10 Ways to Minimise Curve Fitting

Before we talk about minimising curve fitting, we need to understand one important fact:

> Curve fitting **cannot** be completely eliminated when we design trading robots.

There is always an element of curve fitting. The moment we look at past data/charts and draw any type of inspirations from it, we are curve fitting to an extent.

Market prudence contains elements of curve fitting as well. Market inefficiencies leads to certain price behaviour, we know this relationship exists because we saw it in the **past**. For example, when the US central banks prints more USD, we usually expect the US Dollar Index to fall. We expect that because 1) it is logical from an economics point of view and 2) this happened before and we learn from experience. Point 2) contains elements of curve fitting.

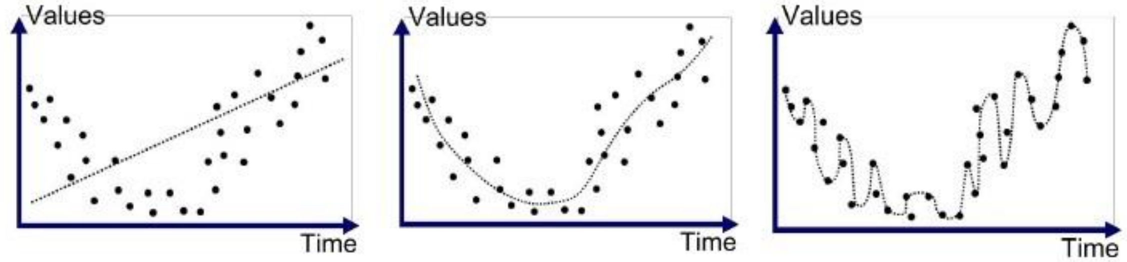

Fig 1: If you have looked at these charts and identified the shape of the data points **before** you design a model for them, you have curve fitted your model (to an extent).

10 Ways to Reduce Curve Fitting

Now that we know curve fitting cannot be eliminated, we look at 10 ways to reduce curve fitting. We will only talk about these 10 methods briefly. In future lectures, we will look at each of them in much greater detail.

1. Limited Number of Rules (Degrees of Freedom)

Keep it simple. Reduce the number of rules in your trading strategy to the bare essentials. The less rules we have, the less freedom our robot has to over-adapt to the past. This concept is related to the idea of Degrees of Freedom[1].

2. Parameter Relevance

There are many variables in a trading strategy, but that doesn't mean we should optimise every parameter. We should only optimise parameter values that are closely related to the market signals which we are interested in.

3. Meaningful Parameter Ranges

☑ sma_short	43	20	1	119
☑ sma_long	41	40	1	139
☑ atr_period	29	20	1	40
☐ atr_shift	11	11	0	0

Fig 2: Parameter Range for sma_short is 20 to 119.

[1] https://en.wikipedia.org/wiki/Degrees_of_freedom_(statistics)

When we optimise a variable, we need to select a range of parameter values to test. It is not prudent to select an extremely wide range and hope to find values which produce great performance. Our parameter range should be closely related to the market inefficiency we are trying to capture.

For example, if our average holding period per trade is 6 months, it is generally not reasonable to select a SMA period of 5 on an hourly timeframe. That will amount to using information from 5 hours of data to decide a trade that will last for 6 months.

4. Meaningful Parameter Steps

Having small parameter step values (aka having large number of passes) has a similar effect to having too many rules in our strategy. Small parameter step values allow the robot to adapt to micro details in the market. These micro details are usually noise.

5. Performance Clusters/Parameter Robustness

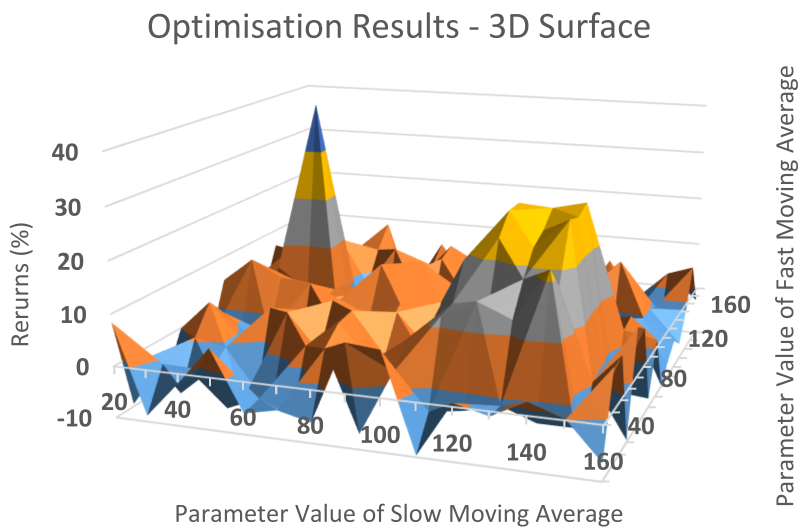

Fig 3: 3D surface of an Optimisation Result.

In Fig 3, the X and Y-axis represents the parameter values of 2 SMAs. The Z-axis represents returns. This is similar to the 2D surface you see in your MT4.

With such a result, would you be more comfortable trading the parameter values representing the sharp performance spike at the left or that of the flatter hills on the right? Take some time to think about this question. We will talk about it again later in this chapter.

6. Independent Variable Optimisation

☑ sma_short	43	20	1	119
☑ sma_long	41	40	1	139
☑ atr_period	29	20	1	40
☐ atr_shift	11	11	0	0

Fig 4: Optimising 3 variables.

Instead of optimising the above 3 variables together, we can split the optimisation into 3 and optimise each variable individually. This will allow us to understand how each variable affects the overall strategy. Better understanding leads to lower tendency for curve fitting. However, if the variables are correlated, independent variable optimisation may lead to misleading optimisation performance.

7. Using In and Out-of-Sample Data

Let's say we optimise our strategy using dataset X. Once we find the optimised pass, we run a backtest with its optimised parameter values on dataset X again. What do you think will happen?

Yes, we will get great performance. But this is useless to us. Our optimised pass is meant to do well on dataset X (aka in-sample data in this context). We need to test the optimised pass on another dataset (aka out-of-sample data) to truly see its value.

8. In and Out-of-Sample Data Size

The size of our in and out-of-sample dataset is related to curve fitting as well. If our dataset is too big, it may contain too much noise. If it is too small, it is likely to either wholly contain signals or noise.

9. Walk-Forward Optimisation

Take the idea of the in and out-of-sample data optimisation, repeat it multiple times, and we will end up with the walk-forward optimisation.

The walk-forward optimisation is a method that entails continuously optimising using in-sample data and testing the optimised passes on out-of-sample data. This is one of the most important concepts in trading optimisation. For more information: https://en.wikipedia.org/wiki/Walk_forward_optimization.

We will dedicate an entire chapter to the walk-forward optimisation in the future.

10. Market Prudence

Lastly, we come to our best defence against curve fitting – market prudence. If a strategy is market prudent, it exploits a market inefficiency.

This leads to a causal effect[2] between market inefficiencies and profitability:

1. Market inefficiency X leads to market behaviour Y (this is causation not correlation[3]).
2. We design robot Z that exploits market behaviour Y.
3. We implement robot Z when we believe market inefficiency X is going to happen.
4. Profit.

As mentioned in the start of this article, curve fitting does exist to a small extent in point 1). That aside, this process allows us to identify market signals and design robots for these signals only. Thus, we minimise the chances of us adapting our robots to the noise in the market.

[2] https://en.wikipedia.org/wiki/Causality
[3] https://en.wikipedia.org/wiki/Correlation_does_not_imply_causation