Trading Strategies Optimization by Genetic Algorithm under the Directional Changes Paradigm

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***Abstract*—The subject of financial forecasting has been researched for decades, and the driver behind its measured data has been fuelled by the selection of physical time series, which summarize data using fixed time intervals. For instance, time-series for daily stock data would be profiled at 252 points in one year. However, this episodic style neglects the important events, or price changes that occur between two intervals. Thus, we use Directional Changes (DC) as an event-based series, which is an alternative way to record price movements. In DC, unlike time-series methods, time intervals are constituted by price changes. The unique feature that decides the price change to be considered as a significant is called a threshold θ. The objective of our paper is to create DC-based trading strategies, and then optimize them using a Genetic Algorithm (GA). To construct such strategies, we use DC-based indicators and scaling laws that have been empirically identified under DC summaries. We first propose four novel DC-based trading strategies and then combine them with existing DC-based strategies and finally optimize them via the GA. We conduct trading experiments over 44 stocks. Results show that the GA-optimized strategies are able to generate new and profitable trading strategies, significantly outperforming the individual DC-based strategies, as well as a buy and sell benchmark.**

***Index Terms*—directional changes, trading strategies, genetic algorithm, financial forecasting, machine learning**

I. Introduction

From the first day of portfolio concept inauguration to the finance field [1], financial forecasting studies have been evolving around the subjects of return and risk in these past 6 decades. During this time, traditional forecasting models have been transformed as well e.g., Technical Analysis (TA) [2]. Among them, selection of physical time-series as a construction of data profiling has been the major driver for the research studies. However, physical time series, e.g. daily closing prices, are unable to identify events that happen between the pre-specified time interval. For instance, if a trader was observing data on a daily or weekly basis, they would have missed the May 2010 US stock market flash crash, where stock market crashed trillion-dollar in the value at the end of 36 minutes time span, only to recover soon afterwards.

In this research, DC is used as an event-based series to prevent such specious outcomes that can rise using physical time-series. One of the advantages that paradigm provides to the users, is the unique feature defined by a threshold θ. This feature can be used to encapsulate a predefined price change. When it comes to the implementation part, we can observe the profiled data in the two different events only, directional change (DC), and overshoot (OS) events. After the summarization of data by DC, it is possible to exploit several indicators and scaling laws from recent works in creating trading strategies. These indicators are used to create 4 novel DC-based trading strategies. In addition, we use 3 more DC-based trading strategies that already exist in the literature. Each trading strategy produces a different recommendation set of open-hold-close positions; then information from each strategy's recommendations is aggregated to form a more informed trading strategy.

The above aggregation takes place through a Genetic Algorithm, which is a nature-inspired algorithm mimicking an evolutionary process. Such evolutionary algorithms have extensively been used in financial forecasting problems and have shown to be extremely effective [3]. The GA-optimized strategies are then compared to the individual DC strategies across 44 datasets from international financial markets. We also test the GA strategies against a buy and sell trading strategy. Our aim is to show that not only DC-based trading strategies can return profitable results, but also that combining them under a GA framework can lead to further improvements and also outperform a traditional financial benchmark, such as buy and sell.

The rest of this paper is organized as follows: Section II covers the literature review, Section III defines DC together with its scaling laws, and indicators. Section IV demonstrates the methodology, then, Section V presents the experimental setup. In the final step, we provide the results from our experiment (Section VI), and conclusion is provided in Section VII.

II. Literature Review

The very early foundation of DC originates from the study in [4], where the authors implemented DC as a complementary frequency ratio to measure the trends' behaviour alongside the volatility ratio. Since then, researchers had been dividing the subjects over four main aspects, including profiling, indicators, scaling laws that are present as regularities across the experiments, and trading strategies integrated with ML techniques under the DC paradigm. Here, we cover these subjects as follows: In Sections II-A and II-B, the scaling laws and indicators are defined, then, the trading strategies are discussed in Section II-C. Finally, we explore the intersection space of machine learning and DC paradigm in II-D.

A. Scaling Laws

From the very early introduction of DC [4], one aspect of DC findings has been focused on the scaling laws. We can translate its definition as regularities that prove a quantitative relationship between two features due to their consistency in numerous empirical experiments. Consequently, [5] has discovered 17 scaling laws across 13 currency exchange rates. That is followed by adding another 12 new ones [6]. Among them, there are two important discoveries that are related to the mathematical relations between DC and OS, event duration and the price changes during these events, which are illustrated more comprehensibly at Section III. Subsequently, scaling laws subject at DC has got wider with the addition of 4 more scaling laws by [7], and further work on stock market assisted in unearthing new 5 laws [8]. Then 4 and one scaling law have been discovered [9], [10]. Eventually, these findings have been already started to examine under a trading strategy in the field, and some additions in the future seems very likely.

