AN INNOVATIVE GA OPTIMIZED INVESTMENT STRATEGY BASED ON A NEW TECHNICAL INDICATOR USING MULTIPLE MAS

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Keywords: Optimization, Technical Analysis, Evolutionary Algorithms, Financial Analysis, Moving Average, Stocks.

Abstract: This paper proposes a new medium/long term investment strategy for stock markets based on a combination of Simple Moving Averages Crossover (SMAC) and Moving Average Derivate (MAD). This strategy is compared with the Buy and Hold, with the Moving Averages Crossover, and with the Moving Average Derivate strategy. The experiments show that the combination of SMAC and MAD outperforms the results of each strategy individually. The presented approach has an average return of investment of 9.0%, compared with the 2.6% return of the Buy and Hold, for the S&P500, FTSE100, DAX30 and NIKKEI225, between 2004 and 2009.

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 (Fama, 1998). 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 (Bodas-Sagi, 2009) (Chan, 2009).

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 (Jegadeesh & Titman, 1993), 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 (Kaufman, 2005) (Kirkpatrick, 2009).

Genetic Algorithms are optimization techniques based on the principles of natural evolution. 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 (Fernández-Blanco, 2008) and to develop investment strategies based on technical indicators (Bodas-Sagi, 2009) (Gorgulho & Neves & Horta, 2009) (Yan & Clack, 2007).

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 has been studied by Brock (1992) and by Kaufman (2005). 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

Simoes A., Neves R. and Horta N..
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DOI: 10.5220/0003058103060310
In *Proceedings of the International Conference on Evolutionary Computation* (ICEC-2010), pages 306-310
ISBN: 978-989-8425-31-7

where the market exhibited a regular uptrend, and no excess profits where possible as reported by Ellis & Parbery (2005). More complete studies of other Technical Indicators has been made, like the one by Canegrati (2008) 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 Fernández-Blanco (2008), 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 by Bodas-Sagi (2009), 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 have been applied to this area of study, like neural networks by Kimoto & Asakawa (1990), where the neural network uses for the inputs the price, volume, interest rate and foreign exchange rate.

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

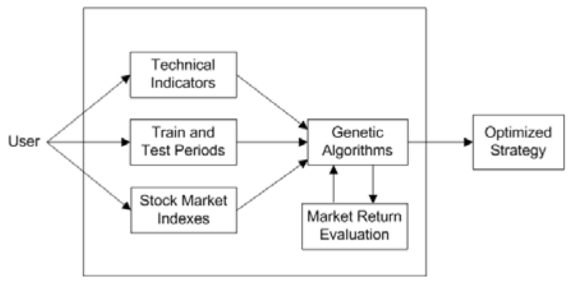

Figure 1: System Overall Architecture.

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 and 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.

The "Technical Indicators" module is responsible for the creation and management of the technical indicators used by all the strategies. The "Train and Testing Periods" module controls the time components of the Stock Indexes. The "Stock Market Indexes" is responsible for loading the stock market indexes from the source (a .csv file).The "Market Return Evaluation**"** module calculates the return and other metrics for evaluating the investment strategy (like the Sharpe Ratio). 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. Finally the Optimized Strategy module is responsible for showing the user the result of the optimization.

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 and the testing period was from 1 January 2004 to 31 December 2009. The markets tested where the S&P500 (USA), FTSE100 (England), DAX30 (Germany) and NIKKEI225 (Japan). They represent the main indexes of the main developed economies.

3.3 Technical Indicators

The first strategy to be tested was the Simple Moving Average Crossover (SMAC) which is composed by two Moving Averages (MA) with different time periods. One of 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.

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 by Kaufman (2005). In the original version it is calculated by subtracting de 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 this generic Derivate of the MA can be calculated based on the definition of Secant of the MA, this way the MAD is calculated by subtracting de value of the current MA with the value of the MA at "n" days ago. Where "n" is one of the variables that will be optimized. The buying signal is given when the MAD is above zero and a selling otherwise.

