

Intermarket Divergence - A robust method for generating robust signals for a wide range of markets

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Abstract—Intermarket analysis studies interrelationships between various related markets. Standard correlations between markets are not useful if our goal is to either predict future prices or generate profitable signals because current correlation does not tell us anything about future prices. A methodology we originally developed in the mid 1990's called intermarket divergence allows us to gauge the predictive power of an intermarket relationship and produce 100% objective signals. During the past 17 years we have used this methodology to develop trading systems which have produced robust and reliable trading signals even 17 years after the models were originally developed without any re-optimization. Other methodologies of processing intermarket relationships to develop trading signals might perform as well during in sample periods, but do not perform as well during walk forward period and during real trading.

In this paper we will explain intermarket divergence and show how this methodology can be applied to a wide range of markets and how it performs better out of sample than other methodologies. Next we will analyze this methodology closer and try to understand why it works so well and how this basic methodology can be improved.

The Intermarket divergence concept is also easy to enhance with various machine learning methods such as neural networks, SVM or rough sets. We will lay out a framework for this analysis.

I. INTRODUCTION

MANY markets are interrelated. These interrelationships can offer predictive capabilities for many markets.

The study of these interrelationships is called intermarket analysis. Intermarket relationships have been used by technicians for almost 40 years, ever since the findings of a relationship between strong dollar policy and agricultural commodities were published in a 1974 paper [1]. One classic resource which explains the interaction between most of the major futures markets is John J. Murphy's book [2]. He teaches many classic intermarket interrelationships using the crash of 1987 as a case study. He also shows how the crash of 1987 could have been foreseen by the events months before in various markets; for example bonds topped in early 1987 and then stocks topped about six months later [3], this outlined the case that many markets lead other markets. This relationship exists on different timeframes for different intermarket relationships.

The work of Murphy [4] and other early intermarket analysis pioneers was chart based without any proof that it

could be used to generate mechanical signals. There was no doubt whether these relationships would lead at major turning points but whether they could be used to generate consistently profitable signals across a given market. If intermarket analysis was required to be ready to take the next step and to generate mechanical signals, we needed to take a different look at this technology since charting and generating 100% object signals required a different type of analysis than just simple visual analysis on charts.

In 1988, I co-founded a software company and was solo inventor of a methodology to embed neural networks into a spreadsheet. I got involved in the financial markets as many of our customers wanted to use our product to predict the stock market [5].

During the early 1990's it was very popular to use neural networks to predict the S&P500. Many of these models used intermarket relationships. My original interest in intermarket analysis came from this perspective. Since there were intermarket relationships which led other markets, for example, the 30 year Treasury bond leads the stock market and CRB index leads bonds, you could build a neural network model to predict the S&P500 [6]. What is important is not the level of interest rates but the direction of them. In my early work, I tried to preprocess these intermarket relationships so that the neural network could detect these patterns.

Many of these early neural network based models had mixed results and also relatively short shelf lives. These early models used signal processing methods for preprocessing which often produces good results during the training period yet degraded out of sample. This leads to a question, "Could applying simple rules produce robust trading signals using intermarket relationships?" This question helps us in two ways, (a) Firstly, we can use these rules directly in trading and (b) Secondly, if we have robust trading rules, we can use these as a form of preprocessing which would lead to more robust neural network models.

A widely known intermarket relationship is the one between the S&P 500 and the 30 year Treasury bond. Bond prices generally are positively correlated with the S&P 500 (while yields are negatively correlated), although this is not always true, bonds should generally lead stocks at turning points. Another important fact is that one of the best trades you can make in the S&P 500 is when 30 year Treasury bond diverge from the S&P 500; for example when (a) bonds are rising and the S&P 500 is falling, buy the S&P 500 and (b) bonds are falling and the S&P 500 is rising, sell S&P 500.

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The direction of bonds prices relative to the S&P 500 is important not the actual interest rate. For this reason, we want to use rates of change of both the 30 year Treasury bond and S&P 500 for our neural network [6]. Although this relationship has broken down over the past few years, its long term existence is of historical importance to the science of intermarket analysis.

