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Abstract

This paper presents a new approach combining Genetic Algorithms (GA), Markov Chains and Risk Parity strategies to create an asset portfolio neutral to market risk. GA is used to select ten companies from the SP 500 index through technical and fundamental analysis. These ten companies are separated into two groups (one group for long position investment and the other one for short-term investment). The Markov Chain tool serves to determine how likely it is that a given company will have higher returns than those mentioned in the SP 500 index. Finally, the weight of each asset in the portfolio was determined by using a Risk Parity allocation strategy. The proposed approach was tested resorting to companies included in the SP 500 index, and considering their performance between 2015 and the first half of 2020. The results obtained for the testing phase showed that this is a market-neutral strategy, as it achieved a return of 49.7% during the first semester of 2020, which corresponds to the early stages of the new SARS-CoV-2 crisis. The average semi-annual return was 14.8%, while the average for the whole SP 500 was only 3.9%.

Keywords: Financial Markets, Market-Neutral Strategy, Genetic Algorithm, Markov Chain, Risk Parity

1. Introduction

When studying the stock market, a reliable forecast of the next economic cycle is the key to success. However, building a strategy that will survive any economic cycle represents a great challenge. The primary goal in portfolio construction is to get a trade-off between return and risk. The pioneering work developed by Markowitz (Markowitz, 1952) remains valuable in modern portfolio theory, as it studies how asset risk, return, correlation and diversification can influence probable investment portfolio returns. However, in periods of financial crisis, such as that of 2008, many of the portfolios used in the Markowitz model did not survive (Kaucic, 2019). As this model depends both on the expected return value and on the correlation between assets, the latter increased during the crisis, which led to a decrease in diversification.

Unaware of the next economic cycle, a market-neutral strategy is a way to build a portfolio that eliminates the systemic risk of long positions. The strategy seeks to generate investment returns that are independent of the market environment through a portfolio coupling long and short positions in different stocks (Wiley, 2005). In this work, we propose a portfolio including ten companies from the Standard Poor’s 500 index (SP 500), which is the most prominent index in the USA composed of 500 commission-selected companies listed on the New York Stock Exchange or NASDAQ (National Association of Securities Dealers Automated Quotations). The ten companies are separated into two groups (an open long position group and an open short position one). To select the set of ten companies, we used an approach that combines Genetic Algorithms (GA) to optimize the indicators, Markov Chain to sort out how probable it is that the company will have returns above those mentioned in SP 500, and Risk Parity for portfolio allocation. This article is organized as follows: Section 1 introduces the problem and sets the goals; Section 2 presents some financial issues used in this study and the proposed solution thereof; Section 3 describes how the algorithm is formulated; Section 4 assesses the system with real data; Section 5 reports the main conclusions of this work and proposes further studies.
2. Background
This section provides fundamental concepts dealing with market-neutral strategy, technical and fundamental indicators and evolutionary computation.

2.1. Financial Concepts
Market-Neutral Strategy does not take advantage of market trends. The main goal is to find a set of assets liable to produce higher returns than the market and another set of assets producing lower returns than the market (Johnson, 2014). This way, this strategy is not dependent on how economy or inflation evolve. Figure 1 shows how one can profit from such a strategy when the market is either rising or falling. The key point is how to select the assets above and below the index in the most adequate way.

2.2. Financial Analysis
There are two types of financial analyses: Technical Analysis and Fundamental Analysis. Technical Analysis is the investor’s prediction of the future prices of financial assets relying on past information based on price, volume, support and resistance levels (Schabacker, 2005). Alternatively, one can use Fundamental Analysis to conclude whether the assets are undervalued or overvalued. Fundamental Analysis probes anything that may affect security value, be it microeconomic or macroeconomic factors (D. Owen). Both techniques presented above have advantages and disadvantages. Therefore, the safest approach to analyse the market is reconciling the two analyses before investing.

2.3. Markov decision process and the genetic algorithm
The GA was proposed in the 1960s by John Holland, who introduced the concept of heredity, inspired by biological processes like evolution, survival, and adaptation to the environment. A differently featured population of individuals composes the GA. Each individual is represented by a sequence of genes and each gene codes for a value of a variable within the search space; this way, each chromosome encodes a different solution for the problem. This solution is evaluated according to a fitness function that reflects how the individual performs. The fitness function (A. Gorgulho, 2011) uses Return on Investment (ROI) to assess each individual. To improve this model, usage is made to a fitness function that reflects how the individual performs. The fitness function (A. Gorgulho, 2011) uses Return on Investment (ROI) to assess each individual. To improve this model, usage is made to a fitness function that reflects how the individual performs.

