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(CONSTRUCTION OF CURRENCY PORTFOLIOS BASED ON OPTIMIZED TRADING STRATEGY AND RISK MANAGEMENT USING ARTIFICIAL INTELLIGENCE)

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ΕΙΣΑΓΩΓΗ

Πρωταρχικός στόχος αυτής της μελέτης είναι η δημιουργία επενδυτικής αξίας (κέρδους) μέσω απολύτως εφαρμοζόμενων και πρακτικών διαδικασιών σε αντίθεση με αρκετές μελέτες που έχουν εκπονηθεί σε θεωρητικό επίπεδο. Για την επίτευξη της επενδυτικής αξίας η έρευνα αυτή χωρίζεται σε δύο φάσεις: α) την δημιουργία χαρτοφυλακίων από νομίσματα με βάση μία βελτιστοποιημένη στρατηγική συναλλαγών και β) την χρησιμοποίηση μεθόδων τεχνικής νοημοσύνης ως εργαλεία διαχείρισης κινδύνου για την περεταίρω βελτίωση των ήδη δημιουργηθέντων χαρτοφυλακίων.
Σχετικά με την πρώτη φάση της εργασίας, αρχικά γίνεται ανάπτυξη μίας στρατηγικής συναλλαγών, η οποία βασίζεται σε κανάλια τιμών. Στο πλαίσιο να καταστεί αυτή η στρατηγική όσο πιο κερδοφόρα γίνεται, αναπτύσσεται ένα καινούριο βοηθητικό εργαλείο συναλλαγών (MRB - Modified Renko Bar), το οποίο επιτυγχάνει μία ακριβέστερη απεικόνιση της αγοράς συναλλαγμάτων σε σύγκριση με τα κοινά διαγράμματα. Συνδυάζοντας την στρατηγική συναλλαγών με το καινούριο βοηθητικό εργαλείο δημιουργείται ένα παραμετρικό σύστημα. Οι μεταβλητές αυτού του συστήματος θα προσδιοριστούν για οκτώ συναλλαγματικές ισοτιμίες μέσα από μια περίοδο τεσσάρων χρόνων (2006-2009) συγκρίνοντας τις αποδόσεις τριών αλγορίθμων βελτιστοποίησης. Οι αλγόριθμοι αυτοί ανήκουν στην κατηγορία των αλγορίθμων εκείνων που δεν απαιτούν τον υπολογισμό των μερικών παραγώγων, της αντικειμενικής συνάρτησης και των περιορισμών. Έπειτα, κάνοντας χρήση του βέλτιστου συνόλου παραμέτρων για κάθε ισοτιμία, θα εφαρμοστεί το αναπτυχθέν σύστημα συναλλαγών για ένα χρονικό διάστημα επτά ετών (2010-2016) ώστε να προκύψουν οι αποδόσεις από το σύνολο των παραγόμενων συναλλαγών. Εφόσον, εξετασθούν οι αποδόσεις για κάθε χρονιά για κάθε ισοτιμία σειρά έχει η δημιουργία των επενδυτικών χαρτοφυλακίων. Κατασκευάστηκαν δύο τύποι χαρτοφυλακίων: α) ένα απλό ισοκατανεμημένο χαρτοφυλάκιο, στο οποίο όλες οι ισοτιμίες διατηρούν ίδιο και ίσο ποσοστό κάθε χρονιά και β) ένα χαρτοφυλάκιο στο οποίο οι ποσοστώσεις που θα κατέχει η καθεμία ισοτιμία θα προσδιορίζονται με βάση την απόδοση των συναλλαγών του προηγούμενου έτους. Εν συνεχεία, ακολουθεί η αξιολόγηση των δημιουργηθέντων επενδυτικών χαρτοφυλακίων μέσω διαφόρων επενδυτικών κριτηρίων. Τέλος, γίνεται σύγκριση των αποδόσεων τους με κάποιους από τους βασικότερους επενδυτικούς δείκτες παγκοσμίως, οι οποίοι χρησιμοποιούνται από τους επενδυτές ως σημείο αναφοράς (π.χ. S&P500, BarclayCTAIndex).

Σχετικά με τη δεύτερη φάση της μελέτης, γίνεται χρήση αλγορίθμων τεχνικών νοημοσύνης ως εργαλεία διαχείρισης κινδύνου για τη βελτίωση των αποδόσεων των δύο τύπων χαρτοφυλακίων της προηγούμενης φάσης. Στην εργασία αυτή, εστιάζουμε σε δύο αλγορίθμους μηχανικής μάθησης: α) νευρωνικά δίκτυα και β) δέντρα αποφάσεων. Μέσω της χρήσης αυτών των εργαλείων επιχειρείται να αξιολογηθούν τα παραχθέντα σήματα από το αναπτυχθέν σύστημα της πρώτης φάσης και να κατηγοριοποιηθούν σε κερδοφόρα και μη κερδοφόρα σήματα πριν μετουσιωθούν σε συναλλαγές. Έτσι, το δημιουργηθέν αυτό σύστημα διαχείρισης κινδύνου θα έχει την δυνατότητα μέσα από την κατάλληλη εκπαίδευση να προβλέπει εξ' αρχής εάν το παραχθέν σήμα θα επιφέρει κέρδος ή ζημία σε περίπτωση που ακολουθηθεί. Τα παραδείγματα πάνω στα οποία θα εκπαιδευτούν οι αλγόριθμοι θα είναι δεδομένα την στιγμή της παραγωγής του σήματος τα οποία θα αξιολογούνται με βάση το αποτέλεσμα της συναλλαγής (κέρδος ή ζημία). Τα δεδομένα εισόδου για την εκπαίδευση των αλγορίθμων είναι κυρίως τιμές τεχνικών δεικτών που

χρησιμοποιούνται ευρέως από τους επενδυτές. Επιπλέον, ως δεδομένα εισόδου χρησιμοποιείται και μία χρονοσειρά που δείχνει το επίπεδο των τιμών της εκάστοτε ισοτιμίας την στιγμή των τελευταίων πέντε σημάτων. Η διαδικασία της εκπαίδευσης - δοκιμής - αξιολόγησης των δύο αυτών αλγορίθμων θα γίνει με βάση την τεχνική της δυναμικής διολίσθησης παραθύρου. Η διαδικασία εκπαίδευσης των αλγορίθμων περιέχει δεδομένα από σήματα που παράχθηκαν από το σύστημα συναλλαγών μέσα στη περίοδο τριών χρόνων. Το μέγεθος του παραθύρου δοκιμής είναι ένας χρόνος όπως επίσης και το μέγεθος του παραθύρου αξιολόγησης των αλγορίθμων. Σκοπός είναι με την πραγματοποίηση μονό των κατηγοριοποιημένων ως κερδοφόρων σημάτων σε συναλλαγές να αποφευχθούν σημαντικές απώλειες για τον επενδυτή μυώντας έτσι την διακύμανση των χαρτοφυλακίων δηλαδή το ρίσκο τους και εμμέσως αυξάνοντας εάν είναι δυνατό και την συνολική τους απόδοση.
Όπως αναφέρθηκε και στην αρχή, σκοπός αυτής της έρευνας είναι να δημιουργήσει τα κατάλληλα εργαλεία και συνθήκες ώστε ο επενδυτής να παράγει πλούτο. Ο άνθρωπος πάντοτε επιδίωκε την υπεραπόδοση των κεφαλαίων, ιδανικά με το μικρότερο δυνατό ρίσκο. Μέχρι πρότινος, τα τραπεζικά ιδρύματα προσέφεραν ασφάλεια και υψηλές αποδόσεις στις καταθέσεις των πελατών. Πλέον που τα δεδομένα αυτά δεν ισχύουν, οι επενδυτές έχουν στραφεί σε πιο περίπλοκες επενδυτικές λύσεις στην αναζήτησής τους για σημαντικές αποδόσεις με τη μικρότερη δυνατή επικινδυνότητα. Αυτή η εργασία αποτελεί μία ολοκληρωμένη πρωτοπόρα επενδυτική λύση για διάφορους τύπους επενδυτών.

INTRODUCTION

The ultimate purpose of this study is the creation of true value (profit) through an absolutely applicable and practical way. In order for this objective to be achieved, two phases are followed: a) the construction of currency portfolios by means of an optimized investment strategy and b) the improvement of the performance of the portfolios using machine learning algorithms as risk management tool.
The first part of this study focuses on the development of a technical breakout trading strategy based on the a Donchian Channel approach, aiming to the construction of profitable portfolios. In this direction, the Modified Renko Bars (MRBs) are developed first herein; 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 this 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 main objective is to create currency portfolios based on a new optimized strategy, which could beat constantly the main investors' benchmarks (i.e. S&P500, Barclay CTA Index).

The second part of this study is focused on the utilization of Machine Learning (ML) as a risk management tool. Two well-known ML techniques are used here in; the Artificial Neural Networks (ANN) and Decision Trees (DT) ones. Specifically, the Deep feedforward Neural Networks (DNN) and Classification And Regression Trees (CART) correspondingly are used. The two ML techniques are used in order to classify the produced signals of the developed MRB trading strategy into two classes: profitable and non-profitable. The resulted two Artificial Intelligent Risk Management Systems (AIRMSs) are applied to five currencies and their performance is examined. The features that are utilized as inputs to the ML models are mainly technical indicators and also time series of past entry points are used as input features. The walk-forward testing routine, also known as dynamic sliding window process, is followed in order to train, test and evaluate the ML models. The main objective of this study is to enhance the performance of two currency portfolios by increasing their sharpe ratio primarily through the reduction of the standard deviation and the increase of the average return.
Every investor has as first priority to construct a portfolio that could provide him with the highest possible return of his initial capital especially now that the interests and the safety that the banks, used to offer, are no longer exist. The selection of portfolio is not a simple but a complicated procedure. In the market there are thousands of portfolio that someone could choose. This study constitutes an complete innovative investment solution for investors with different risk profiles.

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Part I:
Construction of currency portfolios by means of an optimized investment strategy

Part II:
IMPROVE THE PERFORMANCE OF PORTFOLIOS IMPLEMENTING MACHINE LEARNING AS RISK MANAGEMENT TOOL

PART I

CONSTRUCTION OF CURRENCY PORTFOLIOS BY MEANS OF AN OPTIMIZED INVESTMENT STRATEGY

1. INTRODUCTION

The ultimate objective of any investor, trader or manager is to speculate, to generate profits in a consistent basis. Simsek (2013) supported 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 (2014, 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 (1960) 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 (1966); Sweeney (1986)), strategies that focus on the moving averages were presented (Cootner (1962); Dale and Workman (1980)) and strategies based on the relative strength were studied (Jensen and Benington (1970)). One of the most significant studies on this field was carried out by Brock et al. (1992), 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 (1998) confirmed the research outcomes presented by Brock et al. (1992) 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 (1994) indicated that technical trading approach and specifically the channel style when applied to currencies can lead to profits, having also remarkable forecasting ability when the market follows almost random walk. Menkhoff and Taylor (2006) 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 behavior of the market and it might provide information on foreign exchange movements that cannot be explained through fundamental analysis. Gehrig and Menkoff (2006) 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 (2012) 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. (2015) 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 (2015). 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 (2009) 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 (Lakonishok et al. (1994)), 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 (2008) 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 (1970) 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. (2007) 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 (2002) 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. (2012) 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 (2015) 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 (1960). The portfolios, that are formed in this work, are based on the currency market. Barroso and Santa-Clara (2015) 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 percent). 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 is wondered "*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 percent 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 (2006) 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 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 Figure 1, the new chart is formed up or down in 45 degree lines with one brick per vertical column. For example, in an 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.

Figure 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 to 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 (labeled 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 (1960).

2.2 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 Figure 2 and (ii) *System 2* - A short-term system based on a Y-MRB breakout, where X > Y, which can be seen in Figure 3.

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.

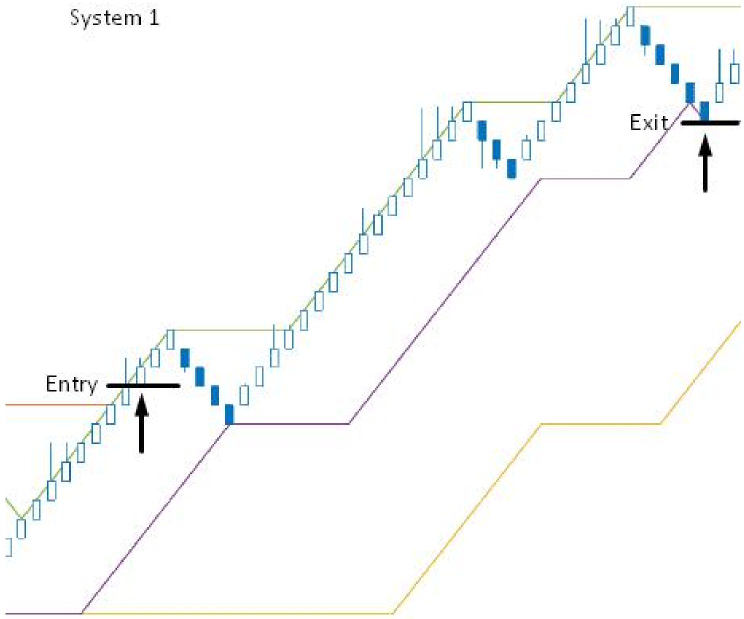

Figure 2. Example of a long trade based on System 1. Also this is how a MRB chart looks like. The tails represent the actual price of the time of the formulation of a MRB.

