Hattrick Skill Scores

April 2025

1 Optimal Training

I have been interested in how to train the best possible players, like those that cycle or NT training plans try to generate. For such players, the zeitgeist has some variation in the target skills for each position, and I set out to figure out what the “right” skills are. This post is an exhaustive look at this work, and the tool that I’ve developed to solve this problem algorithmically.

Contents

2 Introduction to Player Contribution

Through this work, I measure the “value” of a player–or their “Skill Score”–and focus on trying to maximize this value while minimizing the time to train the player. The value I use here is strictly based on how much a player **contributes to the team ratings**. Thus, I lean heavily on the Absolute Contribution tables from the Unwritten Manual[1].

That post describes how to take a player’s skills and figure out what ratings they generate for a team. A few notes for my analysis:

- I want to compare players, not figure out the exact ratings you’ll see in the lineup simulator. So I don’t use HatStats, and I do everything in the number scale that Hattrick reports (so Solid = 7, and any -1 conversions only happen internally in the math)
- Throughout my work I’ve used the agglomeration penalites associated with 2 CDs, 2 IMs, and 2 FWDs
- For normal, defensive, and offensive CDs and IMs, I’ve used the middle position (where they contribute equally to both sides in defense and attack)
- For CDs, IMs, and FWDs with the Torwards Wing order, I’ve used the right position, where they contribute more to the right defense and attack.

2.1 An Example

Let’s do an example using a Normal CD. First we use the link in the Unwritten Manual to find the absolute contributions of a Normal CD if there are 2 total CDs. That contribution is described with this table:

	GK	DE	PM	WG	PS	SC	SP
R Def	0	0.251	0	0	0	0	0
C Def	0	0.602	0	0	0	0	0
L Def	0	0.251	0	0	0	0	0
Midfield	0	0	0.113	0	0	0	0
R Att	0	0	0	0	0	0	0
C Att	0	0	0	0	0	0	0
L Att	0	0	0	0	0	0	0

Table 1: Normal CD Absolute Contributions.

Table 1 says that this player’s contribution to the Right Defense sector would be **0.251** times their defense skill. Two quick notes here:

- The actual contribution uses the defense skill *minus 1*. That is the contribution would be $0.251 \times (defense - 1)$
- The first note doesn’t really matter for us because the resulting contribution is not the Right Defense sector rating you would see in a lineup simulator. The important thing is that the scale with the other values in the table is correct.

Now, there is a very peculiar reason that I’ve put the CD’s contribution in the table like that. It is actually a matrix that converts a player’s skills to ratings like this:

$$R = \begin{bmatrix} RightDefense \\ CenterDefense \\ LeftDefense \\ Midfield \\ RightAttack \\ CenterAttack \\ LeftAttack \end{bmatrix} = P \times (s-1) \tag{1}$$

[1] `https://www89.hattrick.org/Forum/Read.aspx?t=17572304&n=13&v=0`

where P is the absolute contributions for the position (e.g., Table 1), and s is the skills:

$$s = \begin{bmatrix} GK \\ Defense \\ Playmaking \\ Winger \\ Passing \\ Scoring \\ SP \end{bmatrix} \tag{2}$$

2.2 Weighting Different Sector Ratings

So far, we've got the math in order to take any player's skills, and figure out how much they contribute to the sector ratings depending on the position they are playing. An excellent next question is: "How do we compare the relative importance of the various sector ratings?"

This question is maybe the core question in Hattrick, and very important to this discussion. It has no single right answer, and depends on the manager's preferences, tendencies, etc. Luckily, there is an easy **mathematical** answer: we'll use a weighted average! The weights for this average are the values that have no single answer, and are discussed further in detail in the Methodology section. For now, we will just assume that there are some weights that we came up with.

So with those weights (which I will call W), we can simply perform a weighted average on the ratings R we found above. This yields a single value, which I call the player's **skill score**, SS, which represents their total contribution to your team's ratings.

$$SS = W \cdot P \cdot (s - 1) \tag{3}$$

where

$$W = \begin{bmatrix} RDef & CDef & LDef & MF & RAtt & CAtt & LAtt \end{bmatrix} \tag{4}$$

SS is the value we optimize for in the rest of the analysis, and represents the overall improvement in our team ratings we get from adding a player to the lineup.

Quickly going back to our example, if we use the simplest weights for W where every sector is equally rated, we can see that this would indicate that Defense will improve our player's contribution **much** more than Playmaking. In fact, the exact ratio would be that Defense was 9.8 times as important as Playmaking, which comes from

$$\frac{0.251 + 0.602 + 0.251}{0.113} = 9.8 \tag{5}$$

Whereas, if we weight MF as 3 times as important, we would end up defense as 3.3 times as important:

$$\frac{1 * 0.251 + 1 * 0.602 + 1 * 0.251}{3 * 0.113} = 3.3 \tag{6}$$

The values in the above two equations come from Table 1.

3 Axioms for Analysis

There are some assumptions I have made for this analysis, and some axioms that I have followed when making decisions about which assumptions to use. I would like to be very clear about those here to facilitate later discussion. Here are my axioms:

1. **Axiom 1**: Sector ratings are the only thing that matters for this analysis, and sector ratings are only dependent on player skills.

2. **Axiom 2**: Player contribution to sector ratings is strictly linear, but the cost of their skills are highly nonlinear.

3. **Axiom 3**: It does not matter where sector ratings are generated from as long as they are generated.

3.1 Axiom 1

Axiom 1: Sector ratings are the only thing that matters for this analysis, and sector ratings are only dependent on player skills.

Axiom 1 means that the **value** of a player only depends on their skills (precisely, their GK, DE, PM, WG, PS, SC, and SP skills).

I do not consider their experience, stamina, specialty[2], form, loyalty, or homegrown status. The resulting analysis is a tool for comparing player skills, not everything that goes into a player. I think of this as figuring out the best training plan for the **same** starting player. The final player can have any combinations of skills, but will have the same experience, stamina, etc, regardless of what skills are trained.

3.2 Axiom 2

Axiom 2: Player contribution to sector ratings is strictly linear, but the cost of their skills are highly nonlinear.

Axiom 2 is a consequence of the way the game engine is coded. The linearity of the absolute contribution formula is why I could write the equation for the player contribution as a simple matrix equation. This has some huge implications for the analysis.

- Increasing a skill by 1 level yields the same improvement in contribution, regardless of which level was gained.
  - For example, improving the Playmaking of an IM from 4 to 5 is just as valuable as from 14 to 15.
  - Loyalty or HG status have a fixed contribution increase that does not change as the player skills improve
- Using the HatStat scale, including the *minus 1* in the contribution equation, or anything else that linearly scales player contribution has no effect in this analysis
- We can use the null space[3] of the combined matrix WP to easily find players with different skills who contribute the **exact** same to ratings
  - For instance, with some values of W and P we might find that a CD with 15 Defending and 10 Playmaking is equivalent to one with 14 Defending and 11.5 Playmaking. Due to the linearity, we can do this mathematically and find all combinations of skills that yield the same player contribution

The second part of Axiom 2 says the cost of increasing a player's skills are highly nonlinear. For most of my work here, the cost is the training time, but this is also true for player wages. The nonlinear nature of both training time and wages are well known and easy to verify. They are also what makes this analysis interesting. If training time was linear, then increasing PM from 14 to 15 would take the same amount of time as from 4 to 5, and from above this would result in the same improvement in player contribution. If this was the case, the optimal ratio of a players skills would be easy to solve with the psuedo-inverse[4] as

$$(W \cdot P)^{\dagger} \tag{7}$$

If this was the case, this optimal ratio would be *constant over all levels of the main skill.* This is clearly ridiculous, which I will demonstrate with this example. Consider a "perfect" U21 IM has skills 16 PM, 7 PS, 7 DE, and 5 SC. If training was linear, the NT version of this player would be 20 PM, 8.75 PS and DE, and 6.25 SC, which is far more monoskilled than normal NT players.

Dealing with the nonlinear nature of the training is the hard part of this analysis, and training players in Hattrick in general.

[2]Specialty is only considered for the Technical Defensive Forward, which changes the absolute contribution of a defensive forward

[3]`https://en.wikipedia.org/wiki/Kernel_(linear_algebra`

[4]`https://en.wikipedia.org/wiki/MoorePenrose_inverse`

3.3 Axiom 3

Axiom 3: It does not matter where sector ratings are generated from as long as they are generated.

This functionally says that the analysis does not care if we e.g., get our defense ratings from a CD or an IM.

A secondary aspect of this axiom is that we should use the same weights W when analyzing multiple positions. The W matrix fundamentally weights the various importance of different sectors generally, and I would discourage the impulse to weight different sectors higher for different positions. For instance, if you changed the weights for central attack for forwards but not for midfielders, you would be saying that you value central attack generated from forwards more than that from IMs. However, this is not really how the game engine works, and it would make it harder to get the optimization right because you would have to come up with weights for every position.

Let's do an extended example, where we use the same weights across many players. We will use a team of 1 CD, 1 IM, and 1 FWD. To simplify, let's only look at the central defense, midfield, and central attack ratings, and weight each equally. This results in a W

$$W = \begin{bmatrix} 0 & \frac{1}{3} & 0 & \frac{1}{3} & 0 & \frac{1}{3} & 0 \end{bmatrix} \tag{8}$$

If we take a super monoskilled version of this team, we may end with players:

Player	DE	PM	PS	SC
CD	18	3	3	3
IM	3	18	3	3
FWD	3	3	3	18

Table 2: Team of Monoskilled Players.

If we say each player started at 3 in each skill, we can use a training calculator to find out how long it took to train this team, and what their wage is:

Player	Training Weeks	Wage
CD	124	54823
IM	104	66669
FWD	108	60394
Total	336	181887

Table 3: Monoskilled Players Training and Wages.

This results in total team ratings of:

Defense	10.7
Midfield	7.89
Attack	10.55
Team Total	8.36

Table 4: Monoskilled Players Ratings.

Now, if we repeat with more typical players, we get:

3.3.1 Team B

Player	DE	PM	PS	SC
CD	16	9	3	3
IM	8	15	5	3
FWD	3	6	9	15

Table 5: Team of Typical Players.

Player	Training Weeks	Wage
CD	108	27180
IM	96	22545
FWD	93	20642
Total	297	70368

Table 6: Typical Players Training and Wages.

Defense	10.66
Midfield	7.59
Attack	10.90
Team Total	8.40

Table 7: Typical Players Ratings.