B. Indicators

Another aspect of the DC has been targeted by addition of indicators, which have been the major assistant in creating a certain perspective to new users. The study in [9] was an early one to explore 4 indicators, and then more indicators were added by the study in [10]. Monumentally, [11] can be seen as a dictionary of DC based indicators, and how to extract an information from paradigm itself. Among these indicators, we have used some of them with their different variations from an original definition. Their implementation into strategies is mentioned in Section III also. Subsequently, usage of another indicator that gives an understanding of a regime change detection, where time-series was not capable of doing so [12]. This leads to differentiation of a normal and abnormal market regimes across various markets [13].

C. Trading Strategies

Major aspect of this paper is creating trading strategies based on the previous two sections. In literature, one of the early attempts was using fuzzy logic approach to mimic the human reasoning under DC. Demonstration of volatility concept under DC was another addition to the field [14]. Contemporaneously, scaling laws that were discovered through the DC can be started to be seen at trading [15]. To keep up with the today's financial environment, where the high speed automated algorithms are increasingly becoming the decision makers, agents that are developed to model the trader's behaviour have been experimented with Forex instruments. With this aim, modelling the agents under a DC based trading activity, namely Z1-DCT0, into foreign exchange market was first one to be seen [16]. Further strategy improvements can be seen in DCT1 [7], and the advancement can be found in a form of higher profit at DCT1 in comparison to early attempt. At a later stage, improvements on DCT1 are made in an attempt to observe a more dynamic reactionary system to a different threshold by creating a DCT2 [17]. Also, Bakhach introduced strategies to the field as Static Backlash Agent (STA) and Dynamic Backlash Agent (DBA), where the DC based indicator overshoot value took a role [18]. Subsequently, author made improvements the first DBA in order to overcome the weaknesses of not having a size management and not having a risk management scheme [19]. Also, further work was made by the Bakhach at the creation of trading strategy based in forecasting of DC, TSFDC, where he targeted to predict the direction of trend [20]. At the risk side of research, trading strategies' examination with Value at Risk (VaR) broadens another window [21], and it epitomizes how much the framework DC is open to new fields in the finance studies. Another side is inclusion of classification task into DC based trading strategies, which ended up being exceeded the performance of physical-time analysis i.e. technical analysis [22], where FX pairs were investigated and a new option to user was displayed at the decision-making process regarding to early capture of trend reversal with improvements of the early study [23].

D. Machine Learning under DC

At the intersection of machine learning and DC paradigm, literature has been evolved around the two sub-categories. First one is usage of ML for optimization under DC and the second one classification by the ML. Early usage of genetic algorithm for optimization via DC can be seen in [24], where authors try to optimize different thresholds in a target to explore the small and larger thresholds comparatively. Further work also captured two more optimizers as particle swarm optimization (PSO) and continuous shuffled frog leaping algorithm (CS-FLA), and again the research was scrutinized around multi-thresholds [25].

On the other side, DC usage have been started to be seen at various classification tasks. These tasks have been evolved around finding the trend reversal in DC paradigm, by doing so, researchers were in a position of making informed trading decisions. Among them, researchers tried to predict the boolean version OSV_{EXT} at *True* or *False* [26] in order to catch a profitable trend reversion, and that purpose was encapsulated by the classification task, the chosen algorithms were J48Graft and M5P. In another study, the relation of OS and DC events duration were the main exploratory tasks under another classification work by [23], [27], [28], where researchers used the genetic programming in an attempt to discover a trend reversal prediction, furthermore, they improved this work by adding a classification step under 20 Forex currency pairs with 1000 different datasets [22].

III. Directional Changes

This section supplies a background information regarding our research. In Section III-A, we start by defining how DC operates briefly at a hypothetical scenario, where we define our θ as 5%. In Sections III-B and III-C, we continue by presenting the indicators and scaling laws respectively for a better understanding of the proposed paradigm. For brevity, we only discuss indicators and scaling laws that are being used in this paper.