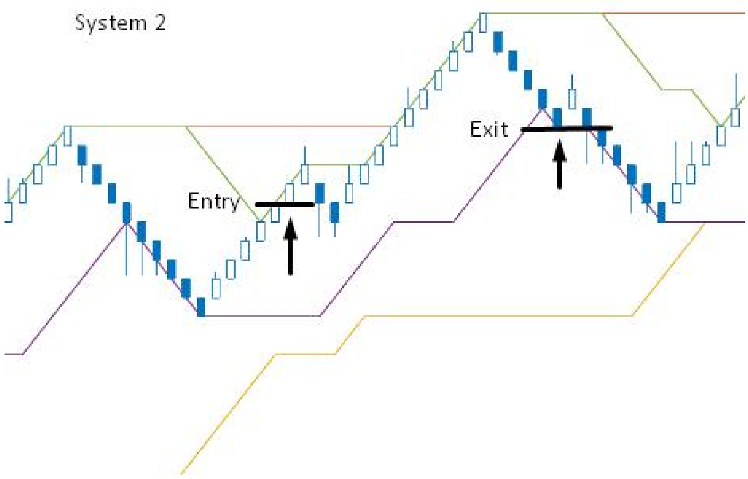

Figure 3. Example of a long trade based on System 2.

In order to achieve the highest possible accuracy for the simulation and results of the back-testing process, traders should apply the system only to the most liquid markets such as future markets; 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 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 E-Micro Forex Futures. The average commission per contract of this instrument is about \$0.20 US. Hence, the transaction costs for the total trades of a year for a FX pair based on the proposed strategy would be approximately 1.5%. 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:

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

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 j^{th} constraint function imposed to the problem while L_i and U_i are the lower and upper bounds of the i^{th} 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(**x**)* that depends on four design variables; x_i, $i = 1, 2, \quad , 4$, while a threshold value on the maximum drawdown is implemented as a constraint function. The four design variables are: (i) [x_1] - The size of the brick (in pips), (ii) [x_2] - The parameter *X*, (iii) [x_3] - The parameter *Y* and (iv) [x_4] - The percent of the capital that each brick will worth.

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 6,000 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 (1956) 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.

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

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.

$$\left[(1+r_1)\cdot(1+r_2) \quad (1+r_n)\right]-1 \quad (3)$$

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. (2017)) 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 behavior, 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. (2017)). 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 behavior of the beetle described previously, five types of host selection pattern are implemented into the proposed algorithm: (i) neighboring 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. (2017)). 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. (1993)) was presented as an extension of Lipschitzian optimization (Shubert, 1972) 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 center 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 centers. Thus, the next step is to divide the unit hyper-cube and to perform function evaluations for the points $c_1 \pm \delta e_j,\ j = 1, 2, \quad, N$, 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:

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

and the dimension with the smallest w_j is divided into thirds, so that $c_1 \pm \delta e_i$ are the centers 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 (1999)) 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 $s > 2n\lceil \min(n_j) + 1 \rceil$, 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 5alues 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 (2012)) 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. (2017)).

The results obtained using the three optimization algorithms for each currency pair are depicted in Table 1. 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. 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. For the *NZD/USD* pair among the three optimization algorithms the highest total return was provided by MCS. The best total return that was achieved is equal to 128.20% with maximum drawdown equal to 36.40% and the corresponding parameters were: Size = 5 (pips), X = 85, Y = 33 and D = 4. For the *AUD/USD* pair among the three optimization algorithms the highest total return was achieved by MCS. The best total return that was achieved is equal to 209.9% with maximum drawdown equal to 34.35% and the corresponding parameters were: Size = 5 (pips), X = 125, Y = 28 and D = 4. For the *EUR/USD* pair among the three optimization algorithms the highest total return was also achieved by MCS. The best total return that was achieved is equal to 303.33% with maximum drawdown equal to 31.35% and the corresponding parameters were: Size = 20 (pips), X = 138, Y = 2 and D = 1. For the *USD/CAD* pair among the three optimization algorithms the highest total return was achieved by DIRECT. The best total return that was achieved is equal to 199.41% with maximum drawdown equal to 39.38% and the corresponding parameters were: Size = 12 (pips), X = 108, Y = 25 and D = 2. For the *GBP/JPY* pair among the three optimization algorithms the highest total return was also achieved by MCS. The best total return that was achieved is equal to 480.4% with maximum drawdown equal to 40.22% and the corresponding parameters were: Size = 5 (pips), X = 75, Y = 34 and D = 8. Concluding, for the *EUR/JPY* pair among the three optimization algorithms the highest total return was achieved by DIRECT. The best total return that was achieved is equal to 302.4% with maximum drawdown equal to 41.09% and the corresponding parameters were: Size = 7 (pips), X = 102, Y = 9 and D = 3. 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 PBD 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.

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

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%.

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

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

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

	GBP/USD		USD/JPY		NZD/USD		AUD/USD	
Year Period	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
	EUR/USD		**USD/CAD**		**GBP/JPY**		**EUR/JPY**	
Year Period	**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 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 the *GBP/USD* pair the total return observed for the 7-year period is equal to 51.02% with an arithmetic average of 7.29%. However, the relatively very high standard deviation of 43.89 provides significantly lower geometric return of 1% and positive but rather low sharpe ratio of 0.11. Correspondingly, 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 *NZD/USD* a negative total return is observed for the 7-year period that is equal to -78.75% with an arithmetic average of -11.25%. Similarly, the relatively high standard deviation of 30.47 provides an even lower geometric return of -15.21% and negative sharpe ratio of -0.45. For the *AUD/USD* also a significantly low negative total return is observed for the 7-year period that is equal to -134.62% with an arithmetic average of -19.23%. Likewise, the relatively high standard deviation of 22.74 results to a geometric return of -22.53% and to an extremely low negative sharpe ratio of -0.96. Contrary, for the *EUR/USD* a very high total return is achieved for the 7-year period that is equal to 155.79% with an arithmetic average of 22.26%, but the high value of the standard deviation of 46.58 provides a geometric return of 15.72% and a positive sharpe ratio of 0.42. 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. 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. Closing, for the *EUR/JPY* also an extremely high total return was reached for the 7-year period that is equal to 208.74% with an arithmetic average of 29.82%, the extremely high standard deviation of 49.21 results into a geometric return of 19.53% and a positive sharpe ratio of 0.56.

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

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.

Table 6 presents the proportions (weight coefficients) for each currency pair per year. As 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 labeled as “Kelly Criterion” one and will denoted below as KCP1. Table 7 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 the first year are equal since there are no data available for year 2009.

Table 6. Allocation of the eight pairs in the Equally Weighted Portfolio-EWP1.

Year Period	Equally Weighted Portfolio-EWP1 (%)							
	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	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
2012	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
2013	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
2014	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
2015	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
2016	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50

Table 7. 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

The annual returns for the two constructed portfolios that are composed by the eight currency pairs are presented in Tables VIII and IX 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 9 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 9, 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 9, 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.

Table 8. Annual returns of EWP1 and KCP1 portfolios.

Year Period	Portfolios	
	EWP1	KCP1
	Total Return (%)	
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 9. 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

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).

Table 10 shows the yearly proportions of each currency pair for EWP2. 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 11 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.

Table 10. Allocation of the five pairs in the improved Equally Weighted Portfolio-EWP2.

Year Period	Equally Weighted Portfolio-EWP2 (%)				
	GBP/USD	**USD/JPY**	**EUR/USD**	**GBP/JPY**	**EUR/JPY**
2010	20.00	20.00	20.00	20.00	20.00
2011	20.00	20.00	20.00	20.00	20.00
2012	20.00	20.00	20.00	20.00	20.00
2013	20.00	20.00	20.00	20.00	20.00
2014	20.00	20.00	20.00	20.00	20.00
2015	20.00	20.00	20.00	20.00	20.00
2016	20.00	20.00	20.00	20.00	20.00

Table 11. 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

The total return for both new portfolios that have been constructed i.e. EWP2 and KCP2 is presented in Table 12, for six out of the seven years both portfolios were improved compared to the original ones. Table 13 contains the evaluation measures that are used in order to assess the performance of the two new portfolios. An average free-risk rate equal to 2.5% is also used for the calculations. As it can be seen in Table 13, 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 13, 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.

Table 12. Annual returns of the improved EWP2 and KCP2 portfolios.

Year Period	Portfolios	
	EWP2	KCP2
	Total Return (%)	
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

Table 13. 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

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 (1952) 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 favorable 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 14 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 15 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 15, 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.

Table 14. 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 15. 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)

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 VIII and XII with Table 14 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 IX and XII with Table 15, 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 depict relatively higher standard deviation values from all selected benchmarks.

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.

PART II

IMPROVE THE PERFORMANCE OF PORTFOLIOS IMPLEMENTING MACHINE LEARNING AS RISK MANAGEMENT TOOL

1. INTRODUCTION

First priority of the investors is to construct a portfolio that could provide them with the highest possible return of the initial capital, especially now that the interests and safety that banks, used to offer, no longer exist. Selecting a portfolio is not a simple but rather a complicated procedure since in the market there are thousands of portfolios that an investor could choose. Apart from the arithmetic average return of the portfolio, the standard deviation of its returns is a major importance factor that an investor should consider in order to access the quality of a portfolio. The standard deviation is a crucial parameter, which affects significantly an important metric of a portfolio such sharpe ratio. If two portfolios have the same arithmetic average, the portfolio with the highest standard deviation will result to a lower sharpe ratio. The highest standard deviation a portfolio has, the riskier it is. As Markowitz (1952) assumed in his *Modern Portfolio Theory*, investors are risk averse, meaning that between two portfolios having the same expected return investors would choose the one with the lower risk. An investor would accept increased risk, only if counterbalanced by higher expected return.

During the last two decades, a trending field of study is to the application of artificial intelligent (AI) techniques in finance trying to generate profits mainly by forecasting the future movement of the market. Kimoto *et.al* (1990) used back propagation neural networks to predict the price of Tokyo Stocks and then determined buying and selling points. A noteworthy result of this study is that succeeded prediction with very high accuracy. Refenes *et.al* (1994) used neural networks to develop a model based on arbitrage pricing theory in order to forecast the stock ranking. The application of the neural networks achieved better performance compared to the classical statistical techniques in terms of accuracy. Chen *et.al* (2003) modelled the market index of Taiwan Stock Exchange trying to predict its future direction. They concluded that the investment strategies based on the probabilistic neural networks succeeded to outperform other common strategies such as the buy-and-hold one. Wu *et.al* (2006) used the decision tree algorithm to trade stocks based on filter rules. Applying this approach to Taiwan and NASDAQ stock markets, they succeeded better performance compared to the results of the filter rules itself. Choudhry and Garg (2008) provided a combined approach of support vector machine (SVM) with genetic algorithms (GA) for predicting stocks' future direction. GA was used for selecting the input features, which contained technical indicators and correlation metrics within the stocks. Also, their study proved that the combination of GA and SVM outperformed the application of SVM only. Chang *et.al* (2009) created a three-stage system based on a dynamic time windows, case based reasoning and a back propagation neural network approach for stock trading prediction. Their attempt succeeded to result high rates of returns for nine stocks with different kind of trends (upward, downward, steady). Teixeira and Oliveira (2010) conducted a research developing a trading system based on technical analysis (moving averages and relative strength indexes) and nearest neighbours' classification. They applied this system to stocks in order to identify buy points and comparing the results to the buy-and-hold approach. Recently, Arvalo *et.al* (2017) proposed an automatic and dynamic trading rule based on identification of flag patterns using several filters. Applying this system to DJIA index, they succeeded to outperform the previous results in this field.

The main objective of this study is to use the artificial neural networks (ANN) and decision trees (DT) as risk management tool; in particular the study will focus on the classification of the produced signals of a trading strategy into profitable and non-profitable signals. Specifically, the two AI techniques will be applied on the modified renko bar (MRB) channel strategy that was introduced in Part I. The aim is to improve the performance of the enhanced equally weighted portfolio (EWP2) and the enhanced Kelly criterion portfolio (KCP2) portfolios that were constructed by the authors in Part I, focusing on the reduction of their standard deviation and the amelioration of the relationship between their total return and the portfolios' standard deviation. The sharpe ratio is the measure that will be used to approximate this relationship. These two machine learning techniques are based on a training-testing-evaluation procedure that in the current study follows a dynamic sliding window approach. The size of the training windows is three years, while the size of the testing and evaluation period is equal to one year each. During the training-testing procedure, both AI techniques are calibrated based on several input parameters. The F1-score is the evaluating metric that is used for both AI techniques. The objective of the calibration procedure is to predict the quality of the produced trading signals by the MRB channel strategy and avoid the signals that might lead to a losing trade. The signals that will be classified as profitable via the developed AI based risk management system (AIRMS) of each AI techniques are transformed to actual trades that will be used in order to construct the new AI based equally weighted portfolios (EWP-DT and EWP-ANN) and the new AI based Kelly criterion portfolios (KCP-DT and KCP-ANN) following the same principals as the original ones. Finally, based on the results obtained the AIRMS will be evaluated.

