AN APPROXIMATE DYNAMIC PROGRAMMING APPROACH TO DETERMINE THE OPTIMAL DRAFT STRATEGY FOR A SINGLE TEAM DURING THE NATIONAL FOOTBALL LEAGUE DRAFT

by

Ira L. Crofford, Jr.

A Dissertation
Submitted to the
Graduate Faculty
of
George Mason University
In Partial fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Systems Engineering and Operations Research

Committee:

G. Rajesh — Dr. Rajesh Ganesan, Dissertation Director

Andrew Loerch — Dr. Andrew Loerch, Committee Member

Rochelle Jones — Dr. Rochelle Jones, Committee Member

Girum Urgessa — Dr. Girum Urgessa, Committee Member

John Shortle — Dr. John Shortle, Department Chair

Kenneth S. Ball — Dr. Kenneth S. Ball, Dean, Volgenau School of Engineering

Date: __________

Spring Semester 2021
George Mason University
Fairfax, VA

An Approximate Dynamic Programming Approach to Determine the Optimal Draft Strategy for a Single Team During the National Football League Draft

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By

Ira L. Crofford, Jr.
Master of Science
Virginia Polytechnic Institute and State University, 2012
Bachelor of Science
United States Military Academy, 2002

Director: Dr. Rajesh Ganesan, Associate Professor
Department of Systems Engineering and Operations Research

Spring Semester 2021
George Mason University
Fairfax, VA

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Dedication

This dissertation is dedicated to my two wonderful children, Nell and Nolan, who, thanks to a global pandemic, spent many hours orbiting me just like our cat, Hermione, while I worked. I would also like to dedicate this dissertation to my beautiful wife, Anne, who encouraged me and provided me with the confidence to even attempt such a feat.

Acknowledgments

I would like to thank my family and friends who helped make this possible. Thank you to my professors and my committee who helped me along the way. Dr. Rajesh Ganesan, thank you for serving as my advisor, and for sharing your enthusiasm for Approximate Dynamic Programming (ADP). It truly has been an honor to work with you on this research. Thank you for always making time for me and my questions. I am also grateful to have had Dr. Andrew Loerch, Dr. Rochelle Jones, and Dr. Girum Urgessa serve on my committee. Thank you for the insightful feedback and review at each step. Mr. Brian Burke, thank you for your added time and effort to sit in on my briefings and provide your input and feedback. I would also like to thank Dr. Loerch for helping me navigate the program at George Mason University early on, as well as opening up his office to talk sports when I needed a break. Thank you, also to Mary Poirier for your hard work and help in completing all the necessary administrative tasks required to graduate.

A special thanks to Jungho Park who shared an office and a few classrooms with me during this journey. It was nice having someone to bounce ideas off, as well as sharing a few stories along the way. You're next!

Most importantly, I want to thank my wife, Anne, for her hard work, love, and support during this process. I never would have signed up for this, if it wasn't for you. Thank you for pushing me to be better and believing in me.

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Abstract

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Ira L. Crofford, Jr.

George Mason University, 2021

Dissertation Director: Dr. Rajesh Ganesan

The purpose of this research is to determine the optimal strategy for a single team when participating in the National Football League (NFL) Draft using Approximate Dynamic Programming (ADP). General managers and coaches currently draft the best player available (BPA), a player that fills a certain positional need, or a hybrid of the two. Also, general managers must make sequential decisions in terms of trading up to go for a specific player while sacrificing future draft capital or possibly trading back and gaining more future draft capital. If done correctly, teams hope to still get their specific player, but for the right cost in terms of when the player gets drafted. In other words, a team wants to draft a player when he should have been drafted according to his skill set, not much earlier. This research attempts to answer when a team should trade up, when a team should trade back, when they should draft for team needs, or when they should take the BPA.

Many jobs and careers are riding on the success of a football team. Nothing can turn around the prosperity of a franchise like a successful weekend at the NFL

Draft. At the same time, an unsuccessful weekend can result in multiple years of disappointment and setbacks, not to mention the effects monetarily on the ownership of the team. Sometimes teams spend too much draft capital to move into position for a player that never materializes into the player they had hoped. There are many ways for a team to fail during the draft. However, most of the tools used to predict the draft or to have a successful draft are not tailored for an actual draft. There are many tools to assist a fan of the game of football to conduct a fantasy football draft. There are even tools to assist a fan with preparing for whom his team should draft, but even these projected drafts are just the best guesses of an "expert" from outside of the organizations (teams).

This research investigates how a team should maneuver themselves during the NFL Draft to draft the best-graded team possible (on paper) using ADP. This research provides insight as to what the best strategy is for a team trying to create the optimal team roster given their current roster and the list of draft-eligible players.

The results indicate that the ADP Hybrid Strategy was better than the pure BPA Strategy in the long-term. This research is, not only expected to contribute to the NFL Community with the application of ADP to help project the NFL Draft, but also to many different organizations who are trying to better themselves. The teams are competing for scarce resources and they must be able to see themselves (their strengths and weaknesses), as well as that of their opponents or competitors. The uncertainty of the competitors' actions and the uncertainty of the real potential of the resources takes this to a whole new level. One such organization could be the United States (U.S.) Army Human Resources Command who could employ a similar methodology to better assign Second Lieutenants to different branches of the U.S. Army to ensure that all teams (branches in this case) are improved and that the league (U.S. Army) is also improved.

Chapter 1: Introduction

General managers in the National Football League (NFL) make numerous, sequential decisions under uncertainty during the NFL Draft to best achieve their goals for their franchise. Goals will differ from team to team depending on the status of their current roster of players. Some teams look to add a few quality players to an already championship-level squad, while other teams look to completely rebuild the team and find their future franchise player. The rest of the teams lie somewhere in the middle. The sequential decisions under uncertainty during the draft include determining the best players to draft for the team, determining if you will be able to draft a certain player in your current position or if you will need to trade for an earlier draft pick ("move/trade up in the draft" to get the player before another team), or can you wait and get the same player with a later draft position ("move/trade back in the draft") and possibly get some more draft capital (more draft picks) in the process. The general manager is attempting to build the best roster possible on paper according to their evaluation process. In the NFL Draft, the general manager is drafting from a pool of players and athletes that have never played professionally. This means that not all players that had success at the collegiate level will exhibit this same success at the next level. The above challenges and the uncertainty of the NFL Draft process makes optimal sequential decision making a difficult task for the general manager.

To determine the best roster possible on paper, the general manager is trying to look at the system his current coaching staff employs on the offensive and defensive sides of the ball and find future players that can improve the team at their positions of weakness. These positions may be a weakness because the previous player(s) who filled the position may have retired, may have left the team in the off-season due to free agency or even a trade, may have been injured in the previous season and will not be ready for the next season, the team may not have enough depth at that position, or the starting player(s) the team does have at that position may not be good enough. There are many reasons why a team can be looking to improve at a certain position, but the majority of the time these situations are resolved before the NFL Draft. Therefore, a general manager has a very good feel for where his team is weakest and through study, knows where and how his team can improve potentially through the draft. To determine the quality of a player in the draft a general manager and possibly, the head coach, have a system in place along with the scouts to grade the available players at what they deem important. An ideal system may also grade their current roster using the same scale to simplify the evaluation process and allow for a quicker determination on where a player drafted would be on a team's depth chart (Holley, 2011). Different teams have different college evaluation systems and have different needs. However, sometimes teams covet the same player.

General managers must digest a wealth of information leading up to and during the draft. Some of it is honest when a team brings in a player for an interview and sometimes it is simply misdirection to not let the other teams know whom they are wanting to draft. Teams will do what they believe is necessary to get the player they want at the price they want. In other words, if a team can draft the player they want with the eighth overall draft pick, they do not want to have to worry about another team trading up to the seventh position to "steal" the pick. If they are worried, then maybe they will spend more of their draft picks trying to move up to sixth or even fifth to get that player. However, was the team they were worried about moving up to seventh really interested or just interested in making them uncomfortable and possibly trading away some of their draft capital?

Moving up in the draft can be expensive. Sometimes teams trade current players and offer money, but many times they use future draft picks. The picks are not always from the current draft either. Sometimes, especially in the first round, moving up may cost a team their first-round draft pick from this year as well as their first-round draft pick from next year. General managers appear to be more willing to part with draft picks than they are with actual players. Actual players are a known commodity, while draft picks are only as good as your evaluation system. If both teams know what is being traded, it is very difficult to "win" the trade. If the only thing you know about the draft pick you are trading is what round the draft pick is in and possibly the quality of some of the players in the draft (depending on how many years out the draft pick is from today), it is hard to know if it is a fair trade. However, if a general manager has faith in his system, he will trust that he can turn that draft pick into gold. Some general managers just like accumulating draft picks because it gives them flexibility for moving up when the draft gets to a player that excites them.

If a team is not excited about a specific player when it is their turn to draft, they will usually wait until the end of their allotted time, hoping another team will call wanting to trade up and take their spot. A general manager will be prepared to draft someone with that draft pick, but if he believes he can get the same player later in the draft, he would like to move back. This is because it will not be seen as "reaching" to get a player. Reaching is when you draft a player sooner than that player was projected to go or sooner than a player of his caliber should be drafted. If you can draft a player in the third round, you should not spend a first-round draft pick on him. If you are worried someone else might draft him before you in the third, maybe you draft him late in the second. You might also be able to accumulate more draft picks by trading back in the draft. It is a really good move if a general manager can trade back in the draft, still get the player they wanted, and also get an extra draft pick or two in the process.

To get an idea of when a certain player is projected or should come "off the board" many of the journalists, which may be referred to as draft experts, create mock drafts. While creating a mock draft, one of these experts may look at the best player available (BPA) and determine if that player fits the need of the team with the current pick (Golic and Wingo, 2019). They assign the player to a draft position and move on to the next team. They do this over and over until all draft picks are assigned. About six months out, once they have an idea of which players may be declaring for the draft, they will create their first mock draft for the first couple of rounds at most. After the college football season is over and the deadline to enter the draft has come, they will continue to update their mock drafts and will do more of the rounds, if not all. The draft experts want to be as correct as possible, so they may include information from their sources to populate their mock drafts. General managers will do their mock drafts as the draft gets closer, but they still listen to the information provided by these draft experts to help shape their mock drafts. But, like any good plan, it does not always survive contact, or in this case, once the draft starts.

On draft day, the draft order is very fluid. Teams will move up and back to get "their player" or to create a more valuable lineup. This movement can be risky, but the losses can sometimes take years to assess. The majority of the players drafted will take years to get on the field as a starter, assuming they make the team. This is not necessarily the case for the players drafted in the first two rounds but for those drafted in rounds three through seven. Also, there have been many college athletes who were graded high but could not make the transition to the professional game for many different reasons. Some players lack the work ethic required to make it at the professional level. At the lower levels, their natural abilities were enough to excel, but not at the next level. Some players played against inferior opponents in college and their grades were inflated and therefore, never realized the potential of their grades in the NFL. Other players get injured or are surrounded by lesser talent and are never able to excel. Sometimes, the team never gives them the chance to succeed by making poor business decisions or constantly changing the coaching staff and preventing them from gaining any continuity between seasons. There have even been players that prevented their success due to their bad habits or drug problems. With all of this being the case, it may not feel like a big risk to move around in the draft. This might be why general managers are always open to listening to trade offers on draft day. Moving or trading could cause a general manager to miss on the player he wanted, but it is a risk they are willing to take to draft more wisely or more efficiently.

A general manager needs to be as efficient as possible throughout the off-season. The general manager will have an evaluation process established that focuses on the different characteristics, traits, and stats about the players that the general manager and/or coach deem important in their system. To get what the general manager and coach are looking for, they will assuredly give better grades or higher value to the players who meet their requirements. Adding in the positional constraints may adjust the priority of these players in the draft. Teams go into the draft with a very good idea of what positions their team needs to draft, while other positions may have dedicated starters who are returning next year, as well as further depth at the position. To the general manager, it may not be worth spending a draft pick to add further depth when there are more positions in need of a player or two.

The round in which a player is drafted often plays a role in the amount of money and length of their contract. It is important to note that this research did not address the money aspect of the draft or its effect on the team's salary cap. This research focused on the draft and did not address a team deciding to improve its roster in free agency. It also did not take into account that general managers have the option to supplement a trade of draft picks with a player currently on the roster. Finally, this research used existing grades for the draft-eligible players and the team rosters to determine the value gained by drafting a specific player. It did not include a player evaluation tool. The research focused on the draft process and determining a better draft strategy based on existing grades and the current rosters at the time we started the research in the Spring of 2020. The research only contained equal (or as equal as possible) trades of draft picks based on historical trades.

The NFL Draft is a gamble. Before the 2020 NFL Draft, Wagner-McGough (2020) wrote an article for CBS Sports where he discussed just how much is at stake with the draft for general managers and their franchises.

> The NFL Draft is a crapshoot. Even the league's top executives renowned for their drafting ability often get it wrong. The degree of difficulty makes the draft all the more important. It's the single most important (non-game) event in the NFL. One mistake can cripple a franchise. One home-run can birth a dynasty. That's what's at stake in the NFL Draft every year.

With this much riding on a few nights in early spring, a general manager needs all the help they can get. If the general manager had a model to tell them when to trade up or when to trade back and what position to draft when they do make a selection, it would simplify their process. Too many times teams trade up to draft a player that most likely would have still been available at their original draft position or a player with a similar grade. Knowing the probability of that player still being on the board would help a general manager from spending too much draft capital to move up and draft a player that they could have stayed put and drafted.

Other mistakes that general managers make are drafting purely for team need or always drafting the BPA. When drafting purely for team need, a team can sometimes get left with a selection they couldn't trade out of and end up "reaching" for a player they could have drafted later. "Need picks are often reaches and lead to busts. The No. 1 goal of an NFL team in the draft should be to add a good player. Need picks undermine that cause" (Stueve, 2012). However, always drafting the BPA can leave your team with many holes left unfilled.

Another trap that general managers fall into is drafting positional players in the wrong order. For example, say a team has two positions of need that it is focused on drafting with their next two selections. The first position has the BPA on the board at the moment, but it also has many other players who are only slightly behind this player in value. The second position has the second-highest rated player on the board, but there is a significant reduction in value at this position after that player. Drafting the player at the first position could result in missing the player at the second position. However, drafting the player at the second position first and then drafting a player of similar value at the first position with the following selection could result in a better use of resources and increase the value to the team.

This research addressed these sub-optimal decisions and potential mistakes by the decision makers and provided them with a tool to assist with navigating the murky waters of the NFL Draft. This research focused on the selection process and not the evaluation process. For the selection process, the model determined when to trade up or trade back (if at all), when to draft a player of need, and when to draft the BPA.

1.1 Research Questions

We wanted to improve how a team approached and made decisions on draft day. The current methods of drafting the best player available or drafting based on your team's needs appear sub-optimal and extremely myopic. A hybrid of the two approaches is probably preferred, but how does a team know that they are choosing the correct approach at the right time? Is it possible for a general manager to maneuver his team more wisely through the draft day process along with the uncertainty associated with the other 31 teams to draft a better or more valuable roster, at least on paper? In other words:

> **What is the strategy for creating the optimal team roster, in terms of graded value, over the course of the NFL Draft when compared to the team's current roster and accounting for the uncertainty of the other 31 teams in the league?**

This research question helped answer, as well as created more questions throughout the process. Some of the additional questions included (1) how does one quantify the risk of "missing on their player", (2) what is the cost of trading additional picks to move up in the draft, (3) what is the reward for gaining more picks in the draft by trading back, (4) what is the cost for not drafting a player at a position of need for the team, (5) how much better is the Approximate Dynamic Programming (ADP) strategy than the greedy strategy or simply drafting the best player available?

1.2 Dissertation Organization

The remainder of this dissertation is outlined in the following manner. Chapter two provides an overview of the NFL Draft, an introduction to current draft strategies, and then a literature review related to this topic. Chapter two also gives a brief description of three modeling techniques used in this research: Bayes' Theorem, dynamic programming (DP), and ADP. Chapter three highlights the purpose of this research, as well as describes in more detail how the modeling techniques introduced in the second chapter were applied within the context of this problem. Chapter four dives deeper into the ADP algorithm employed to solve the problem. Chapter five describes the experimentation and the results. Chapters six and seven discuss the research contributions and the recommended future/parallel research, respectively.

Chapter 2: Literature Review

This research touched on several different disciplines and topics. This chapter highlights the literature review as part of this research. The first section gives an overview of the National Football League (NFL) Draft itself. Next, there is a discussion of current draft strategies that teams employ during the draft. Then we discuss the relevant literature that touches on this topic or overlaps with this research. Finally, we describe three pertinent techniques that were used to help with this research (Bayes' Theorem, Dynamic Programming (DP), Approximate Dynamic Programming (ADP)).

2.1 NFL Draft Overview

Every spring, thirty-two franchises come together for an extremely busy weekend. The goal of the weekend for some is to hire new employees that will turn the luck of their franchise around and make them winners. The other half is looking for a few new employees that will make their team a little better or a little younger without taking any steps backward. These franchises provide millions of fans with pride, joy, and excitement starting in late summer. For the productive franchises, the excitement continues through early winter. For all but one, heartache ensues, followed by withdrawals every Sunday until the next summer. However, for one weekend in late April, the excitement partially comes back for fans of all thirty-two franchises. For hundreds of athletes, the excitement has never been this strong. For the fans, it awakens them from their winter slumber and gets them hungry for the dog days of summer. This weekend is known as the NFL Draft, where the teams select the rights to the best college athletes/football players, who will become the league's newest class of rookies. It has become an extremely large and extravagant spectacle over the years. The 2019 NFL Draft set records for attendance, with more than 600,000 fans showing up over the three-day event to watch names being read off of a card every five-to-ten minutes, as well as television ratings, where "[t]he 2019 NFL Draft event set a record for the highest-rated and most-watched draft ever" (Football Operations, 2020a).

The league has adapted its rules over the years since the first NFL Draft in 1936. Each year brings different competitions, both internally and externally. Internally, the different franchises may create more or less competition based on where they are in their life cycle (rebuilding versus reloading), while externally, different leagues have come and gone over the years to create competition over the talent. The NFL has had to address these changes over the years as it has grown in size and popularity and has had to implement rules and regulations to keep things fair for its clients (Football Operations, 2020b).

As it stands currently, each of the 32 franchises receives one pick in each of the seven rounds of the NFL Draft. The order of selection is determined by the results of the previous season, with the worst teams picking first. Assuming there are no trades between teams, each round starts with the team that finished with the worst record and ends with the Super Bowl champions (Football Operations, 2020b). For the 2021 NFL Draft and going forward, the first eighteen teams are the teams that did not qualify for the playoffs in the previous season. For slots 19 – 32, the order depends on when you lose in the playoffs. There are four rounds of playoffs in the NFL. The first weekend is the NFL Wild Card Round, which will assign the six losers' slots 19 – 24 in the reverse order of their final regular-season records. The second round, or the NFL Divisional Round, will eliminate four more teams from the playoffs and assign slots 25 – 28 in reverse order of their final regular-season records again. The third round eliminates two more teams in the NFL Conference Championships and assigns slots 29 and 30 in the same manner as the previous two weeks. Finally, the team that loses the Super Bowl is assigned the 31st pick in the draft, while the Super Bowl Champion is assigned the 32nd and final slot in each round. There are many different tiebreakers to help iron out the order of any team that finishes with the same record as another team. These tiebreakers apply to both the playoff and the non-playoff teams.

While the teams may spend all year preparing for the draft, it is only a three-day event. The first day is broadcast in primetime on a Thursday and focuses only on the first round. During this round, teams are given ten minutes to make their pick and submit their selection to the league. The second day is also broadcast in primetime on a Friday and showcases the second and third rounds. During the second round, teams get seven minutes to make their selection, but only five minutes during the third round. Finally, on the last day (Saturday), rounds four through seven are completed. The teams continue to get five minutes per pick until the sixth round is complete. In the seventh round, the time limit reduces to four minutes per pick. If a team lets the clock expire, it does not necessarily lose its pick. A team can still make their selection after their time limit expires, but the next team to draft may take the player they were considering (Football Operations, 2020b).

As mentioned in Chapter 1, teams can trade their draft picks, both current and future. Part of the risk/reward of trading a future draft pick is that a team does not know the actual position of that pick. In other words, a future first-round pick could be as high as the first overall pick in the draft or as low as the last pick in the first round (32nd overall pick). Teams are free to trade draft picks and players to whom they hold the rights at any time before and during the draft (Football Operations, 2020b).

While it is not mandatory for the player to be a collegiate football player to be eligible to be drafted, they must be at least three years removed from high school and they must have completed their college football eligibility before the next college football season begins (Football Operations, 2020b). The second part is usually covered by requesting the NFL's approval to enter the draft early. Once a player declares for the draft and is granted permission by the NFL, they are no longer eligible to play football at the collegiate level.

2.2 Current Draft Strategies

With more people than ever watching your every move, judging every decision, and grading every selection, well before the player has even practiced with his new team; owners, general managers, coaches, and the rest of the front office for these thirty-two NFL franchises should look to make many decisions during the draft which will only improve their team's chances of winning and celebrating late into the season. There are many sequential decisions to be made by each team with every pick in the draft. Some of these decisions include: do they draft the best player available, do they draft players that fill their team's biggest needs, do they trade their pick for more picks, or do they trade more of their picks for an earlier draft pick. These decisions can have lasting effects on a franchise and can affect their ability to win over the next few years. "There's a master plan that's associated with that player and where he'll fit in the team. You actually look out over the next four or five years" (Holley, 2011). It can also affect the reputation of the general manager and his ability to build a better team through the draft. Too many bad or unproductive picks can result in the general manager being fired. If you think draft picks and winning don't matter for sports teams, keep in mind that "no other industry has an entire section of each local paper devoted to its happenings" (Berri and Schmidt, 2010). The sports industry is a very public industry in a time where every fan has a voice on social media. So how does the team of decision makers for each franchise make the best decisions?

