# Eliminating Bias in Determining the Player of the Match in Football



A dissertation submitted in fulfillment of the requirements for the degree of BSc Mathematical Sciences

by

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May 2024

## Acknowledgements

I am grateful to Dr. Lateef Jolaoso, my supervisor, for his unwavering support and constructive feedback throughout this project, which has significantly contributed to this report.

#### Abstract

This dissertation employs a Deterministic Operational Research approach to tackle bias in the selection of the Player of the Match. It introduces a linear programming model aimed at standardising the performance evaluation of football players and effectively identifying the Player of the Match. The linear programming model analyses player statistics across performance indicators and includes assigned weights for each statistic based on player positions: Goalkeeper, Defender, Midfielder and Forward. The purpose of applying these weights is to make the model fairer and balanced by taking into account the difficulty and rarity of carrying out different actions due to player positions.

The model provides enhanced insights in player performance which could be used by coaches to make decisions in game strategy, player selection etc. Even though this model specialises in Football, the approach could be adapted to any sport to determine player performance.

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#### 1 Introduction

Football is a very complex game, as the biggest sport in the world, with just the European football market being worth approximately 25.1 billion pounds [1], there are various strategies, positions, statistics, players, etc, to account for. From scoring and assisting goals to defending and saving, each players contribution is crucial for a teams success.

In the English Premier League, fans can vote for who they think should be awarded Player of the Match [2] and in the UEFA Champions League, a technical observer panel decides who deserves to be the Player of the Match [14]. In some instances this choice of player could be based on the fans or panels personal judgment which can be skewed, often painting the wrong picture of how the match went. Furthermore, managers are also liable to having a bias view on their own players and as a result, they will make incorrect decisions and possibly lose a match. This happens in countless games and methods within Deterministic Operational Research can help remedy this problem. This report addresses the current issues surrounding bias on the Player of the Match and how it can be overcome. While subjective assessments have their validity, data analytics in football presents an opportunity to discard these evaluations through data and performance of players in game.

This study proposes a linear programming model, uniting performance indicators of players into a constrained optimization problem. However, the challenge lies in measuring the statistic of the players in a way that fairly represents each players contribution, regardless of their position. To tackle this, the model assigns weighted values to these performance indicators associated with each player position: Goalkeeper, Defender, Midfielder and Forward.

In summary, the objective of this report is to tackle the current method of selecting the Player of the Match from a subjective method to a data driven method. Applications of this report:

- Assist Managers with Player Selection
- Talent Identification and Scouting
- Player Development
- Team Strategy and Tactics

#### 2 Literature Review

Operational Research was introduced to help the military in the second world war and became a branch of mathematics soon after, [4]. As stated in [5], Operational research is the study of how to form mathematical models of complex science, and how to analyse them using mathematical techniques, "A Mathematical model is a collection of variables and the relationships needed to describe important features of a given problem", [5]. There are many types of Operational Research, such as Stochastic Operational Research, where assumptions of parameters are made, this differs from Deterministic Operational Research where parameters are fixed, [5]. Due to this, Deterministic Operational Research was perceived to be the most beneficial model in this context. This literature review will aim to elaborate on utilising linear programming techniques with Deterministic Operational Research.

#### 2.1 Existing Literature on Player Statistics and Performance Analysis

An article by 'R Mackenzie' and 'C Cushion' reviews performance analysis in football, [6]. The article states that an alternative approach to performance analysis in football is needed, it suggests that the current methods of performance analysis mainly focus on quantitative metrics, such as goals scored, number of passes completed, number of tackles completed etc, whilst excluding external factors. Social and cultural influences occurring at the time of performance should be taken into consideration such as chemistry with teammates, match conditions, psychological conditions of the players, etc and so the article suggests that including these factors will provide a more comprehensive and detailed understanding of player performance.

An article by 'S Altmann' examined to what extent the physical match performance of professional soccer players is both position and player specific. Utilising data from the 2019/2020 German Bundesliga season, players that met the criteria of playing a minimum of four matches in at least two different positions were picked out and their physical match performance was analysed separately for each position. Total distance, high-intensity distance, sprinting distance, and acceleration were the four parameters used to determine if physical match performance is dependent on the players position or consistent across different positions. The findings of the study provided potential practical applications relating to the connection between players performance according to their position and their physical capabilities and concluded that a change in playing position has an influence on physical player performance.

An article by 'Varuna De Silva' used movement data collected from global positioning system (GPS) tracking to identify high speed running activity and distance covered during training sessions and competitive matches. The purpose of this study was to analyse player tracking data to understand activity level differences between training and match sessions, with respect to playing positions. The data collected was from 53 football players aged between 18-23 across four season from 2014-2018. The results of the study showed that, while there are significant position-specific differences in activity levels during matches, such differences are not observed for data pertaining to the training sessions. During matches, the attacking playing positions require players to perform more high speed runs compared to other positions. However, the study found no significant difference in the demand for high speed runs at different positions during training sessions.

#### 3 Methodology

Aforementioned above, a linear programming model will be used to identify the player with the highest performance index. This model will be subject to constraints and will also account for statistical bias due to a players position. For example, a Defender scoring a goal will score higher than a Forward scoring a goal. The main purpose of this model is to help give an unbiased analysis on player performance.

#### 3.1 Modelling Process

This section is built from the foundations of section 1.1 of [5] and section 1.3 of [9]:

#### Problem Recognition and Data Collection:

This process involves identifying the problem and gathering any necessary data needed for the model.

#### Creating the Mathematical Model:

As mentioned in [9], it is imperative to be thorough in ensuring all variables have been identified as this will determine the objective. "This process involves determining decision variables, constraints and objectives that are required to solve the problem", [5].

#### Solving the Mathematical Model:

The aim is to find the values of the decision variables corresponding to the most optimum objective function value. However, sometimes this is not solvable, in which case researchers often develop heuristics, [5]. A heuristic is an approximate strategy for problem solving and decision making that does not guarantee a correct solution but yields a reasonable solution quickly, [10].

#### Implementing the Model:

The task involves translating the model recommendations into practice. Usually, the decision variables will be used - however, this is not always the case. For example, if the aim was to achieve an integral solution but the solution was in fact a fractional value, it is possible to round the solution up or down to obtain an integer. However, this is not recommended as an optimal result that satisfies all the constraints will not be achieved, [5].

#### 3.2 Model Problem

Maximise

$$Z = \sum_{i} \sum_{j} S_{i,j} * w_j * x_{i,j}$$

$$\tag{1}$$

Subject to Constraints:

 $\sum_{i} \sum_{j} x_{i,j} \ge 22$ 

 $\sum_{i} \sum_{j} x_{i,j} \le 32$ 

 $3. Y_i \le 1$ 

4.  $R_i \le 0$ 

5.  $f_{\text{Goalkeeper}} \le 0$ 

6.  $f_{\rm Defender} \leq 1$ 

7.  $f_{\rm Midfielder} \leq 2$ 

8.  $f_{\text{Forward}} \leq 2$ 

9.  $x_{i,j}, S_{i,j} \ge 0$ 

Z represents the constrained objective function, the total performance score to maximise.

j represents the position (Goalkeeper, Defender, Midfielder, Forward).

i represents the player.

 $f_{"position"}$  represent the number of fouls committed by a player in a specified position during a match.

 $S_{i,j}$  represents the statistics of player i in position j.

 $w_i$  represents the weight assigned to each statistic based on the player's position j.

 $x_{i,j}$  represents a binary decision variable indicating whether player i is considered for position j in the evaluation process. It is a binary variable defined as:

 $\rightarrow x_{i,j} = 1$ , if player i is selected for position j in the evaluation process,

 $\rightarrow x_{i,j} = 0$ , if player i isn't selected for position j and is not part of the evaluation process, [11].

#### 3.3 Constraints

Constraint 1 shows that the minimum number of players in the evaluation should be 22, meaning that there were no substitutions made by any of the teams throughout the game.

Constraint 2 shows that the maximum number of players in the evaluation should be 32, meaning that both teams used up all their substitutions throughout the game (5 substitutions per team).

Constraint 3 limits a players number of yellow cards to less than or equal to 1, exceeding this would mean the player gets sent off the pitch and would get a 0 for the evaluation.

Constraint 4 limits a players number of red cards to less than or equal to 0, exceeding this would mean the player gets sent off the pitch and would get a 0 for the evaluation.

Constraint 5 limits the number of fouls for a Goalkeeper to less than or equal to 0, exceeding this would mean the player would get a 0 for the evaluation.

Constraint 6 limits the number of fouls for a Defender to less than or equal to 1, exceeding this would mean the player would get a 0 for the evaluation.

Constraint 7 limits the number of fouls for a Midfielder to less than or equal to 2, exceeding this would mean the player would get a 0 for the evaluation.

Constraint 8 limits the number of fouls for a Forward to less than or equal to 2, exceeding this would mean the player would get a 0 for the evaluation.

Constraint 9 serves as the non-negativity constraint, ensuring that the binary decision variable and all statistics for players remain non-negative throughout the evaluation process.

Calculations of constraints 5-8 are provided in section 8.1 of the Appendix.

#### 4 Data Collection and Preparation

The development of the linear programming model requires data collection and preparation. This section elaborates on the process of gathering and organising data, as well as determining the weights assigned to each player position for every statistic.

#### 4.1 Data Collection Process

FotMob is a football statistic website and is renowned for its detailed data on player performance, [32] and holds significance on football players market value, [12]. WhoScored is another football statistic website, [33] that use internal schemes developed by a group of soccer experts to rate player and team performances, [13]. These platforms were chosen for its reliability and depth of data available such as assists, goals, passes, etc. The datasets, used in the analysis of each game, will contain specific statistics for players obtained from these websites.

#### 4.2 Selecting Specific Statistics for Review

Football is a huge sport and there are countless number of ways technology is utilised to gain player statistics, such as Global Positioning System (GPS), [14], and goal line technology, [15]. As a consequence, there are numerous statistics for each player, the model has been refined to emphasize only the most vital statistics.

The statistics included in the model are:

#### 1. Goals Scored

"A goal is scored when the whole of the ball passes over the goal line, between the goalposts and under the crossbar, provided that no offence has been committed by the team scoring the goal", [16].

#### 2. Shots Taken

"In association football, shooting is hitting the ball in an attempt to score a goal. It is usually done using the feet or head. A shot on target or shot on goal is a shot that enters the goal or would have entered the goal if it had not been blocked by the goalkeeper or another defensive player", [17].

#### 3. Passes Completed

"The purpose of passing is to keep possession of the ball by maneuvering it on the ground between different players with the objective of advancing it up the playing field", [18].

#### 4. Assists

"An assist was awarded to the player who had given the last pass to the goalscorer", [19].