2. MACHINE LEARNING

In this work two machine learning techniques are employed namely decision trees and deep neural networks that a short description is provided below.

2.1 Decision Trees

Decision trees (DTs) represent a non-parametric supervised learning method, often used for classification and regression purposes. The goal is to create a model able to predict the value of a target variable by learning simple decision rules inferred from the data features. There are several variants of decision trees such as ID3, C4.5, C5.0 and classification and regression trees (CART). In this work an optimized version of CART is used (see Figure 1).

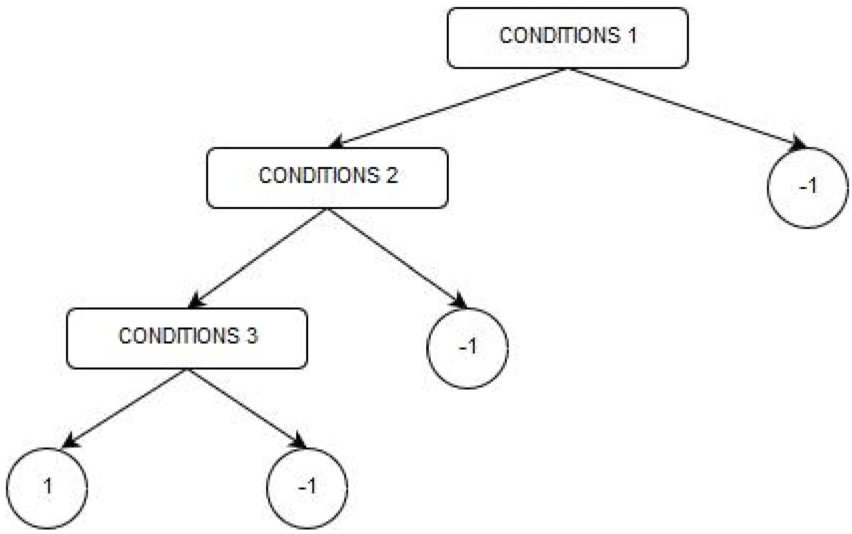

Figure 1. Binary decision tree

2.1.1 CART algorithmic description

Globally-optimal classification tree analysis (GO-CTA) (also called hierarchical optimal discriminant analysis) refers to the generalization of optimal discriminant analysis that can be used to identify the statistical model that achieve the maximum accuracy for predicting the value of a categorical dependent variable for a dataset consisting of categorical and continuous variables. The resulted GO-CTA model is a non-orthogonal tree that combines categorical variables and cut points for continuous variables; yielding maximum prediction accuracy. Hierarchical optimal discriminant analysis may be considered as a generalization of Fisher's linear discriminant analysis. Optimal discriminant analysis is an alternative to analysis of variance (ANOVA) and regression analysis, which attempt to express one dependent variable as a linear combination of other features or measurements. However, ANOVA and regression analysis give a dependent variable that is a numerical variable, while hierarchical optimal discriminant analysis gives a dependent variable that is a class variable.

If a target is a classification outcome taking on values $0,1, \quad ,k-1$, for node *m*, representing a region R_m with N_m observations, let:

$$p_{mk} = \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i = k) \tag{1}$$

be the proportion of class *k* observations in node *m*. Common measures of impurity are the Gini:

$$H(X_m) = \sum_k p_{mk}(1 - p_{mk}) \tag{2}$$

Cross-Entropy:

$$H(X_m) = -\sum_k p_{mk} \log(p_{mk}) \tag{3}$$

and Misclassification:

$$H(X_m) = 1 - \max(p_{mk}) \tag{4}$$

Related to the application of CART to real sector, CART as a classification method contains some important advantages compare to other statistical classification methods. First of all, this method is non-parametric because it does not require specification of any functional form. Furthermore, CART does not require variables to be selected in advance. Therefore, this algorithm will itself identify the most significant variables and eliminate non-significant ones. Besides, CART can easily handle outliers. Outliers can negatively affect the results of some statistical models such as principal component analysis (PCA) and linear regression. However, the splitting algorithm of CART will easily handle noisy data: CART isolates the outliers in a separate node. This property is very important because financial data very often have outliers due to significant financial events, like defaults. Another advantage of CART in financial sector is that it is flexible and has the ability to adjust in time. The main idea is that learning sample is consistently replaced with new observations. It means that CART tree has an important ability to adjust to current situation in the market (Breiman *et.al* (1984)).

2.1.2 Parameters of DT

In each training-testing session, eight parameters of DT are calibrated in order to reach to the DT that will give the highest evaluation metric. The *Criterion* denotes the function to measure the quality of a split. Gini impurity and Cross-Entropy are the two criterions that are used. *Splitter* represents the strategy that is used to choose the split at each node. The supported strategies are “best” to choose the best split and “random” to choose the best random split. *Max features* is the maximum number of features to consider when looking for the best split. *Min samples split* is the minimum number of samples required to split an internal node. *Max depth* is the maximum depth of the tree. It is possible that nodes are expanded until all leaves are pure or until all leaves contain less than *min samples split* samples. *Min samples leaf* is the minimum number of samples required to be at a leaf node. *Class weights* represent the weight coefficients that are associated with classes. It is possible that all classes are supposed to have weight one. *Min impurity split* is the threshold for early stopping in tree growth. A node will split if its impurity is above the threshold, otherwise it is a leaf.

2.2 Deep Neural Networks

Artificial neural networks (ANNs) represent a biologically inspired computational machine learning model; they are composed by elements known as artificial neurons that perform in a manner analogous to the elementary functions of a biological neuron. ANNs are organized in a way that is related to the anatomy of the brain and they exhibit a surprising number of the brain's characteristics. Typically, the neurons are arranged into layers and the signals travel from the first layer (labelled as input) through hidden ones (if any) to the last one (labelled as output) (see Figure 2).

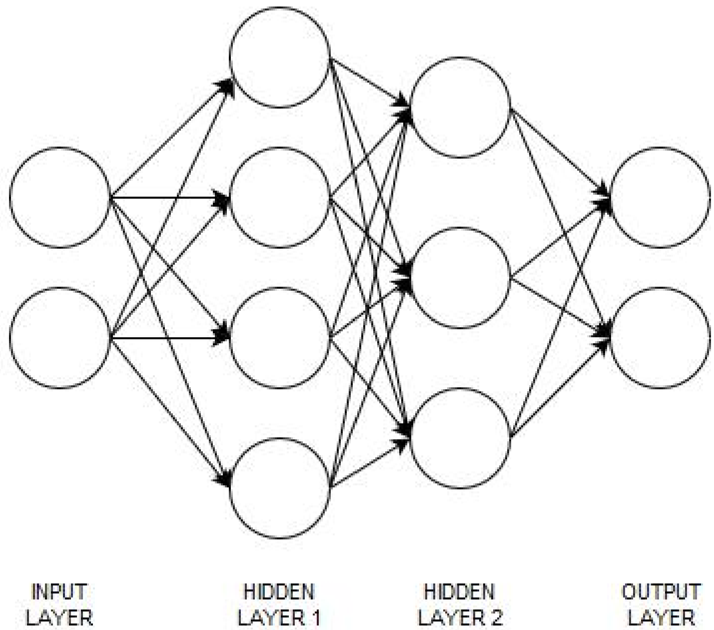

Figure 2. A four-layer feedforward neural network

2.2.1 ANN algorithmic description

The objective of ANNs is to solve problems in the same way that a human would. The human brain learns from experiences. So do ANNs, they "understand" past data in order to use them for future predictions. One the most common use of neural networks is pattern recognition. Pattern recognition systems are in many cases trained from labelled "training" data (supervised learning), but when no labelled data are available other algorithms can be used to discover previously unknown patterns (unsupervised learning). This study focuses on supervised learning through classification. ANNs process records one at a time, and "learn" by comparing their classification of the record (which, at the outset, is largely arbitrary) with the known actual classification of the record. The errors from the initial classification of the first record is fed back into the network, and used to modify the networks algorithm the second time around, and so on for many iterations.

A Neural Network architecture A consists of a specific number of layers, a number of units in each layer and a type of activation function. If a set of weight parameters **w** is assigned to the connections of the network, a mapping $\mathbf{y}(\mathbf{x}^m; \mathbf{w}, A)$ is defined between the input vector $\mathbf{x}^m$ and the output vector **y**. The quality of this mapping is measured using the following error function:

$$E_D(\mathbf{D}|\mathbf{w}, A) = \sum_m \frac{1}{2}\left(\mathbf{y}(\mathbf{x}^m; \mathbf{w}, A) - \mathbf{t}^m\right)^2 \tag{5}$$

A learning algorithm tries to determine the weight parameters **w** in order to minimize the error function E_D. Iterative minimization algorithms are therefore used to obtain the optimum weight parameters **w**. For the solution of the minimization problem the operator O is applied, resulting to the following iterative formula:

$$\mathbf{w}^{(t+1)} = O(\mathbf{w}^{(t)}) = \mathbf{w}^{(t)} + \Delta\mathbf{w}^{(t)} \tag{6}$$

Most of the numerical minimization methods are based on the above expression, while to initiate the algorithm a starting vector of weight parameters $\mathbf{w}^{(0)}$ is necessary. The changing part of the algorithm $\Delta\mathbf{w}^{(t)}$ can be further decomposed in:

$$\Delta\mathbf{w}^{(t)} = a_t \mathbf{d}^{(t)} \tag{7}$$

where $\mathbf{d}^{(t)}$ specifies the direction of search and a_t is the corresponding step size.

The signals that are produced by the MRB channel strategy, are classified in two categories - labels; profitable and no-profitable signals. The developed system attempts to discover possible patterns between the data that are available at the time of the signal and through them to predict if a produced signal will end up to a wining or a losing trade. Due to the number of the classes, which are two, we focus on a binary classification procedure. In this work, the type of ANN, that is used, is the feedforward neural network (FFNN). The special characteristic of this neural network is that the neurons between the units do not form a cycle meaning that the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. Due to the non-linear nature of the problem that this study try to solve, multilayer FFNNs are applied, which also called deep neural networks (DNNs). As Hornik *et.al* (1989) supported and it is also mathematical proved, DNNs are considered universal approximators. This term means that they are capable of approximating any measurable function to any desired degree of accuracy. There are no theoretical limitations of success of DNNs. So, any lack of success is related to inadequate learning, insufficient number of hidden units or the lack of deterministic relationship between input and target.

2.2.2 The hyperparameters of the ANN

The type and the performance of ANN is affected by its parameters. In particular, *hidden layers* are the layers that exist between the input and the output. In this developed system, general tests based on these data were conducted for two and three hidden layers. The approach with the two hidden layers gave consistently better results. *Processing elements per hidden layer* is an important decision for the correct structure of a neural network. In this work, the number of processing elements in each hidden layer is determined by an optimization through the train data in order to succeed the higher results based on the used evaluation metric. *Early stopping* is a form of regularization used to avoid over-fitting when training a learner with an iterative method, such as gradient descent. Such methods update the learner so as to make it better fit the training data with each iteration. Up to a point, this improves the learner's performance on data outside of the training set. Past that point, however, improving the learner's fit to the training data comes at the expense of increased generalization error. Early stopping rules provide guidance as to how many iterations can be run before the learner begins to over-fit. Early stopping rules have been employed in many different machine learning methods, with varying amounts of theoretical foundation. In our calculations, the early stopping parameter is defined as six maximum validation failures. *Iterative Learning Process* is a procedure in which data cases are presented to the network one at a time, and the weights associated with the input values are adjusted each time. After all cases are presented, the process often starts over again. During this learning phase, the network learns by adjusting the weights so as to be able to predict the correct class label of input samples. This developed risk management system uses the gradient descent with momentum and adaptive learning rate back-propagation as iterative learning process. Gradient descent is a first-order iterative optimization algorithm. To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient of the function at the current point. An extension of this gradient descent algorithm is the momentum method that emphasizes on reducing the risk of getting stuck in a local minimum, as well as speeds up the convergence considerably in cases where the process would otherwise zig-zag heavily. The term “back-propagation” means the most common training procedure for feedforward neural networks that consists in an iterative optimization of a so-called error function representing a measure of the performance of the network. As Li *et.al* (2009) introduced in order to avoid oscillation inside the network, such as alternating connection weights, and to improve the rate of convergence, there are refinements of the back-propagation algorithm that use an adaptive learning rate.