A. Basics of DC

As we previously mentioned, DC is an alternative frame of reference to record price movements by events. These events can be seen only in two forms, overshoot (OS) and DC events. Approval of a DC event is based on the pre-defined price change confirmation, once the price change at the opposite direction of current trend is significant, DC event is formed, and then usually OS event follows. The pre-defined price change is constructed by the user preferences, i.e. θ, and it is the unique feature of the approach. Fig. 1 illustrates the DC and OS events formation consecutively at the threshold of 5%. With an imaginary financial product that price starts with 100$ then decreases to 96$ at point A - due to a change that is smaller than our pre-defined θ - the acceptance cannot occur, however, from point A to point B - since a significant level is reached as 5% - we accept a confirmation of DC event. Thus, at point B, two important prices' points emerge, one is directional change confirmation point (P_{DCC}), and the second one is extreme point (P_{EXT}), which is confirmed retrospectively at time 4. In order to catch another DC event, threshold needs to be reached at the opposite direction again, as in the Fig. 1 i.e. point D. Further, these events can be encountered in the trends, which are called uptrend and downtrend.

For instance, uptrend, or upward trend is the total duration of one particular DC and its consecutive OS event, between the points of A and C in Fig. 1. Also, this whole duration can be identified in another way as between the time of two consecutive extreme points. However, one can imagine that confirmation points should not be always a discrete price change. In fact, almost always, we can observe that the price change that occurs to confirm a DC event is bigger than the minimum amount that would be needed to consider that as DC event. Therefore, concept defines a theoretical confirmation point with this intention, (P_{DCC*}). It can be seen from the point B* in Fig. 1, where the price change of 4.8$ would be enough to form an DC event at time 4.

With this way of summarization of the data, we give the users a new perspective on the observation of price changes. The important extension can be emphasized by saying users are now can focus on the key points rather than neglecting the important events due to their time interval preferences at the physical time-series.

B. Indicators

After the general introduction of DC, we now turn our focus into indicators that have been derived from other studies [11] to give better frame of reference to users. Eventually, indicators are the force behind the decision-making process at trading strategies. In the following, detailed description of several indicators used in our study is provided.

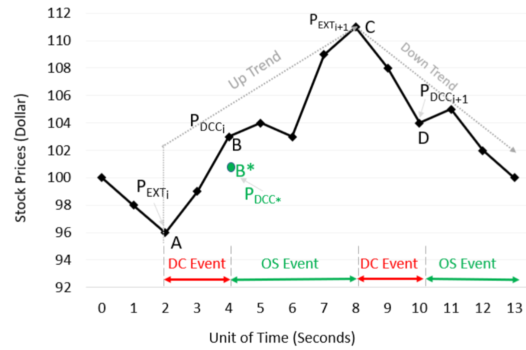

Fig. 1. Transformation of 14 unit of physical time data into event-based series by DC. There are two DC event confirmation at time 4 and 10. Concluded up trend takes place between the two extreme points, A and C, which are confirmed retrospectively at their subsequent confirmation points, B and D.

- Number of DC events (N_{DC}): the total number of DC events through the investigated period. With the scope of the θ implementation, this indicator serves as an exemplar to inspect the volatility of the data at that threshold.
- Number of Overshoot Events (N_{OS}): the total number of OS events in the profiled data. By the definition, one can intuitively think that the N_{DC} is equal to N_{OS}. However, at particular data, which consisted of increases and decreases in the terms of prices are highly steep, DC can be followed by another DC accordingly to its threshold selection, so lower number of OS event in comparison to DC can be a good signal to user as in the expectation of fluctuations.
- Time for Completion of a Trend (TT): the recorded physical time for a trend to conclude. Even though, DC is originated in an attempt to create event-based series from the transformation of physical time-series, we propose that acceptance of DC as complementary paradigm to time-series would be better suited. That is why, indicator T is implemented to paradigm in order to capture the trends at physical time.
- Overshoot Values (OSV): an indicator to spotlight the overshoot event's current price in the eyes of a last confirmation point. It serves as an measurement of magnitude for an OS event. For instance, constant higher absolute values indicates that the fluctuation is relatively small.

$$OSV = ((P_c - P_{DCC}) \div P_{DCC}) \div \theta \qquad (1)$$

Where, P_C and P_{DCC} are the current price and last directional change confirmation price, respectively.
- Theoretical Confirmation Point (P_{DCC*}): The least price that is required to establish a DC event in a trend. In the real world, seeing the actual confirmation point as the minimum price occurrence is highly unlikely.
At the upturn trend:

$$P_{DCC*} = P_{EXT} \times (1 + \theta) \qquad (2)$$

At the downturn trend:

$$P_{DCC*} = P_{EXT} \times (1 - \theta) \qquad (3)$$

Here, P_{DCC*} is theoretical confirmation point, and its calculation is dependent on the current trend.

