An Advanced Approach to Algorithmic Portfolio Management

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Abstract

Algorithm output profit profiles from the Nixon algorithm (RGZ Ltd.) were used to analyse the benefits of diversification within many commodity and asset class sectors in order to generate a superior portfolio profile. Metrics developed were the algorithm optimisation metric (AOM) and the parameter sensitivity index (PSI); the former accounts for noise and stability in profit profiles and optimise algorithms and portfolios yielding superior return-risk characteristics, the latter measures the stability of a given algorithm's parameters and proportional changes in profits with respect to each parameter. Comparing these portfolio profits with those of more standard portfolios, demonstrated the superiority of the developed metrics. Alignment of data was found to be a significant factor. Optimising a portfolio with unaligned data outputs leads to incorrect portfolio weightings and an erroneous profit profile on back-tested data. Correlations of prices and algorithmic returns were analysed showing the resultant dilution of correlation due to the effect of the strategy and the trading of security spreads.

Keywords: Algorithmic trading, commodity spreads, crude oil benchmarks, AOM, RAP, PSI, portfolio management

1. Introduction

This study investigates the superior performance of trading security spreads, primarily inter-commodity spreads, using a commercially-developed trading algorithm (RGZ Ltd.). The chief characteristic of security spreads, for example that of the crude oil benchmarks WTI and Brent, is that they are more stable and more predictable than the individual commodities themselves. This leads to a superior risk-return characteristic upon which the algorithm can capitalise. The algorithms themselves are multi parameter models which are coupled with a trading rule. The algorithms use back-tested daily futures data of settlement prices (over a number of years) to build a time series on which the model parameters are optimised. Typically, trades are very low frequency, lasting a number of days and in some cases weeks. The optimisation of the algorithms is subject to the metrics presented in this study and the diversification benefits of optimising long/short trading systems or portfolios using these metrics are explored.

Given recent turmoil in financial markets, commodities must now play a key role in standard investment portfolios consisting of stocks, bonds and cash deposits (Financial Times 2010). This is because of the fact that there are very low yields on fixed term deposits, stock market returns are currently very risky, and there is significant default risks associated with bonds, particularly those of the PIGS economies. The issues regarding the PIGS has become an increasing issue lately as elections in these countries are bringing in new political parties, as seen lately in Greece. These events have knock on effects to many economies due to various degrees of exposure with respect to currency, trade and other factors. The commercial importance of trading security spreads together with single commodities cannot be understated given the trading yields of the algorithm.

Crude oil, precious metals and other soft commodities such as cocoa and coffee, although fundamentally volatile if considered on their own, can be used in cointegrated pairs and as single securities hedging each other, where they are significantly more stable and predictable. Any price changes in the security due to structural, market or supply and demand factors do not significantly impact the spread of security pairs. An exception to this is the front-second month basis spread where the price structure of the market is considered, depending on whether it is in flat, backwardation or contango. They exhibit trends that can be exploited by virtue of trading algorithms based on such commodity prices and their spreads. The developed strategy can also be extended to other securities including foreign exchange, bonds and equity indices. In practice there are periods of upward and downward trends where the 'noise' component or volatility is low. The strategy is also applied to single securities which can be shown to hedge each other as will be seen later.

A successful algorithm should be able to generate consistent profits in the key regimes of trends and stationary oscillations. The current RGZ algorithm is able to do this with Sharpe Ratios in excess of 4.2 (annualised) and annualised returns in excess 140%. The algorithm is a seven non-linear parameter model back-tested on daily closing price data (Bloomberg/Thomson Reuters 2012) over 5 years throughout the financial crisis. This is contrary to Chatrath et al. (2002) who show commodity prices to be chaotic to a certain degree. Of course this paper only considers the prices of four agricultural commodities that tend to 'spike' more often, usually due to demand and supply shocks. Chatrath et al. (2002) use ARCH models to explain the non-linearity in data (see also Karanasos et al., 2015a) however given the stability of trading algorithms in terms of their returns, the extra volatility obtained in certain seasons exists but is not significant for a trading system which trades at a low frequency. This is because the optimisation of the algorithm takes into account any extra volatility obtained even if it is seasonal.

Vivian et al. (2011) mention that the volatility obtained by commodities in the recent financial crisis is not significant and that there are no real volatility breaks that result. This is however not true for other financial crises where the volatility breaks are more obvious. For this paper the recent financial crisis is more of interest as the optimisations are carried out over 5 years of data (see also Karanasos et al., 2015a for a comprehensive analysis of breaks in the volatility of commodities futures). The fact that Vivian et al.'s (2011) findings show no real evidence of volatility breaks despite the financial crisis is important. This is because the profits obtained from the trading algorithms also show no structural break in volatility even during the financial crisis. This may be supported by viewing the homoskedasticity of the profit profiles.

Current algorithmic trading systems utilise simple 'channel trade' systems available where user is required to view current prices continually ensuring the trade occurs at the correct instant. These types of model take advantage of volatility during certain times of the day where fluctuations may occur perpetually. It allows for consistent trades to be made and give multiple trades of similar value while also sometimes incorporating degrees of sentimental trading. Of course more advanced systems exist where models are used for trading of various securities that incorporate Bollinger bounds and other such established methods. Most models are top secret and therefore remain the intellectual property of the investment bank, hedge fund or other financial institution which developed or purchased it. More advanced models try to capture volatility and trends and usually have a detailed econometric study supporting them. The key is to develop a model that captures trends, spikes and can deal with the volatility between trends and spikes.

Cheung et al. (2010) agree that diversification benefits can be gained by investing in commodities and also that the diversification benefit of commodities is far more complex than is generally understood in finance. The view that commodities regimes change is also interesting as we see a huge amount of heteroskedasticity throughout our analysis. However diversifying into portfolios with commodities yielding a positive risk- return relationship compared to international equities is in line with what we believe. The RGZ (2010,2011) algorithms have proved however that being diversified correctly can lead to a superior portfolio performance even in times of bearish commodity environments. The reason being the existence of spreads and the fact that algorithms, despite correlations in prices, do not display these correlations in their profits since different algorithms are in different buy/sell positions, constantly hedging themselves with respect to historical back-testing.

Karali et al. (2009) support the view of diversification through the inclusion of different instruments in different sectors, especially within commodities so as to balance a portfolio given the increased volatility in recent years in commodities markets. Macroeconomic variables impact commodity prices but affect separate sectors in different ways. This suggests and supports the idea that diversification is crucial even if it is within a single market with sectors within it.

The study is comprised of four main sections which in turn have their own sub-sections:

Section1 details the Introduction

Section 2 details the AOM & RAP Metrics Development with the following sub-sections.

2.1 Spreads
2.2 Diversification and AOM (Algorithm Optimisation Metric)
2.3 RAP (Risk Adjusted Profits)
2.4 Data

Section 3 details the PSI (Parameter Sensitivity Index)

Section 4 details Significance for Portfolio Management AOM & RAP Metrics Development-Spreads with the following sub-sections.

