition, so if they have to choose between dribbling themselves, or passing to this player, the latter is probably a better decision. For this star player, this means his decisions become more focused on getting the ball to the other side of the field, preferably in front of the goal. This means he will be looking for the easiest way out of their own side. This can be either by passing or by dribbling it himself either on the ground or in the air. So, a team's strategy is based on the players on the team. A team is often built around a star player with great mechanical ability to transition the ball.

4.2 Available data from the game

While discussing the different topics mentioned in the section 3.2 with the data analyst it became clear that Rocket League provides data that can be used for improving decision making during a match. This is because of the way replays are saved within Rocket League. Therefore, replays are a valuable source of data for a DSS.

4.2.1 *Replays*

Instead of saving the replay as a recording, a replay is ac-

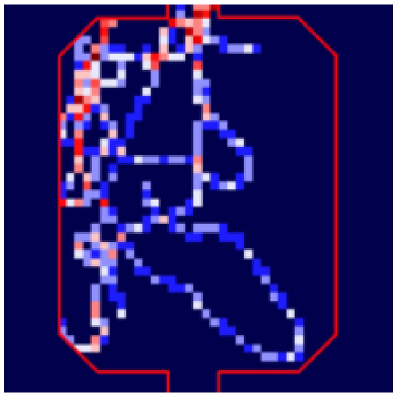

Figure 1. A heatmap 15 seconds before a goal was scored on the top net

tually saved as a sequence of game states. Each game state shows information about all the players, the ball and the boost pads. For players it shows their position in three dimensions, their velocity in three dimensions and their rotation in three dimensions, but also their boost level and whether or not they can still jump for a second time. Everything is measured in the measurement unit from the game engine, called an unreal unit. So the velocity would be measured in unreal unit per second. Mathonat, Boulicaut and Kaytoue gave an example of part of the replay file in their paper on recognizing skill plays [13] which shows the positions of each actor (players and ball) on the field: "$\{\{time : 1.256, P_x : 578, P_y : 5768, P_z : 2245, P_{vx} : 22425, P_{vy} : 15848, P_{vz} : 354, P_{rx} : 0, P_{ry} : 589, P_{rz} : 23, Ball_x : 5588, Ball_y : 789, Ball_z : 22, \ldots, \}, \{time : 1.298, P_x : 7578, P_y : 254, P_z : 4678, P_{vx} : 511, P_{vy} : 555, P_{vz} : 7863, P_{rx} : 6365, P_{ry} : 5665, P_{rz} : 6, Ball_x : 568, Ball_y : 8663, Ball_z : 665 ...\}, \{\ldots\}, \ldots\}$, with P_i being a position of the car in dimension i, P_{si} its velocity, P_{ri} its rotation, etc." So these replay files already contain all the information needed for analysing positional mistakes and challenges.

4.2.2 *Positional mistakes using heatmaps*

As can be seen in the example piece of replay file, the position of every player is logged multiple times a second. Since Rocket League is such a fast-paced game, players are constantly on the move, because being idle on a spot often leads to a goal for the other team. Therefore, it is not possible to use the exact locations of players to see if they are out of position. Instead, a heatmap can be used. A heatmap shows spots on the map where a lot of activity takes place. In figure 1 a heatmap is shown fifteen seconds before a goal is scored on the top goal. The red colour indicates a high amount of activity while blue is less activity.

