Combined Pattern Recognition and Genetic Algorithms For Day Trading Strategy

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ABSTRACT
This paper aims at optimizing investment patterns using genetic algorithms. The patterns selected were the "double bottom" and "double top". These patterns were identified in three case studies, with data from the futures of the S&P500 over a period of seven months and from futures of EUR/USD over a period of one year. The tool finds the pattern in a day trade scenario, using the information at the minute level and trade level. The results are very encouraging revealing that it is possible to identify and optimize the detection of these patterns using a genetic algorithm and achieve good returns after withdrawing the transaction costs.

Categories and Subject Descriptors
I.2.M [Artificial Intelligence]: Miscellaneous

General Terms
Algorithms, Performance, Economics, Experimentation.

Keywords
Financial, market, genetic algorithm, pattern matching, optimization.

1. INTRODUCTION
Computer science has evolved exponentially in recent years, and so has the computing power. It has gone from machines as big as a room to as small as an insect. Computers have a relatively short history on financial markets. It has been only for a few decades that market players have had access to computers with the power to aid in financial transactions. This rapid development was in agreement with the evolution of financial markets. Today there is a generation that tries to create intelligent software in order to respond to the market evolution that is constantly changing. In particular, such matters as Evolutionary Computation, Fuzzy systems, Swarm Intelligence, Support Vector Machines and Neural Networks are being widely used in financial markets in many different ways, for optimizing the collection of investment assets or to attempt for the forecast of the future direction of prices by analyzing past market data. Said that, automated trading methods, which are often, referred as algorithmic trading, are becoming increasingly widespread and with their soft computing techniques are widely applied to stock market problems.

Investments in financial markets in the long term can provide higher returns than other assets. This creates a lot of interests around financial markets. There are so many options on market investments, for example a fund can invest in growth stocks to gain rapidly, or invest in a dividend stock for a long term perspective. The investors are constantly looking for new investments strategies to achieve a greater measure of return above the benchmark. Too much time is being spent in this direction. The strategies can be based on models as a simple purchase of shares at low prices or something more complex like having a derived portfolio based on historical data correlated with a portfolio of fixed income securities while dynamically hedging. Investments strategies can be based on qualitative factors or on quantitative factors such as trading futures based on the historical data of the S&P500 future index.

There are tens of thousands of market participants who buy and sell financial assets for several reasons: Expectations of gains, tax reasons, hedging, afraid of incurring losses, "stop-loss", "price-targets", recommendations, fundamental analysis and technical analysis. The so called patterns ("Graphical patterns") put the purchase and sale into perspective by consolidating the forces of demand and supply in a concise framework. Even more important is the help that together with technical analysis, identifying patterns give the winner of the battle between the "bulls" and "bears". The analysis of patterns can be used to perform predictions of short and long term. The information can be "intraday", daily, weekly, and monthly, and the patterns can take place in just one day, or even several years.

The genetic algorithms belong to a class of machine learning algorithms and have been used with a great success in many areas of research. Is a search algorithm based on the principles of evolution and natural genetics combine the exploitation of past results with the exploration of new areas of the search by using "survival of the fittest" techniques among string structures with a structured yet randomized information exchange. The use of them in the identification of graphical patterns has been revealed also a great success. Therefore the system is going to use a GA to identify graphical patterns. In the present case the method is used to identify the "double bottom" and "double top" patterns.

This paper is organized as follows; In Section 2 the related work is discussed. Section 3 describes the methodology used. Section 4 describes the GA. Section 5 describes the experiments and results. Section 6 draws the conclusions.

2. RELATED WORK
Experts from many markets use technical indicators to assess the market. Many technical analysts believe that the variations in prices are not random, they follow some trends. However they also say that there may be periods of time in which shares may not

follow any tendency. Therefore, of most importance is to correctly identify the tendency to obtain better results. To identify graphical patterns it is necessary to examine historical data. Usually the studies of technical analysis looks at quantitative indicators, such as moving average, relative strength index among other indicators [14,2].

Charting patterns, such as flags, saucers, head-and-shoulders, rounding tops and double bottom have been studied. More recent there is an example of the use of technical analysis in the identification of certain graphical patterns. In [9] it is presented an experiment in identifying the bull flag using pattern recognition software. Other authors also studied some of those patterns before [12, 19].

Different approaches are used for making purchase and sale of different assets. Some have the goal to maximize the profits and not minimize the prediction error [4]. They use genetic network programming with State-Action-Reward-State-Action (GNP-SARSA) learning for creating trading rules on stock markets. It consists of judgment nodes and processing nodes that are connect to each other, returning judgment results for assigned inputs and determined the next node. The processing nodes take actions of buy and sell. Other knows approach is the genetic network programming with rule accumulation [15]. The aim of this approach is not to obtain good individuals, but to accumulate a large number of extracted rules in the rule pools every generation, more than the original GNP. Therefore, the rule accumulation is carried out throughout the generations. So, the rules which contribute to the fitness several times in different periods can be regarded as general rules which avoid over fitting to the rare situation in the training, this is the most important point in this method. This method has a particularity that the number of times a rule can be extract can be limited. For example if the limit is set to two, the software can only use the rules extract at least two time for the decision making in the testing. Another method for automatic stock trading is the method that combines nearest neighbor classification [17] and some well-known tools of technical analysis namely stop loss, stop gain and RSI filter (the stop loss was used to limit the loss in a single trade to 3% and the stop gain was used to protect the gain when it approaches to 10%). Like the others methods the objective is to achieve good results in terms of profitability, comparing the results with the profits that would be obtained with the buy-and-hold strategy.