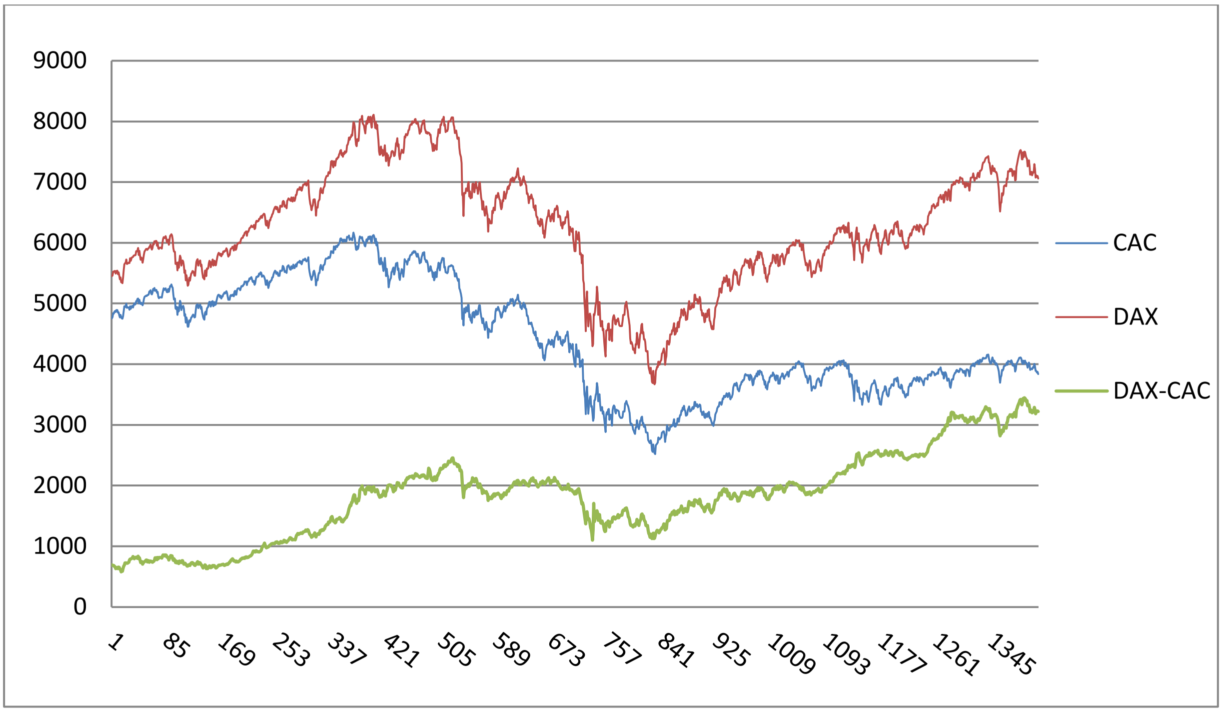
4.1 Portfolios
4.2 Alignment
4.3 Correlations
4.4 Acknowledgements
4.5 Conclusions

The conclusions are then followed by the References and Appendix.

2. AOM and RAP Metrics Development

2.1 Spreads

Trading of spreads allows for a more stable and less risky strategy because one does not expose themselves to intraday or daily volatility of a single particular security. For example when trading equity indices it may be wise to try and capture trends in spreads between similar economies such as the French and German rather than play a single equity index. This is because if there is a financial shock, such as in 2008, the spread of two indices will not be affected nearly as much as a single equity index. The graphs of figure 1 show how the spread is far more stable than the absolute price. This can be seen clearly by comparing the two vertical axes and their scales and is a phenomenon that exists across many cointegrated pairs.



DAX and CAC Daily Closing PX-Last (Bloomberg)

Figure 1

Trading two securities as a spread is particularly interesting (see Margaronis et al. 2011 and Karanasos et al. 2015b for a comprehensive cointegration analysis of commodity futures). For example, the prices of WTI and Brent crude oils seem to be highly cointegrated with WTI leading the price of Brent as proved in the cointegration analysis of the two major crude oil benchmarks.

The current paper will analyse the results of a newly engineered and revolutionary trading algorithm created and owned by RGZ. The algorithm itself will remain property of the company RGZ, however the results of the profit profiles and other outputs will be analysed here in order to obtain a new portfolio optimising metric and investigate algorithmic portfolio behaviour. The algorithm itself was designed to trade commodity spreads but after applying it to various securities it was clear it could be utilised and adapted in other markets and single (outright) securities.

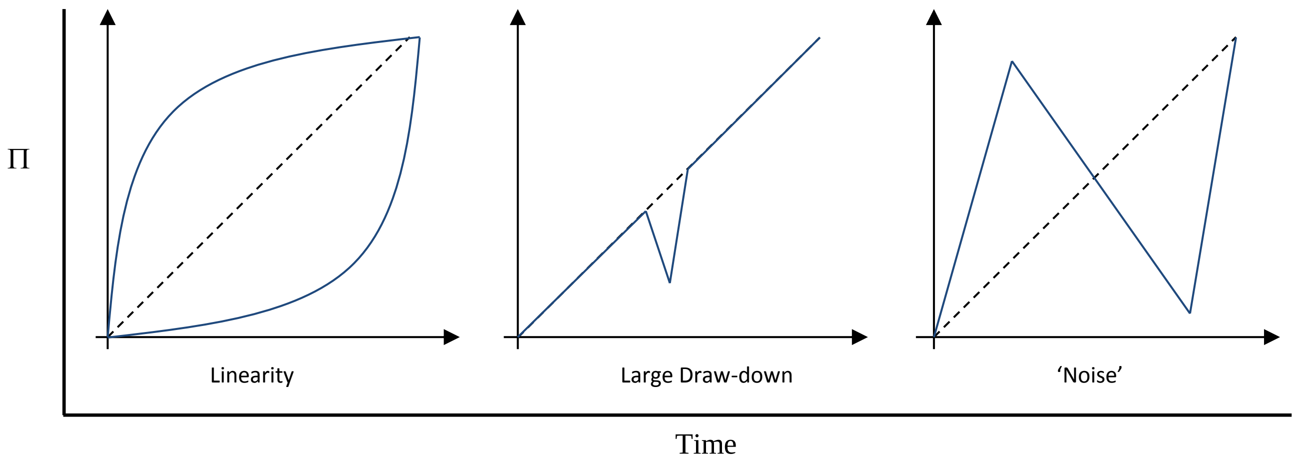
2.2 Diversification and Algorithm Optimisation Metric (AOM)

It is important to apply this to various securities as it allows for diversification within a portfolio which is imperative for day-to-day stability. The types of diversification are important; for example, not all trading systems should be identical across the constituent instruments. Further, different types of securities should be included such as grains, energy, equity indices, metals, foreign exchange, softs and bonds. This is important because the various sectors behave differently as may be observed by their pairwise correlations. The way in which the margin is apportioned is important because over-margining in energy, for instance will make the portfolio unbalanced and lead to unnecessary exposure to this sector. Finally, it is imperative that both spreads and single securities are used since both behave differently in different stages of the business cycle.

As a result, such diversification with a suitable trading system is able to make consistent profits, even in times of financial turmoil, a phenomenon which is frequent more recently.

Qiang et al. (2011) found that the impacts of the oil market spill over into other commodity markets. This may indeed be true in terms of price however it is clear that after applying a trading strategy to many instruments the way in which the algorithm trades and is optimised for different securities varies. It is important to remember the significance of diversification along with the idea of trading spreads which reduces the exposure to any single commodity. This is linked to the correlation analysis where the prices may be correlated but the returns of the algorithms are not, even if prices are correlated the algorithms are not necessarily in the same buy/sell position.

Looking at a profit profile of various trading histories it is clear that a metric can be developed to minimise aspects that would make a portfolio undesirable. It was found that such a metric was more powerful in this respect than the Sharpe ratio. The Algorithm Optimisation Metric (AOM) looks at three aspects of portfolio performance, and optimises performance by minimising noise in a back-tested PnL (profit) profile, rewarding linearity and penalising drops of PnL known as maximum drawdown. The maximum drawdown of a profile is measured as the greatest drop in PnL including successive negative trades as well as small increases resulting from positive trades. Proof that the AOM is a better way to measure stability will be investigated with a series of graphs depicting several extreme scenarios of profit profile and explaining why these might be undesirable. The three undesirable regimes are shown and these include profiles that draw down, have poor positive to negative or 'noise' ratios and are not linear. Also, why the AOM's three components minimise the undesirable aspects wealth managers and other stakeholders desire in a profit profile.



Representation of limiting cases for undesirable portfolio performance with regimes of poor linearity, large draw down and large noise

Figure 2

The profit plotted against time profiles in Figure 2 represent extreme departures from a desirable linear PnL profile (dashed) that stakeholders and wealth managers would find undesirable in a portfolio's performance. These represent limiting cases for which the AOM should be penalised. The idea is for the metric developed to minimise the three scenarios where essentially linearity is key assuming no reinvestment. It is imperative for the noise, as seen in the last graph, to be minimised, and finally for sudden drops such as in the second graph to be penalised.

The AOM is defined thus:

$$AOM = NR \cdot DC \cdot R^2$$

Where:

$$R^2 \; is\ the\ coefficient\ of\ determination$$

$$NR \; is\ the\ noise\ ratio\ defined\ as:$$

$$NR = \frac{\sum \Delta^+ \pi}{\sum \Delta^+ \pi + |\sum \Delta^- \pi|}$$

With

$$\pi \; the\ P\ \&\ L\ (profit\ \&\ loss),$$

$$\Delta^+ \; the\ positive\ daily\ change,$$

$$\Delta^- \; the\ negative\ daily\ change,$$

And

$$DC \; is\ the\ drawdown\ coefficient\ defined\ as:$$

$$DC = 1 - \frac{MD}{MD + \frac{252\pi_{max}}{N}}$$

With:

$$MD \; is\ maximum\ drawdown$$

$$N \; is\ the\ number\ of\ trading\ days\ in\ sample$$

2.3 *Risk-Adjusted Profits*

Risk-Adjusted Profits (RAP) is a term used for the product of the profit of an algorithm for its entire back-tested history and the AOM associated with it. This is because in reality, a trading system is utilised to generate profits. Maximising stability through the AOM can therefore be combined with the PnL generated to form the RAP of an algorithm. The RAP is a standardised way to distinguish between optimal and non-optimal parameters as is the AOM, while also weighting performance on profit too. It is an efficient measure of allowing balancing between securities or security pairs when considering degrees of diversification.