A heatmap can also be used to identify positional mistakes. Results from the interview show that you can use a heatmap to find the optimal positions in certain situations. Using the information from the replay files, it is possible to gather only data from situations where the ball is shot on target and a certain player has a certain amount of boost and momentum. From this data, one heatmap from all the shots that are saved is made and one heatmap from all the shots that went in. These two heatmaps can be subtracted from each other which should create a heatmap that shows one or two red spots where the defence could be positioned best. Now if a shot is not saved, it is possible to compare the positioning of the player who attempted the save to the heatmap showing the optimal position. This way a player will be able to see where they should have positioned to have a better chance at saving the ball. The same can be done on the offensive side, by looking at optimal positioning as well. These heatmaps can be used very broadly, by looking at an overall positioning, or they can be used for very specific situations. The first is more useful in offence, as this is where the instinctive decisions from players are also more important. So an overall positioning is more relevant than the positioning in very specific situations. For example, the data analyst from ETT discovered, using heatmaps, the optimal positioning for every player when this team is on offence. The latter is more useful on the defensive side, as these can show the players what to do in those exact situations instead of giving a very broad positioning. With this insight, players can change the positional decisions they make, as they have more information about where they should be.

4.2.3 *Challenges on the ball*

In Rocket League players constantly challenge the ball, since giving possession to the opponent is not desirable. Therefore, when a player is dribbling, a player from the other team will often challenge him as soon as possible. These challenges play a key part in the game as the results impact who has possession and which team will play offence and which team plays defence. Unfortunately, it is not possible to analyse what the best timing for these challenges are according to the data analyst. However, it is possible to give insights into how challenges are won and what causes a challenge loss. If players know what causes a challenge win or loss, their decision to challenge the ball can be improved. For example, by knowing why he loses his challenges, he can decide to pull off the challenge earlier to try and cause a bad hit by the other player. Or he might change the way he approaches the challenge by slightly turning his care more in a certain direction or hitting the ball higher or lower.

4.3 Framework development

With the results from sections 4.1 and 4.2, the framework can be laid out. The results show potential for a DSS in the form of three different parts. A statistical overview of the players and the team, insights into positional mistakes and insights into challenges. These parts foster the decision making for strategies and training, improvements in positional and rotational decisions and improvements in challenge decisions respectively. The complete conceptual framework can be seen in figure 2. The following parts explain each branch of the framework in more detail.

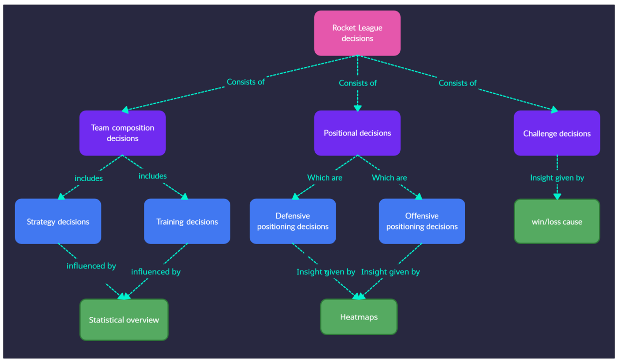

Figure 2. The conceptual framework for a Rocket League DSS

4.3.1 *Statistical overview*

A statistics overview can be used by the players to see what their strengths and weaknesses are as players and as a team. Using the statistics that can be gathered from ballchasing.com [5] and the implementation of recognition of skill shots from Mathonat, Boulicaut and Kaytoue [13] a list of statistics for each player and a list of statistic for the team was created. The result can be seen in table 1.

Table 1. List of player statistics and team statistics

Player statistics	Team statistics
Accuracy	Win rate
Goals/game	Goals/game
Shots/game	Shots/game
Assists/game	Assists/game
Saves/game	Saves/game
Demos/game	Demos/game
Bumps/game	Bumps/game
Boost/second	Boost/second
Big/small boost pickups	Big/small boost pickups
Big/small boost stolen	Big/small boost stolen
Ceiling shots/game	Goals conceded/game
Power shots/game	
Wave dash/game	
Musty flick/game	
Front flick/game	
Air dribble/game	
Flip reset/game	

With these statistics, the players can look for aspects of the game they might have to work on individually and as a team. For example, if a player has high accuracy and a large number of goals per game, this player's strength is scoring, but maybe his saves per game are less high so his defence is something he can work on. This is also applicable to the team's statistics. For example, if the goals conceded per game is very high, their defence is something they have to work on, or while their shots/game might be very high, meaning they have a lot of pressure, but the goals per game and accuracy are very low they have to work on their shooting. Furthermore, these statistics can be used in the process of creating a team to see what players are capable of and what roles they would fill best. A player that scores a lot of Ceiling shots, flip resets and other mechanical shots is more offensive orientated, while a player who has a lot of saves per game is more defensive orientated. In a well-rounded team, you need solid players on both sides of the field. Lastly, these statistics can also be used for new teams to create their strategy, also by looking at the strengths and weaknesses of the players in the same way as mentioned before.