Based on box theory and Support Vector Machine (SVM) algorithm in [20] there is an example of success on a bull and bear market. A two estimator based on SVM regression algorithm is used to forecast the upper and lower bound of the oscillation box respectively. Note that the box theory is that the stock price is supposed to generally oscillates in a certain range during a period of time. After the forecast of the upper bound and lower bound of the price oscillation box are determined, a trading strategy is constructed to make trading decisions. Another effective method to acquire trading strategy in the stock markets that evaluate individuals in genetic algorithms is the neighborhood evaluation [13]. It involves the evaluation of neighboring points of genetic individuals in fitness landscape as well as themselves. This aims for dealing with the difference of the landscapes between the training and the test data.

Another author demonstrates an empirical methodology for creating and testing Artificial Neural Networks (ANNs) for the use within stock market trading system. The methodology presented separates the in-sample benchmarking process, also aims to ensure that if the neural models developed during the in-sample training process are curve-fit, then that is clearly exposed during the out-of-sample benchmarking [18].

To many, technical analysis is a valuable and profitable toll in trading and investment decisions. As a non-arbitrage algorithmic trading system, supplemented by the use of reinforcement learning (RL) we have the Adaptive Network Fuzzy Interface System (ANFIS). The reinforcement learning is used to formalize an automated process for determining stocks cycles by turning the momentum and the average periods [16].

Another success on bull and bear market is the intelligent stock trading system based on improved technical analysis and Echo State Network (ESN) [11]. It conventional technical analysis with genetic algorithm by learning trading rules from history for individual stock and then combine different rules together with ESN. Parameters, such as radius of ESN's reservoir and trading threshold, may influence the profits. Thus the direction of the share price is an opportunity to generate profit in both bull and bear markets. Various types of trend patterns have been categorized, for instance, head-and-shoulders, triangle, ascending and descending channel and cup and handle were characterized [10].

The trend pattern usually indicates a specific trend of the stock price over a period of time. Various types of trend patterns have been categorized [8]. Patterns of price movement that can predict futures prices, such as the "head-and-shoulders" and "double-top" patterns have been analyzed [5].

Although graphical patterns are widely used by traders as an important additional tool in decision making, it is necessary to note how the market is near the graphic pattern. A new approach combining a Symbolic Aggregate approximation (SAX) technique together with an optimization kernel based on genetic algorithms have been describe in [3].

Unlike shares, the futures contracts have a fixed time term. If the contract comes to an end, the future will be settled. In some cases it can be delivery a commodity. Thus many investors make "roll over" on the contract, selling the old future contract and buying the new one that has a new maturity. So the volume data display strong quarterly seasonality due to the "rolling over" of the positions close to the expiry date of the near contract. It´s important to consider that there is a mechanical link between the open interests and the future trading volume [1]. Also others made explicit the relationship between trading volume and change in open interest proving upper bound for this "roll over" [7].

In the futures market it is possible to make a profit by buying a contract to buy when is expected that the market is rising (bull market), or buy a contract to sell when is expected the market is going down (bear market). In table 1 we can see a summary of some of the results of the approaches that have been mentioning.

Table 1 - Investment Algorithms

Ref.	Year	Method	Used Data	Financial Market	Period	Algorithm Performance
[17]	2010	K-NN	Stock Price	Bovespa	01-04-1998 to 09-03-2009	487.74% (Profit rate)
[4]	2009	GNP-Sarsa	Stock Price	Tokyo	05-01-2004 to 30-12-2004	9.8%
[15]	2011	GNP-RA	Stock Price	Tokyo	05-01-2009 to 30-12-2009	13.5%
[20]	2010	Oscilation Box	Stocks and Index	US And S&P500	17-03-2004 to 17-10-2005	Bull-> 37.69% Bear->12.65% Total->25.94%
[13]	2010	GA	Several	Nikkei 225	Jan. 1999 – Dec. 2009	57,4% (Profit rate)
[16]	2011	ANFIS	Stock Price	US	24-08-1994 to 30-08-2006	240.32%
[18]	2010	ANNs	Stock Price	ASX	01-01-2004 to 31-12-2008	338.10%
[11]	2011	GA and ESN	Stock Price	US (S&P500)	01-09-2000 to 01-09-2002	Bull -> 41.6% Bear -> 26.5%

3. METHODOLOGY

The system is going to try to discover the “double bottom” pattern using a genetic algorithm to find what are the parameters of this pattern. This type of pattern is typically formed by two minimums, with a maximum between the minimums, followed by breaking the resistance line. Generally, this pattern marks the transition from the turn of a bearish period for a bullish period. The elements that make up this graphical pattern are the following:

- First minimum (A) - The pattern is recognized by the existence of two minimums, the first minimum usually is the lowest prices of the bearish period;
- Maximum (C) – Between the two minimums there is a maximum that can get some percentage above the value of the minimum. The volume usually increases around the maximum but proves to be inconsequential for a breakout to occur, so the asset declines again;
- Second minimum (B) – Should have a price similar to the first minimum even supposing that there is a slight difference. After this minimum usually there is an increase in the price which is enhanced by an increase in volume. In this situation, breaking the resistance line should be distinguish with the bulls that exert buying pressure that the bears investors cannot undo.