The optimisation and trading algorithms were developed using Fortran 95 programming language where each individual security or pair has its own designated program. The outputs of the optimisation programs include a list of algorithm parameters and all combinations thereof as well as the AOM and RAP associated with each set of parameter combinations. The combination of parameters that give the highest RAP is chosen as the optimal parameters for that particular algorithm. A brute strength approach is used in optimising the algorithm parameters as every possible combination of parameters is tried and tested against the data.

2.4 Data

The data used throughout is daily PX_LAST futures prices obtained from Bloomberg. Specifically, this study considers the front month contract of these various futures and this is typically because the front month tends to have the highest volumes and hence liquidity, making it the prime candidate contract for trading by speculators. PX_LAST is the price at the close of business while the prices themselves were procured over approximately a 5 year period from 2007 onwards during the financial crisis and the beginning of economic recovery. The number of prices (or days as daily prices are considered) varies from instrument to instrument due to different markets following different holiday conventions. The raw data was mapped using a mapping procedure developed by RGZ Ltd. (RGZ Research 2011) while the mapping procedure itself is detailed in Margaronis et al.

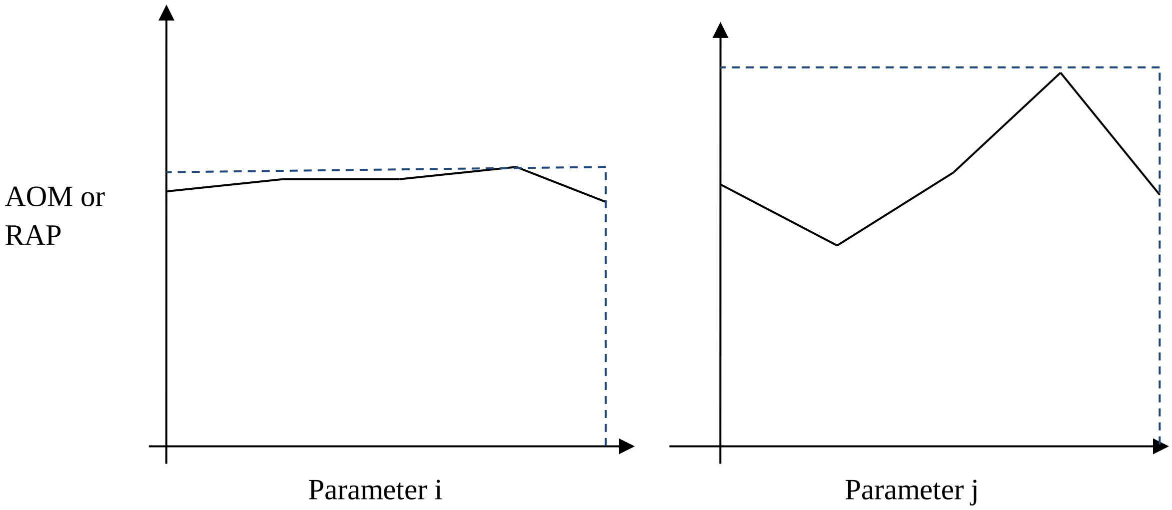
The data considered in this study includes ten raw data sets. From these ten sets, two spreads are considered and the rest are taken as outright positions resulting in a total of eight separately tradable futures.

Three equities indexes are considered which include the Nasdaq, Dax and Cac, which the Dax and Cac are considered as a spread i.e. Dax-Cac. The metals are represented by Copper. The agriculturals considered are Cocoa and Oats while the energies, which are typically the most prominent sector in commodities, are Natural Gas, WTI Crude and Brent Crude. In this study, the crude oils are considered in a spread which is commonly known as the WTI-Brent spread. The construction of spreads within the energies sector allows for hedging and hence lower exposure to the famously highly volatile crude oil markets. Finally, EURUSD is considered representing the foreign exchange futures sector. It is clear that there is a good degree of diversification with respect to the markets and sectors and the analysis which follows will show how portfolio construction in algorithmic trading may benefit by utilising spreads, diversifying markets and of course utilising bespoke and revolutionary metrics.

3. PSI Metric Development

A Parameter Sensitivity Index (PSI) is developed which allows for the stability of the constituent parts of the trading system to be measured by applying it to each security or security pair. The way in which the PSI program works is by varying a single parameter (100% plus or minus its optimised value) while keeping all the others constant and carrying this out for all parameters. The PSI is then evaluated as the ratio of actual versus maximal (optimised) profits. This allows for the user to see how changing a single parameter changes the level of RAP, AOM and profit generated. A matrix is then generated whereby the sensitivities are plotted for the two primary parameters and a surface plot can then be used to visualise the stability of each security. This can be utilised to judge whether an algorithm is too parameter-sensitive (unstable) or not. Also it helps to show if there are multiple regions of higher levels of RAP and AOM. More importantly it can allow for a region of lower AOM and RAP to be selected because of its superior stability. Examples of PSI outputs are shown in Figure 4.

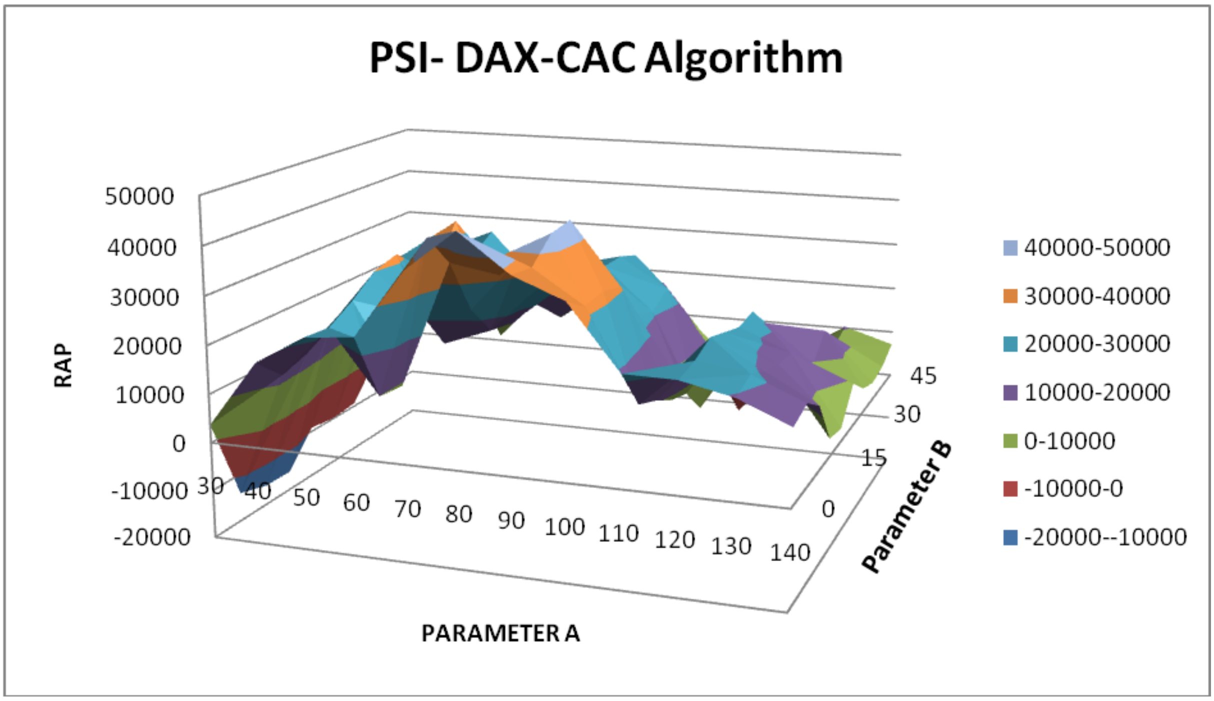
The actual PSI is evaluated by looping through a series of values of single parameters (100% plus or minus its value) by keeping all other parameters constant and then repeating this process for all parameters. In order to be able to create a surface that may be visualised and because it was found that two of the parameters were the most sensitive (primary parameters), the graphs for AOM or RAP are plotted for the primary parameters. The way in which a value of PSI is then generated is by considering the area under the graph of the parameter in question and comparing it to the maximum possible area. This is once again seen more clearly on the graph in Figure 3.



