Leveraging Genetic Algorithms for Directional Change Optimization in Algorithmic Trading

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Abstract

This study presents an innovative approach to algorithmic Forex trading by leveraging the computational power of Genetic Algorithms (GAs) and the analytical potential of Directional Change (DC) strategies. In the face of Forex market complexities, traditional methods often fail to deliver consistent profitability and efficient risk management. To address this, our research implements GAs, with their inherent evolutionary principles, and integrates DC analysis to navigate effectively through market volatility. We evaluate the performance of the combined GA-DC methodology through rigorous backtesting and statistical analysis. The findings reveal a significant improvement in trading outcomes, demonstrating the advantage of synergizing GAs with DC strategies. This leads to the development of more robust, adaptable trading systems that dynamically respond to market conditions.

Acknowledgements

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Acronyms

B&H Buy and Hold.

DC Directional Change.

FX Forex.

GA Genetic Algorithm.

MACD Moving Average Convergence Divergence.

MDD Maximum Drawdown.

MTS Multi-threshold Strategy.

MTSGA Multi-Threshold Strategy Optimized with Genetic Algorithm.

OS Overshoot.

RoR Rate of Return.

RSI Relative Strength Index.

STS Single-threshold Strategy.

Chapter 1

Introduction

The foreign exchange (Forex) market, a global platform for currency trading, offers significant profit potential due to dynamic variations in currency values. However, the effective navigation of this intricate market requires both extensive knowledge and adaptable, effective trading strategies.

Recently, the integration of Genetic Algorithms (GAs) and Directional Change-based strategies has garnered significant attention due to its potential to enhance trading efficiency [1, 2]. GAs, computational models inspired by natural selection, aim to optimize solutions through mutation and recombination [3]. On the other hand, Directional Change-based strategies focus on identifying trend reversals or changes in price direction [4]. The integration of these approaches offers a potential solution to enhance the performance of automated trading systems in the Forex market.

Automated trading systems are a popular choice among traders due to their efficiency in executing trades with precision and speed, based on predetermined rules [5, 6]. However, the challenge lies in identifying profitable patterns amidst the overwhelming amount of data available. To address this issue, a promising approach is combining Genetic Algorithms (GAs) with Directional Change-based strategies. This adaptive framework adds an extra layer of sophistication to automated systems, thus maximizing their potential and optimizing returns for traders.

1.1 Motivation

The main drive behind this research was the growing importance of algorithmic trading, especially in the Forex industry [6, 7], and the need for advanced trading strategies. The potential capabilities of Genetic Algorithms (GAs) and Directional Change strategies, two promising techniques in algorithmic trading, led to their selection. GAs can solve complex optimization problems using principles of natural evolution [8], while Directional Change strategies can effectively identify market trends and patterns [9].

Despite their individual potential, the integration of these techniques in Forex trading is relatively unexplored. This study aimed to bridge this gap, exploring the effectiveness of combining these techniques in the volatile and complex Forex market. Furthermore, it sought to contribute valuable insights to the field of computational finance, informing the development of more effective trading strategies and guiding future research in this rapidly evolving field.

1.2 Aims and Objectives

The objective of this report is to evaluate how machine learning algorithms and the Directional-Change events method can be utilized for analyzing the Forex market. The report utilizes a multi-threshold DC trading algorithm to generate multiple buy-sell-hold recommendations. In order to address any possible conflicts among these suggestions, a Genetic Algorithm will be employed to aid in refining the weights and parameters of every DC threshold, thereby improving the effectiveness of the algorithm as a whole. This comprehensive approach provides a broader perspective of the FX market, improves flexibility, and maximizes opportunities for profitable trades.

1.3 Report Structure

The next chapter provides a comprehensive theoretical background on three critical areas relevant to our study. We first detail basic concepts in the Foreign Exchange (FX) market, including standard terminologies, typical strategies, and evaluation methodologies. We then discuss Directional Change (DC), its strengths, limitations, algorithm, and scaling laws. Finally, we present an overview of Genetic Algorithms, their terminologies, and their structure.

In Chapter 3, we examine relevant literature on the DC framework and the Genetic Algorithm, laying the groundwork for our exploration of amalgamating these two concepts. Chapter 4 provides a comprehensive explanation of the fundamental concepts of our proposed approach, referred to as the Multi-Thresholds Strategy Optimized with Genetic Algorithm (MTSGA). This includes a discussion on the DC transformer and the development of the approach through the integration of multi-thresholds and the genetic algorithm.

Chapter 5 presents the outcomes derived from our experimental methodologies and provides statistical evaluations of the trading outcomes. Chapter 6 will address challenges related to legal, social, ethical, and professional issues during the project. It will also explain how these issues were resolved as per the British Computer Society's guidelines. A conclusion summarizing the key findings and implications of the study is provided in Chapter 7. Furthermore, Appendix A contains further information and extended analyses of our experimental results.

Chapter 2

Background

2.1 Foreign Exchange Market

The foreign exchange market is of great significance in the international financial industry due to its vast magnitude, flexibility, and consequential impact on global economies. This market is notable as the most fluid financial market globally, with a daily trading volume averaging around $7.5 trillion USD [10].

The characteristic feature that sets the Forex market apart is its reliance on foreign exchange rates, which implies that holding one currency inherently requires a transitory position in another currency [11]. The market is distinguished by its ability to generate data at a high frequency, and it possesses ample liquidity and equilibrium. Its constant operation, leading to continuous data production, serves as an invaluable source for real-world applications and academic research [12].

Given its unique characteristics, the foreign exchange market presents an intriguing and dynamic platform for traders and investors, demanding refined and adaptable strategies for successful navigation. In this section, we'll examine the fundamental principles of trading in foreign exchange, diverse technical analysis methods, and approaches to measure the effectiveness of these strategies.

2.1.1 Foundational Concepts in Forex Trading

This section outlines some fundamental concepts critical to understanding and navigating the Forex market.

Currency pairs

Within the Forex market, currencies are exchanged in pairs, which comprise a base currency and a quote currency. The base currency, being the first listed in the pair, serves as the foundation. On the other hand, the quote currency represents its corresponding worth in relation to the base currency.

Quotes

Currency quotes display the worth of one type of currency in relation to another, either directly or indirectly. A direct quote indicates the price of foreign currency in domestic money, whereas an indirect quote reflects the cost of domestic currency in foreign money.

PIP (Percentage in Point)

The minimal price variation that can occur in an exchange rate is called a pip, which is short for "Percentage in Point." In the majority of currency pairs, a single pip corresponds to a value change of 0.0001.

Bid-Ask Spread

The bid-ask spread refers to the divergence between the highest value a purchaser will pay and the lowest value a seller will accept. The narrower the spread, the better for traders as less movement in their favor is needed to generate profits.

2.1.2 Technical Analysis

Using technical strategies that involve examining past price data and applying different indicators can predict future price movements. Various sources [13–15] have demostrated the widespread application of technical analysis in modern time. This underscores the crucial significance of technical strategies for successful trading in Forex market.

In this section, we will introduce two technical strategies—MACD and RSI—which serve as the benchmarks for the experiment being conducted.

MACD

The Moving Average Convergence/Divergence (MACD) tool, formulated by Gerald Appel during the 1960s [16], functions as a reference for determining the appropriate time to purchase or sell. Two exponential moving averages (EMAs), one quick and one slow, are utilized in creating a MACD line. The supplementary line, known as the signal line, denotes the mean value of the MACD line over a predetermined duration. It is advisable to purchase when the MACD line surpasses the signal line, and conversely recommended to sell when it falls below the said signal line.

RSI

The Relative Strength Index (RSI) is a momentum-based tool created by J. Welles Wilder, Jr. This tool measures price fluctuations to ascertain if an asset is overbought or oversold, thus providing speculation on potential future price movements. In essence, an oversold result suggests a likely long position, while an overbought result hints at a potential short position. The RSI averages gains and losses over a specified time period and presents the results on a 0 to 100 scale. An oversold signal is indicated when the RSI falls below 30 on this scale, and an overbought signal is marked when the RSI exceeds 70 [17].

2.1.3 Evaluating Trading Strategy

In the fast-paced and ever-changing world of financial markets, traders face the ongoing challenge of making intelligent decisions to succeed. To gain an edge and navigate this complex landscape, they rely on a powerful tool called backtesting.