Teams and decision makers in the NFL have come a long way from making decisions based on a gut feeling. Most, if not all teams have a system in place which allows them to grade players in certain areas (Smith, 2017). However, this does not prevent owners and gut feelings from getting in the way and throwing those grades aside (Finlay, 2019). At the same time, it doesn't mean that the decision makers in the room will always agree on drafting the same player, but the team needs to have a consensus on how that player can help them in the future (Gaines, 2019). Drafting college athletes to play professional football in the NFL is complicated, more so than other professional sports. There are many more variables involved when a player transitions from college to professional in football (Clark, 2019). Teams have different needs, as well as different requirements. Sometimes the option to trade up or trade back does not materialize and the team is forced to make a selection (Holley, 2011). In the end, teams only have a handful of opportunities during the draft to improve their football team. It is up to them, not necessarily to get the best player available with each draft pick, but to make the selections or trade choices that provide them with the best overall improvement to their team, either now or in the future. The team needs to have a plan before draft day and they always need to be ready for the unexpected.

Everyone in sports loves to throw around the war comparisons and Sun Tzu (2005) put it best in The Art of War "if you know the enemy and know yourself, you need not fear the result of a hundred battles. If you know yourself but not the enemy, for every victory gained you will also suffer a defeat. If you know neither the enemy nor yourself, you will succumb in every battle." In this quote, you can relate each draft pick as a battle. The team of decision makers must not only do their homework of knowing who is available in the draft and how those players can help them win, either now or later, but the team must also know what the other teams need, want, or might be in the market for if the price is right. Bill Belichick, head coach of the New England Patriots and eight-time Super Bowl winner (six as head coach of the Patriots and two more as a defensive coordinator for the New York Giants), is known as a tremendous draft-day decision maker. His New England Patriots have built a dynasty over the past twenty years by rebuilding or reloading through the draft (Holley, 2011). Belichick understands, in his mind, what every team in the league needs going into the draft, so he has a good idea of what to expect from them on draft day. "The Patriots literally have a 'Needs Book' on every team in the league," but after every season, he sits down and writes "in the most important Needs Book the Patriots have on their Foxboro shelves; their own" (Holley, 2011).

Many football experts believe that the best draft strategy is to choose the best player available (BPA) when it is your pick. This means drafting a player at a position, even if your team does not need a player at that position. This is called the BPA strategy. The belief behind the BPA strategy is when given the opportunity to get as close to a "sure-thing" that you are going to find in the draft, you should take it. Many talents never produce or live up to their potential, and so you do not want to be the one who did not draft a generational talent when given the opportunity. Years from now, people will remember that you did not draft the player, but they will not remember that you did not need a player at that position. This is a purely myopic policy or a very simple strategy that is looking for the highest reward now, with this single draft pick, and not taking into consideration the rest of the draft or the bigger picture (Powell, 2011). Remember, most teams are not looking to produce a winning team today in the draft, most teams are looking to sustain or complement a winning team today or produce a winning team tomorrow (Holley, 2011). In other words, teams are looking for a player or two to contribute now, but most of the draft picks are what will allow a team to add depth at a position, get younger at a position, and/or eventually save money by being able to let the expensive veteran go in the next couple of years.

Another common draft strategy is to draft according to your team's needs. In other words, a team has a few positions that it will focus on going into the draft. The team has done its homework beforehand and knows their weaknesses and the strengths of the draft class (Holley, 2011). However, this strategy can also be considered a myopic policy because all the team has done is shrunk the size of the available draft pool by only looking at certain positions. However, in the end, they are still going to draft the best player available of this smaller pool. Most, if not all, of the "experts", are using a modified or hybrid version of these two draft strategies. A myopic policy can be risky because it does not use any forecasted information and is only focused on right now (Powell, 2011). While the team may get praised for the single pick, their overall draft class may not be as strong as it might have been using a slightly different approach that takes into consideration the fact that there are many sequential decisions to be made throughout the draft.

2.3 Prior Models

The ability for a team to trade their picks and move forward and backward in the draft complicates the process of creating an optimal draft. Add this to the fact that there is money to be made in fantasy football and data readily available if using fantasy football statistics, and you now know why nearly all optimization models use a fantasy football draft. Fantasy football is a competition in which participants serve as general managers by choosing a team of real football players from different teams and they score points according to how well the players perform each week (Cambridge English Dictionary, 2020). During a fantasy football draft, teams cannot make trades. They are locked into their position for each round and cannot move up or back. Additionally, because the draft order usually has nothing to do with the previous season, fantasy football leagues tend to use a serpentine draft order instead of the traditional order similar to the NFL. In a serpentine draft, the team that selects first in the first round will have the last pick in the second round. They will then be back to the first pick in the third round. In other words, the second round is the reverse order of the first round. This ordering creates its own dynamics when drafting. Additionally, all teams start with no players and require the same number of starters at each position. Therefore, as the draft progresses, it may make it easier to predict what type of player (position) an opposing team is going to select. There is a huge shortcoming in this approach and cannot be applied to the actual NFL Draft.

Dynamic programming is a mathematical optimization technique for modeling sequential decisions. This lends itself nicely to modeling a sports draft (Fry et al., 2007). Fry et al. (2007) produced the beginning touches of a DP model, however, they chose to introduce additional assumptions and restrictions to translate the model into a linear program (LP), avoid the "curse of dimensionality" (Powell, 2011), and arrive at a solution. These assumptions eliminated the uncertainty associated with the draft, such as how an opposing team ranks or grades the eligible players, what the opposing teams consider their teams' needs, and knowing the opposing teams' selection strategies. Finally, Fry et al. (2007) conducted their analysis using a fantasy football draft for the reasons listed above. This is the only instance of any previous work utilizing a DP approach to model a sports draft. The remaining work discussed in this section covers research involving aspects of a sports draft, not necessarily the NFL.

A different model proposed by Summers et al. (2007) used players and statistics from the National Hockey League (NHL) to determine an optimal draft strategy for drafting a fantasy team. This model incorporated a different sport with different rules, but the authors were still trying to optimize a player draft. Of course, the players being considered were all proven stars at the professional level, so that changed part of the dynamic. In this playoff pool, the participants drafted the players whom they believed would score the most points (goals plus assists) in the NHL Stanley Cup Playoffs utilizing a serpentine draft order. Players that lose in the first round of the playoffs do not have as many opportunities to score points as a player who makes it to the fourth (and final) round. This provided an interesting twist to the model. The participant was forced to also consider the quality of the team of the player in hopes of choosing players with more opportunities throughout the playoffs. Playoff fantasy drafts have this twist in common, as opposed to fantasy leagues that focus on the regular season.

Brams and Straffin (1979) focused on small examples of two- and three-team leagues to consider different selection strategies examined through a game theory lens. In their model, each team had a player preference list, which is known by all other teams. The authors evaluated different draft strategies across the league to determine the optimality of the two main strategies they tested. The authors proved that if each team focused only on their preference list when determining their selections, then the league-wide selections are Pareto-optimal. However, when teams tried to game the system (since they knew whom other teams coveted), they only succeeded in hurting themselves. This sophisticated way of drafting led to the resulting draft not being Pareto-optimal and was referred to by the authors as the “paradox of player selection” (Brams and Straffin, 1979). This differed from our research because we incorporated a player’s value to the team instead of a preference list and we further distinguished players by their positions. Finally, we accounted for all 32 teams, as well as having a non-rigid draft order. In other words, we allowed for some trading of draft positions to occur with the decision maker’s team.

Not all models focused on the optimization of the draft process. The following models were developed to determine the potential of a player at the next level. These models took the players’ statistics from their collegiate careers and/or their results from the NFL Scouting Combine to try to predict what type of career the player would have in the NFL. The NFL Scouting Combine is an annual event, which takes place after both the NFL and college football seasons are over (late February/early March) in Indianapolis. It provides the NFL teams an opportunity to see the prospects perform certain physical and psychological tests, as well as a time to meet with them and interview them before investing a draft pick on them (Football Operations, 2020a). The problem and methodology of these models were fundamentally different from our approach to a sports draft; however, we observed that their results could be useful and serve as inputs to our research. The goal of this research was to be able to use any evaluation technique as an input. The key to accurate results was to ensure that the evaluation technique was consistent across the current rosters, as well as with the college athletes. It also does not matter how one defines the value of a player, whether it be by grading their college careers or projecting what kind of future they have, this research was designed to optimize the value to the team.

King (2019) created a model trained on historical data from the NFL Scouting Combine since 2000. However, the author decided to focus only on the wide receivers. The goal of his analysis was to determine the probabilities a wide receiver had for becoming a Pro-Bowler (All-Star in the NFL), becoming a starting wide receiver (first- or second-best wide receiver on a team), becoming a role player (third-, fourth-, or fifth-best wide receiver on a team), or not making it in the NFL at all. When using this model, it did not take into consideration the strength of the opponents that the player played against in college. This could lead to players from lower divisions, or with other glaring issues, being overvalued.

The MicroStrategy Team (2019) created multiple models to determine the quality of a player. This model also incorporated results from the NFL Scouting Combine to forecast a player's future performance. Through this analysis, the team determined that the NFL Scouting Combine might not be a very good indicator of NFL success, but it could be useful as a data point leading up to the draft. Further analysis from the team pointed to a player's placement in the draft, or where they were taken in the draft, as a much better predictor of future success. This means that the general managers conducting the draft tend to know what they are doing when evaluating the college athletes.

Another approach, employed by a user on the NFL Reddit site (dataScienceThrow1 (Reddit User), 2019) attempted to use random forests trained on the physical measurements, statistics, and video game features to build an NFL Draft model. Random forests consist of a multitude of individual decision trees during training. The individual trees would provide a classification prediction using its predictors and the class with the most votes wins (Kuhn and Johnson, 2013; Yiu, 2019). While the Reddit user employed machine learning in developing his model, his model did not necessarily tell a team whom to draft when. This model simply tried to predict what college athletes were going to excel at the next level or professionally.

Some models took the evaluation step to the next level by applying how it translated to the NFL Draft. In other words, the following models not only created an evaluation/ranking metric but also tried to determine when a player was going to "come off the board" or get drafted. Taylor (2016) used the results of the NFL Scouting Combine to create a linear model to help determine what was the probability of specific players being drafted in the first round. The model's results were comparable to the results of some of the "experts" on the different sports websites and television channels. The author did not incorporate team needs into the model. However, this analysis could be useful since our research did not need to know the probability of a player being taken by a specific team, but it did need to know the probability of when a player is going to come off the board and no longer be eligible for the decision maker to draft.

Burke (2014a) offered up a more complete model while using the concept of Bayesian inference. Burke (2014a) used a pre-existing evaluation system that ranked the available college athletes from the best to the worst (obviously teams are going to do this on their own using their standards). From here, the author used historical data to help provide how accurate these rankings have been in the past in determining when a player was drafted. This helped create a distribution centered around a player's ranking. To expand on these projections, the author then incorporated Bayesian inference to add the draft projections from the "experts." The addition of the expert opinions is how the author considered team needs, unlike the previous model by Taylor (2016). By adding more expert draft projections into the fold, the distribution became narrower, converging on a more confident projection.

Even more models took a deeper look at the financial aspect of the NFL Draft, as well as the league as a whole. Young II (2010) used a mathematical model to address the NFL Draft and the free agency period leading up to the draft as a knapsack problem. Burke (2016) also solved the knapsack problem by focusing on staying under certain salary requirements. While Young II (2010) spent his thesis trying to develop a metric to determine a players' contribution to the team, he did not focus on optimizing the draft strategy. Burke also used his example to build an all-star team of existing NFL players with the primary application being that of fantasy football. Massey and Thaler (2010) showed how teams were overvaluing the very top picks in the NFL Draft when compared to the picks at the bottom of the first round and the top of the second round. The authors used marginal surplus value to prove their point since the salaries of the top picks had grown so large. However, the league adjusted this policy and along with the NFL Players Association (NFLPA), they agreed to a new Collective Bargaining Agreement (CBA) in 2011 that regulated the rookie salary system to limit spending on first-round draft picks (Myers, 2011). Massey and Thaler (2013) updated their findings to include the new CBA but continued to focus on maximizing surplus value. It should be noted that addressing the financial aspect of the NFL Draft and free agency period was beyond the scope of this research.

And yet another model focused on the league policies that helped determine the draft order each year. Price and Rao (1976) looked at the order with which the teams pick in the draft and determined that the current league policy of letting the worst teams pick first was not the best way to create parity between the teams. The authors believed that it took weaker teams too long to improve their roster and they proposed alternative draft schemes to decrease the time required for weaker teams to improve their rosters (Fry et al., 2007).

In summary, the NFL drafting process is a sequential decision making process under uncertainty. Fry et al. (2007) ignored the uncertainty associated with the draft as explained earlier and eventually took an LP approach. In this research, we modeled the NFL drafting process using a stochastic DP formulation and solved it with ADP (or reinforcement learning). Our method incorporated the simulation of the uncertainty model using Bayes' approach. The overall approach overcame the limitations in Fry's approach and provided superior decision making capabilities for the general manager during the drafting process. In the following section, we explain the modeling approach; the adaptation of which to the drafting process is explained in chapter three.

2.4 Modeling Approaches

There are three modeling approaches that we discuss in this section that proved valuable to how we tackled the research questions. We introduce the topics in this section and the next chapter, we will show you how they were applied to the problem. The first technique we briefly discuss is Bayes' Theorem. This process was used to help develop the simulation of the uncertainty of the draft. Finally, we will discuss DP and ADP. The DP and ADP sections are mostly adapted from Powell (2011), Gosavi (2015), Bellman (2003), and Hughes (2017).

2.4.1 Bayes' Theorem

Bayesian inference is the process of inductive learning via Bayes' Theorem (Hoff, 2009). Bayes' Theorem, if you remember from probability and statistics classes, describes the probability of an event occurring, based on prior knowledge of conditions that might be related to the event (Joyce, 2003). Stated simply (and more commonly), the theorem is

$$P(A|B) = P(B|A) * P(A)/P(B), \tag{2.1}$$

which reads as the probability of event A occurring given that event B has already occurred equals the probability of event B occurring given that event A has occurred multiplied by the probability of event A occurring and then divided by the probability of event B occurring.

2.4.2 Dynamic Programming Overview

The field of DP provides different approaches to solving many optimization and control problems. Large-scale optimization and control have increased in importance in recent years. DP focuses on a discrete system state, while in a continuous setting, the term optimal control is used. However, the methods are identical mathematically. Also, adaptive systems with sequential decision making abilities are in demand for effective real-time optimization and control (Bellman, 2003).

Sequential decision problems are problems that involve making decisions, then observing information, then making more decisions, and then observing more information, and so on (Powell, 2011). "Dynamic programming is the collection of mathematical tools used to analyze sequential decision processes" (Denardo, 2003) such as the one above. The goal of DP is to make favorable decisions or actions that take the system from one "good" state to another "good" state. It determines the shortest path to minimize cost or the longest path to maximize the reward of decision-making problems that are solved over a time horizon (Bellman, 2003). "The emphasis in these models is typically in identifying finite (or, at least, low-dimensional) state and action spaces and in assuming some Markovian structure (so that actions and outcomes only depend on the current state)" (Birge and Louveaux, 2011). In addition to maintaining a limited state space, DP also requires that one knows the transition probabilities from one state to the next.

All dynamic programs can be written recursively. This recursion relates the value of being in a particular state at one point in time to the value of the states that the system can visit at the next point in time (Powell, 2011). For stochastic problems, this equation can be written (Powell, 2011)

$$V_t(S_t) = \max_{x_t} \Big(C_t\big(S_t, x_t\big) + \gamma \mathbb{E}\big\{V_{t+1}\big(S_{t+1}\big)\big|S_t\big\}\Big), \tag{2.2}$$

where $V_t(S_t)$ is the total value of a particular state at time t, $C_t\big(S_t, x_t\big)$ is the current contribution value of a particular state (S_t) and action (x_t) pair, γ is a discount factor and is set to a constant value of 0.9, and $\mathbb{E}\big\{V_{t+1}\big(S_{t+1}\big)\big|S_t\big\}$ is the expected value of the next state (S_{t+1}) to the end of the problem given the current state (S_t) (Hughes, 2017). Equation 2.2 is known as Bellman's Equation and it consists of two parts. The first half of Equation 2.2 focuses on the immediate contribution (cost or reward) of making a decision, while the second half of the equation finds the best path (in terms of expected value) to the end of the problem. By using the expected value of the next state (S_{t+1}) to the end of the problem, DP can avoid myopic solutions to the problem.

Dynamic programs consist of state variables, decision variables, a state transition function, an objective function, and an exogenous information process (deterministic or stochastic). (Bellman, 2003). Once the decision maker has an objective function, what they are trying to optimize, and knows the state the system is currently in, they can then make a good decision. The state transition function then uses that decision along with any exogenous information to update the system and describe how the state variables have changed. As stated above, the states are discrete when referring to DP. When coupled with the fact that the next state the system visits is dependent only on the current state and the decision maker's decision, classifies this as a Markov decision process (MDP).

Markov, Semi-Markov, and Decision Processes

An important stochastic process in studying real-life systems is the Markov process. A Markov process follows three key properties: (1) the jumpy property - transitions from one state to the next commonly occur, (2) the memoryless property - the transition from one state to the next only depends on the current state and not any of the previous states visited prior to the current state, and (3) the unit time property - all transitions from one state to the next occur after the unit time (Gosavi, 2015). Gosavi (2015) states that a process is referred to as a semi-Markov process if the transitions occur after a random amount of time (not necessarily a unit time). The next step in the evolution of these problems is to give the decision maker an action to take or a decision to make. When there is more than one available action to choose from in a state before transitioning to the next state, the problem becomes an MDP. As with the Markov and semi-Markov processes, you can also have a semi-Markov decision process (SMDP) when the unit time property is not followed.

Issues in Dynamic Programming

"Curse of Dimensionality"

Equation 2.2 and DP are guaranteed to find an optimal solution for an MDP, assuming all of the information is provided (Gosavi, 2015). In other words, the transition probability matrix (TPM), as well as the contribution/reward matrix must be known. For the TPM, this means knowing the probabilities of transitioning from one state to all other states, for every state. As for the contribution/reward matrix, this means there must be an immediate contribution/reward for each state and possible action pair. When solving an SMDP, one must know the transition times as well (Gosavi, 2015).

DP requires the values of all these quantities. This can often be a difficult, tedious process and if the state space is extremely large it could be impossible. Also, the computational load of solving a DP is related to the size of the outcome space and decision space (Powell, 2011). “Even supercomputers with large amounts of memory would have a tough time storing and recursing through the matrices necessary to solve a DP problem with hundreds of thousands of states, outcomes, and decisions” (Hughes, 2017). This first issue of DP is known as the “curse of dimensionality” (Powell, 2011; Gosavi, 2015).

“**Curse of Modeling**”

One not only has to worry about the power of the computer when trying to solve real-life problems, but also the dynamics of the system itself. In many complex systems, defining a probabilistic model that controls the transitions between states can be extremely difficult. It may also prove difficult to develop an accurate contribution/reward function that allows the model to behave appropriately. This second curse of DP is known as the “curse of modeling” (Powell, 2011; Gosavi, 2015).

2.4.3 Approximate Dynamic Programming Overview

To account for these disadvantages, Approximate Dynamic Programming (ADP) methods have been developed. These methods are going to step forward in time. To be able to simulate the process forward in time, we needed to meet two challenges. The first challenge was finding a way to randomly generate a sample of what might happen (in terms of the various sources of random information). The second challenge was that we needed a way to make decisions.

To step forward in time, we started by implementing a decision. Given the decision, we then needed to know the exogenous information that arrived after the decision and before the next state. For this strategy, we picked a sample realization of the possible information at random. When we stepped forward in time, we could then update the value function for the previous decision.

To be effective, we would need to do this process iteratively, indexing everything by the iteration counter n. This would allow us to produce multiple sample realizations. This means that ω^n would represent the specific value of ω that was sampled for iteration n. At time t, we would be in state S_t^n and would make decision x_t^n using the value function $V^{(n-1)}$. The value function is indexed differently because it was approximated using information from all the previous iterations $(1,\ldots,n-1)$. Therefore, the new optimality equation looked like this

$$\hat{v}_t^n = \max_{x_t \in X_t^n} \Big(C_t\big(S_t^n, x_t\big) + \gamma \Sigma_{S_{t+1} \in S} \mathbb{P}\big(S_{t+1} | S_t^n, x_t\big) \bar{V}_{t+1}^{n-1}\big(S_{t+1}\big) \Big) \tag{2.3}$$

This strategy does not require us to loop over all states. Also, instead of using synchronous updating, we are only going to calculate the value for one state. This is known as asynchronous updating. Unfortunately, Equation 2.3 still required the computation of an expectation. To avoid approximating the expectation, there is another technique that works for many applications. The technique uses the idea of the post-decision state variable. "The post-decision state captures the state of the system immediately after we make a decision but before any new information has arrived. This means that the post-decision state is a deterministic function of S_t (also known as the pre-decision state) and the decision x_t" (Powell, 2011).

Earlier we defined $V_t(S_t)$ as the value of being in state S_t immediately before we made a decision. In the same manner, we defined $V_t^x(S_t^x)$ as the value of being in state S_t^x just after we made a decision. The relationship between the two can be summarized as follows:

$$V_{t-1}^x(S_{t-1}^x) = \mathbb{E}\{V_t(S_t)|S_{t-1}^x\}, \tag{2.4}$$

$$V_t(S_t) = \max_{x_t \in X_t} \Big(C_t(S_t, x_t) + \gamma V_t^x(S_t^x)\Big), \tag{2.5}$$

$$V_t^x(S_t^x) = \mathbb{E}\{V_{t+1}(S_{t+1})|S_t^x\}. \tag{2.6}$$

If we were to then substitute Equation 2.6 into Equation 2.5, we would be left with the expectation form of Bellman's Equation (Equation 2.2 above). However, if we substitute Equation 2.5 into Equation 2.4, we would then have the optimality equation around the post-decision state variable

$$V_{t-1}^x(S_{t-1}^x) = \mathbb{E}\Big\{ \max_{x_t \in X_t} \Big(C_t\big(S_t, x_t\big) + V_t^x\big(S_t^x\big)\Big)|S_{t-1}^x\Big\}. \tag{2.7}$$

We can now run the algorithm iteratively. If we are in iteration n and at time t, then we are in state S_t^n. The optimization problem can now be written as

$$\hat{v}_t^n = \max_{x_t \in X_t^n} \bigg(C_t\big(S_t^n, x_t\big) + \gamma V_t^{n-1}\Big(S^{M,x}\big(S_t^n, x_t\big)\Big)\bigg). \tag{2.8}$$

To indicate that we were in a specific state rather than a set of all possible states, we used the notation S_t^n. Also, x_t^n is the value of x_t that solved Equation 2.7. The key here was that Equation 2.7 was deterministic and we no longer needed to compute or even approximate an expectation as before.