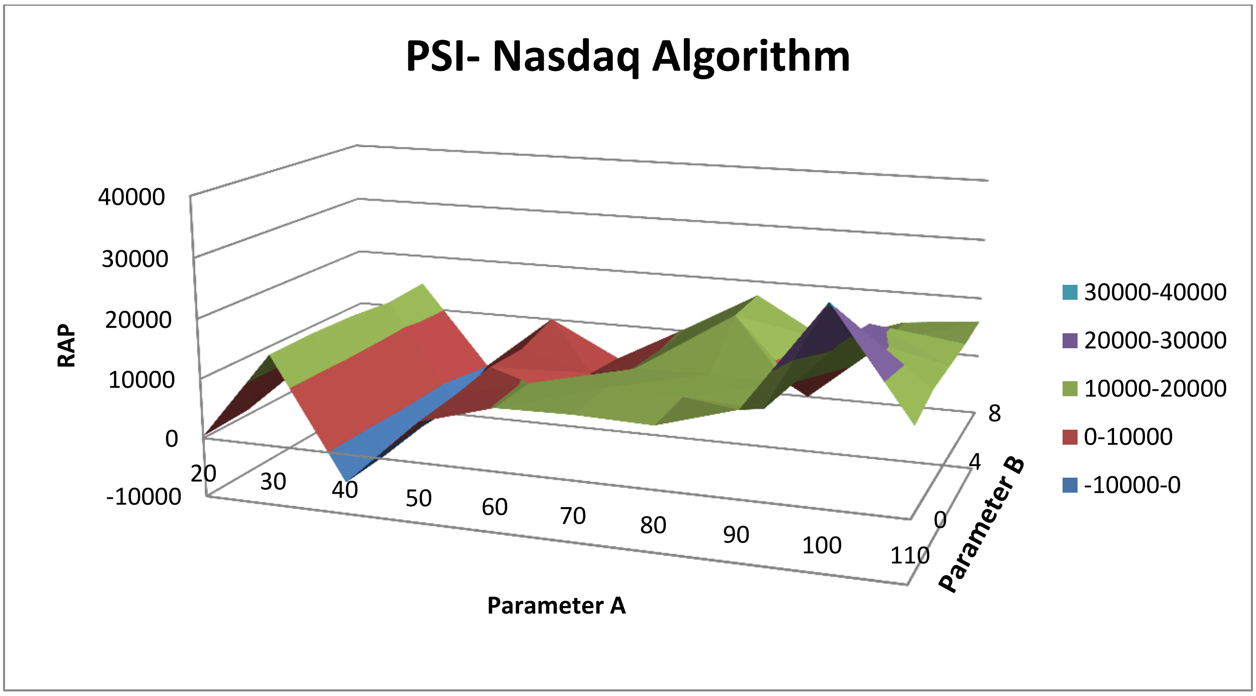
RAP/AOM variations with (a) insensitive parameter and (b) sensitive parameter

Figure 3

The two profiles of Figure 3 depict what the output from a PSI file may look like with the (a) depicting an insensitive parameter since the AOM and RAP values do not vary a great deal with parameter value. On the other hand, (b) shows a relatively sensitive parameter where the values of AOM and RAP seem to change dramatically as parameter value is changed. The dashed lines represent the maximum possible values of AOM or RAP obtainable by the parameter value. The ratio of positive areas under the actual and maximal profiles provides a reasonable measure by which to measure parameter sensitivity. Actual outputs of PSI are shown below where surfaces are presented as they are a plot of two parameter sensitivities. A total PSI can then be calculated by calculating the product of all security sensitivities across all parameters.



(a)



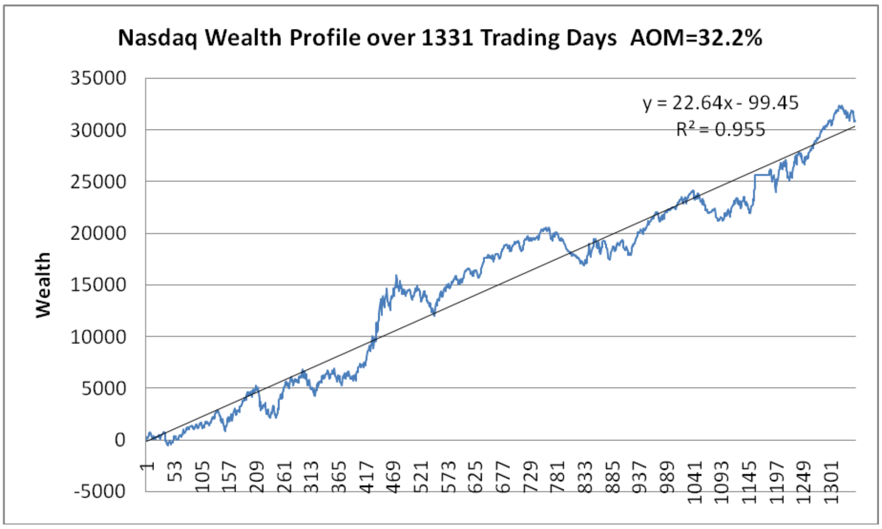
(b)

PSI plot for sensitive and insensitive instruments

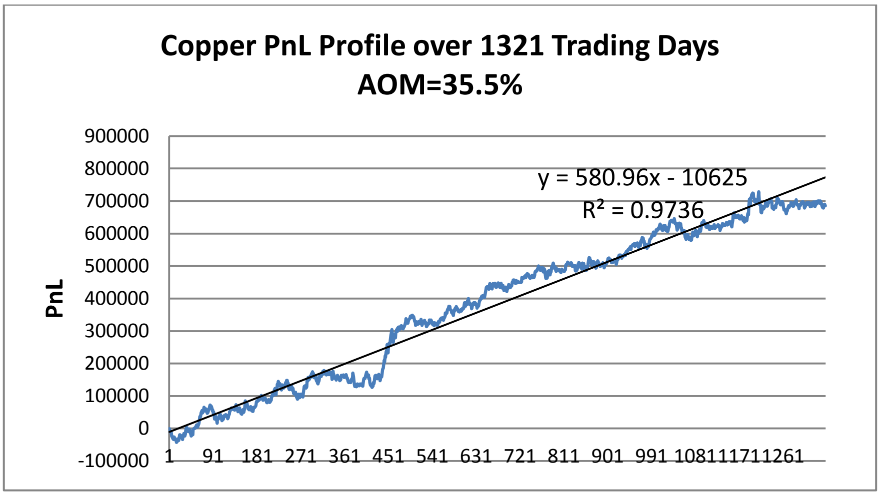
Figure 4

From the two surfaces of Figure 4, it is clear that the Nasdaq algorithm is far more sensitive with respect to parameter A than the DaxCac algorithm. The PSI values for Nasdaq and DaxCac are 14.2% and 27.1% respectively. As a result, the DaxCac algorithm is far more stable because changing these parameters does not translate into a significant drop in the RAP meaning the algorithm will still perform near its peak performance. This is not the case for the Nasdaq algorithm where small changes in parameter A result in significant decreases in RAP which suggests the algorithm may not perform well and may actually, in fact, make losses with small deviations in behaviour.

It is clear that this entire analysis is useful in real-life trading situations and does not aim to simply optimise a theoretical tool by maximising a single outcome. Some profit profiles for various algorithms are presented in Figure 5. The profiles shown in Figure 5 are outputs from the algorithms developed and owned by RGZ (2010, 2011). Those for other instruments are presented in the Appendix. The post analysis is what we are interested in - for managing a portfolio and maximising its performance.



