Combining Channel Trading with Genetic Algorithms to Optimize Investments in Trending Forex Markets

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Abstract

This work proposes an innovative solution to trade in the foreign exchange market, by combining technical and chart analysis with genetic algorithms. The channel pattern and the technical indicator fibonacci pivot points are responsible for classifying the market and create a trading strategy, that aims to predict future price movements. A genetic algorithm is then applied to optimize the trading rules. To train and test the system, EUR/USD currency pair with 1 minute samples data is used, between the years of 2015 and 2020. In the data preparation phase, the ingested data is resampled according to the close price variation (insted of using a fixed time sampling), mitigating the problem of over and undersampling data. Results show the proposed solution is profitable for several currency pairs with different characteristics and reinforce the importance of fibonacci pivot points in assessing a trade's risk. Moreover, training the system with 2 years of EUR/USD data (January 2015 until December 2016), resulted in 34.9% return on investment in the test period (between January 2020 and December 2020).
Keywords: Genetic Algorithm, Forex, Channel Pattern, Technical Analysis

1. Introduction

Nowadays, due to its low requirements regarding initial capital (resourcing to a mechanism called leverage), forex has become very enticing to the individual client, who takes a speculative approach trying to benefit from changes in foreign exchange rates in relative short periods of time. However, even for an experienced trader, forecasting price movements may prove to be a difficult task.

The Efficient Market Hypothesis states that markets are informationally efficient, which means that its prices already reflect all the information available, thus preventing traders from profiting [6]. Nonetheless, traders challenge this theory by studying and extracting features from historical price data. These features are called technical indicators and are no more than mathematical formulas applied to past price movements, that translate into logical rules aiming to assist a trader assessing market conditions. Technical indicators (derived from technical analysis) may themselves constitute a trading strategy - as is the case of this work, in which channel patterns are used to classify the market (i.e., when to buy, sell or to stay idle) and define entry and exit timings – or may be used as features that feed a machine learning algorithm, which in turn is responsible for classification.

The aforementioned concepts constitute enough material to approach the problematic of forecasting financial markets. However, besides the metrics that are meant to evaluate the performance of a model,how does one know if it has reached its best performance possible? The present work purposes the use of Genetic Algorithms (GA) to answer to this problem.

Many solutions with learning capability applied to financial markets have been purposed so far, yet many methodologies remain unexplored. This report introduces an innovative system for price forecasting, using the channel pattern and technical indicators to generate trading rules and build a classification model. The parameters that regulate the trading strategy are then optimized by a genetic algorithm. The proposed solution is built to trade EUR/USD currency pair in the foreign exchange market.

The main contributions of the proposed system are the following: (1) Create a classifier model based on channeling and technical analysis, that provides 3 possible classifications: uptrend, downtrend or sideways; (2) Employ GA to improve the classification method; (3) Generate positive returns in different environments, i.e. applying the model to currency pairs with completely distinct characteristics regarding volume, volatility and transaction costs; (4) Confirm the relevance of fibonacci pivot points in assessing the risk of a trade.

2. Related Work

2.1. Technical Analysis

As opposed to fundamental analysis, technical analysis does not utilize any external economic data or any relevant news events, neither the characteristics of a company or industry [1][6].As mentioned before, technical analysis produces trading rules exclusively based on past price movements and it is based on three premises[14]: (1) Market action discounts everything: Technicians believe that all the fundamentals that influence the market movements are immediately incorporated in the price; (2) Price moves in trends: Predictable trends are essential to the success of technical analysis. When spotted early, one safe way traders may profit is by investing in the same direction as the trend. As technicians counsel, "the trend is your friend"[15]; (3) History repeats itself: Asset traders will tend to react the same way when confronted by the same conditions.

Based on these premises, technical analysts are able to abstract the fundamentals of a company. Succinctly, technicians try to identify patterns in price, volume, breadth and trading activities, that enable them to spot trends and reversal of trends. A technical indicator may be described as a series of data points derived from a mathematical formula that is applied to the price data series, reducing the price prediction problem to a pattern recognition problem where the inputs are the historical prices[18]. Price data includes any composition of the opening, high, low or closing values over a period of time as well as volume data[9].