These two teams (Team A and Team B) are functionally equivalent in ratings they put on the field. This is shown in the Tables 4 and 7, where we can see the Team Total is similar for both teams, and Team B gives up a little bit of defense and midfield for more attack.

However, it is clear to see that Team B's wage is significantly lower than Team A, and that Team B took 3 fewer seasons to train up.

I know you are thinking "Yea Adam, we know that multiskilled players are amazing, big whoop", and that this example didn't really prove anything besides to not buy players with only a crazy high mainskill. But... was Team B actually a good team? Were they the best? This work allows us to analyze that. To skip to the answer, consider Team C.

3.3.2 Team C

Player	DE	PM	PS	SC
CD	16.2	5.4	3	3
IM	9	14.7	8.8	3
FWD	3	4	8	15.4

Table 8: Team C Players.

Player	Training Weeks	Wage
CD	97	28884
IM	107	20392
FWD	88	23727
Total	292	73003

Table 9: Team C Training and Wages.

Defense	11.01
Midfield	6.83
Attack	11.32
Team Total	8.32

Table 10: Team C Ratings.

Team C took 5 fewer weeks to train than team B, with a similar salary and total contribution. Obviously Team C sacrificed a lot of midfield to gain more defense and attack, and the players are a bit less multiskilled, but Team C consists of optimally trained players for this W.

If you are thinking that the contribution of Team C looks worse than that of Team B, that does not mean the optimality of Team C's skills is broken. It means that the W matrix we've chosen is wrong (for you). For discussion on picking better values for W, read on!

4 Methodology

In this section, I discuss how the skills of Team C were generated, and how the same tool is used in the Results section to find my "optimal" players.

For starters, I don't typically do multiple players at a time like the previous example. Instead, I focus on a single position/order such as IM normal. I also like to start with a generic 17.0 player that isn't necessarily a superstar.

With this framing, the question is:

> Given some starting skills and age, a position the player will play, and a fixed number of weeks to train for, what are the trainings and skills that result in the maximum possible player contribution?

To answer this question, I use a pretty basic method. For each of the allowable training weeks, I figure out which skill will have the biggest impact on the player contribution, and train that. To figure out which skill to train, I cycle through the possible training options and figure out the skills that would result if that was trained this week. With the potential skills, I find the player contribution at each, and select the highest. Here is some psuedo-code that might explain well:

```
for each allowable training week:
  for each skill we could train:
    figure out the player skills if we train 1 week of this skill
    figure out the player contribution at these potential skills

  pick the skill that resulted in the highest contribution
```

This is a greedy algorithm that always picks the best option for right now. Usually, these algorithms are susceptible to local minima, but we don't see this happening here and the greedy algorithm appears to find the global optimum.

We can check this with a pretty simple method: try to find a better solution. A better solution would be a set of skills that yield the same player contribution, but take fewer weeks to train. If you recall back to **Axiom 2**, we can find skills that result in the same contribution by using the null space of the combined matrix WP. If we do this many times, we end up with a bunch of different combinations of skills that all result in the same player contribution, but different training times and wages. To come up with different skills of the same contribution, we use

$$s_{new} = s_{old} + \mathcal{N}(W \cdot P)h \tag{9}$$

where h is a vector of random values. The second half of the expression creates a vector of skills that doesn't change the contribution of a player. To calculate the training time, I use the same formula that is used on HT Portal[5]. To calculate wages, I use previous work from the unwritten manual[6]. Note that I don't account for the wage reduction after year 28 (for now, it's a to do). For the work here this wage reduction might matter (the player is above 28), but the general concept holds and this is still a great example.

If we do this many times for a starting player, we should find a bunch of equal-contribution players, but none should take less time to train than our found optimal solution. If we plot the results of the perturbation, we end up with something that looks like Figure 1.

This figure is awesome because it confirms the above algorithm is finding the skills that result in the lowest training time, and it gives us an idea of the training-wage tradeoff for players. In Figure 1, the x-axis is the training weeks, y-axis player wage, and each blue dot represents a player with a different set of skills. Each player in the figure has **the exact same total contribution**, but you can see the training time and wages vary wildly! I have called out a few special players (e.g., "Player 1", etc.) in the graph, and the skills for these players are shown in Table 11.

As you can see from Table 11, the various alternative players trade off main skill for side skills or vise versa, and Figure 1 shows how "optimal" the set of skills are. Here, "optimal" is going to mean players along the left and bottom edge of plot. The player on the plot that is left-most (e.g., the orange X) is the optimally trained player for *training time*, and the player that is bottom-most is the optimally trained player for *wages*. Anything between–but along the bottom edge–is a player that has optimally traded training time for wage reduction. Anything else (e.g., the red and green dots) are players that

[5]`https://www88.hattrick.org/Forum/Read.aspx?t=17404127&n=9&mr=0&v=0`
[6]`https://www88.hattrick.org/Forum/Read.aspx?t=17572304&n=23&v=0`

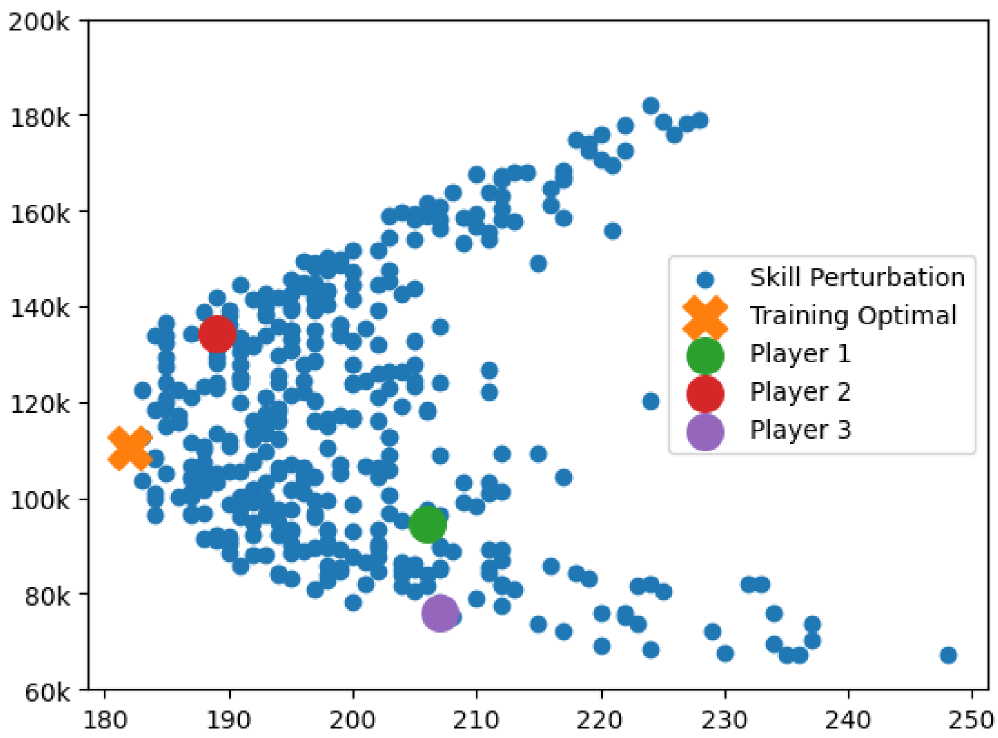

Figure 1: Skill Perturbations on IM Normal Trained for 180 Weeks

Player	DE	PM	PS	SC	Contribution
Training Optimal	11.06	19.35	12.07	6.0	4.07
Player 1	9.0	18.55	16.39	9.37	4.07
Player 2	8.14	19.97	11.91	8.09	4.07
Player 3	12.27	17.93	15.05	10.17	4.07

Table 11: Skill Perturbations for IM Normal

have higher wages or longer training times than they needed. For the results in Figure 1 and Table 11, the orange and purple players are along the optimal path, and the red and green ones are not.

With an algorithm to find the optimal contribution per training week, and a way to analyze it, we are almost ready to start making charts and finding the optimal skills for players. We just need one more thing...

4.1 How to Pick Weights

Up to this point, we've been assuming we have a valid W matrix, or else picking a simplistic one for demonstration purposes. So, how do we go about picking better weights?

The process involves picking 7 numbers that have a huge impact on the results of this analysis. I think about it as choosing the relative importance of various sectors in two ways: first between defense, midfield, and attack, and second between left, center, and right.

The values I use for these in my analysis are

$$[Defense : 1, Midfield : 1.25, Attack : 1]$$

and

$$[Left : 25, Center : 35, Right : 25]$$

If we take each set of weights and normalize them, then multiply relevant sectors together we can get the 7 values for the W matrix. For example, the weight for the left defense would be:

$$\frac{1}{1 + 1.25 + 1} \cdot \frac{25}{25 + 35 + 25} = 0.09 \tag{10}$$

Doing this for all 7 sectors with the values above results in

$$W = \begin{bmatrix}0.090 & 0.127 & 0.090 & 0.385 & 0.090 & 0.127 & 0.090\end{bmatrix} \tag{11}$$

I came up with these mostly by gut feel and tinkering. The weights for left, center, right are pretty obviously the chance distribution values for these sectors, which I think makes sense as you want to weight the same as the chances will be distributed.

For the defense, midfield, attack ratings, I intuited that the defense and attack should be equally weighted. Then I went to my lineup simulator and messed around trying to figure out how much defense or attack I would trade for midfield.

Eventually I decided it felt right to trade 1.25 levels off all 3 defense sectors to gain 1 level of midfield, or vise versa. Unless otherwise mentioned, these are the weights I use for the rest of the analysis.

5 Results

Alright, enough math and context, let's look at some results! Unless otherwise specified, this is the training setup for these results:

- Start player is 6 in all skills at 17.0
- Coach level is 5
- Assistant level is 10
- Intensity 100%
- Stamina 10%
- I only consider the main training options in the 100% slots
- 180 weeks of training for NT players, 80 for U21 players

5.1 Coach Level

First, I will test the bonus in contribution we get from moving from a level 4 coach to a level 5 coach. I'll look at the normal positions for U21 and NT players, and chart the % increase we gain from the better coach. The results are shown in Table 12.

Position	U21	NT
GK	1.24%	0.99%
CD Normal	1.34%	1.25%
WB Normal	1.29%	1.21%
IM Normal	1.19%	1.08%
W Normal	1.29%	1.35%
FWD Normal	1.30%	1.33%
Average	**1.27%**	**1.18%**

Table 12: Contribution Increase from Level 5 Coach

The table shows the percentage gain in contribution from going from a level 4 coach to a level 5 coach. As you can see, the gain is about 1%, and pretty consistent for training young vs old players.