Beside this two indicators a new indicator is created, called SMAC & MAD that includes the two indicators mentioned above (SMAC and MAD) that signals a buy when both the indicators are buying, does nothing when one of the indicators is out of the market and issues a short-sell signal when both indicators advise to short-sell.

3.3.1 Parameters of Technical Indicators

After defining the strategies it is necessary to define the parameters to use both in the SMAC and in the MAD strategies. Both strategies 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. In both parameters they should indicate medium term periods. The new Indicator (SMAC & MAD) has four parameters, two for the SMAC and two for the MAD. These parameters represent the parameter of the underlying strategies.

3.4 Genetic Algorithm Kernel

3.4.1 Genetic Encoding

The chromosome created must represent the Technical Indicators used, 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. In Table 1 it is shown a representation of a possible chromosome for the SMAC & MAD chromosome (which includes both the SMAC and MAD genes):

Table 1: An example of a Chromosome.

	SMAC		MAD	
Chromosome	25	160	40	100

3.4.2 Features of the GA

The Genetic Algorithm used for the optimization uses a standard optimization procedure. The selection of individuals for crossover is chosen based on a roulette wheel selection (but only the best half of the population enters the selection process), and the probability of being chosen is equal to the ratio: individual fitness function / 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 breading generates the two possible distinct children and includes them in the population. In the chromosome of only one indicator (SMAC or MAD) the children are created by swapping the long and shortest MA day. In the SMAC & MAD chromosome the children are created by swapping the 2 genes that represent each Indicator (the first children takes the SMAC genes from parent A, and MAD genes from parent B, and the second children the other way around).

The fitness function used is the average return of the individual for the 4 Stocks Indexes chosen, during the 11 years of the train data (1993 to 2003).

4 RESULTS

The optimization procedure described above was run fifty times for each approach namely, MAD, SMAC and SMAC & MAD, additionally 50 random strategies were evaluated. The random strategy consists in each day deciding a random trade: long, short-sell or do nothing, each with one third chance of occur. In each run the best individual obtained was evaluated for the test period (2004 to 2009) for the yearly return of the average of the 4 Indexes.

In Figure 2 it is shown the histogram for the returns of the 50 runs although the percentage go only to

50% for better perception of the other values, the Buy & Hold is 100% on the 2.5 column, and the random strategy has 88% in the less than 2.5 column.

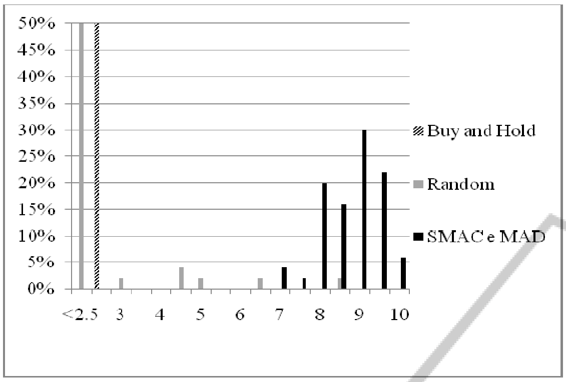

Figure 2: Histogram of returns of the Buy & Hold, Random SMAC& MAD, and SMAC & MAD, from 2004 to 2009.

As we can see in this figure, all the chromosomes beat the Buy and Hold and the random strategy, this confirms the validity of the Technical Indicators proposed.

The SMAC & MAD Compost Chromosome is very similar with a Gaussian curve, which proves that this strategy has the most solid results. The detailed statistics can be seen in Table 2.

In this table it is possible to see that the Buy & Hold and the Random Strategy have the lowest Worst, Median, Average and Best Values. And that the "SMAC & MAD" have Average, Median, and Worst value beating all the other strategies (and the Best value is not far away from the first). This means that using the optimized "SMAC & MAD", not only the expected profit is better, but the possibility of a "bad return" happen during the test period has a low probability of occur, and even if it occurs the return will not be too low (the worst return of the SMAC & MAD in 50 runs in the test period is 7.3%).

Table 2: Statistics of the returns in the test period for the different strategies.