2.2. Works in Forex and Technical Analysis

Dempster and Jones [4] used the channel pattern trading strategy to forecast price movements in the FX market, namely they apply the strategy to the GBP/USD currency pair. In order to form a channel, 4 points (2 peaks and 2 troughs) are selected using a considerable complex algorithm described in the paper. Having a channel, the entry point to trade is when the price has moved 2% of the vertical channel width in the direction of the channel. A trade is exited (position closed) if: the market moves *y%* $\times$ $channelwidth$ or 3 pips in the opposite direction of the channel, if the price hits the target wall or if the market moves $15\% \times channelwidth$ from the source wall outside of the channel. Without the assistance of any intelligent algorithm to refine all the variables involved, their strategy proved to be generally unprofitable, however they were able to find evidence of a correlation between the channel pattern and profitability, that is not accounted for in the Efficient Markets Hypothesis. Also, they were able to prove that the profit largely depended on the channel width. In 1998, Lui and Mole [12] reported the results of a questionnaire survey, conducted in February 1995, on the use of fundamental and technical analysis by foreign exchange dealers in Hong Kong, to forecast exchange rate movements. Their findings reveal that 85% of respondents rely on both fundamental and technical analyses for predicting future rate movements at different time horizons. At shorter time horizons, there exists a skew towards reliance on technical analysis as opposed to fundamental analysis, but the skew becomes steadily reversed as the length of the horizon considered is extended. The most common length of historical data used by the dealers is 12 months and the used trading period is daily data. Technical analysis is considered slightly more useful in forecasting trends than fundamental analysis, but significantly more useful in predicting turning points. Interest rate related news is found to be a relatively important fundamental factor in exchange rate forecasting, while moving averages and other trend-following systems are the most used technical techniques. In 2018, Jakpar et al. [11] also compared technical and fundamental analysis. They conducted a study to analyse the credibility of both, the fundamental and technical analysis, on predicting the Malaysian stock market return. Their study included 80 companies from the food market industry between the years of 2012 to 2016. The fundamental indicators included net profit margin, price earnings ratio and total asset turnover while for technical analysis only MACD was considered. Although both approaches showed predictive ability and positive returns, fundamental analysis proved to be slightly more accurate. The author justifies this result with the fact the study is focused on a specific industry and the number of indicators used for each approach is different (3 for fundamental analysis, 1 for technical), referencing three other studies where technical analysis outperformed fundamental analysis - Needly (2010), Moosa and Li [13] (2011) and also Wafi et al. [19] (2015).

In 2010, Teixeira and Oliveira [18] presented a trading strategy for stock trading, tested on 15 companies quoted in São Paulo Stock Exchange, combining technical analysis with the nearest neighbour classification (k-NN algorithm). Their goal was to study the feasibility of using an intelligent prediction system exclusively based on the history of daily stock closing prices and volumes. To build a daily trading model, the authors employed a diverse set of technical indicators that fed the model (such as: RSI, SMA, Stochastic Oscillator, Bollinger Bands, among others; and all of them with standard parameters setup), a stop loss of 3% of drop in the closing price and a stop gain of 10% of rise in the closing price. They achieved a classifier precision of around 40%, with an average accumulated profit of around 500% in the period between 1998 and 2009, depending on slightly different variations of the algorithm. Compared to the B&H, this strategy outperformed it by a minimum of 34.50% and a maximum of 58.10%, regarding accumulated profits. In 2016, Coakley et al. [3] went further in the research of profitability with technical trading, as they conducted an investigation of profitability of FX technical trading rules, over the period between 1996 and 2015, for 22 currencies quoted in US dollars. This translated in a total of 113448 trading rules using essentially the most common technical indicators in order to build those rules, such as: MACD, RSI, MA's, Bollinger Bands, etc. Their findings suggest that prior to controlling for data snooping bias (data snooping bias happens when a person, intentionally or not, refines too many parameters to increasing a system's performance on a single data set, influencing the final results), quite large numbers of technical trading rules are significantly profitable and can achieve annualised returns up to 30%. Regarding trading systems, et al. [6] performed a study that aimed to analyse price forecasting, using a broad set of machine learning models applied to several financial markets.

2.3. Genetic Algorithms

The genetic algorithm is a search heuristic model applied to optimizations problems, based on Charles Darwin's theory of natural selection. The principle behind this algorithm is that by picking an initial population and applying the principle of natural selection for a finite period of generations, the output will converge to the best possible solution. The potential solutions are encoded as chromosomes. New solutions can be produced by mutating members of the current population, and by mating two solutions together to form a new solution.The better solutions are selected to breed and mutate, the worse ones are discarded. Being an heuristic model, GAs do not return an exact solution, rather they find the best solution in a search-space. By feeding the GA with the parameters that define the forecasting price model, for instance the kernel function hyper-parameter of a Support Vector Machine, we are able to fine tune those parameters, thus increasing the forecasting model performance.