4.3.2 *Positional mistakes*

As mentioned before, heatmaps can give an insight into positional mistakes players make. Using the data from the replay files (see section 4.2.1) it is possible to create these heatmaps. For this framework, it is proposed to use these to highlight mistakes from players after each game. It will show where the player is positioned and where the player could have positioned better. On defence, this can be useful when a goal is scored. On offence, this can be useful when either a goal is not scored because the ball was not reached in time, or when the ball is going over the head of the last player causing the switch from offence to defence. So the system will only point out mistakes and suggest possible positioned which, according to data analysis, is better suitable in that situation. In figure 3 an example of how this indication of a mistake would look like. The circled blue cross indicates the player that needs to make the save but fails. The green dot is the ball that is moving towards the goal, indicated by the arrow. The two red spots on either side of the goal show the positions that the circled player should have roughly been at to save the ball. Next to this, some information about boost levels and speed of the ball and players can be shown, but this would merely give more insights into the type of situation, not in the optimal positioning. Now the player can use this to alter his decision making when a similar situation occurs the next time. He can now for example decide to turn back to goal a little bit earlier in order to be on either of the two red spots, giving him a better chance at saving the ball.

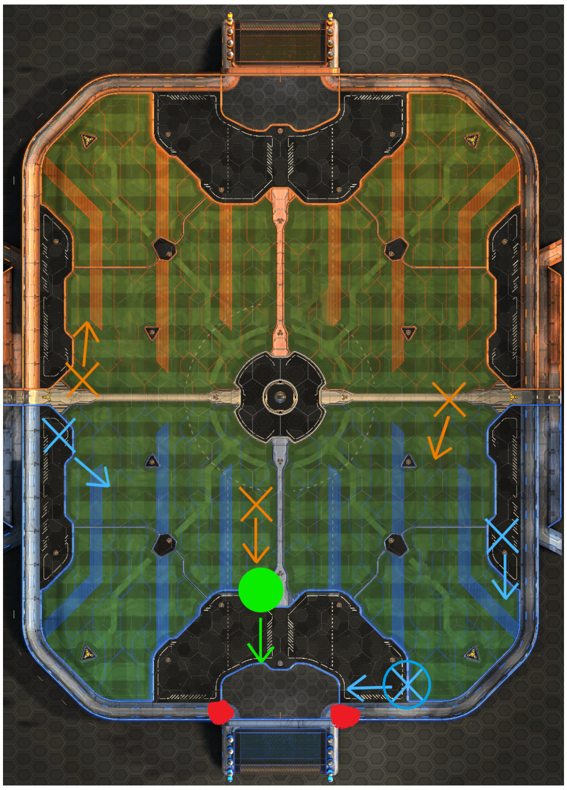

Figure 3. An example of how the DSS will show the positional mistake

4.3.3 Challenges

The final part of the framework is about challenges. The proposed system will show the challenges made during a game and shows what was the reason the player won or lost the challenge. This insight can then be used by players to make a more informed decision when challenging the ball. For example, sometimes it might be more favourable to "lose" a challenge, as it may end up with a teammate that way. When the players have more information about what happens during a challenge, if they rotate their car in a certain way, for example, they can use this in their decisions on how to approach the challenge.