2.3 Evaluation Metric

The evaluation metrics represent the criteria that are used in order to access and ameliorate the performance of the machine learning techniques (ANN and DT). The algorithm, following the performance of the evaluation metric, attempts to ‘understand’ the meaning of its purpose. The true objective of the study is to increase the total return and to reduce the standard deviation. So, traditional metric such as accuracy between predictions and targets are not used due to the fact that each signal is not corresponded to a standard profit (positive or negative). Other trades ends to a big profit and others to small one. The metric that is used based on this special characteristic is the F1 score, which is commonly used in statistical analysis of binary classification. It considers both the precision p and the recall r of the test to compute the score: p is the number of correct positive results divided by the number of all positive results, and r is the number of correct positive results divided by the number of positive results that should have been returned. The F1 score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst at 0.

$$F_1 = 2 \cdot \left[p \cdot \frac{r}{(p+r)} \right] \tag{8}$$

2.4 Training, testing and validation sets

In this work, the approach in order to evaluating both AI techniques is a walk-forward testing routine also known as either sliding or moving window testing. Popular in evaluating commodity trading systems, walk-forward testing involves dividing the data into a series of overlapping training-testing-validation sets. This approach attempts to simulate real-life trading and tests the robustness of the model through frequent retraining on a large out-of-sample data set. In walk-forward testing, the size of the validation set leads the retraining frequency of the machine learning algorithm. Frequent retraining is more time consuming, but allows the decision tree to adapt more quickly and accurately to changing market conditions. Furthermore, the training and testing sets is scaled together since the purpose of the testing set is to determine the ability of the AI method to generalize.

In the previous part, data from five currencies pairs were employed for the period 2006-2016. In this study the data of the first four-year period (2006-2009) were used to optimize the trading system's parameters, while the application of the optimized system corresponds to the 2010-2016 period. Based on the walk-forward testing routine, the size of the training window is a three-year period, the size of the testing window is the following year after the training period and the evaluation set is the next year after the testing year. This model slides through the pass of every year.

Specifically, the signals that are produced by the MRB channel strategy for each currency pair during the three-year period of 2006-2008 are used as training data for the ANNs and DTs. The signals from 2009 represent the testing data of the model, while the evaluation data will be the produced signals during the 2010. So, the developed system will attempt to predict which signals of 2010 will be profitable and which will be not. After the end of 2010, the whole system moves forward by one year meaning that the new training set is the 2007-2009 period, the new testing period is the year of 2010 and the evaluation period is the 2011 (see Figure 3).

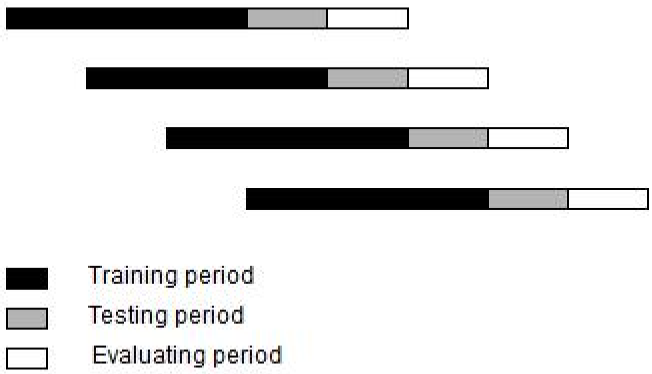

Figure 3. Walk-forward sliding windows testing routine

The return of each year for each pair based on the each machine learning algorithm is determined as the sum of the returns of all the trades that the algorithm classified their signal as profitable. The signals that were categorized as non-profitable will be ignored.

Table 1. Predictions of AIRMS-ANN and AIRMS-DT

No. of Signals	**Profit/Loss (pips)**	**Predictions**			**Results (pips)**		
		Without AIRMS	**AIRMS-ANN**	**AIRMS-DT**	**Without AIRMS**	**AIRMS-ANN**	**AIRMS-DT**
1	(28.40)	1	1	-1	(28.40)	(28.40)	0.00
2	(48.00)	1	1	-1	(48.00)	(48.00)	0.00
3	143.40	1	1	1	143.40	143.40	143.40
4	53.60	1	1	1	53.60	53.60	53.60
5	153.50	1	1	1	153.50	153.50	153.50
6	(15.60)	1	1	-1	(15.60)	(15.60)	0.00
7	(52.10)	1	1	1	(52.10)	(52.10)	(52.10)
8	(74.40)	1	1	-1	(74.40)	(74.40)	0.00

9	324.00	1	1	1	324.00	324.00	324.00
10	(71.90)	1	1	1	(71.90)	(71.90)	(71.90)
11	(36.00)	1	1	-1	(36.00)	(36.00)	0.00
12	181.90	1	1	1	181.90	181.90	181.90
13	60.00	1	1	-1	60.00	60.00	0.00
14	231.80	1	1	1	231.80	231.80	231.80
15	(96.00)	1	1	-1	(96.00)	(96.00)	0.00
16	24.00	1	1	-1	24.00	24.00	0.00
17	(85.00)	1	1	-1	(85.00)	(85.00)	0.00
18	20.90	1	1	-1	20.90	20.90	0.00
19	20.70	1	-1	1	20.70	0.00	20.70
20	(42.70)	1	1	1	(42.70)	(42.70)	(42.70)
21	(12.00)	1	1	-1	(12.00)	(12.00)	0.00
22	28.70	1	1	1	28.70	28.70	28.70
23	(48.00)	1	-1	-1	(48.00)	0.00	0.00
24	58.40	1	-1	1	58.40	0.00	58.40
25	(60.00)	1	1	-1	(60.00)	(60.00)	0.00
26	(17.50)	1	1	-1	(17.50)	(17.50)	0.00
27	(46.80)	1	-1	1	(46.80)	0.00	(46.80)
28	(75.20)	1	1	-1	(75.20)	(75.20)	0.00
29	(81.40)	1	-1	1	(81.40)	0.00	(81.40)
30	61.80	1	1	1	61.80	61.80	61.80
				Total return (pips)	471.70	568.80	962.90

The Table 1 illustrates the way each AIRMS manages the produced signals. These signals constitute a subset of the signals that produced during 2010 in GBP/USD. The mark “1” means that the signal would be a profitable one according to the corresponding AIRMS so it is formed to a trade. The mark “-1” means that the signal would be a non-profitable one so it is ignored. Based in this logic the total return of the thirty trades is formed for each AIRMS. The column “Without AIRMS” represents the original MRB trading strategy where all the signals become trades.

3. FEATURES

Machine learning models aim to “learn” the relationship between a set of input and output data, i.e. attempt to create a desired mapping between the inputs and the targets of a training set that is composed by *m* input-target pairs $\mathbf{D}=[\mathbf{x}^m, \mathbf{t}^m]$. The features that are used as inputs to the ML models aim to describe the class that every specific object belongs to. In this work, in order to help investors to follow the signals that are most likely to generate profit, several input features are combined, aiming to predict when a produced trading signal will conclude to a winning or a losing trade. In total, the number of the input features considered in this study is equal to 20. Most of these features (14 out of the 20 ones), correspond to technical indicators that are calculated based on the prices of the MRB chart. The values of these indicators are defined at the specific time that a signal is produced.

Technical indicators refer to mathematical expressions that are used to predict the financial market direction. These mathematical formulas are based mainly on historic price (open, close, high and low) and volume. Generally, indicators overlay on price chart data to indicate where the price is directed, or whether the price is in an "overbought" or "oversold" state.

The features based on technical indicators that are used in this study are: (i) Cross of simple moving average of the last 200 bars and simple average of the last 100 bars (one feature), (ii) Cross of simple moving average of the last 50 bars and simple average of the last 25 bars (one feature), (iii) Relative strength index of the last 14 MRB (one feature), (iv) Acceleration between 12 last bars (one feature), (v) Moving average convergence/divergence (MACD) (one feature), (vi) Stochastic oscillator (one features), (vii) Momentum of the 12 last MRB (one features), (viii) Bollinger band (two features; upper, lower and middle band), (ix) Weighted close price (one feature), (x) Price rate of change of the close price of the last 12 bars (one feature), (xi) High and low channel of the last *Y* MRB (two features). Where the *Y* has been computed for every pair in Part I. These features are described below:

Simple moving average (SMA) is an arithmetic moving average calculated by adding the closing price of the security for a number of bars and then dividing by the number of bars.

Relative strength index (RSI) is a momentum indicator that compares the magnitude of recent profits and losses over a specific number of bars to calculate speed and change of price movement of a security. It is mainly used to identify overbought or oversold state in the trading of an asset. It has a range between 0 and 100. Generally, when the RSI is under the level 30 is oversold and when is above the level 70 is overbought.

$$RSI = 100 - \left[\frac{100}{(1+RS)} \right] \tag{9}$$

where *RS* denotes the Relative Strength that is calculated as the ratio of average gain / average loss.

Moving average convergence divergence (MACD) is a trend-following momentum indicator that presents the relationship between two moving averages of prices. The *MACD* is computed by subtracting the 26-bar *exponential moving average (EMA)* from the 12-bar *EMA*. A nine-day *EMA* of the *MACD*, called the "signal line", is then plotted on top of the *MACD*, functioning as a trigger for buy and sell signals.

$$\begin{aligned} MACD &= EMAofC(N=12) - EMAofC(N=26) \\ Signal\ Line &= EMAofMACD(N=9) \end{aligned} \tag{10}$$

where

$$EMAofX(N) = X_n \frac{2}{(N+1)} + X_{n-1}\left[1 - \frac{2}{(N+1)}\right] \tag{11}$$

Momentum is a simple technical indicator that shows the difference between recent closing price and the close *N* bars ago.

$$Momentum = \left| C_{current} - C_{current-N} \right| \tag{12}$$

Bollinger band, developed by famous technical trader John Bollinger, is a volatility channel which its levels is determined two standard deviations away from a simple moving average of N bars. Where *middle band* is equal to *SMAofC(N)* and

$$\begin{aligned} Upper\ Band &= Middle\ Band + 2 \cdot stDev(last\ N\ bars) \\ Lower\ Band &= Middle\ Band - 2 \cdot stDev(last\ N\ bars) \end{aligned} \tag{13}$$

High and low channel is a moving average indicator that tracks a security's highest highs and lowest lows over a set number of bars. Where *high channel* is equal to the maximum of the *N* last bars high and *low channel* is equal to the minimum of the *N* last bars low.

Stochastic oscillator is a momentum indicator that compares the closing price of a security to the range of its prices over a certain number of bars. The sensitivity of the oscillator to market movements is reducible by taking a moving average of the result.

$$K = 100\frac{C - L_{10}}{H_{10} - L_{10}}$$
$$D = SMAofK\left(N = 3\right) \quad (14)$$

where L_{10} is the minimum of the 10 last bars low and H_{10} is the maximum of the 10 last bars high.

Price of change (PoC) calculates the price rate of change from the closing price. The price rate of change is calculated between the current closing price and the closing price *N* bars ago.

$$PoC = \frac{(C_{current} - C_{current-N})}{C_{current-N}} \quad (15)$$

Weighted close price (WCP) attempts to normalize the movement of the price. So it is calculated as the average of twice the closing price plus the high and low prices.

$$WCP = \frac{(2 \cdot C + H + L)}{4} \quad (16)$$

Acceleration (AC) is the difference of two momentums separated by *N* bars.

$$AC = Momentum_{current} - Momentum_{current-N} \quad (17)$$

The rest six features are based on some specific characteristics of the way the entry signals of the strategy are formed. Thus, five of these six features contain the last five entry prices where a signal was produced. The idea behind this selection is for the two algorithms to create potential support and resistance levels, which would help them to identify more accurate the quality of the signals. The last feature is focused on the difference between the *MRB* close price and the true price of the currency at the time of the signal. The absolute value of this difference is calculated. It is reasonable that the higher this value is, the smaller the probability of the signal to end to a winning trade will be.

4. NUMERICAL TESTS

The numerical investigation is composed by the implementation of the walk-forward testing routine to both decision trees and artificial neural networks models adopted for extracting the returns for each currency, the re-construction of the portfolios and the comparison to the original ones. A set of four-year signals is used for training and testing (75% of the set is used for training and the rest 25% for testing) while the signals of the next year are used for the evaluation part. This mechanism slides forward at the end of each year by one year (see Figure 2).