II. SIMPLE BUT POWERFUL METHOD OF MARKET PREDICTIONS

We will use classic mechanical methods for trading intermarket relationships, applying them to 30 year Treasury bond using a concept called "*intermarket divergence*," (first coined in 1998) which is when a traded market moves in an opposite direction to what is expected [7]. For example, if we trade the S&P 500, 30 year Treasury bond rising and the S&P 500 falling would be divergence since these are positively correlated. If we were trading the 30 year Treasury bond, both bonds and gold rising would classify as divergence since they are negatively correlated.

We will define an uptrend as when prices are above a moving average and a downtrend as when they are below the moving average. Now we can predict with some reliability the future direction of bonds, stocks, gold, crude and even currencies using this simple intermarket divergence model. Pseudo code for this basic model is as follows:

Price relative to a simple moving average

Let $InterInd = Close\ of\ Intermarket - Average\ (Close\ of\ Intermarket, N)$

Let $MarkInd = Close\ Traded\ Market - Average\ (Close\ of\ Traded\ Market, M)$

Positive correlation

If $InterInd > 0$ and $MarkInd < 0$ then buy at next bars open

If $InterInd < 0$ and $MarkInd > 0$ then sell at next bars open

Negative correlation

If $InterInd < 0$ and $MarkInd < 0$ then at buy at next bars open

If $InterInd > 0$ and $MarkInd > 0$ then sell at next bars open

This simple concept represented above has proven to be a robust methodology for predicting future price action using intermarket analysis. In 1998, I published a simple intermarket based system for trading 30 year Treasury bond futures. This model used '*The NYSE Utility Average (NNA)*', which was a basket of Utility stocks. The NNA was discontinued in 2004. Another utility index which also worked fairly well was the Philadelphia Electrical Utility index which was used as a replacement for NNA in our research. Back in 1998, when I did the original research and article, both indexes worked similarly, but NNA had a longer price history than UTY did.

The original analysis using NNA was done as follows. We used a positive correlated intermarket divergence model and a moving average of eight days for 30 year Treasury bond and 18 days for NNA. We tested over the period Jan 1, 1988 to Dec 31, 1997 [8]. We did not deduct anything for slippage

and commission.

My original published results were as follows:

Net profit: \$111,293.00

Trades: 126

Win %: 60%

Average trade: \$883.38

Drawdown: \$-8,582.00

Profit factor: 2.83

Now let us see how UTY worked during this same period using the original set of parameters used with NNA. This set of parameters was suboptimal for UTY but we are using the NNA set of parameters for consistency to show the robustness of our model.

Total Net Profit: \$83,557.98

Total # of trades: 141

Percent Profitable: 58.87%

Avg. Trade (win & loss): \$592.61

Max intraday drawdown: (\$11,722.50)

Profit Factor: 2.03

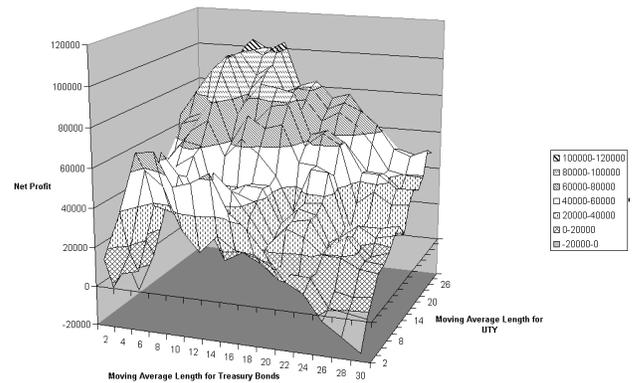


Fig. 1. Optimization 3D chart for Treasury bonds versus UTY and Net Profit from 01/01/1988 to 12/31/1997

Here we show an optimization between values 2-30 in steps of 2 for both sets of parameters (see Fig. 1). We can see a big wide mountain peak. We have a large area in the 80,000 to 100,000 area. Let us now take a closer look at the robust area.