This is a pretty small improvement that corresponds to a quarter or less of a level of form. However, this whole analysis is in the business of splitting hairs and squeezing every last bit of performance, and this is why I use a level 5 coach throughout these results.

5.2 Central Defender

The GK position requires more nuance, so let's start with the CD. Here are the results for central defenders.

Skill	CD N U21	CD N NT	CD O U21	CD O NT	CD TW U21	CD TW NT
DE	15.5	18.9	13.6	17.3	16.2	19
PM	9.2	14	12.7	17	6.3	11.4
WG	-	-	-	-	6.0	11.3

Table 13: Optimal Skills for Central Defenders, at U21 and NT Age

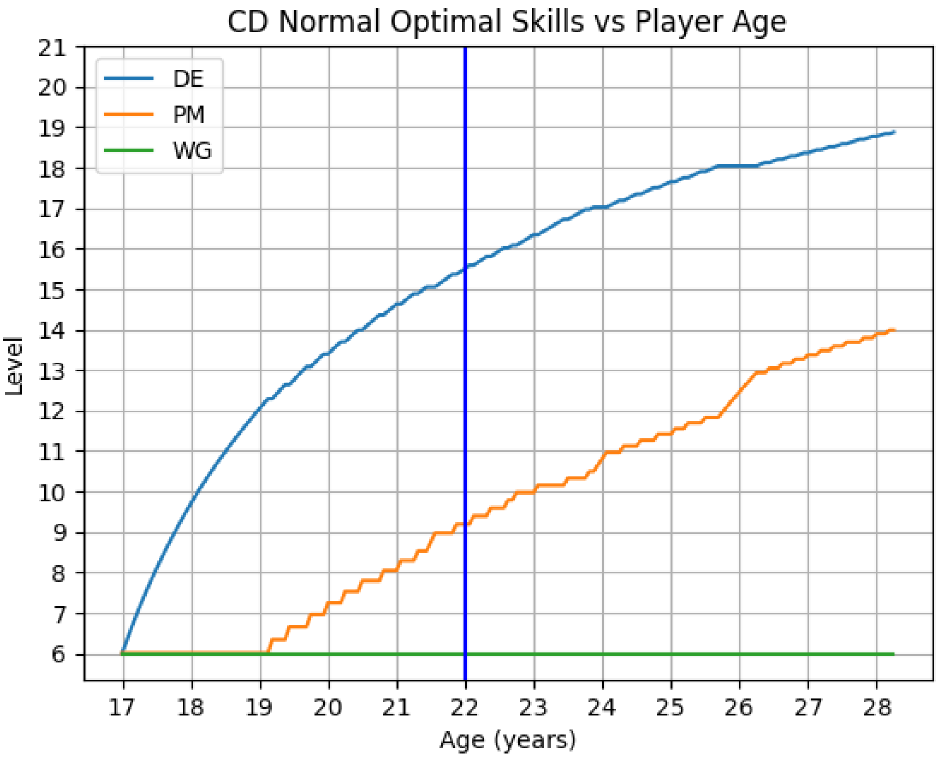

Figure 2: Optimal Training for Normal CD

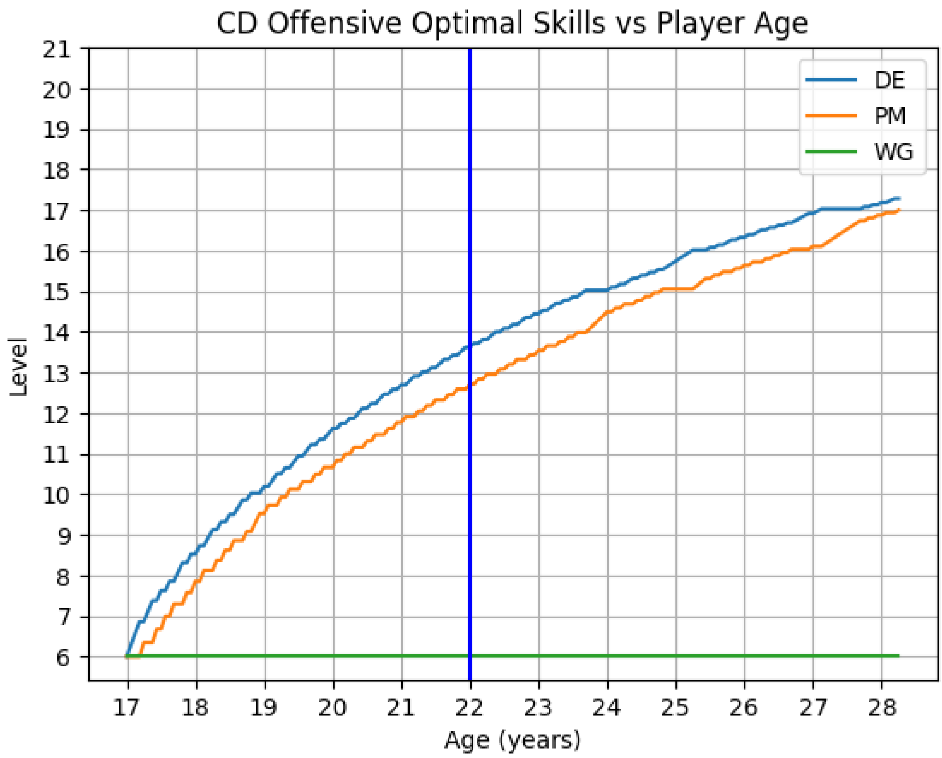

Figure 3: Optimal Training for Offensive CD

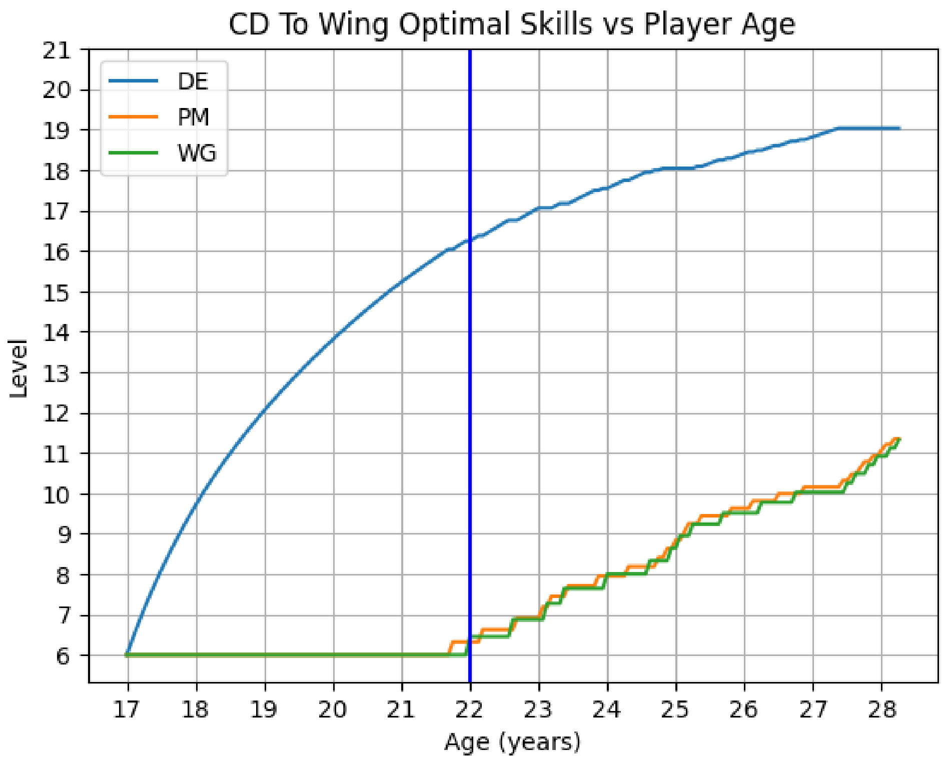

Figure 4: Optimal Training for CD To Wing

5.3 Wing Back

Skill	WB N U21	WB N NT	WB D U21	WB D NT	WB O U21	WB O NT	WB TM U21	WB TM NT
DE	15.1	18.1	15.7	19	13.9	17.3	15.7	18.8
WG	11.5	16	9.7	14.8	12.9	17	8.1	12.2
PM	6	10.1	6	7.4	7.8	11.3	7.5	11.7

