Follow-up Study of an Application of Design of Experiments to a Technical Trading System

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A previous study [1] applying a Design of Experiments (DOE) to a technical trading system described in Connors and Alvarez [2] found an optimal "sweet spot" for the parameter settings that increased the profits by more than 300%. The trading model specified the same period for the RSI indicators but the DOE analysis revealed an interaction between the RSI period and the settings used for making trading decisions. This suggested that using different periods might enhance the outcome. The analysis presented here found profits increased by another 18% using different RSI periods for exit decisions versus entrance decisions. The analysis was also extended to a multi-objective optimization in which risk is minimized and profit maximized using a Euclidean compromise on a Pareto frontier.

Traditionally trading systems were developed and tested using some type of undirected back testing. Usually intuition and tradition determine the attempted settings which are unlikely to produce optimal results. The earlier study [1] showed that Design of Experiments technology which is systematic and efficient is able to find optimal settings that dramatically improve results. DOE however offers more benefits than just optimal settings. It also provides insight into the workings of the trading model suggesting new directions the model might take for even greater profitability.

Previous Results

On page 96 Connors and Alvarez [2] describe the VIX RSI trading system for the SPY:

1. The SPY is above its 200-period moving average.
2. The 2-period RSI of the VIX is greater than 90
3. Today's VIX open is greater than yesterday's close.
4. The 2-period RSI of the SPY is below 30.
5. Buy on the close.
6. Exit when the 2-period RSI of the SPY closes above 65.

This model entails five factors:

1. Period of the SPY moving average
2. RSI setting of the VIX
3. RSI setting of the SPY
4. Exit setting of the SPY RSI
5. Period of the RSI

A winning sweet spot were generated in a daily back-test data set of the SPY and the VIX from January 29, 1993 through October 17th 2003,

Factor 1	Factor2	Factor3	Factor4	Factor5
250	80.0000	45.0000	95.0000	3

which produced the following results when run in the back-test data

Profit/Loss	Annualized Return	Sharpe Ratio	Maximum Drawdown
764341.35	10.01%	1.5362	-69778.50

For validation this sweet spot was run in a forward-test data set, the SPY and VIX from October 17th 2003 through October 12th, 2009. This produced the following result,

Profit/Loss	Annualized Return	Sharpe Ratio	Maximum Drawdown
101995.79	3.27%	2.0457	-24108.84

Because the forward-test period of time included the 2009 Meltdown, this result was regarded as validation despite the lower annualized return.

The results in the back test data set for the Connors and Alvarez [1] settings are,

Profit/Loss	Annualized Return	Sharpe Ratio	Maximum Drawdown
156503.42	2.78%	0.5893	-39988.32

and for the forward-test data set,

Profit/Loss	Annualized Return	Sharpe Ratio	Maximum Drawdown
28329.22	0.93%	0.5819	-20434.68

The DOE sweet spot produced a 388% improvement in outcome over the sweet spot in [2].

While this improvement in results is quite dramatic, further findings reported in [1] suggest that modifications to the model might generate even better results. First, an analysis of the coefficients of the cubic response surface found that the outcome is somewhat insensitive to the period of the SPY moving average, that is, the Factor 1 in the model above. Second, an interrelation between the RSI period and their settings, i.e., between Factor 5 and Factors 3 and 4 was found. This suggests that further improvement in results might be found by allowing the RSI indicators to have different periods.

A Modified Trading Model

First, the period of the SPY moving average will be removed as a factor and set to the traditional 200. The findings from the original study [1] suggest that this will be as good as the one found in the sweet spot. Second, two new Factors will be defined, the period of the VIX and SPY RSI indicators used for the entrance decision, and another for the SPY RSI used for the exit decision. We know have the following five factors:

Factor 1. RSI setting of the VIX
Factor 2. RSI setting of the SPY
Factor 3. Exit setting of the SPY RSI
Factor 4. Period of the RSI's in Factor's 1 and 2
Factor 5. Period of the RSI in Factor 3

For the DOE analysis we must first define the parameter space. This can be refined somewhat from the results in the earlier study.

