

Directional-Change Event Trading Strategy: Profit-Maximizing Learning Strategy

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Abstract—Many investors seek a trading strategy in order to maximize their profit. In the light of this, this paper derived a new trading strategy (DCT1) based on the Zero-Intelligence Directional Change Trading Strategy ZI-DCT0, and found that the resulting strategy outperforms the original one. We enhanced the conventional ZI-DCT0 by learning the size and direction of periodic fixed patterns from the price history for EUR/USD currency pairs. To evaluate DCT1, experiments were carried out using the bid and ask prices for EUR/USD currency pairs from the OANDA trading platform over the year 2008. We compared the resulting profits from ZI-DCT0 and DCT1. The analysis revealed interesting results and evidence that the proposed DCT1 investment strategy can indeed generate effective electronic trading investment returns for investors with a high rate of return. The results of this study can be used further to develop decision support systems and autonomous trading agent strategies for the FX market.

Keywords-Trading strategies; Autonomous trading agent strategies; Pattern recognition; FX Market.

I. INTRODUCTION

Electronic trading strategies have become a hot topic in the field of financial markets, and numerous strategies have been developed. Investors are always looking for a trading strategy that maximizes their profits. The financial literature has featured a long debate on the effectiveness of the technical analysis of financial market time series [1–8]. Some argue that prices are not predictable based on historical information, since all the relevant public information is mirrored in the prices. In contrast, recent studies [8,9] have uncovered empirical evidence of various price anomalies, and therefore have confirmed positive observed evidence on the effectiveness of technical analysis for analyzing financial price time series.

Trend Following (TF) trading strategy is a widely used investment strategy due to the simplicity of the principle on which it is based and its effectiveness [10–13]. TF adopts a rule-based investment strategy based on the directions of market price trends, where a trader takes advantages of the price trend on the assumption that the current price trend will continue in the same direction. Furthermore, the underlying assumption of TF is that a trader will follow the price trend with the assumption that some traders have market information prior to the general public which is reflected in the direction of the price trend [10]. A TF trader places a buy order when the price is rising, while a sell order is placed when the price is falling. The financial literature reveals successful investments based on a TF trading strategy in stock markets [11], currency markets [14] and commodity futures' markets [13]. Similar to the TF investment strategy is the Contrary Trading (CT) strategy with regard to the direction of the market price trend. A CT trading rule places a buy order in anticipation that

the price will move in the opposite direction. For example, a trading rule may indicate a buy order opportunity when the price falls by 0.03% and afterwards places a sell order if the price rises by 0.06%.

Despite the effectiveness of TF and CT investment strategies, comparatively few works have explored the application of learning in order to enhance TF and CF investment strategies. Aloud et al. [15] have constructed a trading strategy called ZI-DCT0 based on pooling two approaches: (i) the DC event approach [16] and (ii) TF and CT investment approaches. Trading in the financial markets is highly active at some times, but calm down at others which makes the flow of physical time discontinuous. For that reason using fixed time scales for studying the price changes in the market runs the risk of missing important price activities. The DC event approach captures periodic activities in the price time series to detect major periodic patterns based on the trader's expectations of the market. Given a fixed threshold size, the DC approach characterizes periodic price trend movements in the price time series, where any occurrence of a DC event represents a new intrinsic time unit, independent of the notion of physical time change. A comparable trading strategy to the ZI-DCT0 is introduced by Alfi et al. [17] in which a trader places an order if the price fluctuations exceed a defined threshold. The threshold is determined by the trader, and remains constant during the traders' trading period in the market. The main difference between ZI-DCT0 and the one introduced in [17], is that ZI-DCT0 considers the direction and the overshoot of price movements in the traders' trading activities.

In the light of this, the work reported in this paper introduces a new trading strategy called Directional-Change Trading (DCT1) derived from ZI-DCT0, where ZI-DCT0 has been enhanced by the incorporation of a learning model fed by historical dataset, with the aim of determining the size and direction of periodic patterns in the price time series. As such, the DCT1 is able to recognize periodic patterns in a price time series such as DC events. This may be the key to providing effective decision support for traders in the financial markets. DCT1 applies a simple learning mechanism which avoids the complexity of artificial intelligent trading strategies and also the vagueness of zero-intelligence and Buy-and-Hold trading strategies in which traders trade randomly, subject to budget constraints.