2.4. Works in Genetic Algorithms

In 2004, Elshamli et al. [5] introduced a genetic algorithm approach for solving mobile robot path planning problems in static and dynamic environments. The Genetic Algorithm Planner (GAP) utilized variable length chromosomes for path encoding, where the population represents the path and each gene of the chromosome is represented by (x,y) coordinates of each point. The experiments included 4 different approaches: the first using low convergence rate, in an attempt to increase diversity; using memory, the GA stores the best solutions so far and keeps replacing the worst individual with these solution at a prefixed rate; using random immigrants, by replacing the worst fitted individuals with randomly generated ones; finally, a combination of memory and random immigrants. Although all solutions produce good results, the combination of memory and random immigrants is the best among the four. In the same year, Evans et al. [7] developed an intra-day FX trading system, using a hybrid solution that combines NN and GA. The forecasting model was based on Feed Forward Neural Networks with BackPropagation fed with data from the three most traded major currency pairs (EUR, GBP, EUR), using a GA to optimize the network topology. In the selection process they used an elitism policy of just one individual and roulette-wheel selection for the remaining population. The rest of the operators used the following configuration: a two-point crossover was applied with 80% of crossover rate, mutation rate of 20% and a termination criterion of 40 generations or 15 generations without evolution. Their work confirmed with a significance of 95%, that daily Forex currency rates time series are not randomly distributed, obtaining 23.3% of annualized net return and 72.5% of prediction accuracy. The evaluation function was composed by a combination of the mean absolute error, sharpe ratio and annual net return. In the work they developed for portfolio optimization, Aranha and Iba [2] also proposes a multi-objective fitness function, where cumulative return evaluated the solution in terms of profit generated and sharpe ratio evaluated the risk associated to an investment. In 2009, Hirabayashi et al. [10], proposed a Genetic Algorithm (GA) system to automatically generate trading rules based on Technical Indexes, focusing on calculating the most appropriate trade timing, instead of predicting the trading prices. The features that feed the GA were derived from know technical indicators. The strategy took leverage into account, where each investment permits a maximum leverage of 10 times. Furthermore, the parents were chosen by tournament selection - a method later studied by Shukla et al. [17] and Razali and Geraghty [16], where they came to the conclusion that it outperformed other selection methods in terms of convergence rate and time complexity.In order to make sure that good genetic material is preserved, elitism was performed passing 1% of the best fitted individuals to the next generation. Also, the worst 30% fit individuals were replaced by random immigrants. Finally, a two-point crossover and mutation were performed, with rates of 60% and 1%, respectively. To train and test the algorithm, 3 currency pairs were took into account with a fixed spread each - USD/JPY, EUR/JPY, AUD/JPY – training and testing for a period of 4 years. To separate the training and test data, the authors used a rolling window method. Using a tested period of 4 years, the results showed a maximum profit gained of: 80% for EUR/JPY, 17% for USD/JPY and 38% for AUD/JPY. Also, a comparison between the purposed solution and the same solution without leverage, NN and B&H strategy revealed that the first outperformed the remaining during the entire period tested. Zhang and Ren [20] focused on making 5 minutes predictions for the EUR/USD currency pair. Aiming to find the best combination of entry and exit rules, they recurred to a GA, with the particularity of having as fitness function the technical indicator stirling ratio, not commonly found in the literature.

3. Proposed Architecture

In order to fulfill the proposed system's goals, this work was divided into 4 modules, each with a distinctive objective and responsible for an independent set of functions, executed in the order presented below:

- **Data Module**: Module responsible for collecting the data from Dukascopy and preparing it to be used by the Technical Rules Module. The preparation/pre-processing phase consists on cleaning and resampling the data.
- **Channel Module**: Module responsible for creating the trading strategy. The strategy is based on the channels found and built, which are defined in this module.
- **Optimization Module**: Module responsible for optimizing the trading strategy, using a Genetic Algorithm to improve the variables involved in the strategy definition.

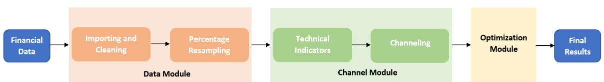

Figure 1: System Architecture.

3.1. Data Module

The first step on the development of the proposed system is to get and prepare the data. First, the data is collected from Dukascopy: it consists on a structured time series dataset in OHLC (open-high-low-close) format of the EUR/USD Ask price and with a granularity of 1 sample per minute. The data is retrieved in a CSV file. The next step is to clean the dataset. Since the data is accurate, the only concern is to guarantee its completeness, i.e. that no missing data is found in any rows of the dataset.

Time bars oversample information during low activity periods and undersampleinformation during high activity periods [41].That said, in this work the dataset is resampled according to the closing price percentage variation,thus obtaining a more homogeneous dataset.

3.2. Channel Module

3.2.1 Technical Indicators

Zig Zag is a lagging indicator that plots points on the chart whenever prices reverse by a percentage or a magnitude greater than a pre-chosen variable. Straight lines are then drawn, connecting these points. By filtering out insignificant price fluctuations, it identifies swing highs and swing lows. Each zig zag point will be the starting point for the search of a channel, since they identify points of trend reversals.

Fibonacci Pivot Points is a leading technical that is used to find areas of support and resistance. By anticipating support and resistance zones, the proposed solution uses Fibonacci pivot points to assess the risk of a trade by measuring the distance to those areas. In this solution, after a channel is found, if the closing price has travelled more than pre-defined % of the distance between the two nearest pivot points that are above and below the price, we consider that the closing price is too close to the upcoming pivot point and that channel formation is ignored, as Figure 2 illustrates, where the yellow and blue lines represent the areas of support and resistance, respectively. The red area begins in the fibonacci pivot points threshold, after that point the price is too close to the next resistance to open a trading position.

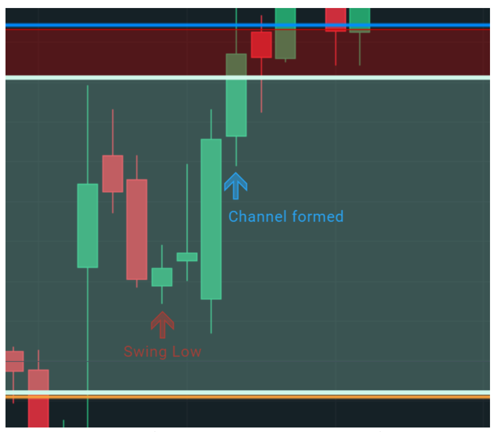

Figure 2: Example of an ascending channel found too close to a Fibonacci Pivot Point.