(a)



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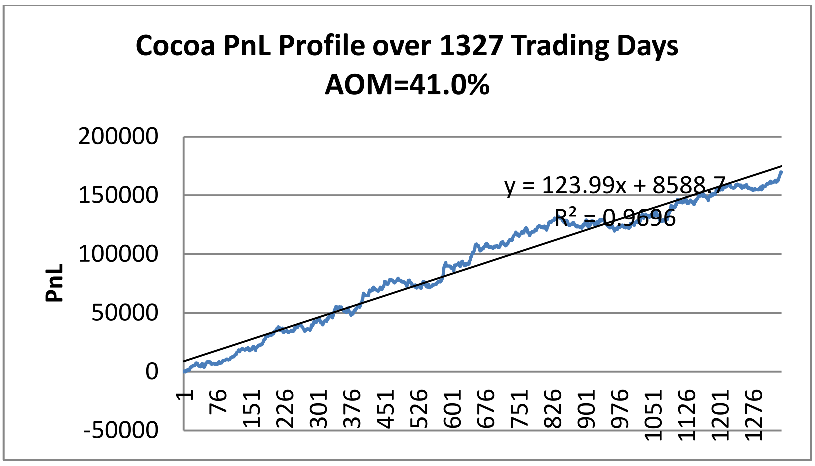

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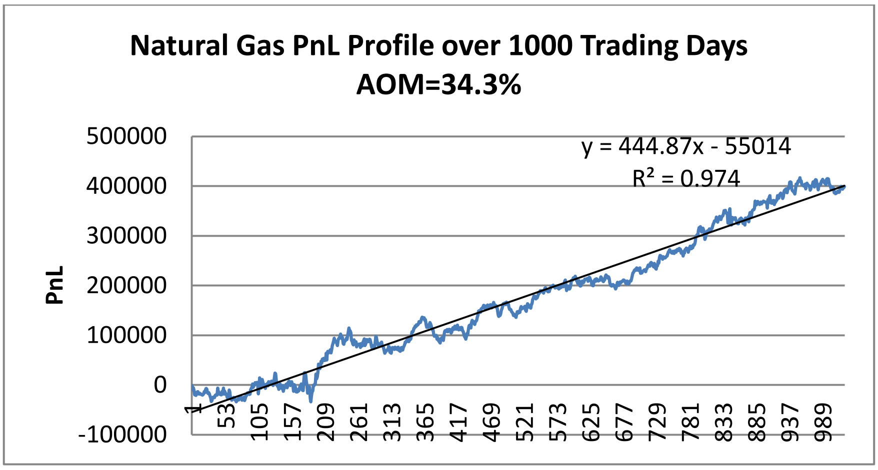

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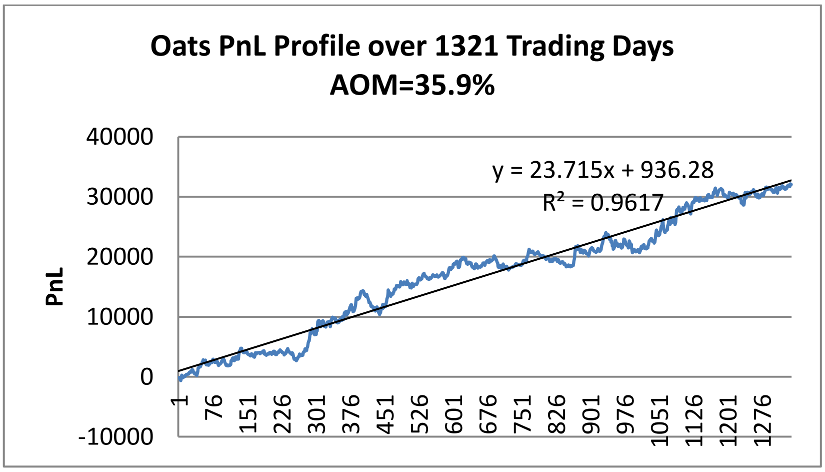


(e)

Profit profiles from algorithm outputs for various instruments

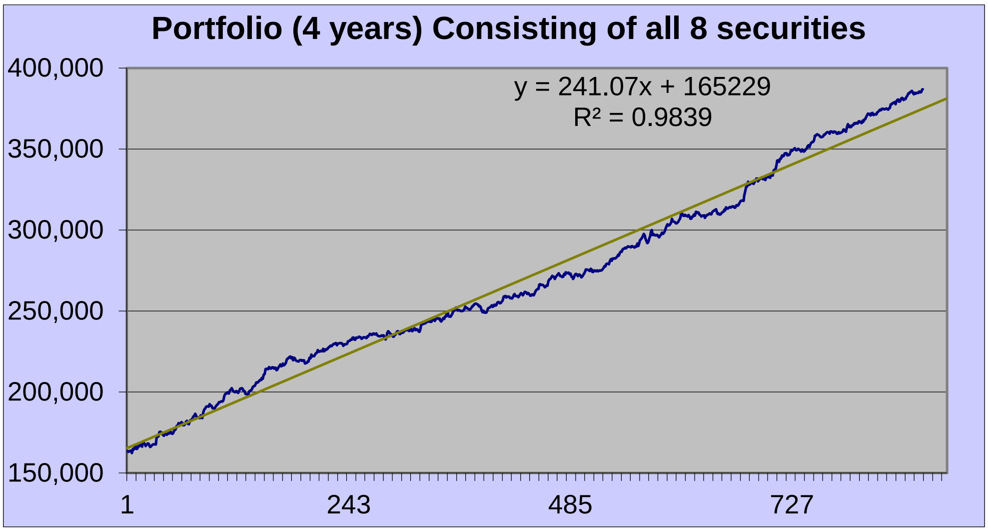
Figure 5

4. Significance in Portfolio Management

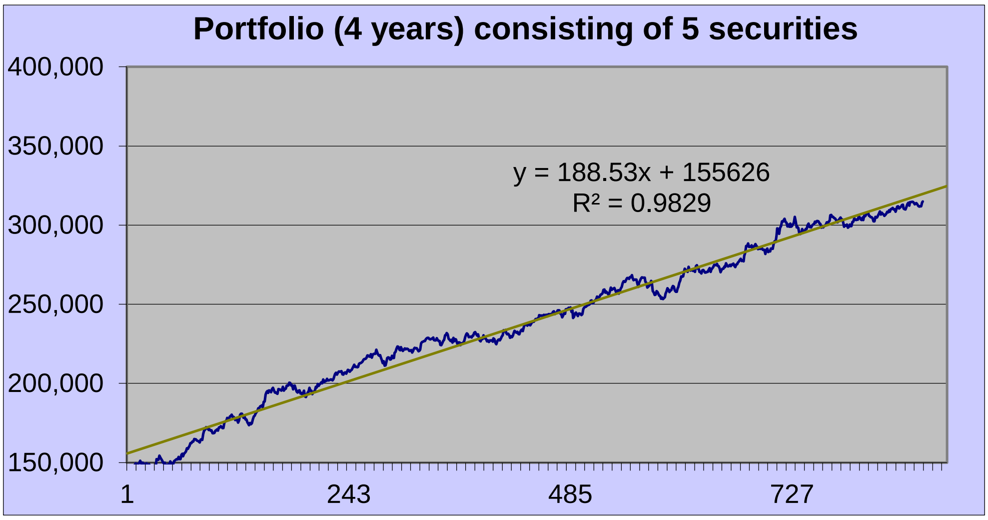
4.1 Portfolios

These individual instrument profiles will now be added given certain weightings in order to obtain a diversified portfolio where the noise component and drawdown are minimised and linearity is maximised given a specific margin investable; that is to say that the overall AOM and RAP of the portfolio is maximised.

The final profit profiles shown in Figure 6 are for portfolios. Figure 6(a) represents a portfolio containing all the securities considered in this study. Figure 6(b) shows the portfolio accumulated when only certain securities, as described in the main section of this paper, are included. The reason for showing both is to show the effects of diversification and how important it is in minimising volatility in a portfolio. Both profiles have been chosen based on RAP and a margin of $100,000 assuming a nominal level of leveraging of 10:1.