Next, we needed to update the value function. $\hat{v}_t^n$ was a sample realization of the value of being in the post-decision state $S_{t-1}^{x,n}$ that allowed us to update the post-decision value function using

$$V_{t-1}^n(S_{t-1}^{x,n}) = (1 - \alpha^{n-1})V_{t-1}^{n-1}(S_{t-1}^{x,n}) + \alpha^{n-1}\hat{v}_t^n. \tag{2.9}$$

α is the learning parameter that allowed us to not put too much weight on one stochastic jump (in Equation 2.9) and allowed us to use what we had learned over multiple iterations. This assisted us in case the model made a bad decision along the way. Together Equations 2.8 and 2.9 represent the learning version of Bellman's Optimality Equation around the post-decision state.

Step 0. Initialization.

Step 0a. Initialize $\overline{V}_t^0$, $t \in \mathcal{T}$.

Step 0b. Set $n = 1$.

Step 0c. Initialize S_0^1.

Step 1. Choose a sample path ω^n.

Step 2. Do for $t = 0, 1, 2, \ldots, T$:

Step 2a. Solve:

$$\hat{v}_t^n = \max_{a_t \in \mathcal{A}_t^n} \left(C_t(S_t^n, a_t) + \overline{V}_t^{n-1}(S^{M,a}(S_t^n, a_t)) \right),$$

and let a_t^n be the value of a_t that solves the maximization problem.

Step 2b. If $t > 0$, update $\overline{V}_{t-1}^{n-1}$ using

$$\overline{V}_{t-1}^n(S_{t-1}^{a,n}) = (1 - \alpha_{n-1})\overline{V}_{t-1}^{n-1}(S_{t-1}^{a,n}) + \alpha_{n-1}\hat{v}_t^n.$$

Step 2c. Find the post-decision state

$$S_t^{a,n} = S^{M,a}(S_t^n, a_t^n)$$

and the next pre-decision state

$$S_{t+1}^n = S^M(S_t^n, a_t^n, W_{t+1}(\omega^n)).$$

Step 3. Increment n. If $n \le N$, go to step 1.

Step 4. Return the value functions $(\overline{V}_t^N)_{t=0}^T$.

Figure 2.1: Forward dynamic programming algorithm using the post-decision state variable (Powell, 2011).

Figure 2.1 is an ADP algorithm from Powell (2011) that used the post-decision state variable. The notation is slightly different with a being used to represent the decisions or actions instead of x. Also, N represents the total number of iterations and α is what is known as the learning parameter and will be discussed later. Like the algorithm, the derivation of the learning version of Bellman's Optimality Equation around the post-decision state was adapted from Powell (2011).

Chapter 3: Research Problem Description

This chapter describes the elements of the dynamic programming (DP) model in detail. It begins with defining the purpose of the research and then focuses on the different parts of the model. It takes the ideas and techniques from the previous chapter and puts them in the context of the research problem.

3.1 Purpose

The objective of this research was to determine the optimal strategy for a single team when participating in the National Football League (NFL) Draft. Unlike many of the previous simulated or mock drafts, this research affords the team the ability to trade up or trade back in the draft while accounting for the uncertainty of the other 31 teams' decisions throughout the draft process. As mentioned earlier, mock drafts do not usually focus on one specific team, so to keep things simple, they tend to not look at teams' trade opportunities. In the defense of the draft experts, they also may not have much information, if any, as to who is offering to trade up or trade back with a specific team. When this information gets leaked or is public knowledge, then you will see it work its way into their mock drafts. This tends to happen most often in the first half of the first round. One also must take into consideration the fact that the teams could be attempting to deceive other teams to better their draft situations.

3.2 Model

To answer the research questions, Bayes' Theorem was used to develop a simulation framework to generate the Markov jumps in the absence of a Transition Probability Matrix (TPM). In addition to Bayes' Theorem, the main aspects of this research were solved using Approximate Dynamic Programming (ADP) and the learning version of Bellman's Optimality Equation. The simulation framework used the prior historical information of the draft and draft class rankings, as well as previous mock drafts from the draft experts. The simulation was used throughout the process to help determine the probability of the other teams drafting certain players. It was also used during the exploration phase to help create random actions to determine whom the decision maker was going to draft. The contribution/reward that was created from drafting the players chosen by this simulation were what the ADP model required to solve Bellman's Equation.

3.2.1 General Model Information

A draft was divided into t draft picks. There are seven rounds in today's NFL Draft with 32 draft picks in each round. This means that each NFL Draft has a minimum of 224 draft picks. There are more than 224 draft picks because of compensatory picks that are positioned between the end of the third round and the end of the sixth round. This research did not address those additional picks and focused on one draft pick per team per round for a total of 32 draft picks per round. This means that this research began with the decision maker having seven draft picks to bargain with.

3.2.2 Draft Simulation Created from Bayes' Theorem

Bayes' Theorem is not new to sports. However, it is usually used to calculate the probability of a 0.500 team having such a historically bad (or good) start to a season (Stuart, 2013; Kincaid, 2011). In this case, Bayes' Theorem was used to produce a draft simulation based on the guidance from Burke (2014a).

To develop a reasonable first guess for the prior distribution, we used ESPN Scouts Inc.'s (2020) Draft Rankings. We looked at the probability that the top-ranked player was drafted first, second, third, and so on. We then looked back at the last ten years of history. A simple example is a distribution for Chase Young, considered to be the number one ranked player in the 2020 NFL Draft. As the number one ranked player, his distribution would be something like 40% for pick #1, 30% for pick #2, 20% for pick #3, and 10% for pick #4. In other words, the top-ranked player does not have to wait long to hear his name called during the draft. This served as P(A) in Bayes' Theorem (Equation 2.1). The distribution, at this point, only took into consideration where the player was ranked and how accurate those rankings had been in the past. It did not consider which teams held which picks and what their team needs were at that point.

From there, we added some of the draft projections from some of the "experts." These projections were how the model started to account for team needs and draft order. We started with Mel Kiper from ESPN. We also had to account for Mel Kiper's accuracy in the past. As Burke (2014a) stated, "the weight of each addition of new information is only as strong as the information has proved to be accurate in the past." To continue our Chase Young example, we now had a 20% chance that Chase Young would be drafted with pick #1 and an 80% chance he would be drafted with pick #2. These probabilities represented $P(B|A)$ in Equation 2.1.

From here, Burke (2014a) multiplies $P(B|A)$ by P(A) to obtain the proportion for each pick number. We could ignore P(B) because the sum of all of the proportion of pick numbers must equal one. We then normalized them to achieve the same result. After $P(B|A) * P(A)$ has been calculated for each possible pick number, we got the following result.

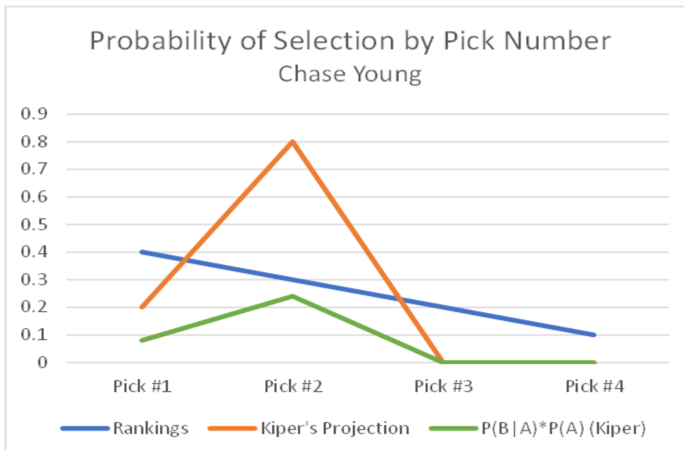

Figure 3.1: Probability Chase Young is selected by pick number using the player rankings and Mel Kiper's projection.

As you can see in Figure 3.1, Mel Kiper's projection was more confident than the player rankings since it included more information, like position, team need, and possibly even other information from the teams and/or players themselves. You can also see that the resulting distribution (green line) was lagging well below the others. However, once we normalized the data to ensure that it summed to one, we got the result in Figure 3.2.

After we calculated the posterior probability using Mel Kiper's projection and normalized the data, we could then do the process again. This posterior distribution served as the prior distribution and then we multiplied that by another

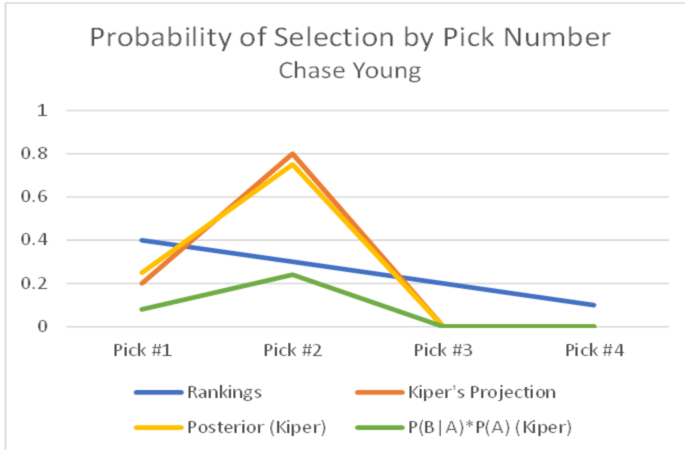

Figure 3.2: Probability Chase Young is selected by pick number using the player rankings and Mel Kiper's projection (after normalization).

"expert's" projection. In this case, we used Todd McShay from ESPN. This result is shown in Figure 3.3 and, as you can see, the $P(A|B)$ or posterior probability for both Kiper and McShay showed that Chase Young was extremely likely to be drafted with the #2 pick.

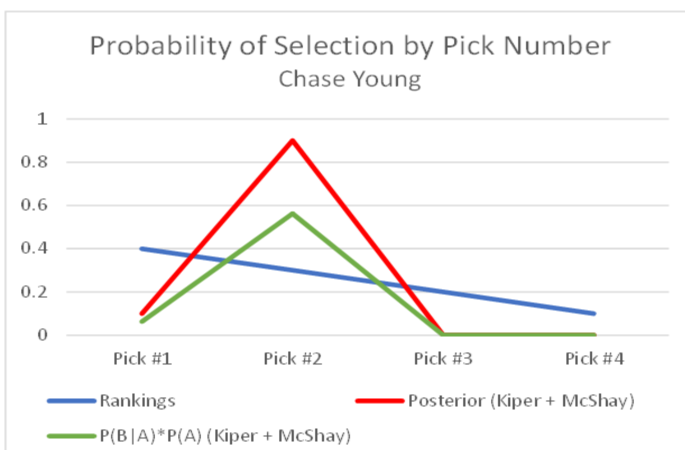

Figure 3.3: Probability Chase Young is selected by pick number using the player rankings and both, Mel Kiper's and Todd McShay's projections (after normalization).

Using the historical data, we were able to create similar probabilities for all the players in the rankings. Because it is much easier to predict the players at the top half of the draft than it is at the bottom, we grouped the players by their rankings similar to Burke (2014b). The players were put into groups of 1-5, 6-14, 15-32, 2nd round, 3rd round, and later to create a unique distribution by group.

3.2.3 Approximate Dynamic Programming Model

According to Powell (2011), there is a minimum of five elements to an ADP. These elements are the state variables, decision variables, exogenous information processes, a transition function, and an objective function. The following definitions are as defined by Powell (2011).

State variable. This captures all the information we need to make a decision as well as the information that we need to describe how the system evolves over time.

Decision variable. Decisions/actions represent how we control the process.

Exogenous information. This is data that first becomes known each time period (e.g., the demand for product, or the price at which it can be purchased or sold). In addition, we have to be told the initial state of our system.

Transition function. This function determines how the system evolves from the state S_t to the state $S_{(t+1)}$ given the decision that was made at time t and the new information that arrived between t and $t+1$.

Objective function. This function specifies the costs being minimized, or the contribution/reward being maximized, over a time horizon.

3.2.4 State Variables

A state is a multi-dimensional state space consisting of the remaining number of draft picks in this year's draft for the decision maker (represented by s_1), the remaining number of players eligible to be drafted by the decision maker at the most important position of need for that team (s_2), the remaining number of players eligible to be drafted by the decision maker at the second most important position of need for that team (s_3), the remaining number of players eligible to be drafted by the decision maker at the third most important position of need for that team (s_4), the remaining number of players eligible to be drafted by the decision maker at the fourth most important position of need for that team (s_5), and the remaining number of players eligible to be drafted by the decision maker at the fifth most important position of need for that team (s_6). Depending on the position and the depth of the draft at that position, the number of possible states could explode rather quickly. For example, in the 2020 NFL Draft, there were over 60 wide receivers eligible for the draft. Also, the average number of draft picks turns out to be just under seven picks. However, in the 2020 NFL Draft, some teams had anywhere from five to twelve picks (not counting the compensatory draft picks, which drove the maximum number of draft picks any team held to fourteen instead of twelve). Compensatory picks are the extra picks the league grants a team in the following year's draft if they lose more value in free agency than they bring in. If wide receiver was the most pressing position of need for the team, inside linebacker was the second most important position of need, offensive tackle was the third most important position of need, running back was the fourth most important position of need, and defensive tackle was the fifth most important position of need, the team would start the draft in the state (7, 62, 26, 28, 42, 25) (Campbell, 2020). This means there would be over 441 Million possible states. However, there are ways to reduce this number slightly.

The teams will do their homework before the draft and focus on the players that will fit in their system. For example, of the 62 potential wide receivers eligible to be drafted, the general manager and his staff will try and determine which ones would fit in their offense (or special teams) and contribute to the team either now or in the near future. They could reduce this number down to 20 or so wide-receivers, if not less. In addition, they could focus on only a subset of those 20 wide receivers depending on which round the draft is in. In other words, only a handful of those 20 would be worth spending a first-round draft pick on. In the second round, a few of the players in that subset may have been drafted already, thus reducing the number of wide receivers in the subset. They then might move a few more into that subset that they would consider drafting in the second round. These are a couple of options to reduce the number of states and make the problem more manageable, as well as realistic.

3.2.5 Decision Variables

The decision maker, the general manager in this case, has many decisions to make throughout the draft process. While most of the trades occur before the draft, especially in the years leading up to it, some trades take place during the draft. The draft-day trades tend to involve draft picks, while the trades that take place before the draft usually involve players, at least on one side of the equation. This research did not address the trades that involved players, cash, or that took place before the draft itself, even if they involved draft picks. Also, to simplify the decision making, this research limited how far up or back the decision maker could trade their draft picks.

The decisions a general manager will have to decide upon will not just boil down to what player to take with each pick as many of the mock drafts suggest. The goal of this research was to allow the decision maker the opportunity to trade up to get their player or the ability to trade back to accrue more draft capital and possibly still get their player. Initially, the decision maker would have the ability to move up or back five draft positions. In other words, if the decision maker held the 30th draft pick, they would have had the ability to trade up to as high as the 25th draft pick or trade back to as low as the 35th draft pick.

Therefore, once the model was within five draft picks of the decision maker, the possible actions were to trade up or do nothing. Trading up consisted of trading up to draft the best player available, trading up to draft a player at a position of team need #1, trading up to draft a player at a position of team need #2, and so forth up to team need #5. If the decision maker did not trade up and it was their turn to make a selection, they would have the same options as above or the ability to trade back anywhere from one to five positions. The assumption made with trading up or back is that these draft picks would not subsequently get traded.

3.2.6 Exogenous Information Processes

The exogenous information process consisted of the changes to the available resources or draft-eligible players still on the board. These changes were represented as W_{t+1}. This random variable represented the changes to the state space that took place based on the information that arrived during the time interval t to $t+1$ as shown in Figure 3.4. In addition to the changes to the available players, we also had to account for the possibility of trading up or back. "A sample realization is represented by ω_i where W_{t+1} (ω_i) is an observation of randomness inherent in the system arriving between time t and $t+1$. The sample can be collected through real-world observation of physical processes, sampling known distributions, or applying computer simulation of a complex process" (Hughes, 2017).

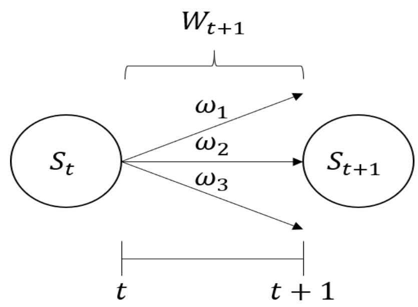

Figure 3.4: State Transition Model Under Uncertainty

For this research, the uncertainty of whom the other teams were going to draft was modeled using historical data as to how accurate the experts were in creating their mock drafts along with the rankings of the eligible players. The rankings served as the initial guess to account for talent, while the draft experts helped account for the teams' needs for each of the other 31 teams. These probabilities served as the inputs to a computer simulation, which then selected players for the other teams. These draft probabilities directly impacted future selections and also played key roles in future state transitions.

3.2.7 Transition Function

To determine the evolution of the system, we used a transition function. The transition function was denoted as

$$S^M(S_t, x_t, W_{t+1}) \tag{3.1}$$

which accounted for the new information W_{t+1} that had arrived between time steps, as well as taking into consideration the current state (S_t) and the action taken at time t (x_t). Therefore, the new state S_{t+1} was dependent on the current state, the action taken at time t, and the random variable representing the uncertainty of whom the other teams selected, W_{t+1}.

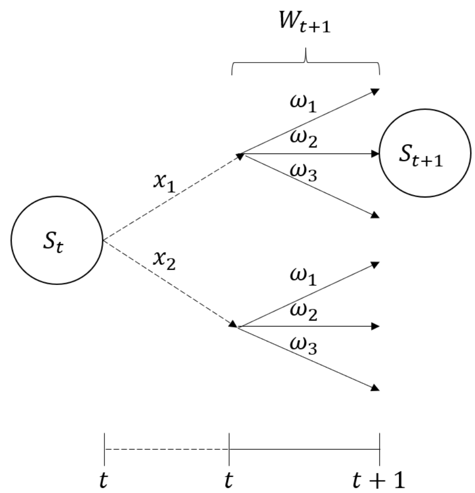

Figure 3.5: Modified State Transition Model

As you can see in the example in Figure 3.5, even just having a second decision or action to choose from doubles the size of the model from three branches to six branches. An important note about the modified state transition model pictured in Figure 3.5 is that the decision is made instantaneously at time t and before the uncertainty sets in with the random variable W_{t+1} (Hughes, 2017). In this research problem, the decision maker had more options than just two. As discussed previously in Section 3.2.5, the decision maker had the following options:

x_1 = draft a player at a position of team need #1

x_2 = draft a player at a position of team need #2

x_3 = draft a player at a position of team need #3

x_4 = draft a player at a position of team need #4

x_5 = draft a player at a position of team need #5

x_6 = draft the best player available (if they do not fill one of the positions of team need)

x_7 = do nothing (if the draft pick is before the decision maker's scheduled pick) or trade back (if it is the decision maker's scheduled pick)

The probability of going from one state to another state was going to differ from simulation to simulation depending on what players were still available. It was possible to have players that did not fall into a team need that were going to be an option in some simulations and not be an option in others. This caused differences in going from one state to another (even the same two states) over different iterations. The probabilities were based on the rankings of the players, as well as the draft expectations of the experts as described in Section 2.4.1. However, after running many iterations of the simulation, the probabilities reached a sort of steady-state. For example, in the long run, Player A was still on the board for the decision maker's first draft pick selection 80% of the time.

3.2.8 Objective Function

According to Powell (2011), there are a number of stochastic applications that require the use of the following objective function:

$$\max_{\pi} \mathbb{E}^{\pi} \left\{ \sum_{t=0}^{T} \gamma^t C_t^{\pi} \Big(S_t, X_t^{\pi}(S_t) \Big) \right\} \tag{3.2}$$

Unfortunately for most problems, solving Equation 3.2 is computationally intractable, but it does provide the basis for identifying the properties of optimal solutions, as well as finding and comparing "good" solutions. Powell (2011) goes on to state that one can solve a stochastic optimization problem of the same form as Equation 3.2 by recursively computing Bellman's Optimality Equation (see Equation 2.2).

If you remember back to Section 2.4.2 and the discussion about Bellman's Equation (Equation 2.2), there are two main parts. The first half of the equation deals with the immediate contribution created by the combination of the current state and the decision maker's action at time t. The second half of the equation calculates the expected total value to the end of the problem.

In this research, once the decision maker decided what action they were going to take, the contribution or reward, $C_t(S_t, x_t)$, was calculated. The contribution depended on the current state S_t, as well as the action x_t that was taken at time t. In this model $C_t(S_t, x_t)$ was a deterministic function of the state and action represented as follows:

$$C_t\big(S_t, x_t\big) = \left(\frac{b_i g_i}{w_i}\right). \tag{3.3}$$

i was the index used to account for the draft pick. b_i was whether or not the player drafted would be considered a backup with the team's current roster. This variable took on a value of 50 if the player was a backup and a value of 100 if the player was projected to be a starter. This assumed that the highest graded players at the positions would be starters. One thing to note here is the number of starters differed by position. For example, only one quarterback was a starter, while two wide receivers would be considered starters. A team could update the number of starters based on the system they run for both offense and defense.

g_i was the graded value of the player drafted. Players eligible for the draft usually have values ranging from 30 to the upper 90s, where closest to 100 is best. Of course, this also depends on your source. We used ESPN for this research. Of course, in reality, the teams are going to assign their grades to draft prospects and the players on their roster. Regardless of where the grades come from, the decision maker needs to ensure that the prospects in the draft are graded on the same scale as the players on their current roster. This will help with the validity of the calculation of b_i.

