ABSTRACT
This paper studies investments strategies for stock markets based on a combination of multiple Technical Indicators rules. The strategies generated are compared with the Buy and Hold, and with the single Technical Indicators. The experiments show that the combined strategies outperform the results of each strategy individually, and also the results of the Buy and Hold for 3 Major Stock Indexes, between 2004 and 2009.

General Terms

Keywords

1. INTRODUCTION
The study of profitable trading rules in the stock market constitutes a widely known problematic in financial markets. Although the existence of those rules still generate great controversy for many economists and academics [6]. On the other hand, investor, traders, and other stakeholders of financial and investment firms, with large experience in the stock market, claim that it is possible to have excessive returns (compared with the Buy and Hold) using algorithmic trading [1][4].

One investment technique commonly used is Technical Analysis, which forecasts the price of stocks based only on the price of the stock and the volume traded in the past. Momentum strategies based on the continuation in the evolution of a stock price on their recent history [10][18], have proved to be consistently more profitable than the indexes where those stocks were included. The foundation of Technical Analysis is the Dow Theory, written by Charles Dow, founder of Wall Street Journal where the main ideas of the Dow Theory where published, in the end of the XIX century [11][13]. The main idea of this Theory is that stock markets move according to trends. These trends are more important with the longer the time-frame they had been active, and can overlap. This means that in a large uptrend small downsizes of short term can occur, but the trend is not over until strong signals of reversal occur.

In this paper we will concentrate on identifying medium to long term trends. Although a theoretical explanation of why these mediums to long term trends occur is not the focus of this paper, several causes can be pointed out. The first and probably the more important is the economical cycles theory, which states that the economy has long periods (months or years) of growth followed by periods of decline or stagnation. With this in mind and knowing that the stock market reflects not only the current performance of companies, but also the expectations about the future it is possible to identify a correlation between economic cycles and stock market cycles. Additionally to the economic cycles are other factors that can contribute to the price fluctuation like share buyback, which mainly occurs when companies generate large profits (it would be a odd idea for a company in financial needs, to allocate money to stock repurchase), which implies that share buy backs are done most of the time in an uptrend economical cycle, when the company generate excess profits. Other important factor is the money flow of the stock market (especially in countries like the U.S.A. where most citizens have investments in the stock market). The effect of the money flow can be found even in companies or mutual funds with good performance, as the aversion to risk increases to the public in the beginning of the Bear Markets, people tend to redirect their capital to more secure investments like bonds, deposits (or even commodities as occurred in this Bear market). This decapitalization of the stock market (and because the number of shares is the same) leads the stocks down following the simply rule of supply and demand: supply increase (as people try to sell) and demand stagnate or even decrease (people change to different markets).

Genetic Algorithms are optimization techniques based on the principles of natural evolution. In [17] is provided a formal study of this subject.

This paper presents a genetic algorithm for optimizing Technical Indicators parameters in order to maximize returns. Other GAs have been previously used to optimize technical indicators parameters, in particular [7] and to develop investment strategies based on technical indicators [1][8][9][20][21].

In this sense, we propose the use of a GA to obtain the set of indicators and their parameters, which should be used to
predict a daily market value. Initially we have applied GAs to find the more suitable parameters for the SMAC, MAD and RSI indicators. After that we combine several strategies, so that a buy or short-sell signal is only made when the majority of the strategies agree, again a GA is used to optimize the Technical Indicators Parameters of all the strategies used.

The next section will discuss the related work on the Genetic Algorithms and various trading strategies currently used in Technical Analyses. Section 3 explains the system architecture and the investment strategies used in this paper, the markets and years used to test those strategies. Also in this section the overall description of the GA is shown, and the fitness, selection, crossover and mutation functions used. In section 4 the results are presented and a highlight of the most relevant results is made. In section 5 the conclusions of this study are shown.

