

-Final Report-

Tottenham Hotspur F.C. Scouting Problem

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I. Background: Overview & Problem Definition



Scenes from the movie *Moneyball*

In the movie *Moneyball* Oakland Athletics' General Manager Billy Beane utilized sabermetrics to evaluate his potential roster by performing data mining on hundreds of individual baseball players, identifying statistics that were highly predictive of how many runs a player would score, a number not typically among those valued by baseball scouts in the day. In doing so, Beane sought lower-cost ballplayers with high on-base percentages, as opposed to high-priced home run hitters with high batting averages. His theory was that players who have a higher on-base percentage would be more valuable, even though they may hit fewer home runs. The efforts proved remarkably effective. Beane was able to utilize predictive analytics to develop a highly successful team despite operating under a tight budget.

Digitization and the pandemic are forcing football clubs to rethink, digitize and improve their scouting processes. Due to the continuously increasing amount of available data and videos, it is nowadays possible to combine a systematic selection with a standardized scouting process, even with limited resources. Data Analytics does not aim to replace scouts. Rather, data analytics provides a valuable complement to the talent identification skills of scouts. A good scouting process consists of several phases and begins with data scouting.

Tottenham Hotspur F.C. is a football club based in London and competes in the Premier League. The club have won the league only twice about 60 years ago and ranked fourth this season(2021-22). Tottenham needs to improve the squad to go higher next year.

Every year after the season, the scouting team needs to find new players to scout and decide which players to release from the original squad. Transfers contain huge risk due to the

information asymmetry. Mr.Tot, the scouting manager, should consider two main points to minimize uncertainty and make the best transfer. 1) Whether the player is under-valuated or not, 2) whether the player's performance can contribute to improving team performance.

Mr.Tot wants to implement data analytics in the scouting process. Let's help out Mr.Tot as a research assistant. The scouting process will go through four big steps. 1) First, you will obtain information about players in the EPL market. This contains valuation, ratings, and other performance statistics. Through obtained information you will find players that are under-valuated. 2) Second, you will analyze the team's games this season and see what factors were the crucial to team's victory. 3) Third, you use linear programming to decide players to scout under certain constraints. 4) Last, you simulate next season with the new squad and estimate next year's victory points.

II. Questions

1. First of all, you decided to make a full list of under-valuated players from which you will choose players to scout. Use the given dataset.
 - a. Conduct a multiple linear regression analysis using given data sheet. Dependent variable should be 'valuation in 10 thousand pounds' while all the other variables be independent variables. However, you have to figure out which independent variables are valid predicting the dependent variable. Using 10% confidence level, detect independent variables which are not valid.
 - b. Conduct a multiple linear regression analysis one more time, after removing invalid variables found in (question 1.a.). How much of the variance of dependent variable is explained by the revised model? If the model doesn't explain well, what would be the reason? Briefly explain your thoughts.
 - c. From the regression model built in (b.), calculate each player's predicted value and add it in the list using a new column on the sheet.
 - d. Divide each player's value by their predicted value and add it in the list. Sort the list by V/PV in ascending manner. Wipe out ones whose values are over estimated.
2. As a team analyst for Tottenham Hotspur F.C., you would like to know how to improve your team's chances of winning. More specifically, you would like to know which factors in game play the biggest role in winning a game. You are given the data for every Tottenham player's statistics for every game played last season. A portion of the data is shown below:

stats that have positive correlation with winning). For this question, you will use the answers from question 1 and question 2 to suggest to the managerial board which new players to scout. Assume that Tottenham's goalkeeper Hugo Lloris has a life-long contract, so you can only scout defenders, midfielders, and forwards.

- a. Suppose that you wish to improve the team's core stat derived in question 2, while minimizing the budget. That is, you wish to find the cheapest way to scout players so that upon scouting, the team's aggregate strong stat increases or the team's weakness related stat decreases. There are 2 additional constraints in this problem. 1) You can scout up to 2 players from the undervalued players pool derived in question 1. 2) Tottenham uses a 3-4-3 formation, meaning if you wish to scout a midfielder, you have to let go of an existing midfielder from the club. You cannot change the formation. Which players should Tottenham seek to scout during the transfer season?
 - b. Now suppose you get greedy with your improvements. The club wishes to scout players such that all your strong stats improve by 5%, while your weak stat is decreased by 5%. Which players should Tottenham sell and scout to achieve this with the cheapest budget?
 - c. Now suppose the club does not care about minimizing budget. You can scout any players from the undervalued players pool. Re-solve the problem to find out the maximum team stat the team can achieve (Note that the 2 additional constraints still hold).
4. With the new squad derived in question 3, you will use simulation to predict Tottenham's league points next season. Assume that there are 38 matches per season, and the team/players' individual stats will not change next season (it is safe to use only 2021-22 season data for simulation). Follow these simulation steps.

[Simulation Steps]

- 1) Extract the new squad's players info data to a new spreadsheet. This spreadsheet should contain. The players' info contains each match data of the player. Only extract significant stats derived in question 2. For example, if the new squad contains Harry Kane, you will need to extract 10 columns of Kane's 2021-22 stats per match. Note that not all players appeared in all 38 matches.
- 2) Create a pivot-table to calculate each player's average and standard deviation per significant stat. The pivot-table will contain 10 rows of player names and 20 columns in total for the average and standard deviation of each stat.
- 3) Now aggregate the player's stat info. For example if Harry Kane's Shots on Target was 2 on average and Son's Shots on Target was 4 on average, we can assume that the total squad's Shots on Target is 6, if other player's Shots on Target is 0. Use the SUM function to aggregate the averages, and DEVSQ function to aggregate the standard deviations.
- 4) Simulate 10 columns worth of stat info for 38 games. Use averages and standard deviations calculated in step 3. For negative values, change it to 0.
- 5) Create a pivot-table of Tottenham's teams stat derived in question 2-b, but with only the relevant 10 stats needed. The cells in this pivot-table is the average of each stat per match outcome.
- 6) You wish to use the averages found in the previous step as threshold points to determine the match outcomes. For example, suppose the average of all the 10 stats in games won is 5. You look into the individual games-won info. Won-Game1's stat value is 6 for all 10 stats. Since there are 5 positive correlated stats and 5 negative correlated stats, you can say that Won-Game1 has gone past 5 of the threshold points (For negative correlated stats, you need to go below the team average to say you broke the threshold point). Calculate the number of

threshold points broken by each game won, and calculate the average of this. Do this for losses as well.