The rest of the paper is organized as follows. A brief literature review of related works is presented in Section II. The ZI-DCT0 trading strategy is described in Section III. The new trading strategy is depicted in Section IV together with a description of the core mechanism of the DCT1 trading strategy. The experimental design and results are presented

in Section V. A summary and conclusions are provided in Section VI.

II. RELATED WORK

A considerable amount of scientific research has explored artificial intelligence and cognition techniques in terms of financial data processing and filtering, knowledge discovery and building potential adaptive trading strategies for investment in the financial markets. Agent-based adaptive systems have been applied effectively to study and understand complex financial market phenomena as a means of studying the behaviour of individual agents within a financial market setting, the trading interaction effects, emergent macro properties, knowledge discovery with regard to trading behaviour, designing adaptive investment trading strategies, and the impact of market rules or policies, among others.

Our paper relates to a large body of literature on investment trading strategies that is too vast to survey here. Therefore, we limit our literature review to the most influential works with regard to designing investment trading strategies. In the literature, the design of the trading strategy ranges from simple budget constrained Zero-Intelligence (ZI) strategy as in [18–20], to complicated intelligent strategy, such as in [21,22].

ZI strategy was introduced by Gode and Sunder [20] to examine the continuous double-auction (CDA) mechanism where the strategy implies random trading, subject to budget constraints. Thus, ZI strategy does not carry out observation nor learning the price trend movements. Gode and Sunder's experimental results show that markets operating with human traders and ZI constrained traders converged to the equilibrium price whereas the market operating with ZI unconstrained traders did not. In following work, Gode and Sunder [23] examined the lower-bounds of the level of learning required for a trading strategy to achieve sufficient outcomes. The results show that a simple budget constrained ZI strategy is capable to accomplish satisfactory outcomes. Thus, they conclude that learning is not required. Their results show that the theoretical equilibrium price in financial markets is determined more by market structure than by the level of intelligence of the traders in that market.

Alfi et al. in [17,24,25] show that representation of trading strategy uses to great extend a simple learning mechanism which depends on observing the price's movements. In particular, each agent commits to a fixed threshold, as a result the agent places an order when the price fluctuations are above this threshold. The strategy does not consider the direction and the overshoot of the price movement where the overshoot represents the size of the price movement beyond the defined threshold by the agent.

The availability of historical financial data provides extensive rich resources for predicting future price changes in financial time series. The possible reward of a useful tool for forecasting changes in the price of financial assets is without doubt a major motivator. Financial forecasting has attracted the attention of researchers from a variety of computer science areas. Techniques from Artificial Intelligence, and in particular Evolutionary Computation, have been used extensively in the

design of financial forecasting techniques for predicting future price changes in financial time series. The most commonly used techniques are Artificial Neural Networks (ANNs) [26], Genetic Algorithms (GAs) [27], Genetic Programming (GP) [28] and Learning Classifier Systems (LCS) [29,30]. Austin et al. [31] provide an overview of the research conducted by the Centre for Financial Research at Cambridge University's Judge Institute of Management, which has been researching trading techniques in FX markets for forecasting intraday or daily exchange rates.

In this section, our intention is to provide a brief illustrative description of the artificial intelligence techniques used in financial forecasting and provide a brief description of some of the most relevant works in the field.

In financial forecasting, ANNs are probably the most heavily exploited artificial intelligence technique. There are many studies in the literature on the subject of ANNs. Amongst them are [32–35]. The ANNs technique has been applied in diverse areas of finance. Wong and Selvi in [26] provide a good survey of the literature on ANNs between 1990 and 1996. An additional recent survey can be found in [36]. Yao and Tan in [37] provide empirical evidence of the appropriateness of ANNs with regard to the prediction of foreign exchange rates.

In financial forecasting, the input data is a fundamental issue in terms of the success or failure of ANNs, as is the case with other forecasting techniques. Nevertheless, this issue is particularly important in the case of ANNs owing to the lack of flexibility of ANNs techniques. A number of works in which ANNs are combined with genetic algorithm techniques is demonstrated by [38]. Further relevant examples are the studies done by [33–35,39–43].