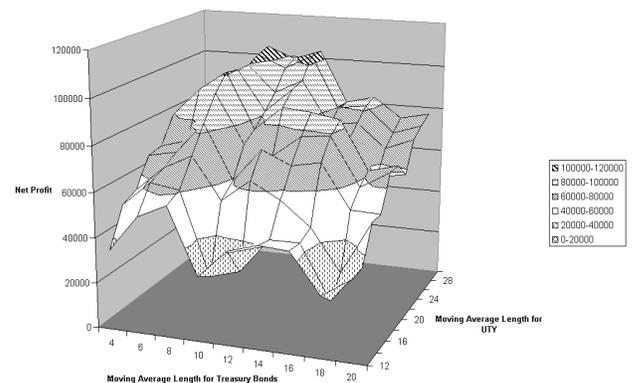


Fig. 2. Close up of the robust area of Optimization 3D chart for Treasury bonds versus UTY and Net Profit from 01/01/1988 to 12/31/1997

The closer look shows how wide the 80,000 to 100,000 area is (see Fig. 2). The 60,000 to 80,000 is very wide. This is an example of a very robust surface. This type of surface is an example of the type we look for, when we are searching for parameters in this type of intermarket model.

Let us now look at the 3D surface plot over the period 01/01/1988 to 10/25/2011 which includes almost 13 years of out of sample results.

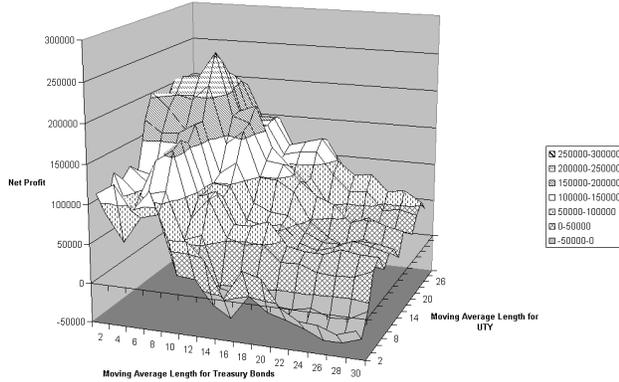


Fig. 3. Optimization 3D chart for Treasury bonds versus UTY and Net Profit from 01/01/1988 to 10/25/2011

We can see that we still have a reasonable wide performance (see Fig. 3). We have a range of +/- 6 on either side of our best sets of parameters which still produce very good results. In addition, our original set of parameters selected in 1998, the 8, 18 produces the following results over the period 01/01/1988 to 10/25/2011.

Total Net Profit: \$215,881.56
Total # of trades: 399
Percent Profitable: 60.90%
Avg. Trade (win & loss): \$541.06
Max intraday drawdown: (\$26,133.36)
Profit Factor: 1.79

Let us study just the out of sample period with a first trade after 01/01/1998 to 10/25/2011.

Total Net Profit: \$129,166.32
Total # of trades: 257
Percent Profitable: 61.87%
Avg. Trade (win & loss): \$502.59
Max intraday drawdown: (\$26,133.36)
Profit Factor: 1.67

We can see these out of sample results are very similar to the results over the whole period and the average trade differs by less than 20% between the in sample and out of sample period. Let us look at the year by year out of sample results (see Table I).