#### 5 Tackles

"Legal tackling in soccer is an action taken by a defender to attempt to, or to actually, take the ball away from an opponent (to "dispossess" them of the ball) where, if contact is involved, the contact does not violate Law 12 of the Laws of the Game, "Fouls and Misconduct." Tackling is very likely to involve contact. It is the responsibility of the tackler to conduct the tackle safely, otherwise a foul or an injury might occur", [20].

#### 6. Clearances

"A defensive action when a player attempts to get the ball away from a dangerous zone on the pitch with no immediate target regarding a recipient for the ball", [21].

#### 7. Interceptions

"Intercepting involves stealing the ball from your opposition. This could happen when you get in the way of a pass or a dribble, take advantage of a poor touch, block a shot or a cross", [22].

#### 8. Saves

"A Goalkeeper preventing the ball from entering the Goal with any part of their body when facing an intentional attempt from an opposition player", [21].

#### 9. Shots Off Target

"A deliberate attempt to score that misses the target, without contact from a player diverting the ball from on target to off target. A shot hitting the frame of the Goal is classified as a Shot Off Target unless the ball subsequently enters the net. A Blocked Shot is not classified as a Shot Off Target", [21].

#### 10. Duels Lost

"A duel is a 50-50 contest between two players of opposing sides in the match. For every Duel Won there is a corresponding Duel Lost depending on the outcome of the contest", [21]

#### 11. Yellow Cards

"Warning issued by the referee to a player as a caution", [29].

#### 12. Red Cards

"Signifies a player's dismissal from the match. It is issued for serious offences and any action that brings the game into disrepute. A red-carded player cannot be replaced, leaving their team short-handed for the remainder of the game", [29].

#### 13. Goals Conceded

"In sport, if you concede goals or points, you are unable to prevent your opponent from scoring them", [30].

#### 4.3 Weights

To calculate the weights, an inverse ratio method was applied, a method assigning significance to rarer events relative to more common events. The initial step would be to define the total number of events (e.g goals scored) completed by each position during a football season. The proportion of goals scored for each player position is calculated as:

$$P_i = \frac{g_i}{C} \tag{2}$$

where  $P_i$  is the proportion of goals scored by position i,  $g_i$  is the number of goals scored by position i and G is the total number of goals scored in the season.

The inverse ratio is calculated by:

$$R_i = \frac{1}{P_i} = \frac{G}{q_i} \tag{3}$$

where  $R_i$  is the inverse ratio for position i.

This formulation assigns higher values to positions with fewer goals, reflecting their scoring rarity.

An issue arises when the event count may be 0, making the inverse ratio undefined. To address this, a small constant is added to the event for all positions. Consequently, by doing this the total number of events change, this change is dependent on the size of the constant. This adjustment allows for a balanced calculation for all positions without disproportionately inflating the calculations.

$$g_i' = g_i + c \tag{4}$$

$$G' = G + C \tag{5}$$

where  $g'_i$  is the adjusted goal count for position i, c is a small constant, G' is the new total number of goals and C = 4c is a constant, where the 4 is multiplied by the constant as there are 4 positions taken into consideration when summing up the total.

However, this method does not accurately reflect player performance evaluations in team sports where different positions have different player counts. For example, in football games there must be one Goalkeeper but there are usually multiple Defenders, Midfielders and Forwards, the amount is dependent on team strategy and formation. Consequently, the actions of a single Goalkeeper are magnified compared to the other positions. To rectify this imbalance, a scale factor is applied to the inverse ratio based on the average number of players in each position:

Goalkeepers have 1 player, leading to a scale factor of 1.

Defenders are generally more in number and have about 3-5 players, averaging a scale factor of 4. Midfielders are generally more in number and have about 3-5 players, averaging a scale factor of 4. Forwards generally have fewer players of about 2-3, averaging a scale factor of 2.5.

By implementing the scale factor based on the number of players in each position, the finalised weights would reflect actual game dynamics and enhance the fairness of the model.

Moreover, the game of football includes statistics which are easier to complete than others due to there being less obstruction from the opposing team, e.g completing a pass is easier than scoring a goal. This would mean that a model not accounting for this would undermine the more challenging actions on the field, making the player performance to be inaccurate.

To overcome this, a scale factor is applied to each statistic, regardless of player position, the scale factors will also be calculated using the inverse ratio method. The calculation to acquire these scale factors for each statistic would simply be the inverse of the proportion of each event relative to the total occurrences across all positions. By implementing this, the model can better differentiate the importance of each statistic and provide a more insightful evaluation to player performance. Calculations for these scale factors are provided in the Appendix, section 7.2.

The following weights are based on the statistics from the 2021/2022 season of the English Premier League, [31]:

1. Goals Scored	
Goalkeeper:	392332.08 (6)
Defender:	10257.05 (7)
Midfielder:	4371.39 (8)
Forward:	1857.63 (9)
2. Shots Taken	
Goalkeeper:	392282.73 (10)
Defender:	821.96 (11)
Midfielder:	414.46 (12)
Forward:	241.85 (13)
3. Passes Completed	

Goalkeeper:

Defender:

Forward:

Midfielder:

18.45

10.04

12.79

22.41

(14)

(15)

(16)

(17)

#### 4 Assists

4. Assists		
	Goalkeeper: 130775.43	(18)
	Defender: 8670.19	(19)
	Midfielder: 4966.16	(20)
	Forward: 4036.38	(21)
5. Tackles		
	Goalkeeper: 17832.24	(22)
	Defender: 298.73	(23)
	Midfielder: 290.81	(24)
	Forward: 564.96	(25)
6. Clearances		
	Goalkeeper: 604.56	(26)
	Defender: 163.62	(27)
	Midfielder: 560.31	(28)
	Forward: 970.23	(29)
7. Interceptions		
	Goalkeeper: 39232.30	(30)
	Defender: 398.10	(31)
	Midfielder: 585.34	(32)
	Forward: 1440.25	(33)
8. Saves		
	Goalkeeper: 174.37	(34)
	Defender: 1569349.68	(35)
	Midfielder: 1569349.68	(36)
	Forward: 980843.55	(37)

Calculations of weights are provided in section 8.2 and 8.3 of the Appendix.

#### 4.4 Negative weighting

Currently, the model only includes players achievements within the game but not their faults, these faults lead to the opposing team gaining a benefit, whether it is a free kick or a penalty gained from a foul or a player losing a duel of the ball leading the opposing team to score. To account for player faults, minus points will be applied to players who fail to fulfill their positional role on the pitch. The following metrics for each position will deduct points from players performance score:

- 1. Goalkeepers: Goals Conceded, Yellow Cards
- 2. Defenders: Goals Conceded, Shots Off Target, Yellow Cards, Duels Lost
- 3. Midfielders: Shots off Target, Yellow Cards, Duels Lost
- 4. Forwards: Shots off Target, Yellow Cards, Duels Lost

#### 4.4.1 Goals Conceded

The following process will be used to obtain a weight for goals conceded for Goalkeepers and Defenders, using the fact that most goals are scored by players in the Forward position, the weight of 1857.63 for goals scored will be used. Even though the main objective for Defenders and Goalkeepers is to stop the ball from entering the net, there may be scenarios where a goal conceded may be due to the fault of their Forward and Midfield players making a fault, to account for this we divide the weight of goals scored by a Forward position by the average number of players playing in both the Forward and Midfield positions:

$$\frac{1857.63}{2.5+4} \approx 285.79\tag{38}$$

where the above answer is rounded to 2 decimal places. This value of 285.79 represents the negative weight a Defender will receive if there is a goal conceded. Accounting for the fact that there is only 1 Goalkeeper and an average of 4 Defenders on the pitch, the value of 285.79 is to be divided by 4 to give the negative weight a Goalkeeper will receive if there is a goal conceded.

$$\frac{285.79}{4} \approx 71.45 \tag{39}$$

where the above answer is rounded to 2 decimal places.

#### 4.4.2 Yellow Cards

The negative weight for a yellow card given to a player will be 200, this is a fixed negative weight for all positions as a player given the yellow card will be based upon their own in game decisions and not a positional effort. Also, this fixed penalty allows for fairness and consistency within the model. The weighting of a deduction of 200 from the players performance score was selected based on comprehensive analysis of match data, reviewing specific player performances before and after receiving yellow cards, how team strategy and formation changes depending on how many players get a yellow card or depending on who gets given the yellow card. A study from [26], showed that receiving yellow cards negatively impacts the chance of winning and so the fixed negative weight of 200 for receiving a yellow card reflects the impacts on player and team performance.

#### 4.4.3 Shots Off Target

In accordance to [27], almost two thirds of the total shots taken in game are off target. To determine the negative weights for shots off target, this information will be utilised, as well as, the calculated weights for shots for Forwards and Midfielders which are 241.85 and 414.46. Taking an average of both weights we obtain:

$$\frac{241.85 + 414.46}{2} \approx 328.16\tag{40}$$

where the above calculation is rounded to 2 decimal places. The fact that two thirds of shots are off target means that this is a common occurrence and should be penalised proportionately to the average of the weights calculated above. A balanced approach would involve setting the penalty to be inversely proportional to the frequency of shots on target, hence, the negative weight for shots off target would be calculated as:

$$\frac{328.16}{3} \approx 109.39\tag{41}$$

where the above calculation is rounded to 2 decimal places. This calculation divides the average of the weights by 3 to reflect the higher probability of shots being off target.

#### 4.4.4 Duels Lost

"A duel is a 50-50 contest between two players of opposing sides in the match. For every Duel Won there is a corresponding Duel Lost depending on the outcome of the contest", [21]. The negative weight for duels lost would vary for different positions. Forward players would have a low weight as their main objective isn't reliant on winning duels and there are other positions to help deal with the opposing player if a duel is lost. Midfield players would have a increased weight compared to the Forwards as their role is to win duels and stop the opposing team from getting towards the goal. Defenders would have the largest weight for duels lost as the Defenders object is to stop the opposing teams attack and to be unsuccessful would mean that the opposing teams chance to score a goal increases significantly.

To determine the negative weighting for duels lost, results from [28] will be used, showing the success rates of ground duels per position based on player in the LaLiga. By taking an average of Central Defenders and Full Backs, the average success rate for Defenders is 55.12%, by taking an average of Defensive Midfielders, Attacking Midfielders and Wide Midfielders, the average success rate for Midfielders is 50.18%, and the success rate for Forwards is 47.70%. With these values, the calculation for the negative weights for duels lost is calculated as follows:

Defender: 
$$\frac{25}{1 - 0.5512} \approx 55.70$$
 (42)

Midfielder: 
$$\frac{25}{1 - 0.5018} = 50.18$$
 (43)

Forward: 
$$\frac{25}{1 - 0.4770} \approx 47.80$$
 (44)

where the above calculations are rounded to 2 decimal places. 25 was chosen as the base value for losing a duel as the value is significant enough to impact performance score of players but not too high to completely overshadow all other contributions made by the player in game. The value of 25 is then divided by 1 - the success rate of a player winning a duel, which is equivalent to the rate of a player losing a duel. The idea behind this formulation is to assign a more severe to penalty to positions where losing a duel could increase the chance of the opposing team to score a goal.