- Overshoot Values at Extreme Points (OSV_{EXT}): As in the OSV, the main goal for the OSV_{EXT} is to measure the magnitude of an OS event. However, there are two differences from the OSV. First one is to use the current trend's extreme point, instead of testing the current price. Second one is P_{DCC*} is used instead of the actual price P_{DCC} that takes place. Equation for the indicator is as follows:

$$OSV_{EXT} = ((P_{EXT} - P_{DCC*}) \div P_{DCC*}) \div \theta \quad (4)$$

Where, P_{EXT} is the price of an extreme point that ends the current trend, which is confirmed at the upcoming confirmation point, retrospectively. P_{DCC*} and θ are theoretical confirmation point and theta, respectively.

- Total Price Movements Value at Extreme Points (TMV_{EXT}): measures the price change size between the two consecutive extreme points in accordance with the threshold. This scale gives an idea of possible profit for that particular trend. Equation for the indicator is as follows:

$$TMV_{EXT} = (P_{EXT_{i+1}} - P_{EXT_i}) \div (P_{EXT_i} \times \theta) \quad (5)$$

Here, P_{EXTi+1} and P_{EXTi} are the price of extreme points at $(i+1)^{th}$ and $(i)^{th}$ time, respectively.

C. Scaling Laws

Regarding the scaling laws that have been practised, we choose to bring light on two important ones that are related to the duration of DC and OS events at average, and the approximate price change equality at consecutive DC and OS events.

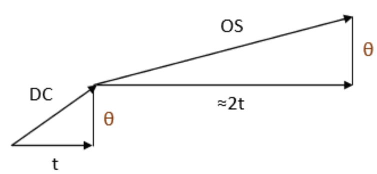

Fig. 2. Two scaling laws from [6], which are implemented in our strategies, that shows (a) price changes in DC and followed OS is approximately same and equals to threshold, (b) if DC event takes *t* physical time, its subsequent OS takes approximately *2t*.

To be specific, [6] discovered an empirical consistency between numerous foreign currency data that the duration of an OS event is approximately twice the duration of its DC event. As we can see from the Fig. 2, the equation for that specific scaling law can be formulated as:

$$OS \approx DC \times 2 \quad (6)$$

Where, DC and OS represent the physical-time duration that lasts in DC and OS events, respectively.

Another important regularity Fig. 2 illustrates is the average price change in DC, which can intuitively be agreed on, that is same as the change in OS event. Again, we can see this formulation by;

$$\triangle P_{OS} \approx \triangle P_{DC} \quad (7)$$

Where, $\triangle P_{DC_t}$ and $\triangle P_{OS_t}$ presents the price change that occurs in each event. In the next section, we discuss how all of these indicators and scaling laws have taken their role in the creation of strategies.

IV. Methodology

This section is divided into two main parts. First of all, in Section IV-A, we present the individual trading strategies that are based in the DC concept. Then, in Section IV-B, we present the GA methodology, and how it was applied to optimize the individual trading strategies.

A. Individual Strategy Creation Process

Table I presents a summary of the 7 individual DC-based trading strategies used in this paper. All strategies follow two important rules: (i) we cannot open a position if the position is already open; thus we first need to close a position before opening a new position, and (ii) short selling is allowed; so, an opening position can be in the form of going long or going short on the financial product. The first three strategies are based on scaling laws and the remaining four on DC indicators. We should also note that we are using variations of Equations 4 and 5 for the OSV and TMV indicators, whereby instead of using the extreme value, we use the current value, thus OSV_{cur} and TMV_{cur}. This allows us to use these indicators at every data point, rather than using them only during the extreme points.

1) Strategies based on scaling laws

Strategy 1 (St1) uses the first scaling law (Equation 6), which says the duration of an OS event is approximately twice the duration of its corresponding DC event. It thus opens a position at P_{DCC} and closes it when $|TMV_{cur} > 2|$ or at the next confirmation point P_{DCC} - whichever happens first. The motivation behind this closing is to make an informed decision by the expectation of scaling law that would hold. Thus, with a t time occurrence between P_{EXT} and P_{DCC}, we try to catch the $2t$ duration, where the reversion would start at the opposite direction of trend.