(a)



(b)

Portfolios (a) consisting of all 8 securities and (b) consisting of 5 securities, representing the impact on performance of successful diversification

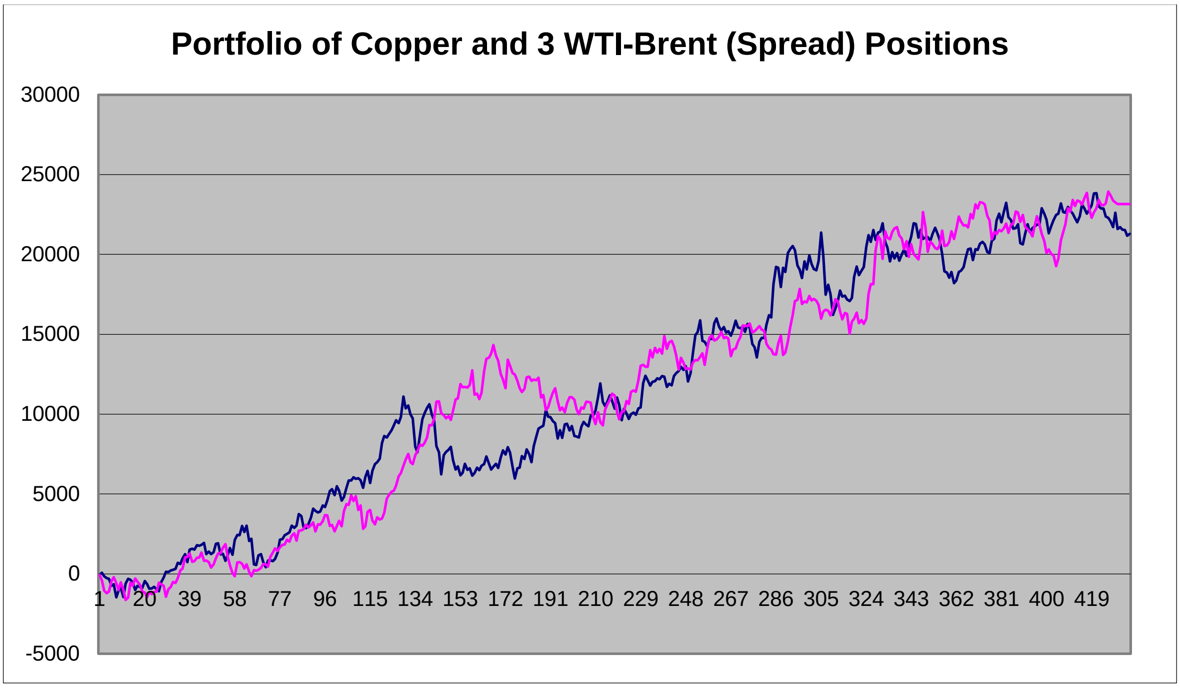
Figure 6

From the two profiles shown in Figure 6, the latter (b) has a larger component of noise in the PnL profile. The volatility of the second portfolio, whose margin is the same, is far greater. Hence, it is concluded that diversification is imperative, even in algorithmic trading, and thus a requirement for stability and consistency of returns in such a portfolio.

4.2 Alignment

In order for an accurate portfolio AOM and RAP to be generated, the output profit data had to be aligned by date. The true performance of a portfolio can only be generated if the dates are known for each particular level of PnL for each security or pair. This is an imperative but tedious process as it involves aligning the daily outputs of a range of securities which have different trading days as they are traded on different exchanges. This was again automated in order to account for non-trading days of certain securities. It allowed correct correlation matrices for the securities to be generated (discussed below) and therefore allowed correct diversification to be obtained. The weightings were obtained by a program which used this aligned data to find the optimal portfolio. The date was used as a reference point. By using a nominal portfolio value and individual security margins based on 10:1 leveraging level, the program generated possible combinations of weightings for each security. This program then selects the optimal combination of weightings based on maximisation of RAP for the entire set representing the real-time daily behaviour of the portfolio. The program is able to apportion initial margin to each security or pair and give a superior outcome of performance regarding RAP. The margins themselves are determined by and procured from (through Bloomberg and Thomson Reuters) the main exchanges used to trade commodities futures (CME and ICE). Computational time was minimised by only creating combinations for portfolio margins within a certain range since the optimisation approach was brute strength. The AOMs generated from this program are substantially superior to any of the individual securities or pairs. In this way, by combining the real-time date, margin and optimised profits of each algorithm, a real historical performance of a portfolio can be seen and then traded with confidence due to its accuracy.

In selecting the correct combination of securities to trade, it is imperative that the program has the true behaviour of algorithms with respect to time in order to minimise noise component of the portfolio. This can therefore result in a true maximised RAP portfolio. A profile of aligned profit profiles and non-aligned profit profiles will be compared to show how significant this error can be. This is also very important because the program needs to have accurate daily behaviours for all traded instruments in order to make a correct selection for a noise-minimising portfolio. An example of how the misalignment can mislead someone when taking positions is shown in Figure 7. Presented here is a simple portfolio profit profile containing only copper and three positions of the crude oil spread (WTI-Brent) shown for 400 days. There are two profiles shown where one is the actual aligned profits with respect to dates and the other is not. It is important to remember that the misalignment in the second profile is up to about 10 days, which is realistic given the time span. Real portfolio drops are underestimated and gains can be overestimated. Also the noise component is ‘ironed out’ or smoothed. It is therefore clear that by inputting the incorrect graph into an optimisation program which maximises RAP, that the noise, drawdown and linearity of a misaligned data set will be erroneous and ultimately incorrect, hence resulting in incorrect weightings and exposure to risk due to this.



Portfolio performance over 400 days showing alignment error between aligned (blue) and unaligned (pink) profits

Figure 7

To prove that the maximum RAP is indeed the most effective method for optimising a portfolio, it must be compared to other more conventional methods such as the return-risk ratio (RR), minimum variance and even perhaps comparing the maximum AOM to maximum RAP combinations to see possible differences in portfolio performance with respect to consistent and stable profits.

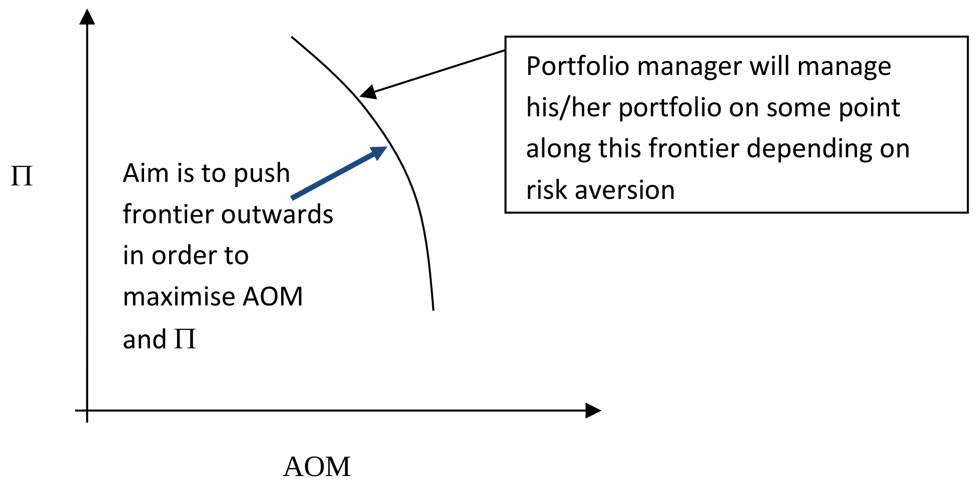
In order to show this, a number of important characteristics need to be considered. This is because the differences will not be clear from a profit profile. A table was created showing the measures of optimising portfolio performance and the characteristics of those portfolios. The characteristics used will include the negative ratio (NR) which is a measure of downward movements in profit of the profile, the coefficient of determination (R^2), the maximum loss which is simply the value (in USD) of the greatest drop in profit over the trading history and the return on margin (ROM) which is the returns generated in relation to the amount of capital margined out initially in the portfolio. The RR is calculated by the ratio of the mean to standard deviation of the daily returns. The equally-weighted portfolio is simply a combination of weightings whose margin is equal. We assume all these portfolios have a nominal margin of $50,000 and trade for a four year period.

	Max RAP	Max RR	Min Variance	Max AOM	Equally-Weighted
AOM (%)	58.9	59.6	58.2	59.4	52.7
NR (%)	65.3	67.0	66.6	66.4	61.8
R^2 (%)	98.0	97.1	96.8	97.7	98.2
Max Loss ($)	34,662	27,401	28,750	29,474	38,144
ROM (%)	1054	755	700	769	621
RAP	824,533	620,588	535,290	654,915	457,489
Profit ($)	1,399,887	1,041,255	919,742	1,102,551	868,101

Portfolio characteristics for various optimisation metrics

Table 1

From the Table 1, it may be observed that the portfolios' performance across the metrics is fairly similar, however the maximum RAP combination is superior in the amount of profit generated and its ROM. Across the table, all other characteristics seem similar and therefore it must be concluded that the maximum RAP combination is most desirable especially due to its significantly larger return.