Backtesting is a fundamental procedure in assessing trading strategies. It involves simulating a trading strategy using historical data and assessing its performance in various market conditions. By conducting backtests, traders can gain insights into the expected performance and risk associated with their strategies. According to [18], backtesting provides valuable insights into the historical success of a forex trading strategy by allowing traders to make more informed decisions based on past results.

When conducting backtests, traders typically adhere to the following steps:

1. Define trading strategies and conditions.

2. Collect comprehensive historical data.

3. Set appropriate backtesting parameters (e.g., initial funds, fees).

4. Execute the backtest and evaluate the results.

5. Optimize strategies based on the findings.

These sequential actions enable traders to assess the performance and potential of their strategies, make informed decisions, and enhance their approaches for optimal results.

The benefits of backtesting encompass eliminating emotional biases, conducting scenario analysis, and identifying potential weaknesses. Nonetheless, it is important to be aware of limitations, including disparities between historical and real-world outcomes, as well as the risk of excessive optimization.

In this dissertation, we thoroughly assess the performance of the planned trading strategies using a set of carefully chosen metrics. These metrics are widely accepted and understood in both academic and professional circles as reliable indicators for evaluating the effectiveness of trading strategies [19].

- **Rate of Return (RoR):**

  The rate of return (RoR) quantifies the percentage change in the value of a financial instrument over a specific time period. It enables performance comparisons across strategies and assets, independent of price levels. RR facilitates effective assessment and comparison of trading performance.

  At high frequencies, simple returns (Equation (2.1)) and log returns (Equation (2.2)) exhibit a high degree of similarity. This implies that the choice between simple returns and log returns depends on the specific application and mathematical models employed [19].

$$R = \frac{P_t - P_0}{P_0} \times 100 \tag{2.1}$$

$$r = \ln\left(\frac{P_t}{P_0}\right) \tag{2.2}$$

- **Maximum Drawdown (MDD):**

  The maximum drawdown (MDD) is the most significant reduction in value of an investment portfolio from its highest point until a new peak is achieved. This metric serves as an insightful measure of the potential for loss over a specified timeframe.

$$\text{MDD} = \| \frac{V_{trough} - V_{peak}}{V_{peak}} \| \tag{2.3}$$

- **Win Rate:**

  A trading approach or trader's efficiency can be evaluated using the Win Rate, which is computed by dividing the total number of profitable trades by all trades executed. The resulting figure is typically presented as a percentage.

$$\text{Win Rate} = \frac{\text{Quantity of Profitable Trades}}{\text{Quantity of Total Trades}} \times 100\% \tag{2.4}$$

Popov and Madlener [20] stated that real-world factors can impact outcomes, such as political changes or natural disasters. Backtesting has limitations as it assumes uniform market conditions and cannot account for unexpected events. Over-optimization is another pitfall to avoid. Traders should not rely solely on backtesting but also pay attention to current trends for long-term success.

2.2 The Intrinsic Time Framework Based on Directional Change

In the field of financial markets, the examination of time series data typically involves a thorough assessment of interval-based summaries derived from high-frequency raw data. To achieve this, a specific duration, such as hourly, daily, or monthly is decided upon and subsequently, the raw data is sampled at fixed time intervals within that particular duration. As a result of this process, a time series dataset is produced wherein each observation ($\mathcal{P}_t$) corresponds to a distinct moment in time (t).

2.2.1 A Comparison between Conventional and Directional Change Time Frameworks

Within the realm of time series analysis, a discrete-time series represents a set of observations that are recorded at fixed intervals, which constitute a discrete set of observation times, denoted as (T_0). The structural robustness of this format enables the application of a variety of analytical methodologies [21].

Despite the prevalence of traditional time series methods, some scholars propose alternative approaches. Specifically, Tsang [22] have postulated that the directional change paradigm offers superior efficiency compared to traditional time series approaches when it comes to processing tick-to-tick data. This claim is rooted in the directional change framework's inherent ability to accurately capture market extremes and periods of high activity without having to interpolate times, a situation that might necessitate the creation of artificial data points within the time series framework.

Indeed, the directional change method identifies significant market highs and lows, thereby ensuring the precise documentation of all significant price alterations. Zhang further underscored the utility of indicators like the Absolute Price Movement (ATMV) and Return (AR) within the directional change context as effective tools for the derivation of potential trading strategies.

Given its enhanced sensitivity to market signals, Zhang argues that the directional change method constitutes a more suitable framework for the analysis of tick-to-tick data than traditional methods. Thus, the directional change time framework may offer significant advantages over the conventional time series approach in certain analytical contexts.

2.2.2 The Introduction for Intrinsic Time

Guillaume et al. [23] introduced a pivotal concept in financial markets: the notion of intrinsic time. Intrinsic time is linked to particular events or interactions that cause the market clock to tick, offering an alternative perspective to physical time. One measure of intrinsic time involves directional changes (DCs), events identified when a price surpasses a defined threshold from a local extreme before reversing.

The DC framework operates akin to a state machine, allocating different states to a univariate time series. These states are the outputs of the DC algorithm, each representing a DC event. Each event signifies a significant market change or occurrence, thereby influencing the behavior of market participants or an asset's price. Categorically, events in DC are classified into two discrete forms- specifically, upturn or downturn events. These events are discerned by their corresponding directions of alteration.

A DC event typically initiates a sustained price movement in the same direction, leading to an overshoot (OS) event. An OS event concludes when the price reverses beyond a defined threshold in the opposite direction, signaling a new DC event. A

DC trend emerges from the combination of a DC and an OS event. The selection of the threshold value plays a pivotal role, with smaller thresholds yielding more DC events and larger thresholds yielding fewer.

The financial market functions within a enduring cycle that encompasses ongoing upward and downward fluctuations. At any given point in time, investors and traders encounter one of two dominant trends: a Downward Run or an Upward Run. According to the definition provided by Tsang [24], the fundamental elements underlying Upward Runs are outlined in Table 2.1. It is worth mentioning that the rationale behind the views on the Downturn Event and the Downward Overshoot is analogous to that of the Upturn Event and the Upward Overshoot; hence, these aspects have been excluded from the current analysis.

<table>
<tr><th>Events</th><th>Points</th><th>Post-ante view</th><th>An-ante confirmation views</th></tr>
<tr><td rowspan="2">Upturn
Event</td><td>Start</td><td>Upturn Point (trough)</td><td>Upturn DC Confirmation Point</td></tr>
<tr><td>End</td><td>Upward DC Confirmation Point</td><td>Upturn DC Confirmation Point</td></tr>
<tr><td rowspan="2">Upward
Overshoot</td><td>Start</td><td>Upward DC Confirmation Point</td><td>Last Upward DC Confirmation Point</td></tr>
<tr><td>End</td><td>Next Downturn Point (peak)</td><td>Next Downward DC Confirmation Point</td></tr>
</table>

Table 2.1: Summary of different vies for different events in Upward Run

During an Upward Run, we distinguish two primary events, namely, the Upturn Event and the Upward Overshoot. The initiation of the Upturn Event is marked by the lowest price point in a given sequence, termed the Upturn Point. This event concludes as soon as the price has increased by a predetermined threshold, signaling the Upward DC Confirmation Point. It is critical to note that while the Upturn Point marks the starting point of this event from a post-ante view, the Upturn Event is only confirmed upon reaching the Upward DC Confirmation Point from an ex-ante perspective.

Subsequent to the Upturn Event is the Upward Overshoot, defined as a period during which the price continues to rise following an Upturn Event. The start of the Upward Overshoot is denoted by the Upward DC Confirmation Point, while its termination aligns with the arrival of the next Downturn Point, that is, when prices begin to fall. However, from an ex-ante view, the Downward Overshoot commences at the last Upward DC Confirmation Point and ceases upon the confirmation of the next Downward DC event.

Event analysis aims to discern significant market changes and incorporate this understanding into trading strategies. The definition of a significant event remains subjective and may vary based on the trader's preferences or the specific market conditions.