| Period | Trades | Winning Trades | Win% | Open Trade | Net Profit | Return % | Running % |
|--------------|------------|----------------|--------|------------|---------------------|----------|-----------|
| 1998 | 17 | 13 | 76.47% | 1 | \$23,757.61 | 156.40% | 156.40% |
| 1999 | 14 | 6 | 42.86% | 1 | \$1,031.58 | 6.79% | 163.19% |
| 2000 | 19 | 11 | 57.89% | 1 | (\$31,281)a | -0.21% | 162.99% |
| 2001 | 20 | 14 | 70.00% | 1 | \$14,598.42 | 96.11% | 259.09% |
| 2002 | 16 | 11 | 68.75% | 1 | \$22,507.20 | 148.17% | 407.26% |
| 2003 | 14 | 10 | 71.43% | 1 | \$24,320.28 | 160.11% | 567.37% |
| 2004 | 20 | 11 | 55.00% | 1 | \$13,910.70 | 91.58% | 658.95% |
| 2005 | 19 | 7 | 36.84% | 1 | (\$12,316.42)a | -81.08% | 577.87% |
| 2006 | 15 | 8 | 53.33% | 1 | \$3,313.54 | 21.81% | 599.68% |
| 2007 | 19 | 12 | 63.16% | 1 | \$8,534.00 | 56.18% | 655.86% |
| 2008 | 22 | 16 | 72.73% | 1 | (\$7,893.17)a | -51.96% | 603.90% |
| 2009 | 21 | 16 | 76.19% | 1 | \$22,929.22 | 150.95% | 754.85% |
| 2010 | 20 | 10 | 50.00% | 1 | \$1,813.08 | 11.94% | 766.79% |
| 2011 | 21 | 14 | 66.67% | 1 | \$13,348.02 | 87.87% | 854.66% |
| Total | 257 | 159 | | | \$129,822.78 | | |

Note: The numbers in brackets are negative numbers.

We can see that although the optimization surface is still reasonably robust, the robust area is not as broad and wide as it was originally during the period of 01/01/1988 to 12/30/1997. This earlier period did not have long periods of decoupling between utility stocks and Treasury bonds that often happen during stock market collapses which lead to a Treasury bonds rally. When bonds rally due to a safe haven effect, using stock indexes as an intermarket can sometimes create problems. Stock based intermarket correlate closer to stocks under extreme market conditions which in turn distorts the intermarket relationships. We will discuss the strategies for limiting this effect in our analysis of intermarket divergence later in this article.

Analyzing the optimization space is both a science and an art and can give us a clue as to how stable and robust a given intermarket relationship should be. Let us look at a relationship between Treasury bonds and the CRB futures index. Commodity prices are negatively correlated to Treasury bond prices. Let us optimize from 2-30 in steps of 2 for both Treasury bonds and CRB index. Let us look at our optimization grid results and see what the surface looks like.

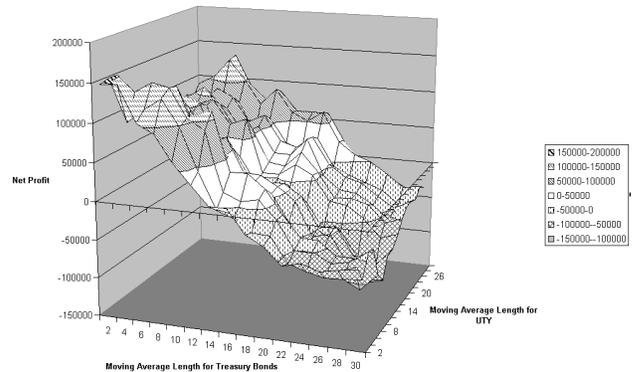


Fig. 4. Optimization 3D chart for Treasury bond versus CRB Index and Net Profit. It is fundamentally sound but not robust.

You can see that the surface has a strong downward slope with very little flat safe areas (see Fig. 4). We can also see that over 75% of the area is under \$50,000. When we looked at UTY, about 30% of the area is below \$50,000. When analyzing these surface plots, we are looking for how many levels are tradable. In the case of CRB index less than 10% of the cases produced more than \$100,000, which over this

complete period is the lower limit of what I consider tradable. When looking at utility stocks about 40% of the space is tradable.

Let us look at the optimization surface for the relationship between the Treasury bond and the CRB index. We will look at the period 01/01/1988 to 12/30/1997. This was our in sample period we used for our 30 year Treasury bond and NNA/UTY example.