4.1 Calibration of Decision Trees

Decision trees have value even with little hard data and they also use a white box model. Based on these characteristics, another parameter that is used in order for the DT algorithm to be calibrated in each training-testing session is the *k* (smaller or equal to twenty) best features from the total 20 features. Tests which were conducted to these kind of data showed that the DT algorithm response better to fewer number of features. The *k*-best model is applied each time to the corresponding training-testing data testing all the possible combination of the feature set contributing to the amelioration of the performance of the DT algorithm. The criterion that the *k*-best algorithm uses in order to select the *k*, each time, best features is the F-value of ANOVA. F-test is any statistical test in which the test statistic has an F-distribution under the null hypothesis. It is most often used when comparing statistical models that have been fitted to a data set, in order to identify the model that best fits the population from which the data were sampled. In one-way ANOVA, the F-statistic is calculate as the ratio: $F = variation\ between\ sample\ means\ /\ variation\ within\ the\ samples$.

Table 2. Number of selected features via k-best algorithm for calibrating the AIRMS-DT

Year Period	Number of selected features for AIRMS-DT				
	GBP/USD	USD/JPY	EUR/USD	GBP/JPY	EUR/JPY
2010	13	19	16	6	5
2011	12	9	7	8	13
2012	7	17	12	11	16
2013	12	10	14	5	10
2014	7	8	18	11	17
2015	15	5	10	18	5
2016	5	16	10	20	6

The features that were selected as inputs to the DT of each currency pair for every year are shown in Table 2.

Table 3. Currency returns based on AIRMS-DT

Years	Returns via AIRMS-DT (%)				
	GBPUSD	**USDJPY**	**EURUSD**	**GBPJPY**	**EURJPY**
2010	16.21	(47.17)	104.24	35.43	102.21
2011	(25.53)	0.90	35.97	19.22	77.18
2012	37.32	45.74	(10.50)	36.46	52.19
2013	(37.87)	33.47	1.54	3.36	15.54
2014	3.54	45.53	59.02	68.19	59.07
2015	20.45	12.50	15.23	(42.81)	(48.82)
2016	97.30	32.21	(11.22)	120.69	16.22
Total return (%)	111.42	123.18	194.28	240.54	273.59

Table 4. Currency returns without any AIRMS

Years	Returns via MRB channel strategy				
	GBPUSD	**USDJPY**	**EURUSD**	**GBPJPY**	**EURJPY**
2010	(2.97)	(51.89)	104.24	35.43	77.89
2011	(29.98)	(22.72)	(2.41)	17.08	77.18
2012	17.00	39.96	(13.57)	36.46	62.35
2013	(31.20)	17.42	0.11	10.83	(20.43)
2014	(11.64)	42.34	69.89	68.19	34.60
2015	12.51	9.73	15.23	(29.14)	(49.95)
2016	97.30	40.02	(17.70)	78.74	27.10
Total return (%)	51.02	74.86	155.79	217.59	208.74

Yearly results obtained by the implementation of the DT based AIRMS for each currency are depicted in Table 3. For each FX pair, the results for 2010 were produced using the calibrated DT model, and the calibration was based on the data of the previous four years (2006-2009). Hence, by training the model using the data of the first 3 years (75%) and testing it to the fourth (25%), it was succeeded to identify the best value for its parameters which provided the highest F1-score. Using this optimal calibrated model the class of the signals of 2010 are predicted. Based on the walk-forward testing routine the same procedure is followed to calculate the returns of the remaining six years. Meaning that, for instance, for the return of 2011, the period of 2007-2010 is worked as training-testing dataset or the period 2012-2015 is used in order for the DT to be calibrated appropriately to determine which signals of 2016 will be transformed to an actual trade and which not. The sum of the outcome of that trades will lead to the return of the 2016. In order to evaluate the value of the AIRMS based on DT, the produced returns of that system should be compared to the original returns from the MRB channel strategy. So, the Table 3 and Table 4, which contains the returns of the MRB trading strategy, are compared.

For the GBPUSD, the DT based AIRMS generated higher or equally well returns for six out of the seven years from the original returns. Specifically, the largest increase related to the original results was achieved during 2010. The AIRMS succeeded to improve the return for year 2010 by about 645%, i.e. from the value of -2.97% to 16.21%. The worst year of AIRMS in relation to the original returns was obtained for year 2015 where a decrease of 21% was encountered. The total return achieved for the AIRMS is equal to 111.42% that in comparison to the original return of 51.02% corresponds to a significant improvement of 118%.

In the case of the USDJPY exchange rate, for six out of the seven years the returns produced by the DT based AIRMS are higher compared to those achieved by the MRB strategy. Specifically, the higher increase related to the original results was achieved during 2011. The AIRMS succeeded to improve the return for year 2011 by about 104%, i.e. from the value of -22.72% to 0.9%. The worst year of AIRMS in relation to the original returns was obtained for year 2016 where a decrease of 19.5% was achieved, maintaining a positive return of 32.21%. The total return achieved for the AIRMS is equal to 123.18% that in comparison to the original return of 74.86% corresponds to a significant improvement of 64.55%.

Accordingly, in the case of the EURUSD exchange rate, for six out of the seven years the returns produced by the DT based AIRMS are higher compared to those achieved by the MRB strategy. Specifically, the largest increase related to the original results was achieved during 2011. The AIRMS succeeded to improve the return for year 2011 by approximately the extreme value of 1500%, i.e. AIRMS succeeded to alter a negative return value of -2.41% to a positive one of 35.97%. The worst year of AIRMS with reference to the original returns was obtained for year 2014 where there was a decrease of 15.55%. The total return achieved for the AIRMS is equal to 194.28% that in comparison to the original return of 155.79% corresponds to a significant improvement of 24.70%.

In the case of the GBPJPY exchange rate, for five out of the seven years the returns produced by the DT based AIRMS are higher or equal compared to those achieved by the MRB strategy. Specifically, the largest increase related to the original results was during 2016. The AIRMS succeeded to improve the return of 2016 by about 53.28%, i.e. AIRMS achieved rise even more the already high return of 78.74% to 120.69%. The worst year of AIRMS related to the original returns was obtained for year 2013 where there was a decrease of 69%, maintaining a positive return of 3.36%. The total return succeeded for the AIRMS is equal to 240.54% in comparison to the original return of 217.59%, bringing off a important increase of 10.55%.

In the case of the EURJPY exchange rate, for five out of the seven years the returns produced by the DT based AIRMS are higher compared to those achieved by the MRB strategy. Specifically, the largest increase to the original results was during 2013. The AIRMS succeeded to improve the return of 2013 by about 176%, i.e. AIRMS achieved to change a negative return of -20.43% to a positive one of 15.54%. The worst year of AIRMS with reference to the original returns was obtained for year 2016 where there was a decrease of 40.15%, maintaining a positive return of 16.22%. The total return achieved for the AIRMS is equal to 273.59% in comparison to the original return of 208.74%, corresponds to an increase of 31%.

An important observation on the results obtained by the DT based AIRMS is that it succeeded to ameliorate the total return for all currency pairs. This observation proves that the DT based AIRMS provides a stable capability to predict the class of the produced signals in such a way in order to generate constantly high profits. Another meaningful observation is that the developed risk management system based on DT achieved to improve most of the negative returns, which produced the MRB channel strategy. The later one is the main usefulness of a risk management system; i.e. to prevent the investors from the significant drawdowns of a trading strategy.

4.2 Re-Construction of EWP2 and KCP2 based on AIRMS-DT

In the previous section the returns for each currency pair, that were produced by the DT based AIRMS, were presented. In this section, the two portfolios constructed in Part I are re-constructed. The first one is a simple average portfolio where all pairs have the same weight coefficient. The second portfolio is rather more advanced and different weight coefficients are assigned to the various currency pairs. The weight coefficients of each currency pair for each year are determined by its performance during the previous year based on the Kelly criterion. The portfolios are formed based on exactly the same approach that was used for EWP2 and KCP2 presented in Part I. The two re-constructed portfolios will be denoted as EWP-DT and KCP-DT, respectively. In order to evaluate the effect of the DT based AIRMS on the performance of the two portfolios, EWP-DT and KCP-DT will be compared to the original ones (i.e. EWP2 and KCP2).

Table 5. Allocation of the five currencies in EWP-DT

Year Period	Equally Weighted Portfolio based on AIRMS-DT (EWP-DT) (%)				
	GBP/USD	USD/JPY	EUR/USD	GBP/JPY	EUR/JPY
2010	20.00	20.00	20.00	20.00	20.00
2011	20.00	20.00	20.00	20.00	20.00
2012	20.00	20.00	20.00	20.00	20.00
2013	20.00	20.00	20.00	20.00	20.00
2014	20.00	20.00	20.00	20.00	20.00
2015	20.00	20.00	20.00	20.00	20.00
2016	20.00	20.00	20.00	20.00	20.00

Table 6. Equally Weighted Portfolio based on AIRMS-DT (EWP-DT)

Years		2010	2011	2012	2013	2014	2015	2016
EWP-DT	**Returns (%)**	42.18	21.55	32.24	3.21	47.07	(8.69)	51.04

Table 7. Equally Weighted Portfolio without any AIRMS (EWP2)

Years		2010	2011	2012	2013	2014	2015	2016
EWP2	**Returns (%)**	32.54	7.83	28.44	(4.65)	40.68	(8.32)	45.09

Table 5 shows the yearly proportions of each currency pair assigned to the EWP-DT portfolio. The allocation chosen is equal to 1/5 since EWP-DT is composed by five currency pairs. Table 6 contains the returns of EWP-DT portfolio, which is based on the AIRMS-DT, while Table 7 presents the returns of the initial portfolio EWP2 that was based on the original MRB channel strategy. Comparing the results of these two tables it can be observed that the re-constructed equally weighted portfolio succeeds to outperform the original one EWP2 for six out of the seven years. Specifically, the broadest increase related to the original results was achieved during year 2011. EWP-DT portfolio succeeded to improve the return for year 2011 by almost 175%, i.e. the return was improved from the value of 7.83% to 21.55%. Another significant amelioration which the equally weighted portfolio succeeded through AIRMS-DT was during 2013, where a losing year with -4.65% return turned it to a winning one with 3.21% return. The only year, which the EWP-DT could not beat the EWP2, was 2015 where the return of -8.32% became -8.69%, a decrease of 4.40%.

Table 8. Evaluation metrics of EWP-DT

Metrics of EWP-DT					
Total return (%)	**Compound growth (%)**	**Arithmetic average (%)**	**Geometric return (%)**	**Standard deviation (%)**	**Sharpe ratio**
188.60	478.43	26.94	25.06	21.07	1.16

Table 9. Evaluation metrics of EWP2

Metrics of EWP2					
Total return (%)	**Compound growth (%)**	**Arithmetic average (%)**	**Geometric return (%)**	**Standard deviation (%)**	**Sharpe ratio**
141.61	327.53	20.23	18.47	21.77	0.83

These improvement that the developed DT based risk management system achieved on the performance of EWP2 are more clearly presented when comparing the evaluation metrics of the two equally weighted portfolios. These metrics are seen at Tables 8 and 9, which contain the total return, the compound growth, the arithmetic average, geometric return, standard deviation and the Sharpe ratio of each portfolio corresponding. Notably, the EWP-DT attained a total return of 188.60% improving the total return of the original equally weighted portfolio by approximate 33%. Regarding to compound growth, the re-constructed equally weighted portfolio reported a return equal to 478.43% that compared to the EWP2's compound growth is increased by 46%. This means that an investor who invest $10,000 in 2010 at EWP-DT, he would have by the end of 2016 $47,800. Furthermore, the standard deviation of the new average portfolio decreased by 3.20%, from 21.77% to 21.07%. One the most important evaluation metrics that investors use to access the quality of a portfolio is the sharpe ratio because it, combining the return and the standard deviation of a portfolio, measures risk-adjusted return. The application of the AIRMS-DT to the EWP2 had as result to raise significantly the sharpe ratio by 42.43%, i.e. from 0.81 to 1.16.

Table 10. Allocation of the five currencies in KCP-DT

Year Period	Kelly Criterion Portfolio based on AIRMS-DT (KCP-DT) (%)				
	GBP/USD	USD/JPY	EUR/USD	GBP/JPY	EUR/JPY
2010	20.00	20.00	20.00	20.00	20.00
2011	10.28	0.00	41.28	27.72	20.73
2012	4.72	59.55	8.10	14.50	13.13
2013	26.26	38.17	0.00	20.67	14.89
2014	0.00	73.27	11.54	3.52	11.67
2015	0.00	40.12	22.67	19.34	17.87
2016	47.45	24.98	27.46	0.00	0.10

Table 11. Kelly Criterion Portfolio based on AIRMS-DT (KCP-DT)

Years		2010	2011	2012	2013	2014	2015	2016
KCP-DT	Returns (%)	41.60	32.73	43.20	8.03	51.64	(4.21)	47.14

Table 12. Kelly Criterion Portfolio without any AIRMS (KCP2)

Years		2010	2011	2012	2013	2014	2015	2016
KCP2	Returns (%)	33.02	18.30	44.13	1.99	43.99	(4.47)	41.39

Table 10 presents the yearly percentages of each currency pair assigned to the KCP-DT. This allocation during a year is based on the Kelly Criterion of each pair from the previous year. For this reason, the 2010's weight coefficients are equal for all the currencies due to the lack of data from 2009. Table 11 contains the returns of the KCP-DT, which is based on the AIRMS-DT, while Table 12 presents the returns of the KCP2 from the original MRB channel strategy. Comparing the results of these two tables, it can be observed that the re-constructed KC based portfolio succeeds to outperform the KCP2 for six out of seven years. Specifically, the bigger increase related to the original returns was during 2013. The KCP-DT succeeded to rocket the return for year 2013 by about 303%, i.e. from 1.99% to 8.03%. This means that achieved to predict with great accuracy the most of the non-profitable signals in order to avoid the loses of that potential trades. Another significant amelioration which the KC based portfolio succeeded through AIRMS-DT was during 2011, where the 18.30% return almost doubled it to 32.73% return. The only year, which the KCP-DT underperformed the KCP2, was 2016 where the return of 44.13% became 43.20%, a small decrease of 2.11%.