#### In summary:

Goalkeepers will be deducted a score of 200 for every yellow card received, as well as, a score of 71.45 for every goal conceded.

Defenders will be deducted a score of 200 for every yellow card received, a score of 285.79 for every goal conceded, a score of 109.39 for every shot off target and a score of 55.70 for every duel lost.

Midfielders will be deducted a score of 200 for every yellow card received, a score of a score of 109.39 for every shot off target and a score of 50.18 for every duel lost.

Forwards will be deducted a score of 200 for every yellow card received, a score of a score of 109.39 for every shot off target and a score of 47.80 for every duel lost.

#### 4.5 Excel Datasets

This section utilises Microsoft Excel for the datasets of football matches that are to be evaluated. Microsoft Excel provides a wide range of features for organising data and allows for flexible data collection, [23]. The datasets contains player statistics from 3 football matches. Each row represents the performance metrics of an individual player during the game. The dataset includes the statistics of all players, along with generic player information: name, position, and team.

As mentioned above, the data for this dataset was collected from football statistic websites FotMob and WhoScored.

The dataset includes the following columns:

- 1. Players
- 2. Position
- 3. Team
- 4. Goals Scored
- 5. Shots Taken
- 6. Passes Completed
- 7. Assists
- 8. Tackles
- 9. Interceptions
- 10. Clearances
- 11. Saves
- 12. Yellow Cards
- 13. Red Cards
- 14. Fouls
- 15. Duels Lost
- 16. Shots Off Target
- 17. Goals Conceded

Players	Position	Team	Goals Scored Shots Tal	ken	Passes Completed Ass	sists	Tackles	Interceptions	Clearances	Saves	Yellow Cards	Red Cards	Fouls	<b>Duels Lost</b>	Shots Off Target	Goals Conceded
Dominik Livakovic	Goalkeeper	Croatia	0	C	29	0		0 (	D	0	5	0 (	) (		0	0
Ivan Perisic	Defender	Croatia	0	C	38	1		2 1	1	6	0	0 (	) (		3	0
Josko Gvardiol	Defender	Croatia	1	1	66	0		0 3	3	4	0	0 (	3		4	0
Josip Sutalo	Defender	Croatia	0	C	66	0		0 (	)	5	0	0 (	) (	)	3	0
Josip Stanisic	Defender	Croatia	0	1	41	0		3 1	1	0	0	0 (	) 1		1	1
Mateo Kovacic	Midfielder	Croatia	0	1	69	0		6 (	)	1	0	0 (	) (		1	1
Luka Modric	Midfielder	Croatia	0	1	67	0		2	2	1	0	0 (	) (	)	2	0
Andrej Kramaric	Midfielder	Croatia	0	1	16	0		1 (	)	0	0	0 (	) (	)	0	0
Nikola Vlasic	Midfielder	Croatia	0	1	7	0		0 1	1	0	0	0 (	) (		1	1
Mario Pasalic	Midfielder	Croatia	0	C	10	0		1 (	)	0	0	0 (	1		2	0
Kristijan Jakic	Midfielder	Croatia	0	C	0	0		0 (	D	0	0	0 (	0 0	)	0	0
Mislav Orsic	Forward	Croatia	1	5	25	0		3 (	D	1	0	0 (	) 2	2	6	2
Lovro Majer	Forward	Croatia	0	C	28	0		1 (	D	1	0	0 (	) 3	3	6	0
Marko Livaja	Forward	Croatia	0	1	13	1		0	D	0	0	0 (	1	:	3	0
Bruno Petkovic	Forward	Croatia	0	C	12	0		1 (	)	0	0	0 (	) 2	!	6	0
Yassine Bounou	Goalkeeper	Morocco	0	C	42	0		0	D	0	10	0 (	) (	)	0	0
Achraf Hakimi	Defender	Morocco	0	C	55	0		3 1	1	1	0	0 (	1		7	0
Badr Benoun	Defender	Morocco	0	C	21	0		0 1	ı	0	0	0 (	1		3	0
Jawad El Yamiq	Defender	Morocco	0	1	35	0		0 1	1	1	0	0 (	1		1	0
Achraf Dari	Defender	Morocco	1	1	31	0		0 2	2	6	0	0 (	) (	)	0	0
Yahia Attiyat Allah	Defender	Morocco	0	C	42	0		0 (	D	2	0	0 (	) 2	2	3	0
Bilal El Khannous	Midfielder	Morocco	0	C	24	0		0	D	2	0	0 (	) (	)	2	0
Selim Amallah	Midfielder	Morocco	0	C	15	0		2 2	2	1	0	1 (	) 2	2	3	0
Azzedine Ounahi	Midfielder	Morocco	0	C	25	0		0	D	0	0	1 (	) (	)	2	0
Sofyan Amrabat	Midfielder	Morocco	0	C	49	0		1 (	D	0	0	0 (	1	:	2	0
Ilias Chair	Midfielder	Morocco	0	C	13	0		1 (	D	0	0	0 (	) (	)	3	0
Abdelhamid Sabir	i Midfielder	Morocco	0	C	10	0		1 (	D	0	0	0 (	0	)	7	0
Hakim Ziyech	Forward	Morocco	0	2	64	0		0 3	3	0	0	0 0	1		5	2
Youssef En-Nesyri	Forward	Morocco	0	4	16	0		0 0	)	1	0	0 (	) 1		2	2
Sofiane Boufal	Forward	Morocco	0	1	20	0		2 (		1	0	0 0	1		3	1
Anass Zaroury	Forward	Morocco	0	C	10	0		0 (	)	0	0	0 (	) (		0	0

Figure 1: Croatia vs Morocco 17th December 2022

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Players	Position		Goals Scored	Shots Taken	Passes Completed	Assists	Tackles	Interceptions	Clearances	Saves	Yellow Cards	Red Cards	Fouls	Duels Lost	Shots Off Target	Goals Conceded
Ederson Moraes	Goalkeeper	Manchester City		0	0	27	0	0	0 (	)	4	0 (	0	0	0	)
Benjamin Mendy	Defender	Manchester City		0	0	60	0	2	0 (	)	0	0 (	0	2	5	
Aymeric Laporte	Defender	Manchester City		0	0	89	0	2	2 3	3	0	0 (	0	0	4	
Vincent Kompany	Defender	Manchester City		0	0	88	0	2	1 3	3	0	0 (	0	0	2	
Kyle Walker	Defender	Manchester City		0	1	68	0	1	0 :	l .	0	0 (	0	1	2	
David Silva	Midfielder	Manchester City		0	2	26	0	1	0 (	)	0	0 (	0	0	2	2
Fernandinho	Midfielder	Manchester City		0	0	23	0	2	0 (	)	0	0 (	0	2	2	
Ilkay Gundogan	Midfielder	Manchester City		0	3	64	0	1	2 (	)	0	0 (	0	0	2	2
Kevin De Bruyne	Midfielder	Manchester City		0	3	38	3	2	0 (	)	0	0 (	0	0	4	1
Raheem Sterling	Forward	Manchester City		2	3	33	0	1	1 (	)	0	0 (	0	0	5	
Sergio Aguero	Forward	Manchester City		1	4	23	1	2	0 (	)	0	0 (	0	0	7	1
Bernardo Silva	Forward	Manchester City		1	4	45	0	5	2 (	)	0	0 (	0	3	5	2
leroy sane	Forward	Manchester City		0	0	8	0	0	0 (	)	0	0 (	0	0	2	
Hugo Lloris	Goalkeeper	Tottenham Hotspur		0	0	28	0	0	0 (	)	4	0 (	0	0	0	
Kieran Trippier	Defender	Tottenham Hotspur		0	0	26	1	3	1 4	1	0	0 (	0	1	2	
Jan Vertonghen	Defender	Tottenham Hotspur		0	0	36	0	5	1 3	3	0	0 (	0	1	3	
Toby Alderweireld	Defender	Tottenham Hotspur		0	0	27	0	1	0 7	7	0	0 (	0	0	3	
Danny Rose	Defender	Tottenham Hotspur		0	0	30	0	0	2 :	L	0	1 (	0	1	6	D
Victor Wanyama	Midfielder	Tottenham Hotspur		0	0	28	0	4	2 2	2	0	1 (	0	4	7	
Moussa Sissoko	Midfielder	Tottenham Hotspur		0	0	12	0	0	1 (	)	0	1 (	0	0	0	
Dele Alli	Forward	Tottenham Hotspur		0	0	39	0	0	2 3	3	0	0 (	0	0	7	
Christian Eriksen	Midfielder	Tottenham Hotspur		0	4	37	1	0	0 2	2	0	0 0	0	0	3	1
Lucas Moura	Forward	Tottenham Hotspur		0	0	16	0	0	0 (		0	0 (	0	1	4	
Son Heung-Min	Forward	Tottenham Hotspur		2	5	21	0	3	0 (		0	1 (	0	1	9	1
Davinson Sanchez	Defender	Tottenham Hotspur		0	0	0	0	0	0 0		0	0 0	0	0	0	
Fernando Llorente	Forward	Tottenham Hotspur		1	2	12	0	0	0 3	3	0	0 0	0	2	8	
Ben Davies	Defender	Tottenham Hotspur		0	0	3	0	1	0	2	0	0 0	0	1	2	