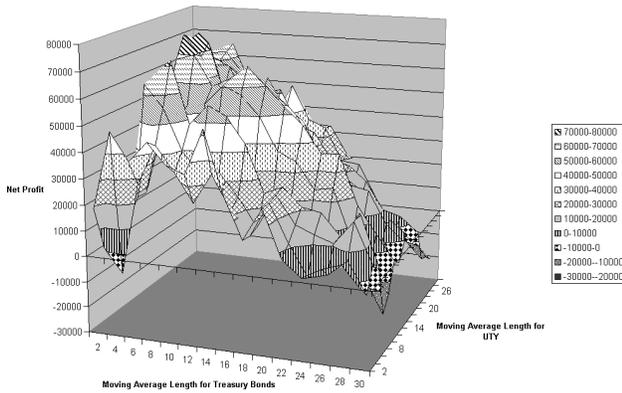


Fig. 5. 3D chart of Treasury bond, CRB Index and Net Profit

Even in the period 01/01/1988 to 12/30/1997, when the Treasury bond CRB was in news; you can see that it was a dangerous relationship to use for signals. We can see that even 13 years ago this surface is dangerous (see Fig. 5). We only have 20-25% of the surface which was tradable back in 1998. The difference in the quality of the surface between this and what the UTY, foresaw that the UTY would hold up better over time.

This analysis shows us a methodology to generate mechanical signals based on intermarket analysis and also a way to gauge possible future reliability. If we look at all of these charts we will see the same similarities between relationships which are robust and relationships which do not hold in out of sample relationships.

We have seen that intermarket divergence is a powerful concept. When an intermarket divergence occurs we stay in that position until an opposite divergence occurs. One question is “Why does this divergence concept work?” Also what is interesting is that my research shows that the zero crossing is significant, we cannot improve the results of intermarket divergence by using a non-zero threshold. It is my belief that this concept works as an arbitrage play. Since we do not know the relative equilibrium between the traded market and underlying market, for example in the case of Treasury bonds and UTY, divergence is the only confirmed mispricing; we have in terms of a reliable arbitrage play.

We know that this cannot be the most efficient signal. We can see by studying our Treasury bond trades that some trades are early; for others we give back large percentage of open profits and sometime large winning trades can become losers, even though intermarket divergence still produces outstanding results (see Fig. 6).



Fig. 6. Price chart with signals. Treasury bonds, UTY divergence 8, 18 parameters, it shows that very profitable signals can still be inefficient.

Let us look at the following trade of the US_REV.CSV market (see Table II)

| Market | Entry Date | Size | Entry Price | Exit Date | Size | Exit Price | Trade P/L | Running P/L |
|------------|------------|------|-------------|------------|------|------------|------------|--------------|
| US_REV.CSV | 08/28/2003 | 1 | 80.0625 | 10/28/2003 | 1 | 83.9375 | \$3,876.24 | \$172,023.78 |

Here, we have a very profitable trade but we gave back almost all of the profit and then the market moved back in the direction of the trade. This shows a problem with intermarket divergence namely “Reversal Strategy” which is always in the market. There are other cases including (a) a winning trade ending up as a losing one and (b) trades which never become profitable. Despite, these issues our results are amazing.

One solution to this problem is to build a finite state machine which covers all possible states of the intermarket relationship during the process of going from ‘long to short’ or ‘short to long’. My research has shown that this state map of all possibilities is the key in greatly improving the performance of these simple divergence models. We can also create a state map which will allow us to combine multiple intermarkets against a market we are trading.

Correlation and forward correlations analysis, between markets can also be used to filter and improve these models. Sometime correlation analysis can make the long term out of sample performance less robust if it is not integrated carefully. Hence, it is important to do the surface analysis discussed earlier to make sure that the correlation relationships we are looking at are robust and stationary [9].

III. INTERMARKET ANALYSIS WORKS ON A WIDE RANGE OF MARKETS.

Intermarket divergence is not something which just works on the bond market. It works on a broad range of markets from bonds, to stock groups, to currencies; even markets like

gold, crude, live cattle and copper.