GAs were invented by John H. Holland in 1975 [27]. GAs belong to the evolutionary algorithms field which offers very popular techniques in optimization and machine learning problems. GAs use a generation of individuals where each individual is a candidate for a possible solution to the problem. A new population is produced by means of selecting the fittest individuals from the current population through the application of genetic operators such as crossover and mutation.

In the finance area, GAs are not limited to forecasting. GAs are not just used for forecasting but they are also important in modelling learning in an ABM. Examples of relevant works which have involved financial forecasting using the GAs technique are [44–48]. There is a number of limitations of GAs, such as the fixed size structure of the individuals and their representation. Nevertheless, GAs can be used as a meta-heuristic or in combination with other forecasting techniques, to advance the predictions' performance as can be seen in the works done in [38,49].

LCS is a machine learning mechanism wherein a population of rules is evolved and modified by genetic algorithms. Since GAs are used to select and modify the population of rules, this means that the representation of the rules has to be done with binary strings. Holland and Miller [50] proposed the use of an LCS to model economic agents. The SF ASM used an LCS to forecast price changes in time series [51]. In addition, an LCS was used to perform financial forecasting in the work

done in [29,30].

LCS has the same limitations as GAs in terms of the representation and the fixed size structure of the individuals of the population. An alternative technique to the GAs and LCS is the genetic programming technique.

The reported studies above adopted different investment strategy methodologies to perform pattern deduction in price financial market time series. However, these methodologies require demanding financial interpretation ability which means that they cannot be used by regular investors in order to interpret actual investment trading behavior.

III. ZI-DCT0

ZI-DCT0 [15] is a trading strategy based on the DC event approach [16]. DC event approach is an approach for studying the financial time series based on intrinsic time rather than physical time. Physical time adopts a point-based system while intrinsic time adopts event-based system. Physical time is homogenous in which time scales equally spaced based on the chosen time unit (e.g., seconds). In contrast, intrinsic time is irregularly-spaced in time given that time triggers at periodic events of price revolution. The basic unit of intrinsic time is an event where event is the total price change exceeding a given fixed threshold defined by the observer.

Given a fixed threshold of size (Δx_{DC}), the absolute price change between two local minimum and maximum prices is decomposed into directional-change (DC) event of size Δx_{DC} and its associated overshoot (OS) event. The OS event is the absolute price change beyond the Δx_{DC} threshold. A DC event can be either an upturn event or a downturn event. An upward run is a period between an upturn DC event and the next downturn event. In contrast, a downward run is a period between a downturn DC event and the next upturn DC event. A downturn (upturn) DC event terminates an upward (downward) run, and starts an upward (downward) run.

Prior to studying and analyzing an asset's price time series, two variables are defined: the last high and low prices where they are assign as initial value the asset's price at the start of the price time series sequence. During an upward run, the last high price is continuously adjusted to the maximum of the current price p_t at time t and the last high price. During the period of a downward run, the last low price is continuously adjusted to the minimum of the current price p_t at time t and the last low price. An upturn DC event occurs once the absolute price change between the current price and the last low price is higher than the defined threshold of size Δx_{DC} . In contrast, a downward DC event occurs once the absolute price change between the current price and the last high price is lower than the defined threshold of size Δx_{DC} .

A ZI-DCT0 commits himself to a fixed threshold and a method for trading where the method can be one of two forms: CT or TF trading. Algorithm 1 demonstrates the trading mechanism for ZI-DCT0. ZI-DCT0 provide evidence in [52] to generate good quality trading strategy in terms of the trader's return of investments, analyzing price movements and reproducing the statistical properties of the FX market trading behavior when used in an agent-based market. The restrictions

Algorithm 1 The core trading mechanism for the ZI-DCT0.