Figure 2: Manchester City vs Tottenham Hotspur 17th April 2019

Players	Position	Team	Goals Scored	Shots Taken	Passes Completed	Assists	Tackles	Interceptions	Clearances	Saves	Yellow Cards	Red Cards	Fouls	Duels Lost	Shots Off Target	Goals Conceded
	Goalkeeper			0	0	14 (		0	0	1	1	0	0 (	) (		)
		Spain		0	0	51 :	1	3	0	0	0	0	0 0	7	,	
		Spain		0	1	107	)	2	0	0	0	0	0	1 4		1
		Spain		0	3	78 (		1	2	0	0	0	0 (	) 3	3	2
Jordi Alba	Defender	Spain		0	0	74 (		1	2	1	0	0	0 (	) 3	3	
Andres Iniesta		Spain		0	2	91 1	ı	1	1	1	0	0	0 (	) 1		1
Sergio Busquets	Midfielder	Spain		0	1	62 (	)	1	1	0	0	0	0 :	1 5	5	1
Thiago Alcantara	Midfielder	Spain		0	2	87 (		3	1	0	0	0	0 :	1 3	3	2
David Silva	Forward	Spain		0	1	41 (		0	1	0	0	0	0 (	) 1		D
Diego Costa	Forward	Spain		0	2	21 (	)	0	0	0	0	0	0 (	) 9		2
Isco	Midfielder	Spain		1	2	98 (		3	2	0	0	0	0 :	1 3	3	
Rodrigo	Forward	Spain		0	1	4 (	)	0	0	0	0	0	0 (	) 2		1
lago Aspas	Forward	Spain		1	2	6 (	)	0	0	1	0	0	0 :	1 2		1
Marco Asensio	Forward	Spain		0	1	8 (	)	0	0	0	0	0	0 (	) 1		1
Munir Mohamedi	Goalkeeper	Morocco		0	0	34 (	)	0	0	0	2	1	0 (	) (	)	
Nabil Dirar	Defender	Morocco		0	0	23 (	)	3	1	3	0	0	0 2	2 9		)
Manuel da Costa	Defender	Morocco		0	0	32 (	)	1	2	4	0	1	0 2	2 4		
Romain Saiss	Defender	Morocco		0	0	22 (	)	2	2	5	0	0	0 (	) (		)
Achraf Hakimi	Defender	Morocco		0	0	25 (		3	0	6	0	1	0 (	) 2	2	)
Karim El Ahmadi	Midfielder	Morocco		0	0	18 (	)	1	0	1	0	1	0 2	2 2	2	)
Nordin Amrabat	Forward	Morocco		0	1	10 (		2	1	0	0	1	0 5	5 10		1
Moubarak Boussoufa	Midfielder	Morocco		0	0	25 (		0	1	1	0	1	0 :	1 8	3	)
Younes Belhanda	Midfielder	Morocco		0	0	13 (	)	1	0	2	0	0	0 :	1 5	5	)
Hakim Ziyech	Forward	Morocco		0	2	16 (		4	3	0	0	0	0 :	1 6	5	1
Khalid Boutaib	Forward	Morocco		1	2	11 (		1	0	0	0	0	0 :	1 4	1	
Aziz Bouhaddouz	Forward	Morocco		0	0	2 (		0	0	0	0	0	0 (	0		
Faycal Fajr	Midfielder	Morocco		0	0	9 :	L	0	0	0	0	0	0 2	2 2	2	
Youssef En-Nesyri	Forward	Morocco		1	1	5 (	)	0	0	0	0	0	0 (	) (		

Figure 3: Spain vs Morocco 25th June 2018

#### 5 Model Implementation

The linear programming model was implemented using Python. Python has a very simple syntax making it useful to use to solve complex tasks, [24], and is the preferred language for data analysis by most professionals, [25]. The integration of Python and Excel was essential for the implementation of the model due to the structure and formatting of the datasets, to do this the pandas library in Python was utilised as it specialises with working with datasets, [26].

The model's algorithm was designed to read player performance data, process it according to the constraints in the model and weightings for different statistics for different player positions, and output a performance score for each player. The player with the highest performance score represents, according to the model, the individual whose contributions most significantly influenced the match's outcome. Hence, the player with the highest performance score would be considered the Player of the Match.

#### 5.1 Python Code

Below is an explanation of the Python code implemented for the linear programming model, which integrates the Excel datasets to conduct player evaluation for all players participating in the match.

```
import pandas as pd
  data_path = 'Dataset.xlsx'
  data = pd.read_excel(data_path)
  data = data.dropna(subset=['Players', 'Position', 'Team'])
  data['evaluation'] = 1
  data.loc[data['Yellow Cards'] > 1, 'evaluation'] = 0
data.loc[data['Red Cards'] > 0, 'evaluation'] = 0
  data.loc[(data['Position'] == 'Goalkeeper') & (data['Fouls'] > 0), 'evaluation'] = 0
  data.loc[(data['Position'] == 'Defender') & (data['Fouls'] > 1), 'evaluation'] = 0
  data.loc[(data['Position'] == 'Midfielder') & (data['Fouls'] > 2), 'evaluation'] = 0
13
  data.loc[(data['Position'] == 'Forward') & (data['Fouls'] > 2), 'evaluation'] = 0
14
15
   if (data [ 'Goals Scored', 'Shots Taken', 'Passes Completed', 'Assists', 'Tackles', '
       Clearances', 'Interceptions', 'Saves', 'Fouls', 'Duels Lost', 'Shots Off Target',
       Goals Conceded []. min(axis=0) < 0. any():
       raise ValueError ("The evaluation cannot be complete; negative values found in
17
       dataset.")
18
   weights = {
        'Goalkeeper': {'Goals Scored': 392332.08, 'Shots Taken': 392282.73, 'Passes
       Completed: 18.45, 'Assists: 130775.43, 'Tackles: 17832.24, 'Clearances: 604.56,
         'Interceptions': 39232.30, 'Saves': 174.37, 'Goals Conceded': -71.45, 'Yellow
       Cards': -200 },
       'Defender': {'Goals Scored': 10257.05, 'Shots Taken': 821.96, 'Passes Completed': 10.04, 'Assists': 8670.19, 'Tackles': 298.73, 'Clearances': 163.62, 'Interceptions
21
       ': 398.10, 'Saves': 1569349.68, 'Goals Conceded': -285.79, 'Shots Off Target': -109.39, 'Yellow Cards': -200, 'Duels Lost': -55.70}, 'Midfielder': {'Goals Scored': 4371.39, 'Shots Taken': 414.46, 'Passes Completed': 12.79, 'Assists': 4966.16, 'Tackles': 290.81, 'Clearances': 560.31, 'Interceptions'
       : 585.34, 'Saves': 1569349.68, 'Shots Off Target': -109.39, 'Yellow Cards': -200,
       Duels Lost': -50.18},
        'Forward': {'Goals Scored': 1857.63, 'Shots Taken': 241.85, 'Passes Completed':
       22.41, 'Assists': 4036.28, 'Tackles': 564.96, 'Clearances': 970.23, 'Interceptions'
       : 1440.25, 'Saves': 980843.55, 'Shots Off Target': -109.39, 'Yellow Cards': -200,
       Duels Lost': -47.80 }
  }
24
25
  stat_columns = ['Goals Scored', 'Shots Taken', 'Passes Completed', 'Assists', 'Tackles'
, 'Clearances', 'Interceptions', 'Saves', 'Yellow Cards', 'Duels Lost', 'Shots Off
```

```
Target', 'Goals Conceded']
     position, pos_weights in weights.items():
27
      for stat in stat_columns:
28
29
          if stat in pos_weights:
               data.loc[data['Position'] == position, stat] *= pos_weights[stat]
30
31
               data.loc[data['Position'] == position, stat] = 0
32
33
  data['Total_Score'] = data[stat_columns].sum(axis=1) * data['evaluation']
34
35
  data.sort_values(by='Total_Score', ascending=False, inplace=True)
36
  print(data[['Players', 'Position', 'Team', 'Total_Score']])
```

Listing 1: Python code for player evaluation

Line 1 imports the 'pandas' library in Python.

Lines 3-4 specify the location of the dataset and loads the 'Dataset.xlsx' dataset into Python.

Line 6 removes rows were 'Players', 'Position', or 'Team' is NaN.

Line 8 adds a new column 'evaluation' to the data frame, setting all the values to 1, this represents that all players are eligible for player evaluation.

Line 9 applies the yellow card constraint, it sets evaluations scores to 0 for players exceeding the limit of 1 yellow card.

Line 10 applies the red card constraint, it sets evaluations scores to 0 for players who have any red cards.

Lines 11-14 applies the foul constraints based on player positions, setting evaluation scores to 0 if any player exceeds the allowed foul limit specific to their position.

Lines 16-17 ensures that all values are greater than or equal to 0, if not it raises an error indicating an issue with the data integrity and does not complete the evaluation.

Lines 19-24 defines the weights for each statistic by position.

Lines 26-34 calculates performance cores for each player by multiplying each statistic by its corresponding weight based on the players position, sums the result to get the total score and then multiplies the score with the evaluation factor, which ensures that players disqualified by the constraints do not receive a score.

Lines 36-37 sorts the performance score in descending order and prints the names, position, teams and total score of all players showing their result of the evaluation.

#### 6 Results

#### 6.1 Croatia vs Morocco

Table 1: Player Performance Scores

Players	Position	Team	Total Score
Achraf Dari	Defender	Morocco	12596.59
Ivan Perisic	Defender	Croatia	10576.10
Mislav Orsic	Forward	Croatia	5786.66
Hakim Ziyech	Forward	Morocco	5780.91
Marko Livaja	Forward	Croatia	4426.06
Luka Modric	Midfielder	Croatia	3483.64
Mateo Kovacic	Midfielder	Croatia	3442.57
Sofiane Boufal	Forward	Morocco	2537.41
Yassine Bounou	Goalkeeper	Morocco	2375.70
Selim Amallah	Midfielder	Morocco	2153.92
Josip Stanisic	Defender	Croatia	2077.01
Youssef En-Nesyri	Forward	Morocco	1981.81
Dominik Livakovic	Goalkeeper	Croatia	1335.45
Bilal El Khannous	Midfielder	Morocco	1327.22
Jawad El Yamiq	Defender	Morocco	1107.80
Achraf Hakimi	Defender	Morocco	1048.63
Josip Sutalo	Defender	Croatia	1027.85
Nikola Vlasic	Midfielder	Croatia	929.76
Andrej Kramaric	Midfielder	Croatia	909.91
Sofyan Amrabat	Midfielder	Morocco	817.16
Bruno Petkovic	Forward	Croatia	547.08
Mario Pasalic	Midfielder	Croatia	318.35
Ilias Chair	Midfielder	Morocco	306.54
Anass Zaroury	Forward	Morocco	224.10
Abdelhamid Sabiri	Midfielder	Morocco	67.45
Azzedine Ounahi	Midfielder	Morocco	19.39
Yahia Attiyat Allah	Defender	Morocco	0.00
Kristijan Jakic	Midfielder	Croatia	0.00
Josko Gvardiol	Defender	Croatia	0.00
Lovro Majer	Forward	Croatia	0.00
Badr Benoun	Defender	Morocco	-129.74

The table above shows the player performance scores, in descending order, of all players participating in the match between Croatia and Morocco. Achraf dari, a Defender for Morocco, received the highest performance score of 12596.59 meaning that, according to the model, he would be considered Player of the Match. Looking at the dataset, Achraf Dari scored a goal for Morocco, and consequently, was awarded a score of 10257.05, making up for most of his points, since this is the weighted value for a Defender scoring a goal. Following Achraf Dari is Ivan Perisic, a Defender for Croatia, who received a score of 10576.10. Looking at the dataset, Ivan Perisic assisted a goal for Croatia, and consequently, was awarded a score of 8670.19, making up for most of his points, since this is the weighted value for a Defender assisting a goal. Following Ivan Perisic is Mislav Orsic, a Forward for Croatia, who received a score of 5786.66, which is a significant drop from Ivan Perisic, which would imply that Achraf and Ivan had more contributions in this game compared to the rest of the players. Looking at the dataset, Mislav scored a goal for Croatia and successfully made three tackles, and consequently, was awarded a score of 1857.63 for scoring a goal as a Forward player and a total score of 1694.88 for making three tackles as a Forward player, each tackle scoring 564.96, making up for most of his points.