Table 13. Evaluation metrics of KCP-DT

Metrics of KCP-DT					
Total return (%)	Compound growth (%)	Arithmetic average (%)	Geometric return (%)	Standard deviation (%)	Sharpe ratio
220.14	621.46	31.44	29.82	19.70	1.47

Table 14. Evaluation metrics of KCP2

Metrics of KCP2					
Total return (%)	Compound growth (%)	Arithmetic average (%)	Geometric return (%)	Standard deviation (%)	Sharpe ratio
178.35	449.89	25.48	23.97	20.42	1.14

These improvements that the developed DT based risk management system achieved on the performance of KCP2 are more clearly presented when comparing the evaluation metrics of the two KC based portfolios. These metrics can be seen in Tables 13 and 14, that contain the total return, the compound growth, the arithmetic average, geometric return, standard deviation and the Sharpe ratio for each portfolio corresponding. Notably, the KCP-DT achieved a significant high total return of 220.14% improving the total return of the original KC based portfolio by approximate 23.43%. Regarding the compound growth, the re-constructed portfolio based on KC achieved a return equal to 621.46% that compared to the KCP2's compound growth is increased by 38%. This means that an investment of $10,000 in 2010 on the KCP-DT portfolio, a capital equal to $62,140 will be returned in year 2016. Furthermore, the standard deviation of the new KC portfolio is decreased by 3.5%, from 20.42% to 19.70%; and the implementation of the system AIRMS-DT to the KCP2 had as results to raise significantly the sharpe ratio by 30.55%, i.e. from 1.14 to 1.47.

The contentious improvements on the performance of the EWP2 and KCP2 portfolios, that the adjustment of the AIRMS-DT offered, underline that its ability to recognize the quality of the signal produced is significant. In both portfolios, the use of AIRMS-DT increased their total return and sharpe ratio, while their standard deviation was decreased. Furthermore, it succeeded to strengthen the profitable stability of the returns for each year, providing a real boost to the power of compounding. Since this is the core of the risk management logic which can help initial investment grow exponentially.

4.3 Calibration of Artificial Neural Networks

Due to the nature of ANN, during its application all the features are used as input data. This happens because ANN structure needs enough data in order to discover patterns, which can lead to more accurate predictions. Continuously fluctuations of the number of input features combining to the calibration of all the other hyperparameters would make the whole process computational costly and could lead the model to overfitting or underfitting failing develop a true predictive ability to the data.

Table 15. Currency returns based on AIRMS-ANN

Years	**Returns via AIRMS-ANN (%)**				
	GBPUSD	**USDJPY**	**EURUSD**	**GBPJPY**	**EURJPY**
2010	37.87	(50.03)	66.40	41.52	43.23
2011	(19.20)	(22.72)	0.08	20.06	79.70
2012	5.95	39.96	25.24	54.44	59.62
2013	(16.24)	13.25	26.84	10.83	(32.98)
2014	(4.63)	42.82	36.35	69.10	34.60
2015	11.01	33.71	15.23	(13.49)	(21.37)
2016	97.30	81.44	(17.70)	42.40	25.78
Total return (%)	112.05	138.43	152.44	224.85	188.57

The results obtained by the use of the ANN based AIRMS for each currency for each year depicted in Table 15. For each FX pair, the results of 2010 were generated by the calibration of the ANN algorithm to data from the four previous years (2006-2009). So, by training the model to the first 3 years (75%) and testing it to the fourth (25%), it was succeeded to find the best value for its parameters that provided the highest F1-score. This calibration process targets train a model capable to predict the class of the signals of 2010. The trades, which produced from this forecasting, led to the return of 2010 for each currency. Based on the walk-forward testing routine the same procedure is followed to calculate the returns of the remaining six years. Meaning that, for instance, for the return of 2012, the period of 2008-2011 is worked as training-testing dataset or the period 2012-2015 is used in order for the ANN to be calibrated appropriately to decide which signals of 2016 will be transformed to an actual trade and which not. The sum of the outcome of that trades will lead to the return of the 2016. In order to access the value of the AIRMS based on ANN, the produced returns of that system should be compared to the original returns from the

MRB channel strategy. So, the Table 15 and the Table 4, which contains the returns of the MRB trading strategy with and without the application of the AIRMS-ANN, are compared.

For the GBPUSD, the AIRMS based on ANN generated higher or equal well returns for five out of seven years from the original returns. Specifically, the biggest increase related to the original results was achieved during 2010. The AIRMS succeeded to improve the return of 2010 by about 1375%, i.e. AIRMS achieved to turn a losing year with -2.97% return to a winning one with 37.87% return. The worst year of AIRMS in relation to the returns based on MRB strategy was obtained for year 2012 where a decrease of 65% was encountered, maintaining a positive outcome of 5.95%. The total return succeeded for the AIRMS is equal to 112.05% in comparison to the original return of 51.02% corresponds to an important increase of 119.60%.

In case of the USDJPY exchange rate, for six out of seven years the returns produced by the ANN based AIRMS are higher or equal compared to those achieved by the MRB strategy. Specifically, the most noticeably increase related to the original returns from MRB strategy was achieved during 2015. The AIRMS succeeded to improve the return of 2015 by about 246%, i.e. from 9.73% to 33.71%. Another significant raise was during 2016, where AIRMS-ANN almost doubled the return, i.e. from the value of 40.02% to 81.44%. The worst year of AIRMS in relation to the original returns was obtained for year 2013 where there was a decrease of 24%, maintaining a positive return of 13.25%. The total return achieved for the AIRMS is equal to 138.43% in comparison to the original return of 74.86%, bringing off an increase of 85%.

Accordingly, in the case of the EURUSD exchange rate, for five out of seven years the returns produced by the ANN based AIRMS are higher or equal compared to those achieved by the MRB strategy. Specifically, the largest increase related to the original results was achieved during 2013. The AIRMS succeeded to improve the return of 2013 by an enormous percentage of 24300%, i.e. AIRMS changed an almost zero return to a strong positive one of 26.84%. The worst year of AIRMS with reference to the original returns was obtained for year 2014 where there was a decrease of 48%, remaining a positive outcome of 36.35%. The total return achieved for the AIRMS is equal to 152.44% in comparison to the original return of 155.79%, bringing off a small decrease of 2%.

In the case of the GBPJPY exchange rate, for six out of seven years the returns produced by AIRMS based on ANN are higher or equal compared to those achieved by the MRB strategy. Specifically, the highest increase related to the original results was observed during 2015. The AIRMS succeeded to improve the return of 2015 by about 53.70%, i.e. from -29.14% to -13.49%. The worst year of AIRMS related to the original returns was obtained for year 2016 where there was a decrease of 46.15%, maintaining a positive return of 42.40%. The total return succeeded for the AIRMS is equal to 224.85% in comparison to the original return of 217.59% corresponds to an increase of 3%.

In the case of the EURJPY exchange rate, for three out of seven the returns generated by the ANN based AIRMS are higher or equal by the original strategy. Specifically, the biggest increase related to the original results was observed during 2015. The AIRMS succeeded to improve the return of 2015 by about 57.22%, reducing to the half a negative year from -49.95% to -21.70%. The worst year of AIRMS with reference to the original returns was obtained for year 2013 where there was a decrease of 61.40%, from -20.43% to -32.98%. The total return achieved for the AIRMS-ANN is equal to 188.57% in comparison to the original return of 208.74% corresponds to a reduction of 9.66%.

The AIRMS based on ANN succeeded to ameliorate the total return of the three out of five currencies. This fact shows that the ANN based AIRMS proves that has a satisfactory ability of predicting the class of the produced signals in such a way in order to generate profits. The most significant fact is that the developed risk management tool based on ANN achieved to improve almost all of the negative returns that produced the MRB channel strategy. The reduction of the negative performances of the trading strategy will be an important advantage at the portfolio construction stage.

4.4 Re-Construction of EWP2 and KCP2 based on AIRMS-ANN

In the previous section, the returns for each currency pair, which were produced by ANN based AIRMS, were presented. In this section, the two portfolios constructed in the previous part, are re-constructed. The first one is a simple average portfolio where all pairs have the same weight coefficient. The second portfolio is rather more advanced while different weight coefficients are assigned to the various currency pairs. The weights of each pair for each year are determined from its performance during the previous year based on Kelly Criterion. The portfolios are formed based on the exact method that was used for EWP2 and KCP2 in Part I. These two re-constructed portfolios will be denoted as EWP-ANN and KCP-ANN accordingly. In order to evaluate the effect of the AIRMS based on ANN on the performance to the portfolios, the EWP-ANN and KCP-ANN will be compared to the original EWP2 and KCP2.

Table 16. Allocation of the five currencies in EWP-ANN

Year Period	Equally Weighted Portfolio based on AIRMS-ANN (EWP-ANN) (%)				
	GBP/USD	USD/JPY	EUR/USD	GBP/JPY	EUR/JPY
2010	20.00	20.00	20.00	20.00	20.00
2011	20.00	20.00	20.00	20.00	20.00
2012	20.00	20.00	20.00	20.00	20.00
2013	20.00	20.00	20.00	20.00	20.00
2014	20.00	20.00	20.00	20.00	20.00
2015	20.00	20.00	20.00	20.00	20.00
2016	20.00	20.00	20.00	20.00	20.00

Table 17. Equally Weighted Portfolio based on AIRMS-ANN (EWP-ANN)

Years		2010	2011	2012	2013	2014	2015	2016
EWP-ANN	**Returns (%)**	27.80	11.58	37.04	0.34	35.65	5.02	45.84

Table 16 shows the yearly proportions of each currency pair assigned to the EWP-ANN. The allocation chosen is equal to 1/5 since the EWP-ANN is composed by five currency pairs. Table 17 contains the returns of the EWP-ANN, which is based on the AIRMS-ANN, while Table 7 presents the returns of the EWP2 from the original MRB channel strategy. By comparing these two tables is observed that the re-constructed equally weighted portfolio succeeds to outperform the EWP2 five out of seven years. The broadest increase related to the original results was achieved during year 2015. The EWP-ANN succeeded to improve the return of 2015 by about 160%, i.e. the lose of -8.32% altered to a profit of 5.02%. Another significant amelioration which the equally weighted portfolio succeeded through AIRMS-ANN was during 2013, where again succeeded to turn a lose to a profit, from -4.65% to 0.34%. The year, which the EWP-DT had the highest reduction from the EWP2, was 2010 where the return of 32.54% became 27.80%, a decrease of 14.58%.

Table 18. Evaluation metrics of EWP-ANN

Metrics of EWP-ANN					
Total return (%)	**Compound growth (%)**	**Arithmetic average (%)**	**Geometric return (%)**	**Standard deviation (%)**	**Sharpe ratio**
163.27	407.38	23.32	22.22	16.34	1.27

These improvement that the developed ANN based risk management system achieved on the performance of EWP2 are more presented when comparing the evaluation metrics of the two equally weighted portfolios. These metrics are seen at Tables 18 and 9, which contain the total return, the compound growth, the arithmetic average, geometric return, standard deviation and the Sharpe ratio of each portfolio corresponding. Notably, the EWP-ANN attained a total return of 163.27% improving the total return of the original equally weighted portfolio by approximate 15.30%. Regarding to compound growth, the re-constructed equally weighted portfolio reported a return equal to 407% that compared the EWP2's compound growth is increased by 24.40%. This means that an investor who invest $10,000 in 2010 at EWP-DT, he would have by the end of 2016 $40,700. Furthermore, the standard deviation of the new average portfolio decreased significantly by 25% from 21.77% to 16.34%. It is noteworthy that this new portfolio achieved to constitute only by profitable years. This characteristic combined to the reduced standard deviation decrease the risk profile of this portfolio. Finally, the application of the AIRMS-ANN to the EWP2 had as result the extremely raise of the sharpe ratio by 56.50% from 0.81 to 1.27.