The application of the DC events methodology is illustrated in Figure 2.1. Price changes that exceed a symmetric δ threshold are considered significant, triggering DC events. The methodology employed divides the market into two categories: upward trends and downward trends. In this figure, DC events are depicted in solid lines and OS events are shown in dashed ones.

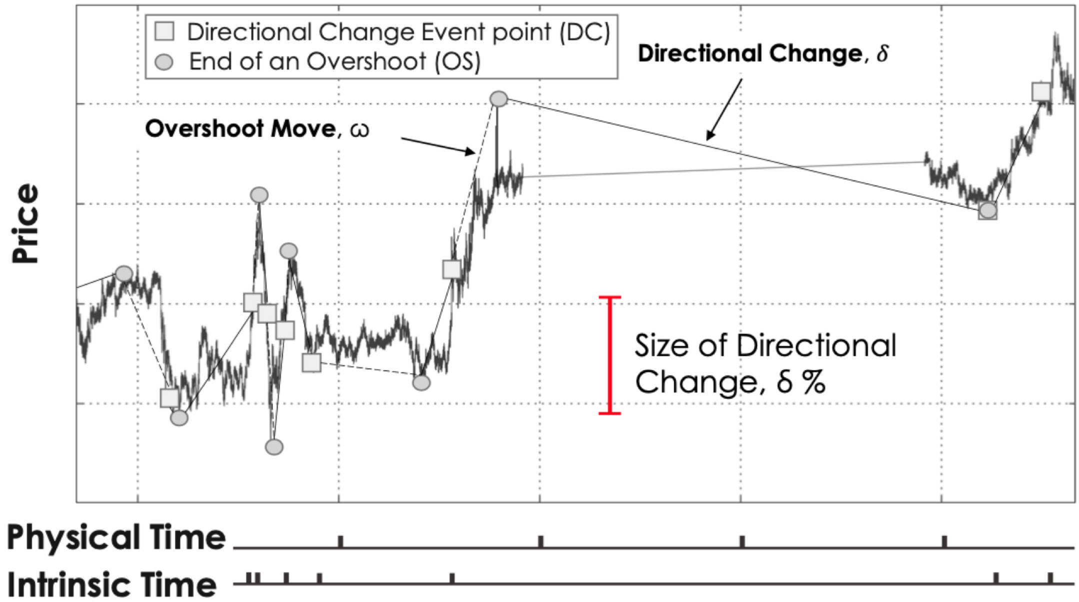

Figure 2.1: Illustration of DC Framework

This figure, sourced from [25], illustrates how a price curve can be divided into directional changes using a threshold δ. Events are categorized as directional-change or overshoot. A directional-change event occurs when the price deviates by δ percent from the highest or lowest observed price, marking a change in direction.

2.2.3 The Algorithm for Intrinsic Time

The transformation of a typical time series into a Directional Change (DC) time series using the DC transformer algorithm, represented as $\mathcal{A}$, has the potential to unveil novel insights into financial markets. The transformed DC series, denoted as $\mathcal{T}_n$, offers an association between each data point and a specific state based on identified directional changes in the market.

This DC transformation of the original time series $\mathcal{P}_n$ can be mathematically expressed as follows:

$$\begin{aligned} \mathcal{T}_n &= \mathcal{A}(\mathcal{P}_n; \delta) \\ &= \{(\mathcal{P}_i, s_i)\}_{i=1,2,\ldots,n};\ s_i \in S. \end{aligned} \tag{2.5}$$

Here, each element of the transformed DC series $\mathcal{T}_n$ is a pair, $(\mathcal{P}_i, s_i)$, where $\mathcal{P}_i$ is a data point from the original series and s_i is the state assigned by the DC algorithm [26].

In this transformation, δ is the key parameters guiding the operation of the DC algorithm. It is a threshold values which define the criteria for transitions between different states.

The symbol S represents the set of potential states identified by the DC transformer algorithm ($\mathcal{A}$). Consecutive values consistently assigned to the same category within S indicate the presence of events with distinct and measurable durations. These events are further classified into two main types: DC events and OS events, which can be further divided into upward trend, upward overshoot, downward trend, and downward overshoot.

The algorithm demonstrates a cyclic pattern, alternating between upward and downward trends. Transitional intervals between these trends are filled by an overshoot, aligning with the direction of the preceding trend. This overshoot facilitates the connection between the previous and subsequent trends, ensuring continuity in the overall trend pattern. Figure 2.2 illustrates the cyclic patter.

Tsang and Chen [27] provides explicit definitions and elucidations for the algorithm's state types, which we proceed to introduce in detail.

- Upturn/Downturn point:

  Upon generation of the first DC confirmation point, the orientation denoted by the initial point of the time series is classified in accordance with the direction revealed by the aforementioned confirmation. If the first DC confirmation signifies an upward trend, the first point is classified as an Upturn Point. Conversely, if the first DC confirmation indicates a downward trend, the first point is categorized as a Downturn Point. Subsequently, each subsequent local

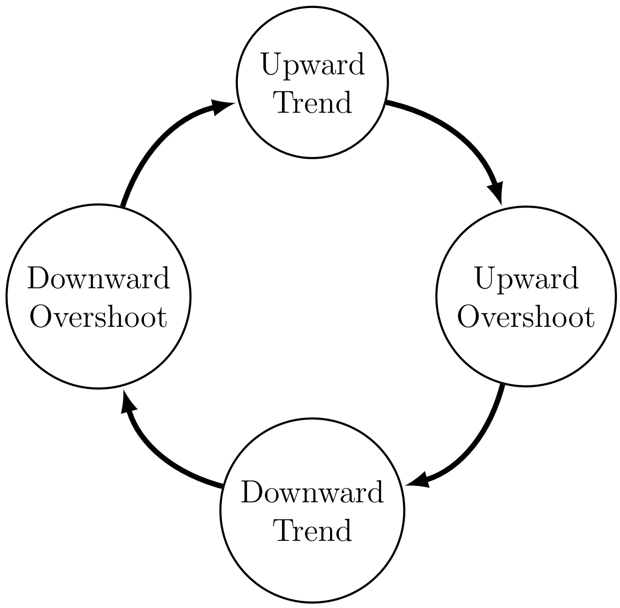

Figure 2.2: Events Transition Diagram illustrating the cyclic dynamics in intrinsic time framework

extreme point is assigned to the appropriate category. A local extreme point is considered a Downturn Point if it represents the highest value within its vicinity. Conversely, if it represents the lowest value, it is categorized as an Upturn Point.

- Upward/Downward DC Confirmation point (DCC_{up}, DCC_{down}):

  During a Downward Run, the Last Low is continually adjusted to the lower value between the current price and the existing Last Low. Conversely, in an Upward Run, the Last High is consistently updated to the higher value between the current price and the previous Last High. If the current price, denoted as $\mathcal{P}$, surpasses the Last Low by a margin of δ, it is referred to as an Upward DC Confirmation point. Conversely, if $\mathcal{P}$ falls below the Last High by a margin of δ, it is termed a Downward DC Confirmation point.

- Upward/Downward DC event

  The occurrence of the price change from the Last Low to the Upward DC Confirmation point is referred to as an Upward DC event. Similarly, the event in which the price changes from the Last High to the Downward DC Confirmation point is known as a Downward DC event.

- Upward/Downward OS event

The occurrence of a price change from the Downward DC Confirmation point to the local minimum point during a Downward Run is termed the Downward OS Event. Conversely, the event of a price change from the Upward DC Confirmation point to the local maximum point within an Upward Run is referred to as the Upward OS Event.

In the DC series $\mathcal{T}_n$, the pair $(\mathcal{P}_i, s_i)$ implies that the data point $\mathcal{P}_i$ has been classified into state s_i by the DC algorithm. This is the intrinsic time series, which includes the prices and states for each time step, providing a richer representation of the market dynamics. This transformation captures the essential market events that trigger significant price changes, thus offering a nuanced understanding of the intrinsic time dynamics beyond traditional physical time representations.

2.2.4 The Scaling Laws of Intrinsic Time

Directional Change (DC) Scaling Laws constitute a crucial aspect of Forex trading, offering valuable insights into market dynamics and facilitating identification of potential trading opportunities. Through a thorough examination of price changes at differennt levels, these laws enable traders to discern possible trends or reversal points that may affect currency pairs.