As for the denominator of the contribution function, this is how the model incorporated a loss for not drafting players at a position of need. The severity of this loss depends on the decision maker, but for this research, we incorporated the following rules. w_i = a binary number corresponding to whether or not the player is at a position of need. In other words, if the player played a position of team need, then the weight of this draft pick, $w_i = 1$. If the player did not play a position of need, then $w_i = 2$.

The expected total value also depended on the players that were selected and the positions they played. The expected total value of landing in all possible post-decision states was different depending on the general manager's decisions. To determine which action or decision produced the maximum value for a given state, we needed to sum both the contribution or reward and the post-decision value function.

These five elements, as described by Powell (2011), along with the estimated value of a state

$$\hat{v}_t^n = \max_{x_t \in X_t^n} \left(C_t\big(S_t^n, x_t\big) + V_t^{n-1}\Big(S^{M,x}\big(S_t^n, x_t\big)\Big)\right) \tag{2.8}$$

worked together to allow us to solve the learning version of Bellman's Optimality Equation around the post-decision state,

$$V_{t-1}^n(S_{t-1}^{x,n}) = (1-\alpha^{n-1})V_{t-1}^{n-1}(S_{t-1}^{x,n}) + \alpha^{n-1}\hat{v}_t^n. \tag{2.9}$$

Another key element of Equation 2.9 was the learning parameter, or α, which is discussed in detail in Section 4.3.

Chapter 4: Solution Methodology

I used reinforcement learning (RL) to solve Bellman's Optimality Equation around the post-decision state (Equations 2.8 and 2.9). RL, or simulation-based Dynamic Programming (DP), is primarily used for solving Markov decision processes (MDP) and semi-Markov decision processes (Gosavi, 2015). It was developed by researchers in the computer science community, where it is referred to as machine learning, artificial intelligence, or RL. The word "reinforcement" is used due to the fact that the RL algorithm learns through trial and error or feedback (Gosavi, 2015). Gosavi (2015) goes on to explain the origin of other name suggestions, such as neuro-dynamic programming (NDP) (Bertsekas and Tsitsiklis, 1996) and adaptive or Approximate Dynamic Programming (ADP) (Werbos, 1987).

This chapter includes a brief discussion of how RL can work around the two curses mentioned in Section 2.4.2, a quick comparison of RL and DP, and an introduction to the Robbins-Monro Algorithm. This chapter also highlights the differences in exploration and exploitation within the Approximate Dynamic Programming (ADP) algorithm. Finally, the chapter concludes with an introduction to the two main metrics used to determine the effectiveness of the different strategies and a discussion on the rules of the draft, as it applied to the research model.

4.1 Navigating the Curses

As discussed in Section 2.4.2, there are two curses that create issues when using DP. The two curses are known as the curse of dimensionality and the curse of modeling. RL provides ways around both of these issues or curses. To avoid the curse of modeling, RL uses simulation to get around the need for the transition probabilities and the reward matrices. In complex problems with many random variables, the task of finding the transition probabilities and reward matrices can be extremely difficult, if not impossible. As for the dimensionality curse, RL uses function approximation to assist in avoiding the need to store all of the values of the state-action pairs (Gosavi, 2015).

For problems that used to be considered intractable, we can now use a combination of RL and DP. RL is used to simulate the system to generate samples of the value function (Gosavi, 2015). RL can also be blended with many function approximation techniques that allow the user to store the value function of hundreds of thousands of states using a few scalars (Gosavi, 2015). Gosavi (2015) goes on to discuss the tradeoffs of using RL, DP and even, heuristics to solve optimization problems. He concludes by stating that RL picks up the slack on problems where DP is infeasible and heuristics do not perform very well. However, Gosavi (2015) also adds that DP should be used when all of the information, such as transition probabilities, rewards, and transition times are known since DP is guaranteed to generate an optimal solution. Table 4.1 looks at the different levels of modeling effort required for each of the three methods and also, the solution quality that is generated by these methods.

Table 4.1: A comparison of the level of modeling effort required and the quality of the solution between RL, DP, and heuristics (Gosavi, 2015).

Method	Level of Modeling Effort	Solution Quality
DP	High	High
RL	Medium	High
Heuristics	Low	Low

4.2 RL and DP

RL branches from DP. It is not its own heuristic, but instead provides the user with a way to perform DP within a simulator. Since we know that DP algorithms are guaranteed to find an optimal solution, we want to keep our RL algorithms as closely tied to DP as possible. In other words, the RL algorithms need to be derived from the DP algorithms as much as possible. While both RL and DP require the distribution of the governing random variables as an input, one can see in Figure 4.1 that the techniques differ from there. DP uses the distributions to determine the transition probability matrix (TPM) and transition reward matrix (TRM). Then, the user finds a suitable algorithm to generate a solution. In RL, the TPM and TRM are not estimated, but instead, the system is simulated using the distributions. Then, the user finds a suitable algorithm, within the simulator, to obtain a solution (Gosavi, 2015).

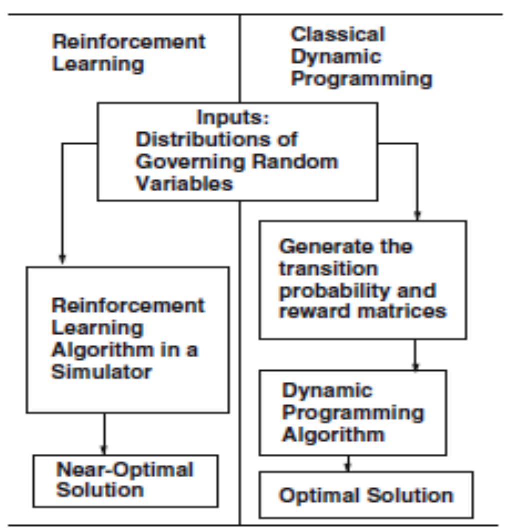

Figure 4.1: A graphic featuring the differences in the methodologies of RL and DP (Gosavi, 2015).

To transition to RL from DP, we need to look back at the algorithm shown in Figure 2.1. More importantly, we need to focus on the learning parameter, α. This parameter is also known as the learning rate or step size, and it plays a critical role in ensuring convergence to the optimal solution (Balakrishna, 2009).

4.3 Robbins-Monro Algorithm

There are many schemes used today for proving the convergence of stochastic gradient algorithms. Powell (2011) discussed the three properties that any alpha decay scheme must have.

$$\alpha_{n-1} \geq 0, \qquad n = 1, 2, ..., \tag{4.1}$$

$$\sum_{n=1}^{\infty} \alpha_{n-1} = \infty, \tag{4.2}$$

$$\sum_{n=1}^{\infty} (\alpha_{n-1})^2 < \infty. \tag{4.3}$$

The first and most obvious property (Equation 4.1) is that the stepsizes must be nonnegative. The second and most important property (Equation 4.2) is that the infinite sum of stepsizes must be infinite. If Equation 4.2 did not hold, the algorithm might stall too soon. Finally, Equation 4.3 requires that the infinite sum of the squares of the stepsizes be finite. This condition essentially requires the stepsize sequence to converge somewhat quickly. In the end, we only need one good scheme that works for ADP. While there are many schemes, not all can survive long-term or that just have a single tunable parameter, but the Robbins-Monro Algorithm works perfectly for ADP.

The Robbins-Monro Algorithm is a popular algorithm invented in the 1950s (Robbins and Monro, 1951) and it can assist us in estimating the mean of a random variable from its samples (Gosavi, 2015). The rest of this section uses the algorithm summaries from both Gosavi (2015) and Balakrishna (2009).

Using a straightforward averaging process, one can estimate the mean of a random variable from n samples. In other words, if X is a random variable, let x_i represent the ith independent sample of X and $E(X)$ denotes the expected value or mean of the random variable X. Then, following the strong law of large numbers, with probability 1,

$$E\left[X\right] = \lim_{n \to \infty} \frac{\sum_{i=1}^{n} x_i}{n} \tag{4.4}$$

A simulator can be used to generate the samples. Gosavi (2015) goes on to derive the Robbins-Monro Algorithm from this simple averaging process. Let X^n represent the estimate of X for the nth iteration (after n samples have been obtained). Thus:

$$X^n = \frac{\sum_{i=1}^{n} x_i}{n}. \tag{4.5}$$

Now,

$$\begin{aligned}
X^{n+1} &= \frac{\sum_{i=1}^{n+1} x_i}{n+1} \\
&= \frac{\sum_{i=1}^{n} x_i + x_{n+1}}{n+1} \\
&= \frac{X^n n + x_{n+1}}{n+1} \qquad \text{(using Equation 4.5)} \\
&= \frac{X^n n + X^n - X^n + x_{n+1}}{n+1}
\end{aligned}$$

$$= \frac{X^n(n+1) - X^n + x_{n+1}}{n+1}$$

$$= \frac{X^n(n+1)}{n+1} - \frac{X^n}{n+1} + \frac{x_{n+1}}{n+1}$$

$$= X^n - \frac{X^n}{n+1} + \frac{x_{n+1}}{n+1}$$

$$= (1 - \alpha^{n+1})X^n + \alpha^{n+1}x_{n+1} \ \ \text{if}\alpha^{n+1} = 1/(n+1),$$

$$\text{i.e., } X^{n+1} = (1 - \alpha^{n+1})X^n + \alpha^{n+1}x_{n+1}. \tag{4.6}$$

Equation 4.6 represents the Robbins-Monro Algorithm, with α representing our learning parameter or learning rate. It should be evident that when $\alpha^{n+1} = 1/(n+1)$, the algorithm is the same as direct averaging. The alpha-decay scheme using the Robbins-Monro Algorithm allows the user to give less weight to the most recent observation and thus, use what we have learned over multiple iterations. It also helps in case the user makes a bad decision along the way.

4.4 Exploration Versus Exploitation

A common problem with ADP that mirrors real life is: do we accept our current estimates and use them to drive our decisions, do we revisit a state to update our estimates, or do we make a different decision, just to try something new? This choice that the decision maker faces is known as the exploration versus exploitation problem in the ADP literature (Powell, 2011). Visiting states can cost the decision maker precious time and money, so the future value of an action must be taken into consideration in terms of improving future decisions. As a decision maker, do you decide to explore a state or do you “exploit” your current estimates of future values to make what appears to be the best available decision (Powell, 2011)?

When one is conducting exploration, they are visiting states with the intent of obtaining better or updated information about the value of being in that specific state. The decision maker does not care if the decision or action is the best based on the current estimated values. This is not the case for exploitation. During exploitation, the decision maker absolutely cares if the decision or action is the best and they are simply trying to "exploit" the best of their current estimated values.

The first way to explore is to randomly choose another state to visit after you update the value of the current state. You do this without paying attention to what state you are in or what state you are going to next. Also, while exploring, you do not use the *max* or *min* operator in Equation 2.8. The second way to explore is to randomly choose an action that then leads to a different state. The second option is a more valuable approach because it allows you to stay in the feasible region of the problem. In other words, if you are picking randomly among possible actions, you are only going to visit a state that you could reasonably reach. You will not be visiting states that you could never reach.

Exploitation, in its pure form, can be seen as a greedy strategy since the decision maker is making what are believed to be the best decisions based on the current estimated values. Exploitation strategies center the decision maker's attention on states that appear prosperous or states with some probability of being valuable states. This, however, can force the decision maker into a local solution if the estimates of the value of some states are not great.

A common strategy is to find a comfortable mix of both, exploration and exploitation (Powell, 2011). One such strategy is known as Epsilon-Greedy Exploration. This strategy forces us to explore to a certain degree, while the exploitation steps do their job and focus on the states that look to be the most valuable.

When the exploration phase is done, the algorithm moves into the learning phase. The learning phase generally has ten times more iterations than the exploration phase. Learning will continue through several iterations until the value functions have converged and the mean squared error (MSE) has stabilized. Once learning is complete, the values of the parameters will be used as inputs to the learnt phase. During the learnt phase, the ADP algorithm is tested. A short-term metric, Team Score, and a long-term metric, Team Value, will be calculated offline following the learnt phase.

4.5 Team Score and Team Value

Once the learnt phase was complete, the results were converted into a Team Score and a Team Value. There were two slightly different calculations taking place offline to grade the drafts, the first one was a Team Score for the upcoming season or short-term and the second one was a Team Value for the next five seasons or long-term. Both metrics took into consideration the average percent of the plays that the position has played in the current scheme. In other words, the #1 wide receiver plays 63% of the offensive snaps, while the #2 wide receiver only plays 59% of the offensive snaps. Even the #5 wide receiver logs 31% of the offensive snaps in the scheme. Different positions had different percentages. Offensive positions only used offensive plays, defensive positions only used defensive plays, and special teams positions only used special teams plays to calculate the percentages. If the user wanted to, they could incorporate the special teams plays into the offensive and defensive numbers since many of those starters are used in certain special teams' roles. Ideally, these percentages could be taken from multiple years in the same offense or from a team that runs a similar scheme if enough years are not available with the current team.

Multiple years would help avoid low numbers due to injuries, however, this can be worked around by not counting snaps lost due to injury. Unfortunately, that would be much tougher to calculate the percentage. The following two subsections explain the calculations of the two metrics.

4.5.1 Short-Term Metric, Team Score

The short-term metric or short-term calculation of Team Score only looked at the score for the upcoming season. This calculation considered the new team roster and re-ranked the positions. If a tight end were taken in the draft, the re-ranking then determined where he would fall on the depth chart given his draft grade compared to the players' grades at that position. The depth chart position is matched with the percent of snaps that position on the depth chart had taken historically and multiplied by the grade of the player filling that role, whether they were drafted or already on the roster. This process continued for all 53 members of the updated roster. If a player drafted was not one of the 53 members, then that player would not contribute to the Team Score for that year. These players were assumed to fill roles on the practice squad and/or cut from the team altogether.

After the scores were calculated for all 53 players, they were summed up based on their side of the ball. All the offensive players were summed up and their total value was divided by 25 to get the offensive Team Score. The same process was followed for the defensive side of the ball, while the special teams was divided by 3 for the punter, the kicker, and the long snapper. The offensive and defensive players that were lower on the depth chart tended to log many special teams' snaps, but as mentioned above, we did not consider those. The denominator of 25 was based on the initial make-up of the 53-man roster. The current team being analyzed just happened to have 25 offensive, 25 defensive and 3 special teams' players identified. The sum of the three sides of the ball was the short-term metric or Team Score.

4.5.2 Long-Term Metric, Team Value

The long-term metric, Team Value took a slightly different approach than the Team Score for the first year. For the first year of the Team Value, it assumed that the younger players were not at their full potential yet. This was assuming that their grade was a full-potential grade, whether they are there yet or not. With each year of experience, the player got a little closer to that full-potential grade until after their fourth year in the league when they reached their full potential. The rookies were going to provide 90% of their grades in the first year. Their grades improved by 2.5 percentage points each season until after their fourth year when they provided all 100% of their graded value. Once again, this not only applied to the rookies in the draft but also the current players on the roster. For example, a player in his third year in the league was still only going to provide 95% of their graded value to the overall Team Value.

As Team Score was calculated by re-ranking the players using the depth chart positions and snap percentages being multiplied by the players' grades, the same was done for the first year of Team Value. For the second year, the players' grades were upgraded by gaining another year of experience or another 2.5 percentage points of their full-potential grade. The players whose contracts had expired and had become free agents or possibly retired were dropped from the 53-man roster. The remaining players were then re-ranked and given their new order on the depth chart. The second year may or may not have had 53 members on the team due to too many players' contracts expiring. However, it would be consistent across the board when evaluating the different drafts.

This process was repeated for the third, fourth, and fifth years. The fifth year only caught any current players with contracts long enough to still be on the team and any first-round draft pick, as their contract under the CBA is allowed to be for five years as opposed to four years. The rest of the draft picks dropped off the roster in the fifth year. The Team Value did not take into consideration free agent signings and extensions but could easily be redone to account for those settings. Players who did not make the 53-man roster, but still had years remaining on their contracts contributed slightly to the value, but not by much. Once all five years were calculated, the values were summed to become the Team Value.

4.6 Rules of The Draft Model: Assumptions and Simplifications

To get the model working correctly and quickly, we simplified the draft process somewhat. When it was feasible, the model operated as the National Football League (NFL) Draft operated. Therefore, the model still maintained 32 teams as part of a seven-round draft. The decision maker represented one of these teams and would initially be assigned the 30th pick in the first round. For the model, this meant the decision maker would start with the 30th pick in every round. While this is truly how the draft operates, not counting compensatory picks, there are so many trades that have taken place before the draft that it is hard to tell what the draft looked like before them all.

The order of the draft followed the initial order of the 2020 NFL Draft as assigned by the standings of the 2019 NFL Season. The model did not take into account any trades that occurred leading up to the draft and not any that took place during the draft. We simply focused on 32 teams each owning one pick in each of the seven rounds. We did allow the decision maker to trade up and trade back a maximum of five positions in the order, but that is the only trading allowed. And it was only allowed for the first three rounds. In the fourth round, things were modified somewhat to accommodate trades in the earlier rounds. Before we discuss these modifications, let's first discuss the trade options that were allowed in the earlier rounds.

Using the NFL and AFL [American Football League] Draft History on Pro-Football-Reference (2021), we were able to gain an idea of the average cost for trading up and back within a small range at the back end of each round. While trading up one is not always going to cost the same as trading up five, we made the assumption initially, that the costs are the same. Thus, trading up a maximum of five positions from the 30th pick in the first round was worth a fourth-round pick. Trading up would cost the decision maker a fourth-round pick while trading back would gain the decision maker a fourth-round pick. In the second round, the same range at the same position of the round was worth a fifth-round pick. Finally, the third round was worth a sixth-round pick. Because the decision maker was the 30th pick, there were only two picks remaining in that same round. Therefore, trading back three, four, or five positions would move the decision maker out of that round. This was why the fourth round had to be handled differently. Tables 4.2 and 4.3 provide examples of trading up two versus trading back four positions in the first round. As you can see in Table 4.3, trading back four drops the decision maker out of the first round, but provides them a pick early in the second round plus another pick early in the fifth round.

Trading up a maximum of five positions in the fourth round had no issue. Even trading back one or two positions did not cause any problems because the cost of trading up or back at this point of the fourth round was worth a seventh-round pick. Trading back three or more positions would push the decision maker out of the fourth round and into the fifth. However, the gaining pick would be after the seventh round and since this model only handled a single draft year, this trade was

Table 4.2: An example of trading up two positions in the first round. As you can see, trading up two positions moves the decision maker from the 30th pick of the first round to the 28th pick of the first round, but cost the decision maker their 30th pick of the fourth round.

Before Trade		
Round	**Pick**	**Team**
1	28	BAL
1	29	TEN
1	**30**	**GB**
1	31	SF
1	32	KC
⋮	⋮	⋮
4	28	BAL
4	29	TEN
4	**30**	**GB**
4	31	SF
4	32	KC

After Trade		
Round	**Pick**	**Team**
1	**28**	**GB**
1	29	TEN
1	30	BAL
1	31	SF
1	32	KC
⋮	⋮	⋮
4	28	BAL
4	29	TEN
4	30	BAL
4	31	SF
4	32	KC

Table 4.3: An example of trading back four positions with the first-round selection. Trading back four positions pushes the decision maker out of the first round altogether. They gained two picks, however, with the second picks in the second and the fifth rounds. This is in addition to maintaining their 30th picks in those same rounds.

Before Trade		
Round	**Pick**	**Team**
1	**30**	**GB**
1	31	SF
1	32	KC
2	1	CIN
2	2	WAS
⋮	⋮	⋮
4	**30**	**GB**
4	31	SF
4	32	KC
5	1	CIN
5	2	WAS

After Trade		
Round	**Pick**	**Team**
1	30	WAS
1	31	SF
1	32	KC
2	1	CIN
2	**2**	**GB**
⋮	⋮	⋮
4	**30**	**GB**
4	31	SF
4	32	KC
5	1	CIN
5	**2**	**GB**

not feasible. In reality, this type of trade would usually involve a late-round pick in the following year's draft.

With this in mind, the fourth round was handled a couple of different ways. If the decision maker did not trade at all in the first round, then the fourth round provided them the option of trading up a maximum of five positions and trading back a maximum of two positions. If the decision maker traded up in the first round, then their fourth-round pick no longer belonged to them and they had no selection in the fourth round. If the decision maker traded back in the first round, this only allowed the decision maker the opportunity to trade up. We did not want the model trying to trade a pick in the fourth round to the decision maker that already belonged to the decision maker based on a trade in the first round. For the pick the decision maker gained in the fourth round, there was no trading at all. This became the norm for all picks gained through trading. An outline of this is shown in Figure 4.2.

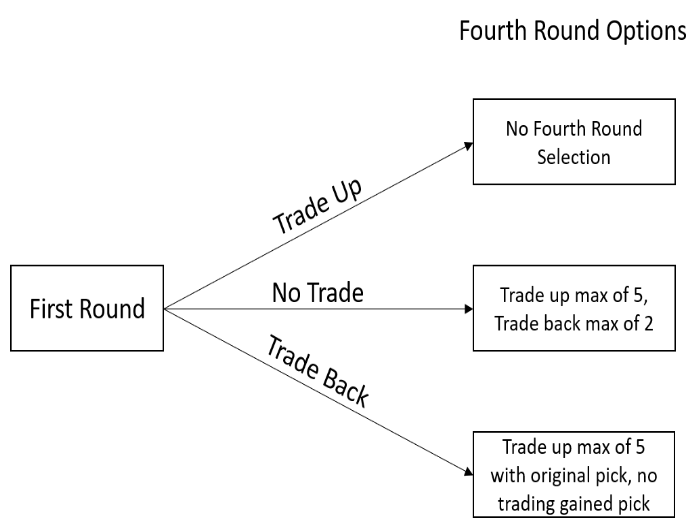

Figure 4.2: Depiction of the results of trading or not trading the first-round pick and its effects on the fourth-round selection(s).

