GENETIC ALGORITHMS BASED COMBINED STRATEGY OPTIMIZATION OF SELECT TECHNICAL TRADING RULES

Jayanthy B[1], Dr. Tamilchelvi N[2]
[1]*Assistant Professor, Department of Commerce with Computer Applications, Nirmala College for Women, Coimbatore*
[2]*Associate Professor and Head, Department of Commerce, TSAAS. Tamil College, Perur, Coimbatore*

Abstract- Technical trading rules have been utilized in the stock market to make profit for more than a century. However, only using a single trading rule may not be sufficient to predict the stock price trend accurately. Complex trading strategies combining various classes of trading rules have been proposed in this paper. An investments strategy for stock markets based on a combination of multiple Technical Indicators rules is analyzed in this work. The strategies generated are compared with the Buy and Hold, and with the single Technical Indicators. From the experimental results, it shows that combined strategies outperform the best results of each strategy, and also the results of the Buy and Hold for 2 Major Indian Stock Indexes.

I. INTRODUCTION

Technical trading rules are widely used in the financial markets as technical analysis tools for security trading. Typically, they predict the future price trend by analyzing historical price movements and initiate buy/sell signals accordingly. Technical trading rules have been developed for more than a century. 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][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 fourteenth 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.

Genetic Algorithms are optimization techniques based on the principles of natural evolution. In [17] is provided a formal study of this subject. This work 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, the use of a GA is considered to obtain the set of indicators and their parameters, which should be used to predict a daily market value. Initially GA has been applied to find the more suitable parameters for the SMAC, MAD and RSI indicators. After that several strategies have been combined, 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.

II. 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 has 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.

III. 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

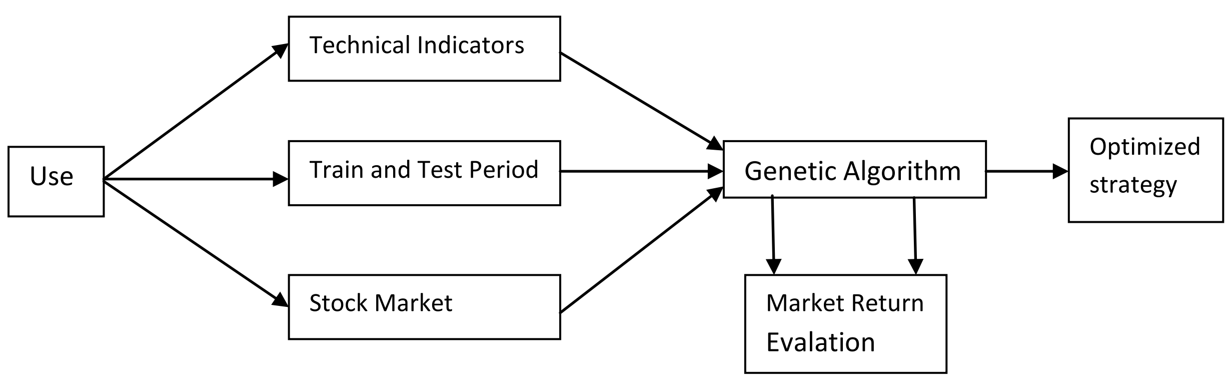

Figure 1 – System Overall Architecture.

The complete process of the architecture shown in Figure 1 is:

• The user starts by specifying the markets to analyze and next chooses the Technical Indicators used in the strategy. Finally, the user chooses the training and testing 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 information is shown to the user displaying the optimized strategy and the return for each market in the test and in the training period.

3.2 TRAIN AND TEST DATA SET

The time period chosen for training was from 1 January 2003 to 31 December 2009, six 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 2010 to 31 December 2013, Three 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 2003 to 2009, 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 BSE and NSE (India). 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)

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

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.

The first strategy to be tested was the Simple Moving Averages 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. 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.

Figure 2 - Evaluation of the SMA(200) from 2003 to 2013 in the BSE.

$$SMAC_{s,l}(d) = \frac{1}{s} \sum_{t=d-s+1}^{d} P(t) - \frac{1}{l} \sum_{t=d-l+1}^{d} P(t) \qquad (2)$$

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.