Factor 1. [75, 95]
Factor 2. [25, 50]
Factor 3. [65, 95]
Factor 4. 2 3 4 5 6
Factor 5. 2 3 4 5 6

Using the Gosset [3] computer program we generated parameter settings for 57 trial runs (see Table 1). Daily data for the SPY and the VIX from January 29, 1993 through October 17th 2003 was selected for the trial runs. A computer program written in the GAUSS programming language [3] was developed for the simulation of the trading system given the parameters. To produce a more realistic result, each simulation started with an account of $500,000, paid a $20 transaction fee per trade, and a bid/asked spread was also included.

Trial runs for each of the 57 set of parameters are executed and the profits for each are recorded. Then a cubic polynomial response surface is defined by regressing the profit on the parameter settings in the design matrix. The response surface is then explored for optima using a hill-climbing method. For this study the GENO program written in GAUSS was used for hill-climbing. GENO is a program for solving nonlinear optimization problems based on a genetic algorithm method.

The success of the response surface depends on how well it represents predicted values away from the observations. To make this representation more robust two initial runs is made and the sweets spots found are themselves added to the observations giving us, in this case, a robust complement of 142 trial runs.

Hill-climbing was again conducted and the following sweet spot was found for the back-testing data,

Factor 1	Factor2	Factor3	Factor4	Factor5
75	50	95	2	4

This sweet spot produced the following results when run in the back-test data,

Profit/Loss	Annualized Return	Sharpe Ratio	Maximum Drawdown
903182.22	10.96%	1.6061	-74151.00

To validate these results we'll run the sweet spot on a forward-test data set, the SPY and VIX from October 17th 2003 through October 12th, 2009. Validation is useful first to protect against over-fitting, of which this model doesn't seem to be in much danger, and second to ensure results are able to generalize across market conditions. The run for this sweet spot on the forward-test data produced the following results

Profit/Loss	Annualized Return	Sharpe Ratio	Maximum Drawdown
162205.50	4.81%	1.0579	-24868.62

To be fair the forward-test data contained the 2009 Meltdown, and so we'll conclude that the model settings have been validated. These results represent an improvement in return, Sharpe ratio, and profit, 18.2% increase in profit to be precise. It is also a 477% improvement over the result from a run with the settings in [2] in the back-test data set.

Optimizing Profit and Risk

DOE also provides methods for considering additional outcomes, for example, risk. These outcomes can be measured along with the outcome of primary interest. In our case, we measured the log volatility along with the profit as a measure of risk. Response curves for both could be plotted and an ideal profit that minimized risk might be visually determined. The GENO program [4] we have used here has the capability to solve problems with multiple objectives. The Euclidean compromise solution is that point on the Pareto frontier that is closest to the ideal solution as measured by the Euclidean distance metric [5]. Basically a point is found where the profit cannot be improved without worsening risk.

Intuitively, we are going to look at regions of the profit response curve that are vertically near the sweet spot. These regions don't have to be adjacent to each other but have profit values that are near the profit values of the sweet spot. Next we look in those regions for the lowest risk.

GENO was applied the problem of maximizing the profit of the modified trading model while minimizing risk as defined by the log volatility of the returns for each trial run. It found the following solution,

Factor 1	Factor2	Factor3	Factor4	Factor5
75	41.25	95	3	4

Profit/Loss	Volatility	Annualized Return	Sharpe Ratio	Maximum Drawdown
793289.66	5.95%	10.05%	1.7882	-70686

This represents a slight decrease in profit over the original sweet spot, but a corresponding decrease in volatility and Sharpe ratio.

Conclusion

The main point to be understood is that the Design of Experiments is much more than just about finding optimal settings. It is also about acquiring an understanding of the trading model itself. An initial study [1] produced information about the model which suggested a modification. The original model used a common period for all of the uses of the RSI indicator, which was determined optimally to be 3 in [1].