4.4 Evaluation

The final research question considers how useful the proposed framework actually is. Overall, the participants of the evaluation were very positive regarding the proposed framework. They would definitively use such a system once it is available, also to know for sure what impact it will actually have, as this is difficult to predict from a conceptual framework alone. For every part of the framework, aspects were discussed that were already up to par as well as improvements that can be made to get even more useful information out of the DSS. In the following sections, these different on par aspects and improvements are discussed for each part of the framework. Overall, the proposed parts were considered to be must-have features in a DSS. The improvements were mostly nice-to-have feature which would make the system even better.

4.4.1 Statistical overview

The proposed statistical overview as discussed in section 4.3.1 could be very useful, according to the participants. Especially the overview of the different mechanical abilities of players can give proper insights into how effective players are with certain mechanics. The first nice-to-have feature they would like to be added is to not only show statistics of mechanical plays that resulted in a goal, but a more detailed overview. So these plays could be divided into different categories, for example, goals, outplays, assisted and conceded possession. Where the first example is an actual goal is scored with the mechanic, the second one or more players from the opposite team are passed, the third resulted in an assist for the player who used the mechanic and the last is a total fail and the ball ended up with a player of the opposing team. Furthermore, they would like to be able to see trends in the gameplay of players. This could be used for example in a players accuracy to see how well this player improves over the span of a year. A possibility could be to show the accuracy for each series over the last year, showing how well a player is shooting currently while this can also be compared to how well this player was shooting half a year or a year ago. A different kind of trend that would be very useful is statistical insights into what loses a game. For example, showing the percentage of time in front of the ball can be an indicator of why you lost a series. If this percentage is very high, so players are in front of the ball a lot, it means that the backfield is more open which can cause more goals to be scored by the opposing team. When showing this over the time span of a year, players and coaches can see whether or not the team or a specific player is improving in this regards. Some extra stats that can be included as well, are the percentage of possession, insights into speed of players and a percentage showing for each side how much time the ball spends on that side. With these statistics, a team can see if they need to work on breaking out of their own half, or maintaining possession or if they need to work on how fast they are playing. Lastly, a must regarding these statistics is that the statistics need to be limited to competitive play only, so these should not include everyday ranked play with friends. In conclusion, the participants believe this statistical overview to be useful for decisions regarding training, what the team or a player needs to work on, and strategies.

4.4.2 Positional mistakes

After explaining the positional mistakes part of the framework to the participants, they were immediately enthusiastic, but also a little sceptical. They were concerned about the accuracy of such a system, as a small deviation in the position of the ball or a single player, can alter the positioning of everything else. They first needed to see such a system before knowing if it is useful and if it could work. However, if it works the way it was explained they saw very much potential. They did wonder if it would be possible to also look at the positioning on the backboard during the defence as the backboard plays a key part in the game for creating offensive chances. Therefore, insights into backboard positioning are would be greatly appreciated as well, however, it is not sure if this is possible, but it seems likely. Since heatmaps do not work in three-dimensional space, since there would be too much data with a value of zero. For the heatmaps already discussed in this paper which can be used for the positional mistakes, the height is not taken into consideration. However, when looking at the backboard it should be possible to only take the height and width of the field into consideration and set the length as a fixed position at either the blue or the orange backboard. In conclusion, this part of the system would be a very useful addition for aiding players in improving their positional decisions, according to the participants.

4.4.3 Challenges

The support in challenges as described in section 4.3.3 could be very useful according to the participants. Seeing what wins or loses a challenge is valuable data for them as players and coach to see how the challenges can be improved. However, they did see a problem with the definition of a challenge win, as what is considered a win can be very different given the circumstances. Therefore, a must-have feature is not to know why a challenge was won or lost, but instead the system must give insights into what happens with the ball in general. So instead of giving insights into why you win or lost the challenge, the system should give insight into what happens with the challenge and what would have happened if the player hits the ball slightly higher, or lower, or if the player rotates the car slightly more to one side. So instead of only looking at what happens in that specific challenge, also show what would happen if the challenge would be done differently. In conclusion, insights into what happens in a challenge can help players in deciding how to approach the ball.