3.2.2 Channeling

This component receives as input the dataset and the list with the zigzag points (list containing the index of swing highs and swing lows), both coming from the component Technical Indicators, as represented in Figure 3.

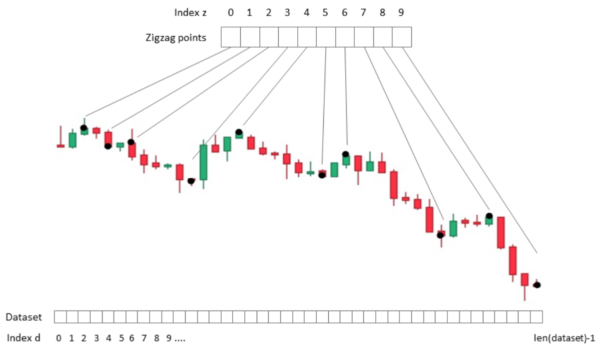

Figure 3: Representation of the relation between the zigzag list and the dataset.

The procedure to find a channel goes as follows: **(1)** Starting on the first zigzag point, analyze the current zigzag point and verify if it is a swing high or a swing low; **(2)** If the zigzag point is a swing high (swing low), search for *N* candles in a row where the closing price is consecutive lower (higher), being *N* the number of candles needed to confirm a trend; **(3)** If no channels were found, update the current zigzag with the next zigzag point in the list and restart this procedure. If a channel was found and the closing price of the *Nth* candle is not above (below) the threshold set by the fibonacci pivot points, indicating that the price is too close to a resistance (support) area, continue iterating the dataset until the closing price breaks through the channel walls. Whenever the data sample being analyzed matches the next zigzag point, update the current zigzag point; **(4)** When the closing price breaks through the channel walls, restart this procedure starting on the current zigzag point.
Figure 4 demonstrates the functioning of this solution's channel trading. Surrounded by a black circle, 2 ascending channels are shown, where the first channel goes through 2 zigzag points (pointed with a arrow), the second channel starts on the last zigzag point seen.

The slope of the channel is given by the slope of the line that passes by the closing price of first and *Nth* that form the channel. Then, the intercept parameter of the line equation is adjusted, in order to encompass the *N* candles that form the channel. Due to its narrow walls, the channel is vulnerable to small random price variations. In order to overcome this problem, additional width is provided to the channel. A parameter, which was named *plus channel width*, regulates how

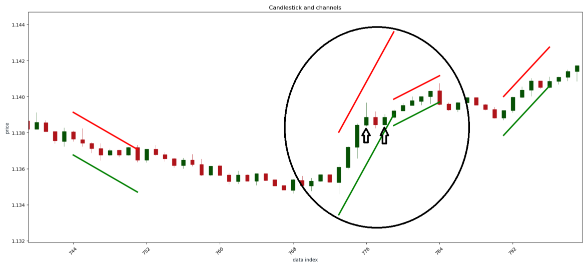

Figure 4: Example of 2 channels, where the first one included 2 zigzag points and the second one starts in the current zigzag point.

much more width is given and initially (during the development phase) a value of 0.5 was established, but this parameter was fine tuned in the Optimization Module. Increase the channel width by 0.5 means that both walls are pushed away $0.5 \times original\ channel\ width$ or 50%, as may be observed in Figure 5

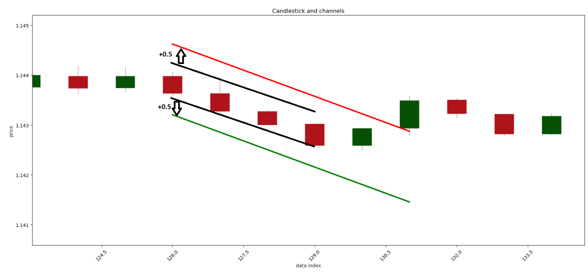

Figure 5: Example of the channel width adjustment.

Classification is the final step to complete the trading strategy. As the dataset is being iterated searching for channels, each sample is being classified, having 3 possible values:

- **0**: If a sample is not inside a channel it's classified with the value 0 and produces the signal Out, which means do not open a position or, if a position is open, close it.
- **-1**: If a sample is inside a descending channel it's classified with the value -1 and produces the signal Sell, which means open or maintain a selling position.
- **1**: If a sample is inside an ascending channel it's classified with the value 1 and produces the signal Buy, which means open or maintain a buying position.

3.3. Optimization Module

This module is responsible for the optimization of the parameters that characterize this investment strategy by using a Genetic Algorithm, which has been introduced in 2.3, a search algorithm based on the Darwin's theory of natural selection.

It starts with a random initial population (set of chromosomes), where each individual (chromosome) represents a possible solution to the problem. Then, based on the evaluation of the quality of each solution (Fitness Function), these individuals mate (Selection), reproduce (Crossover and Mutation) and evolve until some termination criteria is met. Finally, the best individual found (the one whose Fitness Function value is the highest) corresponds to the optimized solution.