2.4. Risk Parity
Risk parity is a portfolio allocation strategy using risk to determine allocations across various components of an investment portfolio. With a risk parity strategy, the investor creates a portfolio with equal risk contributions. It is about having each asset contributing in the same way to the portfolio’s overall volatility. Suppose we have n risky assets and a covariance matrix. The following optimization problem helps to minimize the gap between each contribution (Massimiliano, 2019).

\[
\text{minimize} \quad \frac{1}{N} \sum_{i=1}^{N} \sqrt{x^T \sum x} - x_i \star \frac{\sum_{i=1}^{n} x_i^2}{\sqrt{x^T \sum x}}^2
\]

\[\text{Condição} \quad \sum_{i=1}^{N} x_i = 1\]

where \(x^T\) is the vector of the weights of the assets and \(\sqrt{x^T \sum x}\) is the vector of marginal risk contribution for the assets in the portfolio. Both the minimum variance portfolio and the equally weighted portfolio are presented, which indicates that risk parity could be viewed as a compromise between these two strategies (X. Bai, 2016). Further remarks regarding this paper are in the context of long-short portfolios, while the risk parity is a more difficult problem as it could imply any of a large number of solutions.

3. Proposed approach
The proposed solution is aimed at developing an algorithm to trade assets in SP 500, in order to create a portfolio neutral to the market using GA, Markov Chain and Risk Parity. The system architecture is implemented into two separated layers, where the first layer is the choice of companies and the second layer is the portfolio allocation.

3.1. Overall architecture description
This paper proposes a trading system that uses daily closing prices from last year of each company and the SP 500 ranking, other fundamental data and the date when the company was added to the SP 500. As the goal is to build a market-neutral
strategy, it is necessary to create two groups. One of them comprises five companies managing to achieve the best performance in the following semester, while the second group will include the five companies with the worst performance in the following semester. To come up with this selection, we used the daily prices of the last year, 2019, to calculate six indicators, financial data and the Global Industry Classification Standard (GICS). To optimize these indicators and build a ranking, a GA was used in order to find the five candidates for both the long model and the short one. After choosing the ten companies, 50% of the capital is invested in each group. However, in order to balance the portfolio risk, no two companies share the same percentage values. In order to find the percentages, the Risk Parity associated with a GA is what determines the target risk for each group.

3.2. Data pre-processing
When dealing with real-world data, it can prove faulty, and, what is more important, data quality may affect the results. Therefore, to improve its quality, data needs to be pre-processed. The input data is divided into two distinct sets: the training data set used to train the model and the testing data set used to test the performance of the model.

3.3. Markov Chain
A stationary distribution of a Markov chain is a probability distribution that remains unchanged in the Markov chain as time progresses. A market-neutral strategy is based on the comparison between company/index returns. Therefore, stationary distribution provides information about the stability of a random process and, in certain cases, describes the limiting behaviour of the Markov chain, which can lead us to conclude whether the stationary vector is more likely to produce returns higher than the index ones. The state 1 is when the company has a daily return greater than the SP 500 index and state 2 is when the company has a daily return lower than the SP 500 index. The probabilities A, B, C and D are:

- Transition A: Probability of going from a return status above SP 500 to a return below SP 500
- Transition B: Probability of maintaining a return above the SP 500;
- Transition C: Probability of going from a return status lower than SP 500 to a return greater than SP 500;
- Transition D: Probability of keeping a return lower than the SP 500;

3.4. Technical Analysis
This module receives closed prices and applies own technical indicators and two fundamental analysis indicators (net profit and earnings per share), resulting in a data set with eight features (presented in table 1).