Badr Benoun, a Defender for Morocco, is at the bottom of the table with a score of -129.74, meaning that Badr's negative contributions outweighed his positive contributions. Looking at the dataset, Badr conceded two goals and lost three duels whilst making no significant contributions in any other metric, hence why the negative scoring has been given. Lovro Majer, Josko Gvardiol, Kristijan Jakic and Yahia Attiyat Allah all received a score of 0 which implies that they all did not meet the minimum criteria of following the constraints, this is mostly due to breaking the foul constraint for their respective position.

#### 6.2 Manchester City vs Tottenham Hotspur

Table 2: Player Performance Scores

Player	Position	Team	Total Score
Kevin De Bruyne	Midfielder	Manchester City	16899.39
Kieran Trippier	Defender	Tottenham Hotspur	9625.44
Sergio Aguero	Forward	Manchester City	8062.67
Christian Eriksen	Midfielder	Tottenham Hotspur	7957.92
Raheem Sterling	Forward	Manchester City	6946.55
Son Heung-Min	Forward	Tottenham Hotspur	6350.41
Dele Alli	Forward	Tottenham Hotspur	6330.58
Fernando Llorente	Forward	Tottenham Hotspur	5138.54
Ilkay Gundogan	Midfielder	Manchester City	3204.29
Aymeric Laporte	Defender	Manchester City	1697.91
Jan Vertonghen	Defender	Tottenham Hotspur	1433.79
Vincent Kompany	Defender	Manchester City	1401.17
David Silva	Midfielder	Manchester City	1133.13
Kyle Walker	Defender	Manchester City	998.26
Ederson Moraes	Goalkeeper	Manchester City	981.28
Hugo Lloris	Goalkeeper	Tottenham Hotspur	928.28
Fernandinho	Midfielder	Manchester City	775.43
Ben Davies	Defender	Tottenham Hotspur	544.69
Moussa Sissoko	Midfielder	Tottenham Hotspur	538.82
Toby Alderweireld	Defender	Tottenham Hotspur	404.89
Lucas Moura	Forward	Tottenham Hotspur	167.36
leroy sane	Forward	Manchester City	83.68
Victor Wanyama	Midfielder	Tottenham Hotspur	0.00
Benjamin Mendy	Defender	Manchester City	0.00
Bernardo Silva	Forward	Manchester City	0.00
Danny Rose	Defender	Tottenham Hotspur	-416.34
Davinson Sanchez	Defender	Tottenham Hotspur	-1143.16

The table above shows the player performance scores, in descending order, of all players participating in the match between Manchester City and Tottenham Hotspur. Kevin De Bruyne, a Midfielder for Manchester City, received the highest performance score of 16899.39 meaning that, according to the model, he would be considered Player of the Match. Looking at the dataset, Kevin De Bruyne assisted three goals for Manchester City, and consequently, was awarded a total score of 14898.48 for making three assists as a Midfielder, each assist scoring 4966.16, making up for most of his points. Following Kevin De Bruyne is Kieran Trippier, a Defender for Tottenham Hotspur, who received a score of 9625.44, which is a significant drop from Kevin De Bruyne, which would imply that Kevin De Bruyne had more contributions in the game compared to the rest of the players. Looking at the dataset, Kieran assisted a goal for Tottenham Hotspur, and consequently, was awarded a score of 8670.19 as a Defender, making up for most of his points. Following Kieran Trippier is Sergio Aguero, a Forward for Manchester City, who received a score of 8062.67. Looking a the dataset, Sergio scored a goal and

assisted one of the goals for Manchester City, and consequently, was awarded 1857.63 for the goals scored as a Forward and 4036.38 for the assist as a Forward, making up for most of his points. Davinson Sanchez, a Defender for Tottenham Hotspur, is at the bottom of the table with a score of -1143.16, meaning that Davinson's negative contributions outweighed his positive contributions. Looking at the dataset, Davinson conceded four goals whilst making no contributions to any other metric, hence why the negative scoring has been given. Danny Rose, a Defender for Tottenham Hotspur, is second last on the table with a score of -416.34, meaning that Danny's negative contributions outweighed his positive contributions. Looking at the dataset, Danny conceded four goals and lost six duels whilst making no significant contributions in any other metric, hence why the negative scoring has been given. Bernardo Silva, Benjamin Mendy and Victor Wanyama all received a score of 0 which implies that they all did not meet the minimum criteria of following the constraints, this is mostly due to breaking the foul constraint for their respective position.

#### 6.3 Spain vs Morocco

Table 3: Player Performance Scores

Player	Position	Team	Total Score
Dani Carvajal	Defender	Spain	9116.94
Isco	Midfielder	Spain	8346.30
Andres Iniesta	Midfielder	Spain	8235.86
Hakim Ziyech	Forward	Morocco	7026.66
Faycal Fajr	Midfielder	Morocco	4980.91
Gerard Pique	Defender	Spain	3386.47
Iago Aspa	Forward	Spain	3241.03
Thiago Alcantara	Midfielder	Spain	3030.10
Khalid Boutaib	Forward	Morocco	2961.60
David Silva	Forward	Spain	2553.11
Youssef En-Nesyri	Forward	Morocco	2211.53
Romain Saiss	Defender	Morocco	1861.06
Sergio Busquets	Midfielder	Spain	1723.30
Sergio Ramos	Defender	Spain	1589.93
Younes Belhanda	Midfielder	Morocco	1326.80
Jordi Alba	Defender	Spain	1262.83
Achraf Hakimi	Defender	Morocco	1245.93
David De Gea	Goalkeeper	Spain	894.33
Moubarak Boussoufa	Midfielder	Morocco	863.96
Karim El Ahmadi	Midfielder	Morocco	780.98
Munir Mohamedi	Goalkeeper	Morocco	633.14
Diego Costa	Forward	Spain	305.33
Marco Asensio	Forward	Spain	263.94
Rodrigo	Forward	Spain	126.50
Aziz Bouhaddouz	Forward	Morocco	44.82
Manuel da Costa	Defender	Morocco	0.00
Nordin Amrabat	Forward	Morocco	0.00
Nabil Dirar	Defender	Morocco	0.00

The table above shows the player performance scores, in descending order, of all players participating in the match between Spain and Morocco. Dani Carvajal, a Defender for Spain, received the highest performance score of 9116.94 meaning that, according to the model, he would be considered Player of the Match. Looking at the dataset, Dani assisted a goal for Spain, and consequently, was awarded a score of 8670.19 as a Defender, making up for most of his points. Following Dani Carvajal is Isco, a Midfielder for Spain, who received a score of 8346.30. Looking at the dataset, Isco scored a goal and

made two interceptions for Spain, and consequently, was awarded a score of 4371.39 for the goal scored and a total score of 1170.68 for the two interceptions, making up for most of his points. Following Isco is Andres Iniesta, a Midfielder for Spain, who received a score of 8235.86. Looking at the dataset, Andres assisted a goal for Spain, and consequently, was awarded a score of 4966.16 as a Midfielder, making up for most of his points.

Manuel da Costa, Nordin Amrabat and Nabil Dirar all received a score of 0 which implies that they all did not meet the minimum criteria of following the constraints, this is mostly due to breaking the foul constraint for their respective position.

#### 6.4 Discussion

The model employs a data-driven approach to identify the Player of the Match, utilising weights derived from historical data and player statistic websites. This quantitative methodology differs from the current selection process, which relies on subjective opinions, potentially leading to bias.

The model's output presents a ranked list of player performance scores in descending order. Notably, high scores highlight the model's capability to indicate significant moments that may not conventionally receive attention from spectators, that sometimes are more biased towards goal scorers

#### 6.4.1 Application of the model

The model can assist management to identify players who perform critical roles which contribute to team success since the model can quantify plays which may be overseen by managers. Furthermore, managers can utilise the model to make more informed decisions on player selection for certain matches, for example, players who consistently have high performance scores are a key asset to the teams strategy and success.

It can be used to help identify weaknesses and strengths within a team, if a team has a low performance score for their Forward players and a high performance score for their Midfielders, adjustments can be made in training or formation in order to better the team.

The model can also help in managing players workload by identifying those who are over performing and are at risk of tiring out.

The model can assist in player signings as it can highlight players who are under rated that excel in specific statistical areas that align with a team's tactical needs, e.g a team lacking in defensive stability can pinpoint Defenders from other teams that have a high performance score making their team more effective.

Clubs can track the players whose performance scores are consistently high over matches or seasons which would help them make more informed decisions on if they would like to sign that player to their team.

#### 6.4.2 Limitations

- i Since the development of this project was under a strict deadline the depth of analysis and the extent of data that could be integrated within the model has been restricted.
- ii The model only accounts for a selection of the variety of statistics in football, focusing on key metrics, while disregarding others. This selective use of data may overlook factors that could change the outcome of the results.
- iii The model doesn't account for external factors such as injuries, which can impact player performance. Players returning from an injury might not perform as well as they used to and the model does not adjust for this factor.
- iv Players substituted midway through a football game have less time to play and so would have a lower performance score compared to the other players. The model doesn't account for this, which can skew the models effectiveness.
- v Foul constraints were only based on 5 football games which is a small sample size.
- vi The model's weights are based on only one season of the English Premier League. Football leagues around the world have different playing styles, tactics and guidance and so players may perform differently across competitive environments, which would alter the weights for each metric per position.
- vii The foul constraints and finalised weights were rounded and so were not the exact figure in calculations, which would lead to a change in the performance scores of the players.

#### 7 Conclusion

This study has showed how methods of Deterministic Operational Research methods such as linear programming can be applied to construct a model that can determine the Player of the Match with no subjective bias. By introducing weights for each statistic for each player position integrated with player statistics from games, retrieved from FotMob and WhoScored, the output of the model produces a quantifiable measure of player performance.

The linear programming model has proven to be a useful mathematical function to eliminate subjective bias of peoples opinion that, as mentioned, is the traditional method of selecting the Player of the Match. Applying weights to each performance indicator in the dataset, the model takes into account every contribution each player in the evaluation makes, leaving no unnoticed contributions that might otherwise go unnoticed in the conventional methods.

The application of the model in real world football games has show promising results. The results from the model could alter people's perceptions and view of who they think the best player on the pitch is, for example, the match between Croatia and Morocco on the 17th December 2022, the highest performing player was Achraf Dari, a Defender, which challenges the usual traditional thinking of having the Player of the Match as a Forward or a Midfielder player.

However, there are many limitations with the model, as mentioned in section 6.4.2. The most considerable limitation would be the fact that the model only accounts for a small percentage of statistics within the game, meaning that the output of the model doesn't accurately reflect the real world scenario. Another big limitation would be that all calculations are based of a small sample size of possible matches or seasons to account for meaning that the models application in a real-world scenario across different leagues and play styles may be in accurate based on the historical data used constructing the model, and so further calculation is needed to accommodate for various leagues and play styles across the world.

