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Construction of currency portfolios by means of an optimized investment strategy

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ABSTRACT

This work focuses on the development of a technical breakout trading strategy based on the Donchian Channel approach, aiming to the construction of profitable portfolios. In this direction, the Modified Renko Bars (MRBs) were developed first; that proved to be a useful trading tool that responses more accurately than the normal candle sticks to the nature and characteristics of the FOREX market. Subsequently, the parameters of the trading strategy (or system) are calibrated for eight currency pairs, over a period of four years (2006–2009), by comparing the performance of three global search derivative-free optimization algorithms. Then, the returns of the developed system are tested for the next seven years (2010–2016) for each pair and two types of portfolios are constructed; an equal weighted one and a portfolio based on the Kelly criterion. The ultimate objective of this paper is to create currency portfolios based on a novel optimized trading strategy, which could beat constantly the main investors' benchmarks (i.e. S&P500, Barclay CTA Index).

1. Introduction

The ultimate objective of any investor, trader or manager is to speculate, to generate profits in a consistent basis. Simsek [27] assumed that any financial innovation on portfolio risks is likely to lead to speculation rather than risk sharing due to the motives of the participants in market. An approach that can be implemented in order to maximize profits and simultaneously to minimize the risk of loss, is to define specific rules for buying and selling securities; rules that will be able to predict accurately the future movements of the market. These rules formulate the so-called trading strategy or system. The most common trading strategies are based on fundamental or technical analysis; this work is focused on technical trading strategies that rely on the assumption that historical data can create patterns that repeat themselves in the future.

According to a top technical analyst (Ping [[25], p.2]) the technical analysis is defined as follows: *"The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed."*

The prediction of market's future movements became an important research topic for academicians into a theoretical basis and a challenging task for investors in practical level. One of the earliest empirical studies in this field is the one by Donchian [7] who presented the movement of the market as a channel approach focusing on the breakouts of these channels. Apart from this approach, there is a plethora of technical strategy types. Among others, trading systems that include filters were introduced (Fama and Blume [8]; Sweeney [29]), strategies that focus on the moving averages were presented (Cootner [4]; Dale and Workman [6]) and strategies based on the relative strength were studied (Jensen and Benington [13]). One of the most significant studies on this field was carried out by Brock et al. [3], who strongly supported the efficiency of technical strategies. They tested two simple technical strategies (moving average and range breakout) in Dow Jones Index in their study and using the model-based bootstrap approach they conducted statistical tests on the trading returns. A few years later, Bessembinder and Chan [2] confirmed the research outcomes presented by Brock et al. [3] and provided further support to the technical rules, indicating that they can predict the movement of the market and particularly those of the US Equity Index. In another research, Taylor [30] indicated that technical trading approach and specifically the channel style when applied to currencies can lead

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to profits, having also remarkable forecasting ability when the market follows almost random walk. Menkhoff and Taylor [21] tried to explain the continuously rising use of technical analysis and its apparent profitability. Among their arguments, they sustained that technical analysis could fit to the foreign exchange market due to not-fully-rational behaviour of the market and it might provide information on foreign exchange movements that cannot be explained through fundamental analysis. Gehrig and Menkhoff [11] also underlined the importance of technical analysis into the world of investment; especially they mentioned that it is by far the most important tool when dealing with FX and is rated second in the field of fund management. Later, Osler [23] showed that technical trading strategies can represent rational long run balance given the structure of the currency markets and traders' motivations. Relying also on the relationship between technical analysis and the FOReign EXchange (FOREX) market, in a recent study by Smith et al. [28] it was found that during high-sentiment periods, the use of technical analysis provided an edge to the hedge funds that helped them to succeed higher performance with superior market-timing ability and at the same time achieve lower risk to their investments. Another study that focused on FOREX market was by Novotný et al. [22]. They investigated a strategy based on price jump and indicated how price jumps carry a tradable signal for all currencies.

Back to real life, the experiment performed by Richard Dennis is considered as a unique example representative of the obsession related to trading and the feverish effort to generate profits. Covel [5] described in his book entitled "*The Complete Turtle Trader*" that in mid-1983, the famous commodity trader Richard Dennis conducted an experiment aiming to prove that he could teach people how to become great traders. In order to prove his belief, he published an advertisement in Barron's, the Wall Street Journal and The New York Times seeking to recruit and train people (Michael W. Covel, was one of them). According to the experiment Richard Dennis provided the trainee traders with real accounts in order to trade. These trainee traders were called as "*Turtles*" and Dennis taught them a trend-followed system based on a channel approach. The "*Turtles*" succeeded to earn an aggregate sum of over \$100 million dollars in the next four years and became the most famous experiment in trading history.

Another actual example is the one by Professor Josef Lakonishok [18], who supported that value strategies can beat the market. Based on his study, Lakonishok decided to apply his theoretical research in real-world trading practice and turn it to an almost \$70 billion dollars practice. His strategy is focused on identifying valued shares before the market recognize them. To succeed that, he proposed a system that uses valuation ratios such as price-to-book or price-to-sales and searches for companies with ratios relatively lower than their peers. Then, his system tries to identify possible entry points based on the price momentum of the last six-month period.

As Pardo [24] indicated in his book "*The Evaluation and Optimization of Trading Strategies*" the first step into trading strategy design process is the formulation of the trading strategy while another extremely crucial step is the optimization of that strategy. Optimizing the trading rules is extremely important, since actual traders are likely to choose the best-performing rules in advance. The work by Jensen and Benington [13] is considered as the forerunner study in this direction, they followed an optimization and out-of-sample validation procedure for improving the performance of relative strength index based strategies. Later, Marshall et al. [20] tried to answer if commodity futures can be traded profitably with quantitative timing strategies and to find the most suitable trading rules for each commodity in order to provide statistically significant profits. Fisher [9] in his book "*The logical trader*" introduced the ACD Rules and Pivot Point System, that provided specific entry levels for buying and selling based on the opening range of virtually any security. Tian et al. [31] attempted to optimize the rules of ACD system in an intraday basis in order to ameliorate its performance in Chinese future market. Foltice and Langer [10] focused on the creation of a momentum strategy, which could be found appropriate for an individual investor. They developed and calibrated a simple strategy, which succeeded to outperform its benchmark and it required a small initial capital.

The main objective of this study is to develop an empirical technical trading strategy, which could be applicable to the financial markets and lead to the construction of profitable portfolios. This strategy follows a channel breakout approach based on the study by Donchian [7]. The portfolios that are formed in this work are based on the currency market. Barroso and Santa-Clara [1] proved that the exposure to currency can lead to portfolios with significant higher Sharpe ratio. The strategy developed in the current study is combined with the Modified Renko Bars (MRBs); a trading tool which responses more accurately than the normal candle sticks to the nature and characteristics of the FOREX market. Aiming to create an edge to the investor and to develop a profitable portfolio, an optimization problem is formulated and solutions are carried out. The optimization stage focuses on the calibration of the system for eight FOREX pairs (GBP/USD, USD/JPY, NZD/USD, AUD/USD, EUR/USD, USD/CAD, GBP/JPY and EUR/JPY) using three global search derivative-free optimization algorithms; a Swarm Optimization one called Pity Beetle Algorithm (PBA) along with the DIvide a hyperRECTangle (DIRECT) and Multilevel Coordinate Search (MCS) algorithms. Then, optimized strategy is tested to the specific pairs and based on the returns obtained two kinds of portfolios were constructed; an equally weighted portfolio and a portfolio based on Kelly Criterion. Finally, the performance of the portfolios is assessed based on common and widespread evaluation measures (arithmetic mean, geometric return and sharpe ratio) and then they are compared with well-known benchmarks (S&P500, Barclay CTA Index). Thus, the proper question that can be stated is "*how can a profitable currency portfolio be made based on a specific trading system?*" This is the question that is answered in this study.