3.5. Data normalization module
The data set shown in section 3.2 needs to be normalized using the Min-Max normalization technique presented in Eq. 2, which will rescale every feature in the data sets to the range of [0,1]. This module is important because, in this way, no indicator in Table 1 can dominate the data set

\[ x' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \]  

3.6. Genetic Algorithm
3.6.1 Chromosome Representation
The chromosome structure is an array of floats in which each gene of the chromosome is the parameter for each indicator (and its weigh, accordingly). The values for each gene are randomly set between zero and five. The structure of the chromosome is shown in Table 2. This work uses 9 different genes, 6 of them being own technical indicators, 1 being a stationary vector, and 2 referring to fundamental analysis.
3.6.2 Fitness function

The main goal is to measure the algorithm’s accuracy to choose the top five companies in each group. In Table 2, two solutions are apparent. Individual x has a total score of 5, while individual y has a total score of 2. Thus, the individual x has a better performance than individual y. If the individual chooses a company in the top 5, 2 points are added; if the company is between 6th and 10th position, then 1 point is added; otherwise, points are not added.

<table>
<thead>
<tr>
<th>Score</th>
<th>AMZN</th>
<th>MSFT</th>
<th>AMZN</th>
<th>FB</th>
<th>GOOGL</th>
<th>INJ</th>
<th>BRK.B</th>
<th>NOW</th>
<th>PS</th>
<th>JPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>y</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

3.6.4 Mutation

Individuals may undergo mutation at the end of each generation. Mutation is a random process that depends on the mutation rate and on how likely it is for each individual to get mutation. The mutation rate was set as follows: each individual was 10% likely to get a modification in one gene. When the evolution process is beginning to stagnate and the stop condition is not activated, the hyper mutation technique is added after ten generations. In this case, the mutation rate is increased to 20% and each gene is randomly set between -5 and 5.

3.6.5 Stop Condition

The termination conditions of a GA are important to determining when a GA run should end. Therefore, the termination conditions shall prevent that the GA has a premature termination and, on the other hand, that it runs for too long while making a small improvement. In this system, one of two conditions has to be fulfilled for the GA to be concluded: either the algorithm reaches 100 generations or there is no improvement in the average fitness score of the population for 15 generations.

3.7. Risk Parity

To build a market-neutral model, the same level of risk has to involve both the 5-company long position group and 5-company short position group. Thus, the Parity Risk model is used to comply with this requirement. Risk parity using volatility as the measure of risk and a portfolio with equal risk contribution from each company. In this system, the risk target and the leverage are defined by the GA with two genes. The fitness function measuring the market-obtained profit by semester is called Rate of Return (ROR) - obtained by eq. 4. Other submodules such as selection, mutation and crossover are the same.

3.8. Trading Module

The trading module is the one responsible for simulating the architecture with real financial markets. Its input is the trading signal output by the GA module and financial data. The architecture was tested from January 1st, 2015 to June 30th, 2020.
The trading module starts as the user gets to define whether leverage is enabled or not. This module gives the long and short selection and the weight of each asset in the portfolio. Finally, this module conveys how much a semester returns.

4. Results

The financial data used for training and testing are as follows: daily prices and fundamental analysis (net income and earnings per share). The aim is to test the system responsiveness when facing different economic cycles in SP 500. The SP 500 index was chosen because it is the one with the biggest trading volume. Five case studies (Cs) were implemented to analyse the impact of each type of indicator. Initially, a simple strategy is presented and, later on, indicators will be progressively added until reaching the final strategy.

- Cs1-A strategy that uses only indicators that are calculated through the movement of weekly prices.
- Cs2-A study of how adding the sector indicator bears upon the strategy.
- Cs3-A study of how adding fundamental analysis indicators bears upon the strategy.
- Cs4-A study of how adding Markov chain bears upon the strategy.
- Cs5-A study of the best way to achieve companies’ capital distribution.

4.1. Selection

4.1.1 Case study 1 – Technical Indicators

This case study is aimed at sorting out whether the indicators calculated through the movement of weekly prices prove sufficient to obtain a positive result. In Tables 3 and 4 it is possible to identify in each semester which one of the 10 best companies ended up selected by the algorithm during the test phase. The 10th-ranked company corresponds to the worst option and the 1st-ranked one will be the best option.

It can be seen that the worst period for companies to invest long was the second half of 2016 and, in the case of companies applying for the short position approach, the worst semester was the first half of 2017. In both cases, the algorithm managed to select top 10 companies 4 times. However, these data are not sufficient to conclude whether the algorithm performed well. The algorithm can present an accuracy of, say, 3 companies in the top 10 and the rest being the worst options among the candidates. A good point in case is the first semester of 2016 (Fig. 1), where the algorithm selected two top-10 companies for the long position model and one top-10 company for the short position one.