Profit against AOM plot showing existence of frontier of trading and where portfolio operates

Figure 8

Another tool to show portfolio diversification is the correlation matrix of daily price changes for all the component securities as well as a correlation of all the daily profit changes. This allows a direct comparison to be made between these two correlation matrices.

The reason price returns were not used is due to the CFD (contracts for difference) nature of trading where profits are a function of price differences. Comparing these two correlations will allow any portfolio manager to understand the degree of diversification and which securities are correlated. In addition it can show the effectiveness of using long-short strategies to diversify portfolios. For example, a portfolio can be highly exposed to equity indices because they are indeed correlated. The European economies, for example, find themselves in turmoil at this present time and that is affecting the US and Asian markets because many banks and companies share funding and of course collaborate through trade meaning they are exposed to each other in one way or another. As may be seen in Table 2, the correlations of the profits generated show how using the selected combination of securities as defined by the maximum RAP from the program, reduces the correlations even more. Despite prices being highly correlated, the algorithm output for the two instruments will not be as instruments' positions will not necessarily be in the same long/short position during the history. Hence, this approach may be viewed as a black box which decouples the structural correlation that exists between the securities by using back testing and taking long or short positions accordingly to maximize the diversification effects, and hence the portfolio performance. It should be noted that the Dax-Cac spread is considered in the post correlation as the program runs the spread. The pre correlation however considers the two indexes separately in order to give a better understanding of how the two are related to each other. On the other hand, the WTI-Brent spread is a price which is procured as is. This means the price of the spread was constructed by the exchange. The emboldened correlations represent levels above 15%, the threshold chosen to differentiate significant and insignificant correlations in this study.

4.3 Correlations

Correlations for Absolute Price Change

Pre									
	Copper	**Oats**	**Cocoa**	**Dax**	**Cac**	**Nasdaq**	**EurUsd**	**Natural Gas**	**WTI-Brent**
Copper	100.00%								
Oats	**29.10%**	100.00%							
Cocoa	**29.40%**	14.30%	100.00%						
Dax	**52.10%**	**21.60%**	**23.30%**	100.00%					
Cac	**53.60%**	**25.50%**	**24.30%**	**92.80%**	100.00%				
Nasdaq	**32.50%**	16.60%	15.80%	**59.50%**	**56.50%**	100.00%			
EurUsd	**34.50%**	**22.90%**	**28.10%**	**33.60%**	**33.50%**	**31.40%**	100.00%		
Natural Gas	14.40%	15.90%	10.90%	11.90%	11.40%	9.80%	13.90%	100.00%	
WTI-Brent	**50.50%**	**28.00%**	**26.20%**	**39.90%**	**41.10%**	**33.50%**	**32.30%**	**23.30%**	100.00%

Correlations are chosen to be significant at the 15% level and these are emboldened

(a)

From the correlations carried out on the absolute price changes it is clear there is a significant amount of correlation between many of the securities, for example, EURUSD seems to be quite correlated to all the securities considered. Reasons for this relationship with respect to the agriculturals may arise from the significance of import and export markets of these commodities and their consumption by the European Union. EURUSD is also expected to have a certain degree of correlation with its primary economic indexes and this will in turn spill over to some degree to the agricultural commodities. Copper prices tend to be an economic indicator since copper is a primary base metal used in most electronic equipment and wiring. Its relationships with the oil spread and the indexes may therefore be justified. The indices themselves are expected to have a certain degree of correlation between them, given the structure of financial systems worldwide where countries share debt and trade and this is especially visible by the very significant correlations between Dax, Cac and Nasdaq.

Correlations for Algorithm Profit Change

Post								
	Copper	**WTI-Brent**	**Natural Gas**	**Dax-Cac**	**Nasdaq**	**Oats**	**Cocoa**	**EurUsd**
Copper	100.00%							
WTI-Brent	-1.00%	100.00%						
Natural Gas	-0.10%	-10.10%	100.00%					
Dax-Cac	-5.80%	0.30%	-1.20%	100.00%				
Nasdaq	6.50%	-0.90%	-1.80%	6.30%	100.00%			
Oats	-3.70%	0.50%	-2.20%	-0.40%	-14.80%	100.00%		
Cocoa	**27.80%**	2.50%	-3.60%	**-26.70%**	**21.10%**	-2.10%	100.00%	
EurUsd	**20.50%**	0.40%	-0.20%	-9.40%	12.40%	-4.60%	13.30%	100.00%

Correlations are chosen to be significant at the 15% level and these are emboldened

(b)

Correlation Matrices for (a) Absolute Price Changes and (b) Algorithm Profit Changes

Table 2

From the final correlation shown above it is clear that the correlations of the price returns that exist become insignificant once they have been processed by the trading system (see Table 2(b)). The correlations seem to be insignificant across the table with a few exceptions as there are far fewer pairs with correlation magnitudes greater than 15%. This demonstrates an important effect of correlation dilution that exists by virtue of the trading strategy. The fact that trading allows one to take long/short positions means that profits can be made on both increases and decreases in price of a security. Even though the prices for various securities are linked (correlated), the algorithm is not necessarily in the same position across these securities, and historical back-testing is utilised to offset and hence smooth portfolio profit profiles taking into account historical scenarios of behaviour. Therefore it can be concluded that the diversification impact in such a portfolio in algorithmic trading has substantial impact on the portfolio performance.

4.4 Acknowledgements: The authors would like to thank RGZ Ltd. for the use of their Nixon-class Algorithm outputs.

4.5 Conclusions

In conclusion it may be said that this study shows a portfolio containing both spreads and single securities reduces exposure to certain markets by reducing ‘noise’ and smoothing portfolio performance, while the PSI can be instrumental in establishing how stable an algorithm will be in generating consistent profits. Other findings show that a truly diversified portfolio over many different asset classes yields superior performance and this can include both securities and security pairs, which in turn can diversify risk by hedging against holding outright positions in securities.

Also significant was the alignment of data with respect to date, which was shown to be vital in establishing true portfolio weightings and meaningful correlation matrices. This study also allows us to conclude that correlations of daily price returns are significantly different to those of the output profit changes due to the effect of correlation dilution by virtue of the trading strategy or algorithm. This is because there are differences in the long/short positions across component instruments over the time history. Finally it may be concluded that optimising a portfolio according to the maximum RAP and AOM criterion leads to superior performance, particularly when compared to that of other criteria such as a maximum RR and minimum variance. Utilising the RAP and AOM in this instance (as well as other algorithmic systems governing portfolios or more simple portfolios comprised of a basket of stocks) can result in more profit generated and yield a far more desirable PnL profile.

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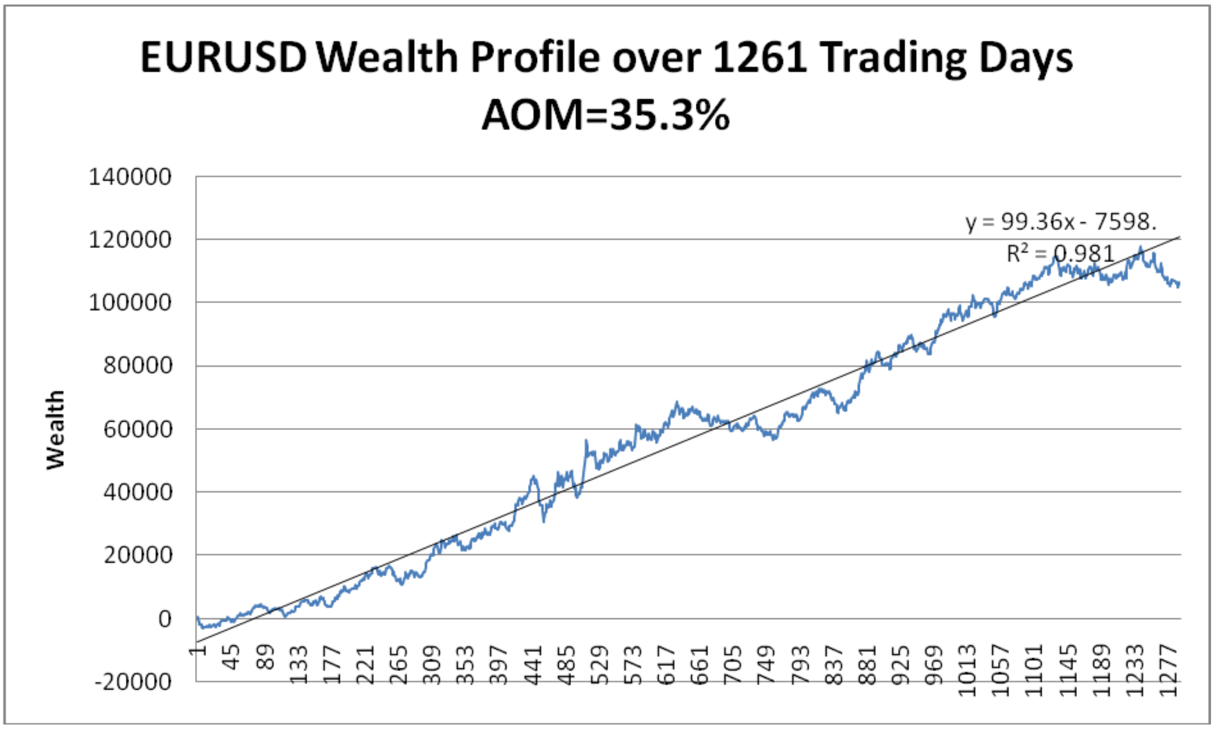
Appendix