The MorningStar Sector Indexes are also a good source of relationships to use with intermarket analysis. In our table we show how these Sector indexes can be used to predict market as diverse as Live Cattle and Copper Futures (see Table III).

| Market | Intermarket | Relationship | Dates under consideration | Selected Parameters | Net Profit (\$) | Winning % (Percent Profitable) | Average Trade in \$ (win & loss) | Max Intraday Drawdown (in \$) |
|-------------------|---|--------------|---------------------------|---------------------|-----------------|--------------------------------|----------------------------------|-------------------------------|
| T-Bonds | Utility Stocks UTY | Positive | 01/01/1988 - 12/30/2011 | 8,18 | \$199,388.98 | 60.55% | \$494.76 | (\$27,545.72) |
| T-Bonds | Silver | Negative | 01/04/1978 - 12/30/2011 | 8,8 | \$251,118.00 | 64.52% | \$317.07 | (\$24,406.88) |
| S&P500 | T-Bonds | Positive | 04/22/1982 - 12/30/2011 | 8,5 | \$667,875.00 | 65.84% | \$829.66 | (\$84,175.00) |
| Dow 30 Index cash | US Dollar Index | Negative | 01/03/1986 - 12/30/2011 | 4,12 | * 17886.49 | 61.19% | \$27.99 | (\$3,231.70) |
| Yen | Crude Futures | Positive | 04/01/1996 - 12/30/2011 | 6,26 | \$132,025.00 | 60.56% | \$619.84 | (\$27,362.50) |
| Canada Dollar | EWG (ETF) | Positive | 05/01/1999 - 12/30/2011 | 12,16 | \$111,700.00 | 69.35% | \$900.81 | (\$13,330.00) |
| Australian | Goldman Sakes index | Positive | 01/04/1993 - 08/10/2011 | 6,24 | \$84,480.00 | 58.37% | \$344.82 | (\$18,900.00) |
| Australian | EWG (ETF) | Positive | 04/01/1996 - 07/28/2011 | 10,14 | \$104,750.00 | 60.00% | \$551.32 | (\$18,160.00) |
| Live Cattle | Morning Star Dairy Products | Positive | 01/04/1988 - 12/30/2011 | 14,24 | \$101,250.00 | 72.86% | \$289.29 | (\$9,920.00) |
| Crude oil | DI Oil Index | Positive | 12/24/2001 - 12/30/2011 | 36,36 | \$249,290.00 | 74.00% | \$4985.80 | (\$32,820.00) |
| Copper | Morning Star Industrial Metals & Minerals | Positive | 01/04/1989 - 12/30/2011 | 4,14 | \$192,687.50 | 58.00% | \$428.19 | (\$29,150.00) |

Note: Numbers in brackets are negative numbers
*Value in points, other values in dollars

Intermarket analysis requires understanding of how a given market works. For example let's look at the Dow Jones 30 Industrial Average, The above table (see Table III) uses the cash price Dow Jones 30 Industrial Average. The Dow 30 is made up of large multi-national companies. US based goods and services are more competitive overseas if the dollar is lower. This is why a negative relationship between the Dow and Dollar index [4], greatly outperforms buy and hold. The dollar index is not predictive of S&P500, because it does not contain as high as a percentage of large multi-national companies as the Dow 30.

Additionally, often many related stock groups are predictive of the underlying commodities. We see many examples of this such as Australian dollar and Canadian dollar which can be predicted with the iShares MSCI Australian Index and iShares MSCI Canada Index.

The parameters for the intermarket divergence in Table III were selected using the same type of analysis we used to select the 30 year Treasury bond, UTY parameters in our 3D chart analysis. There are many classic intermarket relationships. The 30 year Treasury bond has both positively and negatively correlated intermarket, UTY as we discussed earlier is positively correlated. Silver is negatively correlated; this is another relationship which I originally published in the 1990s [8] (see Fig. 7).

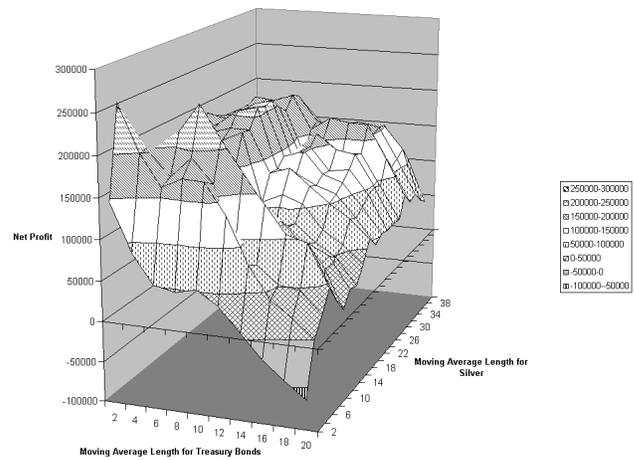


Fig. 7. Optimization 3D chart for Treasury bonds versus Silver and Net Profit from 01/04/1978 to 12/30/2011.