Future work should aim to integrate more statistics in the model, as well as, incorporate machine learning algorithms to adapt the weightings in real time so the model is constantly up to date. Lastly, the model can be modified to account for all sports to determine player performance.

In conclusion, this research contributes to the industry of sport analytics by providing a practical and adaptable linear programming model to enhance fairness and eliminate bias in player performance. The models application to the Football industry are limitless, from informing managing decisions to player scouting, whilst offering a detailed basis for player evaluation.

#### 8 Appendix

#### 8.1 Foul Constraint Calculations

Calculations for the average number of fouls per player position per game are based on the following matches:

1. 11th March 2023 Tottenham Hotspur vs Nottingham Forest:

Fouls committed by Goalkeepers: 0
Fouls committed by Defenders: 7
Fouls committed by Midfielders: 14
Fouls committed by Forwards: 6

2. 18th February 2023 Aston Villa vs Arsenal:

Fouls committed by Goalkeepers: 0
Fouls committed by Defenders: 5
Fouls committed by Midfielders: 6
Fouls committed by Forwards: 6

3. 7th May 2019 Liverpool vs Barcelona:

Fouls committed by Goalkeepers: 0
Fouls committed by Defenders: 5
Fouls committed by Midfielders: 12
Fouls committed by Forwards: 4

4. 8th May 2019 Ajax vs Tottenham Hotspur:

Fouls committed by Goalkeepers: 0
Fouls committed by Defenders: 6
Fouls committed by Midfielders: 5
Fouls committed by Forwards: 13

5. 18th May 2019 Levante vs Atletico Madrid:

Fouls committed by Goalkeepers: 0
Fouls committed by Defenders: 7
Fouls committed by Midfielders: 5
Fouls committed by Forwards: 4

Average number of fouls per player position per game are rounded to 2 decimal places and are calculated by the sum of fouls per position within the 5 games divided by the sum of players in the chosen position throughout the 5 games:

Goalkeeper: 
$$\frac{0}{4}$$
 = 0 (45)

Defender: 
$$\frac{7+6+5+5+7}{5+5+4+4+5} \approx 1.30$$
 (46)

Midfielder: 
$$\frac{5+5+12+6+14}{3+3+8+5+9} = 1.50$$
 (47)

Forward: 
$$\frac{4+13+4+6+6}{2+4+6+3+4} \approx 1.74$$
 (48)

After rounding to the nearest whole number, as having a fractional value for the number of fouls is illogical, the constraints will then be:

$$f_{Goalkeeper} \leq 0$$

$$f_{Defender} \leq 1$$

$$f_{Midfielder} \leq 2$$

$$f_{Forward} \leq 2$$

#### 8.2 Statistic Scale Factor Calculations

Calculations for weights for each statistic are based on the 2021/2022 Premier League Season and are rounded to 2 decimal places:

Total occurrences across all statistics:

$$1041 + 9751 + 344766 + 743 + 12407 + 14053 + 7314 + 2253 = 392328 \tag{49}$$

#### 8.2.1 Goals Scored

$$\frac{392328}{1041} \approx 376.88\tag{50}$$

#### 8.2.2 Shots Taken

$$\frac{392328}{9751} \approx 40.23\tag{51}$$

#### 8.2.3 Passes Completed

$$\frac{392328}{344766} \approx 1.14 \tag{52}$$

#### 8.2.4 Assists

$$\frac{392328}{743} \approx 528.03\tag{53}$$

#### 8.2.5 Tackles

$$\frac{392328}{12407} \approx 31.62 \tag{54}$$

#### 8.2.6 Clearances

$$\frac{392328}{14053} \approx 27.92\tag{55}$$

#### 8.2.7 Interceptions

$$\frac{392328}{7314} \approx 53.64\tag{56}$$

#### 8.2.8 Saves

$$\frac{392328}{2253} \approx 174.14\tag{57}$$

#### 8.3 Weight Calculations

Calculations for weights for each position for every metric are based on the 2021/2022 Premier League Season:

#### 8.3.1 Goals Scored

i Goals scored by Goalkeepers:

$$0 (58)$$

ii Goals score by Defenders:

$$5(2) + 4(5) + 3(12) + 2(18) + 1(50) = 152$$
 (59)

iii Goals scored by Midfielders:

$$15 + 12 + 11 + 10(3) + 9 + 8(5) + 7(3) + 6(7) + 5(7) + 4(9) + 3(7) + 2(25) + 1(36) = 358$$

$$(60)$$

iv Goals scored by Forwards:

$$23(2) + 18 + 17 + 16 + 15(2) + 14 + 13 + 12(2) + 11(5) + 10(3) + 9 + 8(6) + 7(2) + 6(6) + 5(13) + 4(9) + 3(5) + 2(14) + 1(13) = 527$$

$$(61)$$

v Total goals scored:

$$0 + 152 + 358 + 527 = 1037 \tag{62}$$

There is a 0 value for the Goalkeepers and so as mentioned in section 4.3 we have to utilize the method of adding a small constant, in this case 1, to each of the positional value of goals scored. Hence:

Goals scored by Goalkeepers: 1

Goals scored by Defenders: 153

Goals scored by Midfielders: 359

Goals scored by Forwards: 528

Total Goals Scored: 1041

Taking into account the scale factor for the number of players typically in each position and the

statistic scale factor, the finalised weights for 'Goals Scored' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{1041}{1} \times 1 \times 376.88 = 392332.08$$
 (63)

Defender: 
$$\frac{1041}{153} \times 4 \times 376.88 \approx 10257.05$$
 (64)

Midfielder: 
$$\frac{1041}{359} \times 4 \times 376.88 \approx 4371.39$$
 (65)

Forward: 
$$\frac{1041}{528} \times 2.5 \times 376.88 \approx 1857.63$$
 (66)

#### 8.3.2 Shots Taken

i Shots taken by Goalkeepers:

$$0 (67)$$

ii Shots taken by Defenders:

$$81 + 51 + 48 + 43 + 37(2) + 35(3) + 30 + 29 + 26 + 25 + 24$$

$$+ 23(2) + 22(3) + 21(3) + 20(2) + 19(8) + 18(10) + 17 + 16(2)$$

$$+ 15(4) + 14 + 13(9) + 12(6) + 11(6) + 10(7) + 9(3) + 8(9)$$

$$+ 7(9) + 6(10) + 5(10) + 4(11) + 3(8) + 2(14) + 1(9) = 1908$$

$$(68)$$

iii Shots taken by Midfielders:

$$89 + 78 + 77 + 76 + 72 + 66 + 60 + 59 + 57 + 56 + 55(2) + 54$$

$$+ 53 + 52(3) + 47 + 46 + 45(3) + 44(3) + 43(5) + 42(2) + 40$$

$$+ 38 + 35(2) + 34(2) + 33(4) + 32(3) + 31(2) + 30(2) + 29$$

$$+ 28(2) + 27(4) + 26(5) + 25(2) + 24(3) + 23(3) + 22(2) + 21(6)$$

$$+ 20(4) + 19(6) + 18(2) + 17(2) + 16(3) + 15(3) + 14(5) + 12(5)$$

$$+ 11 + 10(5) + 9(4) + 8(6) + 7(7) + 6(5) + 5(7) + 4(6) + 3(4)$$

$$+ 2(6) + 1(19) = 3785$$

iv Shots taken by Forwards:

$$139 + 133 + 110 + 98 + 97 + 90 + 88(2) + 86 + 83 + 79 + 77 + 74 + 72 + 71 + 69 + 65 + 64(2) + 63 + 61(2) + 60 + 57(2) + 54 + 52 + 51 + 50 + 49(2) + 48 + 47(4) + 46 + 45(3) + 44 + 43(2) + 41 + 40(2) + 39 + 38 + 37(2) + 35(3) + 34 + 33 + 32 + 31 + 30(3) + 29 + 27 + 26(3) + 24(2) + 23(3) + 22 + 21(2) + 20 + 19(3) + 18(2) + 17 + 16 + 14 + 13 + 11(2) + 10 + 9 + 8(3) + 6(2) + 5(2) + 4 + 3(2) + 2(4) + 1(6) = 4054$$

$$(70)$$

v Total Shots taken:

$$0 + 1908 + 3785 + 4054 = 9747 \tag{71}$$

There is a 0 value for the Goalkeepers and so as mentioned in section 4.3 we have to utilize the method of adding a small constant, in this case 1, to each of the positional value of Shots taken. Hence:

Shots taken by Goalkeepers: 1

Shots taken by Defenders: 1909

Shots taken by Midfielders: 3786

Shots taken by Forwards: 4055

Total Goals Scored: 9751

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Shots Taken' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{9751}{1} \times 1 \times 40.23 = 392282.73$$
 (72)

Defender: 
$$\frac{9751}{1909} \times 4 \times 40.23 \approx 821.96$$
 (73)

Midfielder: 
$$\frac{9751}{3786} \times 4 \times 40.23 \approx 414.46$$
 (74)

Forward: 
$$\frac{9751}{4055} \times 2.5 \times 40.23 \approx 241.85$$
 (75)

#### 8.3.3 Passes Completed

i Passes completed by Goalkeepers:

$$1333 + 1177 + 1123 + 1115 + 1021 + 1010 + 960(2) + 937 + 929 + 903 + 889 + 849 + 804 + 802 + 797 + 793 + 788 + 753 + 530 + 456 + 430 + 315 + 258 + 247 + 221 + 109 + 107 + 101 + 80 + 78 + 71 + 60 + 55 + 39 + 37 + 36 + 33 + 31 + 29 + 25 + 9 = 21300$$

$$(76)$$

#### ii Passes completed by Defenders:

```
2951 + 2920 + 2646 + 2622 + 2497 + 2346 + 2334 + 2325 + 2319 + 2267
+2155 + 2038 + 1945 + 1928 + 1920 + 1901 + 1810 + 1781 + 1741 + 1709
+1687+1659+1605+1584+1582+1563+1535+1523+1499+1493
+ 1489 + 1445(2) + 1418 + 1416 + 1379 + 1377 + 1366 + 1357 + 1352 + 1321
+1316+1310+1276+1270+1254+1220+1219+1211+1194+1180
+1175+1152+1151+1136+1135+1126+1109+1102+1097+1088
+1046+1029+1023+1021+1007+1005+996+986+980+975+971
+961 + 951 + 937 + 935 + 934 + 924 + 921 + 912 + 906 + 904 + 903 + 877
                                                                   (77)
+874 + 850 + 843 + 778 + 771 + 754 + 751 + 750 + 723 + 708 + 705 + 698
+690(2) +667 +648 +646 +630 +614 +601 +591 +586 +560 +558(2)
+556 + 553 + 538 + 534 + 527 + 519 + 512 + 507 + 477 + 476 + 474 + 469
+467+464+452+441+431+429+422+389+377+364+361+356
+346+336+323+320+319+318+315+297+270+269+254+240
+239 + 230 + 227(2) + 222 + 207 + 203 + 201 + 182 + 145 + 139 + 119 + 118
+115+104+102+92+85+81+80+79+77+63+57+55+52+37
+35 + 21 + 14 + 9 + 8 + 6(2) + 3 + 2 + 1 = 156664
```