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Require: initialise variables (event is upturn event,  $x = p_t$ ,
 $\Delta x_{DC}$  (Fixed)  $\geq 0$ )
if event is upturn event then
  if  $p_t \leq x \times (1 - \Delta x_{DC})$ 
    event  $\leftarrow$  downturn event
     $x \leftarrow p_t$ 
    Sell  $\rightarrow$  ZI-DCT0 CT, Buy  $\rightarrow$  ZI-DCT0 TF
  else
     $x \leftarrow \max(x, p_t)$ 
  end if
else //Event is downturn event
  if  $p_t \geq x \times (1 + \Delta x_{DC})$  then
    event  $\leftarrow$  Upturn event
     $x \leftarrow p_t$ 
    Buy  $\rightarrow$  ZI-DCT0 CT, Sell  $\rightarrow$  ZI-DCT0 TF
  else
     $x \leftarrow \min(x, p_t)$ 
  end if
endif

```

of ZI-DCT0 is the randomness and consistent in choosing the threshold and the type of trading.

IV. DCT1

DCT1 is an intelligence trading strategy driven from the ZI-DCT0 in which the strategy involves learning toward identifying the estimated size and the direction of periodic patterns from an asset's price time series. DCT1 aims to overcome the two major limitations of the ZI-DCT0 which are the randomness in choosing the threshold and the type of trading (CT or TF). To overcome such limitation, the central idea behind the DCT1 is that the trader will learn from the historical dataset of an asset's price time series earlier to the process of choosing a threshold and a type of trading.

Algorithm 2 illustrates the core trading mechanism for a DCT1 trader. Prior to trading in the market, a DCT1 trader will examine the status of the asset's price movements using the historical price dataset for the asset. Such examination aims for defining to great extend the most fitted practical threshold and type of trading for the trader as regard to the profitability.

In detail, a DCT1 trader will examine the profitability of the asset in terms of its historical price data using a defined number of verity thresholds which are generated randomly within a defined range. For each threshold value, the DCT1 trader will examine the historical price data set for the asset using the directional-change event approach from two points of view firstly as a CT while and secondly as a TF trader (as described in Section III). Subsequent to the DCT1 trader making a trade, the Rate of Investment (ROI) as a performance indicator will be computed. ROI is a performance measure defined as the total return to a trader's investment over a defined period, divided by the cost of the investment. The ROI is expressed as a percentage, and is either positive or negative,

Algorithm 2 The core trading mechanism for the DCT1.

Require: initialise variables ($e = \text{upturnEvent}$, $x = p_0$, $\text{highestROI} = 0$)

Input (p_n , λ_{\min} , λ_{\max}) // p_n training price dataset is used to train trader to find the best investment threshold and type of trading; n length of training dataset; λ_{\min} is the minimum threshold; and λ_{\max} is the maximum threshold.

For ($i = 0; i < 30; i++$) **do** // Examining 30 randomly generated thresholds

Begin

$\Delta x_{DC} = \text{GenerateRandomThreshold}[\lambda_{\min}, \lambda_{\max}]$

For ($y = 0; y < 2; y++$) **do** // Examining two trading types where $y = 0$ is CT and $y = 1$ is TF

Begin

For ($t = 0; t < n; t++$) **do** // Loop training price dataset

Begin

if ($e = \text{upturnEvent}$) **then**

if $p_t \leq x \times (1 - \Delta x_{DC})$ **then**

$e \leftarrow \text{downturnEvent}$

$x \leftarrow p_t$

CT \rightarrow Buy, TF \rightarrow Sell

else

$x \leftarrow \max(x, p_t)$

end if - Upturn event price examination

else // $e = \text{downturnEvent}$

if $p_t \geq x \times (1 + \Delta x_{DC})$ **then**

$e \leftarrow \text{upturnEvent}$

$x \leftarrow p_t$

CT \rightarrow Sell, TF \rightarrow Buy

else

$x \leftarrow \min(x, p_t)$

end if - Downturn event price examination

endif - Event Examination

$\text{ROI} = \text{Evaluate}()$ // ROI (rate of investment) is the result of evaluating the trader profit/loss for the given values of Δx_{DC} and y .

end for - End loop training price dataset

if ($\text{ROI} > \text{highestROI}$) **then**

$\lambda = \Delta x_{DC}$ // best threshold λ

$\omega = y$ // best type of trading ω

$\text{highestROI} = \text{ROI}$

endif

end for - End loop trading type

end for - End loop random threshold

which means that correspondingly, the trader achieves either a profit or makes a loss.

Towards the end of the examination, the threshold and the type of trading that results in the most profitable outcome with reference to the ROI will be chosen for the DCT1 trader's decision with regard to placing an order.

V. EXPERIMENTS DESCRIPTION

In this section, we report on the experiments undertaken in the Agent-Based FX Market (ABFXM) that we developed. Our aim in particular, is to examine the profitability of the two strategies in term of the agents' return of investments;

this can subsequently inform the design of trading strategies and decision support systems for the trading in the financial market.