2. Creation of an adaptable to market conditions strategy

In order to answer the question of how a trading strategy can be mostly profitable, it is required to comprehend what makes a strategy not profitable in the long run. Creating a strategy that would be profitable for a small time horizon is rather easy to implement, if not needless. The objective of this study is to develop a trading tool, which will be proved efficient and reliable in the long run. Through a preliminary research and common trading sense, two are the factors that affect mostly the performance of a trading system. The first one is related to the amount of risk that a specific trade involves. The risk itself cannot be meaningful; however, it can become useful to answer the question of how determining if a strategy or better the trades that a strategy generates are valuable to be followed or not. In order to measure the risk of a trade effectively, it needs to be correlated to the potential reward that this trade can generate. In other words, the first factor that is used in the current study is the so-called Risk/Reward Ratio (RRR) where risk and reward are associated. This ratio is calculated by dividing the amount the trader consents to lose if the market moves in the opposite direction of his position (risk) by the amount the trader expects to earn if the price moves in the same to his position (reward) direction. Thus, if a strategy generally generates trades that risk more units and return less, then the chances are not with the trader. In this specific example, the winning trades should be far more than the losing ones in order for the outcome to be positive. This phenomenon might be easily identified at a trending market, however, when the market is flat, that is encountered in most of the cases, then it is extremely difficult to succeed a high number of winning trades (greater than 50%). Therefore, this kind of strategy cannot be characterized as "*mostly profitable*" as it was discussed previously. Consequently, a threshold (edge) needs to be recognized, likewise to a gambler that wonders, "*Where is my edge?*" in order to participate to a game or not. The development of the strategy was initiated with low, less than one RRR values (i.e. for every x units it risks, more units than x should be expected as a profit). Consequently, even for a flat market, when the amount of the winning trades is reduced, the low RRR would guarantee that the strategy would continue to be profitable or at least not detrimental. For instance, a strategy having a 35% probability to win and the corresponding RRR ratio is equal to 0.4, it creates an edge for the trader that is expressed by the following calculation:

$$35\% \times \frac{1.0}{0.4} - 65\% \times 1.0 = 22.5\%.$$

The second parameter is based on the same assumption, i.e. that the market is mostly flat and therefore the probability of a strategy to have positive outcome is becoming smaller. Contrary to Toshchakov [32] who supports in his book entitled "*Beat the odds in FOREX trading*" that the market has two directions, we believe that the market has two conditions, the trending condition and the flat condition. During the trending condition, the market indeed moves up or down. When it comes however to the flat condition, the market presents a neutral direction, which is characterized by plenty of fluctuations. Therefore, the objective is to create a mechanism that diminishes the trades when the market does not move. In this direction, a strategy needs to be developed that would be activated only by the movement of the market, independently of the time. This approach targets to increase the amount of the winning trades meaning the win/loss ratio. Already, there are trading tools that are focused mainly on the movement of the price, the renko bars is one of these tools.

2.1. Why not using candlesticks

Trading techniques that are focused on the price action suffer from the disadvantage of market's noise. The common candlesticks contain a lot of information that most of it, is contradictory. For example, one candlestick might provide a long signal and the next one a short one. This kind of noise that comes from the interaction between traders and institutions trying to establish their opinion for the market. In order for the traders to stay focused on the main trend, many tools have been created to support this approach; i.e. to smooth the movement of the market and to provide only the essential information, Heikin-Ashi and Renko charts are the most common ones. Both aim to remove or reduce the noise through proper manipulation of the simple candlestick. The main difference between Heikin-Ashi and Renko approaches is that the first one formulates bars relying on the time just like the common candlesticks. On the other hand, Renko bars are based on the price movement only, without taking into account the time. This is the main reason that this study will focus on Renko charts, since time represents a major contributor on noise creation.

2.2. How Renko chart works

According to the Renko bars trading tool the common candlestick chart is transformed into a chart where the bars are formed based on the range that the security covers, independent of the time. Renko charts use price "bricks" that represent a fixed price move. As it is seen in Fig. 1, the new chart is formed up or down in 45° lines with one brick per vertical column. For example, in a one-hour chart, each renko bar can represent different numbers of candlesticks depending on the size of the renko bar (or brick). If the brick value is set to 10 points, a move of 10 points or more is required to draw another brick. Price movements less than 10 points will be ignored and the renko chart will remain unchanged. But what "*a move of 10 points*" does it mean? Renko charts can be either closing prices or high-low range based ones. In the case of a close price based renko bar, a brick is formed only when the candlestick close price covers the 10 points (for the above mentioned example), in contrary to a high-low range based renko bar where a brick is formed when the price approaches the 10 points ignoring where the candlestick will close. The most common mode is the closed price based renko bars since they fluctuate less than the high-low range based ones.

Fig. 1. The transformation of normal candlestick chart into a renko chart with 10 pips bricks based on closed price.

Based on empirical tests on both renko charts it was observed that they have different advantages and disadvantages. Specifically, in a same, for instance, uptrend movement, less close-renko bars would be formed than high-low range renko bars because as it is mentioned before they require from the price to close above to a specific price level and just to reach this level. So in this situation, for a long trade the renko bars based on high-low range are superior creating larger margin for profit. But when the direction of the market changes, the high-low range renko bars become too sensitive giving wrong signals to the real shift of the direction and making the trader to close earlier the trade. In the other hand, the close-renko bars, moving slower, give more accurate changing of direction points. So, it become clear to us that any kind of renko bar by itself creates difficulties on the low RRR approach. To overcome this difficulty an alternative algorithm of a modified renko approach was developed herein. The key point of the proposed new concept is that the bricks of the same direction are formed based on the high-low range logic and the bricks when the direction changes are formed based on the closing price logic. The proposed new renko style (labelled as Modified Renko Bars - MRBs) creates more accurate representation of the market's true movement.

Following the development of the MRB charts that represent a reliable trading tool, a trading strategy will be formulated aiming to achieve stable performance. The proposed strategy is a breakout style system applied to the modified renko chart based on the Channel Breakout systems taught by Donchian [7].

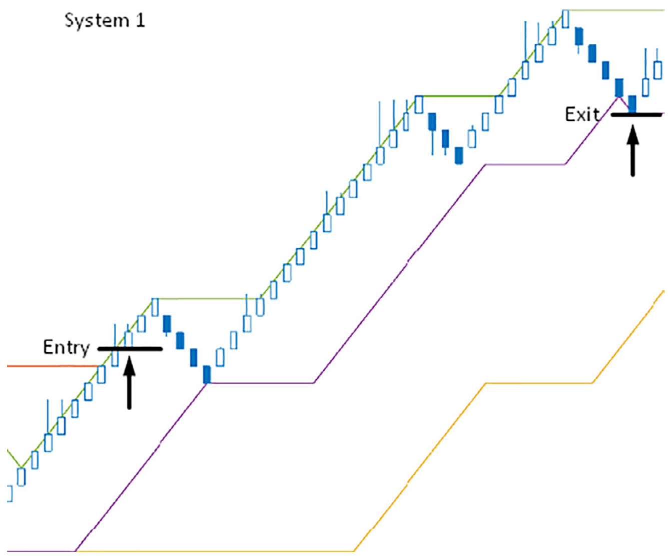

Fig. 2. Example of a long trade based on System 1. Also this is how a MRB chart looks like. The tails represent the actual price of the time of the formulation of a MRB.

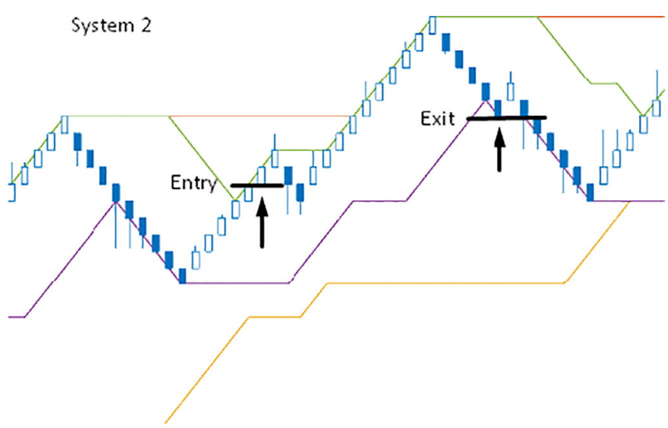

Fig. 3. Example of a long trade based on System 2.

2.3. The trading system

The system consists of two different but related breakout systems: (i) *System 1* - A long-term system based on a X-MRB breakout which is shown in Fig. 2 and (ii) *System 2* - A short-term system based on a Y-MRB breakout, where X > Y, which can be seen in Fig. 3. System 2 is complementary to System 1; more specifically, System 2 aims to catch the continuation of a price movement that triggers the exit of System 2.