- 7) Determine if the games were won, lost or drawn by using data from step 6 and applying it to step 4. In step 4 you calculated the simulated results of stats in 38 games with the new squad. In step 6, you calculated the threshold points for Tottenham to break in order to win (or lose). If none of the win and lose threshold points were broken, assume that match was drawn.
 - 8) Calculate the total league points after 38 games. 3 points are earned when winning, 1 point is earned when drawing and none are earned when losing.
 - 9) Simulate the above steps 1000 times. Calculate the average total league points Tottenham earns with the new squad.
- a. Use the simulation steps above with the new squad obtained in question 3-a. Chelsea, the team one standing above Tottenham, had a total of 74 league points during the 2021-22 season. With the new squad, could Tottenham beat Chelsea the next season?

III. Solutions

1.a. In 10% confidence level, MP and Starts come out to be invalid.

	A	B	C	D	E	F	G	H	I	J	K
24		<i>Coefficients</i>	<i>Std Err</i>	<i>LCL</i>	<i>UCL</i>	<i>t Stat</i>	<i>p-value</i>	<i>H0 (10%)</i>	<i>VIF</i>	<i>TOL</i>	<i>Beta</i>
25	Intercept	-15,200.9852	3,108.1507	-20,334.6696	-10,067.3007	-4.8907	1.9178E-6	Rejected			
26	Age	-116.5613	29.4442	-165.1938	-67.9288	-3.9587	0.0001	Rejected	1.0757	0.9296	-0.1850
27	MP	-20.6263	29.1078	-68.7031	27.4506	-0.7086	0.4793	Accepted	6.3738	0.1569	-0.0806
28	Starts	16.3565	25.4065	-25.6071	58.3200	0.6438	0.5204	Accepted	6.6792	0.1497	0.0750
29	Gls	196.1289	32.0745	143.1520	249.1058	6.1148	4.2563E-9	Rejected	1.8314	0.5460	0.3728
30	Ast	163.0644	51.0059	78.8187	247.3101	3.1970	0.0016	Rejected	1.8573	0.5384	0.1963
31	Cmp%	74.4483	14.3862	50.6868	98.2098	5.1750	5.0602E-7	Rejected	1.2814	0.7804	0.2639
32	Rating	2,093.2385	482.3264	1,296.5874	2,889.8895	4.3399	2.1581E-5	Rejected	2.4983	0.4003	0.3090
33	T (10%)	1.6517									
34	LCL - Lower limit of the 90% confidence interval										
35	UCL - Upper limit of the 90% confidence interval										

1.b.

	A	B	C	D	E	F	G	H	I	J	K
7	Regression Statistics										
8	R		0.7378	R-Squared			0.5444	Adjusted R-Squared			0.5343
9	MSE		2,049,237.9242	\$			1,431.5160	MAPE			55.8474
10	Durbin-Watson (DW)		2.0444	Log likelihood			-2,011.9798				
11	Akaike inf. criterion (AIC)		17.3964	AICc			17.3975				
12	Schwarz criterion (BIC)		17.4855	Hannan-Quinn criterion (HQC)			17.4323				
13	PRESS		491,121,270.2896	PRESS RMSE			1,454.9577	Predicted R-Squared			0.5168
24		<i>Coefficients</i>	<i>Std Err</i>	<i>LCL</i>	<i>UCL</i>	<i>t Stat</i>	<i>p-value</i>	<i>H0 (10%)</i>	<i>VIF</i>	<i>TOL</i>	<i>Beta</i>
25	Intercept	-16,375.8915	2,541.5016	-20,573.4961	-12,178.2868	-6.4434	#####	Rejected			
26	Age	-115.4899	29.2254	-163.7593	-67.2205	-3.9517	0.0001	Rejected	1.0668	0.9374	-0.1833
27	Gls	190.2868	30.6910	139.5968	240.9768	6.2001	2.6528E-9	Rejected	1.6880	0.5924	0.3617
28	Ast	154.4567	49.3339	72.9756	235.9377	3.1308	0.0020	Rejected	1.7492	0.5717	0.1859
29	Cmp%	75.1166	14.2676	51.5519	98.6813	5.2648	3.2607E-7	Rejected	1.2688	0.7882	0.2663
30	Rating	2,232.7088	418.4783	1,541.5400	2,923.8776	5.3353	2.3134E-7	Rejected	1.8932	0.5282	0.3296
31	T (10%)	1.6516									
32	LCL - Lower limit of the 90% confidence interval										
33	UCL - Upper limit of the 90% confidence interval										

The model explains about 55% the variance of the independent variable, that is quite low. The reason for this may be the nature of player's valuation where non-performance features such as fame or popularity comes into account as much as the performance factors considered in the model.

1.c.-d. Regression model should be "Valuation in 10 thousand pounds = - 16,375.8915 - 115.4899 * Age + 190.2868 * Gl's + 154.4567 * Ast + 75.1166 * Cmp% + 2,232.7088 * Rating".

