ABSTRACT

This work proposes an investment strategy using Genetic Algorithms applied to the stock market. In order to build a portfolio of promising stocks we look at fundamental analysis by using indicators such as earnings volatility and growth, Price-to-Earnings ratio and Price/Earnings to Growth ratio. Additionally technical indicators such as moving average crossovers and Relative Strength Index are used to adapt the portfolio to the market’s trends. The proposed solution was applied to the S&P500 Index during the period from 2006 to 2011. In order to evolve a robust strategy these are evaluated according to the average return on investment, Drawdown and Sharpe ratio. The results obtained are promising with the solution outperforming the market with a considerable lower level of risk.

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

Keywords
Computational Finance, Technical Indicators, Fundamental indicators Evolutionary Computation, Investment Strategies

1. INTRODUCTION

When studying financial markets the main issue is of course predicting price movements, but these are highly noisy systems, being influenced by a myriad of economic and politic factors such as companies’ earnings, news or natural disasters. As such they are extremely hard to predict, nonetheless investors widely use market analysis techniques to study and forecast market movements. These methods are technical analysis which studies the price and volume of the assets, using past information to predict the future, and fundamental analysis that deals with various economic and politic factors, looking down from the global economy all the way to the company itself.

Therefore, this work proposes an application of a method from Evolutionary Computation, the Genetic Algorithms, to the stock market, which together with technical and fundamental analysis, can help an investor to decide where and when to invest.

The presented paper is structured as follows: Section 2 describes the architecture of the developed application. Section 3 evaluates the developed system. According to a validation procedure based on various financial metrics the application’s performance is discussed. In Section 4 the conclusions are drawn.
by the most recent scores but by past scores as well, in order to do so, each company’s weekly score is an Exponential Moving Average (EMA) of the past scores, and the smoothing factor of the EMA being controlled by the Genetic Algorithm.

3. RESULTS
For the following case study it was used data from 273 stocks, for which there was both price and earnings data without missing records, from the SP500 Index from August of 2006 to August of 2011. From this data 70% is used for training and the remaining 30% for testing as presented below. In order to access the performance of the developed strategies, and to be able to compare it between our various solutions and the results of other works we define the following measures.

Return on Investment (ROI) is perhaps the most important and simple measure for evaluating an investment. This is simply the gain over a specific period.

Drawdown (DD) is a useful measure of risk, it measures the maximum loss incurred over the investment time. It is usually defined as the percent difference between a peak and posterior decline. The drawdown is very important for the investor as it measures how much he may lose during the investment.

Sharpe Ratio (SR) is a popular measure that measures reward against risk, more specifically it measures the excess return against a risk free investment per unit of risk. This ratio calculates the excess gain against a risk free investment and then adjusts it by the strategy’s risk, this way the Sharpe Ratio measures if the investor is being appropriately rewarded for the risk he is taking.

3.1 Case Study – Bull/Bear Separation
Based on the classification of the market trend as Bull or Bear, the current experiment computes the performance separately for the Bear and Bull periods in order to guarantee that each individual has a good performance for both trends. The classification is based on an RSI of 8 weeks with some ‘noise removal’ so that each sub-period lasts longer than one month. The fitness value is computed separately for each, with the final value being the product of the two fitness values (with the sign being logically adjusted). The results are presented in Table 1.

![Figure 1 - Results of the Best and Typical Bull/Bear Solutions](image)

Table 1 – Results for the Overall and Bull/Bear Solutions

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Bull/Bear</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Training</td>
<td>Test</td>
</tr>
<tr>
<td>ROI</td>
<td>Maximum</td>
<td>20.01%</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>15.04%</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>10.11%</td>
</tr>
<tr>
<td>DD</td>
<td>Maximum</td>
<td>11.47%</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>7.54%</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>4.72%</td>
</tr>
<tr>
<td>SR</td>
<td>Maximum</td>
<td>0.514</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>0.368</td>
</tr>
<tr>
<td></td>
<td>Minimum</td>
<td>0.243</td>
</tr>
</tbody>
</table>

The solutions for which the performance was measured separately for Bull and Bear phases outperform the overall solution. Since the solutions should exhibit good performances during both ascending and descending markets, solutions which amassed great results during one of the market trend but were bad at the other are filtered as the Bull/Bear solution should filter some overfitting. This improvement is evident as the results during test for the separated performance solutions (Bull/Bear) are considerably better than those for the overall performance solution. The same applies to drawdown where when testing the solutions evolved via the separated performance model successfully reduce drawdown values to around 14% for most cases against 20% for the Overall performance solutions.

This later model presents notable improvements from the simpler GA but there is still a considerable downgrade in the solutions performance when testing. This can be seen below where the evolution of accumulated ROI is depicted during the training and test periods for the Best and Typical/Average GA (during Test) against the Index B&H.

It is noticeable, as we can see in Figure 1, that the typical GA has a better performance until the market crash but that afterwards the best (during test) GA quickly outperforms the typical GA solution.

4. CONCLUSIONS
This work presented an application of Genetic Algorithms for optimizing investment strategies applied to the stock market. For this purpose the application uses fundamental analysis for finding promising stocks and building a portfolio, and uses technical analysis for managing the portfolio according to price movements. The testing of the case study using training with a Bull and Bear market separation outperform the solution based in a single type of market, creating a more robust implementation.

5. REFERENCES