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

General Terms

Keywords

1. INTRODUCTION
The study of profitable trading rules in the stock market constitutes a widely known problematic in financial markets. Although the existence of those rules still generate great controversy for many economists and academics [6]. On the other hand, investor, traders, and other stakeholders of financial and investment firms, with large experience in the stock market, claim that it is possible to have excessive returns (compared with the Buy and Hold) using algorithmic trading [1][4].

One investment technique commonly used is Technical Analysis, which forecasts the price of stocks based 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 XIX 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.

In this paper we will concentrate on identifying medium to long term trends. Although a theoretical explanation of why these mediums to long term trends occur is not the focus of this paper, several causes can be pointed out. The first and probably the more important is the economical cycles theory, which states that the economy has long periods (months or years) of growth followed by periods of decline or stagnation. With this in mind and knowing that the stock market reflects not only the current performance of companies, but also the expectations about the future it is possible to identify a correlation between economic cycles and stock market cycles. Additionally to the economic cycles are other factors that can contribute to the price fluctuation like share buyback, which mainly occurs when companies generate large profits (it would be a odd idea for a company in financial needs, to allocate money to stock repurchase), which implies that share buy backs are done most of the time in a uptrend economical cycle, when the company generate excess profits. Other important factor is the money flow of the stock market (especially in countries like the U.S.A. where most citizens have investments in the stock market). The effect of the money flow can be found even in companies or mutual funds with good performance, as the aversion to risk increases to the public in the beginning of the Bear Markets, people tend to redirect their capital to more secure investments like bonds, deposits (or even commodities as occurred in this Bear market). This decapitalization of the stock market (and because the number of shares is the same) leads the stocks down following the simply rule of supply and demand: supply increase (as people try to sell) and demand stagnate or even decrease (people change to different markets).

Genetic Algorithms are optimization techniques based on the principles of natural evolution. In [17] is provided a formal study of this subject.

This paper presents a genetic algorithm for optimizing Technical Indicators parameters in order to maximize returns. Other GAs have been previously used to optimize technical indicators parameters, in particular [7] and to develop investment strategies based on technical indicators [1][8][9][20][21].

In this sense, we propose the use of a GA to obtain the set of indicators and their parameters, which should be used to predict a daily market value. Initially we have applied GAs to find the more suitable parameters of the SMAC and MAD indicator for medium and long term trading. After that we combine both strategies, so that a buy or short-sell signal is only made when both strategies agree, again a GA is used to optimize the four Technical Indicators Parameters of the two strategies at the same time.
The next section will discuss the related work on the Genetic Algorithms and various trading strategies currently used in Technical Analyses. Section 3 explains the system architecture and the investment strategies used in this paper, the markets and years used to test those strategies. Also in this section the overall description of the GA is shown, and the fitness, selection, crossover and mutation functions used. In section 4 the results are presented and a highlight of the most relevant results is made. In section 5 the conclusions of this study are shown.

2. RELATED WORK
One of the most used and oldest strategies to identify trends is the crossing of Moving Averages. This strategy 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 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 as 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.

3. METHODOLOGY
The proposed system consists on a Genetic Algorithm coupled with a market return evaluation module based on the return of the strategies in different markets in specific time-frames.

3.1 SYSTEM ARCHITECTURE

Figure 1 – System Overall Architecture.

The complete process can be summarized as:

- The user starts by specifying the markets to analyze and next chooses the Technical Indicators used in the strategy. Finally, the user chooses the train and test period.
- Afterwards, the Genetic Algorithm Kernel runs several number of times, optimizing the parameters of the strategy for the markets and training period chosen.
- Finally for each run of the GA, its return on the test period is calculated. Detail info is shown to the user displaying the optimized strategy and the return for each market in the test and in the training period.

3.1.1 MODULES DESCRIPTION
This section presents the overall description of each module and their main responsibilities.

Technical Indicators:
This module is responsible for the creation and management of the technical indicators used by all the strategies. This unit calculates the value of the technical indicators for a specified index and time period and stores it's calculation for later reuse. This module is also responsible for calculating the strategies decisions (if it should buy, short-sell or be out of the market).

Train and Testing Periods:
The “Time Period” module controls the time components of the Stock Indexes, in this unit the user can specify which time periods the Genetic Algorithm will use for optimization, and which time period should be used for test, and its configuration (continuous, sliding window, and others.)

Stock Market Indexes:
This module is responsible for loading the stock market indexes from the source (a .csv file) and giving access to the data to the other parts, the stored information includes the close value, the open, high, low and the date.