It can be seen in Figure 1, a generic example of the “double bottom” pattern. The point A is the first bottom of the pattern that follows a downward trend and suddenly a shift to a rising trend. The maximum (point C) is detected when the upward trend changes to a downward trend. For the pattern to be complete, another change of the tendency has to happen like on the first bottom, if that happens a new second bottom is identify (point B).

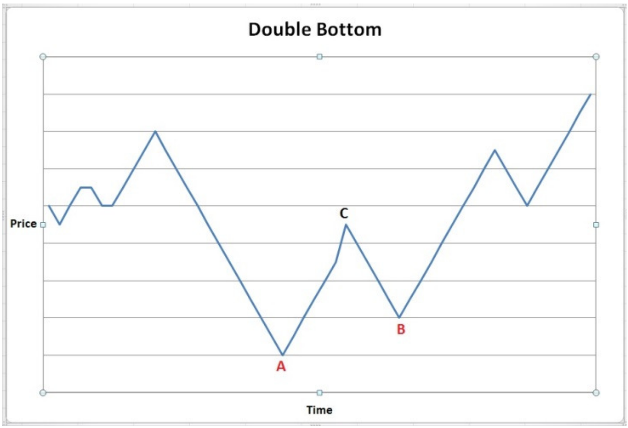

Figure 1 – Generic “Double bottom” Pattern

The hardest part to identify this pattern is to distinguish the false breakouts. This means that after having discovered the second bottom, the first breakup might happen passing the resistance line without there being a reversal in the trend actually. If this happen we probably going to be in a loss, because after having been identified the pattern is the moment when the “long” position is opened. Moreover if the pattern is correct and the trend is upward some profit will be made.

The methodology presented below is generalized to allow various methods of identifying technical patterns, figure 2. The methodology consists of three parts:

- On the first part there is the validation, which consists of four steps. Begins by checking if there is no open position on the market. If there is an open position go for part three. When there is no open position go for the next step, which validates that the minimum time since the close of the last position was reached. In the next step examines whether the tendency of the price on that day is in line with the pattern used, and finally is analyzed the time at which the operation is performed is within the allotted time for the same transaction;

- The second part will only occur if the four steps on the first part are validated true otherwise the first part is repeated. Then it is used the detection method of the pattern chosen. If the pattern is not detected it is repeated the part one, otherwise is opened a position;
- This last part consists in the close of the position. In the first step it is validated if the operation is still within the time allowed for daily permanence in the market. On the second step it will be checked if the target or the stop loss was achieved. If one of the steps is actually true, the position is closed and will be set a minimum value for the time that is validated in the first part.

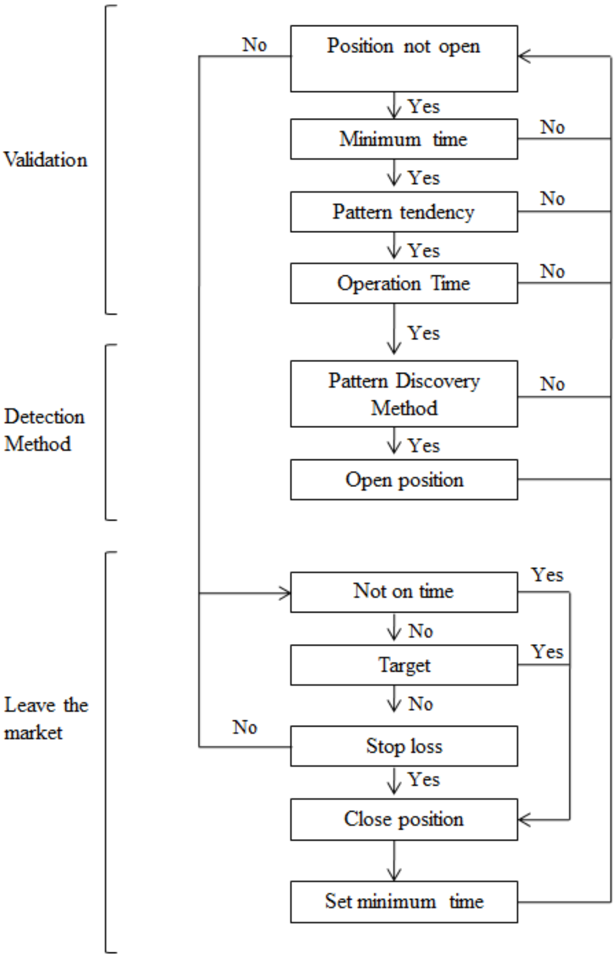

Figure 2 – Methodology

4. GA

This algorithm analyzes each chromosome of the population by applying this methodology. Later uses an evaluation function to select the best individuals that will produce the next generation. This new generation result from the use of selection, crossover and mutation operations. The stop condition is a minimum number of iterations when there is no improvement in the best chromosome.

The parameters used in the algorithm are:

- Population size;
- Minimum number of generations;
- Probability of occurrence of crossover for every two individuals;
- Probability of mutation of the gene position.

It was chosen as an example the technical pattern “double bottom”.