Table 14: Optimal Skills for Wingbacks, at U21 and NT Age

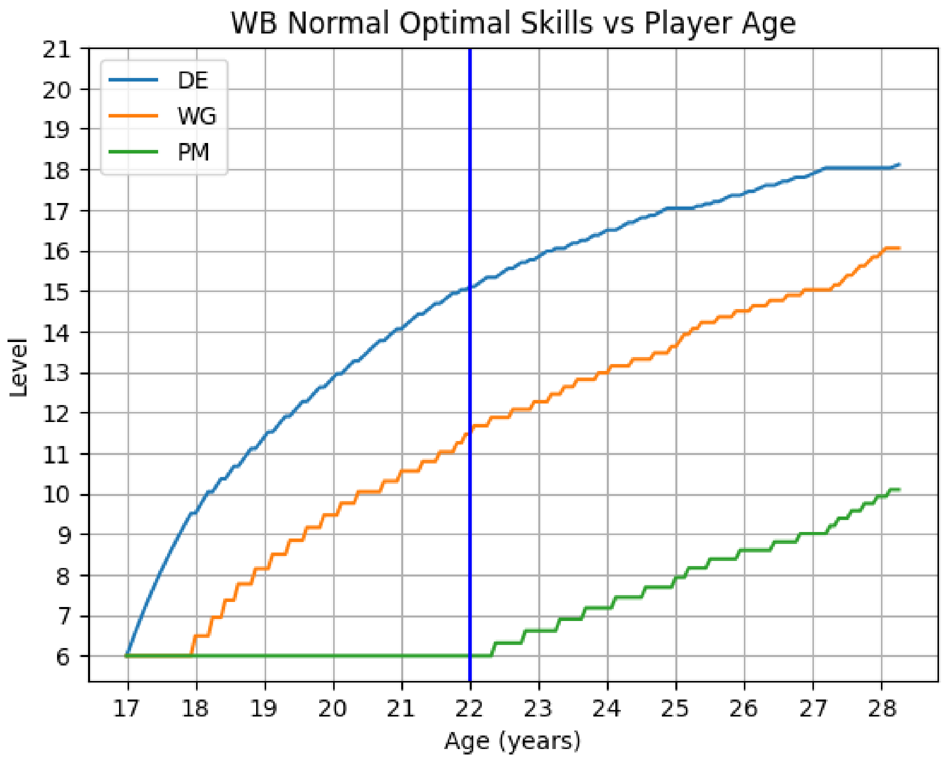

Figure 5: Optimal Training for Normal WB

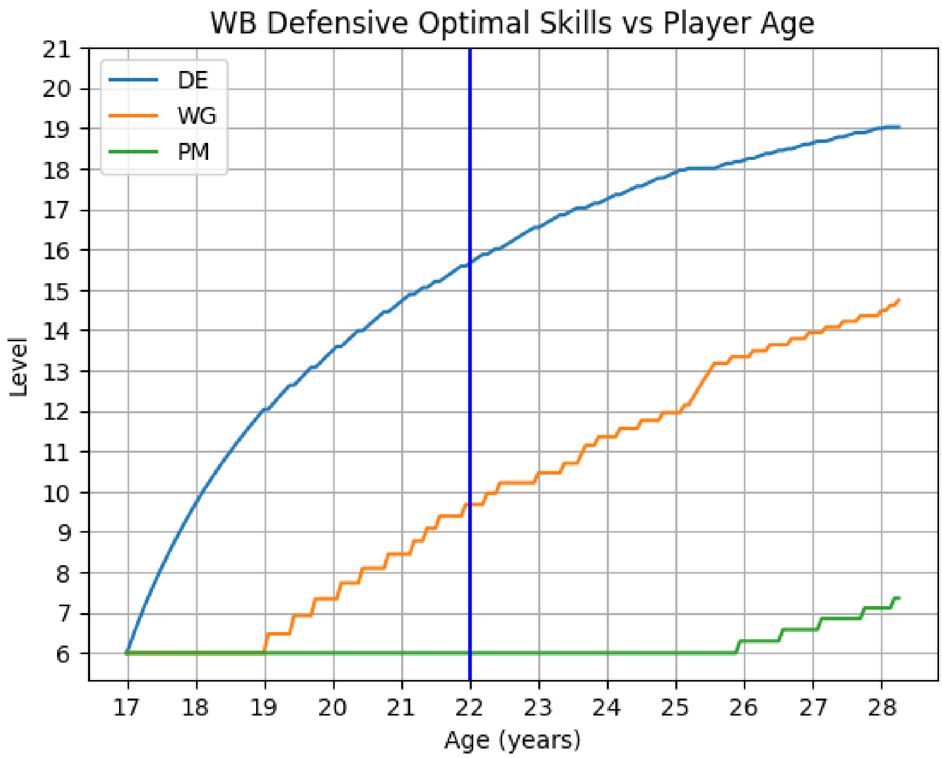

Figure 6: Optimal Training for Defensive WB

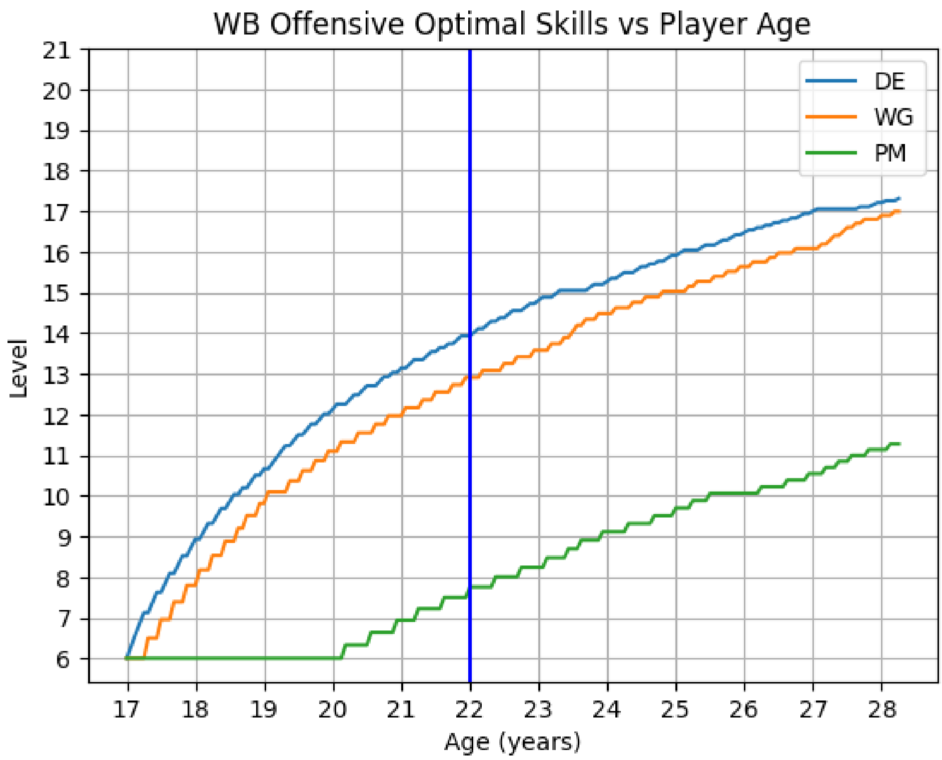

Figure 7: Optimal Training for Offensive WB

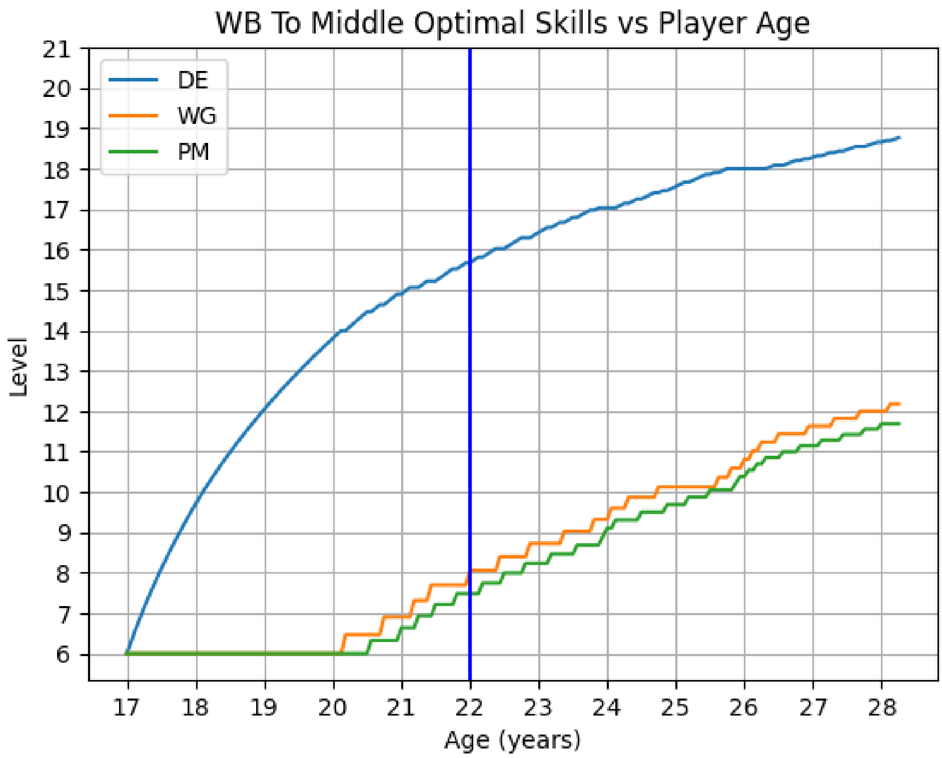

Figure 8: Optimal Training for WB To Middle

5.4 Inner Midfielder

Skill	IM N U21	IM N NT	IM D U21	IM D NT	IM O U21	IM O NT	IM TW U21	IM TW NT
PM	17	19.4	16.4	19.1	16.3	19.3	16	18.6
PS	7	12.1	6	7.7	9.6	15	6.3	10
DE	6.3	11.1	8.8	14.2	6	6	6	9.7
SC	6	6	6	6	6	7.3	6	6
WG	-	-	-	-	-	-	11	15.1