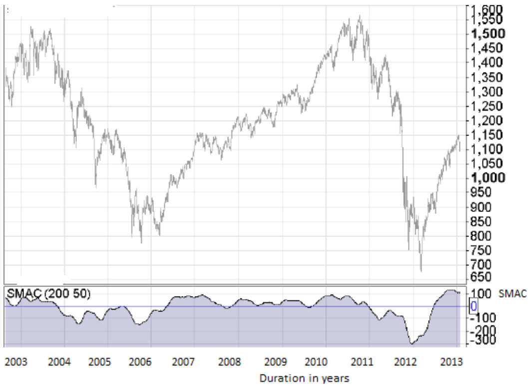

Figure 3 - Evaluation of the SMAC(200, 50) from 2003 to 2013 in the BSE

Another indicator that will be used in this work 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 value1).

$$MAD_{n,g}(d) = \frac{\sum_{t=d-n+1}^{d} P(t) - \sum_{t=d-n+1}^{d} P(t-g)}{ng} \tag{3}$$

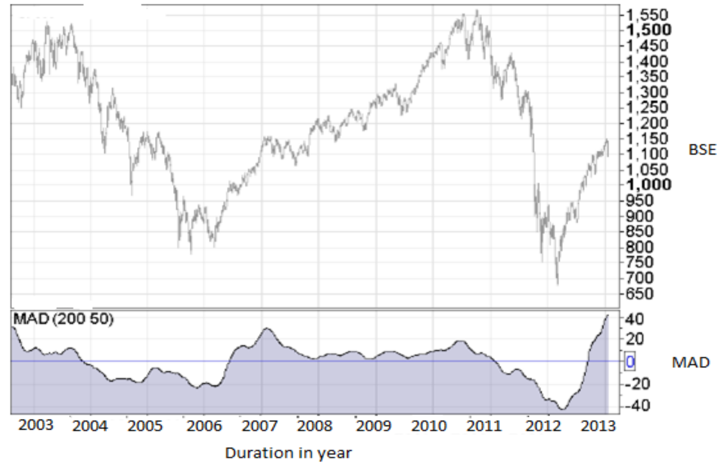

Figure 4 - Evaluation of the MAD(200, 50) from 2003 to 2013 in the BSE.

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 work 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", is visualized in Figure 4, where is shown the evolution of the BSE from 2003 to 2013 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:

$$RSI_n(d) = 100 - \frac{100}{1 + \frac{Ups(n)}{Downs(n)}} \quad (4)$$

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.

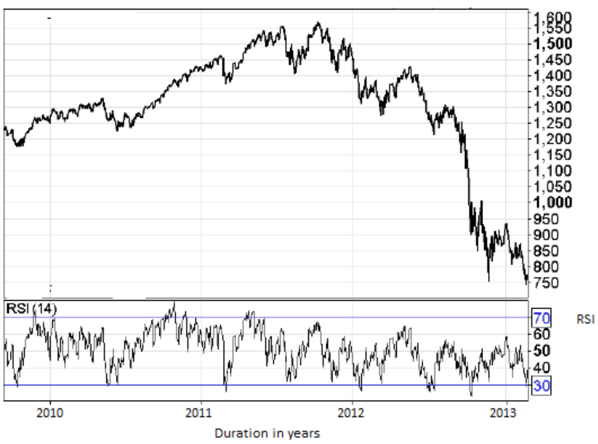

Figure 5 - Evaluation of the RSI 14 from 2006 to 2009 in the BSE

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

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. The RSI is represented with five genes, all being natural numbers, one for each parameter. In the next table is represented the maximum and minimum level allowed for each gene.

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 theb 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 shortsell) 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.

3.4.1 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, MAD or RSI) the children are created by swapping the long and shortest MA day. In the 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 their description and their results can be found on the next chapter.

IV. RESULTS

4.1 METRICS USED

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

$$ROI = \frac{V_f - V_i}{V_i} \quad (5)$$

Drawdown: This metric is used to calculate 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 measure allows comparing two strategies with different returns, and seeing 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)

Sharp Ratio = (R-Rf)/σ (6)

Where, R is the average return of the strategy, R_f is the risk free rate and σ is the standard deviation of the strategy. The risk free rate must be on a treasury security with the same time frame that the investment strategy.

Sortino Ratio: Sortino Ratio is similar to the sharp ratio, because it's also a reward/risk ratio. The main difference is it only penalizes the negative returns but dispersed results as the Sharpe Ratio does. 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.