#### iii Passes completed by Midfielders:

$$2865 + 2531 + 2157 + 2153 + 1929 + 1920 + 1901 + 1888 + 1883 + 1827 \\ + 1708 + 1673 + 1665 + 1559 + 1543 + 1542 + 1498 + 1452 + 1358 + 1344 \\ + 1343 + 1316 + 1292 + 1269 + 1242 + 1233 + 1205 + 1202 + 1193 + 1187 \\ + 1148 + 1144 + 1136 + 1124 + 1115 + 1113 + 1111 + 1083 + 1049 + 1039 \\ + 1035 + 1014 + 1007 + 995 + 990 + 977 + 960 + 959 + 958 + 957 + 955 \\ + 950 + 948 + 929 + 928 + 909 + 899 + 877 + 870 + 851 + 845 + 838 + 826 \\ + 818 + 812 + 799 + 767 + 760 + 747 + 743 + 730 + 706 + 704 + 702 + 698 \\ + 678 + 670 + 668 + 654 + 653 + 650 + 645 + 641 + 638 + 632 + 629 + 604 \\ + 596 + 590 + 587 + 576 + 565(2) + 562 + 547 + 544(2) + 536 + 526 + 505 \\ + 504 + 501 + 485 + 470 + 459 + 456 + 451 + 450 + 444 + 437 + 433 + 427 \\ + 393 + 386 + 385 + 384(2) + 378 + 366 + 346 + 336 + 332 + 325 + 313 \\ + 306 + 302 + 298 + 297 + 293(2) + 276 + 275 + 274 + 273(2) + 264 + 241 \\ + 232 + 208 + 203 + 188(2) + 165 + 161 + 153 + 151 + 150 + 149 + 145 \\ + 140 + 135 + 132 + 121 + 120 + 115 + 103 + 87 + 81 + 75 + 73 + 68 + 66 \\ + 63 + 61 + 57 + 53 + 51 + 46 + 35 + 33 + 29 + 27(2) + 24 + 22 + 21 \\ + 13(2) + 12 + 9(2) + 6(2) + 3 + 2(5) + 1 = 122958$$

iv Passes completed by Forwards:

$$\begin{aligned} &1120 + 1079 + 1074 + 1062 + 1036 + 1015 + 939 + 935 + 911 + 909 \\ &+ 879 + 874 + 872 + 826 + 820 + 762 + 751 + 744 + 739 + 733 \\ &+ 725 + 714 + 696 + 675 + 674 + 669 + 633 + 626(2) + 615 + 613 \\ &+ 603 + 575 + 548 + 524(2) + 507 + 499 + 486 + 464 + 461 + 444 \\ &+ 439 + 427 + 426 + 415 + 413(2) + 396 + 393(2) + 377 + 372 \\ &+ 361 + 354 + 349 + 337 + 319 + 317 + 303 + 302 + 298(2) + 280 \\ &+ 277 + 273 + 251 + 230(2) + 224 + 220 + 199 + 194 + 190(2) \\ &+ 186 + 165 + 160 + 151 + 150 + 136 + 132 + 112 + 104 + 102 \\ &+ 101 + 96 + 82 + 81 + 78 + 71 + 70 + 66 + 61 + 56 + 37 + 36(2) \\ &+ 19 + 18 + 16 + 12 + 9 + 8 + 7 + 6 + 5(3) + 4(2) + 3(2) + 2(2) \\ &+ 1(6) = 43844 \end{aligned}$$

v Total number of Passes completed:

$$21300 + 156664 + 122958 + 43844 = 344766 \tag{80}$$

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Passes' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{344766}{21300} \times 1 \times 1.14 \approx 18.45$$
 (81)

Defender: 
$$\frac{344766}{156664} \times 4 \times 1.14 \approx 10.04$$
 (82)

Midfielder: 
$$\frac{344766}{122958} \times 4 \times 1.14 \approx 12.79$$
 (83)

Forward: 
$$\frac{344766}{43844} \times 2.5 \times 1.14 \approx 22.41$$
 (84)

#### 8.3.4 Assists

i Number of Assists by Goalkeepers:

$$1 + 1 + 1 = 3 \tag{85}$$

ii Number of Assists by Defenders:

$$12 + 10 + 9 + 7 + 5 + 4(7) + 3(11) + 2(19) + 1(39) = 181$$
(86)

iii Number of Assists by Midfielders:

$$10(2) + 9 + 8(3) + 7 + 6(3) + 5(6) + 4(17) + 3(15) + 2(29) + 1(37) = 316$$
(87)

iv Number of Assists by Forwards:

$$13 + 10 + 9 + 8(2) + 7(3) + 6(4) + 5(6) + 4(4) + 3(14) + 2(18) + 1(26) = 243$$
 (88)

v Total Number of Assists:

$$3 + 181 + 316 + 243 = 743 \tag{89}$$

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Assists' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{743}{3} \times 1 \times 528.03 = 130775.43$$
 (90)

Defender: 
$$\frac{743}{181} \times 4 \times 528.03 \approx 8670.19$$
 (91)

Midfielder: 
$$\frac{743}{316} \times 4 \times 528.03 \approx 4966.16$$
 (92)

Forward: 
$$\frac{743}{243} \times 2.5 \times 528.03 \approx 4036.28$$
 (93)

#### 8.3.5 Tackles

i Tackles completed by Goalkeepers:

$$3 + 2(4) + 1(11) = 22 (94)$$

ii Tackles completed by Defenders:

$$104 + 93(2) + 89 + 83 + 80 + 75 + 74(2) + 72 + 67 + 64(3) + 62$$

$$+ 61(2) + 60 + 58 + 57 + 55(2) + 54 + 53(2) + 51(2) + 50(3)$$

$$+ 49 + 48(2) + 47(3) + 46(2) + 45(2) + 44(3) + 42 + 41(3)$$

$$+ 40(5) + 39 + 38(3) + 37(3) + 36(4) + 35(4) + 34(2) + 33(2)$$

$$+ 32(3) + 31(3) + 30 + 29(2) + 28(4) + 27 + 26(4) + 25(5) + 24(4)$$

$$+ 23(3) + 22 + 21(5) + 20(2) + 19 + 18(5) + 17(2) + 16(6) + 15(5)$$

$$+ 14(3) + 13(2) + 12(2) + 11(3) + 10(6) + 8(7) + 7(4) + 6 + 5(7)$$

$$+ 4(2) + 3(4) + 2(2) + 1(4) = 5253$$

$$(95)$$

iii Tackles completed by Midfielders:

$$109 + 106 + 80 + 78 + 77 + 76 + 75 + 74(3) + 73 + 72 + 68(2) + 67 + 66$$

$$+ 65(2) + 64(2) + 63 + 61 + 60 + 59(3) + 58 + 57(2) + 56 + 54(4) + 53(2)$$

$$+ 52 + 51 + 49(2) + 48 + 47(2) + 46(3) + 44 + 43 + 42(3) + 41(4) + 40 + 39$$

$$+ 38 + 37 + 36(3) + 34(2) + 33(5) + 32(3) + 31(5) + 30(2) + 29(2) + 28(5)$$

$$+ 27(3) + 26 + 25 + 23 + 22(7) + 21(5) + 20(2) + 19(3) + 18(5) + 17(3)$$

$$+ 16(6) + 15(3) + 14(2) + 13(3) + 12(3) + 11(3) + 10(5) + 9(5) + 8(4)$$

$$+ 7 + 6 + 5(3) + 4(4) + 3(4) + 2(4) + 1(8) = 5396$$

iv Tackles completed by Forwards:

$$78 + 72 + 54 + 51(2) + 47 + 40(4) + 39 + 36 + 34$$

$$+ 33(2) + 32 + 30 + 29 + 28(2) + 27(2) + 26(2) + 25$$

$$+ 23(5) + 20(3) + 19 + 18 + 17(5) + 16(3) + 15(4)$$

$$+ 14(3) + 13(3) + 12(3) + 11(4) + 10(2) + 9(6)$$

$$+ 8(5) + 6(3) + 5(2) + 4(6) + 3(7) + 2(6) + 1(5) = 1736$$

$$(97)$$

v Total Tackles:

$$22 + 5253 + 5396 + 1736 = 12407 \tag{98}$$

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Tackles' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{12407}{22} \times 1 \times 31.62 \approx 17832.24$$
 (99)

Defender: 
$$\frac{12407}{5253} \times 4 \times 31.62 \approx 298.73$$
 (100)

Midfielder: 
$$\frac{12407}{5396} \times 4 \times 31.62 \approx 290.81$$
 (101)

Forward: 
$$\frac{12407}{1736} \times 2.5 \times 31.62 \approx 564.96$$
 (102)

#### 8.3.6 Clearances

i Clearances made by Goalkeepers:

$$47 + 46 + 45 + 39 + 38 + 36 + 35 + 34$$

$$+ 27(2) + 24 + 22(2) + 21(3) + 17 + 15$$

$$+ 13 + 12(2) + 9(2) + 8(3) + 6(2) + 5$$

$$+ 3(2) + 2 + 1(8) = 649$$
(103)

ii Clearances made by Defenders:

$$186 + 183 + 173 + 150(2) + 149 + 148 + 144 + 141 + 139(2) + 138 + 137 + 132 + 129 + 128 + 126 + 123 + 121 + 112 + 111 + 109 + 107 + 106 + 101 + 100 + 95(3) + 94 + 93 + 92 + 91(2) + 90 + 87 + 85 + 83 + 82(2) + 81(3) + 78(2) + 75(2) + 74 + 73 + 72(3) + 71(2) + 65(3) + 64 + 62(3) + 61(2) + 60(2) + 59 + 57 + 56(4) + 55 + 54 + 52(2) + 51(3) + 50(2) + 49(3) + 48 + 47(2) + 46 + 45(2) + 43(2) + 42(4) + 41(2) + 40 + 39(2) + 38 + 37(3) + 35(2) + 34 + 33(2) + 32(3) + 31 + 30(6) + 29 + 27(2) + 26(5) + 25(2) + 24(2) + 22 + 21 + 20(2) + 19(4) + 18(2) + 17 + 16 + 15(2) + 14(2) + 13(2) + 12(2) + 11 + 10(3) + 9 + 8(5) + 7(3) + 6(3) + 5(3) + 4 + 3(2) + 1(2) = 9592$$

iii Clearances made by Midfielders:

$$97 + 60(2) + 56 + 52(2) + 51 + 49(2) + 47 + 46 + 44 + 42 + 41 + 40(3) + 39 + 36(2) + 35 + 34(2) + 33 + 32(2) + 31 + 30(3) + 29 + 28(2) + 27 + 26(2) + 25 + 23(7) + 22(2) + 21 + 20(6) + 19(2) + 18(7) + 17 + 16(6) + 15(3) + 14(4) + 13(6) + 12(5) + 11(7) + 10(11) + 9(4) + 8(11) + 7(3) + 6(4) + 5(5) + 4(5) + 3(6) + 2(9) + 1(15) = 2801$$

$$(105)$$

iv Clearances made by Forwards:

$$47 + 42 + 39 + 33(2) + 29(2) + 26(2) + 25(3) + 21(2) + 20(2) + 18(3) + 17(3) + 16 + 14 + 13(4) + 12(5) + 11(2) + 10(5) + 9(3) + 8(5) + 7(5) + 6(4) + 5(8) + 4(6) + 3(2) + 2(11) + 1(13) = 1011$$

$$(106)$$

v Total number of Clearances:

$$649 + 9592 + 2801 + 1011 = 14053 \tag{107}$$

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Clearances' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{14053}{649} \times 1 \times 27.92 \approx 604.56$$
 (108)