2.a. Create a table with the same exact labels but excluding the players' names and their individual information. Create a new label for match number and fill the rest of the table with this formula: =SUMIF(\$B\$5:\$B\$535,\$F540,H\$5:H\$535). This formula sums the array (H\$5:H\$535) that contains the stats that you have to sum up, only if the match number (\$B\$5:\$B\$535) is equal to the match number we are looking for (\$F540). Remember that we have to account for data with %. Therefore for datas with % we add a /COUNTIF(\$B\$5:\$B\$535,F540). This divides the total % by number of player ran in each match so that we calculate the mean % of the desired stats. The result will look like the following:

2.b. Using the new data provided , create a new label indicating whether each match was a win or not a win. Using a filter, arrange the games by win/ not wins. Calculate the area of wins by using =AVERAGE(E539:E560) where (E539:E560) is the area of the wins. Do the same for not wins. Then use =(E578-E579)/(MAX(E578:E579)) for the % differences. (E578-E579)

		Performance										Expected				SCA				Total				Short			Medium			Long	
	result	Min	Gls	Asst	PK	PKatt	Sh	SoT	xG	npG	xA	SCA	GCA	Cmp	Att	Cmp%	TotDist	PrgDist	Cmp	Cmp	Att	Cmp%	Cmp	Cmp	Att	Cmp%	Cmp	Att	Cmp%		
W	1	990	1	1	0	0	1	14	2	1.2	1.2	0.9	21	2	240	316	74.31429	5030	2070	199	112	82.87857	92	111	69.75714	41	79	47.32857			
W	2	990	1	1	0	0	1	7	5	1.6	0.8	0.5	12	2	289	376	70.65	5283	2090	136	148	86.15	122	155	73.60714	28	63	28.94286			
W	3	990	1	0	0	0	0	15	8	0.9	0.9	0.6	20	2	438	516	75.79231	8156	2200	202	218	84.88462	187	205	81.23846	46	83	47.19231			
W	7	990	1	1	0	0	0	17	7	1.6	1.6	1.5	33	2	379	474	80.58462	6873	2495	174	194	92.50769	158	190	73.61538	39	69	41.15385			
W	8	990	3	1	0	0	0	13	4	1.7	1.7	1.5	23	6	542	641	83.63636	9345	3076	266	292	92.13636	220	252	82.17273	49	62	64.54545			
W	12	990	2	3	0	0	0	14	4	2.2	2.2	1.2	19	3	329	427	70.39286	6000	2367	138	160	80.72143	151	180	73.05	37	71	48.91429			
W	14	990	1	1	0	0	0	11	6	2.3	2.3	2	19	2	377	497	73.27143	7022	2234	162	187	76.13571	166	201	76.35	43	82	40.14286			
W	15	990	3	2	0	0	0	17	7	1.8	1.8	1.4	27	6	404	482	81.43571	7491	2356	197	218	90.2	135	161	81.22143	45	60	67.18571			
W	16	990	2	2	0	0	0	17	7	2.3	2.3	1	26	505	578	80.10714	8991	2463	243	265	86.34286	185	212	77.15	64	83	60.35714				
W	17	990	3	3	0	0	0	27	8	3.7	3.7	2.3	43	4	533	618	85.53571	10492	2794	288	318	87.69286	258	288	83.92143	77	99	63.35			
W	19	990	3	3	0	0	0	17	6	2.6	2.6	2.3	31	6	571	637	86.45714	11114	3080	223	245	89.88571	270	290	70.70714	70	90	70.70714			
W	21	990	1	1	0	0	0	21	5	1.8	1.8	1.3	33	2	668	772	86.45	12241	3682	300	329	90.17143	287	317	93.32143	70	98	65.55714			
W	22	990	3	1	0	0	0	15	5	3.2	2.4	1.7	27	3	514	576	87.00714	10055	2329	196	210	86.53571	242	255	92.32857	73	101	61.13571			
W	26	990	3	3	0	0	0	6	5	1.9	1.9	1.8	12	6	258	322	70.75714	5055	1987	107	118	77.49286	105	119	75.32143	40	71	45.39286			
W	27	990	4	3	0	0	0	15	10	2.3	2.3	2.2	26	7	427	488	81.83571	8368	2930	161	174	85.74286	195	210	79.55	61	85	50.2			
W	28	990	4	4	0	0	0	14	7	3	3	2.8	25	8	591	670	86.77857	10777	2916	247	266	92.74286	286	310	88.23571	54	76	51.74286			
W	30	990	2	2	0	0	0	14	4	2.3	2.3	2.3	27	4	555	628	86.74286	10199	2737	239	251	87.97857	247	267	92.35	66	97	52.82143			
W	31	990	5	5	0	0	0	19	6	3.1	3.1	2.6	37	10	554	616	89.39286	10488	2629	196	206	95.56429	297	318	91.73571	53	60	56.2429			
W	32	990	4	3	0	0	0	13	5	4	4	1.45	24	409	473	81.45	8145	2194	184	197	93.05	164	188	87.17857	54	72	67.57143				
W	33	990	3	3	0	0	0	13	7	3	3	1.4	22	6	350	440	80.15714	7514	2584	116	140	82.16429	164	187	87.81429	68	96	60.36429			
W	37	990	1	1	0	1	1	20	6	2.1	1.4	1.2	36	2	598	701	80.46923	12239	3298	210	237	87.18462	284	314	74.61542	97	128	60.33077			
W	38	990	5	4	0	0	0	19	12	3.6	3.6	3.1	30	7	556	626	85.82143	10874	2981	212	225	93.62857	261	286	88.52143	76	103	57.93571			
L	4	957	0	0	0	0	0	2	1	0.1	0.1	0	4	0	245	320	76.23077	4820	1766	106	121	75.26923	159	114	87.29231	36	71	47.22308			
L	5	990	0	0	0	0	0	2	0	0.6	0.6	0.3	13	0	406	494	81.92857	7388	2121	179	206	88.57857	155	170	89.4286	55	88	64.16429			
L	6	990	1	1	0	0	0	10	4	1.1	1.1	0.9	15	2	430	508	83.45	8394	2454	186	199	91.65	171	188	89.64286	65	105	63.12857			
L	9	990	0	0	0	0	0	7	4	0.6	0.6	0.7	9	0	561	662	75.15714	10811	2759	208	225	86.17143	293	321	74.66429	58	104	56.07143			
win average			2.545455	2.090909	0.136364	0.136364	15.404909	6.363636	2.163636	2.050901	1.627273	25.509091	4.545455	458.5	539.7722	80.46544	8695.909	2613.136	190.723	209.1864	87.35418	203.4545	227.5399	81.11443	57.7273	86.13636	55.25605				
not win average			987.91375	0.41375	0.875	0.125	0.125	0.125	1.075	0.868687	15.875	6.875	436.875	520.75	81.4938	8154.938	2480.75	150.7425	174.8125	180.5	84.83333	188.75	213.375	81.84633	55.75	90.0625	55.14643				
% difference			0.002083	0.828125	0.880435	0.083333	0.083333	0.548214	0.501515	0.52449	0.504539	0.379661	0.8075	0.063984	0.035242	0.033654	0.06221	0.063334	0.083443	0.065203	0.028855	0.07166	0.062463	-0.00894	0.035012	-0.04359	0.001597				
Formula for E 578 -AVERAGE(E539:E560)										Formula for E579 -AVERAGE(E561:E576)																					
Formula for E580 -(E578-E579)/IMAX(E578:E579)																															