Table 15: Optimal Skills for Inner Midfielders, at U21 and NT Age

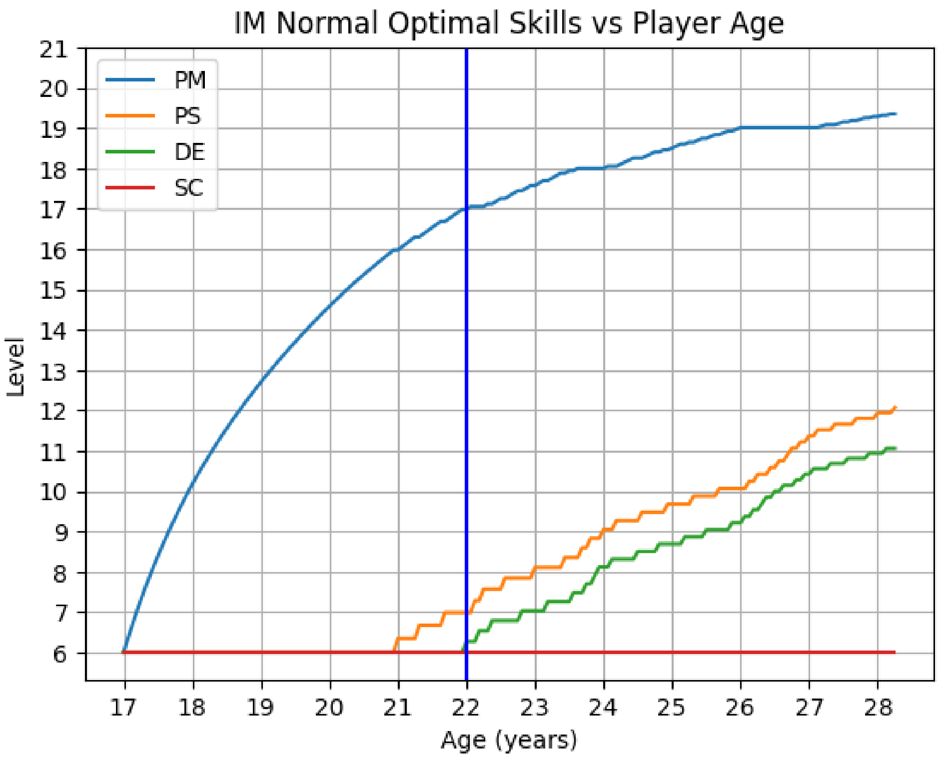

Figure 9: Optimal Training for Normal IM

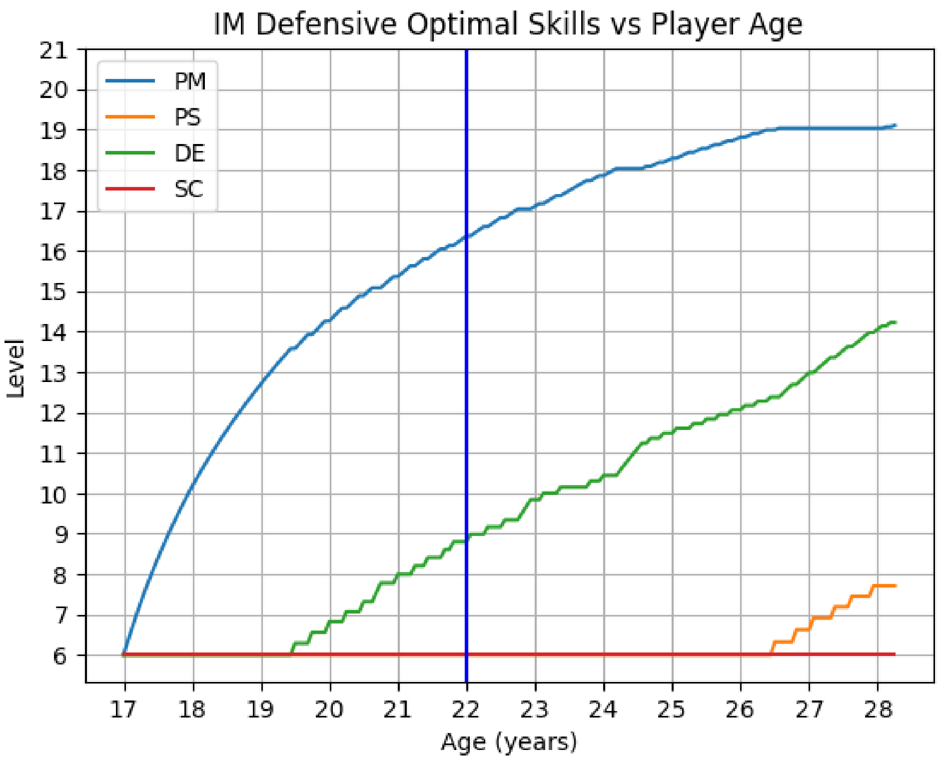

Figure 10: Optimal Training for Defensive IM

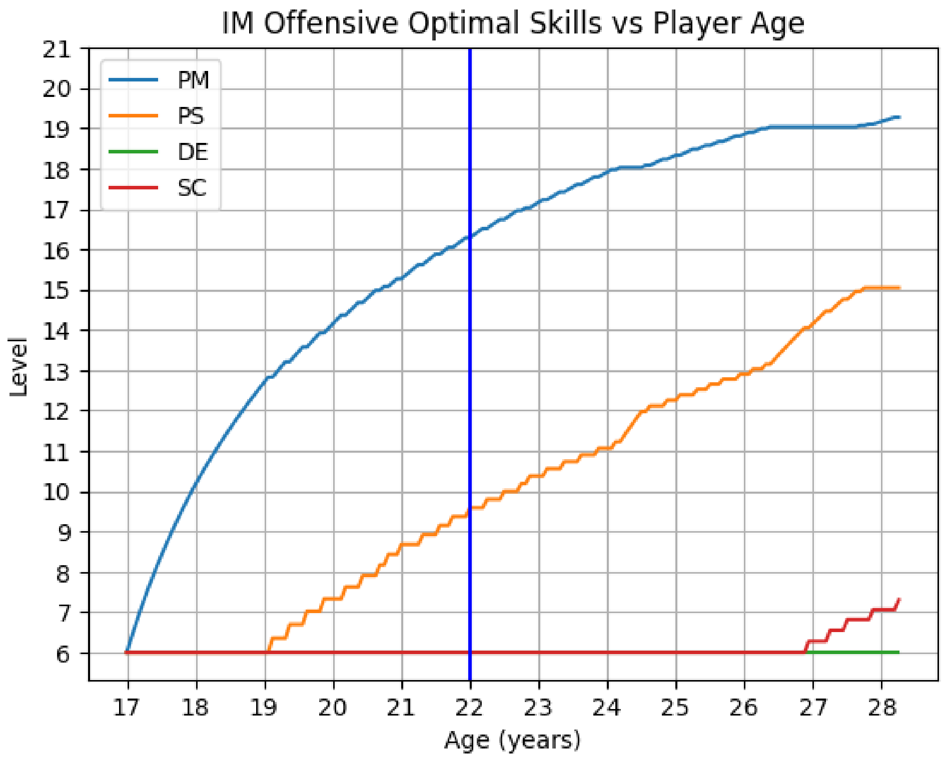

Figure 11: Optimal Training for Offensive IM

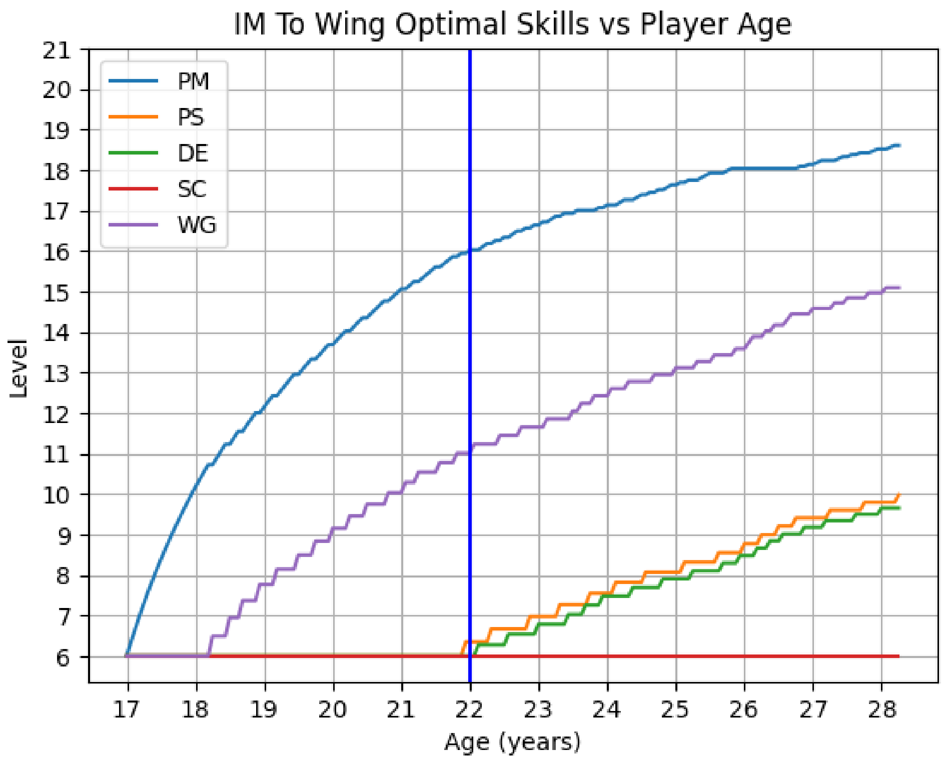

Figure 12: Optimal Training for IM To Wing

5.5 Winger

	W N		W D		W O		W TM	
Skill	U21	NT	U21	NT	U21	NT	U21	NT
WG	14.4	17.6	13.1	16.6	16.6	19.1	12.7	16.6
PM	13.1	16.5	10.6	14.2	11.1	15.1	14.5	17.7
DE	8.6	11.8	12.4	15.8	6.5	10.1	8.2	11.5
PS	6	9.4	6	7.5	8.1	11.4	6	8