4.4.4 Extras

During the evaluation, the participants also came up with some extra nice-to-have features which they would like to see in a DSS. There were two main functions they would like to see added to the system. The first is a way of seeing the effectiveness of touches in general. As mentioned before, it is possible to recognize mechanical plays and see what the result of those plays are, but the participants mentioned that not every player will go for those mechanical plays. Therefore, it would be even more useful to get insights into certain trends in a player's overall touches. The system could for example identify that a certain player misses the ball very often when the ball is at a certain height, or when this player approaches the ball from a certain angle. In this part of the system, it would then also be useful to see what happens after a player hits the ball, so how effective was the touch. If the touch ends up giving away possession to the enemy, this touch was not very effective, but if the touch allows the team to move onto offence, it was a very effective touch. This information again aids players and teams in decisions on training. Furthermore, this information can also help players to decide what kind of touch to get in different situations. If they know a certain type of touch is difficult for them, they can opt to go for a different touch.

The second added feature they would love to have is putting the communications next to the replay. During a match the players are in a voice call together, telling each other every piece of information about their position, boost level and where they place the ball, but also if another player has the time or is being chased. Sometimes, information is not communicated or not communicated well enough. If it is possible to put the communications next to the replay in such a way that the calls that were made during the actual match are synced with the replay, a coach or the players could see what they did wrong in their communication. For example, it would be possible to notice that a player did not communicate something properly which was very important information for his teammates. Especially the coach mentioned that if he could see trends in certain information not being communicated, the gameplay of his team could be improved greatly since this missing piece of information can lead to a different decision by someone else which can, in turn, be more favourable. It also gives the coach to ask players why they decided not to communicate something. This can then be used to improve communications in future matches.

5. CONCLUSION

To conclude, there is definitively possibilities for decision support systems in Rocket League which can help players and teams improve. By interviewing a coach and player insights was gained into what kind of decisions are made during a match and what information they use for this. In preparation for matches, the coach and players watch replays and try to find the mistakes the team makes. The most important decisions, as mentioned by the participants, are positional decisions and when to go for the ball. The most important aspect is the mistakes in these decisions, as this is where support can be given. These mistakes are identified by looking at the positioning of the team in replays when goals are scored against them or when their overall position during the match could be better. Next to those decisions, there are also decisions made when deciding upon a strategy. This is mostly dependent on the team composition. The team composition is based on the capabilities of each player, which can be seen in the statistics available to the coach and players. Next, insights were gained into the information that can be retrieved from the game. By interviewing an analyst, insight was gained into how replay files can be used to analyze positional mistakes and challenges. The positional mistakes can be analyzed by using heatmaps, which can be used to identify positions on the map which give a player a better chance at saving the ball, or which show where a player could have positioned on offence to avoid the ball from going over his head. It turned out it was not possible to gather insights into when to go for a ball, but instead, challenges could be analyzed to improve a players ability to get a favourable outcome when they do decide to go for the ball. Afterwards, the information from both interviews was combined to develop a conceptual framework. This framework consists of three parts. First, a statistical overview of team and player statistics. This can be used to see what a player or the team needs to work on, or what strengths of certain players are to develop a strategy. Second, support in positional mistakes can be given. By showing possible improvements to the players when they were unable to save a shot, the players can improve their positioning for the next match. The final part of the framework is about challenges. This part of the system would give insights into what causes a player to lose or win a challenge. This can then be used to replicate won challenges and improve the player's way of challenging the ball overall. Lastly, this conceptual framework was evaluated. During the evaluation, each part of the framework was discussed and improvements and concerns were mentioned by the participants which resulted in some must-have functionalities and some nice-to-have features. The must-have features included the proposed statistics in the statistical overview and the proposed feature of showing positional improvements. However, for this last feature, there were some concerns regarding the accuracy of such a system. Furthermore, a must-have feature would be to give insight into why the ball goes the direction it goes after a challenge and how certain aspects, like the rotation of the car or how high the ball is hit, influence this direction of the ball, instead of looking at what wins or loses a challenge. This is due to the fact that a win for one person can be considered a loss for another, as it depends on the intention behind the challenge. Next, there were some extra nice-to-have features on top of the proposed features. These included, extra statistics in the statistical overview and next to positional mistakes on the ground, the participants would like to get insights into backboard positioning. Lastly, the participants also gave some nice-to-have functionalities outside of the proposed functionalities. These included the effectiveness of touches overall and the ability to put their communications over a replay file to see what is missing in their communication. The participants of the evaluation definitively saw potential in a system such as explained in the framework, as this could reduce the time they need to spend analyzing replays by a great portion. They believed it would be very useful to have and they would definitively try it out if they got the chance.