represents the win average- loss average and (MAX(E578:E579) will get the bigger number from win or loss. The data will look as such:

2.c. Transpose the data above and ascend the % differences to gain insight in what stats are most important in winning a game vs what stats are detrimental to the team.

		% difference	Performance	PKwon	
Corner Kicks	Str	-0.81818	Long	KP	0.3125
Blocks	ShSv	-0.75758	Carries	CPA	0.34728
Outcomes	Int	-0.55669	SCA	SCA	0.36458
Outcomes	Blocks	-0.47419	Performance	Sh	0.37966
Dribbles	Succ%	-0.42553	Dribbles	Megs	0.38348
Body Parts	Head	-0.34065	Expected	xG	0.4375
Pass Types	Dead	-0.28252	Expected	xA	0.50315
Performance	PKcon	-0.27273	Long	xA	0.50454
Body Parts	TI	-0.26621	Expected	npG	0.50454
Corner Kicks	Out	-0.20455	Blocks	Err	0.52649
Outcomes	Off	-0.18881	Performance	SoT	0.54167
Pass Types	FK	-0.17552	Pass Types	TB	0.54821
Blocks	Sh	-0.17125	SCA	GCA	0.70745
Carries	Mis	-0.15636	Long	Ast	0.8075
Carries	Dis	-0.1342	Performance	Gls	0.88043
Long	CrsPA	-0.12727	Performance	Ast	0.91813
Pressures	Att 3rd	-0.12377	Performance	Ast	0.93487

picture it might not tactic that pressures the opponent's offense might be a more 'skillful' type of defense that doesn't rely too heavily on the luck factor that comes from simply blocking by standing in its path.

Most helpful 5 stats are number of two offensive actions directly leading to a goal such as passes/dribbles/drawing fouls (Goal creating actions: GCA), # of Long passes that led to an assist (AST), # of Completed pass sent between back defenders into open space (TB), # of shots on target (SoT), actions leading to an opponent's error (Err). Since goals and assists are results of a winning game and these statistics don't provide insight to the game, we excluded them from potential factors. Another interesting insight is # of completed pass sent between back to defenders. Giving a pass to the backspace demonstrates a team's ability to use the field widely and proficiently penetrate through an empty space. This is why TB stats might be so important in winning a game.

Here on the left we see the top list of qualities that the more often seen, the lower the chances of the team winning (will be defined as detrimental) vs on the right top list of qualities that have a positive correlation with winning (will be defined as helpful). On the tail end of detrimental attributes are in order, # of straight corner kicks (str), # of times a shot was blocked by a target standing in its path (shsv), # of passes intercepted(int), # of passes Blocked by the opponent who was standing it the path (blocks), and % of dribbles succeeded (succ%). An interesting insight is that the # of straight corner kicks seems to be extremely detrimental to a team's victory. Although used as an offensive tool, corner kicks that are kicked in a straight motion might have to do with the FW's confidence or level of play. Another interesting point is shsv. Although if a Tottenham defender stands in the path of the opponent's shot might be a good thing in isolation, looking at the bigger be a reliable defense strategy. More rigid defense

3.a.

The constraints and objective function are developed below. We let go of Son Heung-Min and Bentancur, and scout Jarrod Bowen and Philippe Coutinho.

OBJ				Min	35900	=SUMPRODUCT(B26:B163,E26:E163)		
Constraints								
Squad	FW Max	3	=	3		=B26+B27+B33+SUM(B75:B115)		
	MF Max	3	=	3		=SUM(B116:B163)+B28+B29+B30		
	DF Max	4	=	4		=SUM(B36:B74)+B31+B32+B34+B35		
Stat	SoT	159	>=	152.25	145	=SUMPRODUCT(\$B\$26:\$B\$163,L26:L163)*1.05		
	Ast	41	>=	36.75	35	=SUMPRODUCT(\$B\$26:\$B\$163,M26:M163)*1.05		
	TB	42	>=	37.8	36	=SUMPRODUCT(\$B\$26:\$B\$163,N26:N163)*1.05		
	GCA	91	>=	85.05	81	=SUMPRODUCT(\$B\$26:\$B\$163,O26:O163)*1.05		
	Err	0	>=	0	0	=SUMPRODUCT(\$B\$26:\$B\$163,P26:P163)*1.05		
	Succ%	504.9	<=	546		=SUMPRODUCT(\$B\$26:\$B\$163,Q26:Q163)		
	Str	4	<=	4		=SUMPRODUCT(\$B\$26:\$B\$163,R26:R163)		
	Int	325	<=	331		=SUMPRODUCT(\$B\$26:\$B\$163,S26:S163)		
	Blocks	297	<=	300		=SUMPRODUCT(\$B\$26:\$B\$163,T26:T163)		
	ShSv	4	<=	4		=SUMPRODUCT(\$B\$26:\$B\$163,U26:U163)		
	MAX 2	2	<=	2		=SUM(B36:B163)		

3.b.