Market Return Evaluation:
In this block it is calculated the return and other metrics for evaluating the investment strategy (like the Sharpe Ratio, number of trades executed, ROI, and others.). The results can be evaluated
for several types of metrics, yearly or monthly and with simple or compound average.

**Genetic Algorithm:**

The Genetic Algorithm Module is the most important because it is the one who does the core functions of the system. This module uses data from all the other modules to calculate the perfect strategy with the Technical Indicators specified by the user for the specified markets, in the training period. The crossover is a one-point crossover, and parents are chosen based on a roulette-wheel selection.

**Optimized Strategy:**

Finally this module is responsible for showing the user the result of the optimization. Beside the best strategy obtained, it also shows results from various runs of the Genetic Algorithm, so the user can test the average results and robustness of the solution. For each strategy it shows the return in the test and training period, the yearly return and the Sharpe Ratio.

### 3.2 TRAIN AND TEST DATA SET

The time period chosen for training was from 1 January 1993 to 31 December 2003, eleven years of daily data. This time period was chosen for two main reasons. The first one is that the time period should be big enough to be statistically 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 2004 to 31 December 2009, six 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 1993 to 2003, 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 were the S&P500 (USA), FTSE100 (England), DAX30 (Germany) and NIKKEI225 (Japan). 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):

\[ \text{SMA}_n(t) = \frac{1}{n} \sum_{i=t-n+1}^{t} P(i) \]

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.

Another indicator that will be used in this paper is the Moving Average Derivate (MAD). It is an extended version of the “MA Change” described in [11]. In the original version it is calculated by subtracting de value of the current MA with the value of the MA in the previous day.

In mathematics this is simply the secant to the MA curve in the last two days. In this way the Derivate of the MA can be calculated based on the definition of Secant of the MA (Eq. 3). Where “a” 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.

\[ \text{SMAC}_{l,s}(d) = \frac{1}{s} \sum_{i=t-s+1}^{t} P(i) - \frac{1}{l} \sum_{i=t-l+1}^{t} P(i) \]

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.

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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 “a” 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 value 1).

\[ \text{MAD}_{n,g}(d) = \frac{\sum_{i=t-g+1}^{t} P(i) - \sum_{i=t-g+1}^{t} P(i-g)}{ng} \]

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.
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 paper 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”, can be seen in Figure 4, where is shown the evolution of the S&P 500 from 2000 to 2010 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.

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

Other indicators were tested like Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) [13]. 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:

$$RSI_n(d) = 100 - \frac{100}{1 + \frac{Ups(n)}{Downs(n)}}$$  \hspace{1cm} (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.

The Moving Average Convergence Divergence (MACD) indicator constitutes one of the most reliable indicators within the market. It is a trend following momentum indicator that exhibits the relation between two distinct moving averages. Essentially, it defines two lines; the MACD line which corresponds to the difference between a 26-week and 12-week EMA and a trigger line which corresponds to an EMA of the MACD line. The difference between the former lines allows us to obtain a histogram which can be easily analyzed and offering us perspectives on price evolution.

3.3.1 PARAMETERS OF TECHNICAL INDICATORS

After defining the strategies it is necessary to define the parameters to use both in the SMAC and in the MAD strategies. As both strategies have two parameters, with similar meanings:

The first parameter is similar to both strategies, the time period of the long term MA.

The second parameter in one strategy is the time period of a short term MA and in the other strategy is the distance between the two points used to calculate the secant. Both this parameters should be a medium term periods.

The new Indicator (SMAC & MAD) has four parameters, two for the SMAC and two for the MAD. These parameters represent the parameter of the underlying strategies.

3.4 GENETIC ALGORITHM KERNEL

3.4.1 GENETIC ENCODING

The chromosome created must represent the Technical Indicators used, in this way the SMAC chromosome is represented by two genes, one for the shortest MA other for the longest MA in days (natural numbers), the interval of this values is between 1 and 250 (this value is above the largely used MA for long term analysis: 200 days). The same rule applies to the MAD chromosome, where one of the parameters is the “gap” and the
other the number of days of the MA. In Table 1 it is shown a representation of a possible chromosome for the SMAC & MAD chromosome (which includes both the SMAC and MAD genes):

<table>
<thead>
<tr>
<th>Table 1 - An example of a Chromosome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chromosome</td>
</tr>
<tr>
<td>25</td>
</tr>
<tr>
<td>100</td>
</tr>
</tbody>
</table>

3.4.2 FEATURES OF THE GA
The Genetic Algorithm used for the optimization uses a standard optimization procedure. The selection of individuals for crossover is chosen based on a roulette wheel selection (but only the best half of the population enters the selection process), and the probability of being chosen is equal to the ratio: individual fitness function / Sum of fitness of all individuals. Each individual can be chosen any number of times for crossover (the only exception is that an individual cannot be chosen to crossover with himself).