Table 16: Optimal Skills for Wingers, at U21 and NT Age

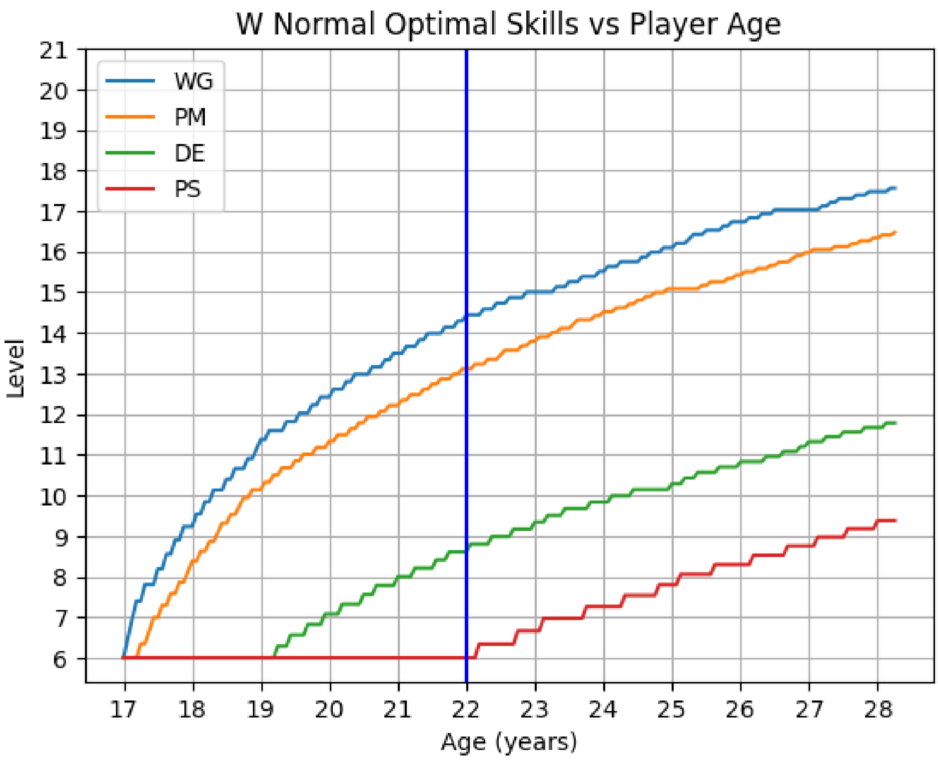

Figure 13: Optimal Training for Normal Winger

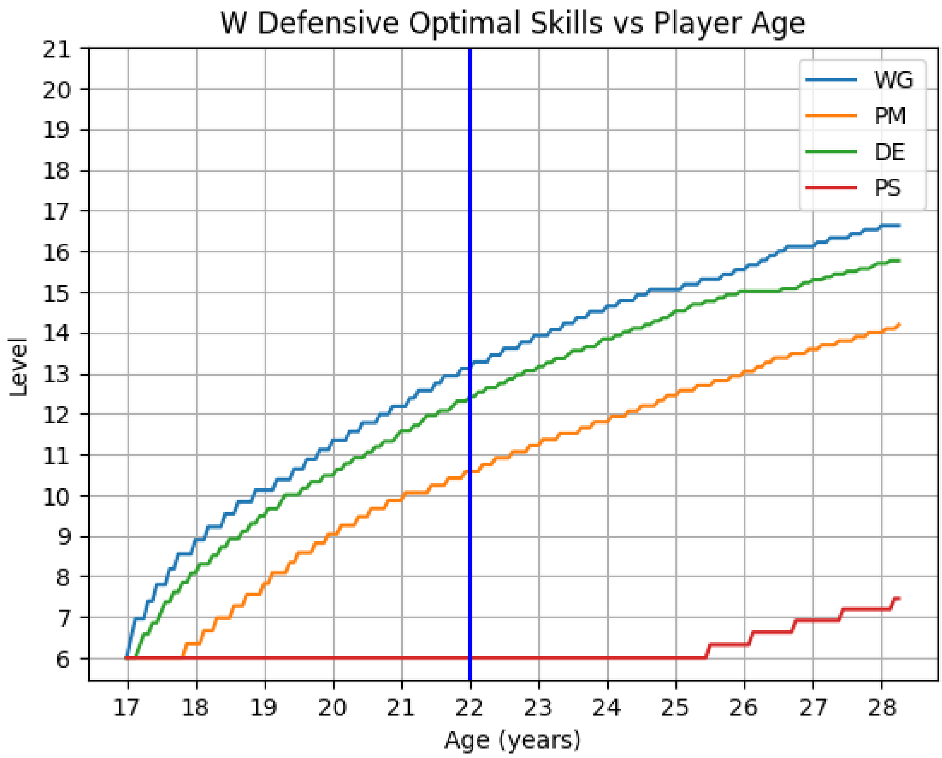

Figure 14: Optimal Training for Defensive Winger

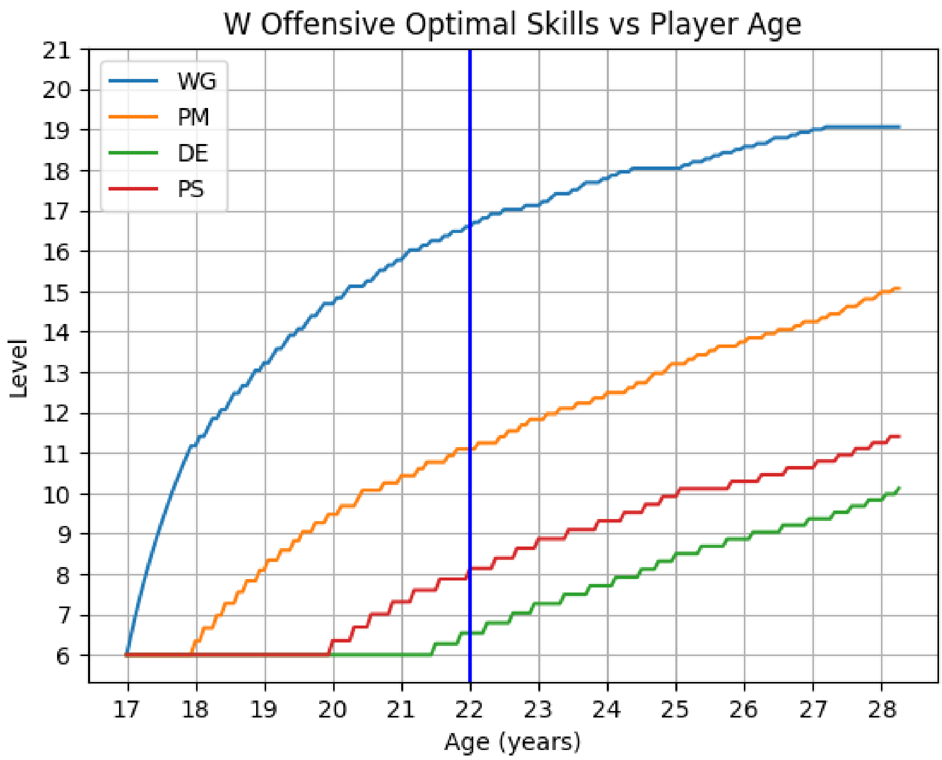

Figure 15: Optimal Training for Offensive Winger

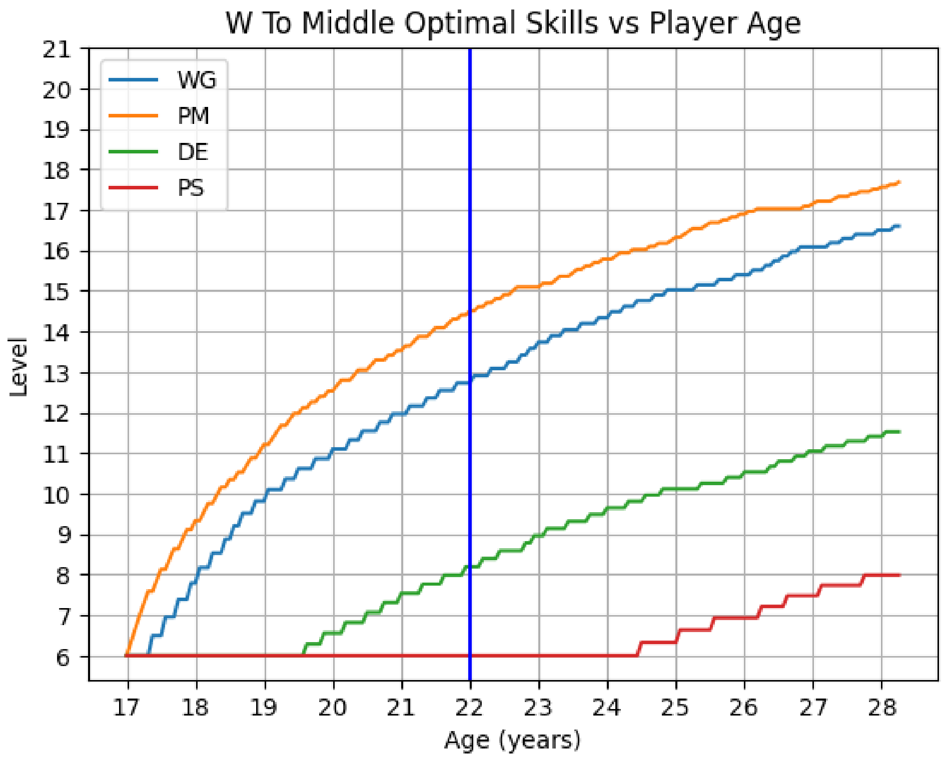

Figure 16: Optimal Training for Winger To Middle

5.6 Forward

	FWD N		FWD D		TDF		FWD TW	
Skill	U21	NT	U21	NT	U21	NT	U21	NT
SC	15	18	10.5	13.9	10.1	13.6	14.3	17.5
PS	8.9	12.3	13.8	17.1	14.5	17.7	7.6	11.1
PM	8.3	11.7	11.1	14.6	10.4	14.2	6	8.8
WG	9.1	12.4	6	8.3	6	7.9	13.5	17