2. RELATED WORK
One of the most used and oldest strategies to identify trends is the crossing of Moving Averages. This strategy consists of having two Moving Averages, one of long term, and other of medium term. A buying signal is generated when the Medium Moving Average crosses up the Long Moving Average, whenever the cross is downwards a selling signal is generated. This strategy has been studied by [2] and by [11]. This studies concluded that from 1910 to 2000 the Crossing of the Moving Average perform better than the Buy and Hold strategy, except for the period from 1980 to 2000 where the market exhibited a regular uptrend, and no excess profits where possible as reported in [5]. More complete studies of other Technical Indicators has been made, like the one in [3] who studies the profitability of 76 Technical Indicators with robust results for some indicators.

Many papers have been recently published on the use of GAs to optimize technical indicators like [7], which use GAs to optimize the parameter of a single Technical Indicator, the MACD (Moving Average Convergence-Divergence) with 3 parameters, and an extra parameter for the history window size.

Another solution based also on optimizing Technical Indicators parameters is the one used in [1], where the chromosome is composed by the MACD, RSI and history window size, also a comparison between single and multi-objective is made.

Besides GAs others optimization techniques has been applied to this area of study, like neural networks in [12], where the neural network uses for the inputs the price, volume, interest rate and foreign exchange rate. Also other more unexplored approaches like pattern recognition as been tried in [15] which explores a more visual approach to Technical Analysis.

Other technical information has been studied. The influence of volume as a predicting tool was studied in [14] [16], the indicator is based in the sudden increase of the volume to generate a buy signal.

This study concentrates in the optimization of technical trading rules which has not been yet tested with GAs, like the SMAC and MAD strategies, and also, combines these two strategies in one chromosome trying to achieve better and solid returns than with the solo strategies.

3. METHODOLOGY
The proposed system consists on a Genetic Algorithm coupled with a market return evaluation module based on the return of the strategies in different markets in specific time-frames.

3.1 SYSTEM ARCHITECTURE

The complete process can be summarized as:

- The user starts by specifying the markets to analyze and next chooses the Technical Indicators used in the strategy. Finally, the user chooses the train and test period.
- Afterwards, the Genetic Algorithm Kernel runs several number of times, optimizing the parameters of the strategy for the markets and training period chosen.
- Finally for each run of the GA, its return on the test period is calculated. Detail info is shown to the user displaying the optimized strategy and the return for each market in the test and in the training period.

3.1.1 MODULES DESCRIPTION
This section presents the overall description of each module and their main responsibilities.

Technical Indicators:
This module is responsible for the creation and management of the technical indicators used by all the strategies. This unit calculates the value of the technical indicators for a specified index and time period and stores
it’s calculation for later reuse. This module is also responsible for calculating the strategies decisions (if it should buy, short-sell or be out of the market).

**Train and Testing Periods:**

The “Time Period” module controls the time components of the Stock Indexes, in this unit the user can specify which time periods the Genetic Algorithm will use for optimization, and which time period should be used for test, and its configuration (continuous, sliding window, and others.)

**Stock Market Indexes:**

This module is responsible for loading the stock market indexes from the source (a .csv file) and giving access to the data to the other parts, the stored information includes the close value, the open, high, low and the date.

**Market Return Evaluation:**

In this block it is calculated the return and other metrics for evaluating the investment strategy (like the Sharpe Ratio, number of trades executed, ROI, and others.). The results can be evaluated for several types of metrics, yearly or monthly and with simple or compound average.

**Genetic Algorithm:**

The Genetic Algorithm Module is the most important because it is the one who does the core functions of the system. This module uses data from all the other modules to calculate the perfect strategy with the Technical Indicators specified by the user for the specified markets, in the training period. The crossover is a one-point crossover, and parents are chosen based on a roulette-wheel selection.

**Optimized Strategy:**

Finally this module is responsible for showing the user the result of the optimization. Beside the best strategy obtained, it also shows results from various runs of the Genetic Algorithm, so the user can test the average results and robustness of the solution. For each strategy it shows the return in the test and training period, the yearly return and the Sharpe Ratio.