The Impact of the Fitness function (Test):

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 are: Return, Return – 2 x Drawdown, Sharpe Ratio and Sortino Ratio.

Figure 6 shows the Histogram for the test period of the Annualized Returns for the 50 runs for each fitness function.

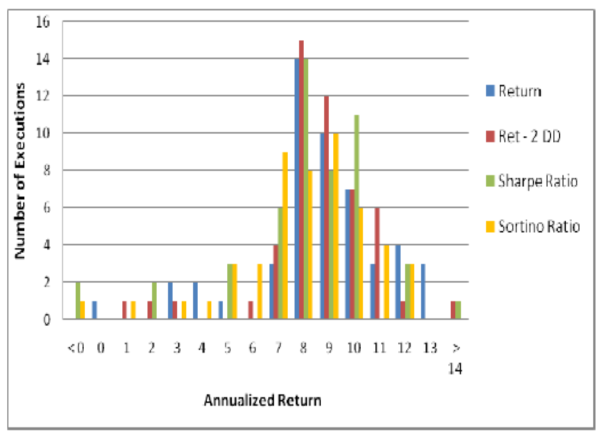

Figure 6 – Histogram of the Annualized Returns for the 4 Fitness Functions.

The Figure 6 shows that, functions have identical results and can be approximated to Gauss distribution.

In Table 1 shows 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.

Table 1 – Evaluation Metrics for the 4 fitness

Evaluation Metric	Returns	Rent – 2 x DD	Sharpe Ratio	Sortino Ratio
Av. Annualized Return	**9.20 %**	9.00 %	8.50 %	8.20 %
Average Drawdown	27.90 %	27.20 %	**29.20 %**	27.90 %
Average Sharpe Ratio	**0.62**	**0.62**	0.58	0.52
Average Sortino Ratio	111.43	**164.58**	161.03	120.24

The evolution of overall return is shown in Figure 7, where once again, the final returns are very similar.

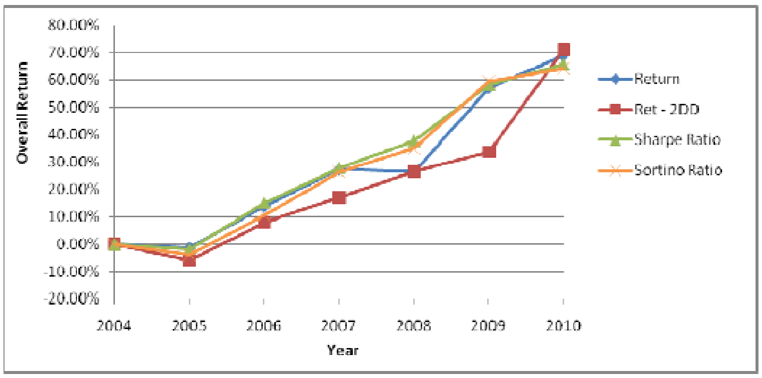

Figure 7 – Evolution of overall return for the 4 fitness functions in the test

Table 2 Statistics for the cumulative profit on the training period.

Type of Profit	Average	Median	Minimum	Maximum	St. dev	Nr Profitable	Skewness	Kurtosis	JB	P val
Real	1,900.05	1,876.10	1,314.00	2,898.00	284.15	300	0.49	2.95	12.25	0.0022
Without Cost	2,007.83	1,968.65	1,436.40	2,967.70	275.93	300	0.57	3.13	16.33	0.0003

Table.2 shows the statistics for the cumulative profit on the training period. In addition, the variability of the outcomes is higher in the testing period (the standard deviation is almost double in the testing period than in the training one). The values of the Skewness and Kurtosis statistics provide evidence that the profit distribution over the testing period may be normal. Table 3 shows the statistics for the cumulative profit on the testing period.

Table 3 Statistics for the cumulative profit on the testing period.

Type of Profit	Average	Median	Minimum	Maximum	St. dev	Nr Profitable	Skewness	Kurtosis	JB	P val
Real	-198.94	-224.00	-1,780.00	1,702.00	550.86	107	0.07	3.04	0.26	0.8788
Without Cost	-109.94	-130.85	-1,672.90	1,749.60	560.75	126	0.05	2.92	0.22	0.8978

V. CONCLUSIONS

This work 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 "2xMAD. SMAC" strategy had an average of 9.2% 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.

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