	Buy & Hold	SMAC	MAD	Random Strategy	SMAC & MAD
Best:	2.6%	10.1%	10.5%	8.58%	10.2%
Average:	2.6%	8.5%	8.7%	-1.01%	9.0%
Median:	2.6%	8.9%	8.0%	-1.11%	9.2%
Worst:	2.6%	6.3%	6.8%	-7.33%	7.3%

4.1 Return on Investment

In the next table we can see the yearly average return in the test period of the three best chromosomes found in the training period, with the respective number of trades, contrary to the return (which is annualized), during all the testing period (6 years).

Table 3: Yearly average return and Total Number of Trades of the various strategies tested from 2004 to 2009.

	Average Return	Average Sharpe Ratio
Buy & Hold	2.55%	0.030
SMAC (227, 210)	8.34%	0.570
SMAC (225, 210)	8.27%	0.531
SMAC (222, 210)	7.73%	0.352
MAD (110, 11)	8.15%	0.365
MAD (112, 10)	8.01%	0.349
MAD (112, 11)	7.52%	0.314
MAD(186, 45) & SMAC(202, 193)	9.37%	0.522
MAD (108, 20) & SMAC(206, 195)	8.38%	0.466
MAD(112, 11) & SMAC(242, 128)	8.27%	0.458

In this table we can see that the "MAD & SMAC" strategy have the best, the second and fourth best results. This means that this is the most optimal and robust strategy, because it's the one who maintains the best results from the training period to the testing period.

4.2 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 (Sharpe, 1994). 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.

In Table 3 we can see that the "MAD & SMAC" strategy has worse Sharpe Ratio results that the SMAC strategy (the SMAC has the best and second best result, while the "MAD & SMAC" has the third and fourth and fifth best Sharpe Ratio. The values of the "MAD & SMAC" are more stable with small differences between the best and the worst. This means that the returns showed in Table 3 are due to the "MAD & SMAC strategy" being a bit more riskier (with more variance in the yearly returns) than the SMAC strategy. This means that the deciding factor on the choice of these two strategies is the investor profile risk. The investor can choose between a strategy with better returns but more volatility (the “SMAC & MAD”) and the SMAC with more regular but less attractive results.

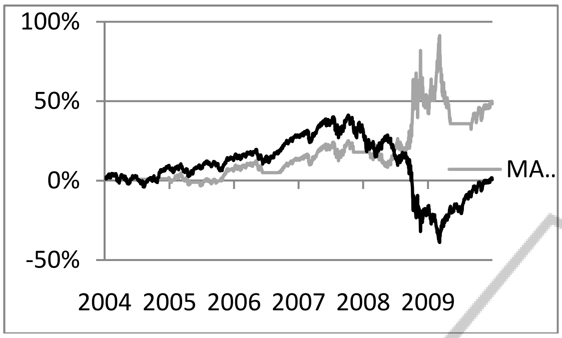

Figure 3: Evolution of the return of the Buy and Hold, and the “MAD (108, 20) & SMAC(206, 195)” strategy, on S&P500 from 2004 to 2009.

In Figure 3 we can see the evolution of the return of the strategy with the best results in the training period, during the test period, compared with the evolution of the Buy and Hold.

The proposed strategy is best suited for medium and long term investment since it only takes a decision after the confirmation of a trend is clear, it has the great advantage of avoiding long periods of downtrends. The classical stategy of Buy and Hold that is only good in markets that do not exibited bear markets like the 80s and 90s in the S&P500 does not perform well in markets characterized by long bear markets.

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 obtain showed that this strategies beat significantly the Buy and Hold (the “MAD & SMAC” strategy had an average of 9.0% against the 2.6% of the Buy and Hold), once more proving the validity of Technical Analysis. Finally the optimized “MAD & SMAC” strategy is compared with the random strategy, with excellent results: the optimized has an average of return of 9.0% against the -1.01% of the random strategy. The use of the “MAD & SMAC” has also shown better results than the use of any of the indicators individually.

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