### 3.2 TRAIN AND TEST DATA SET

The time period chosen for training was from 1 January 1993 to 31 December 2003, eleven years of daily data. This time period was chosen for two main reasons. The first one is that the time period should be big enough to be statically relevant and to avoid any kind of bias due to a small sample period. Secondly, the market data should be similar in nature to the markets where the system is going to be applied. With the constant changes in the stock market in the last years, like online trading, algorithmic trading, high volume trading, and with the increase in the speed and amount of exchanged information and short delays for new information to reach and change markets evolution, early and mid 20th century data may be meaningless to current models to predict stock markets behavior.

The testing period was from 1 January 2004 to 31 December 2009, six years of testing. This period was chosen to test the GAs in an almost real situation, simulating that the investor had run the training in 1993 to 2003, and applied these strategies until the present. Also, the fact that the markets had been very stressful and that this has been a very difficult period for all the operators in the market, meaning that finding a successful strategy in this type of market is not an easy task.

The markets tested where the S&P500 (USA), FTSE100 (England) and DAX30 (Germany). They represent the main indexes of the main developed economies. These are markets that behave in a stable and orderly fashion for long periods. They also include several big companies in different sectors which gives an extra stability to them. They react mainly to company profits and major economic events. They also have high volume of transactions and are difficult to manipulate due to high standards of regulation and size.

### 3.3 TECHNICAL INDICATORS

For the strategies used the Simple Moving Average will be applied, which can be calculated using the following expression (1):

$$SMA_n(d) = \frac{1}{n} \sum_{t=d-n+1}^{d} P(t)$$

(1)

Where “n” is the time period (in days), “d” is the day where the moving average is calculated, $P(t)$ is the value of the Index at day “t”. An example of this indicator for a SMA of 200 days is presented in Figure 2.

![Figure 2 - Evaluation of the SMA(200) from 2000 to 2010 in the S&P 500.](image_url)
the MA is a long term MA, and the other is a short term MA. A buying signal is generated whenever the short term MA crosses over the long term MA, and a sell signal is generated whenever the short term MA crosses under the long term MA.

Following this strategy the investor will buy (or maintain) the Index whenever Eq. (2) is higher than zero, and will short sell whenever Eq. (2) will be lower than zero.

\[
SMAC_{l,s}(t) = \frac{1}{l} \sum_{i=d-l+1}^{d} P(t) - \frac{1}{s} \sum_{i=d-s+1}^{d} P(t)
\]  

(2)

Where \( l \) is the time period used for long term, \( s \) the time period for short term, and \( P(t) \) the value of the Index at day “\( t \)”. An example of this indicator for a SMAC of 200 and 50 days is presented in Figure 3.

Figure 3 - Evaluation of the SMAC(200, 50) from 2000 to 2010 in the S&P 500.

Another indicator that will be used in this paper is the Moving Average Derivate (MAD). It is an extended version of the “MA Change” described in [11]. In the original version it is calculated by subtracting the value of the current MA with the value of the MA in the previous day.

In mathematics this is simply the secant to the MA curve in the last two days. In this way the Derivate of the MA can be calculated based on the definition of Secant of the MA (Eq. 3).

Where “\( n \)” is the time period used to calculate the MA and “\( g \)” is the distance between the two days to calculate the secant (the original strategy consists of a fixed \( g \) with value 1).

\[
MAD_{n,g}(d) = \frac{\sum_{i=d-g+1}^{d} P(t) - \sum_{i=d-g+1}^{d} P(t-g)}{ng}
\]  

(3)

In this way the value of the MAD reflects the current value of the Index. As mentioned the strategy consists of buying when the MAD is larger than zero and short sell when it is less than zero. The strategy introduced in this paper is the MAD (Moving Average Derivate) and consists on having only one MA. The idea behind this strategy is to buy the Index when the Derivate of the MA is positive (meaning that the Index will go up), and short sell when the Derivate is negative.