It is robust over a broad range of parameters even with over 13 years out of sample (see Fig. 7).

Another example we have is Crude oil and oil stocks, for example using the Dow Jones Oil Index. Let's look at this example using our 3D parameter analysis (see Fig. 8). We shall show the intermarket parameters and net profit using intermarket divergence. In these results we have \$50.00 deducted for slippage and commissions.

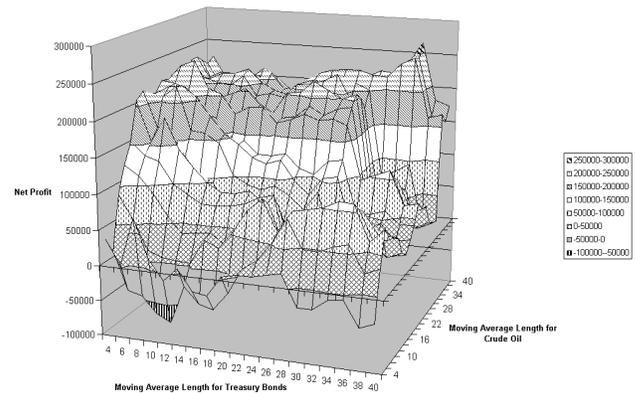


Fig. 8. Optimization 3D chart for Crude oil versus Dow Jones oil index and Net Profit from 12/24/2001 to 12/30/2011

You can see that we have a broad wide area of strong net profits. This is an example of a robust relationship (see Fig. 8).

We can also see another classic relationship S&P500 and 30 year Treasury bond [4]; this relationship had periods where it works well and others where it works badly. The problem is that during times of trouble, S&P500 and Treasury bonds move in opposite directions. When the stock market is crashing, people buy bonds as a safe haven (see Fig. 9).

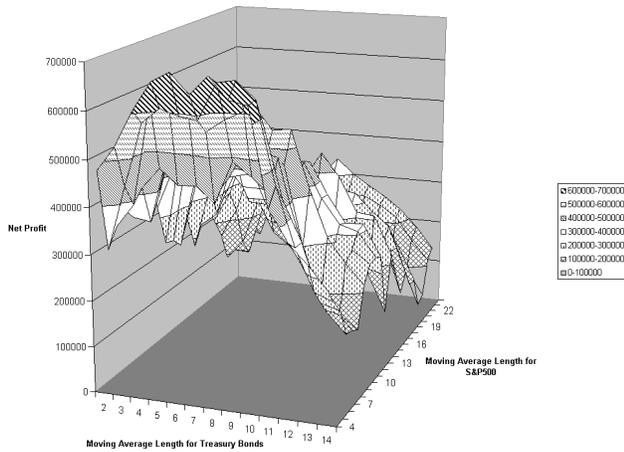


Fig. 9. Optimization 3D chart for S&P500 versus Treasury bonds and Net Profit from 04/22/1982 to 12/30/2011.

We can see that we have a nice robust area but once we move away from the area, it performs badly. Hence, the S&P500 moving average period must be less than 10 days for you to have a good safe area (see Fig. 9).

You can see that we have a relatively large area of profits from \$500,000 to \$700,000, and after that we have a fall off. The robustness of this relationship between S&P500 and Treasury Bonds has not been strong since the 2008 banking crisis. The relationship did badly in 2009-2010. Using 8, 5 the set of parameters we selected for performance and robustness; we lost money in these two years, almost \$26,000 in 2009 and a little over \$12,000 in 2010. In 2011 we had a big year making over \$113,000.