The crossover is a one-point crossover, each breeding generates the two possible distinct children and includes them in the population. In the chromosome of only one indicator (SMAC or MAD) the children are created by swapping the long and shortest MA day. In the SMAC & MAD chromosome the children are created by swapping the 2 genes that represent each Indicator (the first children takes the SMAC genes from parent A, and MAD genes from parent B, and the second children the other way around).

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

4. RESULTS
The optimization procedure described above was run fifty times for each approach namely, MAD, SMAC and SMAC & MAD, additionally 50 random strategies were evaluated (The random strategy consists in each day deciding a random trade: long, short, or do nothing, each with one third chance of occur.). In each run the best individual obtained was evaluated for the test period (2004 to 2009) for the yearly return of the average of the 4 Indexes. The histogram for the returns of the 50 runs for each chromosome is presented in Figure 5 and Figure 6 (values are in % of occurrences in the 50 runs).

In Figure 7 although the percentage go only to 50% for better perception of the other values, the Buy & Hold as 100% on the 2.5 column, and the random strategy has 88% on the less than 2.5 column.

As we can see in this figures, all the chromosomes beat the Buy and Hold and the random strategy, this confirms the validity of the Technical Indicators used.
Additionally we can see that the optimized chromosomes have better results that the random chromosome that as an almost uniforms distribution along all the return values. In the other hand the SMAC has a curve similar to the Gaussian curve exhibiting pronounced tails. The MAD accumulates around two values: 7.5% and 9.5%. And finally the SMAC & MAD Compost Chromosome is very similar with a Gaussian curve, which proves that this strategy has the most solid results. The detailed statistics can be seen in Table 2.

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

<table>
<thead>
<tr>
<th></th>
<th>Best:</th>
<th>Average:</th>
<th>Median:</th>
<th>Worst:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy &amp; Hold</td>
<td>2.6%</td>
<td>2.6%</td>
<td>2.6%</td>
<td>2.6%</td>
</tr>
<tr>
<td>SMAC (227, 210)</td>
<td>10.1%</td>
<td>8.5%</td>
<td>8.9%</td>
<td>6.3%</td>
</tr>
<tr>
<td>MAD</td>
<td>10.5%</td>
<td>8.7%</td>
<td>8.0%</td>
<td>6.8%</td>
</tr>
<tr>
<td>Random Strategy</td>
<td>8.58%</td>
<td>-1.01%</td>
<td>-1.11%</td>
<td>-7.33%</td>
</tr>
<tr>
<td>SMAC &amp; MAD</td>
<td>10.2%</td>
<td>9.0%</td>
<td>9.2%</td>
<td>7.3%</td>
</tr>
</tbody>
</table>

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

Results including the use of RSI and MACD were not included since they performed worse than using only the “SMAC & MAD”. The reason is that RSI and MACD are short term indicators, and in this strategy we are looking for a medium-long term time period. This teaches a precious lesson that is not by including many indicators that a better strategy can be produced. In reality using only two indicators performed better than using the four indicators. The reason can be explained by over fitting in the training period that does not translate to good results in the testing period.

4.1 RETURN ON INVESTMENT

In the next table we can see the yearly average return in the test period of the three best chromosomes found in the training period, with the respective number of trades, contrary to the return (which is annualized), the number of trades displayed is the average number of trades for the four Indexes, during all the testing period (6 years). In this table we can see that the “MAD & SMAC” strategy have the best, the second and fourth best results. This means that this is the most optimal and robust strategy, because it’s the one who maintains the best results from the training period to the testing period.

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

<table>
<thead>
<tr>
<th></th>
<th>Average Return</th>
<th>Total Nº Trades</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy &amp; Hold</td>
<td>2.55%</td>
<td>1</td>
</tr>
<tr>
<td>SMAC (227, 210)</td>
<td>8.34%</td>
<td>8</td>
</tr>
<tr>
<td>SMAC (225, 210)</td>
<td>8.27%</td>
<td>9</td>
</tr>
<tr>
<td>SMAC (222, 210)</td>
<td>7.73%</td>
<td>10</td>
</tr>
<tr>
<td>MAD (110, 11)</td>
<td>8.15%</td>
<td>16</td>
</tr>
<tr>
<td>MAD (112, 10)</td>
<td>8.01%</td>
<td>15</td>
</tr>
<tr>
<td>MAD (112, 11)</td>
<td>7.52%</td>
<td>14</td>
</tr>
<tr>
<td>MAD(186, 45) &amp; SMAC(202, 193)</td>
<td>9.37%</td>
<td>10</td>
</tr>
<tr>
<td>MAD (108, 20) &amp; SMAC(206, 195)</td>
<td>8.38%</td>
<td>12</td>
</tr>
<tr>
<td>MAD(112, 11) &amp; SMAC(242, 128)</td>
<td>8.27%</td>
<td>11</td>
</tr>
</tbody>
</table>