Table 17: Optimal Skills for Forwards, at U21 and NT Age

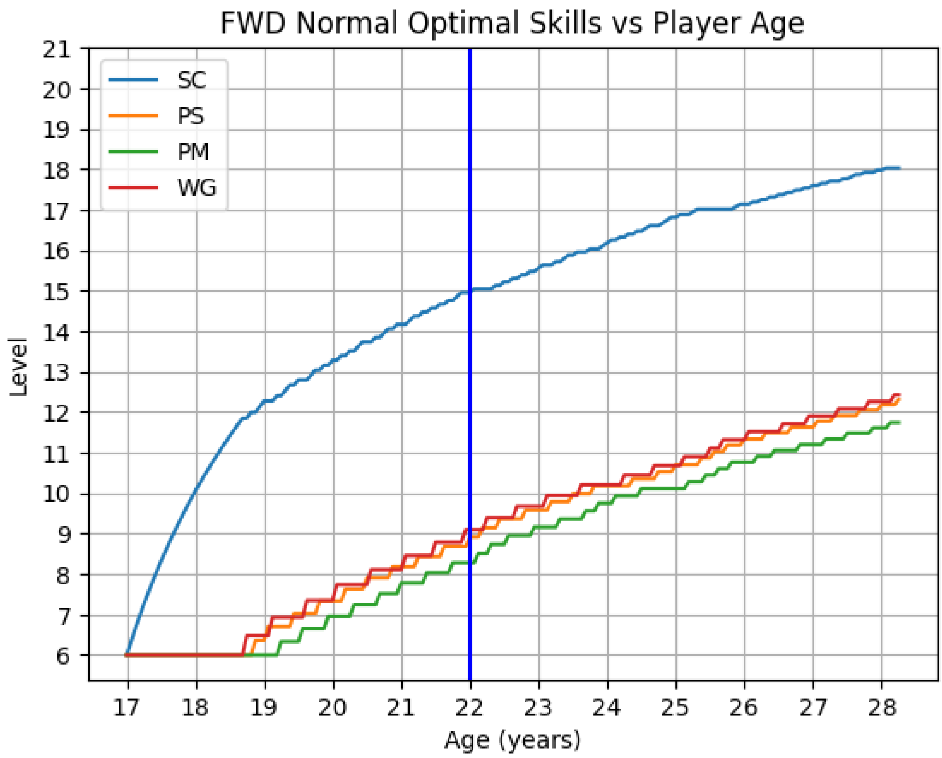

Figure 17: Optimal Training for Normal Forward

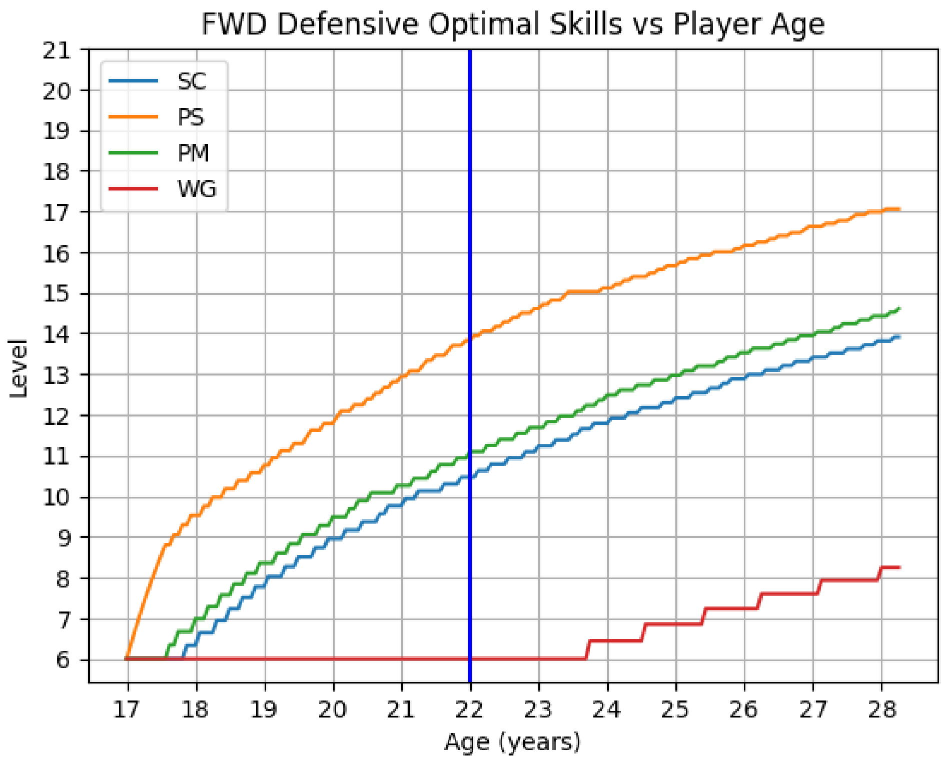

Figure 18: Optimal Training for Defensive Forward

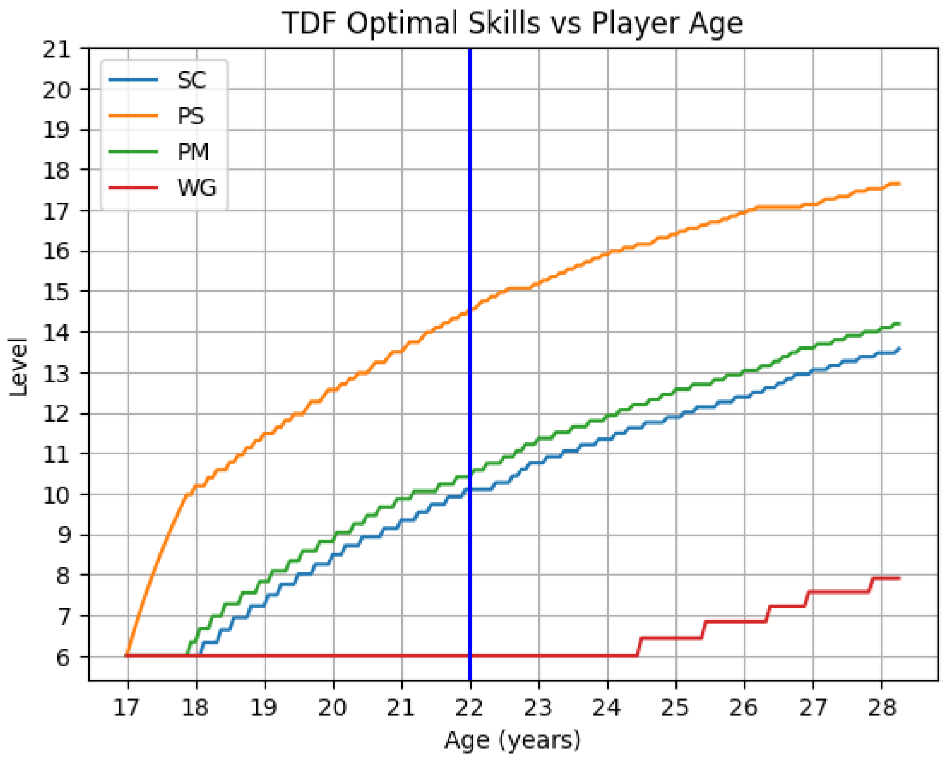

Figure 19: Optimal Training for Technical Defensive Forward

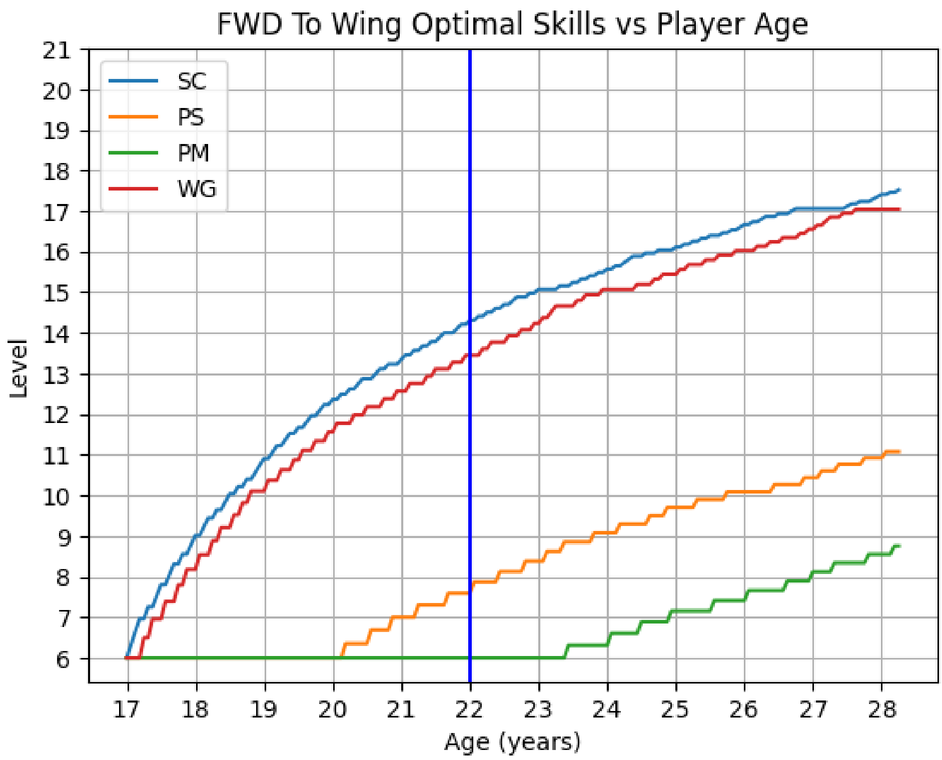

Figure 20: Optimal Training for Forward To Wing

5.7 Goalkeeper

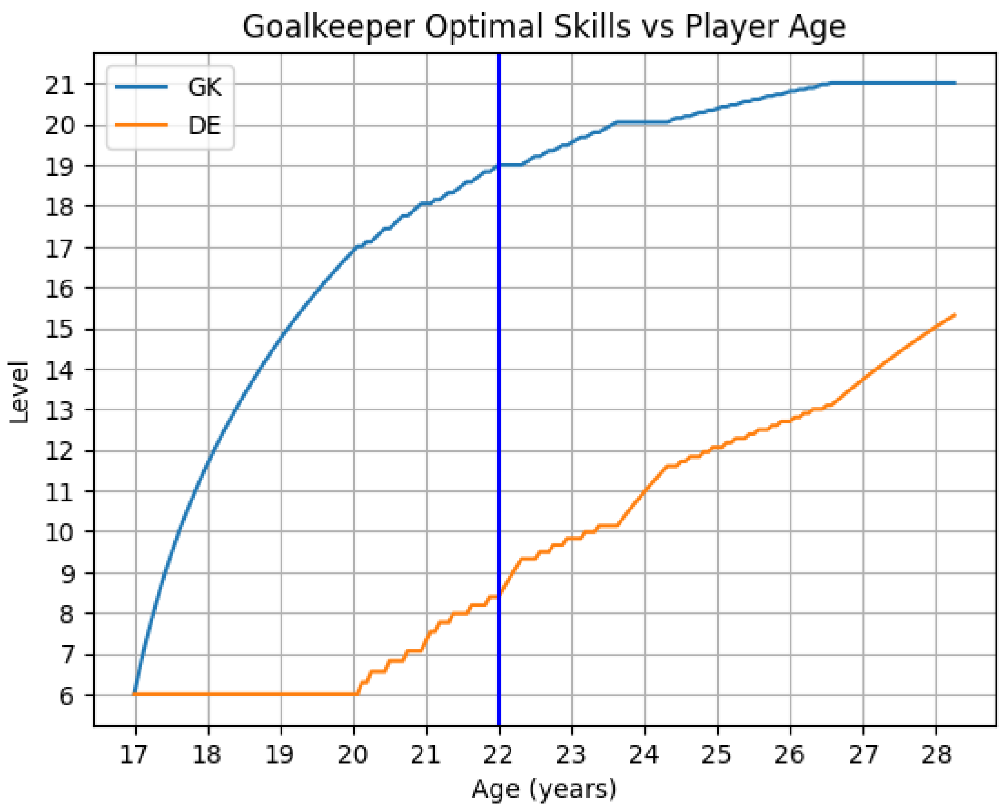

Figure 21: Optimal Training for Goalkeeper

Note that these results do not include set pieces. The position matrix for the GK does not include SP because it does not change the ratings. One of the limitations of this formulation is that it only looks at the ratings.