The constraints and objective function are developed below. We let go of Emerson and Bergwijn, and scout Rob Holding and Michail Antonio.

OBJ				Min	33000	=SUMPRODUCT(B26:B163,E26:E163)		
Constraints								
Squad	FW Max	3	=	3		C5	=B26+B27+B33+SUM(B75:B115)	
	MF Max	3	=	3		C6	=SUM(B116:B163)+B28+B29+B30	
	DF Max	4	=	4		C7	=SUM(B36:B74)+B31+B32+B34+B35	
Stat	SoT	145	>=	145		C8	=SUMPRODUCT(\$B\$26:\$B\$163,L26:L163)	
	Ast	37	>=	35		C9	=SUMPRODUCT(\$B\$26:\$B\$163,M26:M163)	
	TB	39	>=	36		C10	=SUMPRODUCT(\$B\$26:\$B\$163,N26:N163)	
	GCA	86	>=	81		C11	=SUMPRODUCT(\$B\$26:\$B\$163,O26:O163)	
	Err	0	>=	0		C12	=SUMPRODUCT(\$B\$26:\$B\$163,P26:P163)	
	Succ%	519.7	<=	546		C13	=SUMPRODUCT(\$B\$26:\$B\$163,Q26:Q163)	
	Str	4	<=	4		C14	=SUMPRODUCT(\$B\$26:\$B\$163,R26:R163)	
	Int	329	<=	331		C15	=SUMPRODUCT(\$B\$26:\$B\$163,S26:S163)	
	Blocks	296	<=	300		C16	=SUMPRODUCT(\$B\$26:\$B\$163,T26:T163)	
	ShSv	4	<=	4		C17	=SUMPRODUCT(\$B\$26:\$B\$163,U26:U163)	
	MAX 2	2	<=	2		C18	=SUM(B36:B163)	

3.c.

The constraints and objective function are developed below. We let go of Pierre Højbjerg and Emerson, and scout Nathan Aké and Mohamed Elneny.

OBJ	Max	-635.1				B2	=SUMPRODUCT(\$B\$26:\$B\$163,L26:L163) + SUMPRODUCT(\$B\$26:\$B\$163,M26:M163) + SUMPRODUCT(\$B\$26:\$B\$163,N26:N163) + SUMPRODUCT(\$B\$26:\$B\$163,O26:O163) - SUMPRODUCT(\$B\$26:\$B\$163,Q26:Q163) - SUMPRODUCT(\$B\$26:\$B\$163,R26:R163) - SUMPRODUCT(\$B\$26:\$B\$163,S26:S163) - SUMPRODUCT(\$B\$26:\$B\$163,T26:T163) -	
Constraints								
Squad	FW Max	3	=	3				
	MF Max	3	=	3				
	DF Max	4	=	4				
						C5	=B26+B27+B33+SUM(B75:B115)	
						C6	=SUM(B116:B163)+B28+B29+B30	
						C7	=SUM(B36:B74)+B31+B32+B34+B35	

4.a. The solution for each step is below.

1)

Player	Pos	Ast	SoT	GCA	TB	Str	Int	Blocks	ShSv	Err	Succ%
Son HeungMin	FW	0	1	0	0	0	0	0	0	0	100
Son HeungMin	FW	0	1	0	0	0	1	1	0	0	100
Son HeungMin	FW	0	2	0	0	0	2	2	0	0	75
Son HeungMin	FW	0	1	0	0	0	1	0	0	0	66.7
Son HeungMin	FW	0	2	0	0	0	0	1	0	0	0
Son HeungMin	FW	1	1	1	0	0	2	1	0	0	60
Son HeungMin	FW	0	1	0	0	0	1	0	0	0	0
Son HeungMin	FW	0	1	0	0	0	1	1	0	0	100
Son HeungMin	FW	0	0	0	0	0	0	4	0	0	50
Son HeungMin	FW	0	0	0	0	0	2	2	0	0	100
Son HeungMin	FW	0	0	0	0	0	2	1	0	0	62.5
Son HeungMin	FW	0	2	0	0	0	0	1	0	0	0
Son HeungMin	FW	1	1	2	0	0	2	0	0	0	50
Son HeungMin	FW	0	1	0	0	0	1	2	0	0	0
Son HeungMin	FW	0	2	0	0	0	1	0	0	0	100
Son HeungMin	FW	0	2	1	1	0	1	5	0	0	100
Son HeungMin	FW	1	1	2	0	0	2	4	0	0	71.4
Son HeungMin	FW	0	1	0	0	0	0	0	0	0	40
Son HeungMin	FW	0	2	0	0	3	3	2	0	0	0

2)