System 1 Entry - Trader enters a position when the price exceeds by one MRB the previous high or the low value of the preceding X MRBs. If the price exceeds the previous X-MRB high, then trader buys one unit to initiate a long position in the corresponding commodity. If the price drops by one MRB below the previous X-MRB low, trader sells one unit to initiate a short position.

System 2 Entry - The system 2 is activated only when the trade from System 1 has closed. Trader enters position when the price is exceeded by one MRB the previous high or the low of the preceding Y MRBs. If the price exceeds the previous Y-MRB high and at the same time the price is over the previous X-MRB high, then trader buys one unit to initiate a long position in the corresponding commodity. If the price drops one MRB below the previous low of the last Y MRBs and is below the previous X-MRB low, trader sells one unit to initiate a short position.

System 1 Exit - The exit signal is the Y-MRB low for long positions and the Y-MRB high for short positions. The unit in the position will be exited if the price goes against the position for a Y-MRB breakout.

System 2 Exit - which is identical with that of system 1. Where the exit signal is the Y-MRB low for long positions and the Y-MRB high for short positions. A long position would be closed if the price drops on MRB below the previous Y-MRB low. Respectively, the trader would be exited from a short position if the price exceeds the previous Y-MRB high by one MRB.

The two systems are constructed in such a way that their entry signals do not affect each other. Although their philosophy is complementary, their execution is completely independent.

An advantage of the proposed trading system is the range of its applicability, where input data from any kind of financial asset can be used (i.e. stocks, indexes, interest rates, commodities and currencies). In order to achieve the highest possible accuracy for the simulation, the results of the back-testing process and the actual trading, traders should apply the system mainly to the most liquid markets such as futures markets (commodities, indexes, currencies, etc.); otherwise it will be too difficult under real market conditions to enter and to exit positions without taking large losses. Futures markets have several features that make them a more attractive market for active trading strategies than stock markets. Specifically, transaction costs are lower and it is easier to short-sell. All the data that are employed in this study represents spot FX rates (the most liquid financial asset) of different currency pairs.

Finally, worth mentioning that in order for the strategy developed in this study to be available under real market conditions, it will be applied based on spot FX market. The average commission per trade of this instrument is about 0.2 pips (based on the commission section of Interactive Brokers for FOREX). For each FX pair, the developed strategy generates about 100 trades per year. Hence, the transaction costs for the total trades of a year for a FX pair would be approximately 1.5% of the initial capital. This issue would not make any significant different in the obtained results, for this reason it was decided to make the calculation with no transaction costs in order to emphasize mainly to the more precise development of the proposed strategy.

3. Optimized strategy problem formulation

A major importance problem that is addressed in this study corresponds to the mathematical formulation of an optimization problem that can be expressed in standard mathematical terms as a non-linear programming problem, that in general form can be stated as follows:

$$\begin{cases} \underset{\boldsymbol{x}\in R^n}{opt}\, F(\boldsymbol{x}) : R^n \to R \\ s.t. \begin{cases} g_j(\boldsymbol{x}) \le 0,\ j = 1, 2, \ldots, m \\ L_i \le x_i \le U_i,\ i = 1, 2, \ldots, n \end{cases} \end{cases} \tag{1}$$

where F: $R^n \to R$ is a real-valued objective function to be optimized, $\boldsymbol{x} \in R^n$ is the design variables vector of dimension n, $g_j(\boldsymbol{x})$ is the jth constraint function imposed to the problem while $L_i$andU_i are the lower and upper bounds of the ith design variable.

The problem that is formulated mathematically is related to the identification of the best possible conditions in order for the developed strategy to fit smoothly to different currency pairs; i.e. entry and exit rules of the strategy, described previously, are expressed in mathematical terms. The problem at hand is formulated as a maximization problem, where the total return represents the objective function $F(\boldsymbol{x})$ that depends on four design variables: $x_i, i = 1, 2, \ldots, 4$, while a threshold value on the maximum drawdown is implemented as a constraint function. The four design variables are: (i) x_1 corresponds to the size of the brick (in pips),

(ii) x_2 is the value of parameter *X*, (iii) x_3 is the value of parameter *Y* and (iv) x_4 denotes the number of bricks that corresponds to 1% of the initial capital.

Concerning the fourth design variable, although, the observation that the smaller the size of the brick is, the higher the total return will be, is obvious; it is not able to check in advance if the drawdown (in pips) will be lower than the total initial capital. If this is not the case, then the optimized parameters resulted from the optimization of Eq. (1) will not be valuable. In order to deal with this issue, the fourth parameter was expressed as the percentage of the capital that each brick corresponds to. For this reason, the total return, that is the objective function of the optimization process to be maximized and the maximum drawdown that will be treated as a constraint are calculated at percentages.

The assessment of the trading strategy over a set of data is carried out in two phases: the strategy optimization and portfolio construction ones, which are described in detail bellow.

3.1. Data used for the calibration

The constructed portfolios are assessed over a set of data composed by one-hour time frames corresponding to the period of 2006 to 2016 for each currency pair employed for the needs of the current study. The full data is composed by 65,000 candlesticks, and they are divided into years' periods, thus each year period contains 6000 candlesticks.

In order to achieve increased accuracy concerning the actual representation of the candlestick chart into MRB charts one-hour data are employed. Aiming to minimize the effect of the gaps and the closing prices one-hour data are used. Although, the MRB chart depends on the range, if for the same security data from a small time frame and from a higher one are used, the results will not be the same. This is because part of the modified renko algorithmic formulation (the change direction part) depends on the closing price of the candlesticks. Thus, the spread between the closing price of the MRB and the actual closing price is smaller when short time frames are used and consequently the representation of movement of the market from the modified renko chart is more normalized.

3.2. Optimization phase

Through a parametric study the optimization phase was decided to rely on the first 36% part of the data (24,000 candlesticks = 4 years) as a whole, aiming to achieve the highest total return and at the same time to keep the maximum drawdown lower than 100% for each currency pair so that the result to be realistic for any starting time. The main objective of this parametric study was to create the largest testing margin (i.e. reduce the part of the data required for the optimization phase). According to the parametric study, the optimization phase initially was based on the first 60% part of the data and gradually this percentage was reduced. It was observed that the minimum percentage of the data that is required in order for the optimization phase to converge to the optimal values of four variables is equal to 36%.

The optimization phase is performed using the three optimization algorithms that are described in the following section. Relying on the first 36% part of the data (i.e. 24,000 elements), for each currency pair, optimized values for the four variables are obtained implementing each of the three algorithms. Out of the three algorithms the variables corresponding the highest total return are selected in order to be used in the testing phase. On the next phase, the calibrated strategy was tested and its performance was calculated over the remaining part of the data (i.e. elements 24,001 to 65,000 corresponding to 7 years) on a yearly basis.

3.3. Construction of the portfolio phase

Based on the optimized results obtained for each pair, two portfolios are constructed composed by these currency pairs. The first corresponds to a simple average portfolio where all pairs have the same weight coefficient. The second one is rather more advanced while different weight coefficients are assigned to the various currency pairs. Kelly [16] introduced a formula in order to determine the ideal size of a series of bets. This formula was called Kelly Criterion (KC) and it has been applied in numerous fields such as asset allocation, etc. In addition, Kelly Criterion was also used in order to determinate the weight coefficients assigned to currency pairs for the next year. In the money management sector, KC is used as a measure in order to determine the proportion of the capital that an investor should invest at a risky security.

$$Kelly\% = W - \left[\frac{(1-W)}{R}\right] \tag{2}$$

where, *W* is the win probability that is calculated by dividing the number of last period trades that returned a positive amount by the total number of trades and *R* is the win/loss ratio that is calculated by dividing the average gain of the positive trades of the last period by the average loss of the negative trades. Then the KC's proportion calculated for each currency pair is normalized for identifying their weight coefficients of the built portfolio for the next year.