An example of the calculation of this Indicator with the parameters, 200 for the long Moving Average, and 50 for the “gap”, can be seen in Figure 4, where is shown the evolution of the S&P 500 from 2000 to 2010 and the respective values of the MAD. This indicator gives a buy order when the MAD crosses the zero in an ascending slope and a sell order when it crosses the zero in a descending slope.

Other indicator used was the Relative Strength Index (RSI). The RSI indicator is a momentum oscillator used to compare the magnitude of a stock’s recent gains to the magnitude of its recent losses, in order to determine overbought or oversold conditions. The formula used on its calculation is:

\[
RSI_n(d) = 100 - \frac{100}{1 + \frac{Ups(n)}{Downs(n)}}
\]  

(4)

Where “\( n \)” is the time period (in days), “\( d \)” is the day where the indicator is calculated. Ups is the sum of gains over the “\( n \)” period and Downs is the sum of losses over the “\( n \)” period. When calculated, the RSI line forms a signal between 0 and 100, which specifies determined overbought or oversold conditions when its value is above or below specific levels.
An example of the graphical representation of the RSI 14, with buy signal on level 30, and sell signal on level 70, is shown on Figure 5.

In the next table is represented the maximum and minimum level allowed for each gene:

<table>
<thead>
<tr>
<th>Gene</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMAC – Longest MA</td>
<td>5</td>
<td>250</td>
</tr>
<tr>
<td>SMAC – Shortest MA</td>
<td>1</td>
<td>200</td>
</tr>
<tr>
<td>MAD – Longest MA</td>
<td>1</td>
<td>250</td>
</tr>
<tr>
<td>MAD – Gap</td>
<td>1</td>
<td>250</td>
</tr>
<tr>
<td>RSI – Period</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>RSI – Buy Entry Level</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>RSI – Buy Exit Level</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>RSI – Short-Sell Entry Level</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>RSI – Short-Sell Exit Level</td>
<td>0</td>
<td>100</td>
</tr>
</tbody>
</table>

Additionally to that and since the Chromosome will have several Indicators it’s necessary to have a weight mechanism in the chromosome. To tackle this problem with each Technical Indicator in the Chromosome is associated a weight between 0 and 5. And each chromosome will also have a weight required to trade, between 1 and the maximum weight possible (number of Technical Indicators in the chromosome times 5). To calculate the final decision in each day, each rule decision (1 for a buy decision, 0 for no decision, and -1 for short-sell) will be multiplied for the weight associated with that rule. If the total some of the decisions is higher than the Weight Required to Trade, a buy signal is generated, and if the sum is lower than the negative value of the Weight Required to Trade, a short-sell signal is generated.

In Table 2 it is shown a representation of a possible chromosome with two strategies, the SMAC and the MAD:

<table>
<thead>
<tr>
<th>Chromosome</th>
<th>WTT</th>
<th>W</th>
<th>SMAC</th>
<th>W</th>
<th>MAD</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1</td>
<td>25</td>
<td>160</td>
<td>1</td>
<td>40</td>
</tr>
</tbody>
</table>

The table also shows the Weight to Negotiate (WTT), and the Weight associated with each one of the strategies.

### 3.3.1 PARAMETERS OF TECHNICAL INDICATORS

After defining the strategies it is necessary to define the parameters to use both in the SMAC, MAD, and RSI strategies. As the strategies based on Moving Averages have two parameters, with similar meanings:

The first parameter is similar to both strategies, the time period of the long term MA.

The second parameter in one strategy is the time period of a short term MA and in the other strategy is the distance between the two points used to calculate the secant. Both this parameters should be a medium term periods.

The RSI strategy used has 5 parameters. The first one is the period of the RSI, the second one is the level for buying long positions, the third one is the sell level to exit this positions. The fourth and fifth parameters refer to the short-selling strategy, the fourth is the level for enter a short-selling position, and the last parameter is the level for exiting short-selling position.