Player Pool		Average of Ast	Average of SoT	Average of GCA	Average of TB	Average of Str	Average of Int	Average of Blocks	Average of ShSv	Average of Err	Average of Succ%	StdDev of Ast	StdDev of SoT	StdDev of GCA	StdDev of TB	StdDev of Str	StdDev of Int	StdDev of Blocks	StdDev of ShSv	StdDev of Err	StdDev of Succ%
Row Labels	IT	0.034482759	0.24137931	0.137931034	0	0	1.379310345	1.172413793	0.068965517	0	14.36896552	0.185695338	0.43549417	0.350931203	0	0	1.497946049	1.167077104	0.257880715	0	
Ben Davies	0.375	0.5625	0.75	0	0	0.8125	1.375	0	0	38.53125	0.619139187	0.81394103	1	0	0	1.376892637	1.147460965	0.167077104	0.257880715	0	
Dejan Kulusevski	0.032258065	0.129032258	0.129032258	0	0	1.193548387	1.838709677	0	0	30	0.179605302	0.340777101	0.427546137	0	0	1.249516035	1.485412944	0	0	0	
Emerson	0	0.114285714	0.114285714	0.114285714	0	1.028571429	0.457142857	0.028571429	0	0	0	0.322802851	0.322802851	0.322802851	0	0	1.014185106	0.657215926	0.169030851	0	
Eric Dier	0.243243243	1.378378378	0.567567568	0.513513514	0	1.72972973	1.756756757	0.027027027	0	57.92972973	0.547996624	1.186763839	0.800712896	1.145626007	0	1.465314692	1.382538033	0.164399887	0	0	
Harry Kane	0.277777778	0.916666667	0.583333333	0.138888889	0.111111111	1.055555556	1.305555556	0	0	32.08055556	0.646363637	0.937321412	0.967323258	0.424451093	0.398409536	1.040451672	1.237957668	0	0	0	
Jarrod Bowen	0.157894737	0.842105263	0.315789474	0.157894737	0	1.210526316	0.894736842	0	0	49.12631579	0.501459857	0.688247202	0.671038298	0.374634325	0	1.315672509	0.87526103	0	0	0	
Philipe Coutinho	0.055555556	0.277777778	0.138888889	0.194444444	0	1.611111111	0.5	0	0	55.09166667	0.232310084	0.51331478	0.424451093	0.524782646	0	1.049565292	0.878310066	0	0	0	
Pierre Højbjerg	0.133333333	0.066666667	0.266666667	0	0	0.8	1.333333333	0	0	13.88666667	0.351865775	0.25819889	0.457377708	0	0	0.941123948	1.2344268	0	0	0	
Ryan Sessegnon	0.04	0.4	0.12	0.04	0	0.4	0.24	0	0	15.6	0.2	0.645407224	0.331662479	0.2	0	0.645407224	0.435889894	0	0	0	
Steven Berghwin	0.125448029	0.519713262	0.301075269	0.139784946	0.014336918	1.186379928	1.082437276	0.014336918	0	31.45698925	0.400581048	0.817175292	0.647994398	0.528118511	0.146206085	1.229593493	1.216055575	0.119089053	0	0	

3)

Aggregate AVG									
1.34954547	4.928792035	3.123494937	1.159027298	0.111111111	11.22085287	10.87364882	0.124563973	0	31.45698925
=SUM(B13:B22)	=SUM(C13:C22)								
Aggregate SD									
0.419042848	0.807118538	0.625891873	1.15707464	0.142857143	0.647082032	0.984134518	0.087136102		
=DEVSQL(L13:L22)	=DEVSQL(M13:M22)								

4)

Need to eliminate negative values, assume negative values corresponds to 0											
Game Num	Ast	SoT	GCA	TB	Str	Int	Blocks	ShSv	Err	Succ%	
1	1.521052566	5.128683705	3.280312251	1.870117788	0.063816452	12.01179049	10.5744338	0.17374372	0	48.00297602	
2	1.370606791	4.165819666	2.692874713	1.640744553	0.09940537	12.05460531	10.65828765	0.138624825	0	-17.02178552	
3	1.256006522	4.600127552	1.801032474	0.973855192	0.063798118	11.07411732	11.43240539	0.108372039	0	22.31747832	
4	1.100563635	4.567574956	2.828749856	-0.192881022	-0.052186746	10.93189199	10.58119827	0.137312453	0	20.79222685	
5	1.508517862	5.606547495	3.482734437	-0.302408834	0.221580637	12.08187723	10.51099181	0.104957849	0	96.02034959	
6	1.297859446	4.784182984	2.814058906	-0.686877822	0.161369908	11.43792739	10.32460396	0.050624597	0	-35.3673063	
7	1.546077433	4.335679667	3.5850388	-0.780183075	0.146956743	12.59377793	10.19025753	0.051932841	0	61.66357897	
8	1.095786527	4.055950875	3.523381121	-1.367267072	-0.015437678	11.24468122	12.13576272	0.077852608	0	50.68366489	
9	0.76173795	4.584196017	3.299137514	-0.639094751	0.413221764	10.42754567	11.00206589	-0.068219627	0	36.70511426	
10	1.509806254	5.823433722	3.619692628	3.229935196	0.105228496	11.64664041	11.61022525	0.117716399	0	4.420591332	
11	1.097290891	3.843085138	3.271969376	0.57153252	0.1973142803	10.49179517	11.04151362	0.057764114	0	-41.71076995	
12	1.324225935	5.401775932	2.926909423	1.459828581	0.367830019	11.52115767	9.26048608	0.160791587	0	46.46892677	
13	1.170944091	4.518139891	2.808216574	-0.227829067	0.285904496	11.01614819	9.96410756	0.282410076	0	62.69096056	
14	1.381823333	5.27658812	2.934127052	0.617953656	0.073495444	9.599520636	9.954004922	0.175046297	0	74.3775302	
15	1.694890111	5.803141437	3.913668589	2.284622354	0.151382902	11.38791819	11.3985357	0.115925638	0	-24.27420322	
16	1.886783622	5.84314353	3.45690448	0.53476462	-0.053086729	11.71779422	11.78668286	0.124983432	0	5.109701798	
17	1.319039535	4.71655607	2.879283398	-0.643496417	0.339280424	11.15180696	10.60554073	0.202828135	0	56.48574629	
18	1.035453441	5.075045559	2.905980522	0.546403693	0.238290098	11.09395892	11.43033633	0.027038415	0	61.212592604	
19	1.029305336	2.998385133	3.88099165	0.111791598	0.262917118	10.79415021	8.825872875	0.161981169	0	70.49641117	
20	1.81110564	4.76696427	2.789868633	0.037508897	0.199572876	11.54474673	10.66511246	0.098686966	0	5.877174296	
21	1.088461957	4.860334099	3.433315623	-1.057888272	0.157183281	11.59563767	12.24940107	0.065185419	0	56.34105951	
22	1.569014838	5.535890974	2.477872492	1.93577945	0.193616602	10.83747162	9.444938555	0.139833456	0	59.88499185	
23	0.808171925	4.544704634	3.263901688	1.271131119	0.123320873	10.67092065	10.66034073	0.14141914	0	25.06070375	
24	1.431470778	4.973410412	2.428057843	1.989027137	0.081255101	11.27512191	12.57766673	0.191382887	0	-16.26257262	
25	1.781355133	3.96265781	2.929570145	1.692874703	0.209939048	11.10829834	10.51517876	0.317531064	0	33.00204602	
26	0.748155425	5.391519254	1.313109577	1.988800675	0.017694619	11.07611906	10.20285634	0.286521128	0	-33.85040419	
27	1.094581224	5.17065716	3.53749204	-0.178573104	0.116427404	11.12878849	9.713485433	0.270489672	0	37.45027797	
28	0.769142981	5.96039611	1.854174384	1.274066197	0.028491595	10.78012337	11.23616163	0.039112577	0	18.45389656	
29	1.205817547	5.81115932	2.918267301	0.672108071	0.274197518	10.30975982	11.79593918	0.127890755	0	72.35256465	
30	1.656703789	5.738241557	3.453667257	0.377204107	0.086343535	11.23863419	11.50322394	0.228568286	0	86.72172635	
31	1.103016401	5.78440143	2.98777493	2.49786976	0.140649535	12.22004445	10.89718225	0.174144551	0	37.43411286	
32	0.753541484	6.008401181	2.4553674	2.28237505	0.026510866	11.53736416	12.18161622	0.078873888	0	-2.825681189	
33	1.504699847	4.752596533	3.145051428	1.839628094	-0.02785891	11.52874344	11.56909519	0.107379416	0	74.86450297	
34	0.792894978	4.420032909	3.931026349	0.861294954	0.125679277	11.35487463	11.13835699	0.121694975	0	36.03028026	
35	1.679370669	5.569554407	3.996182732	1.02726565	0.183812062	10.89919599	9.025885876	0.075211032	0	45.47059654	
36	1.474704942	3.288821601	2.836537921	1.71675845	0.316819296	10.99765364	11.07731823	0.226403389	0	39.60346761	
37	1.432757328	4.390399891	1.770886181	2.980880833	0.420182297	12.37291326	9.19988656	0.329389271	0	39.88614242	
38	0.678111017	3.598812675	2.973485401	1.172513269	0.020712271	11.53640407	10.81707562	0.192761111	0	65.14679629	