3.4. Evaluation

Aiming to evaluate the constructed portfolios their arithmetic mean, geometric return and sharpe ratio are calculated. The *arithmetic mean*, or simple average, treats each year's return as an isolated event and excludes the impact of compounding. The *geometric average* treats returns as part of a continuous, single experience and takes into account the impact of compounding. The geometric or time-weighted return is measured by linking periodic returns through multiplication. The geometric average reflects the actual growth or reduction of capital in a portfolio more accurately than the arithmetic mean.

$$[(1+r_1)\cdot(1+r_2)\cdots(1+r_n)]-1 \tag{3}$$

The *sharpe ratio* measures the efficiency of a portfolio. It quantifies the return received in exchange for risk assumed. It is calculated using the return of a portfolio above a risk-free rate divided by the portfolio standard deviation. The efficiency of the portfolio, defined as the return net of cash per unit of volatility around a portfolio's average return. Sharpe ratio helps equalize returns of managers within the same asset class so they can be compared on a risk-adjusted basis.

$$\frac{(R_p - R_f)}{\sigma} \tag{4}$$

where R_p is the arithmetic mean of the returns of the portfolio, R_f is the free-risk rate and σ is the standard deviation of the returns of the portfolio.

4. Search algorithms

As it will be described subsequently, the derivative of the objective function *F* used in Eq. (1) is not analytically available, thus this type of problems is generally referred as Derivative-Free Optimization (DFO). We further refer to any algorithm applied to type of problems as a Derivative-Free Algorithm, which are classified as direct and model-based ones. Direct algorithms determine search directions by computing values of the function *F* directly, whereas model-based algorithms construct and utilize a surrogate model of the objective F to guide the search process. Algorithms are further classified as local or global, with the latter having the ability to refine the search domain arbitrarily. Finally, algorithms are classified as stochastic or deterministic, depending upon whether they require random search steps or not. In the framework of the present study three DFO global search algorithms are considered. The first one is called Pity Beetle Algorithm (PBA) which is metaheuristic algorithm belonging to the type of Particle Swarm Optimization algorithms that is also a global stochastic search algorithm, along with the DIvide a hyperRECTangle (DIRECT) and Multilevel Coordinate Search (MCS) algorithms that belong to the category of global deterministic search algorithms. A short description of all three of them is provided below.

4.1. Pity beetle algorithm

Swarm optimization characterize a stochastic, population-based group of algorithms inspired by the social behaviour of birds flocking, fish schooling etc., PBA proposed by the authors (Kallioras et al. [15]) belongs to this class of algorithms and its efficiency was found superior to other well established metaheuristic algorithms according to the CEC 2014 benchmark test, this is why was chosen as a representative of metaheuristics for the purposes of this study. It was inspired by the aggregation behaviour, searching for nest and food, of the beetle named Pityogenes chalcographus, also known as six-toothed spruce bark beetle. This beetle has the ability to locate and harvest on the bark of weakened trees into a forest, while when its population exceeds a specific threshold it can infest healthy and robust trees as well. PBA consists of three basic steps: initialization, host selection pattern and update location of broods, while a population consists of males and females; some males act as pioneer beetles that search for the most suitable (weakened) host.

The random selection of the initial population is a common practice of the application of the metaheuristics. In this implementation the initial population is generated by means of Random Sampling Technique (RST) (Kallioras et al. [15]). In this step of the algorithm, the first beetle brood (gallery/colony) is generated randomly into the search space (first generation). In general, three to six broods are created (composed of N_{pop} pioneer beetles each). Once all new broods are created, a host selection pattern is decided for each new brood.

All newly-emerged beetles will fly inside the search space looking for a better solution (host tree, preferably a weakened one) in order to create their own brood. Based on the behaviour of the beetle described previously, five types of host selection pattern are implemented into the proposed algorithm: (i) neighbouring search flight, (ii) mid-scale search flight, (iii) large-scale search flight, (iv) global-scale search flight and (v) memory consideration search flight where the best positions found so far are used. The analytical description of their algorithmic implementation can be found in (Kallioras et al. [15]). According to the host selection pattern chosen, a search area is created around the birth position of the beetles. For each pattern the definition of this area is implemented using a properly selected pattern factor (f_{pat}) and represents a parameter of PBA. According to every pattern, N_{pop} new pioneer beetles are randomly positioned into this search area by means of RST. In the last step the location of the broods (location of mating males and females) are updated and the past ones are dropped, except those stored in memory. In particular, all previous broods are extinct and the new locations become birth-places for the new generations. Flight patterns are selected for the newborns. This procedure is repeated until the termination criterion of PBA is satisfied.

4.2. Divide a hyper-rectangle algorithm

The DIvide a hyperRECTangle optimization algorithm (Jones et al. [14]) was presented as an extension of Lipschitzian optimization [26] to derivative-free optimization problems. The DIRECT sampling algorithm consists of three basic steps: initialization, identify and divide potentially optimal hyper-rectangles. Initially a transformation of the problem's search domain into a normalized unit hyper-cube space is performed. Reference to the original search space is required only when function evaluation calls are performed.

The main idea of the DIRECT algorithm is to choose among the current hyper-rectangles the one that (a) has the best objective function value and (b) is associate with a large potential rate of objective function value improvement. If c_1 is the centre of the normalized space, the value of $F(c_1)$ is calculated first. Aiming to identifying potentially optimal hyper-rectangles, dividing appropriately these rectangles, and sampling among their centres. Thus, the next step is to divide the unit hyper-cube and to perform function evaluations for the points$c_1 \pm \delta e_j,\ j = 1, 2, \ldots, N$, where δ is one-third the side-length of the hyper-cube, and e_i is the j^{th} unit vector for the case of N-dimensional problems. The division of the dimensions of the hyper-rectangle is based on the value of the factor w_j that is calculated as:

$$w_j = \min\left[F(c_1 + \delta e_j), F(c_1 - \delta e_j)\right],\ j = 1, 2, \ldots, N \tag{5}$$

and the dimension with the smallest w_j is divided into thirds, so that $c_1 \pm \delta e_j$ are the centres of the new hyper-rectangles. This pattern is repeated for all dimensions on the central hyper-rectangle, choosing the next dimension by determining the next smallest w_j. Once a hyper-rectangle has been identified as potentially optimal, the algorithm divides this hyper rectangle in to smaller ones. This procedure is repeated until the convergence criteria are satisfied.

4.3. Multilevel coordinate search algorithm

Multilevel coordinate search algorithm (Huyer and Neumaier [12]) was inspired by the DIRECT algorithm and based on multilevel coordinate search partitions the search space into hyper-rectangles with one evaluated *base point*. Contrary to DIRECT, MCS algorithm allows base points anywhere in the hyper-rectangles. Global-local search based on balanced multilevel approach is performed, where a level s is assigned to every hyper-rectangle defined as an increasing function of the number of times the hyper-rectangle has been split. Those with level s equal to s_{max} are considered too small to be further split.

In every iteration of the algorithm, for each level value the hyper-rectangles with the lowest objective value are selected and are marked as candidates for splitting. Let the number n_j be the times coordinate j has been split in the course of the algorithm, there are two cases when a hyper-rectangle of level $s < s_{max}$ is a candidate for splitting: *Splitting by rank case*: If$s > 2n[\min(n_j) + 1]$, the hyper-rectangle is always split, and the splitting index of a coordinate i is chosen such that $n_i = \min(n_j)$, and *Splitting by expected gain case:* Otherwise, the hyper-rectangle may be split along a coordinate where the splitting index and coordinate value are selected by optimizing a local separable quadratic model using previously evaluated points. However, if the expected gain is not large enough, the hyper-rectangle is not split at all but its level is increased by one. MCS be means of local search performs local searches over hyper-rectangles with level s_{max}, provided that the corresponding base points are not near previously investigated points. As s_{max} approaches infinity, the base points of MCS form a dense subset of the search space and the algorithm converges to a global minimum.

5. Numerical tests

The numerical investigation is composed by four parts, in the first one the trading strategy is calibrated based on three search algorithms, all belonging to the derivative-free optimization type of algorithms. In the second part the optimized strategies resulted from the first part are tested. In the third part invest portfolios are built while in the last one the constructed portfolios are compared with Benchmarks.