### 3.4 GENETIC ALGORITHM KERNEL

#### 3.4.1 GENETIC ENCODING

The chromosome created must represent the Technical Indicators used in, in this way the SMAC chromosome is represented by two genes, one for the shortest MA other for the longest MA in days (natural numbers), the interval of this values is between 1 and 250 (this value is above the largely used MA for long term analysis: 200 days). The same rule applies to the MAD chromosome, where one of the parameters is the “gap” and the other the number of days of the MA. The RSI is represented with five genes, all being natural numbers, one for each parameter.
Sum of fitness of all individuals. Each individual can be chosen any number of times for crossover (the only exception is that an individual cannot be chosen to crossover with himself).

The crossover is a one-point crossover, each breeding generates the two possible distinct children and includes them in the population. In the chromosome of only one indicator (SMAC, MAD or RSI) the children are created by swapping the long and shortest MA day. In the multiple strategies chromosome the children are created by randomly selecting a point in the middle of the chromosome and swapping the genes (of the two parents) to the left and to the right of the crossover point.

The fitness function used was also being analyzed on this research, so several research functions where tested, and their description and their results can be found on the next chapter.

4. RESULTS

4.1 METRICS USED

Return On Investment: This is the most basic metric used for evaluating investment strategies, and it calculates how much money you earn, for each unit of money invested, the formula to calculate the ROI is in (5).

\[ ROI = \frac{V_f - V_i}{V_i} \]  \hspace{1cm} (5)

Drawdown: This metric is used to calculate risk and it measures the maximum lost (in percentage) that the strategy has suffered over time.

Sharpe Ratio: The Sharpe Ratio is a measure that was created by Nobel Prize William Sharpe, to measure the reward-to-variability ratio of a trading strategy [19]. This measure allow to compare two strategies with different returns, and see if the additional return of one strategy is due to applying a more risky strategy, or to a smarter investment strategy. The Sharpe Ratio formula is (6):

\[ SharpeRatio = \frac{R - R_f}{\sigma} \]  \hspace{1cm} (6)

Where R is the average return of the strategy, \( R_f \) is the risk free rate (normally the rate of the US Treasuries security). And \( \sigma \) is the standard deviation of the rate of strategy. The risk free rate must be on a treasury security with the same time-frame that the investment strategy, since we are considering 6 years, the more suitable security is the 5 year Treasury Note. A secure investment would be buying a 5 year Treasury Note on 2004 and with a 3.36% yield.

Sortino Ratio: Sortino Ratio is similar to the Sharpe Ratio, because it’s also a reward/risk ratio. The main difference is it only penalizes the negative returns and not the positive but dispersed results as the Sharpe Ratio does. The Sortino Ratio is calculated like the Sharpe Ratio, but instead of the Standard Deviation it uses the Downside Risk. The downside risk is the deviation of the values that are below some threshold (for example, below 0%).

4.2 COMPARISON OF RESULTS

All the results presented in this chapter were based on 50 runs made for each strategy, the histograms present the results of the 50 runs, and the values presented in the tables are the average value of the 50 runs.

First Test – The Impact of the Fitness function:

The first approach was to try several different fitness functions, the fitness functions chosen where based on the metrics presented above, and the main goal was to identify fitness functions that could find less risky solutions, even if they had lower returns.

The four fitness functions used were:

- Return
- Return – 2 x Drawdown
- Sharpe Ratio
- Sortino Ratio

In Figure 6 we can see the Histogram for the test period of the Annualized Returns for the 50 runs for each fitness function.

![Figure 6 – Histogram of the Annualized Returns for the 4 Fitness Functions.](image)

In this figure we can see that the functions have identical results and can be approximated to Gauss distribution.

In Table 3 we can see the Evaluation Metrics of the 4 Fitness Functions during the test period.

For each evaluation metric (line of the table) the best result is highlighted in bold.
We can see that the results of all strategies are not very significant differences, for example, average returns ranging between 8.2% and 9.1%, and the average Sharpe ratio between 0.52 and 0.61.