A. Dataset

In this study, we used a high-frequency dataset (HFD) for EUR/USD historical prices provided by OANDA Corporation which is an online foreign currencies trading platform. HFD in finance refers to an extremely huge quantity of data which is the complete record of transactions and their associated characteristics at frequencies higher than on a daily basis [53]. According to Dacarogna et al. "The number of observations in one single day of a liquid market is equivalent to the number of daily data within 30 years" ([9], p. 6).

The dataset contains data samples of EUR/USD prices spanning the year of 2008 where each record contains three fields: (a) a bid and (b) an ask EUR/USD price at (c) a timestamp. This dataset is fed into the ABFXM via the market-maker. The time-span of the price dataset is very important in the study, given that different amounts of data examination possibly will provide ratios of precision interesting to study.

B. Agent-Based FX Market

In this section, we provide an overview of the ABFXM [15], which was developed to simulate the intraday trading activity at the level of an FX market-maker market. For a further detailed description of the ABFXM design, we refer interested reader to [15].

The FX market is where the exchange of currencies in which buying and selling currencies takes place. It is a decentralized market and operates 24 hours a day hence it is considered the largest and most liquid financial market in the world. The FX market is not an individual market given that it is composed of a global network of market-maker markets that connect investors from all around the world. Investors can be governments, central and commercial banks, institutional and individual investors, etc. Generally FX trading firms are market-makers [9]. A market-maker is a firm which supplies liquidity for currencies, and subsequently quotes both a buy and a sell price for a currency on its platform. The market-maker buys from and sells to its investors as well as other market-makers accordingly makes earnings from the difference between the bid and the offer price.

The ABFXM developed in [15] populated with N trading agents who participate in the market by means of buying and selling currencies. For simplicity, there is one currency pair (EUR/USD) available for trading in the ABFXM. A currency pair in the ABFXM is represented as base/quote wherein these two currencies are traded. We denote b_t at time t as the bid price by which a trading agent j can sell the base currency and buy an equivalent amount of the quoted currency to buy the base currency. This means agent j is opening a short position. Similarly, the ask price a_t at time t is the offer price at which agent j can buy the base currency and sell an equivalent amount of the quoted currency to pay for the base currency, opening a long position. During the market run, the market-maker uses a historical high-frequency EUR/USD

prices dataset to issue price quotes and feed these prices into the market. The prices are fed over a defined one month period and therefore the trading agents act in response.

Each trading agent is capable of holding, at time t during the market run, two different types of asset: a risk free asset (cash), and a risky asset (currency). Before the ABFXM launch, based on a continuous uniform distribution, each individual trading agent will be assigned a home currency and a margin ratio. Every trading agent j has a portfolio expressed in its home currency. The portfolio records the results of the agent's transactions during the market run. The Net Asset Value (NAV) at time t denoted by $NAV_{j,t}$ represents the current cash value of an agent j 's account. In particular, the $NAV_{j,t}$ is the amount of cash in the agent j 's account plus all unrealized profits and minus all unrealized losses associated with all the account's open positions.

The clearance mechanism of the ABFXM is simple where every market order at time t will be totally executed, whereas limit orders will be executed when their constraints are satisfied. A market order is an order for immediate execution in the market at the current price of the currency. On the contrary, a limit order is an order in which an agent specifies the price at which it is willing to buy/sell a number of currency. An update will take place for each agent's portfolio that has an executable order at time t . Afterward, the market's time turns from t to $t + 1$. Thus, the bid and ask prices are adjusted to the prices at time $t + 1$ using the historical bid and ask prices. Hence based on the recent bid and ask prices, the portfolio will be updated for each agent holds an open position at time $t + 1$. Finally, each open position at time $t + 1$ will be verify for a margin call, which is a procedure to close out the agent's open position once the amount of cash in its account is under the minimum margin required to cover the size of its currently open position. The purpose of the margin call act is to stop an agent from losing more than the amount of cash available in its account.