IV. INTERMARKET ANALYSIS AND MACHINE LEARNING

Machine learning methods like neural networks, rough sets, genetic algorithm and genetic programming have been used for trading applications since the late 1980's [10]. Halbert White, in his paper in 1988, had tried to use a simple backpropagation neural network to predict the changes in IBM stock [11]. Although unsuccessful in showing any conclusive results, he showed the interest in this area of research only a year after backpropagation was popularized by Rumelhart and invented by P. J. Werbos [12], [13], [14]. In 1996, Chiang used a backpropagation network to forecast year end net asset values (NAV) of mutual funds. He concluded that the neural network forecasts significantly outperformed regression models in cases where limited data is available. Ruggiero developed neural network models which predicted the sign of the five week change in the SP500 using a variant of backpropagation [15], [6]. We also developed a neural network model which predicted a forward stochastic like indicator which had a five day lookahead for the 30 year Treasury bond [16]. Refer to "1".

$$\frac{\text{Average} ((\text{Close}[+5] - \text{Lowest}(\text{Close}[+5],5))/(\text{Highest}(\text{Close}[+5],5) - \text{Lowest}(\text{Close}[+5],5)),5)}{\quad} \quad (1)$$

Both my works on the S&P500 and Treasury bonds used

intermarket analysis as part of the models. The interest in neural networks peaked during the 1990's and began to wane afterwards due to the unduly high expectations from these networks in market base solutions. These networks need to be used as a component in the system such that they do not cause a system failure when the performance of the neural network system degrades and also at the same time improves results significantly when the systems work as expected. Neural network also have some other issues. Firstly, when we start trading neural systems, we initialize them using random weights meaning if we trade a neural network with initial weights a hundred times we will not get the exact same results. This is part of the science yet real traders do not feel comfortable using the technology as they cannot duplicate backtested results. The "Support Vector Machine Regression (SVM)" methodology are a good solution since they perform similarly to neural networks in many cases and for a given configuration produces the same results as they are not dependent on initial conditions. In 2010 Ming-Chang Lee and Chang to showed that the performance difference between SVM and Back Propagation Neural Network is marginal with SVM giving higher precision and lower error rates [17].

Another methodology used in trading models is "Rough Sets" which require a higher level of preprocessing because it requires data to be broken into bins. Rough sets require discrete data types. Since time series data is normally continuous in order to use rough sets you need to take the continuous time data series and convert it into discrete data types. We can use various algorithms, for example breaking up variables using domain expertise or using some type of frequency algorithm [18]. Rough sets are not just one algorithm but consist of many different subsets of algorithms. Many of them do not handle conflict cases like two identical records with the same outcome. This is a problem for time series data which often contains conflicts. Thus, a solution is to examine the probability; for example, if out of a given set of conflicting cases, an event is true 70% of the time; this event can be said to be a good rule for trading applications. There are two different popular rough set algorithms which handle probability these are *Variable Precision Rough Set Model* [19] and *Variable Precision Version of the Dominance based Rough Set Model* [20]. These two methods will give us rules which not only have a robustness factor i.e. showing how many supporting cases but also the probability of falling into that particular discrete class. During the 1990's, I used rough set analysis to develop a trading system for the S&P500 as well as trading bonds. This was done using Data Logic /R. The key was adjusting the rule precision factors and how the data was made discrete. This required a bit of trial and error and as an art form required domain expertise. The goal was to maximize the existence of strong rules i.e. rules with many supporting cases and still have a precision level to make them valuable. My research using only strong rules produced good results for predicting the S&P500 [21].

None of the current algorithms handle the properties of neighboring classes and the probability of an input case being classified into one of those neighboring classes. The problem is the cost of missing a given class is not predefined and need to be taken into account. Hence, work on refining rough sets for trading applications is an exciting area of research.

V. CONCLUSION

Intermarket analysis is an exciting area of market production. New methodologies of representing these relationships will help not only classic trading system development but also using advance technologies as for example using a finite state model can allow machine learning methods to easily see patterns which can be used to build more reliable models.

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