5.1. Calibration – optimization of the trading model

The main objective for this part of the study is to identify the most suitable values of the four parameters, in order to calibrate the proposed trading strategy model for each pair of currencies. The calibration of the trading strategy model is performed over the first 24,000 elements for each currency pair, aiming to find the values of the parameters that produce the highest total return. The design bounds of the four parameters were set as follow:

- $Size \in [5, 25]$
- $X \in [50, 200]$
- $Y \in [1, 49]$
- $D \in [1, 25]$

Thus, the proposed optimization problem is formulated as follows:

$$\begin{cases} \max\limits_{\boldsymbol{x}=[Size,X,Y,D]} TR(\boldsymbol{x}) : R^n \to R \\ s.t. \begin{cases} 5 \le Size \le 25 \\ 50 \le X \le 200 \\ 1 \le Y \le 49 \\ 1 \le D \le 25 \\ DrD_{max} \le 40\% \end{cases} \end{cases} \tag{6}$$

where $TR(\boldsymbol{x})$ stands for the total return value and $DrD_{max}(\boldsymbol{x})$ for the maximum drawdown. The partial derivatives of the calculation formulas of both $TR(\boldsymbol{x})$ and $DrD_{max}(\boldsymbol{x})$ with respect to the four design variables cannot be defined thus the use of derivative-free search algorithms was decided. For solving the optimization problem of Eq. (6) PBA, DIRECT, and MCS algorithms are employed. This should not been considered as an implication related to the efficiency of other algorithms; based on user's experience, any numerical search algorithm capable of dealing with this type of problems can be implemented for solving the optimization problem.

According to the formulation of Eq. (6), further to the four box constraints imposed to the parameters of the trading strategy model, a single constraint related to the maximum drawdown that should be lower than 100% is implemented. Specifically in the tests performed, from money management approach, it is not accepted maximum drawdown greater than 40%. For comparative reasons the method adopted for handling the constraints was the same for all search algorithms examined in the current study. In particular, the simple yet effective, multiple linear segment penalty function (Lagaros and Papadrakakis [17]) was adopted for handling the constraints. According to this technique if no violation is detected, then no penalty is imposed on the objective function. If any of the constraints is violated, a penalty, relative to the maximum degree of constraints' violation, is applied to the objective function. More specifically for the problem of Eq. (6) the objective function is penalized according to the formula:

$$TR = \begin{cases} TR = \dfrac{TR}{\left[1+\dfrac{(DrD_{max}-40)}{10}\right]} \; if\, DrD_{max} > 40 \\ TR \, \text{otherwise} \end{cases} \tag{7}$$

The performance of the search algorithms is influenced by the values of their control parameters; however, their selection is not a straightforward procedure. In the current study the values proposed by the developers of the three algorithms are used. More specifically for the case of PBA search algorithm, although it is not possible to define specific values for its algorithmic parameters that will be the proper ones for all test examples considered, the values that were used in the current study were found to be the proper ones as a balance between robustness and computational efficiency out of multiple numerical tests performed by the authors (Kallioras et al. [15]).

The results obtained using the three optimization algorithms for each currency pair are depicted in Table 1. As it can be observed, the total returns of the currency pairs in the optimization level are significantly high. This fact provides a first evidence of the value the proposed trading strategy.

The parameters corresponding to the highest total return for each pair will be the ones that will be used for the testing period of the 7 next years. Indicatively, for the *GBP/USD* pair among the three optimization algorithms the highest total return was obtained by PBA. The best total return that was achieved is equal to 280.84% with maximum drawdown equal to 35.83% and the corresponding parameters were: Size = 12 (pips), X = 138, Y = 13 and D = 2. Accordingly, for the *USD/JPY* pair among the three optimization algorithms the highest total return was achieved by DIRECT. The optimum total return achieved for this pair is equal to 226.59% with maximum drawdown equal to 30.00% and the corresponding parameters were: Size = 9 (pips), X = 178, Y = 17 and D = 2. Summarizing the results, although MCS achieved the best total return for four out of eight currency pairs, DIRECT for three out of eight ones and PBA for one out of eight ones, as shown in Table 1 all three algorithms achieved rather similar results concerning the value of the total return, establishing that the research is statistically significant.

In previous section, it was stated that a strategy in order to be mostly profitable and valuable in a long-term basis should be adapted to the market conditions. In this direction, the MRB were developed that aim to make the proposed trading strategy more sustainable. To check if the proposed trading tool succeeded its purpose, at the optimization process we follow the exact same procedure to the same channel breakout strategy but without this time the application of the MRB. If the optimum performance of each pair for the 4 years (optimization period data) is better when the channel strategy is applied to the MRB than it does not, then the importance of the developed trading tool is confirmed.

As it can be observed in Table 2, the MRB-based channel strategy provides steadily higher performance for the most of the FX pairs than the strategy without the use of the MRB. Specifically, the use of MRBs provides an edge in all the cases apart from USD/CAD. Worth mentioning also that the improvement of the total return in the cases of GBP/JPY, AUD/USD and GBP/USD is outstanding high. Additionally, it can be observed through Table 3 that with reference to the total return of the FX pairs, the average improvement achieved when applying the trading tool of MRBs was about 30%.

5.2. Testing of the trading model

The values of the design parameters that were identified in the first part of the numerical investigation are subsequently used in order to check the quality of the optimization process and the profitability of the developed strategy in the future (i.e. during the next seven years). Table 4 represents the testing results for each currency pair based on the calibration of the trading strategy model achieved through the optimization stage. In particular, Table 4 provides the total return and the maximum drawdown for each of the eight pairs. The tests were conducted at a yearly basis for the period 2010 to 2016 and each raw denotes the values

Table 1
Optimization process to the channel strategy with the use of MRBs.

Optimization Algorithms	Total return (%)	Max Drawdown (%)	Size (pips)	X	Y	D
GBP/USD						
PBA	280.84	35.83	12	138	13	2
DIRECT	197.1	40.95	7	162	23	3
MCS	229.5	39.65	5	50	33	5
USD/JPY						
PBA	213.57	31.28	8	200	16	2
DIRECT	226.59	30	9	178	17	2
MCS	195.8	39.47	5	50	38	3
NZD/USD						
PBA	101.54	38.23	5	103	23	4
DIRECT	79.5	42.75	8	178	16	2
MCS	128.2	36.4	5	85	33	4
AUD/USD						
PBA	178.2	38.26	7	70	14	3
DIRECT	152.24	30.5	12	121	9	2
MCS	209.9	34.35	5	125	28	4
EUR/USD						
PBA	268.94	37.76	22	147	6	1
DIRECT	273.2	28.63	6	89	26	3
MCS	303.33	31.35	20	138	2	1
USD/CAD						
PBA	168.62	39.37	12	102	24	2
DIRECT	199.41	39.38	12	108	25	2
MCS	175.8	39.37	8	199	36	3
GBP/JPY						
PBA	471.25	36.71	6	63	28	7
DIRECT	326.17	36.86	7	75	25	6
MCS	480.4	40.22	5	75	34	8
EUR/JPY						
PBA	295.95	31.96	9	69	6	3
DIRECT	302.4	41.09	7	102	9	3
MCS	286.9	41.03	5	58	22	6

Table 2
Optimization process to the channel strategy without the use of MRBs.

Optimization Algorithms	Total return (%)	Max Drawdown (%)	Size (pips)	X	Y	D
GBP/USD						
PBA	152.40	45.30	5.00	59	14	5
DIRECT	173.10	39.17	7.00	65	42	6
MCS	168.60	37.56	5.00	55	42	9
USD/JPY						
PBA	189.41	40.23	11.00	150	16	2
DIRECT	208.65	36.70	8.00	192	17	3
MCS	188.00	36.75	6.00	199	18	4
NZD/USD						
PBA	104.31	32.63	8.00	64	48	3
DIRECT	122.15	39.43	7.00	128	46	3
MCS	121.30	39.43	7.00	126	46	3
AUD/USD						
PBA	143.02	37.28	9.00	128	12	2
DIRECT	89.22	400.19	6.00	117	26	6
MCS	83.18	37.13	5.00	117	25	8
EUR/USD						
PBA	204.77	28.76	5.00	111	8	5
DIRECT	296.87	35.11	6.00	108	6	3
MCS	124.90	36.65	5.00	50	49	8
USD/CAD						
PBA	144.27	35.75	14.00	97	25	2
DIRECT	162.13	40.00	7.00	57	48	5
MCS	220.90	37.88	5.00	69	19	5
GBP/JPY						
PBA	218.97	37.77	6.00	198	9	8
DIRECT	223.14	38.90	7.00	62	9	6
MCS	164.00	39.51	5.00	62	17	15
EUR/JPY						
PBA	220.42	38.23	14.00	86	19	2
DIRECT	248.13	39.52	5.00	83	3	5
MCS	230.10	39.70	9.00	84	19	3

Table 3
Comparison of the optimum performance of the channel strategy with and without the use of MRBs.