Table 3 – Evaluation Metrics for the 4 fitness functions tested.

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>Return</th>
<th>Rent. - 2x DD</th>
<th>Sharpe Ratio</th>
<th>Sortino Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Av. Annualized Return</td>
<td>9.10%</td>
<td>9.00%</td>
<td>8.50%</td>
<td>8.20%</td>
</tr>
<tr>
<td>Average Drawdown</td>
<td>27.90%</td>
<td>27.20%</td>
<td>29.10%</td>
<td>27.90%</td>
</tr>
<tr>
<td>Average Sharpe Ratio</td>
<td>0.61</td>
<td>0.61</td>
<td>0.58</td>
<td>0.52</td>
</tr>
<tr>
<td>Average Sortino Ratio</td>
<td>111.43</td>
<td>164.58</td>
<td>161.03</td>
<td>120.24</td>
</tr>
</tbody>
</table>

In the next picture we see the evolution of overall return, where once again we can see that the final returns are very similar.

Second Test - Chromosome with only one Technical Indicator:

Several tests were made, with different chromosome configurations. This test has a chromosome with only one trading rule. The three trading rules presented before (MAD, SMAC and RSI) were used and the Histogram comparing these strategies is on Figure 8:

Figure 7 – Evolution of overall return for the 4 fitness functions in the test period (2004 to 2009).

As can be seen from the figure, chromosomes with MAD and SMAC strategies take clear advantage over the strategy based on RSI. Since the MAD and SMAC have a curve similar to the normal distribution with mean around 8% to 9% and the strategy based on RSI has the majority of the executions with returns of less than zero.

In the next table are the evaluation metrics for these strategies. Again, for each evaluation metric (line of the table) the best result is highlighted in bold.

Table 4 – Evaluation Metrics for the MAD, SMAC and RSI.

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>MAD</th>
<th>SMAC</th>
<th>RSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Av. Annualized Return</td>
<td>8.80%</td>
<td>6.20%</td>
<td>-2.40%</td>
</tr>
<tr>
<td>Average Drawdown</td>
<td>27.30%</td>
<td>31.90%</td>
<td>19.20%</td>
</tr>
<tr>
<td>Average Sharpe Ratio</td>
<td>0.61</td>
<td>0.29</td>
<td>-43.22</td>
</tr>
<tr>
<td>Average Sortino Ratio</td>
<td>142.24</td>
<td>52.22</td>
<td>-44.13%</td>
</tr>
</tbody>
</table>

The results of this table confirms what had already been found in histogram, MAD and SMAC have positive results, and the MAD is clearly the best strategy, because it has the best result in most metrics.

The fact that the strategy RSI has drawdown’s better than the others is due to the fact that the strategy is very little time on the market (as it is a losing strategy, the optimization performed by the GA is to negotiate the least possible) and therefore limit the losses.

Third Test – Chromosome with the same two strategies (but different parameters):

In the next test the chromosomes where modified in order to double the strategies presented in the previous example. In this way the chromosomes tested had the following strategies: “MAD, MAD”, “SMAC, SMAC”, and “RSI, RSI”.

The histogram of these chromosomes results are in Figure 9.

Figure 8 - Histogram of the Annualized Returns of the three original Technical Indicators.

Figure 9 – Histogram of the Annualized Returns of the chromosomes with double trading rules.
Regarding the previous test, it can be seen that the strategies SMAC and MAD improved their results by reducing elements with the worst returns, which are much less than in the previous test. As for the RSI it remained with poor performance.

In Table 5 are the evaluation metrics for these strategies.