Defender: 
$$\frac{14053}{9592} \times 4 \times 27.92 \approx 163.62$$
 (109)

Midfielder: 
$$\frac{14053}{2801} \times 4 \times 27.92 \approx 560.31$$
 (110)

Forward: 
$$\frac{14053}{1011} \times 2.5 \times 27.92 \approx 970.23$$
 (111)

#### 8.3.7 Interceptions

i Interceptions made by Goalkeepers:

$$2(2) + 1(6) = 10 \tag{112}$$

ii Interceptions made by Defenders:

$$78 + 72 + 69 + 62 + 59 + 58(2) + 57 + 56 + 52$$

$$+ 49(2) + 48 + 47 + 46 + 45(2) + 44(5) + 43(4)$$

$$+ 42 + 41 + 40(2) + 37(4) + 35 + 34(2) + 33(2)$$

$$+ 32(5) + 31(2) + 30(4) + 29(4) + 28(6) + 27(3)$$

$$+ 26(5) + 25(2) + 24(4) + 23(3) + 22(6) + 21(3)$$

$$+ 20(4) + 19(3) + 18(2) + 17(5) + 16(6) + 15(4)$$

$$+ 14(5) + 13(6) + 12(2) + 11(4) + 10(6) + 9(4)$$

$$+ 8(2) + 7(4) + 6(5) + 5(4) + 4(6) + 3(5) + 2(4)$$

$$+ 1(6) = 3942$$

iii Interceptions made by Midfielders:

$$68 + 64 + 63 + 52 + 51 + 50 + 48 + 42(2) + 41 + 40(2)$$

$$+ 38 + 36 + 35 + 34(3) + 32 + 31(3) + 30(3) + 29 + 28(3)$$

$$+ 27(2) + 26 + 25 + 24(2) + 23(4) + 22(4) + 21(5) + 20(4)$$

$$+ 19(3) + 18(3) + 17(5) + 16(2) + 15(3) + 14(8) + 13(6)$$

$$+ 12(7) + 11(10) + 10(7) + 9(9) + 8(9) + 7(4) + 6(5)$$

$$+ 5(5) + 4(4) + 3(2) + 2(11) + 1(16) = 2681$$

$$(114)$$

iv Interceptions made by Forwards:

$$35 + 34 + 29 + 22(2) + 21 + 20 + 18 + 15(7)$$

$$+ 14 + 13(3) + 12(4) + 11(3) + 10(2) + 9(3) + 8(4)$$

$$+ 6(6) + 5(7) + 4(7) + 3(10) + 2(12) + 1(9) = 681$$
(115)

v Total number of Interceptions:

$$10 + 3942 + 2681 + 681 = 7314 \tag{116}$$

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Interceptions' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{7314}{10} \times 1 \times 53.64 \approx 39232.30$$
 (117)

Defender: 
$$\frac{7314}{3942} \times 4 \times 53.64 \approx 398.10$$
 (118)

Midfielder: 
$$\frac{7314}{2681} \times 4 \times 53.64 \approx 585.34$$
 (119)

Forward: 
$$\frac{7314}{681} \times 2.5 \times 53.64 \approx 1440.25$$
 (120)

#### 8.3.8 Saves

i Interceptions made by Goalkeepers:

$$143 + 131 + 128 + 121(2) + 117 + 114 + 106 + 101$$

$$+ 98 + 95 + 90 + 84 + 78 + 76 + 73(2) + 70 + 68$$

$$+ 60 + 49 + 47 + 44 + 35 + 24 + 17 + 11(2) + 10(2)$$

$$+ 8 + 6(2) + 4(3) + 3 + 2(4) + 1 = 2249$$
(121)

ii Saves made by Defenders:

$$0 (122)$$

iii Saves made by Midfielders:

$$0 (123)$$

iv Saves made by Forwards:

$$0 (124)$$

v Total number of Saves:

$$2249 + 0 + 0 + 0 = 2249 \tag{125}$$

There is a 0 value for the Defenders, Midfielders and Forwards and so as mentioned in section 4.3 we have to utilize the method of adding a small constant, in this case 1, to each of the positional value of goals scored. Hence:

Saves made by Goalkeepers: 2250

Saves made by Defenders: 1

Saves made by Midfielders: 1

Saves made by Forwards: 1

Total Saves completed: 2253

Taking into account the scale factor for the number of players typically in each position and the statistic scale factor, the finalised weights for 'Goals Scored' for each position are rounded to two decimal places:

Goalkeeper: 
$$\frac{2253}{2250} \times 1 \times 174.14 \approx 174.37$$
 (126)

Defender: 
$$\frac{2253}{1} \times 4 \times 174.14 = 1569349.68$$
 (127)

Midfielder: 
$$\frac{2253}{1} \times 4 \times 174.14 = 1569349.68$$
 (128)

Forward: 
$$\frac{2253}{1} \times 2.5 \times 174.14 = 980843.55$$
 (129)

#### 9 References

- [1] J Marie JP Schregela. Identifying football management variables that lead to sustainable success in professional European football clubs. 2021.
- [2] Premier League. Man of the Match. https://www.premierleague.com/man-of-the-match.
- [3] Premier League Every UEFA Champions League Player of the Match. UEFA Champions League Player of the Match Article.
- [4] MB Wright. Fifty Years of Operational Research in Sport. Journal of the Operational Research Society, 60:161–168, 2009.
- [5] DJ Rader. Deterministic Operations Research: Models and Methods in Linear Optimization. J Wiley Sons, 2010.
- [6] C Cushion R Mackenzie. Performance Analysis in Football: A Critical Review and Implications for Future Research. Journal of Sports Sciences, 31(6):639–676, 2013.
- [7] L Ruf, A Beavan, T Groß, P Lussi, A Woll, S H Artel, S Altmann, L Forcher. Match-Related Physical Performance in Professional Soccer: Position or Player Specific? PLOS ONE, 16(9):1–13, 2021.
- [8] V De Silva. Player Tracking Data Analytics as a Tool for Physical Performance Management in Football: A Case Study from Chelsea Football Club Academy. Sports, 6(4):130, 2018.
- [9] CL Sandblo, HA Eiselt. Operations Research: A Model-Based Approach. Springer Nature, 2022.
- [10] PM Todd, R Hertwig. Heuristics. In Encyclopedia of the Human Brain, pages 449–460. Academic Press, 2002.
- [11] YT I c R Kasımbeyli, G Budak, I Kara. New Mathematical Models for Team Formation of Sports Clubs Before the Match. Central European Journal of Operations Research, 27:93–109, 2019.
- [12] C Thrane. Using Composite Performance Variables to Explain Football Players' Market Values. Managing Sport and Leisure, pages 1–14, 2024.
- [13] N Carlsson, E Nsolo, P Lambrix. Player Valuation in European Football. In Machine Learning and Data Mining for Sports Analytics, pages 42–54. Springer, 2019.
- [14] D Raabe, D Memmert. Data analytics in Football: Positional Data Collection, Modelling and Analysis. Routledge, 2018.
- [15] E Ryall. Are There Any Good Arguments Against Goal-Line Technology? Sport, Ethics and Philosophy, 6(4):439–450, 2012.
- [16] International Football Association Board. Law 10 determining the outcome of a match. IFAB Law 10: Determining the Outcome of a Match.

- [17] Shooting (Association Football). Wikipedia. https://en.wikipedia.org/wiki/Shooting\_(association\_football).
- [18] D Olsen. Passing: An Oddity in how it's Measured in Soccer, 2014. Article on Passing Measurement Oddities in Soccer.
- [19] E Vogel, J Bonetti. Argentina's road to the world title, 1986.
- [20] PM Todd, R Hertwig. Heuristics. In Encyclopedia of the Human Brain, pages 449–460. Academic Press, 2002.
- [21] Opta Event Definitions. https://www.statsperform.com/opta-event-definitions/.
- [22] England Football Learning. What is an Interception?, 2021. What is an Interception? England Football Learning.
- [23] IR Black, A Efron, C Ioannou, JM Rose. Designing and Implementing Internet Questionnaires using Microsoft Excel. Australasian Marketing Journal (AMJ), 13(2):61–72, 2005.
- [24] B Licina, D Viduka, V Kraguljac. A Comparative Analysis of the Benefits of Python and Java for Beginners. Quaestus, (19):318–327, 2021.
- [25] N Hutchins, G Biswas, D Girma, B Yett. Development of a Python-Based Platform for Teaching Computer Science. Young Scientist, A Hight School Research Journal, 2020.
- [26] A Anders, K.W Rotthoff. Yellow cards: Do they matter?. Journal of Quantitative Analysis in Sports, 7(1), 2011.
- [27] Baron, Ethan, Sandholtz, Nathan, Pleuler, Devin, Chan, Timothy CY. Miss it like Messi: Extracting Value from Off-Target Shots in Soccer. Journal of Quantitative Analysis in Sports. De Gruyter, 2024.
- [28] Dellal, Alexandre, Chamari, Karim, Wong, Del P, Ahmaidi, Said, Keller, Dominique, Barros, Ricardo, Bisciotti, G Nicola, Carling, Christopher. Comparison of Physical and Technical Performance in European Soccer Match-Play: FA Premier League and La Liga. European journal of sport science, 11(1), 51-59, 2011.
- [29] When to Give a Red or Yellow Card in Football. 2023. https://refsix.com/news/yellow-and-red-cards.
- [30] Concede a Goal. Collins Dictionary. Concede a Goal.
- [31] 2021/2022 English Premier League Statistics, 2021/2022. https://www.premierleague.com/stats/top/players/goals.
- [32] FotMob: Football Statistic Website. https://www.fotmob.com/en-GB.
- [33] WhoScored: Football Statistic Website. https://www.whoscored.com/.