Table 19. Allocation of the five currencies in KCP-ANN

Year Period	**Kelly Criterion Portfolio based on AIRMS-ANN (KCP-ANN) (%)**				
	GBP/USD	**USD/JPY**	**EUR/USD**	**GBP/JPY**	**EUR/JPY**
2010	20.00	20.00	20.00	20.00	20.00
2011	16.37	0.00	39.68	32.29	11.66
2012	0.10	0.00	0.10	52.10	47.70
2013	4.28	19.21	17.69	37.18	21.64

2014	0.00	27.98	70.46	1.56	0.00
2015	0.00	41.52	25.12	20.60	12.76
2016	28.97	34.37	36.66	0.00	0.00

Table 20. Kelly Criterion Portfolio based on AIRMS-ANN (KCP-ANN)

Years		2010	2011	2012	2013	2014	2015	2016
KCP-ANN	**Returns (%)**	27.80	11.58	37.04	0.34	35.65	5.02	45.84

Table 19 presents the yearly percentages of each currency pair assigned to the KCP-ANN. This allocation during a year is based on the Kelly Criterion of each pair from the previous year. For this reason, the 2010's weight coefficients are equal for all the currencies due to the lack of data from 2009. Table 20 contains the returns of the KCP-ANN, which is based on the AIRMS-ANN, while Table 12 presents the returns of the KCP2 from the original MRB channel strategy. Specifically, the bigger increase related to the original returns was during 2015. The KCP-ANN succeeded to raise the return of 2015 by about 375%, i.e. AIRMS succeeded to turn a losing year with -4.47% to 12.31%. Another significant amelioration which the KC based portfolio succeeded through AIRMS-ANN was during 2016, where increased even more an already high return of 41.39% to 49.69%. This example proves the prediction of the AIRMS-ANN are statistical significant, because is further more difficult for a system to improve an already good result than to increase a negative outcome. The worst year of the KCP-ANN's performance with reference to the KCP2, was obtained in 2011 where the return of 18.30% became 12.66%, a decrease of 30% while maintaining the positive outcome.

Table 21. Evaluation metrics of KCP-ANN

Metrics of KCP-ANN					
Total return (%)	**Compound growth (%)**	**Arithmetic average (%)**	**Geometric return (%)**	**Standard deviation (%)**	**Sharpe ratio**
201.47	544.84	28.78	27.40	18.88	1.39

These improvements that the developed ANN based risk management system achieved on the performance of KCP2 are more clearly presented when comparing the evaluation metrics of the two KC based portfolios. These metrics can be seen at

Tables 21 and 14, which contain evaluation metrics of each portfolio. Notably, the KCP-ANN achieved a significant high total return of 201.47% improving the total return of the original KC based portfolio by approximate 13.00%. Regarding to compound growth, the updated portfolio based on KC reported a return equal to 544.84% that compared to the EWP2's compound growth is increased by 21%. This means that an investor who invest $10,000 in 2010 at EWP-ANN, he would have by the end of 2016 $54,480. Furthermore, the standard deviation of the new KC portfolio was lower by 7.50%, from 20.42% to 18.89%. The application of the AIRMS-ANN to the KCP2 had as results to raise the sharpe ratio by 23.70%, i.e. from 1.14 to 1.39.

The contentious improvements on the performance of the EWP2 and KCP2 portfolios, that the adjustment of the AIRMS-ANN offered, underline that its ability to recognize the quality of the signal produced is significant. In both portfolios, the use of AIRMS-ANN increased their total return and sharpe ratio, while their standard deviation was decreased.. It succeeded to strengthen the profitable stability of the returns each year giving a real boost to the power of compounding by creating two portfolios with seven consequent profitable years. Warren Buffett, responding to an interview question for the single most powerful factor behind his investing success answered "compound interest". According to this factor, this great investor had developed an investing advice, a motto: "The first rule is not to lose money. The second rule is not to forget the first rule."

4.5 Comparison of the performance of the application of the ANN and DT

Firstly, the effect of the utilization of AIRMS-DT and AIRMS-ANN are compared in the performance of the five currencies.

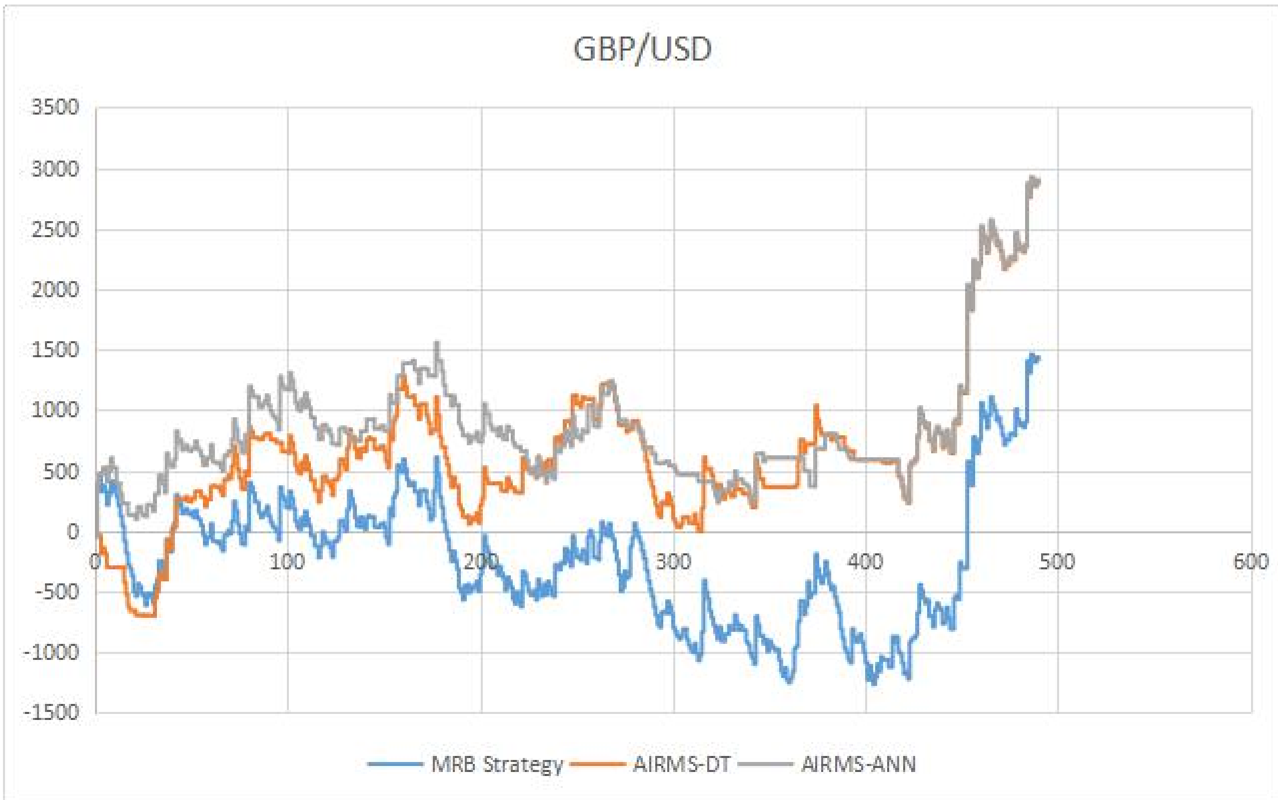

Figure 4. Representation of the performance per trade of GBP/USD between 2010-2016 based on MRB strategy, AIRMS-DT and AIRMS-ANN.

For GBP/USD, as it can be seen in Figure 4, both AIRMS succeeded to outperform the total return of the MRB strategy. A notable fact is that the AIRMS-ANN achieved to maintain always positive total return after any given trade during the entire seven year period.

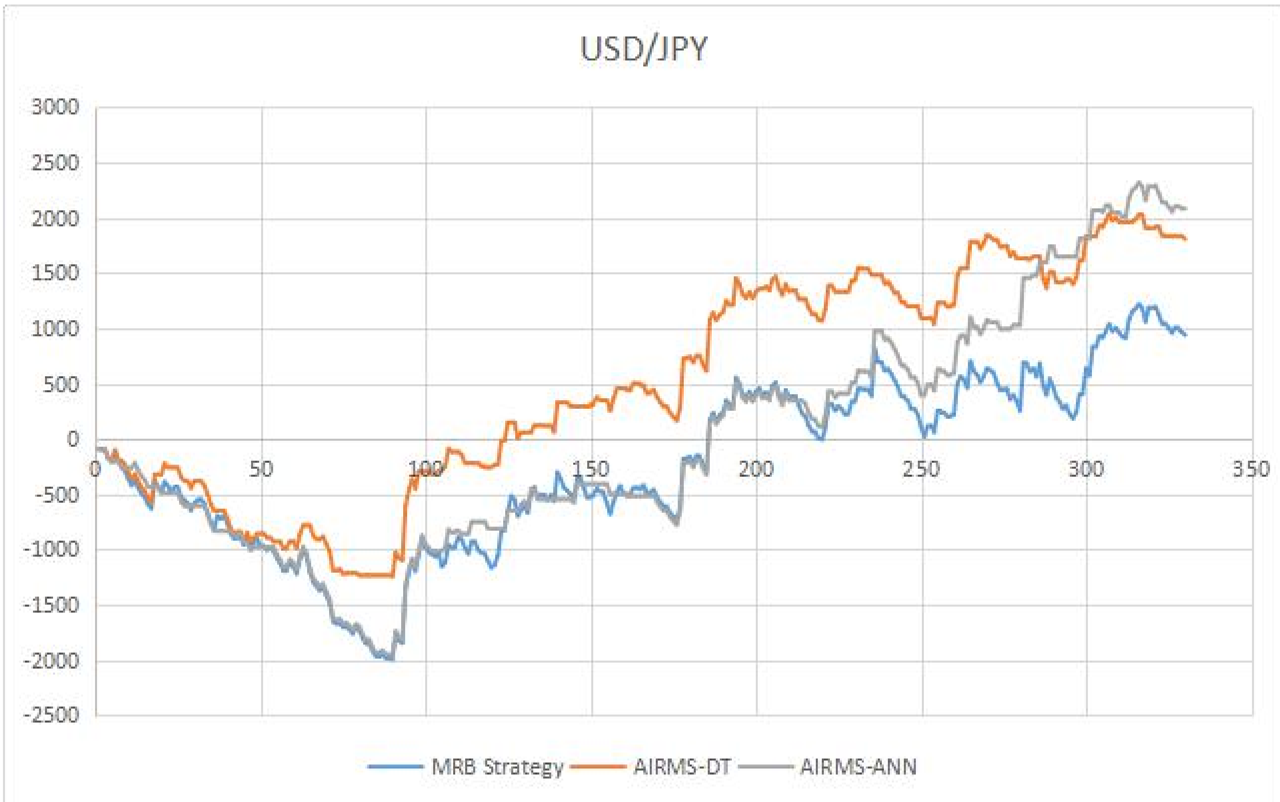

Figure 5. Representation of the performance per trade of USD/JPY between 2010-2016 based on MRB strategy, AIRMS-DT and AIRMS-ANN.

In the case of USD/JPY, as it can be observed in Figure 5, both AIRMS produced higher profits than the original strategy. Furthermore, the AIRMS-DT succeeded to decrease significantly the maximum drawdown during 2010-2016.

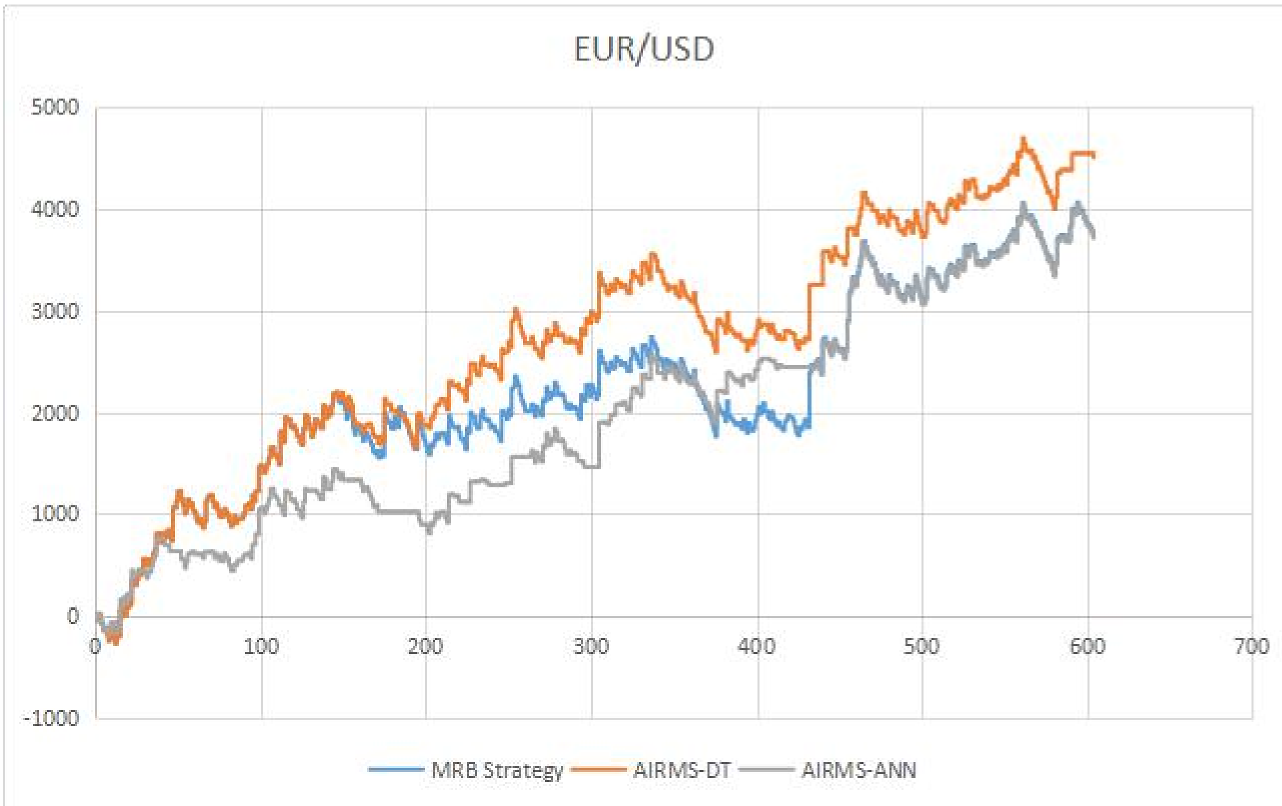

Figure 6. Representation of the performance per trade of EUR/USD between 2010-2016 based on MRB strategy, AIRMS-DT and AIRMS-ANN.