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>MAD, MAD</th>
<th>SMAC, SMAC</th>
<th>RSI, RSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Av. Annualized Return</td>
<td>8.90%</td>
<td>8.20%</td>
<td>-3.00%</td>
</tr>
<tr>
<td>Average Drawdown</td>
<td>27.20%</td>
<td>27.40%</td>
<td>24.00%</td>
</tr>
<tr>
<td>Average Sharpe Ratio</td>
<td>0.60</td>
<td>0.49</td>
<td>-41.79</td>
</tr>
<tr>
<td>Average Sortino Ratio</td>
<td>131.98</td>
<td>110.67</td>
<td>-41</td>
</tr>
</tbody>
</table>

Again we conclude that the strategies MAD and SMAC get much better results that the RSI. MAD strategy has some advantage by having the best performance on most metrics. In comparison with this table and the previous:
The Average Return get’s better, while the MAD going from 8.4% to 8.9% and the SMAC going from 6.2% to 8.2%. Regarding the Sharpe Ratio, MAD remains practically (0.61 vs. 0.60), and SMAC rises from 0.29 to 0.49.
We can conclude that doubling the strategies has a positive effect on returns, with almost no impact on risk, the average drawdown does not increase, and the Sharpe and Sortino Ratio do not decrease.

**Last Test – Chromosome with 3 combined strategies and comparison with the Buy & Hold:**

In this test the best strategies from the previous tests have been combined. The strategies based on MAD and SMAC are combined in to a single chromosome, in order to achieve even better results. In this way, the strategies created are a combination of 3 Technical Indicators, one from the first test, and two repeated strategies from the second test. These strategies are the SMAC, SMAC, MAD” (or simply “2xSMAC, MAD”) and the “MAD, MAD, SMAC” (or “2xMAD, SMAC”).
These strategies are then compared with the Buy & Hold to see if they can beat the market.

In Figure 10 are the annualized returns of these two strategies and the Buy & Hold, both strategies beat the Buy & Hold. As they have the majority of the executions in intervals with big return than the Buy & Hold.

In Table 6 we can see the Evaluation Metrics for the “2xSMAC, MAD”, “2xMAD, SMAC” and Buy & Hold strategies.

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>2xSMAC, MAD</th>
<th>2xMAD, SMAC</th>
<th>Buy &amp; Hold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Av. Annualized Return</td>
<td>9.10%</td>
<td>9.10%</td>
<td>3.40%</td>
</tr>
<tr>
<td>Average Drawdown</td>
<td>26.80%</td>
<td>27.70%</td>
<td>56.80%</td>
</tr>
<tr>
<td>Average Sharpe Ratio</td>
<td>0.61</td>
<td>0.64</td>
<td>0.06</td>
</tr>
<tr>
<td>Average Sortino Ratio</td>
<td>136.69</td>
<td>163.38</td>
<td>0.09</td>
</tr>
</tbody>
</table>

In this table we can see that the “2xMAD, SMAC” is the best strategy because it has the best results in almost all metrics. Although the “2xSMAC, MAD” is not far away in most metrics, and has a lower drawdown than the other strategy (once more the difference is tiny).
In comparison with the Buy & Hold, once again, both strategies demonstrate clear advantages, in all metrics. Not only the returns are better, but the risk associated metrics are also better. Meaning that these strategies obtain better gains that the Buy & Hold without increase the strategies risk.

**Figure 10 – Histogram of the Annualized Returns of the new strategies and Buy & Hold.**

In Figure 11 we can see the evolution of the strategies in the test period. We can see that both strategies cannot
obtain relevant gains in the Bull Market (2004 to the end of 2007) compared to the Buy & Hold. In fact, the “2xMAD, SMAC” use the Buy & Hold strategy during that period, staying all the time in the market. But when the Bear Market of 2008 arrives, the optimized strategies can detect the change of the trend in time, and profit by starting short-selling positions.

5. CONCLUSIONS

This document presented the use of Genetic Algorithms to optimize the parameters of various Technical Indicators and with them create various trading strategies. The results obtained showed that these strategies beat significantly the Buy and Hold (the “2xMAD, SMAC” strategy had an average of 9.1% against the 3.4% of the Buy and Hold), once more proving the validity of Technical Analysis. The use of the composed chromosomes has also shown better results than the use of any of the indicators individually.

6. BIBLIOGRAPHY