Strategy 2 (St2) uses the second scaling law (Equation 7), which says that the difference in price change between a DC and its corresponding OS event is approximately the same. We again open a position at P_{DCC} and close it when $\triangle P_{OS} \geq \triangle P_{DC}$ or at the next confirmation point P_{DCC} - whichever happens first. The rationale behind this strategy is to make a decision in an attempt to catch the price change during an OS, before it is recorded.

Strategy 3 (St3) can be seen as an 'mirror strategy' to Strategy 1, where we define our openers based on the duration scaling law, instead of using it as a position closer as in Strategy 1. We thus open a position when $|TMV_{cur} > 2|$ and close it at the following P_{DCC}.

TABLE I
INDIVIDUAL STRATEGIES

Strategy	Opening	Closing
St1	P_{DCC}	$\mid TMV_{cur} \mid \geq$ 2.0; otherwise P_{DCC}
St2	P_{DCC}	$\triangle P_{OS} \geq \triangle P_{DC}$; otherwise P_{DCC}
St3	$\mid TMV_{cur} \mid \geq$ 2.0	P_{DCC}
St4	$\mid OSV_{cur} \mid \geq \mid OSVBest \mid$	P_{DCC}
St5	$\mid TMV_{cur} \mid \geq \mid TMVBest \mid$	P_{DCC}
St6	$OS \div DC \geq OS \div DC$	P_{DCC}
St7	$N_{OS} \div N_{DC} > R$	P$_{DCC}$

2) Strategies based on indicators

In this section, we use DC-based indicators and compare them against a fixed threshold[1] value. When the indicator goes below this value, then we open a position. The position remains open until we reach the following P_{DCC}. This threshold value comes from the distribution of the relevant DC indicator used in each strategy - please see below for more information.

In the case of Strategy 4 (St4), we check if $|OSV_{cur}| \geq |OSVBest|$, where $|OSV_{cur}|$ is the absolute of current value of OSV. In order to estimate the $|OSVBest|$, we do the following: first we obtain the distribution of all OSV_{cur} values for our event-based series; then we divide these values into deciles and then we calculate the median OSV_{cur} value per decide; in the end, we identify the median OSV_{cur} with the highest Sharpe ratio (in a validation set) and select it as the threshold $|OSVBest|$ against each $|OSV_{cur}|$ value.

Similarly, in Strategy 5 (St5), we check if $|TMV_{cur}| \geq |TMVBest|$, where $|TMV_{cur}$ is the current absolute TMV value at a given data point, and $|TMVBest|$ is selected in the same process as $|OSVBest|$ above.

In Strategy 6 (St6), we compare the OS:DC ratio of each event against the overall OS:DC ratio (i.e. the ratio for the whole training dataset). If the first ratio is greater than or equal to the second ratio, then we open a position. Position closes at the next P_{DCC}.

Strategy 7 (St7) is essentially a random strategy to allow diversification among the individual strategies. What it does is to compare the ratio of the number of OS and DC events against a randomly generated real value between 0 and 1; if the ratio is higher than this number, then we open a position *at the current* P_{DCC}. Closing happens again at the following P_{DCC}. Basically this strategy opens and closes its positions at P_{DCC} points; the advantage of this is that this can work very well when we are dealing with bull markets, as the next P_{DCC} will tend to be at a higher (lower) price point than the one we took a buy (sell) action, thus making a profitable transaction.

B. Genetic Algorithm (GA)

As mentioned earlier, each one of the above trading strategies creates its own set of open-hold-close positions. The advantage of having multiple trading strategies is that we can have multiple recommendations per data point, thus richer information. However, if a trader wanted to take into account the recommendations from more than one of these trading strategies, they could face conflicting action; for example, one trading strategy could be recommending to open a position, whereas another one to close. To deal with these conflicts, we assign a weight to each trading strategy and then evolve these weights. Thus, when it comes to decision-making, we will follow the recommendation that has the highest sum of weights. Below we present the details of the GA algorithm.

[1]Not to be confused with the DC threshold θ.