Similar to the issue with the fourth round and trading too far back, the cost of trading in the fifth, sixth, and seventh rounds usually contained a late-round draft pick from the following year's draft. Therefore, trading in these rounds also became infeasible. At least, until one or more years are added to the draft model.

Chapter 5: Experimentation

In trying to determine the optimal draft strategy, we looked at the two main strategies employed by the general managers today in the National Football League (NFL), as well as the hybrid approach. These two strategies are the best player available (BPA) and team needs. The BPA strategy is also referred to as the greedy strategy because the decision maker is always looking to take the best player available, whether the player fills a positional need for the team or not. It is greedy because the model is going to focus solely on the immediate contribution and draft the highest of the available players. The team needs strategy focuses on only a handful of positions that the team sees as their priorities to fill in the draft. The hybrid strategy means the decision maker sometimes takes the highest BPA, while other times the decision maker drafts for team need. The Approximate Dynamic Programming (ADP) strategy we used falls under the hybrid approach. Unless specified to be driven by only team needs, the ADP strategy is the hybrid approach. The ADP strategy looked over the entire draft, not just the immediate contribution to determine whom to draft. In this chapter, we describe the experimentation used to determine the optimal draft strategy.

5.1 Learning Phase

5.1.1 Exploration

Looking back at Section 4.4, we discussed a few different ways to conduct exploration and exploitation. Instead of specifying a specific fraction of iterations for the decisions to be chosen at random (exploration) (Powell, 2011), we created an exploration parameter and allowed it to die off after about 15,000 iterations. The exploration parameter started at 0.8 and decreased with each iteration. The process was like the alpha decay scheme, with the exception that we wanted the exploration parameter to die off completely, whereas the alpha parameter needed to stay above 0.3 after 100,000 iterations. A random number was taken with each round of the draft and if the random number was greater than the exploration parameter, then the *max* operator of Equation 2.8 was used. If it was less than the exploration parameter, then we explored using random actions. This initial decision is depicted in Figure 5.1.

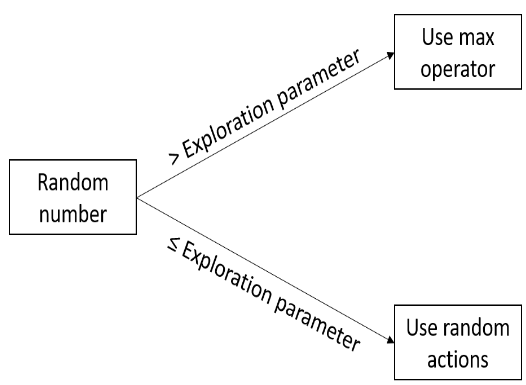

Figure 5.1: Exploration parameter process.

Initially, the model spent most of the decisions by choosing random actions.

However, as the number of iterations grew and the exploration parameter got smaller, the number of random actions or exploration decreased, until the model no longer explored. This point was designed to be around 15,000 iterations as you can see with the orange points in Figure 5.2. Also depicted in this graph is the alpha parameter, which was decayed according to the Robbins-Monro Algorithm discussed in Section 4.3.

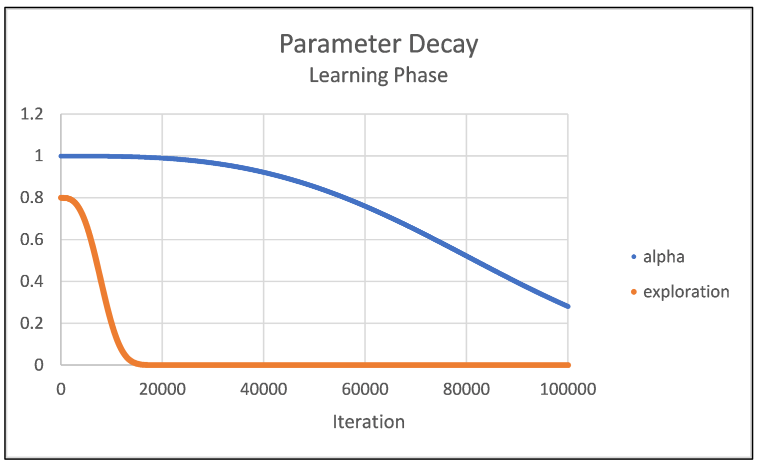

Figure 5.2: Alpha and exploration parameter decay experienced throughout the exploration and learning phases. The exploration parameter died off, allowing the model to move into exploitation. The alpha parameter decreased but never totally died off to allow for further learning.

To keep this problem manageable, one of the limitations we had to create was to limit how far a decision maker could trade up or trade back in the draft. We decided to limit the trading to plus or minus five picks in the draft. In other words, the decision maker with the 30th pick, could trade up as high as the 25th pick or trade back as low as the 35th pick. We will refer to these eleven draft positions or picks as the draft window. During exploration, when the model is taking random actions, this means there were eleven equally likely options for the model to take. These options are depicted in Figure 5.3.

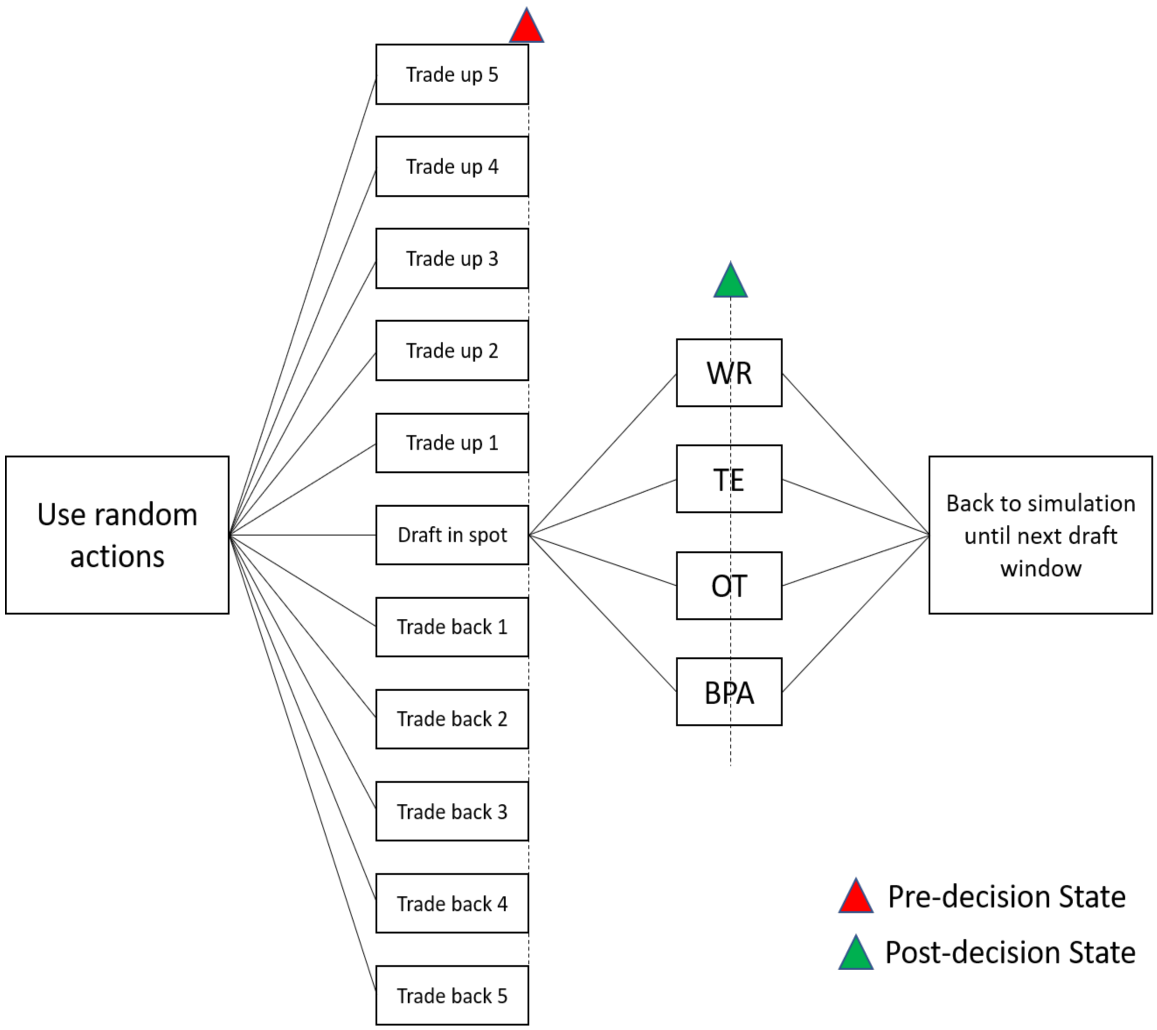

Figure 5.3: Depiction of the draft window and the multiple options available using random actions.

Each of the trade positions (25−35) had a 1/11 chance of being selected. Once a draft position was chosen the uncertainty was simulated up until that point and the pre-decision state was identified. Then, another random number was taken with a 25% chance of selecting a wide receiver, a tight end, an offensive tackle, or the best player still available on the draft board. After a pick had been made, the post-decision state was marked, and the value of the previous state was updated using Equation 2.9. Finally, the model handed things back over to the simulation, and the uncertainty of whom the other teams would draft up until the next draft window was simulated.

5.1.2 Exploitation

Once the exploration parameter had died off, the exploration phase transitioned over to exploitation. This was not a straightforward transition because the model could conduct either exploration or exploitation for nearly the first 15,000 iterations. However, after this point, the exploration phase transitioned fully to exploitation. During exploitation, the *max* operator, as depicted in Figure 5.4, was used exclusively.

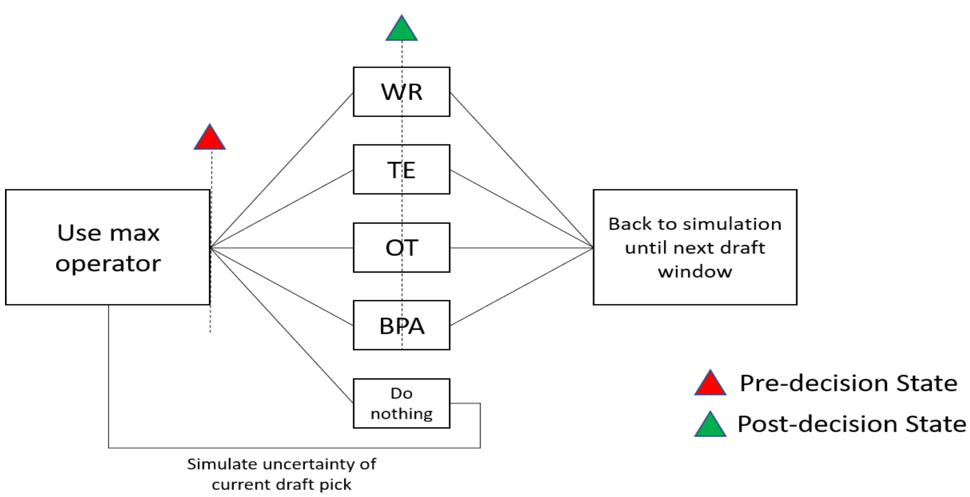

Figure 5.4: Depiction of the options available when the *max* operator was used.

When the model used the *max* operator, things would go slightly different from before. The *max* operator compared the values of the future states plus the immediate contribution for making that decision as depicted in the objective function, Equation 2.8. It did this at the beginning of the draft window. In this case, there were five future states and their immediate contributions being compared. It is the same four positions as before with a wide receiver, a tight end, an offensive tackle, or the best player still available on the board. However, the fifth option for the model to consider was the value of doing nothing or in other words, not trading up five positions to select a player.

If selecting 'do nothing' had the higher value, the model would allow the simulation to simulate the uncertainty for one team's draft pick and re-evaluate the values of the new future states at the new pre-decision state. If 'do nothing' was selected for the 25th overall pick, it would mean that the team was not trading up from 30th to 25th to draft a player. The draft would then move to pick 26 after simulating the uncertainty of one pick and the *max* operator would be used again. This process was allowed to continue until a player was chosen or the draft window closed. In this case, that would be with pick 35, at which point the model would then only have the four choices corresponding to the four positions. If one of the positions had a higher value, the model would select the player at that position, update the post-decision state, as well as the value of the previous state using Equation 2.9. Then, just like in the random action process, the model would turn things back over to the simulation to simulate the uncertainty up until the beginning of the next draft window.

5.1.3 Convergence

In both exploration and exploitation, we observed the mean squared error (MSE) of the gradient. The MSE provided a single window for us to assess whether the model was learning correctly. During exploration, MSE was expected to climb, but as the model started to reach out to a few more states and it seemed to gravitate towards some "good states" with different actions, the MSE was expected to take a downward turn. This can be seen in Figure 5.5 and coincided with the exploration parameter starting to die out. Around the middle of the exploration window, you see the MSE start its downward trend. We then looked for the downward trend to continue and eventually, the MSE should start to slow down in terms of decreasing, without rising, and start to converge. All of this was as alpha decayed. In Figure 5.5, you can see the MSE was starting to flatten somewhat towards the end of the 100,000 iterations.

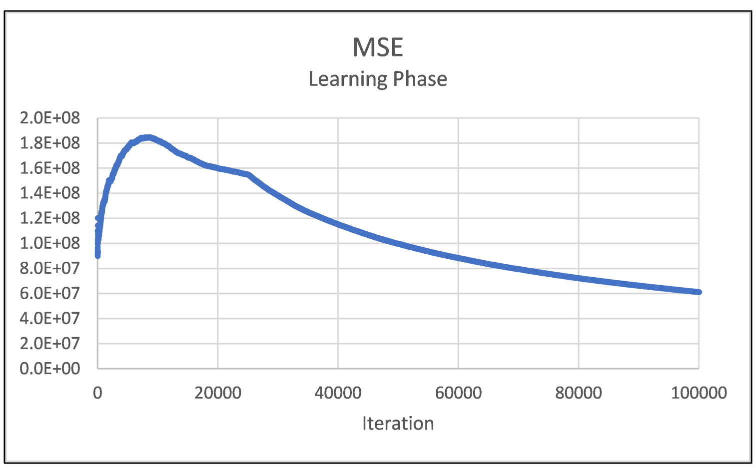

Figure 5.5: Observation of the mean squared error (MSE) of the gradient during the learning phase.

5.2 Learnt Phase and Scoring

After completing the learning phase, it was then time to run a learnt phase for a single draft using the results and a table obtained from the 100,000-iteration run that contained the states and the future values associated with being in those states. This table allowed us to recursively solve Equation 2.8, to make the decisions on which position to draft by evaluating all possible actions at each t. When the gamma value was set to 0.9, the model determined the ADP draft, but when we changed the gamma value to 0.0, the model selected the draft using a greedy strategy. The greedy strategy is also referred to as the BPA Strategy. In other words, it always took the largest immediate contribution and did not worry about the future value of states. In what follows, the results for several experiments are presented.

5.2.1 Team Score

Using the table from the learning phase, we simulated 25, 7-round drafts for each strategy, ADP and greedy. We used seeded values to simulate the uncertainty created by the other 31 teams and their draft selections to keep the comparisons fair. The boxplots in Figure 5.6 show the Team Scores for the current year following each draft. It is obvious the ADP strategy performed better than the greedy strategy when using either the median or the average in this short-term scenario. For a full list of the descriptive statistics from this scenario for each strategy, see Figure 5.7.

To gain a better visual of how often the ADP strategy outscored the greedy strategy, we subtracted the Team Score of the greedy strategy from the ADP strategy of each seeded draft. This means the drafts that resulted in an ADP strategy beating a greedy strategy would be positive and shown in black in Figure 5.8. A negative result (shown in red) meant the opposite, that the greedy strategy outperformed the

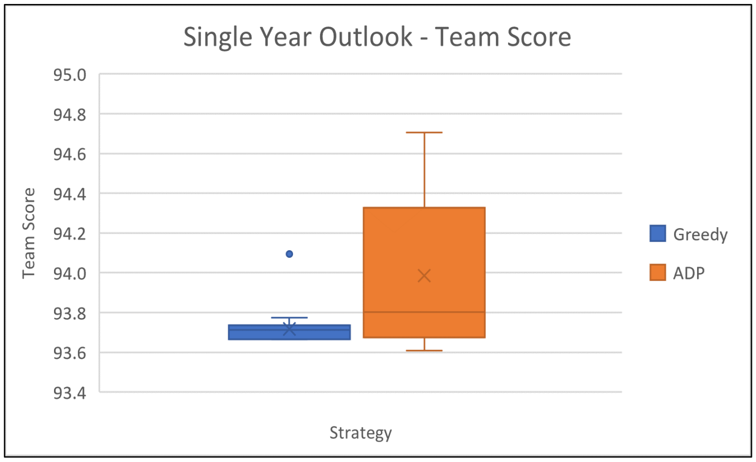

Figure 5.6: Boxplot Comparison of ADP vs. Greedy Strategies with original grades for Team Score.

Team Score - Greedy	
Mean	93.717
Standard Error	0.017
Median	93.712
Mode	93.664
Standard Deviation	0.087
Sample Variance	0.008
Kurtosis	15.550
Skewness	3.618
Range	0.430
Minimum	93.664
Maximum	94.094
Sum	2342.936
Count	25.000
Confidence Level(95.0%)	0.036

Team Score - ADP	
Mean	93.985
Standard Error	0.072
Median	93.802
Mode	93.674
Standard Deviation	0.362
Sample Variance	0.131
Kurtosis	-1.060
Skewness	0.716
Range	1.097
Minimum	93.609
Maximum	94.706
Sum	2349.630
Count	25.000
Confidence Level(95.0%)	0.149

Figure 5.7: Microsoft Excel Descriptive Statistics output for the Team Score Comparison of ADP vs. Greedy Strategies with original grades.

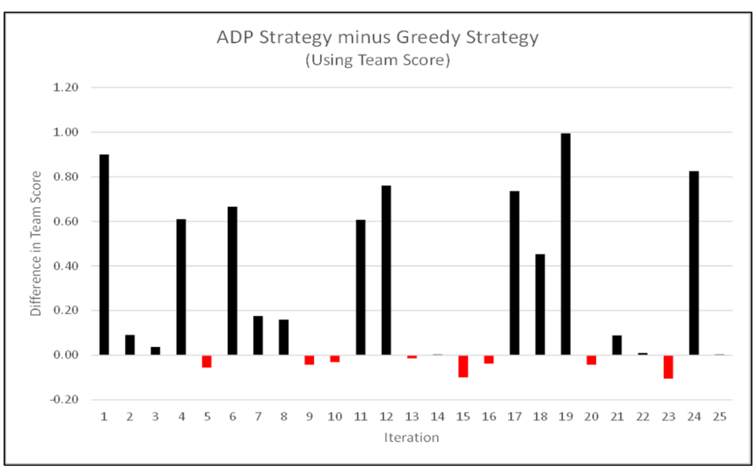

Figure 5.8: ADP Strategy Team Score minus Greedy Strategy Team Score using original grades.

ADP strategy. This only happened on eight of the 25 drafts or 32% of the time. ADP was the better performing strategy on 68% of the drafts.

5.2.2 Team Value

The majority of the teams in the NFL Draft are looking for future players. Very few of the players coming out of college are going to be able to contribute right away to a professional team. Looking back at Section 4.5, we discussed a long-term metric that would be calculated, in addition to the short-term Team Score. This long-term metric or Team Value would look at the added value of the players drafted over the next five years. So how did the two strategies perform in the long-term?

The same 25 drafts of each strategy, which were scored in the short-term up above were also scored in the long-term with the greedy strategy this time outperforming the ADP strategy on 68% of the drafts. The boxplots for the Team Value are depicted in Figure 5.9. This time it was a surprise with the greedy strategy having

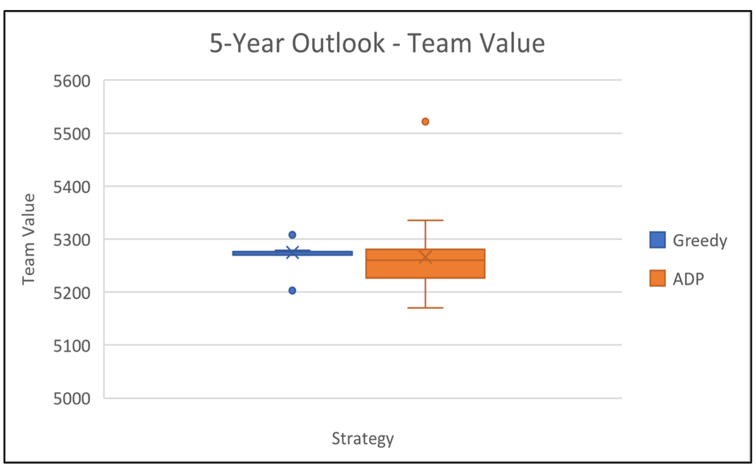

Figure 5.9: Boxplot Comparison of ADP vs. Greedy Strategies with original grades for Team Value.

higher scores in every comparison metric (as seen in Figure 5.10), except the maximum Team Value. Of the 25 drafts simulated, the ADP strategy had the five highest Team Values, but it also had the lowest. So what was surprising about this result?

Team Value - Greedy	
Mean	5274.604
Standard Error	3.838
Median	5275.886
Mode	5270.050
Standard Deviation	19.191
Sample Variance	368.292
Kurtosis	8.773
Skewness	-1.685
Range	105.687
Minimum	5202.466
Maximum	5308.152
Sum	131865.097
Count	25.000
Confidence Level(95.0%)	7.922

Team Value - ADP	
Mean	5266.013
Standard Error	13.746
Median	5260.005
Mode	5226.647
Standard Deviation	68.731
Sample Variance	4723.987
Kurtosis	7.447
Skewness	2.145
Range	351.673
Minimum	5170.077
Maximum	5521.750
Sum	131650.325
Count	25.000
Confidence Level(95.0%)	28.371

Figure 5.10: Microsoft Excel Descriptive Statistics output for the Team Value Comparison of ADP vs. Greedy Strategies with original grades.