The main objective of the scaling laws in DC is to create precise correlations between price fluctuations, time periods, and occurrence rates. The study of scaling principles has provided significant knowledge into the conduct of the foreign exchange market. A total of 12 new scaling laws relating to 13 pairs were presented to researchers [28]. Specifically, our research utilizes two of these laws.

One observation is that the OS events recorded in the profiled data have an average duration of approximately twice that of a DC event. To refer to this, we can adopt the notation used in [28] by denoting the average duration of an OS and DC event as $\langle \Delta t^{OS} \rangle$ and $\langle \Delta t^{DC} \rangle$, respectively. Thus, the scaling law described above can be expressed as follows:

$$\langle \Delta t^{OS} \rangle \approx 2 \cdot \langle \Delta t^{DC} \rangle \tag{2.6}$$

According to the second scaling law, a directional change, denoted as Δx_{DC}, is typically followed by an OS of similar magnitude. This behavior can be expressed mathematically as:

$$\langle \|\Delta x^{OS}\| \rangle \approx \Delta x_{DC} \tag{2.7}$$

where $\langle \|\Delta x^{OS}\| \rangle$ represents the average magnitude of an OS.

2.3 Genetic Algorithms (GAs)

The Genetic Algorithm (GA) is a problem-solving approach that draws inspiration from the principles of natural evolution and the Darwinian concept of "survival of the fittest". It belongs to the domain of Evolutionary Computation (EC), which is a sturdy subfield of artificial intelligence, renowned for its usefulness in addressing complex optimization problems. Instead of using an individual solution, genetic algorithms operate on a population-based approach by producing a set of potential solutions and leveraging fitness functions to evaluate each individual's ability to adapt. This enables GAs to detect the most optimal solution for any given problem.

2.3.1 Fundamental Parameters

This section outlines the essential factors that form the basis of the optimization process. These factors, including the fitness function, fitness threshold, population size, crossover rate, and mutation rate, determine how the genetic algorithm behaves and performs.

- Fitness Function: A scoring mechanism referred to as the fitness function is utilized to assess the ability of each member in the population.

- Fitness threshold: A fitness threshold is a predetermined boundary that marks the conclusion of the optimization procedure.

- Population Size (p): The initial population size, denoted by p, refers to the number of potential solutions present in the population.

- Crossover Rate (r): The Crossover Rate (denoted as r) holds high significance as it determines the percentage of individuals from a population that will engage in crossover operations per generation.

- Mutation Rate (m): The probability of mutation occurring during reproduction is represented by the Mutation Rate (m), which is a formal measure used to indicate the likelihood of genetic changes taking place.

2.3.2 Correlating Terminologies

This section presents a list of key terms used in the context of problem-solving through population-based algorithms.

- Population: This refers to a group of possible solutions, also known as individuals or chromosomes. This assembly serves as the source from which likely responses to a given issue can be extracted.

- Individuals: They are commonly referred to as 'chromosomes', constitute the fundamental components of a 'population'. Every individual represents an exclusive feasible resolution within the problem domain.

- Gene: This represents a specific aspect or characteristic of the solution encoded within a chromosome.

- Fitness: The assigned numerical value, termed 'fitness', quantifies an individual's ability to solve the problem, with higher scores indicating more optimal solutions.

- Fitness Function: A specific function associated with the problem domain, used to assign a fitness value to each individual.

2.3.3 The Basic Algorithm

To gain a comprehensive understanding of the GA's operation, it's beneficial to delve into each stage of the process.

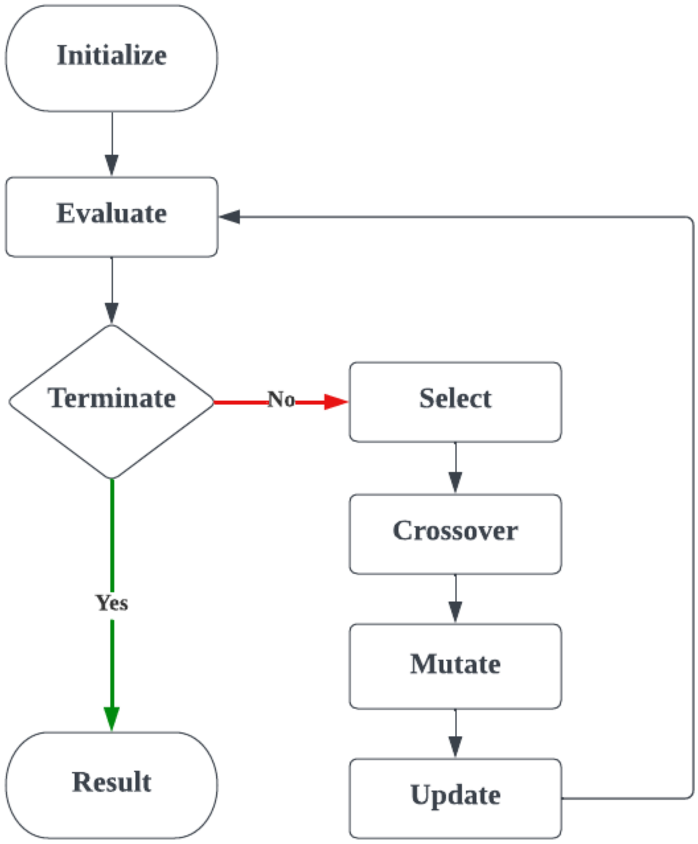

Figure 2.3: Genetic Algorithm Flow Chart

Initialize: A population P of p random hypotheses is generated. Each hypothesis embodies a potential solution to the current issue.

Evaluate: Compute the fitness of each hypothesis within population P. This is achieved by applying the fitness function $Fitness(h)$ to each hypothesis h. The function provides a measure of how effectively the hypothesis addresses the problem that needs optimization.

Select: Members are chosen from the current population P for propagation into the next generation. In the standard genetic algorithm, selection is performed using a probabilistic mechanism, favoring individuals with higher fitness. Specifically, $(1-r)p$ members of P are chosen for inclusion into the selected population P_S.

Crossover: Randomly select $\frac{r \times p}{2}$ pairs of hypotheses from P using a probabilistic method. For each pair $\langle h_1, h_2 \rangle$, the crossover operator exchanges genetic material beyond a randomly chosen point of intersection, yielding two offspring. These offspring are subsequently added to P_S. (See Figure 2.4)

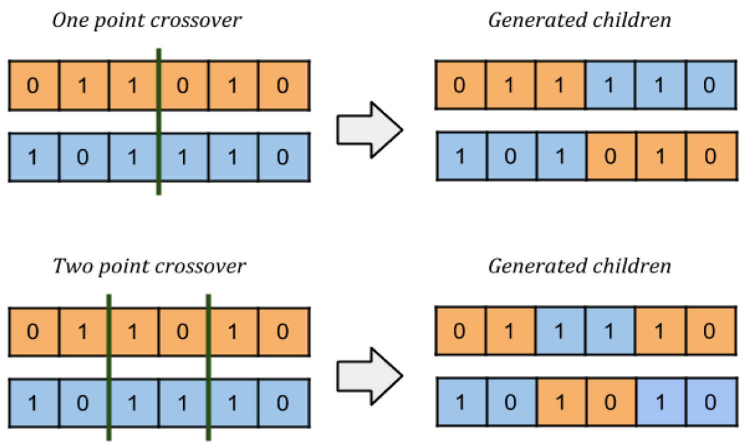

Figure 2.4: Crossover Operation
This figure is a direct reference to the one in [29]

Mutate: Select a percentage m of the population P_S uniformly at random, and invert a randomly chosen bit in the genetic representation of each selected individual. This process introduces variability into the population and prevents premature convergence.

Update: The current population P is replaced with the newly formed population P_s.

Terminate: The termination condition for the algorithm is met when the maximum fitness value in the population, denoted by $\max_h Fitness(h)$, surpasses the pre-defined fitness threshold.

Result: Return the candidate solution h from the final population P that boasts the highest fitness value.