Obviously, SP is very important for a GK. With that in mind, I've re-run the GK analysis where the player is trained to the USA's U21 target SP for GK first, and then to the NT target at age 22. Those results are shown below

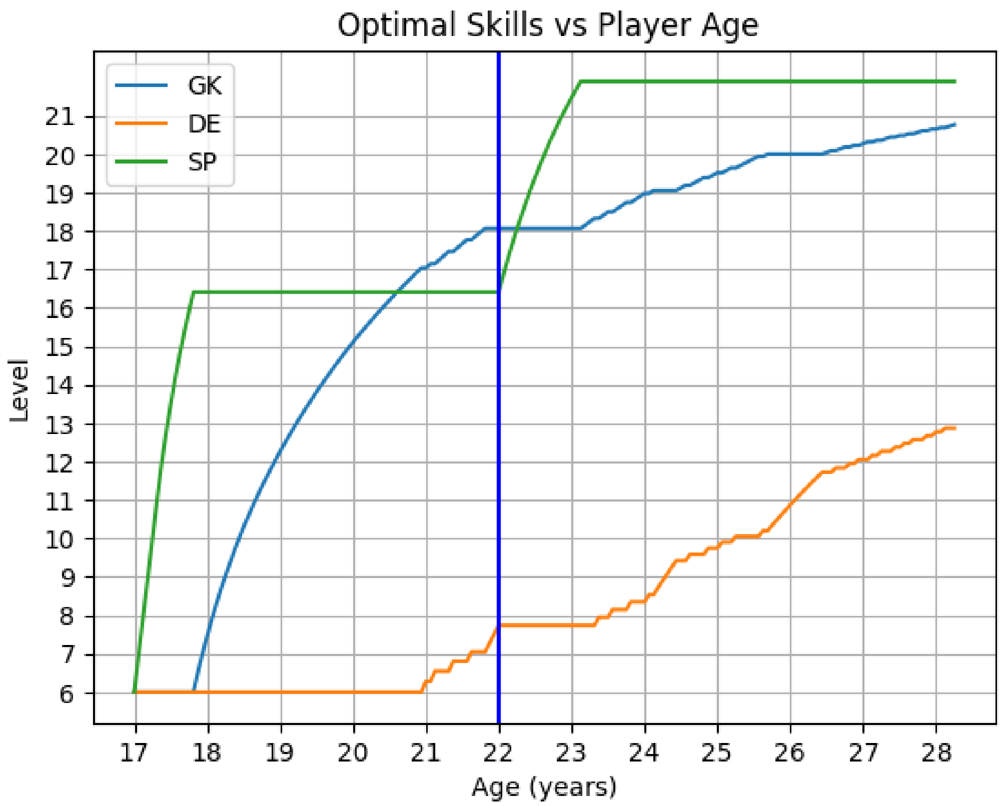

Figure 22: Optimal Training for Goalkeeper Including Set Pieces

	GK		GK SP	
Skill	U21	NT	U21	NT
GK	19	21	18.1	20.8
DE	8.4	15.3	7.7	12.9
SP	-	-	16.1	21.9

Table 18: Optimal Skills for Goalkeepers, at U21 and NT Age

6 Discussion

The above results are what I would consider optimally-trained players *for the W weights that I've used*. However, the real value in this tool is not these results, but the ability to generate similar charts with any weights. This allows comparison between different players, training schemes, positions, and more. I would encourage you to play with the weights in the interactive tool and see what skills you come up with!

For the weights I have used, I personally was surprised about

- the lack of scoring on IM's,
- how even the side skills of normal Forwards should be,
- how dominant passing is on Defensive Forwards (especially compared to PM),
- and just how pronounced the difference in different orders for the same position was.

6.1 Training Order

The graphs in the Results section are all similar–with skills logarithmically approaching some limit. They represent switching training types every few weeks, which will give you optimality through the players lifetime, but we don't really care about that. If you play around with training calculators, you will find there is little difference in training order (e.g., training PM before defending for CDs, or switching back and forth between them).

So, I am not actually proposing that the best training method is to continuously switch what you are training. Not only would that be hard to keep track of, it messes with batching up players for things like cycle training. Instead, I would recommend looking at the resulting graphs and picking an age where you want to start being competitive (e.g., at the start of a U21 or NT cup cycle, at some point during your cycle, etc), and train to those skills in whichever way is most convenient.

6.2 Comparing with NT and Other Targets

We can use the tool to compare to NT targets. I will use the USA targets[7], which I have found to be the closest to what this analysis has found to be optimal.

Table 19 shows the comparison between the NT target for a midfielder and my found optimal skills.

Skill	NT Target	Optimal
DE	11	11.1
PM	19	19.4
PS	12+	12.1
SC	8	6
Skill Score	4.03	4.07

Table 19: USA NT IM Targets vs Optimal

Our found optimal skills are *very* close to the USA targets! The optimal trains a little bit more PM at the expense of the scoring, resulting in our optimal IM outperforming the USA target by 0.8% in terms of total contribution.

Let's look at another one: Wingbacks. Here, I've taken the passing straight from the NT target to make the comparison easier. Passing on the WB and CD positions are similar to the GK with set pieces - where those skills are important but do not contribute to the ratings, and thus do not contribute to the Skill Score.

Skill	NT Target	Optimal
DE	18	18
PM	9	9.6
WG	16+	15.6
PS	9	9
Skill Score	2.777	2.780

Table 20: USA NT WB Targets vs Optimal

Again, the final skills are very close, and our optimal here is only 0.1% more contribution than the NT target! Awesome!

Feeling good about this tool working as intended (and that my weights match the NT coaches' weights), lets look at wingers. From the NT target:

Skill	NT Target	Optimal
WG	18+	17.4
PM	17	16.3
DE	9	11.7
PS	9	9.2
Skill Score	2.85	2.89

Table 21: USA NT Winger Targets vs Optimal

and our winger contributes 1.4% more than the NT target–about the same difference as using a level 5 coach. Here the skills diverge a bit, and the optimal winger has given up both winger and playmaking for more defense.

[7] `https://www83.hattrick.org/Forum/Read.aspx?t=17591522&n=1&v=0`

Let's do one more: forwards.

Skill	NT Target	Optimal
SC	18	18
PS	13+	12.3
WG	10	12.4
PM	12	11.7
Skill Score	3.11	3.14

Table 22: USA NT Forward Targets vs Optimal

Interestingly, here we only see a 0.9% performance gain, but the skills are different. We've got a substantial amount more of Winger, with less Passing and PM. So there are clearly different archetypes of players that contribute roughly the same. This is an interesting topic which I hope to investigate further in the future.

6.3 Comparing Between Positions

Because I use the same W matrix everywhere, this tool allows comparing across positions instead of players. Intuitively, some players (like IMs) will contribute more to ratings than others. This is a function of the actual contribution as coded by the game engine. Table 23 shows the relative contribution of a 26 year old optimally-trained player:

Position	Skill Score
GK	4.41
CD	2.57
WB	2.64
IM	3.85
W	2.72
FWD	2.93

Table 23: Skill Contribution of Optimally-Trained Players by Position

As you can see, GK and IMs eclipse everybody else in terms of contribution, with CDs lagging the most. All standard W-related disclaimers apply.

6.4 A Case Study

While I was preparing the Skill Score Calculator, I came across a forum post[8] lamenting the death of Defensive Forwards. There are some estimations[9] in there about how much weaker a DF is from a Normal Forward, with the range 1-3% thrown out there.

There were also some question[10] about the combination of skills for a DF that would be the best.

My tool can help answer both questions. First, let's consider which version of a DF is the best. These were the options from the post:

Skill	Option 1	Option 2	Option 3	Option 4	Option 5	"Answer"
SC	13	14	15	16	15	15
PS	17	17	17	16	18	17
PM	17	16	15	15	14	16
WG	9	9	9	9	9	8

Table 24: TDF Options from Forum Post

It is simple enough to run the Skill Score and training time numbers on these:

[8] https://www83.hattrick.org/Forum/Read.aspx?t=17603079&n=1&v=0
[9] https://www83.hattrick.org/Forum/Read.aspx?t=17603079&n=12&v=0
[10] https://www83.hattrick.org/Forum/Read.aspx?t=17603079&n=9&v=0

	Option 1	Option 2	Option 3	Option 4	Option 5	“Answer”
SS (Not Tech)	3.06	3.06	3.06	3.03	3.08	3.10
SS (Tech)	3.28	3.28	3.27	3.24	3.31	3.32
Training Weks	206	202	200	201	206	210

Table 25: TDF Options Skill Scores and Training Time

These are functionally all the same, with the “Answer” having the best contribution (by a little) but a longer training time (by a lot). We can, of course look at what the training-optimal player looks like, for both the Technical and non-Technical cases. Let’s use the 210 training weeks duration.

Skill	Forum “Answer”	Optimal (Tech)	Optimal (Non-Tech)
SC	15	14.5	14.9
PS	17	18.1	17.7
PM	16	15.1	15.1
WG	8	8.8	9.1
Skill Score	3.32	3.34	3.11
SS Change	0%	+0.9%	+0.5%

Table 26: Skills and Scores for DF Options

As you can see, we can squeeze a bit of performance over the forum answer if we train to the same number of weeks. Notice the difference in skills between Technical vs Non-Technical forwards.

The other question asked in the thread is whether or not DF’s are ”Dead”, meaning they contribute significantly less than normal forwards do. This is easy enough to answer. Using the optimal players from above, and from our optimal skills for a Normal forward:

Player	Skill Score	SS as % of FWD N
FWD N	3.30	100%
TDF	3.34	101.4%
DF (Non-Tech)	3.11	94.4%

Table 27: Skill Score Comparison of Optimally-Trained Forwards

Here we can see that TDFs actually outperform normal FWDs (Man Marking concerns aside), and that non-technical DFs are in fact much worse than normal FWDs... by about 5.6%. That is gigantic compared to all the other $< 1\%$ values we have been looking at.

To be clear... based on this analysis I would say that a perfectly trained NF in *solid* form contributes more in ratings than a perfectly trained DF in *excellent* form.

7 Conclusion

If you are still reading, thank you for bearing with me through all this math and analysis! This work developed a way to weight the contribution of a player to the match ratings–called skill scores–and used them to optimize training players. We looked at different example players, training set ups, and I gave the optimal skills for my default skill score weights.

This method does have some limitations, like:

- Firstly, it only looks at ratings. Things that do not contribute to ratings are lost, like SP or passing on defenders for CA ratings.
- Next, it only considers single position/orders. Right now there is not an ability to optimize for a player that will play multiple positions/orders. As an example, we cannot analyze a player who is expected to split time between Winger Toward Middle and IM Toward Wing.
- Finally, it is highly dependent on how you value the different sectors. This weighting is the core of Hattrick, and there is no real “right” answer. However, you have seen a bunch of “performance improvements” that are very small (less than 1%). It is easy to imagine the weights I’ve chosen being off by more than 1%, which would throw the rest of the analysis off.

Aside from those limitations, I hope that this work and the interactive tool are helpful for y'all to plan your training!