Total Return	GBP/USD	USD/JPY	NZD/USD	AUD/USD	EUR/USD	USD/CAD	GBP/JPY	EUR/JPY
No MRB (%)	173.10	208.65	122.15	143.02	296.87	220.90	223.14	248.13
MRB (%)	280.84	226.59	128.20	209.90	303.33	199.41	480.40	302.40
Change based on no MRB (%)	62.24	8.60	4.95	46.76	2.18	(9.73)	115.29	21.87

Table 4
Annual performance of the currency pairs over the 7-year period.

Year Period	GBP/USD		USD/JPY		NZD/USD		AUD/USD	
	Total Return (%)	Max Drawdown (%)	Total Return (%)	Max Drawdown (%)	Total Return (%)	Max Drawdown (%)	Total Return (%)	Max Drawdown (%)
2010	(2.97)	24.15	(51.89)	20.43	41.11	21.70	(20.29)	23.75
2011	(29.98)	20.00	(22.72)	34.35	(31.18)	29.56	(4.85)	24.80
2012	17.00	15.77	39.96	36.21	20.63	17.92	11.11	23.73
2013	(31.20)	17.70	17.42	25.42	(27.18)	17.50	(13.75)	17.79
2014	(11.64)	22.40	42.34	34.41	(40.99)	23.79	(59.33)	13.80
2015	12.51	19.00	9.73	36.46	(27.77)	19.00	(11.60)	13.98
2016	97.30	42.50	40.02	38.78	(13.37)	12.54	(35.91)	17.00
Year Period	EUR/USD		USD/CAD		GBP/JPY		EUR/JPY	
	Total Return (%)	Max Drawdown (%)	Total Return (%)	Max Drawdown (%)	Total Return (%)	Max Drawdown (%)	Total Return (%)	Max Drawdown (%)
2010	104.24	21.29	(33.05)	13.53	35.43	14.32	77.89	23.49
2011	(2.41)	26.02	(8.87)	18.67	17.08	12.56	77.18	22.44
2012	(13.57)	28.31	(7.92)	18.52	36.46	13.74	62.35	27.39
2013	0.11	23.15	(8.45)	20.55	10.83	10.90	(20.43)	17.80
2014	69.89	30.63	4.22	23.88	68.19	20.92	34.60	16.25
2015	15.23	16.28	52.10	27.87	(29.14)	19.41	(49.95)	21.00
2016	(17.70)	15.27	(27.13)	12.22	78.74	50.67	27.10	34.41

Table 5
Evaluation measures of the currency pairs over the 7-year period.

Metrics	GBP/USD	USD/JPY	NZD/USD	AUD/USD	EUR/USD	USD/CAD	GBP/JPY	EUR/JPY
Total Sum (%)	51.02	74.86	(78.75)	(134.62)	155.79	(29.10)	217.59	208.74
Arithmetic Average (%)	7.29	10.69	(11.25)	(19.23)	22.26	(4.16)	31.08	29.82
Geometric Return (%)	1.01	4.23	(15.21)	(22.53)	15.72	(7.17)	26.24	19.53
Standard Deviation (%)	43.89	36.05	30.47	22.74	46.58	27.85	36.35	49.21
Sharpe Ratio	0.11	0.23	(0.45)	(0.96)	0.42	(0.24)	0.79	0.56

of the total return and the maximum drawdown for the particular pair for a specific year.

Table 5 shows the evaluation measures that are used to assess the total quality of the testing process for each FX pair; specifically, Total Sum, Arithmetic average, Geometric return, Standard deviation and Sharpe ratio are employed. For example, for the *USD/JPY* pair the total return observed for the 7-year period is equal to 74.86% with an arithmetic average of 10.69%, but the relatively high standard deviation of 36.05 provides geometric return of 4.23% and sharpe ratio of 0.23. For the *USD/CAD* also a negative total return is observed for the 7-year period that is equal to −29.10% with an arithmetic average of −4.16%, the relatively high standard deviation of 27.85 results into a geometric return of −7.17% and a negative sharpe ratio of −0.24. Moreover, for the *GBP/JPY* an extremely high total return was attained for the 7-year period that is equal to 217.59% with an arithmetic average of 31.08%. The high standard deviation of 36.35 provides a geometric return of 26.24% and a very positive sharpe ratio of 0.79.

5.3. Construction of portfolios based on the trading model

Table 5 depicts the values of total sum (%), arithmetic average, geometric return, standard deviation and sharpe ratio for each currency pair. As it can be observed from this comparative study some of the pairs performed very well and some had rather poor performance. As a first attempt, in order to eliminate poor performances that were related to the nature of each pair and to minimize the risk, it was decided to construct a portfolio formed by the eight currency pairs contributing with equal percentages.

It was mentioned previously this is a simple average portfolio, where all currency pairs have exactly the same percentage in the allocation chosen that is equal to 1/8 (i.e. participation of every pair by 12.50%) and will be referenced as “Equally Weighted” portfolio and denoted below as EWP1. In order to further improve the constructed portfolio’s statistics, it was decided to rely mainly on the pairs that performed better. In order to succeed that, the Kelly Criterion was used in order to evaluate the quality of the annual performance of each currency pair, the formulated portfolio is labelled as “Kelly Criterion” one and will denoted below as KCP1. Table 6 shows the percentages that each currency pair constitutes in Kelly Criterion portfolio for every particular year. All other proportions emerge from the data of the precious year. Specifically, the percentage of a pair in the given year is equal to its Kelly number obtained from the previous year divided by the sum of the Kelly numbers of all currency pairs for the previous year. In case that during the previous year a currency pair resulted into a negative Kelly number, then its percentage for the next year becomes equal to zero. Furthermore, the weight coefficients of each pair of

Table 6
Allocation of the eight pairs in the Kelly Criterion Portfolio-KCP1.

Year Period	Kelly Criterion Portfolio-KCP1 (%)							
	GBP/USD	USD/JPY	NZD/USD	AUD/USD	EUR/USD	USD/CAD	GBP/JPY	EUR/JPY
2010	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
2011	0.00	0.00	13.44	6.19	39.13	0.00	26.92	14.32
2012	9.61	9.27	0.00	18.31	0.00	0.00	32.66	30.16
2013	4.20	18.78	23.55	22.68	0.00	0.00	17.27	13.52
2014	0.00	85.31	0.00	9.25	5.44	0.00	0.00	0.00
2015	0.00	31.63	0.00	0.00	25.52	14.11	17.09	11.66
2016	23.57	10.47	0.00	8.45	21.87	34.83	0.00	0.81

Table 7
Annual returns of EWP1 and KCP1 portfolios.

Year Period	Portfolios	
	EWP1 Total Return (%)	KCP1
2010	18.81	18.81
2011	(0.72)	10.22
2012	20.75	38.08
2013	(9.08)	(8.45)
2014	13.41	34.44
2015	(3.61)	3.51
2016	18.63	10.99

Table 8
Evaluation measures of EWP1 and KCP1 portfolios.

Metrics	Portfolios	
	EWP1	KCP1
Total Sum (%)	58.19	107.60
Arithmetic Average (%)	8.31	15.37
Geometric Return (%)	7.69	14.35
Standard Deviation (%)	12.41	16.56
Sharpe Ratio	0.47	0.79

Table 9
Allocation of the five pairs in the improved Kelly Criterion Portfolio-KCP2.

Year Period	Kelly Criterion Portfolio-KCP2 (%)				
	GBP/USD	USD/JPY	EUR/USD	GBP/JPY	EUR/JPY
2010	20.00	20.00	20.00	20.00	20.00
2011	0.00	0.00	48.69	33.50	17.82
2012	11.76	11.35	0.00	39.98	36.92
2013	7.82	34.93	0.00	32.11	25.14
2014	0.00	94.00	6.00	0.00	0.00
2015	0.00	36.82	29.71	19.90	13.57
2016	41.56	18.46	38.56	0.00	1.43

Table 10
Annual returns of the improved EWP2 and KCP2 portfolios.