The chromosome of the genetic algorithm used for this pattern consists of the following genes:

- Pattern trend;
- Distance from the first bottom to top;
- Distance from the second bottom to top;
- Strength of the first bottom;
- Strength of the top;
- Strength of the second bottom.

The chromosome is divided into two parts. The first consists of one gene that determines whether a tendency of the price is according to the pattern used. The second is composed of two genes that define the distances between the top and the bottom, and three more genes that identify the trend within the pattern figure 3.

Parameters for rule decision					
Pattern Trend	Distance Bot1 to Top	Distance Bot2 to Top	Bot1 Strenght	Top Strenght	Bot2 Strenght

Figure 3 – Basic chromossome used in the GA.

The pattern trend gene is used in order to make the GA to decide whether or not to open a position according to the investment trend and the market trend, for that it will be used the value of the gene to consider the trend from a certain period of time. The two genes that defines the distance from the bottoms to the top, represents the minimum distance of the prices between those two points. This validation can be done at the end or while discovering the points. The last three genes represent the strength of the trend between the three points. Prices are always changing, and not always follow the same trend. For example, in a one hour period, the price could increase 35 times, decrease 20 and maintain in 5 (considering the price per minute). According with that and the type of the investment, “long” or “short”, the GA will consider the increase or the decrease of the price and calculate a strength that has to be bigger than the value of the gene.

- Other genes that were tried but were discarded because they did not bring improvements in the results were:
- One gene to consider the window for the pattern discovery,

- Two genes to set a minimum time between the three points (bottom 1, top and bottom 2),
- Three genes that defines the minimum distance between the price of the MA (50,100 and 200) and the price,
- One gene based on the value of the VIX that calculates a theoretical maximum variation of the price on the day and validate with the possible gain if a position is open.

Besides the pattern detection, other parameters are used on this work. For example, depending if the investment is "long" or "short" the price variation of the day has to be positive or negative. A minimum and a maximum time to enter on the market is require. After a position is closed, a minimum time "out of the market" is require to open a new position.

The GA uses a random selection process that will only apply to half of the population. In the process of crossover it is used only a one cutoff point. It was studied the option for more points but because of the size of the chromosome is small it was decided to put aside that possibility. The mutation process uses a 20% rate at which each individual chosen will mutate one gene.

The generation of a new population is elitist, because the best individuals will be preserved. The fitness function for this algorithm is represented in equation 1. P represents the profitability and N is the number of winning trades. Unlike many fitness functions that use only the total profit in the training period, it was added the total number of winning trades to give some relevance to the amount of trades performed. The objective is to increase the number of trades, because a solution with a higher number of trades and equal return will be more robust in the test period.

$$P^2\left(\frac{N}{\sqrt{N}}\right) \qquad (1)$$

It was considered to add the maximum drawdown in our fitness function [21]. But because the algorithm is of type day trade and one of the condition of entry into the market is the trend of the day has to be according to the trend of the pattern, we discard this possibility.

5. EXPERIMENTAL RESULTS

In this section three case studies are presented. The application was tested in real market conditions. In the first two the data used was from S&P500 futures contract size $250 and $50. The application of these tests was performed taking into account real market conditions and the data correspond to the period between 01-05-2012 and 31-12-2012. Particularly, the training and testing period were, respectively, from 01-05-2012 to 11-06-2012 and from 12-06-2012 to 31-12-2012. In the third case study the date used was from EUR/USD futures. The application condition was the same as the first two studies. The data correspond to the period between 01-01-2012 and 14-03-2013. The training period and the testing period were, respectively, from 01-01-2012 to 31-01-2012 and 01-02-2012 to 14-03-2013. It was considered a recent period of data, a transaction cost of $3 and $1.5 on buy and $3 and $1.5 on sale. All transactions are made with only one future contract, providing up a scenario closest to the reality. The future "roll over" doesn't affect the experiments since the type of trade chosen is day trade.

On the first two case studies the system starts the trading day with $50,000 for the $250 size contract and $10,000 for the $50 size contract, in cash assets. It was also considered an initial margin of $21,875 and maintenance of $17,500 for the $250 size contract and an initial margin of $4,375 and maintenance of $3,500 for the $50 size contract. On the third study the system starts with $100,000 and the contract is 0.0001 per euro increments ($12.50/contract) and has an initial margin of $2,475 and maintenance of $2,250 which represents paying a total of $6 commission for opening and closing one position.

5.1 Case Study I

The big difference between the first two case studies is how the data is organized. In this case study it was considered the data with a minute time frame. The parameters used were a population of 200 elements and the minimum number of generations without improvement used as stop criteria is 20. The test was repeated t for 10 runs.

As already mentioned previously, one of the patterns chosen as example, was the "Double Bottom". The test follow the methodology describe earlier. After the first part of validations it follows the pattern detection.