Game Num	No Negative Values											Err	Succ%
	Ast	SoT	GCA	TB	Str	Int	Blocks	Shy					
1	1.521052566	5.128683705	3.280312251	1.87011788	0.063816452	12.01179049	10.5744338	0.17374372				0	48.00297602
2	1.370606791	4.165819666	2.692874713	1.640744553	0.09940537	12.05460531	10.65828765	0.138624825				0	
3	1.256006522	4.600127552	1.801032474	0.973855192	0.063798118	11.07411732	11.43240539	0.108372039				0	22.31747832
4	1.100563635	4.567574956	2.828749856	0	0	10.93189199	10.58119827	0.137312453				0	20.79226859
5	1.508517862	5.606547495	3.482734437	0	0.221580637	12.08187723	10.51099181	0.104957849				0	96.02034965
6	1.297859446	4.784182984	2.814058906	0	0.161369908	11.43792739	10.32460396	0.050624597				0	
7	1.546077433	4.335679667	3.5850388	0	0.146956743	12.59377793	10.19025753	0.051932841				0	61.66357897
8	1.095786527	4.055950875	3.523381121	0	0	11.24468122	12.13576272	0.077852608				0	50.68366489
9	0.76173795	4.584196017	3.299137514	0	0.413221764	10.42754567	11.00206589	0				0	36.70511426
10	1.509806254	5.823433722	3.619692628	3.229935196	0.105228496	11.64664041	11.61022525	0.117716399				0	4.420591332
11	1.097290891	3.843085138	3.271969376	0.57153252	0.197142803	10.49179517	11.04151362	0.057764114				0	
12	1.324225935	5.401775932	2.926909423	1.459828581	0.367830019	11.52115767	9.26048608	0.160791587				0	46.46892677
13	1.170944091	4.518139891	2.808216574	0	0.285904496	11.01614819	9.96410756	0.282410076				0	62.69096056
14	1.381823333	5.27658812	2.934127052	0.617953656	0.073495444	9.599520636	9.954004922	0.175046297				0	74.3775302
15	1.694890111	5.80341437	3.913668589	2.284622354	0.151382902	11.38791819	11.3985357	0.115925638				0	
16	1.886783622	5.84314353	3.45690448	0.53476462	0	11.71779422	11.78668286	0.124983432				0	5.109701798
17	1.319039535	4.71655607	2.879283398	0	0.339280424	11.15180696	10.60554073	0.202828135				0	56.48574629
18	1.035453441	5.075045559	2.905980522	0.546403693	0.238290098	11.09395892	11.43033633	0.027038415				0	61.21592604
19	1.029305336	2.998385133	3.88099165	0.111791598	0.262917118	10.79415021	8.825872875	0.161891169				0	70.49641117
20	1.81110564	4.76696427	2.789868633	0.037508897	0.199572876	11.54744673	10.66511246	0.098686966				0	5.877174296
21	1.088461957	4.860334099	3.433315623	0	0.157183281	11.95963767	12.24940107	0.065185419				0	56.34105951
22	1.569014838	5.353890974	2.477872492	1.93577945	0.193616602	10.83747162	9.444938555	0.139833456				0	59.88499185
23	0.808171925	4.544704634	2.63901688	2.127113119	0.123320873	10.67092065	10.66034073	0.14141914				0	25.06070375
24	1.431470778	4.973410412	2.428057843	1.989027137	0.081255101	11.27512191	12.57766673	0.191382887				0	
25	1.713551333	3.962665781	2.929570145	1.692874703	0.209939048	11.10829834	10.51517876	0.317531064				0	33.00204602
26	0.74815425	5.391519254	1.313109577	1.988800675	0.017694619	11.07611906	10.20285634	0.286521128				0	
27	1.094581224	5.17065716	3.53749204	0	0.116427404	11.12878849	9.713485433	0.270489672				0	37.45027797
28	0.769142981	5.96039611	1.854174384	1.274066197	0.028491595	10.78012337	11.23616163	0.039112577				0	18.45389656
29	1.205817547	5.811115932	2.918267301	0.672108071	0.274197518	10.30975982	11.79593918	0.127890755				0	72.35235645
30	1.656703789	5.738241557	3.453667257	0.377204107	0.086343535	12.33863419	11.50322394	0.228568286				0	86.72172635
31	1.103016401	5.678440143	2.98777493	2.49786976	0.140649535	12.22004445	10.89718225	0.174144551				0	37.43411286
32	0.753541484	6.008401181	2.4553674	2.28237505	0.026510866	11.53736416	12.18161622	0.078873888				0	
33	1.504699847	4.752596533	3.145051428	1.839628094	0	11.52874344	11.56909519	0.107379416				0	74.86450297
34	0.792894978	4.420032909	3.931026349	0.861294954	0.125679277	11.35487463	11.13835699	0.121694975				0	36.03028026
35	1.679370669	5.569554407	3.996182732	1.02726565	0.183812062	10.89919599	9.025885876	0.075211032				0	45.47059654
36	1.474704942	3.288821601	2.836537927	1.716765845	0.316819296	10.99765364	11.07731823	0.226403389				0	39.60346761
37	1.432757328	4.390399891	1.770886181	2.980880833	0.420182297	12.37291326	9.19988656	0.329389271				0	39.88614242
38	0.678111017	3.598812675	2.973485401	1.172513269	0.020712271	11.53640407	10.81707562	0.192761111				0	65.14679629