The lack of success regarding this semester is due to the selection of companies for the short position approach. When selecting companies such as MUR (return of 47%), CNC (return 92%), and SWN (return 69%) for the short position approach, there would have to be long position approach companies with an appreciation well above the average to compensate for this appreciation. Thus, it is necessary to understand the reason why the algorithm chooses these three companies and why this group values

<table>
<thead>
<tr>
<th>Year</th>
<th>Semester</th>
<th>Number of candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>1st</td>
<td>26</td>
</tr>
<tr>
<td>2016</td>
<td>2nd</td>
<td>22</td>
</tr>
<tr>
<td>2017</td>
<td>3rd</td>
<td>27</td>
</tr>
<tr>
<td>2018</td>
<td>4th</td>
<td>20</td>
</tr>
<tr>
<td>2019</td>
<td>5th</td>
<td>25</td>
</tr>
<tr>
<td>2020</td>
<td>6th</td>
<td>26</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year</th>
<th>Semester</th>
<th>Number of candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>1st</td>
<td>14</td>
</tr>
<tr>
<td>2016</td>
<td>1st</td>
<td>19</td>
</tr>
<tr>
<td>2017</td>
<td>1st</td>
<td>29</td>
</tr>
<tr>
<td>2018</td>
<td>1st</td>
<td>26</td>
</tr>
<tr>
<td>2019</td>
<td>1st</td>
<td>19</td>
</tr>
<tr>
<td>2020</td>
<td>1st</td>
<td>26</td>
</tr>
</tbody>
</table>

Table 3: Results of the selection of companies for long

Table 4: Results of the selection of companies for short

Figure 1: Worst result of the case study 1

![Graph showing the worst result of the case study 1](image-url)
above average. Since the algorithm uses data from the last year to forecast the next semester, 2015 was analysed to ascertain the performance of each of them. The three companies depreciated more than half of their price in the previous year. Thus, with these indicators, it was inevitable that the algorithm would not classify them as weak companies. Another observation that can be made is that the three companies’ appreciation and depreciation occur at the same time, with a strong correlation. The reason for this correlation is the fact that they all belong to the same sector. These three companies belong to the energy sector and so this strategy has a problem of diversity and an imbalance of volatility between the two groups.

4.1.2 Case study 2 - Financial Sectors

In order to fill the gap in the previous strategy, a gene was added to identify which sectors should be discarded from the portfolio and which sectors are most important. When comparing the results of this strategy with the previous results, one could shift from 22 to 28 (in long position companies) and from 26 to 29 (in the case of short position companies). With this indicator, we could set aside the bad result of 2016. However, another bad result appears in the second semester of 2019. The average return of the short position companies was 19.2%, while the average return of the long group was 7.22%. Figure 3 shows the accumulated return of the companies selected for the short term investment.

4.1.3 Case Study 3 – Fundamental Analysis

The purpose of this indicator is to apply the idea that markets are not efficient. Should you abide by this principle, you will find no company at a fair price. In this way, it is necessary to find out which companies are cheap and expensive. When adding the Fundamental Analysis indicators, there is no significant improvement in the choice of the top 10. However, this indicator helped to discard certain companies, as seen in the first semester of 2019 (during which companies were undervalued, thus implying a recovery in the following 6 months).

4.1.4 Case Study 4 – All indicators

Finally, in order to find out which companies are more likely to have higher and lower returns compared to the SP 500 index, a Markov chain was introduced. When implementing a simple Markov chain with two states, the stationary vector of each company is calculated, which provides long model information (i.e. how likely it is to have returns higher than the SP 500 index). A gene has been added to the chromosome that defines the impact of such an information. Observing the precision of the algorithm (Tables 5 and 6), we may draw the conclusion that this case study is the one with the best results. As for the long position investment group of companies, the algorithm was able to select 17 companies out of the first 5 and, in the short position group of companies, the algorithm selected 16 out of first 5. While selecting the best company among all candidates, it was possible to select 4 times more in the long group than in the short position one.