It was surprising at first to see the ADP strategy perform better in the short-term and then, essentially lose to the greedy strategy in the long-term. At least it was at first. Then, the more we thought about it, it was not as big of a deal as initially believed. ADP is supposed to be geared toward the long-term and finding the better path to the finish line. Under the conditions that the ADP strategy faced, it is hard to say whether it was trying to satisfy the model by taking the middle ground between the team needs and the best players or by taking the middle ground between short-term and long-term goals. Because of these competing goals, it is not surprising that the greedy strategy, that was solely focused on choosing the best player won in the long-term because of the way the Team Value was calculated, all positions would be of need within the next three to five years, so the best players remaining are all going to contribute mightily to the value of the team.

In addition, all the perceived team needs may not necessarily fit the strengths of the draft. Therefore, it is possible for drafting the best player available to result in a much better score. Strong or highly graded individuals at certain positions outside of the team needs can alter the score. Because these players were the best players available, it improved the team but was not necessarily what the staff considered the missing piece the team needed. Thus, the team would still have the same gaps as before the draft and would be deeper at positions they were already strong. In this scenario, the greedy strategy outperformed the ADP strategy in the long-term at the cost of not meeting the team needs in the short-term. It was clear the ADP strategy did not favor one over the other in terms of team needs vs the best players. It was willing to take either if the opportunity presented itself and the numbers were right. We think this was why there was a much wider spread in both the Team Score and the Team Value for the ADP strategy. The same cannot be said for the greedy strategy. It was completely skewed toward the best player available. Hence, the greedy strategy did not always satisfy the team needs but could be on par in the long-term, in terms of average and a more narrowed spread.

5.2.3 Significance

Upon further analysis, we were able to determine that on average the ADP and greedy strategies were not statistically different in the long-term. Conducting a t-test for two-samples assuming equal variances due to the number of samples in each group being the same, the result was fail to reject the null hypothesis. The null hypothesis, in this case, was that the mean of the two populations (the ADP strategy and the greedy strategy) were statistically equal. The alternative hypothesis, which determined the tail of the test, was that the two means were not equal. Therefore, we used a two-tail t-test. To make the decision on rejecting (or failing to reject) the null hypothesis, we had to look at the three Excel output values highlighted in Figure 5.11: the t statistic, the two-tail p-value, and the two-tail t critical value (Wright, 2019). For this two-tail test, we did not reject the null hypothesis and we

	Greedy	*ADP*
Mean	5274.604	5266.013
Variance	368.292	4723.987
Observations	25	25
Pooled Variance	2546.139	
Hypothesized Mean Difference	0	
df	48	
t Stat	**0.602**	
P(T<=t) one-tail	0.275	
t Critical one-tail	1.677	
P(T<=t) two-tail	**0.550**	
t Critical two-tail	**2.011**	

Figure 5.11: Microsoft Excel t-test output for the Team Value Comparison of ADP vs. Greedy Strategies with original grades.

concluded that there was no statistically significant difference in the two strategies because the t statistic fell within the two-tail critical value for t, as shown in Figure 5.12.

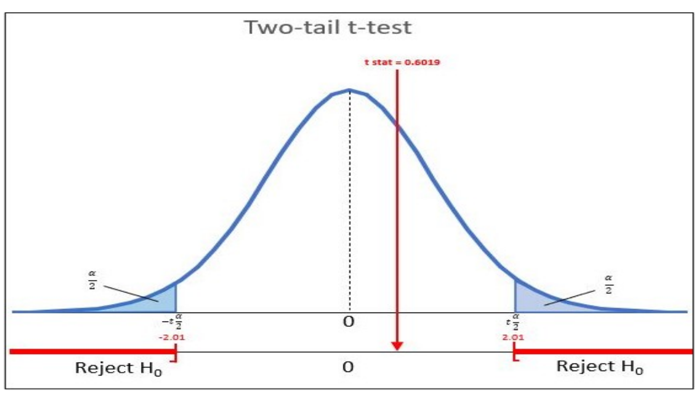

Figure 5.12: Depiction of a two-tail t-test. The t statistic of 0.6019 falls into the Fail to Reject (FTR) region of the distribution. This implies that the user should fail to reject the null hypothesis, that the means were statistically equal.

However, when we performed an f-test to determine whether the variances of these same two populations were statistically equal (null hypothesis), we got the result of reject the null hypothesis. By focusing on the Excel outputs highlighted in Figure 5.13, if F is greater than the F Critical one-tail value, then we reject the null hypothesis. In this case, 12.826 was greater than 1.984 and we rejected the null hypothesis that the variances of the ADP and greedy strategy populations were statistically equal (Excel Easy, 2021). We expected this result due to the fact the

	ADP	*Greedy*
Mean	5266.013	5274.604
Variance	4723.987	368.292
Observations	25	25
df	24	24
F	**12.827**	
P(F<=f) one-tail	0.000	
F Critical one-tail	**1.984**	

Figure 5.13: Microsoft Excel f-test output for the Team Value Comparison of ADP vs. Greedy Strategies with original grades.

ADP strategy was being split between the competing demands of team needs or best player, as well as short-term or long-term success.

Now let us go back and look at the short-term metric, Team Score, and determine if ADP was clearly the better choice. Looking back at the boxplots in Figure 5.6 and the data in Figure 5.7 highlighting the full list of descriptive statistics for the ADP and greedy strategies for Team Score, you can remember that ADP outperformed the greedy strategy, but was it significant? Once again, we used the t-test to determine if on average ADP outperformed greedy. This test was different from before because we no longer wanted to show if they were statistically equal or not, but we were looking at whether the greedy strategy on average was less than the ADP strategy in terms of Team Score. Therefore, the null hypothesis was that the mean of the greedy strategy was greater than or equal to the mean of the ADP strategy. The alternative hypothesis was that the mean of the greedy strategy was less than the mean of the ADP strategy. The output for the Team Score t-test is shown in Figure 5.14. In this case, Excel reports the absolute value of the critical

	Greedy	*ADP*
Mean	93.717	93.985
Variance	0.008	0.131
Observations	25	25
Pooled Variance	0.069	
Hypothesized Mean Difference	0	
df	48	
t Stat	**-3.600**	
P(T<=t) one-tail	**0.000**	
t Critical one-tail	**1.677**	
P(T<=t) two-tail	0.001	
t Critical two-tail	2.011	

Figure 5.14: Microsoft Excel t-test output for the Team Score Comparison of ADP vs. Greedy Strategies with original grades.

values and we used the negative t Critical one-tail which would be -1.677 (Wright, 2019). This time, the t statistic (-3.600) fell into the rejection region as shown in Figure 5.15, so the result was to reject the null hypothesis.

After analyzing these results more, it was time to try something new. While the reasons for the results potentially being the reverse of what we had expected were plausible, we needed to determine how different availability within the draft-eligible population would affect the results. The next section describes this sensitivity analysis.

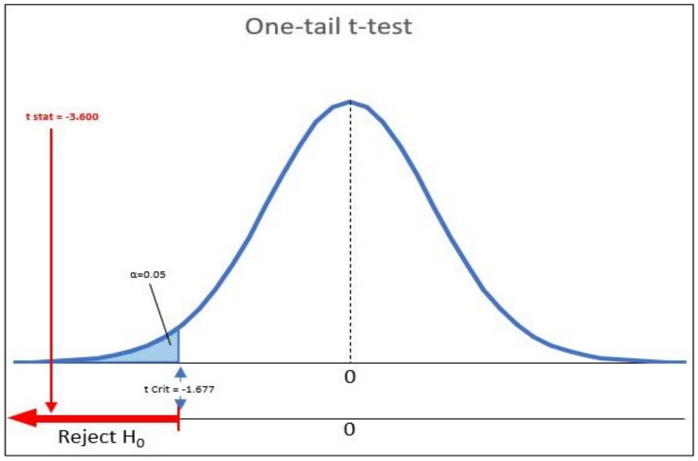

Figure 5.15: Depiction of a one-tail t-test where the t statistic falls into the rejection region. This implies that the user should reject the null hypothesis, that the mean of the greedy strategy was greater than or equal to the mean of the ADP Strategy.

5.3 Variant #1: Reduced Talent Pool

Initially, we looked at removing the top 10 wide receivers, from what was already considered an extremely deep class at wide receiver. However, this put the model into many states that were previously not visited during the learning phase, and therefore, the ADP strategy would simply match the greedy strategy since the future value of the states were equal to zero because those routes had never been taken. Instead, we reduced the quality of all the players in the draft pool by taking 90% of their grades as their new grades. This produced results that were more in-line with the initial estimates. We believe this happened because the grades for the current rosters and the grades for the draft-eligible players in the draft did not come from the same grading scale. We were not able to find (for free) anyone who graded both current players and players in the draft on the same scale. We know we said it was very important to do this and so, as our fathers told us many times growing up, 'do as I say, not as I do.' While the grading scales were different, they were close.

With the draft-eligible players having slightly elevated grades when compared to the actual NFL players, it did allow the greedy strategy a slight advantage because the strategy was consistently able to find players to draft that would be considered starters, sometimes even as late as the seventh round. While this is not impossible, it is rare, especially with the grades some of the players had. By reducing the value of these players, the results are closer in-line with what we had originally expected. Using the table from the learning phase again, but now using the reduced grades, we simulated 25, 7-round drafts for each strategy, ADP and greedy. We used seeded values to simulate the uncertainty created by the other 31 teams and their draft selections to keep the comparisons fair.

5.3.1 Team Score

The greedy strategy outperformed ADP in the short-term metric, Team Score as shown in the boxplots in Figure 5.16. This was the short-term result we were expecting, to have the greedy strategy beat the ADP strategy in every descriptive

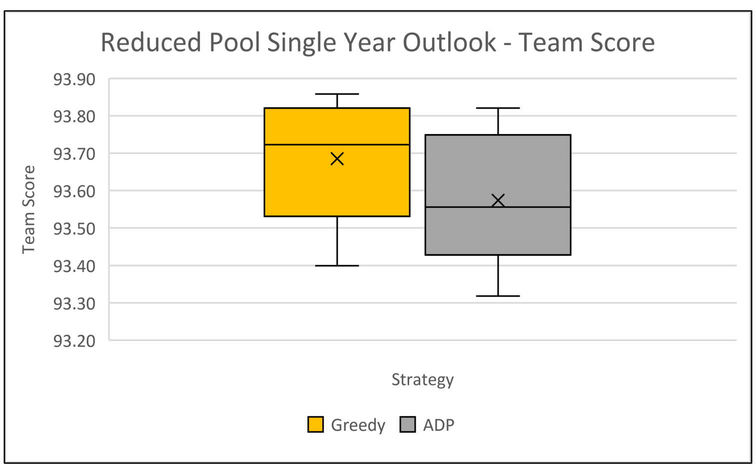

Figure 5.16: Boxplot Comparison of ADP vs. Greedy Strategies with reduced grades for Team Score.

statistic, as seen in Figure 5.17.

Team Score - Greedy		Team Score - ADP	
Mean	93.685	Mean	93.574
Standard Error	0.030	Standard Error	0.033
Median	93.722	Median	93.556
Mode	93.722	Mode	93.482
Standard Deviation	0.152	Standard Deviation	0.167
Sample Variance	0.023	Sample Variance	0.028
Kurtosis	-1.089	Kurtosis	-1.546
Skewness	-0.602	Skewness	0.083
Range	0.459	Range	0.503
Minimum	93.399	Minimum	93.318
Maximum	93.858	Maximum	93.821
Sum	2342.127	Sum	2339.356
Count	25.000	Count	25.000
Confidence Level(95.0%)	0.063	Confidence Level(95.0%)	0.069

Figure 5.17: Microsoft Excel Descriptive Statistics output for the Team Score Comparison of ADP vs. Greedy Strategies with reduced grades.

In a complete flip of the first scenario, the greedy strategy performed better on 68% of the drafts. Figure 5.18 is a similar graph to that which was used in the

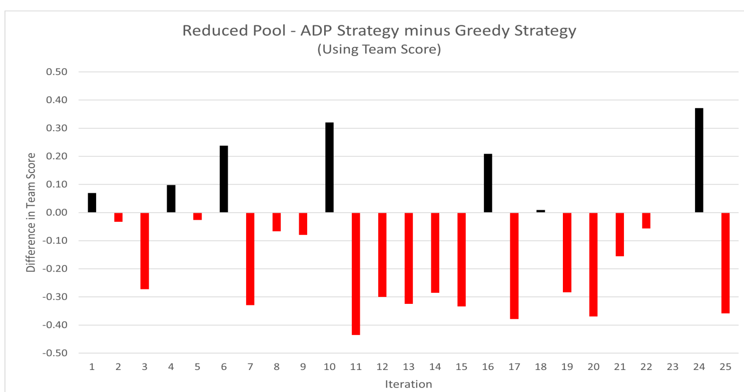

Figure 5.18: ADP Strategy Team Score minus Greedy Strategy Team Score using reduced grades.

first scenario, using the Team Score from the greedy strategy being subtracted from the Team Score of the ADP strategy. The positive, black results were drafts where ADP outperformed the greedy strategy and the negative, red results were the drafts where the greedy strategy resulted in a higher Team Score.

5.3.2 Team Value

The long-term results continued to show what we had originally expected. The ADP strategy missed out on the single-season run but performed stronger than the greedy strategy in the 5-year outlook. Figure 5.19 shows the two boxplots for the different strategies in terms of Team Value. The complete list of descriptive statistics is in Figure 5.20. Finally, the Team Value of the ADP strategy minus the Team Value

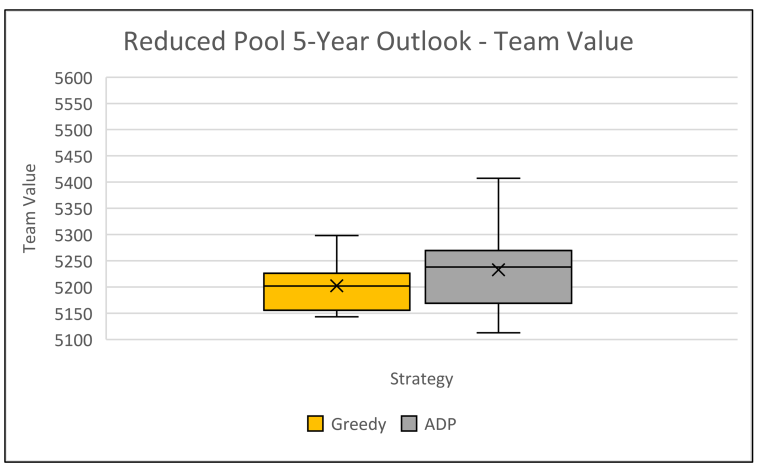

Figure 5.19: Boxplot Comparison of ADP vs. Greedy Strategies with reduced grades for Team Value.

of the greedy strategy (Figure 5.21) shows that the ADP strategy outperformed the greedy strategy on 64% of the drafts in the long-term.

Team Value - Greedy	
Mean	5202.531
Standard Error	9.308
Median	5201.960
Mode	5146.070
Standard Deviation	46.539
Sample Variance	2165.861
Kurtosis	-0.647
Skewness	0.519
Range	155.060
Minimum	5143.370
Maximum	5298.430
Sum	130063.280
Count	25.000
Confidence Level(95.0%)	19.210

Team Value - ADP	
Mean	5233.151
Standard Error	16.272
Median	5238.360
Mode	-
Standard Deviation	81.358
Sample Variance	6619.061
Kurtosis	-0.459
Skewness	0.317
Range	294.220
Minimum	5112.920
Maximum	5407.140
Sum	130828.770
Count	25.000
Confidence Level(95.0%)	33.583

Figure 5.20: Microsoft Excel Descriptive Statistics output for the Team Value Comparison of ADP vs. Greedy Strategies with reduced grades.

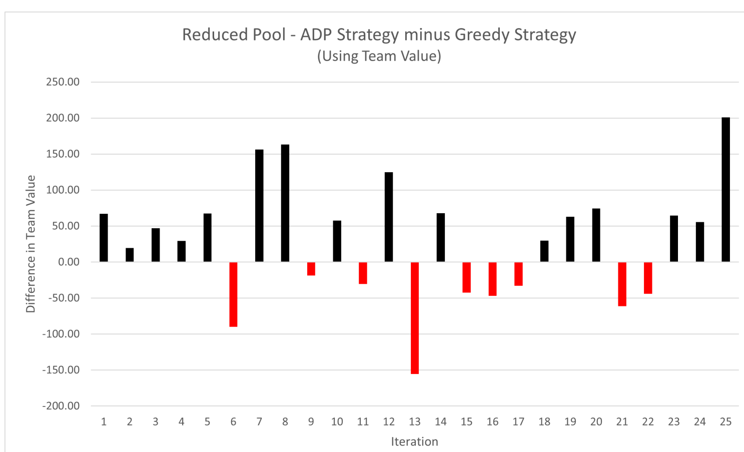

Figure 5.21: ADP Strategy Team Score minus Greedy Strategy Team Score using reduced grades.

5.3.3 Significance

We repeated the t-tests as before in the first scenario to determine if the results were significantly different. Interestingly, the t-test for the Team Score populations resulted in us rejecting the null hypothesis that the mean of the ADP strategy Team Score was equal to the greedy strategy Team Score. This means the greedy strategy significantly outperformed the ADP strategy in the short-term with the reduced pool. For the long-term metric of Team Value, the ADP strategy scored higher than the greedy strategy, but the t-test failed to reject the null hypothesis that the means of the two strategies were different. While the ADP strategy had the highest five Team Values, it also had the lowest four. This led us to check the spread of the Team Values using the f-test again. This result followed the first scenario and showed that the variance of the two populations were statistically unequal. Once again, the ADP strategy was torn between the team needs and the best players available and between long-term and short-term goals.

5.4 Variant #2: Team Needs

Up to this point, we had analyzed the hybrid approach to drafting. In other words, sometimes the decision maker drafted a player at a position of team need and other times the decision maker drafted the best player still available. It is a hybrid of the two mindsets often used by general managers and their staffs. In this scenario, we wanted to see what happens when the decision maker chooses one extreme and only selects players that fill a team need. Once again, we used the table from the learning phase and the reduced grades to simulate 25, 7-round drafts for each strategy, ADP and greedy, but only allowing them to draft players at one of the three positions of need. We used seeded values to simulate the uncertainty created by the other 31 teams and their draft selections to keep the comparisons fair.

We still used two strategies for the Team Needs runs; a greedy strategy and an ADP strategy. In the greedy strategy, the model was only focused on the immediate contribution of players at a position of team need. The ADP strategy was focused on the same players, but was looking at their value over the entire seven rounds of the draft and not just selecting a player based on their immediate contribution.

5.4.1 Team Score

In the short-term, the greedy strategy did slightly better than the ADP strategy in terms of Team Score. The greedy strategy was better than the ADP strategy 60% of the time and recorded the highest Team Score. After checking the t-test and rejecting the null hypothesis that the means were statistically equal, the greedy strategy could be declared the clear winner on average in the short-term.

5.4.2 Team Value

The long-term looked slightly better for the ADP strategy than the short-term. In terms of Team Value, the ADP strategy outscored the greedy strategy 52% of the time. However, the t-test failed to reject the null hypothesis, which stated the means of the two populations were statistically equal. Therefore, there is not a significant difference between the two population means in the long-term. We decided to check the variances using the f-test and as before, the variances were significantly different. Just like before, the ADP strategy was torn between multiple goals. This can be seen in the boxplots in Figure 5.22.

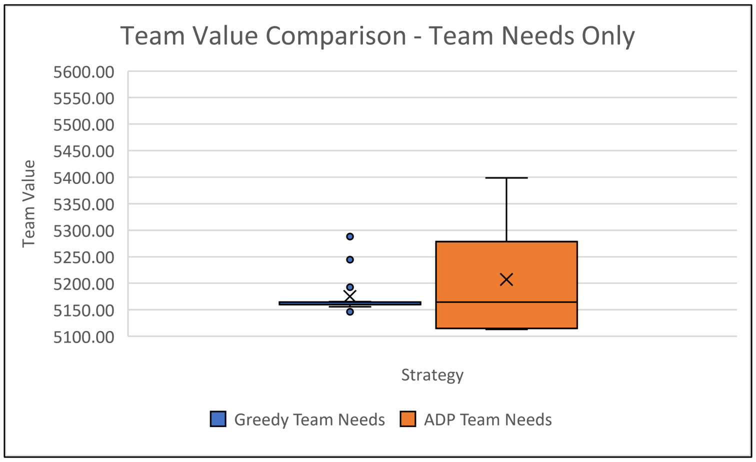

Figure 5.22: Boxplot Comparison of Greedy Team Needs vs. ADP Team Needs Strategies with reduced grades for Team Value.

5.4.3 Team Needs Compared to the ADP Hybrid Approach

The ADP Strategy using the reduced grades from Section 5.3 will now be referred to as the ADP Hybrid approach to further distinguish it from other ADP variants. In terms of Team Score, the ADP Hybrid approach was the clear winner. This is not only depicted in the boxplots in Figure 5.23 but was also proven to be significantly different between each of the Team Needs strategies. In the long-term, the ADP Hybrid Strategy was significantly different from the greedy Team Needs Strategy, but the t-test failed to reject the null hypothesis when the ADP Hybrid was compared to the ADP Team Needs. The boxplots for the Team Value are shown in Figure 5.24.

As you can see in Figure 5.24, the spread is not significantly different between the ADP Team Needs and the ADP Hybrid strategies either. This was backed up by the f-test, which failed to reject the null hypothesis that the variances were statistically equal.