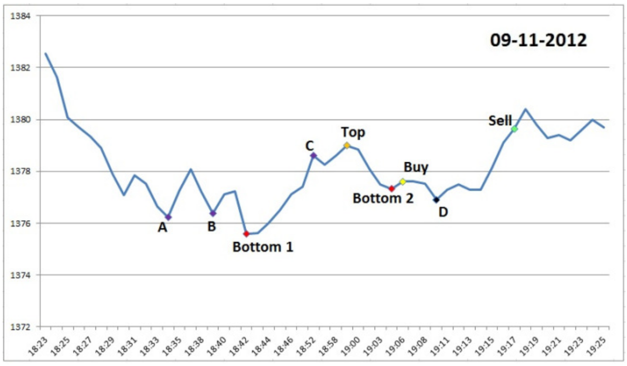

Figure 4 – Double Bottom Pattern identified by the method for the SP500

Figure 4 represents an example of the identification of the "double bottom" pattern with our method during the test. The algorithm first detects Point A at 18:34 with a price of 1376.23, which is just after a downward trend and will marks it as a possible first bottom. Now the software is going to look for a better first bottom point or for a maximum to mark as a possible top. The price is rising but the value is not high enough to mark any point as top. Then the price starts again in a downward trend and the algorithm see Point B at 18:39 with a price of 1376.38. Point B is not a better bottom 1 then Point A so he will keep Point A as a possible first bottom. At 18:42 he finds a point with the price of 1375.59 that is a better bottom then point A and then he marks that point as possible first bottom. After that the algorithm detects a maximum at point C at 18:52 with a price of 1378.61, by this time he marks bottom 1 as the first bottom and marks point C as a possible top. Then he finds another maximum at 18:59 with a price of 1379 that is better than the point C, so he marks as a new possible top. He keeps bottom 1 as first bottom by this time, since he only found a better top. At 19:05 with a price of 1377.33 he finds a bottom that he marks as a second bottom. So in the next minute at 19:06 with a price of 1377.6 he opens a "long position" and sets the target and the stop loss. At 19:09 he finds point D with a price of 1336.9. This is a minimum but the stop loss is lower than this price so he keeps the position opened. After that at 19:17 the target is reached with the price of 1379.64 and he closes the position with a profit of 2 points. The algorithm uses always a stop loss to minimize losses and a target to preserve the earnings. In this case the position is close when it reaches the target (2 points) though when looking at the graph it was possible to make a bigger profit.

Not always the algorithm makes profit. The following figure 5 is an example where the algorithm detects the pattern double bottom with loss. Then the price is going in a downward trend and the algorithm finds a better point for Bottom 1 at 16:56 with a price of 1418.85.

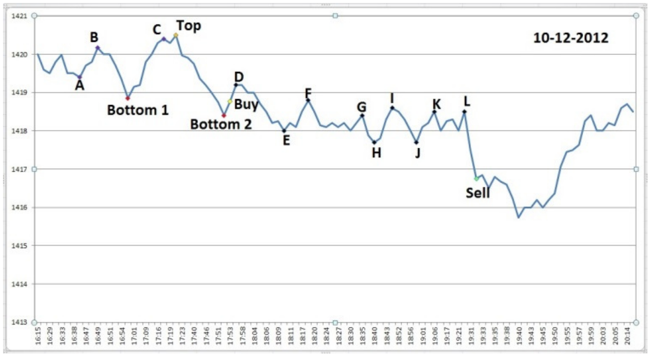

Figure 5 – Double Bottom Pattern identified by the method for the S&P500 with loss

As was said before, figure 5 represents an example of the identification of the "double bottom" pattern with our method during the test period with loss. First, the algorithm detects point A at 16:42 with a price of 1419.4 and marks it as a possible first bottom. The price is rising and the algorithm finds point B at 16:49 with a price of 1420.17, however the price is not high enough to mark this point as top. Again the price is rising and the point C if mark as a possible top at 17:18 with a price of 1420.4, the price continues to rise and at 17:22 with a price of 1420.5 the algorithms finds a better top and marks it. The price starts again in a downward trend and the algorithm find bottom 2 at 17:52 with a price of 1418.4 and in the next minute it open a "long position" at 17:53 with a price of 1418.77 (Buy), setting the target and the stop loss respectively at 1420.77 and 1416.77. The algorithm continues the matching of all prices while we are in the market with the target and the stop loss. Points D, E, F, G, H, I, J, K and L and extreme points where the trend changes and have more chance to reach a target or the stop loss. However the price never reaches 1420.77 or 1416.77 until at 19:32 with a price of 1416.75 where the algorithms reach the stop loss and close the position with a loss. We can see at figure 13 that the price will rise again and if the stop loss was greater it was possible to not close the position at that time with loss, however that could increase the losses in situations where the price keep falling. Another option was to set a maximum of the time in the market, where even if the target or the stop loss wasn't reached the algorithm closes the position. On this example if there were a maximum time in the market of 30 minutes the position was close with a higher price decreasing the loss. This could be useful to predict when the market is undecided and the probability of the pattern to fully form is inferior.

All the transactions have to be made on the same day (open and close the position) and between 08:30 and 21:00, and also the trend on that trading day has to follow what is configured for the method. For example can reasonably be argued that the trend on the last two hours has to be upward, or that based on VIX the maximum daily variation is near the limit of the day so cannot be opened a position right now, or in the extreme we only trade in a positive day.

The following table represents the test result of the ten runs. During the training, the winning percentages were between 64.15 and 64.64 and the total training trades are between 99 and 106. It can be observed that the results of the training are relatively close to the results obtained during the test presented on table 2. During the test there was an average trade of 436 of which 265 were winning trades.