Table 5: Results of the selection of companies for long

<table>
<thead>
<tr>
<th>Rank</th>
<th>Sector</th>
<th>Companies</th>
<th>H</th>
<th>R</th>
<th>TM</th>
<th>M10</th>
<th>M20</th>
<th>M30</th>
<th>M40</th>
<th>M50</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>F</td>
<td>19</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>16</td>
</tr>
<tr>
<td>2</td>
<td>F</td>
<td>21</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>23</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

As it was not possible to access all the data of the companies that existed in 2008 (in order to study the performance of the algorithm in a crisis), an in-depth study was carried out in the first half of 2020, at a time when there was biggest volatility in the markets due to the Covid-19 crisis. March 23rd corresponds to the minimum of the semester, with
Table 6: Results of the selection of companies for short

<table>
<thead>
<tr>
<th>Year</th>
<th>Semester</th>
<th>Number of candidates</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>1st</td>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>5</td>
</tr>
<tr>
<td>2017</td>
<td>1st</td>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>5</td>
</tr>
<tr>
<td>2016</td>
<td>2nd</td>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>5</td>
</tr>
<tr>
<td>2017</td>
<td>2nd</td>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>5</td>
</tr>
<tr>
<td>2016</td>
<td>3rd</td>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>5</td>
</tr>
<tr>
<td>2017</td>
<td>3rd</td>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
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<td></td>
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<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>150</td>
</tr>
</tbody>
</table>

a devaluation of 30% compared to the beginning of the year. Figure 3 shows all companies that are candidates in the long position model (upper graph) and the short position one (lower graph).

Figure 3: Results for 1/1/2020 to 24/03/2020

The companies selected in green are those that, in the case of the first graph, the algorithm “chose” as the strongest ones; in the second graph, the 5 weakest ones are shown. In the case of long position model companies, the algorithm selected only 2 out of the top 5 and the average return of the 5 companies was -21%. At this specific moment, out of the selected short position companies, only one is in the set of the 5 best companies for short investment. However, it is possible that this result will change throughout the semester because the balance sheet is made every six months and, in this case, we are analysing only the first 3 months. Furthermore, if the portfolio were prepared for market increases alone, at this point, the strategy would have a return of -21%. If the investor, with fear of greater losses, had closed all positions, he would have needed a 27% return on the next investment to recover his money. If the portfolio were only prepared for market increases, at this point, the strategy would have a return of -21%. Finally, if the investor, with fear of greater losses, had closed all positions, he would have needed a 27% return on the next investment to recover his money. With the inversion of the index, companies with a growth rate above the average when the economy is growing are expected to be the first to show signs of inversion as soon as there is a sharp drop in the markets. In figure 4, it is apparent that in the group of long position model companies, 5 out of the 20 already show positive returns, while only one of the long-term model companies shows positive return.

Figure 4: Total change in the investment

4.2. Portfolio Allocation

4.2.1 Equal weights

If the investor chooses to divide the capital equally amongst companies, he/she will get results as shown in figure 5. This technique fails to ensure that the two groups have the same volatility.

Figure 5: Results with equal weights

However, this difference may not be significant because the companies have very similar volatilities. With this capital distribution over the 11 semesters, ROI was lower than the SP 500 index in 4 semesters. The worst semester was the first of 2017, with a loss of -3.3%, while the SP 500 index showed a 7.3% ROI. The best result was obtained in the first half of 2020, with a 43% ROI. If the initial capital was 1000, it means that, at the end of these 11 semesters, the investor would retrieve 3736.9 euros (assuming there are no commissions and taxes).
4.2.2 Risk Parity

Applying the Risk Parity optimization model (so that each company contributes equally to the portfolio risk) will turn out results as shown in figure 6. Compared with the previous model, these results do not represent an improvement because a higher ROI was only observed in 4 semesters. Abiding by this model will cause a worse final balance, since investing in the same conditions means that, in the end, the investor will be getting 33085.5 euros.

Figure 6: Results with Risk Parity

4.2.3 Risk Parity with GA

In the following case, the GA selects the level of risk that the investor should be exposed to - and this model delivers better results. As for this case study, the ROI proves worse than the SP 500 index during 4 semesters. However, out of the three presented, this is the one with the best final balance at 41460 euros. Figure 7 shows the strategy’s evolution during the first semester of 2020. The strategy presents negative values to the minimum of -10%. Subsequently, it recovers until reaching 60%, on May 7. It should be noted that, the portfolio starts to show positive returns right from when devaluation of the SP 500 index begins. This is because short position companies are able to compensate for long position company losses.