Algorithm 1 Basic Genetic Algorithm

Initialize: Generate P, a set of p random hypotheses
Evaluate: For each h in P, compute its fitness $Fitness(h)$
while $max_h Fitness(h) < Fitness_thresh old$ **do**
  Select individuals for the next generation
  Perform crossover operations
  Apply mutations
  Update the population
  Re-evaluate the fitness of each individual
end while
Return: the h from P that has the highest fitness

Chapter 3

Literature Review

3.1 Directional Change Intrinsic Time Framework

The DC Intrinsic Time Framework has gained significant popularity in financial markets, particularly in currency trading, due to its ability to detect changes in market trend and to reveal potential trading opportunities. This section aims to provide a comprehensive overview of the research that has substantially contributed to the development and advancements of this framework.

3.1.1 Foundational Research

The DC algorithm, introduced by Guillaume et al. [23], identified new stylized facts in intra-daily financial market data. These include time-heterogeneity, price formation, market efficiency and liquidity. These findings advanced the understanding of market dynamics and facilitated modeling and learning of the market process. The DC Intrinsic Time Framework is now a powerful tool for identifying changes in market trends and determining trading opportunities.

Tsang established the definition of a DC [24], while Glattfelder discovered twelve scaling laws which contribute to the theoretical foundation of the DC Intrinsic Time Framework [28]. These laws show that time-series state information carries both qualitative and quantitative features related to regularities and statistical aspects in financial markets.

In their study, Aloud et al. [30] proposed four additional scaling laws to build upon the previous research of Glattfelder et al. [28]. This enhanced the existing framework and provided new insights. Tsang later developed a comprehensive set of indicators for the DC Intrinsic Time Framework based on this foundation [31, 32].

3.1.2 Intrinsic Time Modeling

Significant difficulties arise when examining time series data, primarily attributable to the reliance on physical time as the primary temporal dimension. Aloud et al. [33] have emphasized that DC Intrinsic Time Framework can significantly aid in overcoming these challenges. They propose that financial time series data should be converted into intrinsic time, which enables filtering of extraneous information and disturbances and reveals valuable market insights. Therefore, utilizing intrinsic time provides a more accurate and contextually relevant depiction of market dynamics than relying solely on physical time. This approach is particularly effective in identifying crucial patterns and trends that might not be apparent when analyzing data using physical time.

A significant example of the DC Intrinsic Time Framework's practical application was demonstrated by Petrov et al. [25], who employed agent-based modeling to create a simulated market where trading agents function based on event-based intrinsic time. The findings of this simulation provided additional empirical evidence for the framework's exceptional intrinsic time modeling capabilities. It is noteworthy that the price variations observed in the simulated market were comparable to the statistical patterns generally observed in genuine markets, emphasizing the crucial role played by the intrinsic time mechanism in shaping market dynamics.

An important breakthrough in the DC Intrinsic Time Framework was achieved by Glattfelder and Golub [34], who established an analytical relationship between the physical time-based illustration of financial data and its intrinsic time equivalent. This relationship, deduced using the scaling laws of the framework, enables dissection of physical-time series movements into intrinsic-time components. As a result, this approach facilitates a more thorough exploration and comprehension of market behavior in physical time through intrinsic-time modeling. This contribution highlights the ongoing development and potential of the DC Intrinsic Time Framework in financial time series analysis.

3.1.3 Development and Application of DC-Based Trading Strategies

Several research studies have been conducted to explore the development and application of DC-based trading strategies. Kablan [35] has devised an adaptive neuro-fuzzy inference system (ANFIS) with the purpose of financial trading, using the DC approach to predict price movements and outperform traditional strategies such as B&H or linear forecasting. Aloud [9] has created automated trading strategies using DC and OS events, while Alkhamees [36] introduced the Dynamic Threshold Trading Strategy (DT-TS), which combines the DC method with a threshold that adapts dynamically. Bakhach [37] proposed TSFDC, which is rooted in the DC framework and aims to capitalize on contrarian investment opportunities, and Aloud [38] put forth two algorithmic trading strategies using the DCRL model. These strategies display potential in generating high returns and outperforming traditional approaches.

The DC approach has also been implemented to model and predict market trends. Bakhack [39] used the BTheta variable to predict the probability of a current market trend continuing prior to its conclusion. Correspondingly, Adegboye [40] formulated a genetic programming (GP) algorithm for forecasting FX market trends based on DC and OS events. These predictive models have shown commendable accuracy in forecasting, frequently exceeding 80%.

The application of the DC approach has been expanded by researchers through the advancement and extension of the DC Intrinsic Time Framework. The works of Golub [29, 41] and Petrov [42] have contributed significantly to the theoretical advancements in this field, developing a liquidity measure and an instantaneous volatility measure, respectively. Furthermore, Mayerhofer [43] has proposed a generalization that considers various types of stochastic processes, while Petrov [44] has extended the framework to multidimensional space. These advancements underscore the potential for further exploration of this framework.

The study conducted by Palsma [45] delved into the application of optimization methods, specifically Particle Swarm Optimization (PSO) and Continuous Shuffled Frog Leaping Algorithm (CSFLA), to enhance the profitability of trading strategies based on DC. The research revealed that these techniques exhibited superior performance compared to the previously utilized Genetic Algorithm (GA). Consequently, there is potential for utilizing PSO and CSFLA for augmenting DC-based trading strategies.

The DC approach has shown significant potential in financial trading, particularly in the development of profitable trading strategies and forecasting market trends. The possibilities have been further amplified by advancements made in the DC Intrinsic Time Framework and the utilization of optimization techniques. Nonetheless, additional investigation is necessary to tackle the limitations recognized in these studies and confirm the efficacy of these procedures across various market environments.

3.2 Optimizing Trading Strategies with Genetic Algorithm

The introduction of machine learning (ML) has led to significant improvements in decision-making and efficiency across various fields. However, the application of ML is not exempt from challenges such as the need for high-quality data and concerns regarding interpretability [46–48]. These obstacles are particularly prominent in the enhancement of trading strategies, which lies at the confluence of finance, data science, and ML [49–51].

The optimization of trading strategies through conventional techniques, whether it is done manually or through automation such as Grid Search and Random Search, has certain challenges and constraints [52, 53]. However, Genetic Algorithms (GAs), which are established on the principles of biological evolution through natural selection, have proven to be capable of efficiently solving high-dimensional problems [54, 55].

Genetic Algorithm Integration in Directional Change Strategy

Evolutionary algorithms have a prosperous past in the realm of financial forecasting issues, and their effectiveness has been demonstrated in [56–59]. A notable example is the GP-DC method proposed by Xinpeng Long, which employs genetic programming in trading strategies based on DC, outperforming competing strategies in most cases [60].

Markets can be perceived as alternating between upward and downward trends, which offers an informative basis for traders' decisions [61]. Building upon this notion, the multi-threshold DCs strategy introduced by Adegboye et al. effectively uses this trend segmentation [1].

Through the integration of GA with DC-based trading strategies, the potential to enhance Forex market trading outcomes arises. The use of GA provides enables flexible adjustments to strategies, a critical feature in the highly unstable financial markets while also circumventing drawbacks associated with conventional optimization approaches such as local optima.

A study conducted by Kampouridis found that a GA-integrated DC strategy outperformed traditional benchmarks in Forex markets, although it was dependent on certain thresholds [4]. 255 datasets across 6 currency pairs were analyzed using tick data and 10-minute interval data to test DC trading strategies extensively. The results indicate that the optimized DC+GA strategy outperforms traditional benchmarks such as technical analysis and B&H strategies.

The flaw in Kampouridis and Otero's regression analysis was assuming that all DC events lead to OS events [4], which is not always the case, as some DC events lead to further DC events instead of OS events. To address this issue, Kampouridis et al. classified whether a DC event would lead to an OS event or another DC event before conducting the regression analysis [2]. This approach allowed for better modeling of the conditional relationship between DC and OS events. Furthermore, they demonstrated that using a multi-threshold DC algorithm optimized with a GA outperformed traditional technical trading benchmarks on a risk-adjusted basis. By accounting for the various outcomes of DC events and optimizing the algorithm with GA, Kampouridis et al. showed a significant improvement compared to their preliminary findings with Otero.

Conclusion and Future Directions

Enhancing trading efficiency and profitability in Forex markets can be achieved through the intersection of GA and DC. This method has a great potential to adapt to ever-changing market conditions, which can significantly optimize decision-making.