Table 2 – Test results

Average Trades	Average Winning Trades	Average Winning %	Standard Deviation
436	265	60,77	0,75

The average time on the market is 23703 minutes what represents an average of 54 minutes for trade. Also the average maximum consecutive wins are 13 against 7 maximum consecutive losses.

It's also important to mention that between the training and the testing the winning percentage dropped 3%, which is acceptable.

The profitability over the test rises in a constant way, which indicates that there are not long periods where there are big losses. In figure 6 is shown the profits in the S&P500 futures contract $250 considering transactions costs of $10 and $6 respectively.

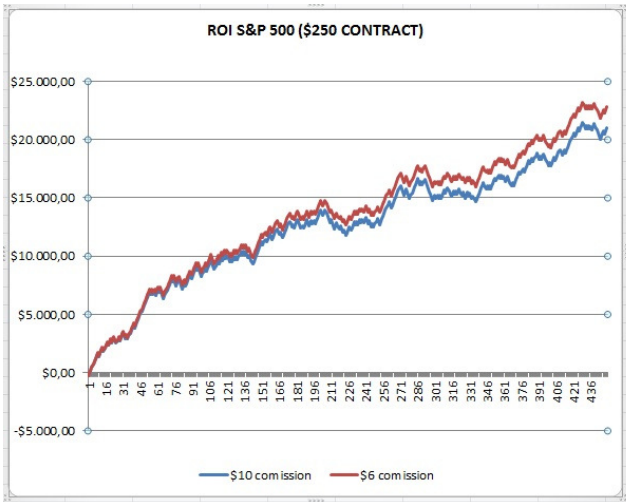

Figure 6 – Profitability over the period in case study I, assuming the $250 contract

However, if the future contract purchase is the $50, as can be seen in figure 7, the transaction costs has a huge weight in income. The difference of paying $6 instead of $10 cannot be regarded.

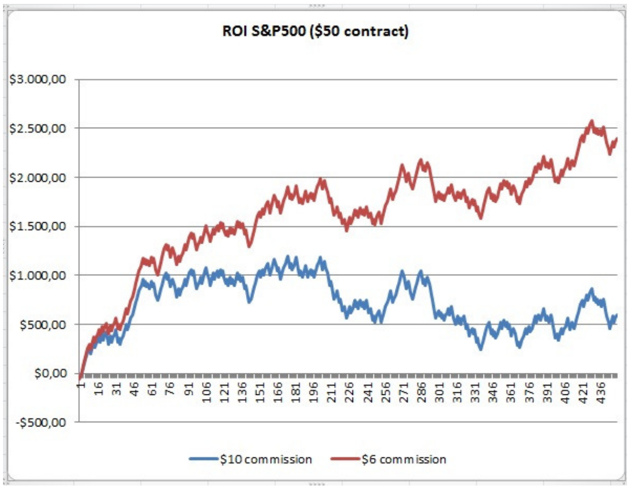

Figure 7 – Profitability over the period case study I, assuming the $50 contract

5.2 Case Study II

As was said at the beginning of section five, in the first two case studies, the data is relative to the S&P500 futures contract size 250 for the same period of time. In this case the software is going to use more information about the actual trading using all the individuals trades in every minute, in other words, all the data transactions rather than the minutes only. This means that on the same minute there are 20 or even 40 trades. The total data used had more than 400 thousand trades. That is four times the number of trades used on case study 1 for the same period.

It should be taken into consideration that although the data used in both study cases is from a period of only seven months, the number of datasets is large, because on the first case it was used the data on a minute basis and on the second is even more large because it contains all the transactions.

Only one contract will be traded each time and it was considered a total cost of $10 for the transactions costs. The parameters used on this test were the same used in case study I. It was also repeated the test for 10 runs. In this case it was detected the "double bottom" and "double top" pattern like it was performed on case study 1.

Was also studied the possibility to add a position further in the same direction when a profit was incurred for a given traded position [6]. It was put aside this possibility, because it was intended to be the minimum possible time in the market.

On figure 8 can be seen the results of the winning percentage of the 10 runs of the test. As can be seen the linear is constant thought the runs that mean was obtained a good consistence on the winning percentage.

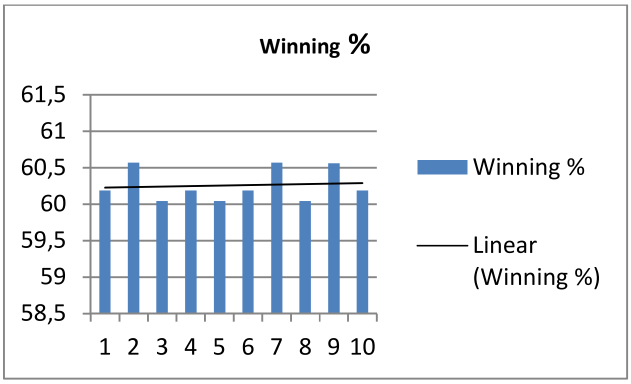

Figure 8 – Winning percentage of the 10 Runs

On table 3 is presented the average trades and winning trades as the average of the winning percentage of all runs. The average trades were 2.1 times more than the average number of trades of case study 1, with an average winning of 60.27 %, what is a good result. The fact that the standard deviation is low indicates that the results are solid.