Figure 7: Cumulative return with Risk Parity and GA in 2020

Figure 8: Results with Risk Parity associated GA

Figure 9: Returns obtained by the system with leverage

Chart behaviour is the same (with only an increased volatility of the portfolio). While the other 2020 strategies managed to reach the maximum at 60%, 100% is reached in this case. As for 2007, -18% was the minimum recorded. This means that, if the investor had closed all positions, he would have doubled his investment. The other side of the

4.2.4 Enabling leverage as regards the Risk Parity with GA model

Finally, the same model, but with the leverage indicator whereby GA chooses (between 1 and 2), which level of leverage is best suited to maximize profit. Looking at Figure 9, we go on 4 semesters worse than the index. However, the final balance is the one that presents the best result at 65065 euros.
Table 7: Final Results

<table>
<thead>
<tr>
<th>Year</th>
<th>Semester</th>
<th>Equal weights</th>
<th>Risk Parity</th>
<th>Risk Parity + GA to SP 500</th>
</tr>
</thead>
</table>
| 2015 | 1<sup>st</sup> | 39.6% | 41.8% | 38.5% | 66.3% | 0.9%
| 2016 | 1<sup>st</sup> | 17.3% | 12.2% | 15.6% | 22.3% | -1.6%
|       | 2<sup>nd</sup> | 2.5% | -0.1% | -2.3% | -3.4% | 4.5%
| 2017 | 1<sup>st</sup> | -3.3% | -5.2% | -4.2% | -5.0% | 7.3%
|       | 2<sup>nd</sup> | 17.3% | 14.5% | 21.7% | 17.3% | 10.1%
| 2018 | 1<sup>st</sup> | 10.5% | 9.2% | 12.6% | 14.9% | 0.8%
|       | 2<sup>nd</sup> | 6.5% | 8.1% | 7.1% | 7.3% | -8.1%
| 2019 | 1<sup>st</sup> | 9.3% | 8.1% | 13.3% | 15.5% | 18.1%
|       | 2<sup>nd</sup> | 9.0% | 7.8% | 9.9% | 16.2% | 9.0%
| 2020 | 1<sup>st</sup> | 43.0% | 42.6% | 49.7% | 81.1% | 0.1%

Average: 13.6% | 12.4% | 14.8% | 21% | 4.3%

4.3. Incorporating all Strategies

Through table 7, we conclude that reduction of the number of times that the strategy has lower ROI than the SP 500 index was not possible in all models. However, due to the results obtained with any of the strategies, the balance is above that of the SP 500 index. Therefore, we can conclude that this architecture can obtain better results than the SP 500 index. The best final balance of the 4 strategies is when we enable leverage that gets an average ROI of 21% per semester. However, it is also the one posing the greatest risk to the investor. It is a strategy that must be applied to investors, allowing them to be more exposed to risk (as losses can be huge). The strategy presenting the least loss was the one that assigns equal weights to each company. Distributing the weights equally in this strategy seems to be a good option because SP 500 companies have a strong correlation and their volatility is similar.

5. Conclusions

This work proposes an approach combining GA, Markov chain and Risk Parity to generate a neutral strategy capable of obtaining high returns independent of whether the index is a bull or bear market. One of the major conclusions that can be drawn is that GA accuracy remains the same, whether chosen companies’ approach is long or short. A second conclusion is that associating GA to risk parity to choose the risk target and leverage will improve results. The balance of the semesters was positive, achieving a return higher than that of the SP 500 (regarding most of semesters), and an average return of 14.8% per semester without leverage (and 21% with leverage). It should be noted that the strategy producing the best balance was the one that resorted to leverage, but it is the most risky strategy studied in this work. Out of the four capital-distribution studies undertaken, none managed to surpass the 8-semester mark better than the Index one. Some ideas for further research (or some potentially useful contributions to the strategy presented in this paper): development of a strategy for monitoring assets throughout the semester and identifying exit points in order to minimize losses. Another valid task would be to investigate whether adding more indicators could prove beneficial to the strategy. Finally, developing a more robust Markov model could also prove interesting.

References