Future research should focus on exploring different configurations of GA and DC, as well as refining parameters within these methods to further augment their efficiency in optimizing trading strategies. In this regard, our research endeavours to utilize GA in optimizing both the weightages of thresholds and the parameters associated with the strategy.

Chapter 4

Methodology

4.1 DC Transformer

DC Transformer is skilled at recognizing crucial turning points in market trends called directional change events. These events bring about considerable market movements either in an upward (bullish) or downward (bearish) direction. The algorithm uses a preset threshold value and a return measure function to accurately track these changes over time.

Algorithm 2 outlines the steps utilized to create the directional change event. The result of applying transformations after the event is a modified DC series, denoted as $\mathcal{T}_n$. Each element in this series (y_i, s_i) contains an original data point y_i and an assigned state s_i determined by the DC algorithm.

Algorithm 2 Directional Change Event Generation Algorithm

Require: Time series $Y = \{y_{t_i}\}_{i=1,2,\ldots,k}$
Require: Threshold δ
Require: Return measure $\mathcal{R}(y, P_{\text{EXT}})$
Initialize: mode as None, status, and local extreme P_{EXT}
for each $y_{t_i} \in Y$ **do**
  if i==1 **then**
    $P_{\text{EXT}} \leftarrow y_{t_i}$
  end if
  if mode is None **then**
    $r \leftarrow \mathcal{R}(y_{t_i}, P_{\text{EXT}})$
    if $r \geq \delta$ **then** mode $\leftarrow$ 'bullish'
    else if $r < \delta$ **then** mode $\leftarrow$ 'bearish'
    end if
  else if mode is 'bullish' **then**
    if $y_{t_i} > P_{\text{EXT}}$ **then** $P_{\text{EXT}} \leftarrow y_{t_i}$
    end if
    $r \leftarrow \mathcal{R}(y_{t_i}, P_{\text{EXT}})$
    if $r \leq \delta$ **then** mode $\leftarrow$ 'bearish'
    end if
  else if mode is 'bearish' **then**
    if $y_{t_i} < P_{\text{EXT}}$ **then** $P_{\text{EXT}} \leftarrow y_{t_i}$
    end if
    $r \leftarrow \mathcal{R}(y_{t_i}, P_{\text{EXT}})$
    if $r > \delta$ **then** mode $\leftarrow$ 'bullish'
    end if
  end if
end for

4.2 DC-derived Trading Strategies

In this section, we delve into the exploration of various trading strategies that are derived from DC analysis.

4.2.1 Single-threshold DC Trading Strategy (STS)

This section elaborates on the Single-Threshold Directional Change Trading Strategy (STS), a method that employs the transformed DC series $\mathcal{T}_n$ to discern and exploit market trends in FX rates. The STS strategy depends on various parameters, including r, a, b_1, b_2, and δ which plays as key role in determining when to purchase or sell currencies pairs.

Application of STS Across Divergent Market Trends

STS uses trading strategies that are designed to match current market trends, as explained below:

- **Upward Market Trend (DCC_{up})**

  An Upturn Directional Change (DCC_{up}) event is triggered if the FX rates increase by a certain threshold (δ) from the prior minimum value. This indicates a rising market trend and suggest a favorable moment for asset acquisition. After the purchase, the current FX rate (y_{t_i}) is recorded as P_{DCC} to guide future decisions. Additionally, two time periods, namely, *a longing period* and *a shorting period*, are set based on the parameters r, a, b_1, and b_2. These periods respectively signal ideal opportunities for additional purchases and considerations for asset sales.

- **Downward Market Trend (DCC_{down})**

  In contrast, a Downturn Directional Change event (DCC_{down}) occurs when there is a significant decrease in FX rates that surpasses the δ threshold from the last peak. This type of trend can be advantageous for selling assets, which can help minimize potential losses as asset values continue to decline.

The underlying principle of STS aligns with the basic trading strategy 'buying low and selling high'. The main objective is to purchase assets during an upward trend and disposed of them when they're decreasing, to benefit from potential gains and avoid possible losses respectively.

Detailed Exploration of the Parameters in STS

The parameters r, a, b_1, and b_2 are critical in designing the decision framework for STS. A thorough comprehension of their roles can enhance their utilization:

- **Parameter r**

  The parameter r represents the anticipated ratio of the OS period to the DC period. It is conventionally set to 2, indicating that the OS period is typically double the length of the DC period, a notion derived from observed market behavior (Glattfelder et al. [28]).

  In our experiment, the individuality of each dataset was taken into account (Kampouridis and Otero [4]). As a result, r is further divided into r_u and r_d to represent the mean proportions of upward and downward OS events, respectively.

- **Parameters a, b_1, and b_2**

  These parameters play an crucial role in establishing the viable trading window within the OS period. The duration allocated for asset acquisition is defined by parameter a, whereas variables b_1 and b_2 specify the optimal timespan for disposing of assets in the same phase.

These parameters greatly influence the timing of trading actions, consequently impacting the overall effectiveness of the trading strategy. Therefore, it is imperative to give due consideration to the selection process while taking into account the trader's risk tolerance and current market conditions. This ensures that the maximal potential of the strategy is realized.

Trading Actions within Defined Periods

Utilizing the parameters such as r, a, b_1, b_2 and δ, STS defines three different stages of activity within each trading cycle, namely the 'longing period' and 'shorting period' and 'post-shorting period'. The main purpose behind these stages is to optimize trading decisions by incorporating market trends.

- **Longing Period**

  This refers to the period during which the strategy promotes asset purchase. As defined by parameter a, the initial portion of the OS period is deemed the optimal purchasing window. For instance, if a equals 0.2, the strategy recommends procuring the asset during the first 20% of the OS period. If the current time t_i falls within this acquisition period (suggesting an expected persistent upward market trend) and sufficient capital is available, a buy action is executed to increase asset holdings.

- **Shorting Period**

  During a specific phase of the OS period, the asset is targeted for potential sale under certain conditions that are specified by parameters b_1, b_2, and δ. According to Glattfelder et al. [28], it has been observed that the average OS corresponds to the magnitude of its preceding DC. Therefore, in our experiment, we strategically place a short position when it rises to a level equaling $(1+0.8\cdot\delta)$ of the P_{DCC} in order to achieve profit.

  The algorithm sells when certain criteria are met. For example, when $b_1 = 0.5$ and $b_2 = 0.7$ during an expected OS duration of 10 hours, the algorithm suggests selling between the 5th and 7th hours. If the last recorded Directional Change Confirmation Price (P_{DCC}) equals 1.2 and δ value is 0.5%, the algorithm triggers a sell action at a foreign exchange rate of 1.2048, which is computed using the formula $(1 + 0.8 \times 0.005) \times 1.2$. To execute a sell action successfully, it's necessary to have an adequate volume of quote currency available.

- **Post-Shorting Period**

  If the current time t_i exceeds the shorting period, STS triggers an asset sale, irrespective of the ongoing market trend. Continuing from the previous example, if the specified conditions for selling within the 5th to 7th hour are not met, the algorithm proceeds with the sell action. This ensures that positions are closed after a certain duration, reducing exposure to protracted market fluctuations.

STS provides a robust, rule-based approach to navigate the FX market. By leveraging market trends and utilizing parameters such as r, a, b_1, b_2, and δ, it offers clear guidelines for informed trading decisions. Algorithm 3 outlines the pseudocode for this strategy.

Algorithm 3 Single-threshold DC Trading Strategy (STS)

Require: Time series $\{y_{t_i}\}_{i=1,2,\ldots,k}$
Require: Parameters $r = [r_u, r_d]$, a, b_1, b_2, and δ
for $y_{t_i} \in \{y_{t_i}\}_{i=1,2,\ldots,k}$ **do**
  if status is DCC_{up} **then**
    Perform a buy action
    $P_{DCC} \leftarrow y_{t_i}$
    long_period $\leftarrow [t_i,\, t_i + DC_{length} \times r_u \times a]$
    short_period $\leftarrow [t_i + DC_{length} \times r_u \times b_1,\, t_i + DC_{length} \times r_u \times b_2]$
  else if status is DCC_{down} **then**
    Perform a sell action
    $P_{DCC} \leftarrow$ None
  else if t_i in long_period **then**
    Perform a buy action
  else if t_i in short_period and $y_{t_i} \geq 0.8\delta$ **then**
    Perform a sell action
  else if t_i exceeds short_period **then**
    Perform a sell action
  end if
end for

4.2.2 Multi-Threshold Directional Change Trading Strategy (MTS)

Building upon the concept of STS discussed in section 4.2.1, a more advanced approach, namely the Multi-Threshold Directional Change Trading Strategy (MTS), can be introduced. Contrary to the STS, which revolves around a singular threshold value, the MTS accumulates data from multiple thresholds, exploiting the distinctive insights provided by each threshold value.