1) Representation of Individuals

Since there are 7 trading strategies, each GA individual consists of 7 genes. Each gene represents a trading strategy. The value of each gene is a weight, which is a real number between 0 and 1. Fig. 3 presents a sample individual. The first row is labels and is provided for reference. As we can see, each one of the 7 trading strategies has been assigned a weight. At any given data point, each trading strategy makes a recommendation, namely open a position, hold, close a position. Thus, at any given data point, we can have different recommendations. Let us assume that St1 and St2 recommend to open a position, St3-St5 to hold, and St6-St7 to close a position. We then sum up the weights for each recommendation, i.e. the sum of opening a position is $0.14 + 0.16 = 0.3$ (St1-St2); the sum of holding is $0.25+0.05+0.11 = 0.41$ (St3-St5); and the sum of closing a position is $0.19 + 0.10 = 0.29$ (St6-St7). As we can observe, the hold position has the highest sum of weights (0.41). Thus the decision at that specific data point would be to hold. The idea behind this is that the GA will evolve the weights in such way to favour trading strategies that maximize its fitness function.

Strategies	St1	St2	St3	St4	St5	St6	St7
Weights	0.14	0.16	0.25	0.05	0.11	0.19	0.10

Fig. 3. Individual chromosome representation. First row is the strategy names and is provided for reference.

2) Genetic Operators

We use one-point crossover with a probability p and one-point mutation with a probability $1-p$. We also use elitism, to ensure that the best individual is copied to the next generation.

3) Fitness Function

We use Sharpe Ratio (SR) as our fitness function to take into account risk-adjusted returns. The equation for SR is as follows:

$$SR = \frac{(R_{\text{p}} - R_{\text{f}})}{\sigma_{\text{p}}} \tag{8}$$

where, R_p is total rate of return for a given GA individual, R_f is risk-free asset, which is selected as 2.5% for a two-year dataset to preserve the resemblance of USA government bonds, and σ_{p} is the standard deviation of returns, i.e. the risk of the trading strategy.

4) *Population Initialization*

Although we use random initialization for population in the first generation, there is one important added modification. We embed N chromosomes to represent each individual trading strategy. Since in our case we have 7 individual DC-based trading strategies (summarized earlier in Table I), $N = 7$. So we embed 7 chromosomes in the following way: for the first chromosome, representing individual Strategy 1, we assign a 100% weight to the first gene (value of 1), and a weight of 0 to all other genes. Similarly, for individual Strategy 2, we assign a weight of 1 to the second gene, and a weight of 0 to all other genes. The same applies for the remaining strategies. This process is also summarized in Fig. 4. Manually adding the individual trading strategies provides the GA with an initial 'good' knowledge of the trading strategies, and can then focus its search in improving these strategies.[2]

Ind1	**1.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Ind2	**0.0**	**1.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Ind3	**0.0**	**0.0**	**1.0**	**0.0**	**0.0**	**0.0**	**0.0**
Ind4	**0.0**	**0.0**	**0.0**	**1.0**	**0.0**	**0.0**	**0.0**
Ind5	**0.0**	**0.0**	**0.0**	**0.0**	**1.0**	**0.0**	**0.0**
Ind6	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**1.0**	**0.0**
Ind7	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**1.0**

Fig. 4. The gene values for the first 7 chromosomes in the initial GA population, representing the 7 individual strategies.

V. EXPERIMENTAL SETUP

In this section, we start by defining our data in Section V-A, and then, we describe the tuning procedure for the GA parameters in Section V-B.

A. *Data*

In this research, we use 44 public stocks from the New York Stock Exchange, and their stickers are as follows: AAL, AAPL, ALV, AMGN, AMZN, BKR, BP, BX, CCL, CPB, CSCO, DIS, DVN, EOG, EVR, EXC, F, FB, FCX, FTI, GHL, HES, IBM, JNJ, JPM, KO, LAZ, MCD, MMM, MS, NCLH, OKE, ORCL, OXY, PCG, PEP, PM, RIG, UNM, V, VLO, VNO, WMT, XOM. The daily adjusted price is the selected form, in order to avoid artificial price changes that can occur from such as stock splits, which would break the dynamic of DC paradigm. The start and end dates are 20.03.2011 and 20.03.2021, respectively. The source of data is YAHOO Finance by the library of *'yfinance'* for python. The data is divided into three parts; 60% for training, 20% for validation, and 20% for testing.

[2]In early experiments we also considered GA initialization without embedding the 7 strategies, but we found that the fitness was significantly worse.

B. *GA parameters tuning*

We performed a grid search on different sets of the following parameters: population size (possible values: 100, 300, 500); generations number (possible values: 15, 25, 35); and crossover probability p (possible values 0.75, 0.85, 0.95, 0.99). A reminder that mutation probability equals $1 - p$, so we did not need to include it into the tuning phase. Table II presents the best parameters that were selected in the validation set.