5)

Spurs Data											
Row Labels	Average of Ast	Average of SoT	Average of GCA	Average of TB	Average of Str	Average of Int	Average of Blocks	Average of ShSv	Average of Err	Average of Succ%	
D	0.4	3.6	1.6	1.4	0	15.8	20.2	0.2	0	31.9032967	
L	0.181818182	2.545454545	0.545454545	0.272727273	0.363636364	14.54545455	14.72727273	0.181818182	0.090909091	32.80689311	
W	2.090909091	6.363636364	4.545454545	2.136363636	0.045454545	14.22727273	15.86363636	0.045454545	0.136363636	25.51452411	
Grand Total	1.315789474	4.894736842	3	1.5	0.131578947	14.52631579	16.10526316	0.105263158	0.105263158	28.466101	

6)

Win Threshold Point Calculation											
Ast	SoT	GCA	TB	Str	Int	Blocks	ShSv	Err	Succ%		
2.090909091	6.36363636	4.54545455	2.13636364	0.04545455	14.2272727	15.8636364	0.04545455	0.13636364	25.5145241	SUM	
0	0	0	0	1	0	0	1	0	0	2	P420 =IF(E420>SP5A19,1,0)
0	0	0	0	1	0	0	1	0	1	4	Y420 =IF(N420>SY5A19,1,0)
0	1	0	0	1	0	0	1	0	1	4	Z420 =SUM(P420:Y420)
0	1	0	0	1	1	1	1	0	0	5	
1	0	1	0	1	1	1	1	0	1	7	
0	0	0	0	1	0	1	1	0	1	4	
0	0	0	1	1	1	1	1	0	1	5	
0	1	1	0	1	0	1	1	0	0	5	
0	1	0	0	1	1	0	1	0	1	5	
1	1	0	1	0	1	0	0	1	0	5	
1	0	1	0	1	1	1	1	0	1	7	
0	1	0	0	1	1	1	1	0	0	5	
0	0	0	0	1	1	1	1	0	1	5	
1	0	1	1	1	0	0	1	1	1	7	
1	1	1	1	1	0	0	0	1	0	6	
1	1	1	1	0	1	1	0	1	0	7	
0	0	0	1	1	1	1	1	0	1	6	
1	0	1	0	1	0	0	1	1	1	6	
1	1	1	0	1	1	0	1	0	0	6	
0	0	0	0	1	1	1	1	0	0	4	
1	1	1	1	1	0	1	1	0	1	8 AVG	5.40909091 =AVERAGE(Z420:Z441)
Lose Threshold Point Calculation											
Ast	SoT	GCA	TB	Str	Int	Blocks	ShSv	Err	Succ%		
0.181818182	2.54545455	0.54545455	0.27272727	0.36363636	14.5454545	14.7272727	0.18181818	0.09090909	32.8068931	SUM	
1	1	1	1	0	1	1	1	1	1	8	P447 =IF(E442<SP5A46,1,0)
0	0	0	0	0	0	0	0	1	1	8	Y447 =IF(N442>SY5A46,1,0)
1	0	1	0	0	0	0	0	1	1	5	Z447 =SUM(P449:Y449)
1	1	1	1	1	1	0	0	1	0	7	
1	0	1	1	0	0	1	0	1	1	6	
1	0	1	1	0	1	1	0	1	1	7	
0	0	0	1	0	1	0	1	1	0	4	
1	0	1	0	1	1	0	0	1	0	5	
1	1	0	1	0	0	0	0	1	1	5	
1	1	1	1	0	0	1	0	0	1	6 AVG	5.63636364 =AVERAGE(Z447:Z457)

[illegible]

Simulation		Points
1	SimTable	80
2	0	74
3	0.001002	78
4	0.00200401	80
5	0.00300601	74
6	0.00400802	74
7	0.00501002	84
8	0.00601202	82
9	0.00701403	88
999	0.998998	76
1000	1	84

MIN POINTS				
81.04				