A sensitive nature of the lower threshold leads to the recognition of numerous events, which ensures rapid response even for minimal fluctuations in price. Conversely, higher thresholds are less sensitive and only initiate actions for significant price changes. Combining these unique thresholds may offer comprehensive insights and improve the performance of multi-threshold systems compared to their single-threshold counterparts ([4]).

Implementation of the MTS

Contrasting with the STS, which prescribes buying during an upward DC confirmation and selling at trend termination, the MTS employs a more multifaceted approach. A notable characteristic of MTS is its capacity to buy recommendations based on one threshold, whereas sell suggestions are grounded on a different threshold, thus taking multiple market conditions into account.

The primary strength of employing multiple thresholds in MTS resides in the diverse range of suggested actions at each data point. To determine the optimal action, each threshold is considered equally significant, thereby forming a collective decision-making process rooted in a 'majority rules' system.

In this methodology, a series of propositions -namely buy, sell, or hold indications-are produced by each threshold. The ultimate decision is derived from the number of recommendations for each option, with the one receiving the most votes being chosen. Consequently, if the majority of thresholds advocate for a buy, then a purchase is executed, and similarly for a sell.

Limitations of MTS

While the MTS provides numerous advantages like diversified insights from multiple thresholds, swift responses to market changes, and better adaptability, it also comes with certain limitations:

- **Complexity:** The MTS, due to its numerous thresholds, is more intricate than the STS. This increased complexity may also lead to difficulties in strategy tuning and interpretation of the results.

- **Parameter Sensitivity:** The effectiveness of MTS, similar to the STS, is sensitive to the chosen parameters. Determining the optimal set of thresholds can be a challenging task, requiring extensive backtesting and adjustments based on the particular FX rate and market conditions.

To summarize, the MTS offers a more comprehensive approach compared to the STS. This is owing to its consideration of a wider range of market dynamics, which has the potential to result in better-informed and more efficacious trading choices. Nevertheless, due to the increased complexity and the parameter sensitivity, it is imperative that the strategy be implemented with great care and continually monitored.

4.2.3 Multi-Threshold Directional Change Trading Strategy Optimized with Genetic Algorithm (MTSGA)

The effectiveness of the MTS is notably influenced by the allocation of weightage to each threshold. In its conventional form, equal weightage is attributed to all thresholds which might not provide an precise indication of the individual significance and efficacy of each threshold. To address this challenge, we have incorporate a Genetic Algorithm (GA) into the MTS to assign weightage values for each DC threshold. This approach, identified as the Multi-Threshold Directional Change Trading Strategy Optimized with Genetic Algorithm (MTSGA), facilitates a more accurate allocation of significance across all thresholds.

GA, inspired by the principles of natural evolution, is employed to enhance system optimization. Implementing a GA within the MTS framework enables us to modify not only the weights linked with each threshold but also crucial DC parameters. This ongoing process of optimization ensures that our trading strategy retains its efficacy and resilience.

Representation in the MTSGA

Within the framework of the GA that has been implemented in the MTSGA, each chromosome is comprised of N_δ thresholds. Consequently, the total count of genes in a chromosome amounts to $3 + N_\delta$. The optimization process considers three additional parameters (a, b_1, and b_2) that are associated with DC as described in Section 4.2.1.

The remaining genes present in the chromosome correspond to the weight assigned to a particular threshold. Both the weightage and DC parameters a, b_1, and b_2 must be optimized to enhance the overall trading strategy. This comprehensive approach enables us to consider both the importance of each threshold and the influence of key DC parameters.

Fitness Function

The fitness function serves as an crucial element of the GA. Evaluating investment performance can be challenging because different studies use diverse fitness functions. Previous research has employed metrics such as drawdown [62–64], return [65], and level of risk aversion [65] to evaluate the effectiveness of investment strategies, emphasizing the significant role of risk management in making investment decisions.

The fitness function we propose, defined as Fitness = Return - $\alpha \times$ MDD, contributes to the discourse on investment strategy evaluation. This function achieves a balance between RoR and MDD. This provides an estimation of the worst-case scenario an investor might encounter. The variable α introduces flexibility into this function by allowing adaption based on an investor's risk tolerance. A higher α reflects a more risk-averse strategy, prioritizing potential loss minimization. This versatility enables the fitness function to accommodate various investment styles and risk tolerances. For our experimental purposes, we have set α at 0.1.

To conclude, the MTSGA, by combining the MTS with a GA, presents a refined approach to weightage allocation among thresholds and key DC parameters, ensuring a more efficient and adaptive trading strategy.

4.3 Experiment Setup

Model Assumptions

The following assumptions are made in this study:

1. Uniform Order Quantities: All investors are assumed to place orders of the same size, specifically a unit quantity of one for any asset.

2. No Regulatory or Fiscal Interference: The study presumes no impact from regulatory restrictions or transaction taxes, creating a purely strategy-focused trading environment.

3. No Short Selling: The assumption here is that short selling activities are not permitted, limiting strategies to direct asset purchases and sales.

Data

The main focus of this investigation centers on the datasets associated with three currency pairs; namely USD/CAD, AUD/JPY, and EUR/NZD. These datasets were procured from HistData.com [66]. The duration of data collection spanned from January 31st, 2021 to June 30th, 2022.

The determination of r_u and r_d values for each currency pair is established by analyzing six months' worth of data, covering the duration from January 2021 through June 2021. During the training stage, solely data from June 2021 is utilized. Finally, to assess its effectiveness, the model is tested using data collected over a full year, specifically between July 2021 and June 2022.

Consideration of bid and ask price

It is imperative to note that the foreign exchange market operates on the basis of dual prices provided by market makers, namely the ask rate and the bid rate.

In this research, meticulous attention will be paid to the prevailing bid and ask prices across all experiments conducted. The mid-price calculated by the corresponding market maker's ask and bid price will serve as the basis for trading signals generated by the tested strategies. Moreover, in order to account for transaction costs, purchases will be executed at the ask rate while sales will occurs at the bid rate under all strategies.

The statistical parameters, which include the mean and standard deviation of the bid-ask spread for the three currency pairs traded during a specific trading interval, are presented in Table 4.1. The value denoted as "Quantile 25" in Table 4.1 indicates that only about 25% or less of the spreads are lower than this particular value. The same interpretation applies to "Quantile 75".

Table 4.1: Statistical Analysis of Bid-Ask Spreads for Selected Currency Pairs (7/1/2021 - 31/6/2022)

	Mean	**Standard deviation**	**Quantile 25**	**Quantile 75**
USD/CAD	0.00013	0.00006	0.00011	0.00013
EUR/NZD	0.00039	0.00024	0.00032	0.00039
AUD/JPY	0.00859	0.00881	0.00600	0.00900

GA-associated parameters

The GA-associated parameters for this experiment were established in the Table 4.2, following a consideration of the configurations outlined in the associated literature sources [4] and [2].

Benchmarks

Our proposed algorithm MTSGA shall undergo benchmarking procedures, which involve comparing its performance against that of other trading strategies.

Table 4.2: GA-associated parameters

Population size	200
Number of generations	35
Crossover rate	0.8
Gene exchange rate	0.5
Mutation rate	0.1
Tournament size	7

The listed strategies can be divided into two categories: DC-related and non-DC related. The former consists of five different approaches, which are STS1, STS2, STS3, STS4 (STS that utilize four distinct thresholds), and MTS. As for the latter category, it comprises three tactics: Buy and hold (B&H), MACD, and RSI.

Experimental parameters

The parameters employed in our experiment involve the utilization of four different thresholds for strategies related to DC. These thresholds are set at 0.2%, 0.3%, 0.5%, and 0.8%.