Chromosome Representation Each chromosome is represented by a list of of genes:

- **Number of candles**: Number of candles necessary for a channel to be formed. It is an integer value and can vary between 1 and 10. Throughout development phase this value had been predefined to 4 candles.
- **Additional channel width**: As the name tells, it is the additional width given to a channel. It is represented by a float with 2 decimal digits and can vary between 0.00 and 1.00 or 0% and 100%. Throughout development phase this value had been predefined to 0.5 or 50%.
- **Percentage resampling**: Percentage threshold defined when rearranging the original financial data. It is represented by a float with 2 decimal digits and can vary between 0.00 and 0.50 or 0% and 50%. The reason why this gene upper boundary is ”only” 50% is that 50% of percentage variation corresponds to a variation of approximately 70 pips in magnitude between each simple, which already is a very high value. Throughout development this value has been predefined to 0.02%.
- **Zig zag filter**: Filter of the zig zag technical indicator used in Channel Module, where it has been predefined to 3 pips during development. It is represented by an integer and can vary between 0 and 50 (pips).
- **Pivot Point filter**: Filter of the Fibonacci Pivot Point. As explained in Section 3.2, a channel is ignored when formed above the level of this filter. It is represented by a float with 2 decimal digits and can vary between 0.00 and 1.00 or 0% and 100%. It has been predefined to 90% during development phase.

Table 1 summarizes the chromosome representation.

Fitness Function The fitness function used in this solution is the Return on Investment (ROI), where the goal is to maximize it. Therefore, the greater the ROI value the fitter the individual.

Gene	Number of candles	Additional channel width	Percentage resampling	Zig zag filter	Pivot Point filter
Genotype representation	int	float	float	int	float
Interval	[1,10]	[0.00,1.00]	[0.00,0.50]	[0,50]	[0.00,1.00]

Table 1: Chromosome representation.

Population Size The more complex the problem the bigger the population should be. Most of the GA solutions found tune this parameter to 100 or more. However, since each chromosome only has 5 genes, the population size was set to 50, which correspond to 10 times the number of genes, already providing a substantial degree of diversity to the population.

Selection A combination between Elitist Selection and Tournament Selection was used. In this solution, the 10% most fit individuals survive to the next generation by Elitist Selection. The disadvantage is that it requires the population to be sorted first, according to its individuals fitness values.
The other selection method chosen applies to the remaining 90% of the population, it is the Tournament Selection. The selection pressure is adjusted by varying the variable k, being that if k is equal to 1 the parent selection is totally random and as it is incremented the selection pressure increases. In this solution, k=3. Furthermore, Tournament Selection allows the usage of negative fitness values, which may occur in the proposed system.

Crossover Crossover is the method that mimics the natural reproduction. The idea is that by combining 2 already fit individuals, the offspring will be even fitter, by inheriting genes from each parent.

In this work, the crossover method adopted is Uniform Crossover, with a crossover rate of 50% during the development phase. In the long term Uniform Crossover becomes less biased and the search is more global than, for example, Single-point Crossover, where in the beginning a lot of genetic material is swapped between the parents, but rapidly convergences to local solutions.

Mutation Mutation is a process used to maintain genetic diversity in the population. Without it, all the combinations that we would ever possibly reach during the successive generations would be already in the initial population.

During the development phase, a mutation rate of 10% was employed.

Random Immigrants Random Immigrants is another method responsible for introducing diversity in the population by replacing the least adapted individuals of the population for new and randomly generated individuals. An immigrant rate of 20% was used.

Termination Criteria The GA stops if one of two conditions is met:

- The algorithm completes 100 generations. After 100 generations it is assumed that the algorithm has already converged to best solution found.
- The population does not evolve, i.e. the fitness value of the best individual found so far does not increase, during 10 consecutive generations. If the algorithm converges before 100 generations, there is no need to run the algorithm until it completes 100 generations.

Table 2 summarizes the GA parameters setting.

Parameters	Value
Chromosome Size	5 genes
Population Size	50 individuals
Elitism Rate	10%
Tournament Selection - Selection Pressure	k = 3
Mutation Rate	10%
Random Immigrants Rate	20%
Termination Criteria	100 generations or 10 generations without evolution

Table 2: Genetic Algorithm parameters setting.

4. System Validation

In order to verify the quality of the proposed system and the tuning of the parameters used in this system, 4 case studies were conducted: **(A)** Studies the approach taken regarding the trading strategy, more specifically the use of Fibonacci Pivot Points; **(B)** Studies the influence that GA parameters have in the system's performance; **(C)** Compares the system's performance when trading different currency pairs: one major pair, one minor pair and one exotic pair; **(D)** Presents the best performing results. The two case studies found more relevant, A and C, are presented in this document.

4.1. Evaluation Metrics

In order to evaluate the performance of the proposed solution and to be able to make comparisons between different approaches, the following measures were taken into account.

ROI Return on Investment (ROI) is a performance measure used to evaluate the profitability of an investment, by measuring the amount of return on an investment relative to its cost. ROI is expressed in percentage and it is calculated by dividing an investment's net profit (or loss) by its initial cost[8]:

$$ROI = \frac{Current\ Value\ of\ Investment - Initial\ Value\ of\ Investment}{Initial\ Value\ of\ Investment} \quad (1)$$

If an investment's ROI is positive, then it is worth investing. When comparing two investments, the one with a higher ROI is going to be the most profitable.