4.2 SHARPE RATIO

The Sharpe Ratio is a measure that was created by Nobel Prize William Sharpe, to measure the reward-to-variability ratio of a trading strategy [19]. This measure allow to compare two strategies with different returns, and see if the additional return of one strategy is due to applying a more risky strategy, or to a smarter investment strategy. The Sharpe Ratio formula is (5):

\[
\text{SharpeRatio} = \frac{R - R_f}{\sigma}
\]

Where R is the average return of the strategy, \(R_f\) is the risk free rate (normally the rate of the US treasuries security). And \(\sigma\) 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, since we are considering 6 years, the more suitable security is the 5 year Treasury Note. A secure investment would be buying a 5 year Treasury Note on 2004 and with a 3.36% yield.

Table 4 - Sharpe Ratio of the various strategies

<table>
<thead>
<tr>
<th></th>
<th>Average Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy &amp; Hold</td>
<td>0.030</td>
</tr>
<tr>
<td>SMAC (227, 210)</td>
<td>0.570</td>
</tr>
<tr>
<td>SMAC (225, 210)</td>
<td>0.531</td>
</tr>
<tr>
<td>SMAC (222, 210)</td>
<td>0.352</td>
</tr>
<tr>
<td>MAD (110, 11)</td>
<td>0.365</td>
</tr>
<tr>
<td>MAD (112, 10)</td>
<td>0.349</td>
</tr>
<tr>
<td>MAD (112, 11)</td>
<td>0.314</td>
</tr>
<tr>
<td>MAD(186, 45) &amp; SMAC(202, 193)</td>
<td>0.522</td>
</tr>
<tr>
<td>MAD (108, 20) &amp; SMAC(206, 195)</td>
<td>0.466</td>
</tr>
<tr>
<td>MAD(112, 11) &amp; SMAC(242, 128)</td>
<td>0.458</td>
</tr>
</tbody>
</table>
In Figure 8 we can see the evolution of the return of the strategy with the best results in the training period, during the test period, compared with the evolution of the Buy and Hold. In this graphic we can see that in Bull Markets the Buy and Hold strategy has better returns that other strategies, but the situation changes completely when the Bear Bear appears, and the MAD & SMAC, not only does not loses capital, but also has a great recovery of capital. Finally in the end of the Bear Market, the MAD & SMAC does not recognize right away the change and looses some capital and then stays out of the market for a while, until it detects the current uptrend and enters long again.

In Figure 9 we can see the trading signals generated for the same strategy during the testing period. The arrows means opening positions (up arrow represent long buys, and down arrows short-sells.) and the crosses means the close of the open positions. In the beginning of the period we can see the strategy tries to follow the short upward trends of the market and avoiding the downward trends. When the market exhibits clear trends, like the end of the Bull Market in 2006 and 2007 the strategy clearly identifies and follows the trends, and when the trends are changing (end of 2007 and middle of 2009) it first sells the active position, and enter the contrary position upon more confirmation of the effective trend change. Then when the markets starts up again in 2009 first it exists the short position, stays out of the market until it is sure that there is a new uptrend and then enters long again.

The proposed strategy is best suited for medium and long term investment since it only takes a decision after the confirmation of a trend is clear, it has the great advantage of avoiding long periods of downturns. The classical strategy of Buy and Hold that is only good in markets that do not exhibit bear markets like the 80s and 90s in the S&P500 does not perform well in markets characterized by long bear markets.
5. CONCLUSIONS
This document presented the use of Genetic Algorithms to optimize the parameters of various Technical Indicators and with them create various trading strategies. The results obtained showed that these strategies beat significantly the Buy and Hold (the “MAD & SMAC” strategy had an average of 9.0% against the 2.6% of the Buy and Hold), once more proving the validity of Technical Analysis. Finally the optimized “MAD & SMAC” strategy is compared with the random strategy, with excellent results: the optimized has an average of return of 9.0% against the -1.01% of the random strategy. The use of the “MAD & SMAC” has also shown better results than the use of any of the indicators individually.

6. BIBLIOGRAPHY