TABLE II
GA PARAMETER TUNING

Population size	100
Generations	35
Crossover probability	0.95
Mutation probability	0.05
Tournament size	2

VI. RESULTS

Table III presents the GA's average results over 50 runs for Sharpe ratio (SR), rate of return (RoR), and standard deviation (STD) under a 2.5% DC threshold θ. We leave it to future work to investigate DC strategies performance under different thresholds. Table III also presents the same metrics (SR, RoR, STD) for St1-St7. All results are for the 44 datasets from NYSE that were presented in the previous section.

TABLE III
AVERAGE SHARPE RATIO, RATE OF RETURN, AND STANDARD DEVIATION RESULTS ACROSS 44 DATASETS FOR THE GA AND THE 7 INDIVIDUAL DC-BASED STRATEGIES. WE PRESENT THE BEST VALUE PER METRIC IN BOLDFACE.

Metric	**Strategies**							
Results	***GA***	***St1***	***St2***	***St3***	***St4***	***St5***	***St6***	***St7***
SR	**6.47**	0.09	5.32	-2.06	0.79	-0.31	2.87	6.06
RoR	**0.49**	0.01	0.27	0.01	0.19	0.16	0.31	0.46
STD	0.06	**0.04**	**0.04**	0.06	0.06	0.06	0.06	0.06

The first thing to observe from Table III is many individual DC-based strategies are able to perform strongly across all three metrics. To begin with, with regards to the Sharpe ratio, we can observe that St2, St6, and St7 have received relatively high values (5.32, 2.87, 6.06, respectively). These strategies have also performed strongly in terms of rate of return (27%, 31%, 46%); but one could add St4 (19%) and St 5 (16%). Lastly, with regards to risk, we can see that all strategies have performed similarly well, with values in the range of 4%-6%. We can thus conclude that apart from the TMV_{cur}, which was used in St1 and St3, all other DC-based indicators and strategies were able to report strong performance in at least one of the three financial metrics examined. This leads us to argue that the DC paradigm and its indicators are able to offer favourable returns and risk.

In addition, to the individual trading strategies, Table III also presents the financial performance of the GA, which combined the recommendations of the individual trading strategies. As we can observe, the GA returned the highest Sharpe ratio and rate of return when compared to the individual strategies. Its average difference does not appear to be significantly higher to the SR and RoR performance of St7, which was the best individual strategy; nevertheless, the GA has improved on St7, which demonstrates the benefits of optimizing the weights of the individual trading strategies. As a result, the GA is able to build on the good performance of an individual strategy and improve it by combining information from other strategies.

With regards to risk, we can observe that the GA ranks second, along with St3-St7 with a STD value of 6%. The value is not too different from the best value of 4%.

It is worth mentioning that the impressive results above in terms of SR and RoR can be partially explained by the fact that the NYSE datasets used in this paper experience a heavy bullish behaviour. Especially a strategy like St7, which leverages heavily on bull markets, is able to lead to very profitable results. Of course, the bull market can only have a partial effect on the SR and RoR performance; the other contributor is the DC paradigm. This will be become apparent when we also discuss the results of the passive buy-sell strategy towards the end of this section, where we will observe similarly high returns, but not as high as the DC-based results.

To confirm the above results, we present in Tables IV, V, and VI the Friedman non-parametric statistical test, under the null hypothesis that all strategies (including the GA) come from the same continuous distribution. The second column (Ranking) presents the average rank of each strategy. The third column (p_{Homm}) presents the adjusted p-value of the test when that algorithms average rank is compared to the average rank of the control algorithm (i.e. algorithm with the best rank; denoted with a '(c)'). The adjusted p-value is calculated with the Hommel post-hoc test. As we can observe, under Sharpe ratio (Table IV), the GA statistically outperforms at the 5% significance level the following strategies: St1, St3, St4, St5 and St6. It does not statistically outperform St2 and St7, but still ranks higher. Furthermore, with regards to rate of return (Table V), GA ranks again first and statistically outperforms St1, St3, St4, and St5. Lastly, with regards to standard deviation (Table VI), St1 ranks first and statistically outperforms the GA, as well as St3, St4, St5, St6 and St7. The statistical tests thus confirm what we had also observed in Table III, i.e. that the GA is able to build and improve on the SR and RoR performance of the individual trading strategies. With regards to risk, the GA did not perform as well. Future work could thus focus on directing the GA search towards less risky solutions. However, we should again note that the difference between the GA and the best individual strategy in terms of risk was only at 2%, while the improvements it brought on SR and RoR were much higher.