C. Assumption

We make the following six assumptions in modelling the agents' trading mechanism:

Assumption 1 We assume that the trading agents endowed with 10,000 amounts of cash and without any shares.

Assumption 2 We assume that a position cannot be adjusted.

Assumption 3 A position is only opened by a market order or a limit order.

Assumption 4 We restrict the quantity of positions held by an agent a at time t to be one opened position.

Assumption 5 The market does not imply fees for the transactions.

Assumption 6 A trading agent invests 100% of it cash when buying, and 100% of it shares when selling.

In essence, the most important reason for these simplification assumptions is that by making these assumptions the complexity of the trading strategy is reduced to a level that can be studied and compared within the scope of this work. Simplicity and unification the initial variable of the agents'

Table I
ROI RESULTS FROM THE SIMULATION

| Trading Strategy | Trend Type | AVG. Threshold | ROI |
|------------------|------------|----------------|---------|
| ZI-DCT0 | TF | 0.7 % | 0.5 % |
| ZI-DCT0 | CT | 0.7 % | - 8.9 % |
| DCT1 | TF | 0.9 % | 6.2 % |

characteristics is fundamental block to clearly compare the efficiency of the two trading strategies. Therefore, allocating variable quantities results in a substantial complication of the comparison analysis. The relaxation of these six assumptions does not affect the generality of the simulation results shown in our paper. However, we are aware of the importance of the role of quantity and diversity as a choice variable.

D. Results

One way to evaluate the performance of the DCT1 trading strategy is to look at the trading profits it generates. Therefore, we used the ROI as a performance indicator. The simulation uses historical bid and ask prices for the EUR/USD currency pair over a defined six month period during 2008, by feeding these prices into the market via the market-maker, and having the agents act in response to the price changes. The learning process for the DCT1 traders is over a four month period. The results generated from the simulation run are averaged over 10 independent simulation runs, each run adopting different initial seeds provided by random number generators, and different ranges of threshold values. We performed each independent simulation run with the same parameter configuration values, but with different seeds and ranges of threshold values, to ensure that the results of the simulation are consistent; this allows us to establish the robustness and accuracy of the simulation results.

We report the ROI results from the simulation run for three investment strategies: (i) TF ZI-DCT0; (ii) CT ZI-DCT0 and (iii) DCT1. The comparison of the performance of DCT1 with that of the ZI-DCT0 over a six month period is given in Table I. For the sample test period, the average ROI of the DCT1 is 6.2%, while for ZI-DCT0 TF is only 0.5%. An important observation to highlight is that the detected DCT1 threshold value and type of trading for the different simulation runs are roughly the same. Thus, this confirms that financial price time series exhibit periodic patterns. This is a good starting result regarding automats' trading strategies; though a full study through comparison with different trading strategies over different time periods and using different assets price time series will be more comprehensive, as this will show the full picture and effectiveness of the adopted trading strategy.

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed a new trading strategy (DCT1) designed as a decision making support system tool for financial investors. It is derived from the ZI-DCT0. The main contribution of this paper is the combination of classical TF and CT investment rules and a learning model from historical prices with regard to financial time series, which can significantly

improve computational effectiveness and the predictability of price trend directions, and uncover periodic patterns. TF and CT strategies, owing to their investment efficiency, have been widely adopted by investors. To the best of our knowledge, no related research in the literature has investigated TF and CF investment strategies within a learning model based on the detection of periodic directional change patterns. This study has demonstrated the feasibility of employing learning as part of a trading strategy in that DCT1 is designed to adapt to market price trend directions and hence deduct periodic patterns. Future work will consider the combination of evolutionary learning techniques with a DC event approach for developing trading strategies for investment in financial markets.

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