6. DISCUSSION

Given the circumstances, the final proposed framework is a significant step in the right direction. It definitively gives perspective for an actual DSS within Rocket League to be developed. As can also be seen in the evaluation, the participants' reactions were quite positive and they would use such a product once it is developed. However, room for improvement is also there. In the following sections, some small improvements and shortcomings of this research will be discussed, followed by the future work and some difficulties to overcome in this future work.

6.1 Improvements & shortcomings

The biggest improvement can be achieved in the reliability of this research since there has only been conducted one interview with a coach to find out what kind of decisions are made. Due to the fact that a very specific type of players was required it was difficult to find these. The players needed to compete at a high enough level that they also prepared for their matches by looking at replays. Teams that just played a lot together and then join tournaments for fun were not considered as they could not give insights into a preparation cycle for higher-level teams. Therefore, the research could have been more reliable by interviewing more than one coach. However, the one interview that was conducted was with a coach from multiple teams who had a lot of knowledge on the subject, so this interview still gave plenty of insights into the preparation of teams and the decisions they make. Furthermore, there was also a player from one of the teams present who could give insights into the decisions that players make and what the difference is between their decisions and those made by the coach. Overall, there was enough information to create a proper framework, but the information could have been verified with more interviewees.

Furthermore, even though the participants of the evaluation were positive regarding the framework, they did mention that they could not predict how useful this system would actually be until they have used it. They had high expectations, but this can only be known for sure once a system is developed and tested.

6.2 Continuation for this research

Since the result of this research is a framework, the next step would be to actually develop the DSS. Some additional research could be conducted on additions to the DSS first, but implementation is the biggest prospect. With the ideas proposed in this paper, some difficulties immediately arise when implementation would start. The biggest issue is the fact that there is no proper way of working with the replay data. Even though everything is stored properly in the file, this is all stored in a format which can not be used for data analysis. The data analyst from ETT who was interviewed has created his own library to transform the raw binary game data into Pythonic data. This library is not yet available to the public, so there is no proper way of analysing the data for any developer willing to take this up. The analyst was busy documenting everything so it is probable that this will be made available soon, but it is not there yet. Furthermore, when developing the positional mistakes implementation, an aspect that came up during the evaluation was the positioning on the backboard of the goal. As heatmaps are nearly impossible to create in three dimensions as a lot of the data points will have a value of zero, the idea came up to fold open the entire field and take the positioning on the wall and backboard as if the players were positioned on an extension of the actual field. It is not guaranteed that this can work, but there is potential.

6.3 Future work

In a more general sense, the methods applied in this research are also suitable to be applied in other research regarding decision support. These methods can be applied to research on DSS within esports or on DSS in general. Conducting interviews to see what kind of decisions need to be made and what information is used for them can be used for any research regarding DSS. Furthermore, interviews are also a suitable way of gather information on what data is available. For data analysis, some general trends can also be identified. First data needs to be gathered and relevant data needs to be filtered out. Next, the data needs to be transformed into a useable format. Finally, the actual analysis can be performed.

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