In addition, we investigated how many times GA ranks first for a given dataset in terms of SR, RoR, and STD. Table VII demonstrates that the GA comes first in 17 stocks out of 44. The closest to it is St7 with 12 times. The same number of occurrences at the RoR has been found as well. Whereas, we have not found any favorable STD results for GA.

TABLE IV
STATISTICAL TEST RESULTS FOR SHARPE RATIO ACCORDING TO THE NON-PARAMETRIC FRIEDMAN TEST WITH THE HOMMEL POST-HOC TEST. SIGNIFICANT DIFFERENCES AT THE $\alpha = 0.05$ LEVEL ARE SHOWN IN BOLDFACE.

Sharpe Ratio Friedman Rank		
Algorithm	***Ranking***	p_{Homm}
GA (c)	2.74	-
St7	3.09	0.53
St2	3.47	0.33
St6	**4.07**	0.03
St1	**5.16**	1.4E-5
St4	**5.35**	2.8E-6
St5	**5.77**	3.7E-8
St3	**6.38**	2.3E-11

TABLE V
STATISTICAL TEST RESULTS FOR RATE OF RETURN ACCORDING TO THE NON-PARAMETRIC FRIEDMAN TEST WITH THE HOMMEL POST-HOC TEST. SIGNIFICANT DIFFERENCES AT THE $\alpha = 0.05$ LEVEL ARE SHOWN IN BOLDFACE.

Rate of Return Friedman Rank		
Algorithm	***Ranking***	p_{Homm}
GA (c)	2.8	-
St7	2.86	0.91
St2	3.76	0.13
St6	4.0	0.06
St4	**5.33**	5.4E-6
St1	**5.36**	4.9E-6
St5	**5.7**	1.7E-7
St3	**6.17**	8.3E-10

TABLE VI
STATISTICAL TEST RESULTS FOR STANDARD DEVIATION ACCORDING TO THE NON-PARAMETRIC FRIEDMAN TEST WITH THE HOMMEL POST-HOC TEST. SIGNIFICANT DIFFERENCES AT THE $\alpha = 0.05$ LEVEL ARE SHOWN IN BOLDFACE.

Standard Deviation Friedman Rank		
Algorithm	***Ranking***	p_{Homm}
St1 (c)	2.23	-
St2	2.63	0.44
St3	**4.51**	2.4E-5
St6	**4.77**	3.3E-6
St5	**5.23**	3.7E-8
St4	**5.38**	8.3E-9
GA	**5.42**	5.8E-9
St7	**5.84**	3.2E-11

TABLE VII
NUMBER OF TIMES STRATEGY GIVES THE BEST RESULTS

Number of Occurrences								
Algorithm	***GA***	***St1***	***St2***	***St3***	***St4***	***St5***	***St6***	***St7***
SR	17	1	6	0	1	2	5	12
RoR	17	1	6	0	1	2	5	12
STD	0	22	9	7	0	2	4	0

Lastly, we compare the GA results with a buy-sell strategy, which opens a long position on the first day of trading and closes it by going short on the last. Given all of our datasets are in a predominately bull market, it is worth examine the performance of this strategy (as it is expected it will perform really well) and see how it compares to the GA results. Our experiments showed that on average the GA experience a rate of return of 49%, while the buy-sell strategy 19.4%. This thus confirmed that the strong performance of the GA was not only because of the bull market, but also because of the advantages of the DC-based strategies and optimization. A Kolmogorov-Smirnov two sample test (null hypothesis: the GA and buy-sell distributions of returns come from the same continuos distribution) rejected the null hypothesis with a p-value of 0.02266, thus confirming that the difference in the results was statistically significant at the 5% level.

VII. Conclusion

In conclusion, this research proposes trading strategies under the paradigm of directional changes. We believe that adding an optimization process using the GA algorithm to these individual strategies is a unique contribution to the field. To accomplish that, 44 stocks have been experimented at the DC threshold of 2.5%. We can draw the following conclusions from our experiments: (i) The DC-paradigm is able to produce profitable and not risky trading strategies, (ii) Implementation of GA as an optimizer produces the SR and RoR best results among the individual strategies, and (iii) The GA strategy is able to statistically outperform a buy-sell benchmark.

In future work, we aim to use GA optimization process to consider trading strategies under different DC thresholds and then combine those strategies under the multi-strategy approach presented in this paper. We hope that taking into account the information of multiple DC thresholds and strategies will further improve our results.

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