Table 3 – Test results

Average Trades	Average Winning Trades	Average Winning %	Standard Deviation
959	578	60,27	0,22

As happened in case study 1 the profitability over the period assuming the $250 contract is consistent as shown in figure 9, also as the number of trades are higher the difference between the $10 transaction costs and the $6 transaction costs occurs increasingly less.

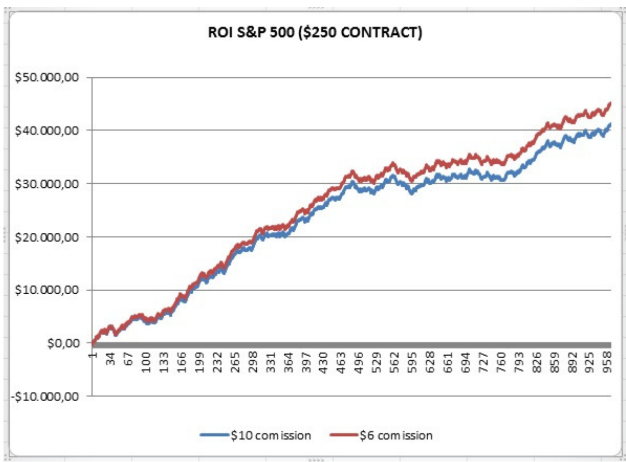

Figure 9 – Profitability over the period in case study II, assuming the $250 contract

Figure 10 shows why the cost of the transactions may be an important factor which cannot be ruled out. The difference of the $10 transaction cost to the $6 clearly defines the success. In both cases the maintenance margins have always been complied.

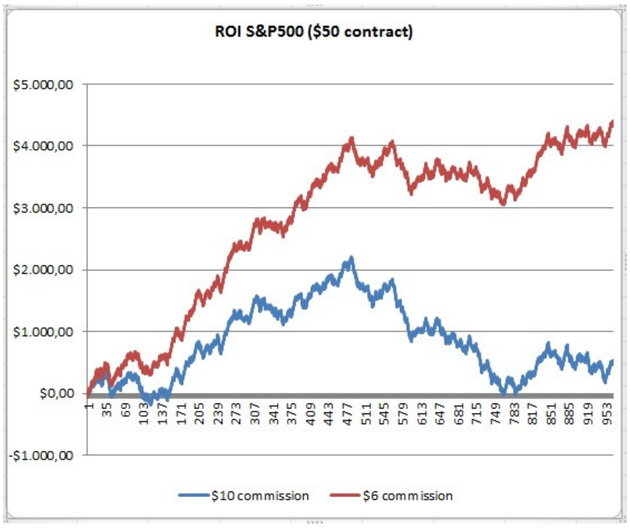

Figure 10 – Profitability over the period in case study II, assuming the $50 contract

The “short” investment on the period is not as good as the long investment since is a bull period what is reflected in the number of transactions that is proximally 5 times less (figure 11). Unlike what happened with the “long” investment during the period on this contract, the ROI was not always positive.

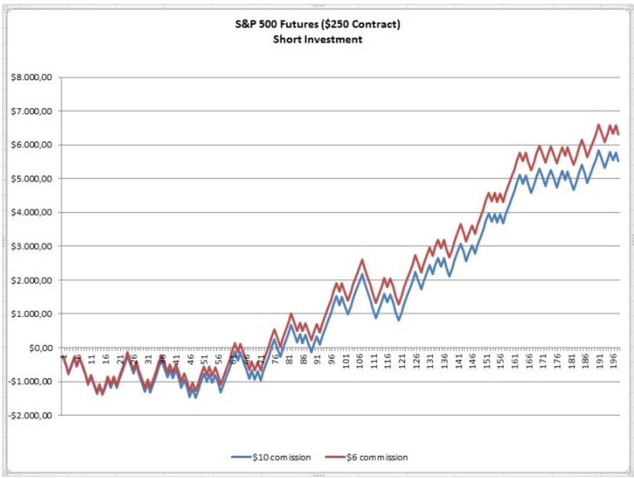

Figure 11 –Profitability over the period assuming the $250 contract on short investment

5.3 Case Study III

The data used on this case study differs from the first two since it was used the EUR/USD futures instead of S&P500 futures.

The parameters used on this test and also the pattern detect were the same used and detected in the other cases. It was also repeated the test for 10 runs. The commission prices for this type of contract it changes based on the amount invested during the year. In this case and taking the consideration of the number of transactions made and the amount invested on each transaction it was considered a total of $6 for $100000 investment and $3 for 500000 investment. It is important to notice that with the leveraged it is not need to have that amount in the account.

Figure 12 represents the result of case study III considering the $6 and $3 commissions. Despite the result at the end is very positive, there were periods when the investment had high losses specially assuming the $3 commission that had an investment of $500000. Nevertheless the $25000 available for investment was never reached. The ROI of both amount of investment is considerable different, on the first we have a more controllable gain/loss than on the second where is paid half the price for the commission but the gain and the losses are greater. Some investors are not capable of have periods with such losses and will prefer the first amount of investment even with the high hypotheses of have very good profits.