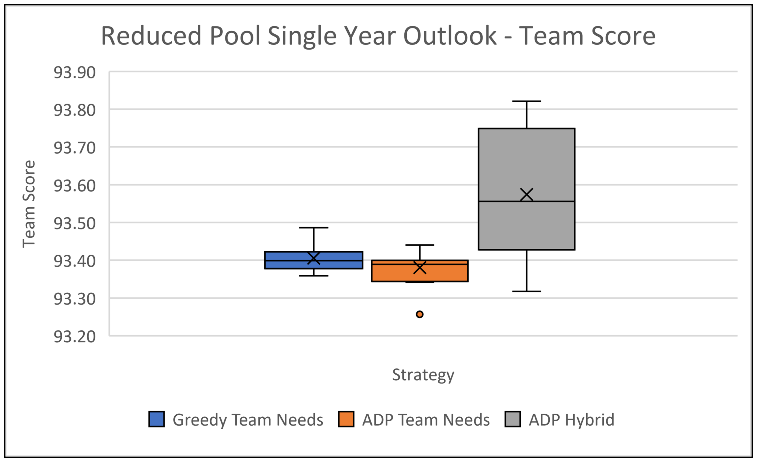

Figure 5.23: Boxplot Comparison of Greedy Team Needs vs. ADP Team Needs vs. ADP Hybrid Strategies with reduced grades for Team Score.

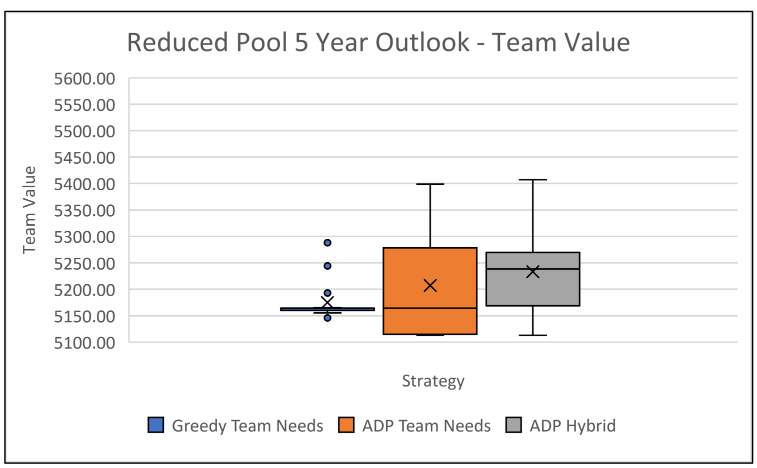

Figure 5.24: Boxplot Comparison of Greedy Team Needs vs. ADP Team Needs vs. ADP Hybrid Strategies with reduced grades for Team Value.

5.5 Variant #3: Pure BPA Without Trades

It seems that for every person you find that says you should draft a player at a position of team need, you can also find one that will tell you to draft the best player available. For this scenario, the model was limited to the other extreme and only allowed the decision maker to draft the best player available, whether they filled a team need or not. We did not allow the model to trade up the maximum number of positions since that is what the greedy strategy already accomplished. That led to this BPA variant making seven draft selections during the draft, instead of only four like the original greedy strategy. We used the table from the learning phase and the reduced grades to simulate 25, 7-round drafts for only the greedy strategy. We used seeded values to simulate the uncertainty created by the other 31 teams and their draft selections to keep the comparisons fair. We also compared these results against the reduced pool greedy strategy.

5.5.1 Team Score

The comparison of these two greedy (BPA) strategies, with and without trades, shows that allowing the model to trade up is more beneficial in the short-term. The greedy strategy with trades has a slight edge in the key descriptive statistics and on average, the means are significantly different according to the t-test. Figure 5.25 shows the boxplots for these two strategies.

5.5.2 Team Value

The result is different in the long-term. Trading up hurts the model in terms of Team Value. This variant did not trade up and thus kept its picks in the later rounds. These picks gave this variant the advantage in the long-term over the

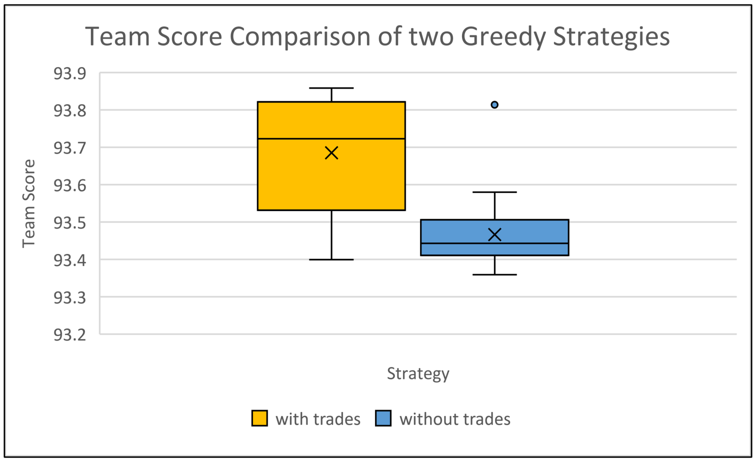

Figure 5.25: Boxplot Comparison of Greedy Strategy with trades vs. Greedy Strategy without trades with reduced grades for Team Score.

greedy strategy with trades. This is depicted in the boxplots in Figure 5.26. The

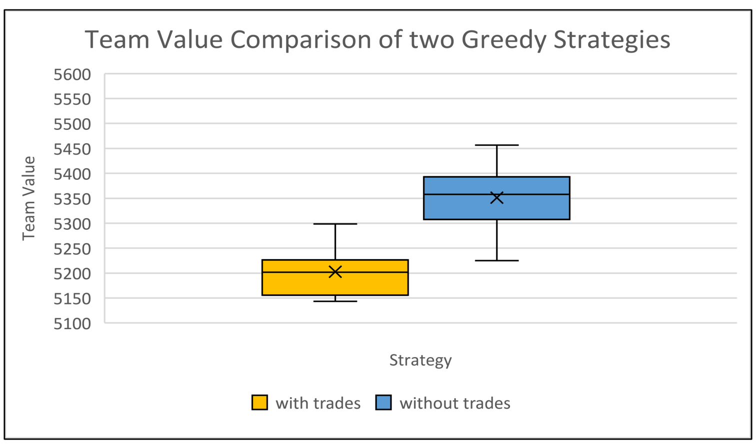

Figure 5.26: Boxplot Comparison of Greedy Strategy with trades vs. Greedy Strategy without trades with reduced grades for Team Value.

players drafted in the earlier rounds were not graded as highly since they were coming five picks later. Therefore, the greedy variant that traded up performed better in the short-term. The greedy variant that did not trade up, had more players contributing in the long run and thus scored better in Team Value.

5.6 Variant #4: ADP Strategy Without Trades

To have a fair comparison to the previous scenario, drafting only BPA without trading, we wanted to run an ADP strategy variant that was also restricted to no trading. We used the table from the learning phase and the reduced grades to simulate 25, 7-round drafts for only the ADP strategy. We used seeded values to simulate the uncertainty created by the other 31 teams and their draft selections to keep the comparisons fair. In addition to comparing it against the BPA strategy without trades, we also compared this variant against the reduced pool ADP strategy.

5.6.1 Comparison Between ADP Strategies

Just as we saw between the two greedy strategies in Section 5.5, we noticed the ADP strategies also performed better in the short-term with trades and better in the long-term without trades. Just as before, the more picks allowed for more players selected to assist in increasing the Team Value metric. These results are seen in the boxplots in Figures 5.27 and 5.28.

In the comparison of both ADP strategies, with and without trades, the means are significantly different according to the results of the t-tests. However, the variances are not significantly different. Both ADP strategies have the same complications and the same goals. The ADP strategy without trades allowed for the decision maker to focus on whom to draft without having to worry about when to draft.

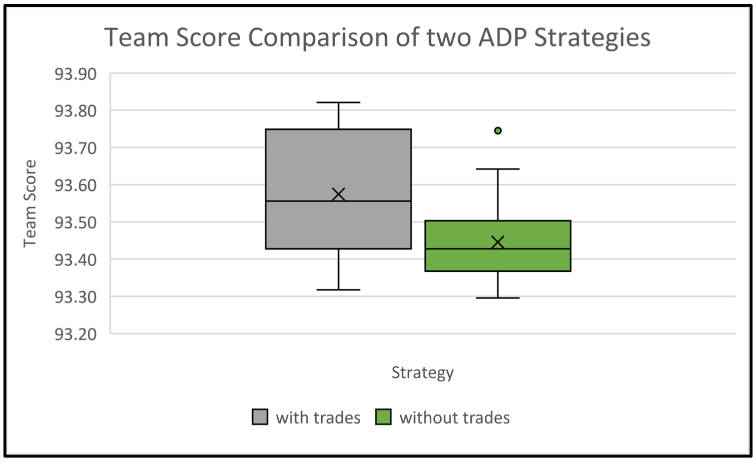

Figure 5.27: Boxplot Comparison of ADP Hybrid Strategy (ADP with trades) vs. ADP Strategy without trades with reduced grades for Team Score.

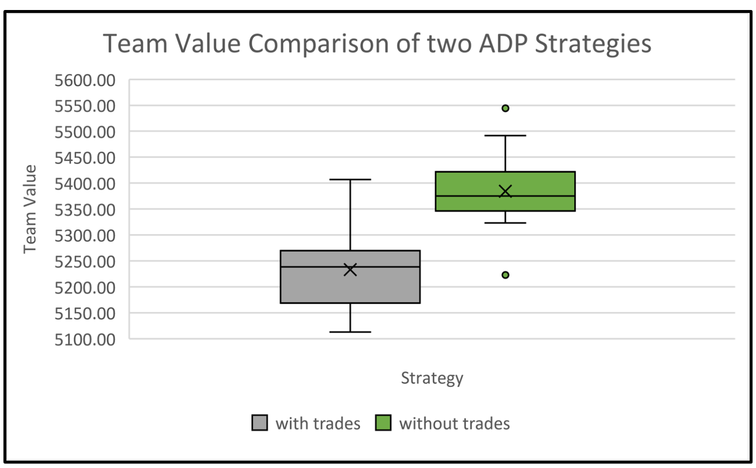

Figure 5.28: Boxplot Comparison of ADP Hybrid Strategy (ADP with trades) vs. ADP Strategy without trades with reduced grades for Team Value.

5.6.2 Comparison Between Strategies Without Trades

When this same luxury of purely focusing on whom to draft was afforded to the greedy strategy, it performed as well as the ADP strategy. While neither strategy separated itself from the other in the short-term or the long-term, the greedy strategy did have the maximum Team Score and a slightly higher mean in the short-term. On the other hand, the ADP strategy had the maximum Team Value and had a slightly higher mean in the long-term. However, neither of the differences in the means or the variances were significant. This is seen in the boxplots in Figures 5.29 and 5.30.

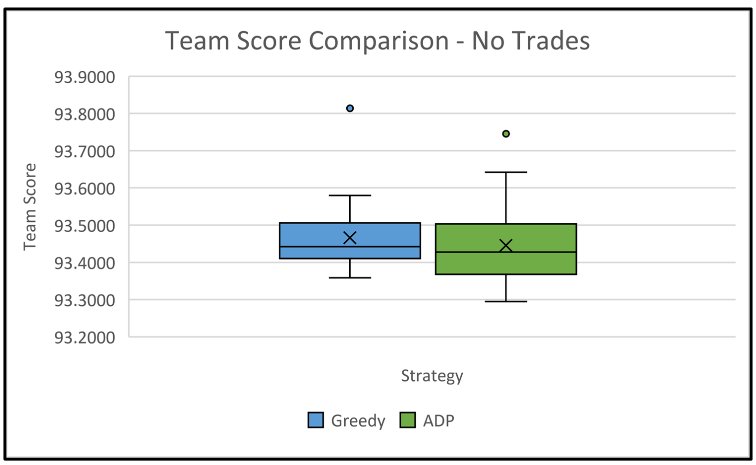

Figure 5.29: Boxplot Comparison of Greedy Strategy without trades vs. ADP Strategy without trades with reduced grades for Team Score.

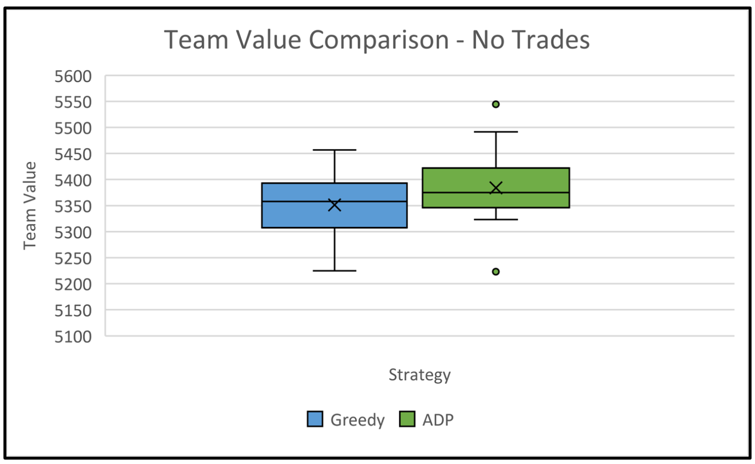

Figure 5.30: Boxplot Comparison of Greedy Strategy without trades vs. ADP Strategy without trades with reduced grades for Team Value.

5.7 Translation to the NFL

So, what does all this mean to the General Manager of an NFL franchise? We will use this section to dig deeper into the actual drafts of some of the better performing results, short-term, long-term, original grades, and the reduced pool to see if there were any similarities. One interesting note that stretched across both scenarios was that the greedy strategy always traded up the maximum number of positions allowed when it could, as shown in Table 5.1.

Table 5.1: Percent of time the Greedy Strategy traded up the maximum number of positions allowed. Due to the model trading up in the first round, there was no longer a fourth-round pick to trade.

Round	**Traded Up**	**No Trade**	**Traded Back**
First	100%	0%	0%
Second	100%	0%	0%
Third	100%	0%	0%
Fourth	0%	0%	0%

5.7.1 Original Grading Scheme and Team Value

In the long-term with the original grading scheme, remember that the ADP strategy did extremely well when compared to the top overall scores. However, the greedy strategy looked better statistically even though it was not significantly different. What was it about those top drafts in the ADP strategy that helped them stand out? What was it about the bottom ones that prevented the strategy from performing well statistically?

The top overall Team Value for the ADP strategy realized 71.6% of the best possible Team Value, while the top overall Team Value for the greedy strategy only realized 50.1%. Looking more at the top ADP draft, we noticed that it was one of the few drafts that traded back in the first round to gain an extra draft pick. It also chose to go after the BPA in the first round, we can only assume because the draft was so deep at the position of the most pressing team need, wide receiver. In the second round, the model stayed in its position and did not trade up or back. This time it took a wide receiver. In the third and fourth rounds, it traded up the maximum number of positions allowed and took the BPA and a tight end, respectively. With the added fourth-round pick, it could not trade up or back and it selected an offensive tackle. In the fifth round, with its last pick of the draft, it selected a wide receiver. Once again, based on our simplifications, it could not trade up or back in the fifth round. This draft was nearly twenty percentage points higher in terms of how much of the best possible Team Value it covered than the next highest draft, which also came from the ADP strategy. The second-best draft also traded back with the first-round pick to take the BPA and traded up in the second round to take a wide receiver.

Trading back in the first round worked well for two of the three instances as seen in Table 5.2. The third instance did not work as well because it drafted a position in tight end (TE), a position it could have gotten a similar value for in the second round, as it did in many other drafts. The player it drafted with the pick was

Table 5.2: Percent of time the highest scoring Team Values created by the ADP Strategy with original grades traded up, traded back, and stayed put.

Round	**Traded Up**	**No Trade**	**Traded Back**
First	72%	16%	12%
Second	92%	8%	0%
Third	88%	12%	0%
Fourth	100%	0%	0%

a player that was usually gone by the 25th or 28th pick, so we understand the desire to be able to trade back and still get your pick. However, his grade was that of a second-round draft pick and not a late first-round pick. This resulted in a loss of about ten graded points, instead of getting a player with a grade in the low 90s, it got a player with a grade in the low 80s. Not only that, the starting TE in this offense plays fewer snaps than some of the other play-makers that were available with higher grades. Yes, tight end was a team need, but it was not pressing enough to spend a first-round draft pick, given the grades of the top TEs available. This was the flaw of many of the lower scoring drafts.

Two of the three lowest scoring drafts drafted a tight end with the first-round pick. Of the nine lowest scoring Team Value drafts, eight of them drafted more than one tight end. Once again, tight end was a team need, but with the draft as deep as it was at wide receiver, that was also a team need, it would have made more sense to go after multiple wide receivers. That is exactly what both strategies did. Both strategies had similar wide receiver numbers with the ADP strategy spending 48% of its picks on wide receivers and the greedy strategy spending 49% of its picks on that skill position.

5.7.2 Original Grading Scheme and Team Score

We cannot be too hard on the ADP strategy for drafting a tight end in the first round. While it did not prove to be a prosperous move in the long-term, it paid off in the short-term. The five best Team Scores, all came from the ADP strategy, and four of the five traded up the maximum number of positions allowed to take the same TE we discussed earlier. In the short-term, this was a smart move because his grade was high enough to make him a starter on day one. This means the team would reap the benefits of drafting him in the first year, thus increasing the Team Score for that draft.

The other noticeable similarity of the best Team Scores was the fact that whenever the model had a chance to trade up, it did every single time. All but one of those times, it traded up the maximum number of positions allowed. Another common trend was the presence of a BPA on each of those drafts. In the short-term, if you are going to move up and trade away later draft picks, you need to draft starters even if they do not fill a team need.

5.7.3 Reduced Grading Scheme and Team Value

The best ADP draft in the long-term accounted for 75% of the best possible Team Value using the reduced grading scheme, while the best greedy strategy draft only accounted for 62%. This ADP draft, like the original grading scheme highest Team Value, also traded back one in the first round. However, this trade resulted in the selection of a wide receiver. With the second-round pick, the BPA was taken after trading up the maximum number of positions allowed. Then something unique happened in that the third and fourth-round picks were taken at their normal position. The model did not trade up or back. This allowed the model to keep its sixth- and seventh-round picks. In the end, the draft produced seven draft picks.

The other highest-scoring ADP drafts produced similar numbers to the highest scoring original grading scheme numbers in terms of how often it traded or did not trade and when it traded with a couple of exceptions. Table 5.3 shows the numbers for the reduced grading scenario. The biggest difference between Table 5.2 and Table 5.3 is that in this scenario, the model always traded its first-round selection. Not once did it stay with the original selection. Instead, it traded back in the first round more often. The fourth round was the reverse where it kept its original draft pick without trading a small percentage of the time, whereas in the original grading scenario it always traded up in the fourth round.

Table 5.3: Percent of time the highest scoring Team Values created by the ADP Hybrid Strategy with reduced grades traded up, traded back, and stayed put.

Round	**Traded Up**	**No Trade**	**Traded Back**
First	72%	0%	28%
Second	88%	12%	0%
Third	92%	8%	0%
Fourth	85.7%	14.3%	0%

The top-scoring drafts from the greedy strategy had a similar action in that they all drafted a wide receiver in the first round. They also targeted the other team needs along with some which also drafted a BPA or two. Once again, the greedy strategy traded up the maximum number of positions allowed with every pick, leaving each draft with a first-, second-, third-, and seventh-round selection. This strategy paid off in the short-term, but not in the long-term.

The worst drafts for Team Value in this category were very similar to the original grading scheme in that it overvalued the TE position. In addition, all the lowest scoring Team Values traded up at every opportunity.

5.7.4 Reduced Grading Scheme and Team Score

The top-scoring drafts in this scenario all came from the greedy strategy and all of them spent a first- and a seventh-round selection on a wide receiver. The second- and third-round picks were used to draft a tight end and an offensive tackle. Most of the time, the tight end was drafted in the second round, but not in all circumstances.

As for the ADP strategies, the best Team Value scores tended not to trade all their picks away, while in terms of Team Score, that is the way to score higher. The highest ADP draft Team Score came from a draft that traded up the maximum number of positions allowed in the first and second rounds, while only trading up three positions in the third round. In order, the ADP drafted the BPA, a wide receiver, and another BPA. In the seventh-round, it drafted a tight end. This strategy created the best ADP Team Score in this scenario, but only the sixth-best Team Score overall.

5.7.5 Validation

The validation of our scaled-down version of the NFL Draft model was done by comparing the ADP Hybrid Strategy with the myopic or BPA Strategy. Our prototype proves that the ADP Hybrid Strategy is competitive and worth the effort to build a full model. As part of the future research, it would be ideal to recreate the 2020 NFL Draft from the perspective of the Green Bay Packers, since they were the team we used as the decision maker. Then validation could be accomplished in comparing Green Bay's actual draft against the ADP Hybrid Strategy, the BPA Strategy, and both of the Team Needs' Strategies. In order to compare the fully developed model, the rosters would have to be updated to the last known roster prior to the draft. Our roster for Green Bay was locked in a couple of months before the draft and contained some players that were lost during free agency and trades leading up to the draft. Also, the actual draft order was very different from the draft order that we used. We removed all prior trades and kept the draft at its original state along with removing all of the compensatory picks. Green Bay had 10 total picks versus our scaled-down draft model which only had seven. Updating the draft order would also create the need to completely redo the Bayes' Theorem section to match the updated draft probabilities to the new draft order. Once the model and its inputs were updated, we would then have to rerun the Exploration and Learning Phases of the solution strategy, along with scoring the Learnt Phases for each of the experiments. Finally, the same scoring process would need to be completed for Green Bay's draft in order to compare the results for validation.

5.7.6 Operational Aspects

Once a team has validated a fully developed model, how could they expect to use the model for the draft. Well in advance of the draft, they would be able to tailor their model using their inputs and their assumptions. After the model is developed, the team would then be able to run all phases of the solution strategy. Once the experiments are completed and scored, they would then be able to use the results to develop their draft day strategies for each of the days of the draft. Following the completion of each day of the draft, they could then update the model with any trades and all selections that had taken place. This would allow them to rerun the Learnt Phase so that they could develop their strategy for the next day of the draft. This is how the model could be used to prepare for the draft, but how could it be used in real-time during the draft?