Year Period	Portfolios	
	EWP2 Total Return (%)	KCP2
2010	32.54	33.02
2011	7.83	18.30
2012	28.44	44.13
2013	(4.65)	1.99
2014	40.68	43.99
2015	(8.32)	(4.47)
2016	45.09	41.39

the first year are equal since there are no data available for year 2009.

The annual returns for the two constructed portfolios that are composed by the eight currency pairs are presented in Tables 7 and 8 that contain also the evaluation measure used in order to assess the performance of the two constructed portfolios. In the calculations presented herein an average free-risk rate equal to 2.5% was used. Table 8 provides the values of total sum (%), arithmetic average, geometric return, standard deviation and sharpe ratio both for EWP1 and KCP1 portfolios. As it can be observed in Table 8, EWP1 portfolio has a 7-year total return of 58.19% with an arithmetic average of 8.31% and a rather low standard deviation of 12.19, which results into a geometric return of 7.69% and a positive sharpe ratio of 0.47. As it can be seen in Table 8, KCP1 portfolio presents a significantly better performance compared to EWP1 portfolio. It has a 7-year total return of 98.45% with an arithmetic average of 14.06%, the standard deviation is equal to 16.6, which provides a geometric return of 10.54% and a higher sharpe ratio value equal to 0.71.

Aiming to improve the performance of the two portfolios, the results of the above-described comparative optimization study were exploited. In particular, the value of the average total return was calculated based on the total return of the three optimization algorithms for each currency pair. It was observed that the pairs having average total return lower than the threshold value of 200% had negative performance in the testing part. This performance can be somehow justified, since, if a currency pair cannot generate high total returns in ideal conditions (i.e. over the period that was calibrated), then during the testing part is not expected to perform well. The currency pairs that had an average total return greater than 200% were GBP/USD, USD/JPY, EUR/USD, EUR/JPY and GBP/JPY. Based on this assumption, the proposed strategy is not suitable for NZD/USD, AUD/USD and USD/CAD pairs. Thus, it was decided to construct two new portfolios, a second Equally Weighted one (EWP2) and one based on Kelly Criterion (KCP2), using only the five pairs that responded better during the optimization stage. The structure of these portfolios is the same with the original ones, i.e. with the Equally Weighted (EWP1) and Kelly Criterion (KCP1) portfolios, varying only on the number of currency pairs, the new ones contain only five out of the eight currency pairs (i.e. GBP/USD, USD/JPY, EUR/USD, EUR/JPY and GBP/JPY).

The difference from the original EWP1 portfolio is the value of the weight coefficients; since it is composed by five currency pairs only, the allocation chosen is equal to 1/5 (i.e. participation of 20%). Table 9 shows the annual proportions of each currency pair for the second Kelly Criterion portfolio. Similar to KCP1 the weight coefficients for each currency pair of the first year are equal since no data are available from year 2009 and the other percentages emerge from the data of the precious year. The only difference with KCP1 is that the new one contains only the pairs that succeeded an average total return above the threshold value of than 200% during the calibration procedure.

The annual returns for both new portfolios that have been constructed i.e. EWP2 and KCP2 is presented in Table 10, for six out of the seven years both portfolios were improved compared to the original ones. Table 11 contains the evaluation measures that are used in order to assess the performance of the two new portfolios.

Table 11
Evaluation measures of the improved EWP2 and KCP2 portfolios.

Metrics	Portfolios	
	EWP2	KCP2
Total Sum (%)	141.60	178.34
Arithmetic Average (%)	20.23	25.48
Geometric Return (%)	18.47	23.96
Standard Deviation (%)	21.77	20.42
Sharpe Ratio	0.83	1.14

An average free-risk rate equal to 2.5% is also used for the calculations. As it can be seen in Table 11, the new equally weighted portfolio outperformed the original one. Specifically, it has a total return of 141.60% with an arithmetic average of 20.23%, and a standard deviation of 21.77 that provides a geometric return of 18.47% and a positive sharpe ratio of 0.83. The new KC portfolio presents impressive results having a total return almost twice that of the original Kelly based portfolio. As it can be observed from the results shown in Table 11, it has a 7-year total return of 178.34% with an arithmetic average of 25.48%, and a standard deviation of 20.42 that provides a geometric return of 23.96% and significantly high positive sharpe ratio of 1.14. Another noteworthy issue is that this portfolio presents only one negative year (2015 return −4.47%). This means that KCP2 portfolio is characterized from a high stability in its performance.

5.4. Comparison of the constructed portfolios with benchmarks

A measure for an investor to choose a specific portfolio over another is its performance compared to its benchmarks. If the portfolio has the same or poorer returns than its benchmarks then it is more rational for the investor to choose the benchmarks itself. The benchmarks contain larger variety of securities than a portfolio. Hence, a benchmark resembles a well-diversified portfolio that reduces the unsystematic risk from the specific asset, maintaining only the systematic or market risk that cannot be eliminated. Therefore, it can be stated that when a specific portfolio cannot generate returns higher than its benchmarks, the later ones is a better alternative solution mainly due to their lower risk. As Markowitz [19] supported in his book "*Modern Portfolio Theory*" that a rational investor will not invest in a portfolio, if a second portfolio exists with a more favourable risk-expected return profile.

However, currency cannot be considered as part of a "default market", making the formation of currency benchmarks a challenging issue. Currencies were always traded in pairs; therefore, if a manager or trader is long in EUR/USD i.e. buys Euros and sell U.S. dollars. Investing in currencies represent an active investment decision. Every trade leads to be a relative value trade. As a result, there is no real natural market portfolio to measure and capture foreign exchange beta.

In order to further emphasize on the significance of the results obtained, it was decided to compare the performance of the four portfolios constructed in this study with that of benchmarks that are considered as fundamentals for the investors; i.e. the Standard & Poor's 500, Barclay CTA Index, Barclay BTOP FX Index, Barclay Currency Traders Index and Barclay Systematic Traders Index benchmarks. The Standard & Poor's 500, often abbreviated as the S&P 500, is an American stock market index based on the market capitalizations of the 500 large companies having common stock listed on the NYSE or NASDAQ. Although, the specific benchmark is not directly related to the constructed portfolios since it is constituted by stocks, it was decided to use it, because is the most popular benchmark in the world of finance and it succeeds constantly high returns making the comparison with the constructed portfolios more challenging. The Barclay CTA Index is a leading industry benchmark of representative performance of more than 500 commodity trading advisors, while an advisor must have four years of prior performance history.

The Barclay BTOP FX Index seeks to replicate the overall composition of the currency sector of the managed futures industry with regard to trading style and overall market exposure. The BTOP FX Index employs a top-down approach in selecting its constituents. The largest investable currency trading programs, as measured by assets under management, are selected for inclusion in the BTOP FX Index. The Barclay Currency Traders Index is an equal weighted composite of managed programs that trade currency futures and/or cash forwards in the interbank market. It contains more than 50 currency programs. The Barclay Systematic Traders Index is an equal weighted composite of managed programs whose approach is at least 95% systematic. It contains more than 300 systematic programs.

Table 12 shows the yearly returns of the five benchmarks for the period 2010–2016, where it can be noticed that during this period (2010–2016) only S&P500 and Barclay Currency Traders Index have positive returns for every year, showing that both have a stable performance with respect to the time. Table 13 presents the evaluation measures that were used to assess the performance of the five benchmarks. The comparison was focused on the same metrics used for the constructed portfolios in order to make results directly comparable. As it can be observed through Table 13, S&P500 seems to have the best performance out of all benchmarks that were selected. It outperforms the three out of the four Barclay's indexes with reference to the total sum, arithmetic average, geometric return and sharpe ratio. The standard deviation is the only disadvantages for S&P500. It has an almost double standard deviation value compared to Barclay CTA Index, Barclay BTOP FX Index and Barclay Systematic Traders Index, worth mentioning that Barclay Currency Traders Index attains an extremely low standard deviation value equal to 1.33%. Among the four Barclay's indexes, Currency Traders Index is the only one that provides a positive sharpe ratio. Furthermore, it presents better performance than the other three indexes in all the other measures.