In the case of EUR/USD, in Figure 6, the AIRMS-DT achieved to rise the total return of the initial trading strategy, while the AIRMS-ANN performed similarly to the MRB strategy.

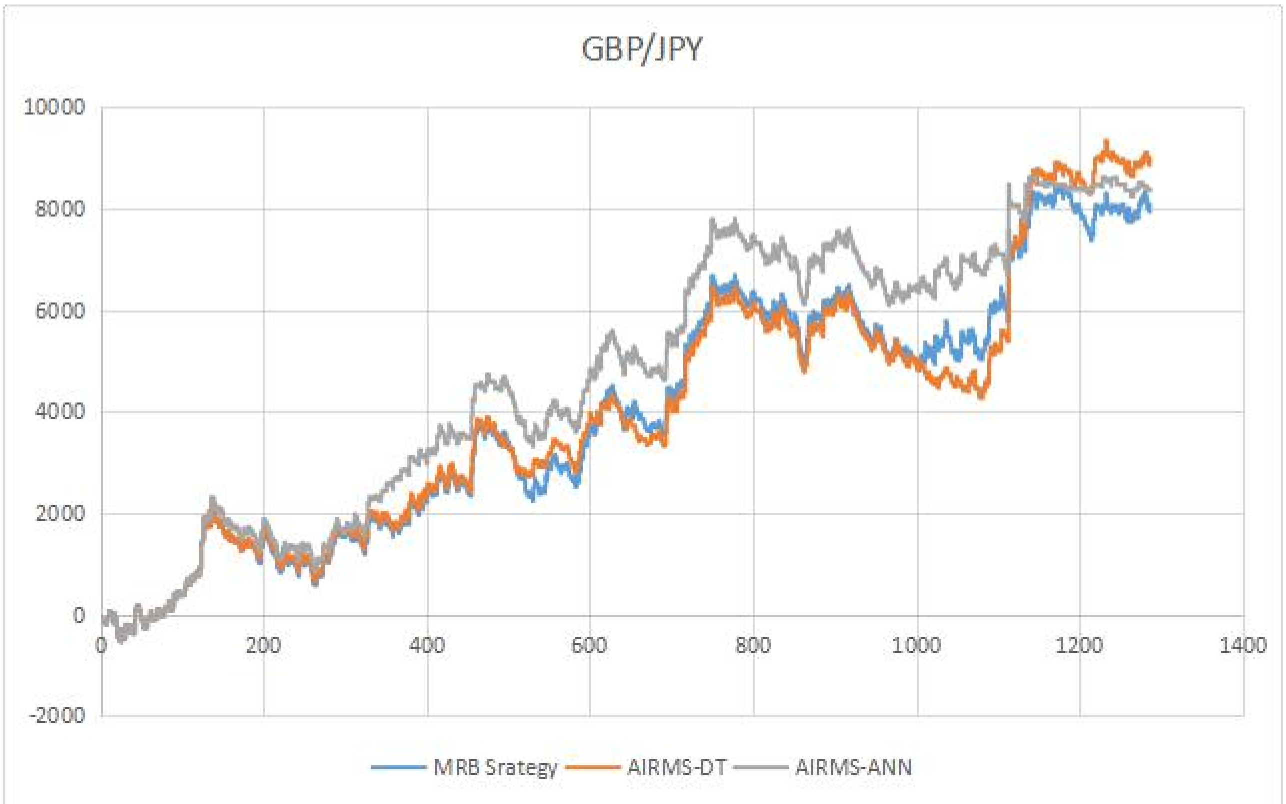

Figure 7. Representation of the performance per trade of GBP/JPY between 2010-2016 based on MRB strategy, AIRMS-DT and AIRMS-ANN.

For GBP/JPY, in Figure 7, the AIRMS increased the total return, while the AIRMS-ANN reduced significantly the drawdowns during this seven year period.

Figure 8. Representation of the performance per trade of EUR/JPY between 2010-2016 based on MRB strategy, AIRMS-DT and AIRMS-ANN.

For EUR/JPY, as it can be seen Figure 8, the AIRMS-DT not only rose the total return but also achieve to reduce the average drawdown of the MRB strategy, while the AIRMS-ANN underperformed slightly the original return.

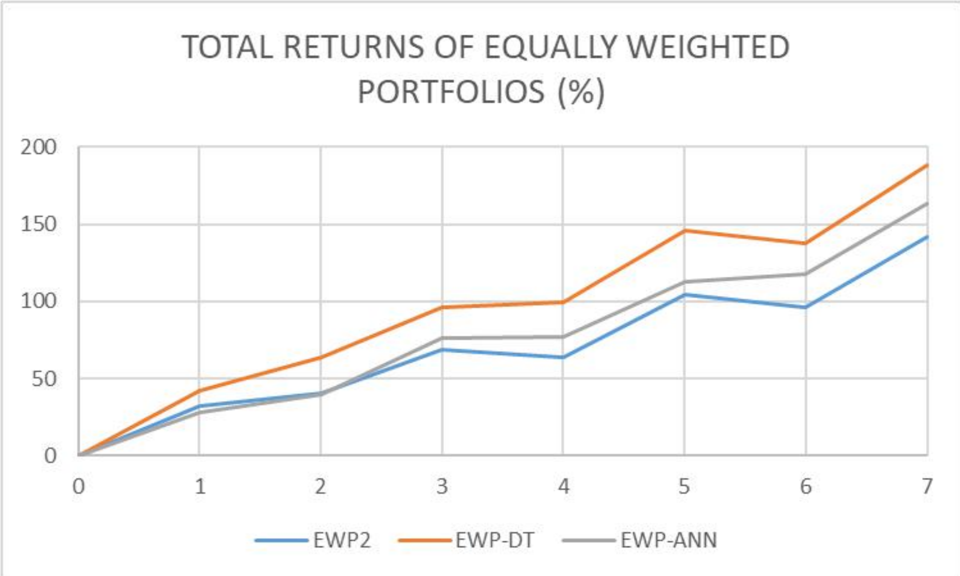

Figure 9. Representation of the performance of the equally weighted portfolios based on MRB strategy, AIRMS-DT and AIRMS-ANN.

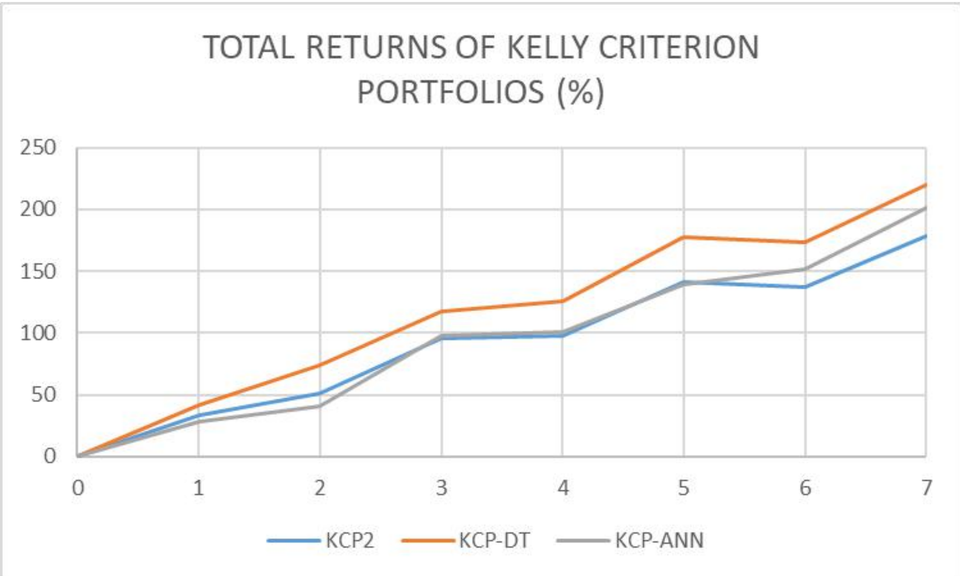

Figure 10. Representation of the performance of the Kelly Criterion portfolios based on MRB strategy, AIRMS-DT and AIRMS-ANN.

Then, the performance of the equally weighted and Kelly criterion portfolios based on AIRMS-ANN and AIRMS-DT are compared. For EWPs, as it can be observed in Figure 9, the EWP-DT and EWP-ANN beat the original EWP2, while EWP based on DT outperformed the one based on ANN in terms of total return. However, the AIRMS-ANN succeeded to construct an EWP with lower standard deviation and higher sharpe ratio than EWP-DT. For KCPs, in Figure 10, the KCP-DT and KCP-ANN achieved higher total return during the seven year period than the original KCP2, while the KCP-DT beat the KCP-ANN related to total return. Nevertheless, the use of AIRMS-ANN led to a KCP with lower standard deviation that the KCP-DT.

5. CONCLUSION

The major achievement of this study was the successful use of two machine learning models for risk management purposes; in particular an artificial intelligent risk management system (AIRMS) was developed. Decision trees (DT) and artificial neural networks (ANN) are the algorithms that were used in this work. In Part I, the two profitable currency portfolios (labelled as EWP2 and KCP2) are proposed that were based on the optimized channel MRB strategy. These two portfolios are constituted by five currencies (GBP/USD, USD/JPY, EUR/USD, GBP/JPY and EUR/JPY) and their returns refer to a seven-year period, from year 2010 to 2016.

The main target of the developed AIRMS was to improve the performance of the two portfolios not by generating new profits but preventing them from loses. Therefore, AIRMS was applied to the optimized trading strategy in order to recognize which signal will be profitable and which one will not, before it becomes an actual trade. For both risk management systems developed in the current study (i.e. DT and ANN based ones, labeled as AIRMS-DT and AIRMS-ANN, respectively) the dynamic moving window was used in order to train, test and finally predict the quality of the produced signals of the next year. Worth mentioning that the way that the two machine learning models were calibrated is crucial for the results produced, and that the two systems succeeded to provide significant amelioration on the performance of both EWP2 and KCP2 currency portfolios, resulting into improved portfolios that can be even more attractive to potential investors. The two systems not only increased the profitability of both portfolios but also mainly managed to further strengthen their sharpe ratio by reducing the standard deviation.

Analyzing the results that AIRMS-DT and AIRMS-ANN provided, it was observed the stability of their predicting performance that is a crucial importance characteristic for machine learning models. By its definition, the ultimate goal of the two risk management systems was difficult; since they were employed in order to increase the performance of two already significantly profitable portfolios and they succeeded both in terms of total return and sharpe ratio. DT based AIRMS firstly managed to launch the total return of each of the currencies increasing it by an average rate of 50%. This fact had as a result for the developed DT system to improve even more the high total return and the sharpe ratio decreasing at the same time the standard deviation for both portfolios. Similarly, ANN based AIRMS managed to raise the total return of the five currencies by an averagely 40% succeeding the same impressive results to during the constructions of both portfolios.

A noteworthy evidence of the successful application of the DTs and ANNs machine learning techniques as risk management tools was their ability not only to slightly improve negative returns but to turn most of the losing years into profitable ones and also to increase even more already high profitable years. All these facts proved undeniable the significance of the results of this study. They proved that this study achieve to utilize successfully these two machine learning algorithms for a quite innovative objective; to control the risk of investment portfolios. Another notable observation is that, comparing the two AIRMS, the utilization of DT constantly led to higher returns, while the ANN succeeded in both kind of the constructed portfolios lower standard deviations.

6. REFERENCES

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