Sharpe Ratio Sharpe Ratio is a metric that evaluates the risk-adjusted profitability of an investment. Its calculation is given by:

$$Sharpe\ Ratio = \frac{ROI - RF}{\sigma} \quad (2)$$

Where:

- ROI corresponds to the return of an investment.
- RF is the risk-free rate, which is the theoretical return of an investment with zero risk associated. The risk-free rate used in this work is 3.5% (of ROI).
- Standard deviation, represented as σ, introduces the component of volatility measure in the formula.

The higher the Sharpe ratio is, the better the investment/strategy is considered to be. Conversely, the lower the Sharpe Ratio is, the riskier the strategy is likely to be, and consequently probably also the less profitable over the long-term.

Other Metrics

- **Maximum Drawdown (MDD):** Measures the maximum lost in terms of accumulated ROI%, by capturing the greatest movement from a peak to a trough.
- **Percentage of profitable trades:** Given the total number of opened positions, how many were profitable.
- **Average profit per trade:** Average profit(loss), provided in *ROI%*. The higher the value the better.
- **Percentage of time in the market**: Measures how active in the market a trader (an intelligent system in this case) is.
- **Transaction costs:** Sum of transaction costs, in pips, throughout the test period.

4.2. Case Study A - Comparing different strategy approaches

In this case study the aim is to understand the influence of Fibonacci Pivot Points by comparing the strategy results with normal Pivot Points and without Pivot Points assistance at all. Normal Pivot Points distinguish themselves from Fibonacci Pivot

Points by not incorporating Fibonacci ratios in their calculation.

The strategy simulation was conducted for the EUR/USD currency pair, with a data set of one year of data whose data frequency is one sample per minute. Independently of the market conditions, it is assumed a fixed spread of one pip and a fixed position size of one standard lot, as table 3 shows.

Simulation Parameters	Value
Market	Forex – EUR/USD
Training Period	2017
Test Period	2018
Position Size / Lot	100000 units / 1 Standard Lot
Spread	Fixed to 1 pip

Table 3: Case Study A - Simulation Parameters.

The GA parameters used in this simulation are shown in table 4.

GA Parameters	Value
Population Size	50
Elitism Rate	10%
Tournament Selection – Selection Pressure	k = 3
Mutation Rate	10%
Random Immigrants Rate	20%
Crossover Rate	50%
Termination Criteria	100 generations or 10 generations without evolution

Table 4: Case Study A - GA Parameters.

The training results are shown in table 5

	Nº generations to converge	Nº candles	Additional channel width	Resampling %	Zig Zag filter (in pips)	Pivot Point threshold	ROI
Fibonnaci Pivot Points	26	2	0.08	0.08	3	0.82	23.5%
Normal Pivot Points	20	2	0.94	0.05	45	0.99	25.9%
No Pivot Points	28	2	0.46	0.04	13	---	26.5%

Table 5: Case Study A - Training Results.

	ROI	Sharpe Ratio	MDD (in accumulated ROI%)	Nº of open positions	Percentage of profitable trades	Avg. profit per trade (in ROI%)	Percentage of periods in the market	Transaction costs (in pips/dollars)
Fibonnaci Pivot Points	18.1%	3.85	- 0.31%	746	32.8%	0.024%	23.5%	746 pips / 7460 $
Normal Pivot Points	11.1%	2.02	- 1.34%	1649	37.2%	0.007%	39.0%	1649 pips / 16490 $
No Pivot Points	4.5%	0.28	- 1.80%	2810	34.2%	0.002%	33.6%	2810 pips / 28100 $

Table 6: Case Study A - Testing Results.

In conjunction with the data from table 6, the following conclusions can be drawn:

- The FPP strategy, which had obtained the worst ROI during the training period, was the strategy that performed the best during the test period.

- The Sharpe Ratio of each strategy indicates that better risk-reward relation is achieved using the FPP strategy. It proves that trading with Fibonacci Pivot Points is better than trading with normal Pivot Points which in turn is always better than not using Pivot Points at all. This value is corroborated by the MDD value, where minimum fall in the accumulated ROI occurs using the FPP strategy. The difference in the Sharpe Ratio value between FPP and NPP may also be explained by the additional channel width in the NPP strategy, because a channel with such a large width becomes very insensitive to price variations that translate into having difficulty finding good exit (trading) points. Moreover, although NPP applies Pivot Points, it is tested using a 99% Pivot Point threshold, since it was the configuration of the best individual found by the GA.

- All strategies had a very similar rate of profitable trades, even more that the best strategy (FPP) is the one with the lowest rate of profitable trades. By inspecting the average profit per trade and the percentage of periods in the market, we can see that FPP was the strategy with highest profits per trade and where the proposed trading system was the least active on the market, only opened a position in 23.5% of all possible trades. NPP produces the highest rate of profitable trades, however each trade had much less profit than the FPP strategy, only summing 0.007% in ROI and was the most active on the market, taking 39% of all possible trades. The strategy with *No Pivot Points* (NonePP) stands out for having only 0.002% of average profit per trade.