EURUSD Wealth Profile over 1261 Trading Days
AOM=35.3%
y = 99.36x - 7598.
R² = 0.981
Wealth
140000
120000
100000
80000
60000
40000
20000
0
-20000
1
45
89
133
177
221
265
309
353
397
441
485
529
573
617
661
705
749
793
837
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1145
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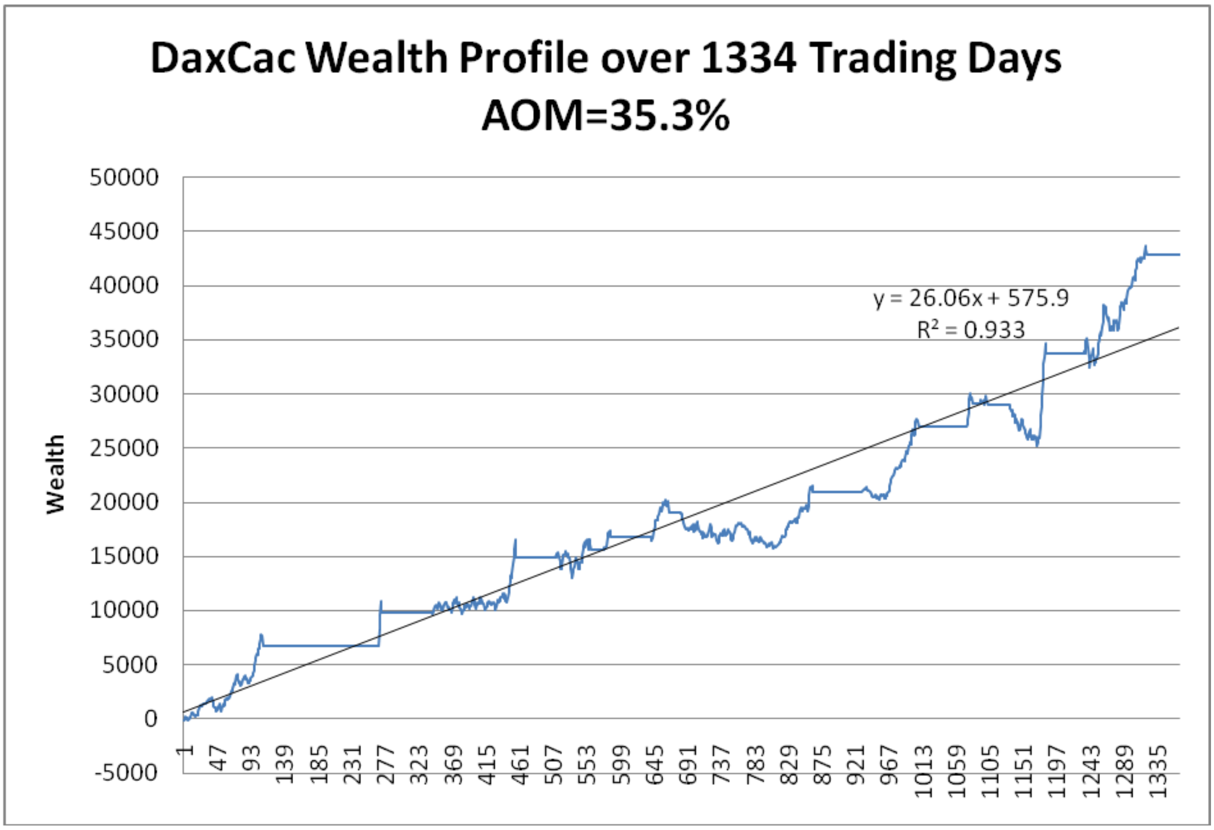
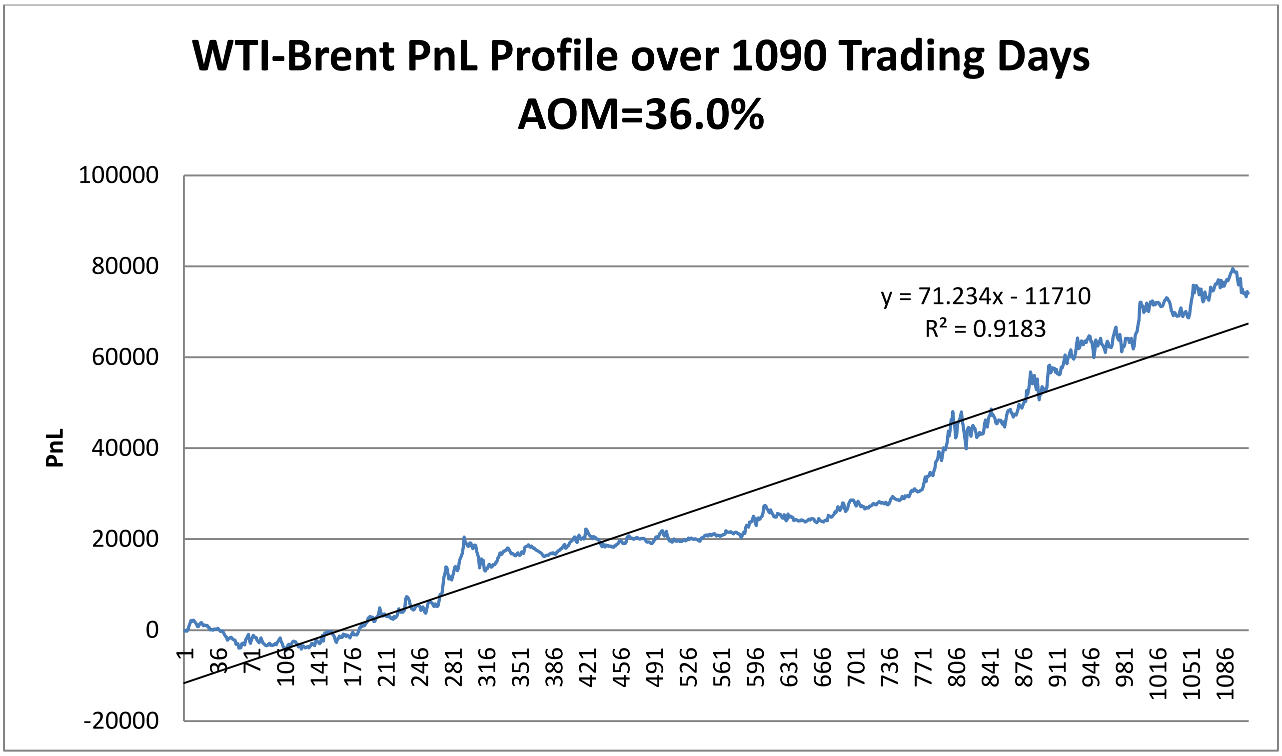
1233
1277


DaxCac Wealth Profile over 1334 Trading Days
AOM=35.3%
y = 26.06x + 575.9
R² = 0.933
Wealth
50000
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
-5000
1
47
93
139
185
231
277
323
369
415
461
507
553
599
645
691
737
783
829
875
921
967
1013
1059
1105
1151
1197
1243
1289
1335



WTI-Brent PnL Profile over 1090 Trading Days
AOM=36.0%
PnL
100000
80000
60000
40000
20000
0
-20000
y = 71.234x - 11710
R² = 0.9183
1
36
71
106
141
176
211
246
281
316
351
386
421
456
491
526
561
596
631
666
701
736
771
806
841
876
911
946
981
1016
1051
1086