Through the assessment process, the constructed portfolios were compared to S&P500 and Barclay Currency Traders Index only that proved to be the most competitive benchmarks. In particular, comparing Tables 7 and 10 with Table 12 for a year-per-year basis, it can be seen that EWP1 portfolio outperforms S&P500 for three out of the seven years and Barclay Currency Traders Index for four out of the seven years, while EWP2 portfolio outplays both benchmarks for five out of the seven years. Concerning the KCP1 portfolio, it succeeds higher returns than both benchmarks, outperforming both benchmarks for four out of the seven years and the KCP2 portfolio also outperforms S&P500 for four out of the seven years while for the case of Barclay Currency Traders Index for six out of the seven years KCP2 has better returns. However, comparing Tables 8 and 11 with Table 13, it can be seen that the evaluation measures provides a more detailed overview concerning the quality of the portfolios constructed in this study. The four constructed portfolio outperformed the Barclay Currency Traders Index with enormous difference with respect to the total sum, arithmetic average, geometric return and sharpe ratio. Specifically, the geometric return and sharpe ratio of KCP2 portfolio exceed the Barclay Currency Trader Index's by 924% and 418%, respectively. Only EWP1 portfolio failed to beat S&P500 in terms of the total sum. Although, the true advantage of the S&P500 is its sharpe ratio, KCP2 portfolio achieved a positive sharpe ratio of 1.14 outperforming by almost 10% the corresponding value of the S&P500 benchmark. Moreover, the KCP2 portfolio seems to achieve better performance with respect to all measures compared to both benchmarks. The only drawdown of the constructed portfolios is that they de-

Table 12
Annual returns of Benchmarks.

Year Period	Benchmarks				
	S&P500	Barclay CTA	Barclay BTOP FX	Barclay Currency Traders	Barclay Systematic Traders
	Total Return (%)				
2010	15.06	7.05	7.36	3.45	7.82
2011	2.11	(3.09)	(4.37)	2.25	(3.83)
2012	16.00	(1.70)	2.37	1.71	(3.20)
2013	32.39	(1.42)	(2.73)	0.87	(1.10)
2014	13.69	7.61	8.69	3.35	10.32
2015	1.38	(1.50)	1.93	4.65	(2.92)
2016	11.96	(1.19)	(5.44)	1.52	(1.78)

Table 13
Evaluation measures of Benchmarks.

Metrics	Benchmarks				
	S&P500	Barclay CTA	Barclay BTOP FX	Barclay Currency Traders	Barclay Systematic Traders
Total Sum (%)	92.59	5.76	7.82	17.80	5.31
Arithmetic Average (%)	13.23	0.82	1.12	2.54	0.76
Geometric Return (%)	12.83	0.74	1.00	2.54	0.62
Standard Deviation (%)	10.36	4.49	5.58	1.33	5.79
Sharpe Ratio	1.06	(0.32)	(0.20)	0.22	(0.26)

Table 14
Annual returns of the MRB channel strategy and the buy-and-hold (BaH) approach calculated in pips.

Year Period	GBP/USD		USD/JPY		EUR/USD		GBP/JPY		EUR/JPY	
	BaH	MRB	BaH	MRB	BaH	MRB	BaH	MRB	BaH	MRB
2010	1250	−71	−816.8	−934	1497	2085	−405	1417.3	−192.3	1635.6
2011	−220	−720	−254.5	−409	−1706	−48	−518.4	683.3	−1055.1	1620.8
2012	−371	408	1303.9	719.2	530	−271	2976	1458.3	2800.4	1309.3
2013	813	−749	1002.6	313.5	628	2.3	1854.1	433.2	1000.8	−429.1
2014	−1256	−279	1591.8	762.1	−2237	1398	1624.4	2727.7	258.5	726.7
2015	−754	300	−82.6	175.2	177	305	−3302.3	−1165.6	−1788.8	−1049
2016	−1904	2392	−537.3	1145.2	−956	−354	−1366.1	3149.7	−160.2	568.8
Total	−2442	1281	2207.1	1772.2	−2067	3117.3	862.7	8703.9	863.3	4383.1

pict relatively higher standard deviation values from all selected benchmarks.

5.5. Comparison of the performance of MRB strategy with the buy-and-hold approach

For further elaborating on the significance of this study, the performance of the proposed MRB channel strategy system when applied to the best (derived from the optimization process) currency pairs (GBP/USD, USD/JPY, EUR/USD, GBP/JPY and EUR/JPY) is compared to the buy-and-hold (BaH) strategy. According to the BaH strategy a pair is bought at the beginning of the year and is held until the end of the year. As it can be seen in Table 14, the proposed trading strategy outperforms the BaH one in the four of the five pairs. Only for the case of the USD/JPY pair MRB fails to beat the BaH returns achieving, however, significant profits. Worth mentioning that the MRB channel strategy generates better results even for the absolute value of the returns of the buy-and-hold (assuming that a sell-and-hold approach is followed).

6. Conclusion

The major achievement of this study was the construction of a portfolio having steadily profitable performance. In order to achieve this target, a friendlier and more adaptable to market conditions trading tool was developed first. In particular, the Modified Renko Bars (MRBs) were proposed in this study that comply much better with the market's movement and represent more accurately its true directions than the simple or the common renko bars. Thus, based on MRB charts a Channel breakout strategy was implemented. Subsequently, it was proved that in order to formulate a profitable strategy an optimization phase is necessary to be performed first. The optimization phase, which was carried out over a 4-year period, helped us to calibrate the parameters of the trading strategy for eight currency pairs. For the requirements of the optimization phase, three derivative-free algorithms were employed aiming to identify the parameters that achieve the highest total return for each currency pair; the parameters that develop the highest result among the three algorithms were chosen to be used in the testing and portfolios construction phases.

Afterwards, the optimized parameters obtained for each pair were tested over a 7-year period. The results obtained, especially, for five out of the eight currency pairs were found to be impressive. Specifically, when a threshold value of 200% average total return for the three optimization algorithms was set for each currency pair, it was observed that five out of the eight currency pairs resulted into average total return greater than the 200% threshold value. This observation indicates that this kind of strategy will not fit smoothly to the three pairs that failed to achieve 200% average total return. Subsequently, two couples of portfolios were constructed using equally weighted proportions and based on the Kelly criterion. The first group was constructed using the eight currency pairs (the two portfolios of the group were denoted as EWP1 and KCP1) and the second one using the five best pairs (distinguished according to the 200% threshold value principle, and the two portfolios of the group were denoted as EWP2 and KCP2). Relying on the five best currency pairs, the sharpe ratio of both portfolios was improved when compared to the original ones (i.e. EWP1 and KCP1), while the total returns of the simple average portfolio (EWP2) was increased by 143% compared to EWP1 and that of the KCP2 by 66% with reference to KCP1.

Afterwards, the portfolios constructed were compared with well-known benchmarks. In particular, comparing the 7-year performance of the improved Kelly Criterion portfolio (KCP2) with the corresponding one of the S&P500, Barclay CTA Index, Barclay BTOP FX Index, Barclay Currency Traders Index and Barclay Systematic Traders Index benchmarks it was observed that KCP2 outperformed the S&P500's total return by 92.6% and that of the Barclay Currency Traders Index by 900%, the rest of the benchmarks had rather poor to very poor performances. In general, it can be stated that the four portfolios constructed in this study performed extremely well alongside all benchmarks selected, succeeding remarkably better results in most of the cases. The only disadvantage of the constructed portfolios is the higher standard deviation that is observed; however it can be justified by the larger and better diversification in terms of securities that is available by the benchmarks that leads to lower risk and mildest fluctuation.

The development of the proposed trading system (the optimization process included) and the construction of the two portfolios derived, followed a completely systematic approach that is applicable to any financial instrument. A major advantage of the proposed investment philosophy is that it can be operated entirely by a computer generating the trading signals automatically. There is no need for investor's intervention in the trading procedure since it is strictly defined, while it composed by no "black box" parts. Worth mentioning also that, even in the case of excluding some currency pairs from the constructed portfolios due to their poor performance, the procedure followed, was also strictly mathematical and easy to be operated automatically. It consists from the comparison of the performance (i.e. total return achieved from the optimization process) part between relative financial instruments to their average. The instruments that achieve performance above average will participate on the constructed portfolios and the ones below will be excluded.

Future work will be focused mainly on the reduction of the standard deviation of the constructed portfolios and further improvement of their performance. In order to achieve these objectives, machine learning techniques will be applied, trying to evaluate the quality of every produced signal from the proposed strategy and recognize those that will be more likely to end at a losing trade.

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