In summary, Fibonacci Pivot Points proved to be the best alternative to manage risk in the proposed strategy. This conclusion could have been reached just by inspecting ROI and Sharpe Ratio values.

4.3. Case Study C - Comparing the trading strategy for major, minor and exotic currency pairs

This case study aims to compare the proposed trading strategy's performance for one major, one minor and one exotic currency pair. Major currency pairs have high volume, offer a large amount of liquidity and a fairly amount of volatility, while offering price stability. Minor currency pairs offer a moderate liquidity, hence their spreads tend to be higher than the ones provided for trading majors. Also, their volatility is moderate as well. Exotic currency pairs use currencies that are thinly traded in Forex market, usually belonging to emergent market economies. They are highly illiquid and, since there are not enough buyers and sellers that trade in these markets, have very high spreads. In order to have a term of comparison between each currency pair performance, EUR/JPY and USD/NOK were chosen to conduct this study, because they have a very high correlation value with EUR/USD and between themselves. This means that when the value of one pair increases the other increases too, in the case of a positive correlation; when the value of one pair increases the other decreases, in the case of a negative correlation. Figure 6 shows the correlation between these currency pairs.

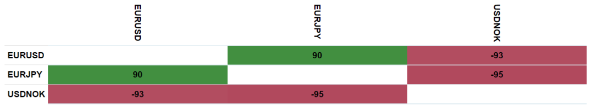

Figure 6: Case Study C - Currency pairs correlations.

The GA parameters applied were the same as in 4.2 (Case Study A). The simulation parameters are described in table 7.

Simulation Parameters	Value
Market	Forex – EUR/USD, EUR/JPY, USD/NOK
Training Period	2017
Test Period	2018
Position Size / Lot	100000 units / 1 Standard Lot
Spread	1 pip, 2 pips, 50 pips

Table 7: Case Study C - Simulation Parameters.

	Nº generations to converge	Nº candles	Additional channel width	Resampling %	Zig Zag filter (in pips)	Pivot Point threshold	ROI
EUR/USD	26	2	0.08	0.08	3	0.82	23.5%
EUR/JPY	24	2	0.03	0.02	1	0.98	96.0%
USD/NOK	43	2	0.24	0.29	46	0.86	21.6%

Table 8: Case Study C - Training Results.

	ROI	Sharpe Ratio	MDD (in accumulated ROI%)	Nº of open positions	Percentage of profitable trades	Avg. profit per trade (in ROI%)	Percentage of periods in the market	Transaction costs (in pips/dollars)
EUR/USD	18.1%	3.85	- 0.31%	746	32.8%	0.024%	23.5%	746 pips / 7460 $
EUR/JPY	73.5%	0.28	- 0.22%	15045	21.7%	0.005%	31.1%	15045 pips / 300900 $
USD/NOK	7.7%	0.15	- 1.42%	98	42.9%	0.079%	21.7%	98 pips / 49000 $

Table 9: Case Study C - Testing Results.

The best parameters configuration for each currency pair, found in the training phase (8), were applied in the testing phase. In conjunction with the data from Figure 9, the following conclusions can be drawn:

- EUR/JPY had a ROI more than 4 times the ROI with EUR/USD. USD/NOK presents a low ROI.

- Despite the high value of EUR/JPY's ROI, EUR/USD showed a far superior sharpe ratio. Both EUR/JPY and USD/NOK got very low values, which could be explained by their moderate and high volatility (respectively), meaning that EUR/USD would be a better choice concerning risk-adjusted return.

- Due to its minimum zig zag filter value and low resampling % resulted from the training, the EUR/JPY strategy opened 15045 positions, with a win rate of only 21.7% and being the most active strategy in the market (among the three tested) with 31.1% of time spent trading. On the other hand, the trading system using USD/NOK data was much more conservative, only opening 98 positions. In this case the opposite happened, a high resampling % combined with a high zig zag filter resulted in a data set with few points, which leads to less channels built and hence less opened positions. Nonetheless, those characteristics allowed this strategy to achieve a win rate of 42.9%.

- Admitting a fixed spread, it is possible to compare the difference in transaction cost between an exotic currency pair and a major/minor currency pair. Surprisingly, the USD/NOK was able to achieve a positive ROI, given the low amount of opened positions. The USD/NOK strategy did not face major drawdowns, as can be seen in Figure 7, probably due to its conservative characteristics, otherwise, being a volatile market, it would receive more false trading signals.

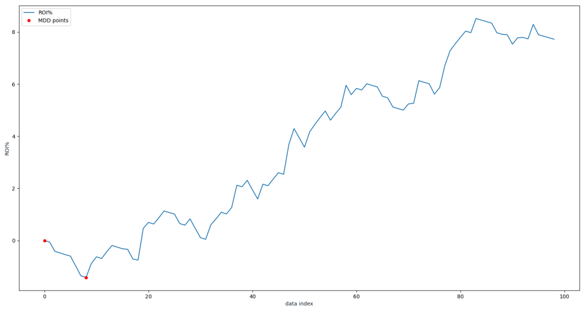

Figure 7: USD/NOK - ROI.