The new study finds a significant outcome from using a different period for the entrance RSI than for the exit RSI. They turn out to be 2 and 4. [2] argued strongly for a 2 period RSI which seemed to be modified to 3 by [1]. However, this study re-affirms the 2 period RSI for entering trading decisions while arguing for a 4 period RSI for the exit trades. Finally, the risk-adjusted DOE analysis suggests the following for the VIX RSI trading strategy,

1. The SPY is above its 200-period moving average.
2. The 3-period RSI of the VIX is greater than 75
3. Today's VIX open is greater than yesterday's close.
4. The 3-period RSI of the SPY is below 41.25.
5. Buy on the close.
6. Exit when the 4-period RSI of the SPY closes above 95.

Table 1

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	82.5510	43.7125	74.2265	2	2
2	76.6630	37.8113	65.0000	2	5
3	75.0000	25.0000	66.3695	2	2
4	95.0000	50.0000	70.5935	6	6
5	83.4390	31.5912	65.0000	4	2
6	76.1440	46.8113	85.0490	6	4
7	75.0000	50.0000	90.1430	2	2
8	80.4750	25.0000	78.8915	6	2
9	95.0000	35.9775	95.0000	2	2
10	75.4920	31.3938	67.8965	6	3
11	75.0000	25.0000	86.6855	4	4
12	75.0000	48.8425	65.0000	5	5
13	85.5450	50.0000	95.0000	2	4
14	85.1740	25.6463	95.0000	6	4
15	95.0000	50.0000	95.0000	2	6
16	95.0000	50.0000	65.0000	2	2
17	95.0000	26.3813	95.0000	5	3
18	94.8390	25.0000	65.4350	6	2
19	90.6380	31.6200	67.9085	2	3
20	90.5210	25.7713	78.5345	5	6
21	95.0000	41.7963	67.4915	5	3
22	75.0000	26.6750	95.0000	6	2
23	89.4330	50.0000	74.9825	5	2
24	95.0000	25.0000	95.0000	6	6
25	93.1750	31.3788	65.0000	6	6
26	93.2870	46.5575	88.9415	3	3
27	75.0000	37.3375	80.2100	4	2
28	94.8570	46.8725	75.0935	2	5
29	82.2530	25.5050	75.4130	2	5
30	75.0000	50.0000	95.0000	6	6
31	75.0000	25.0000	82.1930	6	6
32	76.4610	50.0000	68.3075	3	3
33	80.0550	47.1513	95.0000	5	2
34	77.8700	32.4975	90.1670	2	3
35	93.8280	28.7000	95.0000	3	5
36	92.1090	45.6800	93.5225	5	5
37	87.4540	50.0000	65.0510	6	4
38	88.0450	38.7888	88.5860	2	6

39	83.2520	42.4675	74.3255	6	6
40	95.0000	25.0000	89.3990	2	3
41	75.3820	48.3550	65.0000	6	2
42	78.3640	32.8537	93.2135	5	6
43	75.0000	44.5063	95.0000	3	5
44	89.1060	37.9738	89.6090	6	2
45	95.0000	31.1100	80.2760	6	4
46	85.1520	25.0000	94.1810	3	2
47	75.0940	50.0000	66.7370	2	6
48	78.7150	25.0000	65.0000	4	6
49	80.6620	50.0000	86.0570	4	6
50	95.0000	30.3475	78.2750	3	2
51	95.0000	25.8250	65.9045	2	6
52	75.0000	25.0000	95.0000	2	6
53	75.0000	33.7175	75.5510	3	6
54	95.0000	25.0000	65.0000	4	4
56	89.6170	45.9838	66.1115	3	6
57	95.0000	50.0000	95.0000	6	2

References

[1] Schoenberg, Ronald J., "Application of Design of Experiments to a Technical Trading System", to be published in Futures Magazine, Summit Business Media, January, 2010.

[2] Connors, L. and C. Alvarez, *Short Term Trading Strategies That Work*, TradingMarkets Publishing Group, 2009.

[3] R. H. Hardin and N. J. A. Sloane, "A New Approach to the Construction of Optimal Designs", *Journal of Statistical Planning and Inference,* vol. 37, 1993, pp. 339-369

[4] Aptech Systems, Inc., http://www.aptech.com.

[5] FONSECA, C. M. and P. J. Flemming (1995), "An Overview of Evolutionary Algorithms in Multi-objective Optimisation." *Evolutionary Computation*, 3, pp. 1-16.