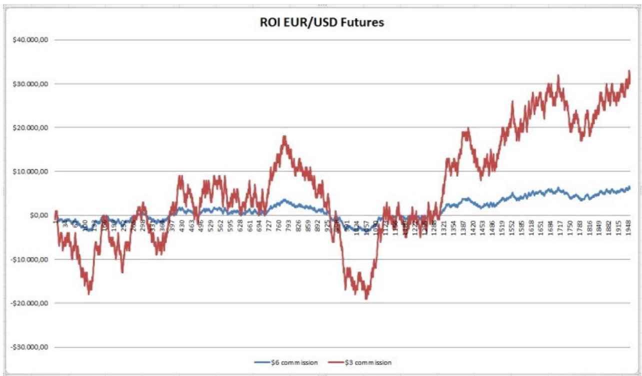

Figure 2 –Profitability over the period assuming the EUR/USD future

The difference on the ROI because of the amount of investment is notary. Figure 13 represents the ROI based on the “Short” investment algorithm paying $6 and $3 commission. On this example the pattern identified was the “double top” pattern.

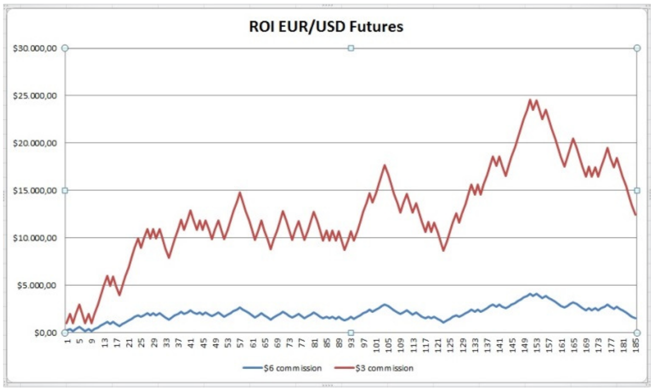

Figure 13 – Profitability over the period assuming the EUR/USD future (short investment)

During the year 2012 the B&H of EUR/USD future had a small amount of profit or loss depending if was “short” or “long” and finish the 14-03-2013 with a small profit of $830 and $4150 for the “short” investment and with a small loss of -$830 and -$4150 for the “long” investment. Figure 14 illustrates the profitability of

B&H with a long investment and with a short investment during the period for $100000 and $500000 amounts.

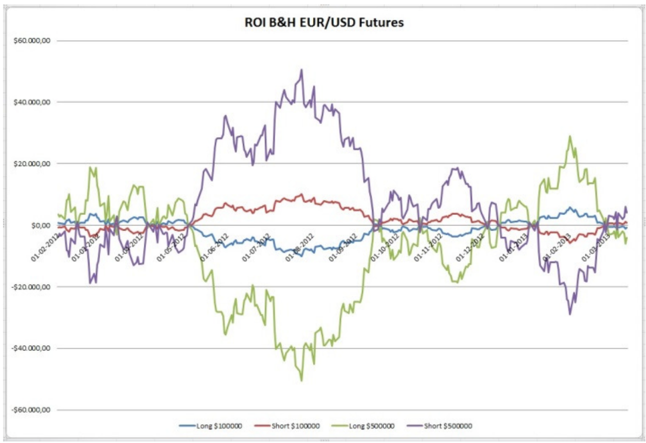

Figure 14 – B&H profitability over the period assuming the EUR/USD future

The first result presented on this case study and the B&H long investment (B&HL) had big losses over the period. The maximum accumulated losses from the GA reach -$3806 for the $6 commission ($100000 amount) and -$19003 for the $3 commission ($500000 amount) on the "long" investment, on the "short" investment the ROI never become negative. The B&H had a maximum accumulated of losses from -$50600 and -$28950 for the $500000 amount of investment in the "long" and "short" respectively and -$10120 and -$5790 for the $100000 amount of investment. At the end GA for the "long" investment had a profit of $5994 for the $100000 investment and a profit of $29997 for the $500000 investment. On the "short" investment it had a profit for the $100000 amount of $1490 and for the $500000 of $12445.

6. CONCLUSIONS

A sturdy GA system was applied to optimize the parameters that describe the pattern chosen as an example ("double bottom" and "double top") that has been identified with great success during the intraday S&P500 futures trading and EUR/USD futures. The first two case studies that were presented have performed well with a winning percentage higher than 60% on both cases and a low standard deviation that indicates consistence. It was also verified that the transaction costs in short term transactions can have big influence in the overall earnings obtained.

Throughout the work developed it was found that the use of the genetic algorithm in order to improve the performance and obtain better results was a success. The way that the GA optimizes the search for the best solution in order to obtain optimal results is important. Is possible to further improve the search in order to seek better results with a few changes in the configuration file. For example it is possible to increase the number of generations or the number of the population, though the time spent will also increase substantially. Another way of trying to increase the success the outcomes may be changing the probability of the crossover or the mutation of the genetic algorithm. The selection used on this dissertation was elitist. The results will probably be different if another type of selection could be used.

The results obtained using the developed trading system make it possible to say that this system may be successfully used for futures trading in systems for automatic trading. Overall, our results show that is possible to create strategies conditioned by the occurrence of "Double Bottom" and "Double Top", with positive returns, which indicates that these patterns can capture from stock historical prices some signals about their future price trend that makes possible to create profitable strategies even when the effects of transaction costs are considered. The results in favor of the ability to forecast of the patterns, even when taken into account transaction costs inherent in the stock market are elevated enough to maintain their economic attractiveness for the investors, in special the bigger ones, with access to lower transaction cost.

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