The proposed trading system demonstrated capability of being profitable when trading with any of the currency pairs studied. However, given the immense difference between their sharpe ratio values, it can be concluded that a major currency pair would be more suitable to trade with this system.

5. Conclusions

This work implements a solution to trade Forex currency pairs in trending markets. This system combines Technical Analysis and GA. Technical Analysis is used to create the investment investment strategy, GA is used to optimize the parameters involved in the strategy. Achieved results showed the proposed system is better suited to trade major currency pairs, namely EUR/USD (Case Study C). Also, the best strategy achieved used Fibonacci Pivot Points (Case Study A). Furthermore, the results showed that a better performance is achieved when training the GA with a bigger population size (Case Study B). The proposed system was able to reach 34.9% ROI in 2020 test data, training the GA with 2015 and 2016 data (Case Study D).

References

[1] Yaser S. Abu-Mostafa and Amir F. Atiya. Introduction to financial forecasting. *Kluwer Academic Publishers*, 1996.

[2] C. Aranha and H. Iba. Modelling cost into a genetic algorithm-based portfolio optimization system by seeding and objective sharing. *IEEE*, 2007. doi:10.1109/CEC.2007.4424472.

[3] Jerry Coakley, Michele Marzano, and John Nankervis. How profitable are fx technical trading rules? *IEEE*, 2016. http://dx.doi.org/10.1016/j.irfa.2016.03.010.

[4] M. A. H. Dempster and C. M. Jones. Can channel pattern trading be profitably automated? *The European Journal of Finance*, 2010. doi:10.1080/13518470110052831.

[5] Ahmed Elshamli, Hussein A. Abdullah, and Shawki Areibi. Genetic algorithm for dynamic path planning. *IEEE*, 2004. doi:10.1109/CCECE.2004.1345203.

[6] R.C. Cavalcante et al. Computational intelligence and financial markets: A survey and future directions. *Expert Systems with Applications*, 2016. doi:10.1016/j.eswa.2016.02.006.

[7] Cain Evans, Konstantinos Pappas, and Fatos Xhafa. Utilizing artificial neural networks and genetic algorithms to build an algo-trading model for intra-day foreign exchange speculation. *Mathematical and Computer Modelling*, 2013. https://doi.org/10.1016/j.mcm.2013.02.002.

[8] Jason Fernando. Return on investment (roi). `https://www.investopedia.com/terms/r/returnoninvestment.asp`.

[9] Pablo Fernández-Blanco, Diego J. Bodas Sagi, Francisco Soltero, and Ignacio Hidalgo. Technical market indicators optimization using evolutionary algorithms. *Genetic and Evolutionary Computation Conference, GECCO 2008*, 2008. doi:10.1145/1388969.1388989.

[10] Akinori Hirabayashi, Claus Aranha, and Hitoshi Iba. Optimization of the trading rule in foreign exchange using genetic algorithm. *Genetic and Evolutionary Computation Conference, GECCO 2009, Proceedings, Montreal, Québec, Canada*, 2009. doi:10.1145/1569901.1570106.

[11] Shaharudin Jakpar, Michael Tinggi, Akmal Hisham Tak, and Chong Wen Yi. Fundamental analysis vs technical analysis: The comparison of two analysis in malaysia stock market. *UNIMAS Review of Accounting and Finance*, 2018. doi:10.33736/uraf.1208.2018.

[12] Yu-Hon Lui and David Mole. The use of fundamental and technical analyses by foreign exchange dealers: Hong kong evidence. *Journal of International Money and Finance*, 1998. https://doi.org/10.1016/S0261-5606(98)00011-4.

[13] Imad Moosa and Larry Li. Technical and fundamental trading in the chinese stock market: Evidence based on time-series and panel data. *Emerging Markets Finance and Trade*, 2011. doi:10.2753/REE1540-496X4701S103.

[14] John J. Murphy. *TECHNICAL ANALYSIS OF THE FINANCIAL MARKETS*. New York Institute of Finance, 2^{nd} edition, 1999. ISBN:0-7352-066-1.

[15] Christopher J. Neely. Technical analysis in the foreign exchange market: A layman's guide. *Federal Reserve Bank of St. Louis*, 1997. doi:10.20955/r.79.23-38.

[16] Noraini Mohd Razali and John Geraghty. Genetic algorithm performance with different selection strategies in solving tsp. *Newswood Limited*, 2011. ISBN: 978-988-19251-4-5.

[17] Anupriya Shukla, Hari Mohan Pandey, and Deepti Mehrotra. Comparative review of selection techniques in genetic algorithm. *IEEE*, 2015. doi:10.1109/ABLAZE.2015.7154916.

[18] Lamartine A. Teixeira and Andriano L. Oliveira. A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications*, 2010. doi:10.1016/j.eswa.2010.03.033.

[19] Ahmed. S. Wafi, Hassan Hassan, and Adel Mabrouk. Fundamental analysis vs technical analysis in the egyptian stock exchange – empirical study. *IJBMS*, 2015.

[20] Hua Zhang and Ruoen Ren. High frequency foreign exchange trading strategies based on genetic algorithms. *IEEE*, 2010. doi:10.1109/NSWCTC.2010.234.