Instead of waiting until the end of the day to update the model, it could potentially be updated during the draft while the decision maker is waiting to get within what they consider their draft window. Here, a decision maker would be less concerned about trying to update the draft order with any trades that may have taken place and are solely concerned with updating the draft-eligible pool. With a fast enough computer, a team could expect to be able to run a Learnt Phase for an experiment and quickly analyze some initial results. However, this gets more difficult as the draft moves forward and the time between picks shrinks. The first few rounds are probably the most realistic to be able to expect to use the model in real-time.

5.8 Summary

The results indicated different answers as to the optimal strategy for conducting the NFL Draft based on the different grading schemes. Within the grading schemes, the answers differed based upon which strategy was used. This shows that each of the strategies has its advantages and disadvantages depending on the situation the team finds themselves. Using the reduced grading scheme, the short-term advantage was found using the greedy strategy. This is similar to a team looking to win now by adding the best available players on the board. Whether they get starters or some very capable backups out of the draft, they are not focused on filling any team needs and definitely not focused on the long-term. The team must be willing to trade away their late-round picks to move up in the draft to take the best players while they are still available. In the long-term, the ADP strategies excelled. More specifically, the ADP strategy that was not allowed to trade up consistently outscored all the other variants in Team Value over the five years measured. These drafts not only filled holes in the roster, but they also had enough draft picks to spend a couple of them on the best players available. No matter which strategy was used, greedy or ADP, the best possible Team Value was realized by not trading away any draft picks. The short-term was the opposite in that it traded as much as possible.

5.9 Additional Research Questions and Discussion

Many other research questions came to mind while trying to think about solving the primary research question: What is the strategy for creating the optimal team roster, in terms of graded value, over the course of the NFL Draft when compared to the team's current roster and accounting for the uncertainty of the other 31 teams in the league. We did our best to keep these other questions in mind while trying to solve the primary research question. Here are the best solutions to these subsequent research questions utilizing the work and research required to answer the primary question. Unless noted otherwise, all of these answers come from the work utilizing the original grading scheme. The patterns identified in these answers would be similar for the reduced grading scheme as well. Also, the grades of the players drafted are averages from the 100,000 iterations of the learning phase. While the value of a state would have fluctuated throughout the learning phase, their grades were left unchanged.

5.9.1 How does one quantify the risk of "missing on their player?"

We think this is a moving target in terms of what round of the draft the decision maker was in, as well as was the decision maker contemplating trading up or back to try to get their player. Table 5.4 shows the average grade of each first pick

Table 5.4: Average grade of the players drafted by the decision maker during the learning phase within the draft window of the first selection.

	Pick	**Avg. Grade**
First Selection	25	87.94
	26	87.62
	27	85.46
	28	85.66
	29	85.45
	30	**89.11**
	31	89.41
	32	86.96
	33	87.31
	34	86.32
	35	86.73

taken by the decision maker during the 100,000 iterations of the learning phase. Picks 25 through 29 meant the decision maker traded up to get a certain player or a player at a certain position. This may have led to the decision maker taking a slight cut in grade to ensure they got a better quality at the position they drafted. Picks 31 through 35 showed when the decision maker traded back thinking that they might still be able to get their player or a high-quality player at a certain position. As you can see in Table 5.4, the highest grades on average came from trading back one position or not trading at all.

Trading up within this range from the bottom of the first round, the decision maker would probably give up a fourth-round pick from this same draft. There is less risk in missing on their player because it would be more about the cost of trading up in the draft. Trading up may not only cost the decision maker a few points off the grade of the player drafted on average but would likely cost them their fourth-round pick as well, which averaged a grade of 80.1. Trading back on the other hand would cost less, in terms of the grade of the player selected, but the decision maker would also gain an extra fourth-round pick. And if the decision maker only traded back one position, they would most likely get a similarly graded player plus an extra fourth-round pick. Therefore, we would conclude the risk of missing on a player at this point in the first round during this draft was not high at all. Yes, the decision maker may not get their player, but they should still walk away with a solid draft pick. Two things were working together to create this outcome. First, the overall grades of the draft-eligible players were slightly higher compared to the grades of the current roster with this grading scheme, which allowed for strongly graded players to exist further into the draft (or to still be on the board). Secondly, the depth at one of the positions of team need was very strong, allowing for the model to drop back and still get a highly graded player at one of those positions.

The subsequent rounds had a slightly different outcome. As the talent pool got thinner and thinner, not only at the positions of team need but as a whole, the risk of missing on a player went up. For example, in the third round, as depicted in Table 5.5, the average grade of the players drafted by the decision maker went down with each pick until the bottom of the draft window, where it ticked back up slightly. At this point in the draft, as the talent pool thinned, the potential gap between the highest-graded player at a position and the next highest-graded player at the same position could be substantial. Because of this, the decision maker's risk of missing on

Table 5.5: Average grade of the players drafted by the decision maker during the learning phase within the draft window of the third selection.

	Pick	**Avg. Grade**
	89	83.31
	90	82.14
	91	81.91
	92	81.66
	93	81.65
Third Selection	**94**	**81.62**
	95	80.48
	96	77.91
	97	77.69
	98	77.69
	99	78.03

their player goes up. The decision maker will have to determine if the risk of a drop of a couple of points is worth the potential sixth-round pick they would have to trade to move up. On average a sixth-round pick was graded at 68.9 during the learning phase.

It is worth keeping in mind that depending on the depth of the draft at a certain position, there will be a point where a missed opportunity may be the final chance at grabbing a player worth drafting. In drafts that are not deep at a position, this may increase the risk of missing on a player in the eyes of the decision maker. This is something else that needs to weigh into their decision making. This can also be adjusted within their grading scheme.

5.9.2 What is the cost of trading additional picks to move up in the draft?

On average the decision maker was getting the highest-graded player in the first round by trading back one position to the thirty-first overall pick. The next highest grade was by staying with the thirtieth overall pick and not trading at all. Trading up was costing the decision maker, on average, one to two points off the grade of the first-round pick, in addition to their fourth-round pick that was worth an average of an 80.1 grade.

It is important to remember that we limited the model to moving up five positions in the draft. Not only that, but we were doing it at the bottom of each round, not the top of the round. Trading up within the top ten, especially of the first round, is much more expensive. Usually, trading up in that range will cost a decision maker multiple first-round picks. Trading up at different points in the round will have different costs. This is something that will have to be adjusted by the decision maker based on the situation.

In the subsequent rounds, trading up resulted in a slightly higher graded player than not trading up. The cost also decreased because the draft pick being traded away was from a later round, with a lower grade, on average. Therefore, after the first round, the cost of trading up goes down, while the benefits increase.

5.9.3 What is the reward for gaining more picks in the draft by trading back?

Once again, this question depends on what round of the draft and needs to be more specific than that in terms of what part of the round. We have already shown you how the decision maker can potentially gain a slight increase in the grade of the player drafted by trading back one pick in the first round. The second round is even more favorable for trading back, although still not as prosperous on average as trading up for the grade of the drafted player, but could be considered more prosperous when you take into account the fact that the decision maker would be gaining an extra pick later in the draft instead of losing one.

In the third round, the decision maker can expect a slight decrease in the grade of the player drafted when trading back. The fourth round was close with trading back one, but it was still a slightly higher grade than not trading at all. Trading back any more than one position resulted in a much larger decrease in the grade of the player drafted. Once again though, the decision maker would most likely gain an extra pick later in the draft when trading back.

5.9.4 What is the cost for not drafting a player at a position of need for the team?

In the model, we charged the immediate contribution half of its contribution if the position drafted was not a position of team need. In the end, this is a decision that the team should make and is highly debatable. Determining this would require more learning at different levels of loss. Even with the loss at half, the model still drafted players not at positions of team need, but nearly 75% of the time it drafted a player at a position of team need.

5.9.5 How much better is the ADP strategy than the myopic (BPA) strategy or the pure team needs strategy?

When all three strategies had the opportunity to trade up or to trade back, the short-term was won by the greedy strategy or purely selecting the best player available strategy. It was closely trailed by the ADP strategy. The team needs strategy did not do well using either ADP or greedy but focusing entirely on the positions of team need. In the end, it just eliminated too many good players from the pool, that regardless of position, could still have improved the football team on paper.

In the long-term, the ADP Team Needs, the greedy (BPA), and the ADP Hybrid strategies all performed equally well. The ADP Hybrid had a slightly larger mean than the other two strategies and it also had the maximum Team Value of any draft. However, it was also tied for the minimum Team Value of any draft with a draft from the ADP Team Needs. None of the means were significantly different from the others. In terms of variance, the two ADP strategies were not significantly different from each other, but both were significantly greater than the greedy strategy. This shows that both ADP strategies were torn between the multiple goals.

Looking at the descriptive statistics for Team Score for all three strategies, it is clear the greedy strategy dominated in the short-term, both on average and with the maximum draft recorded. The greedy strategy, on average for Team Score, doubled up the ADP Team Needs strategy, while still outperforming the ADP Hybrid by almost 27%. For the maximum Team Score recorded by a single draft, the greedy strategy still outperformed the other two. It still more than doubled the ADP Team Needs Strategy, but only outperformed the ADP Hybrid strategy by 5.6%.

Doing this same analysis for the Team Value for all three strategies, it is a much closer race. On average, the ADP Hybrid Strategy was 7.2% better than the greedy strategy and 6.1% better than the ADP Team Needs Strategy. In terms of the maximum Team Value for a single draft, the ADP Hybrid was only 1.4% better than the best ADP Team Needs draft, but was nearly 21% better than the best greedy strategy draft.

Chapter 6: Research Contributions and Conclusions

6.1 Research Contributions

This research indicates the first time Approximate Dynamic Programming (ADP) was used to improve a National Football League (NFL) Draft strategy for a single decision maker or franchise. The ADP model used grades for the current NFL rosters and for the draft-eligible players to optimize the team's decisions to produce the best team possible on paper given their draft positions. It also used a simulation of the NFL Draft to help the model determine which players would be eligible to be drafted when it was the decision maker's turn to choose when and whom to draft.

Other key research contributions were the different variants that were developed and ran to analyze the sensitivity of the outputs. Some key results from the previous chapter are highlighted below:

Original Grading Scheme

- The ADP strategy significantly outperformed the greedy strategy 68% of the time in Team Score using the original grading scheme (the mean of the greedy strategy was significantly less than the mean of the ADP strategy)

- The greedy strategy outperformed the ADP strategy 68% of the time in Team Value using the original grading scheme (the means were not significantly different, but the variances were)

Reduced Grading Scheme - Variant #1

- The greedy strategy significantly outperformed the ADP strategy 68% of the time in Team Score using the reduced grading scheme

- The ADP strategy outperformed the greedy strategy 64% of the time in Team Value using the reduced grading scheme (the means were not significantly different, but the variances were)

Team Needs Only - Variant #2

- The greedy team needs strategy significantly outperformed the ADP team needs strategy 60% of the time in Team Score using the reduced grading scheme

- The ADP team needs strategy outperformed the greedy team needs strategy 52% of the time in Team Value using the reduced grading scheme (the means were not significantly different, but the variances were)

- The ADP hybrid strategy significantly outperformed both the greedy and ADP team needs strategies in Team Score

- The ADP hybrid strategy significantly outperformed the greedy team needs strategy in Team Value but was not statistically different from the ADP team needs strategy in Team Value

No Trades Allowed - Variants #3 and #4

- Both no trade strategies significantly outperformed their counterparts when trades were allowed in Team Score

- Both trades allowed strategies significantly outperformed their no trade counterparts in Team Value

Team Score Overview - Reduced Grading Scheme

- The greedy strategy dominated both on average and with the maximum Team Score draft recorded
- The greedy strategy outperformed the ADP hybrid strategy by almost 27% on average

Team Value Overview - Reduced Grading Scheme

- The ADP hybrid strategy was over 7% better than the greedy strategy and over 6% better than the ADP team needs strategy
- The ADP hybrid strategy had the maximum Team Value draft recorded, which was less than 2% better than the ADP team needs strategy but nearly 21% better than the best greedy strategy

There were many instances where the ADP strategies outperformed the greedy strategies but their population means were not statistically different. However, the variances for the populations were significantly different. In these occurrences, the ADP strategy appeared to be torn between competing needs. On one hand, it was competing between taking a player of team need and taking the best player available. On the other hand, it was competing between long-term and short-term goals. These competing demands showed that the ADP strategies were not taking sides and thus, had a much wider spread. The greedy strategies on the contrary always went after the best player available and did not try to satisfy the team's needs. The greedy strategies remained competitive in terms of average Team Value and had a narrowed spread because they were skewed towards the best player available and it had time to catch up in the long-term.

Another research contribution is that the ADP model allowed the decision maker to trade up or trade back in the draft. The research did not uncover any other models that provided this option to the decision maker. This is partly due to the fact that many of the models are developed with fantasy football in mind. Fantasy football handles drafting differently than the actual NFL Draft and thus, does not allow for trades to occur.

6.2 Conclusions

While this research indicates the first time ADP was used to improve an NFL Draft strategy for a single decision maker or franchise, there is more work to be done. Firstly, we are not sure of the feasibility of using the model in real-time during the NFL Draft due to the time constraints for the teams to make their picks, but it would be extremely useful in the days leading up to the draft. This research shows the potential gains and losses of trading up, trading back, or staying put in the draft and it provides the general managers a blueprint on how to approach the draft. Teams and front offices would be able to develop multiple strategies to assist in navigating the uncertainty created by the other teams. Secondly, the inputs could be improved upon with some guidance from subject matter experts, such as the general manager's staff. With the teams improving upon many of the inputs of the model, it would overhaul our answers and rewrite the script. We are certain the ADP strategy would outperform the greedy strategy even further in the long-term given a more consistent grading scheme and stronger inputs from the teams themselves.

Under the reduced grading scheme, which was more realistic in our opinion, the greedy strategy played to its strengths. The greedy strategy consistently and significantly outperformed the ADP strategy in Team Score, or the short-term. The greedy strategy traded up the maximum allowable positions nearly every time to get the best player available, regardless of the player's position. The ADP strategy also played to its strengths and performed better in the long-term. The best drafts for the ADP strategy showed that trading back and trading up are both beneficial and can be used in the same draft successfully. This aspect of the model, allowing the decision maker the option to trade up or trade back, was also a first. The different variants tested showed that the greedy strategy was more beneficial in the short-term, while the hybrid strategy appeared to be the most successful approach in the long-term. The team needs strategy was also effective in the long-term.

As mentioned up above, trading, when done correctly, can have very positive results. Of course, it also helps if the player you trade up to get has a great career and the player your opponent drafts because you traded back does not have a great career. However, we compared some variants that used the greedy and the ADP strategies with trades and without trades. In the short-term, trading paid off, which is why we saw the greedy strategy do so well since it was trading up all the time. In the long-term, trading did not pay off. The best Team Value scores of all of the variants, came from the ADP hybrid with no trading allowed. In other words, the strategy was not allowed to trade, but it could take players that filled a team need or the best player available. This result is partly due to how we calculated Team Value and the fact that no trades offered the model a chance to maintain its draft capital.

Other analytical approaches are making their way into football more and more every day. Teams decide to go for it more on 4th down now than ever before because they are using expected points and analytics to drive their decisions. They are using these same analytics to help with their play-calling and even whether or not to go for two, or just attempt the extra point. If analytics are continuing to grow in the sport, then why stop on the field. Shouldn't this same train of thought assist the general manager in optimizing his team's abilities off the field, especially if the coach is going to use it to optimize their chance of winning on the field? The ADP results will aid the general manager in their decision making during and in the weeks leading up to the draft.

Chapter 7: Future Work

As analytics and simulations continue to make their way further into sports, the research will only continue to grow. As our research found, many casual football fans are performing some high-level analysis. We will point out some potential research areas to further our work, as well as some other parallel areas where our work might be beneficial.

7.1 Future Research

Before it can be decided as to the usefulness of Approximate Dynamic Programming (ADP) in conjunction with the National Football League (NFL) Draft, it needs to be further analyzed. The research has shown there is potential, but further research may be required. Ideally, further research with a team or possibly a group of subject matter experts. Someone who would be willing and able to provide more inputs, allowing for the reduction of the number of assumptions used in the model.

These inputs would start with the grading scheme. Teams would obviously be better suited to provide a single grading scheme for both the players on their current roster, as well as for the draft-eligible players. Teams would also be able to provide better inputs into what they see as their team needs. The teams are truly the only ones who know what they are trying to accomplish with the draft. For instance, in the 2020 NFL Draft, everyone thought for sure that Green Bay was in the market for a play-maker, such as a wide receiver, to give Aaron Rodgers another weapon on the outside. It was, after all, a very deep draft at wide receiver. Instead, they traded up four spots and drafted his potential successor. While the Packers' front office got roasted over the summer and during the early part of the season, Aaron Rodgers led the Packers offense to be the number one scoring offense in the league, all without that new shiny toy at wide receiver everyone thought they needed. Everyone, but for them.

For the teams that are interested in using the model to help shape their team needs, that is a possibility as well. The team needs could potentially be developed through the model as team draft targets. One would be able to analyze the strengths of the draft with the weaknesses of the team. Teams could also create a similar model for free agency or combine the two. Further analysis would allow the teams to compare the strengths of the draft and the free agency market to help develop a more thorough plan of addressing their team needs in the off-season.

Teams could also assign better costs of trading up and trading back based on their experiences or simply, by making a phone call. Plus, teams will know the feasibility of certain trade partners, whether it be from the cost of trading or the relationship between the front offices. Some teams do not like to make trades within their divisions. These are assumptions that can be addressed and removed by the teams themselves.

Most importantly, teams will be better positioned to develop a contribution function to better steer the ADP strategy. Offline metrics, such as the Team Score and the Team Value, could also be improved upon by the teams and worked into the model instead of being offline. With these inputs, the number of assumptions would be reduced, only improving the model and increasing the benefits and interpretability of the model to the team.

Without the inputs from a team or a group of experts, there are still some steps to further this research. One of the first adjustments we would make with more time would be to move the decision maker's position or draft pick to different parts of the round. We used the 30th position or the back end of each round. We would like to move it up to the front of the draft and the middle at a minimum. This would also increase the costs of trading, but is a straightforward adjustment. This could provide more information to answer some of the research questions as to the cost of trading in the draft.

Another addition to the model, that would also make the model more realistic, is to have the model span over two to three drafts and not just one. There would be some added assumptions, specifically about the players in the latter two drafts, but could help teams who are looking at a long-term solution to their problems and not just trying to win now. Spanning the model over multiple years would also allow more trading of draft picks in the first year of the model. As you may remember from the model, the decision maker was restricted from trading in the fifth, sixth, and seventh rounds. This was mainly since most of those trades historically involved a draft pick of the same round from the following year.

Finally, if we had more time, we would have adjusted the draft order to resemble the actual 2020 NFL Draft order. We eliminated all previous trades and kept the draft at its original state before compensatory picks were added. In other words, every team had one draft pick in every round. The team with the 30th pick in the first round, had the 30th pick in every subsequent round until they traded within the model. This would make the model more comparable to real life and we could even grade the real-life draft using our metrics in order to validate the model.

In summary, there are plenty of opportunities to further this research that could benefit this specific topic but could also benefit some parallel fields. In the next section, we will cover some parallel fields that could profit from a similar methodology. In the end, this is simply a resource allocation problem.

7.2 Parallels to Other Applications

There are many applications in which this research could be applied. As a member of the United States (U.S.) Army, resource allocation is one of our biggest requirements. Whether you are talking about its people or its equipment, the U.S. Army is constantly dealing with this type of problem. We have to know when to replace older equipment or vehicles and how to go about acquiring new equipment.

In addition to replacing older equipment, the military has many operational challenges that require the positioning of resources across the globe (and even space) to anticipate future demands. When conducting operations in a foreign country, the military must make many decisions in terms of positioning forces on the battlefield. These scarce resources could be certain buildings or terrain features, or certain roads or highways. The placement of forces or even forward operating bases is paramount in setting the conditions for accomplishing the mission.

These are just a few military examples that could benefit from further research on resource allocation problems with ADP. Other military parallels are re-supply routes or missions and inventory management. As for the personnel side of things, there is potential that a model such as this could be adapted to assist the U.S. Army Human Resources Command with their branch assignment of officers or Soldiers.

Outside of the military, many large businesses could benefit from this research as well. Many businesses are worried about their carbon footprints and environmental effects. This is leading them down the path of acquiring and developing future technologies to address these issues. Many net zero programs across the country could use similar research in resource allocation problems.

Similar to the Army adapting this model to assist with their branch assignment of officers or Soldiers, many organizations could use a similar model to aid in their team building. This research is not limited to professional sports teams. It is clear that with a little thought, there are plenty of parallels for this research. There is more work to be done to make it more beneficial to a professional football team, but we have shown that the methodology works and could be extremely useful in many applications.

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Biography

Ira L. Crofford, Jr. graduated from David Crockett High School, Austin, Texas, in 1998. He received his Bachelor of Science from the United States Military Academy in 2002. He served as an Armor Officer for the U.S. Army from 2002-2010, deploying three times to Iraq. In his third deployment, he served as a Troop Commander for Bravo Troop, 1st Squadron, 9th U.S. Cavalry, and later in the deployment for Headquarters and Headquarters Troop, 1st Squadron, 9th U.S. Cavalry. After command, he obtained his Master of Science from Virginia Polytechnic Institute and State University (Virginia Tech) in 2012. While at Virginia Tech, Ira also became a shareholder for the Green Bay Packers of the National Football League. After a three-year teaching assignment in the Department of Mathematical Sciences at the United States Military Academy, he was assigned to the Military Strength Analysis and Forecasting Division, Plans and Resources, U.S. Army G-1 at the Pentagon for three years. While working in the G-1, he was selected to return to West Point in the summer of 2021 to teach in the Department of Mathematical Sciences, following the completion of his Ph.D. at George Mason University. Ira is married to the former Anne Hockley of Overland Park, Kansas, and has two children: Nell and Nolan.