In regards to STS and MTS, it has been determined that the value of a is 0.3, while b_1 and b_2 are assigned values of 0.6 and 1, respectively.

Diverse markets require different initial budgets to ensure satisfactory trading in the FX market. In our experiment, a budget of 150,000 is for CAD/USD market, while a budget of 180,000 is for EUR/NZD market, and AUD/JPY market demands a budget of 9,500,000.

Evaluating the performance of a trading strategy

In the course of our experimentation, we evaluate the efficiency of a trading strategy by incorporating diverse metrics. These encompass Profit and Loss (PnL), Rate of Return (RR), Maximum Drawdown (MDD), Winning Rate, and Total Number of Trades (nTrade).

Chapter 5

Result

5.1 Comparative Analysis

A comparative examination of various strategies was performed employing three datasets, which were presented in Tables 5.1, Table 5.2, and Table 5.3. Our thorough analysis showcased the performance of each strategy through extensive backtesting. To streamline the presentation, we exhibited solely the most optimal threshold values in the STS strategies section of every table. Specifically, STS2 is highlighted in Table 5.2, whereas both Table 5.1 and Table 5.3 feature STS3.

USD/CAD Market

Table 5.1 provides an insightful perspective into the performance of different strategies within the USD/CAD market. It notably brings into focus the dominance of the MTSGA strategy, which outshines other strategies in numerous performance indicators.

Table 5.1: Evaluation Matrix for USD/CAD

	B&H	RSI	MACD	STS3	MTS	MTSGA
PnL	394.42	295.17	-684.83	451.83	718.42	**1060.92**
Fitness	0.11%	0.16%	-0.56%	0.32%	0.54%	**0.81%**
RoR	0.32%	0.25%	-0.52%	0.36%	0.58%	**0.85%**
std(RoR)		0.25%	0.22%	0.34%	0.20%	**0.17%**
MDD	2.16%	0.95%	0.38%	0.42%	0.39%	**0.35%**
Win Rate	**58.33%**	56.55%	31.25%	54.40%	47.64%	49.79%
nTrade	1	45	52	7	33	41

The comparison begins with the RoR where it is observed that the technical strategy involving the RSI and MACD indicators does not stand up to the B&H strategy. STS3, a benchmark strategy, outperforms other STSs with a threshold of 0.005% by delivering an average total return of 0.36%, exceeding both the B&H strategy (0.32%) and the technical strategies that employ RSI and MACD (0.25% and -0.52%, respectively). The MTS utilizing four thresholds exceeds STS, providing an average monthly return of 0.58%. With the integration of GA, MTSGA's mean monthly returns rise dramatically to 0.85%.

Moving forward to the MDD metric, the B&H strategy undergoes the most significant MDD of 2.16%. Comparatively, the RSI strategy exhibits the second-highest MDD at 0.95%. Meanwhile, MACD and MTS illustrate relatively similar MDD values at 0.38% and 0.39%, respectively. Nevertheless, MTSGA outperforms all other strategies by highlighting the lowest MDD of 0.35%.

Given the Fitness score was obtained by computing the RoR and MDD, it is unsurprising to find MTSGA, which demonstrated superior performance in both categories, also attain the highest Fitness value.

It is noteworthy that MTSGA stands out as the strategy with the lowest level of volatility, as indicated by the std(RoR). This aspect makes it a desirable choice for risk-averse investors.

When examining the win rate of each strategy, MTSGA does not demonstrate an unremarkable performance. The strategy with the most favorable outcome is the B&H. Meanwhile, the RSI and STS3 strategies report win rates of 56.55% and 54.40% respectively. MTSGA yields a win rate of 49.79%, closely followed by MTS at 47.64%. It is worth noting that the MACD strategy displays a notably lower win rate of 31.25%.

Consistency with these observations is still evident in the outcomes for the remaining two currency pairs.

AUD/JPY Market

The results pertaining to the AUD/JPY market, summarized in Table 5.2, support the findings of a previous study on the USD/CAD market, further reinforcing MTSGA's superiority over other strategies. Notwithstanding, it is essential to acknowledge that there are some variations in performance among the strategies in this particular market circumstance.

Table 5.2: Evaluation Matrix for AUD/JPY

	B&H	RSI	MACD	STS2	MTS	MTSGA
PnL	72058.33	-45600.00	-15300.00	29375.00	140375.00	**144691.67**
Fitness	0.49%	-0.61%	-0.19%	0.29%	1.51%	**1.59%**
RoR	0.91%	-0.49%	-0.13%	0.33%	1.57%	**1.64%**
std(RoR)		0.25%	0.26%	0.30%	0.21%	**0.17%**
MDD	4.13%	1.10%	0.65%	**0.42%**	0.57%	0.55%
Win Rate	50.00%	**57.54%**	32.73%	47.64%	44.79%	49.48%
nTrade	1	98	77	33	81	110

In particular, both RSI and MACD technical strategies yield negative average monthly returns in the AUD/JPY market, starkly contrasting their performance in the USD/CAD market. The B&H strategy presents more promising results, reporting a return of 0.91%, surpassing STS2 with its 0.29% return. Remarkably, the MTS strategy shines in this context, leveraging multiple thresholds to secure a more impressive return, further amplified when coupled with GA, with MTSGA reporting a remarkable return of 1.64%.

It is noteworthy that MTSGA consistently exhibits the lowest std(RoR), indicating more focused, less volatile returns, it does not secure the highest win rate. Instead, the RSI strategy outperforms all others with a win rate of 57.54%, with the B&H strategy following suit at 50.00%. Despite this, MTSGA's win rate of 49.48% remains competitive and its overall performance remains robust, as indicated by its exceptional Fitness score.

Furthermore, MTSGA's performance concerning MDD differs slightly in the AUD/JPY market, failing to secure the lowest value. STS2, on the other hand, claims this achievement with an MDD of 0.42%. Nonetheless, with an MDD of 0.55%, MTSGA continues to outperform the majority of the other strategies, further highlighting its dependability and strength.

The consistently superior performance of the MTSGA across both the USD/CAD and AUD/JPY markets, coupled with its robustness across various performance metrics, solidifies its potential as an effective instrument for trading strategy optimization.

EUR/NZD Market

In the context of the EUR/NZD market, MTSGA continues to demonstrate robust performance as evidenced by the statistics provided in Table 5.3. It is significant to note that MTSGA is the sole strategy yielding positive values in terms of PnL, RoR, and Fitness. On the other hand, the rest of the strategies display negative values for these metrics. These findings indicate that MTSGA can persevere even in bearish market conditions where traditional technical analysis and basic DC-related strategies fail.

Table 5.3: Evaluation Matrix for EUR/NZD

	B&H	RSI	MACD	STS3	MTS	MTSGA
PnL	-134.83	-1850.75	-3735.83	-368.33	-297.50	**114.17**
Fitness	-0.31%	-1.21%	-2.29%	-0.26%	-0.22%	**0.01%**
RoR	-0.05%	-1.11%	-2.24%	-0.21%	-0.17%	**0.06%**
std(RoR)		0.24%	0.21%	0.30%	0.21%	**0.19%**
MDD	2.51%	0.97%	0.52%	0.53%	**0.51%**	0.54%
Win Rate	**66.67%**	52.28%	27.39%	43.53%	42.58%	44.42%
nTrade	1	46	75	10	48	52

Further underlining its stable performance, MTSGA manages to maintain the minimal std(RoR) among the compared strategies. Although it does not achieve the lowest MDD, MTSGA's MDD of 0.54% is relatively close to the lowest MDD of 0.51% secured by the MTS strategy, underscoring MTSGA's resilience in the face of market volatility.

Although it does not clinch the highest win rate — a title held by the B&H strategy with a win rate of 66.67% — MTSGA's win rate of 44.42% is relatively competitive. These results imply that despite the market's bearish trends, MTSGA still manages to navigate successfully and provide a commendable performance.

To sum up, the outcomes derived from the EUR/NZD market further solidify MTSGA's reputation as a resilient and robust trading strategy that stands its ground, even in challenging market conditions.

Discussion

Based on the examination of the three tables, we can deduce that MTSGA shows superior performance compared to other methods across diverse currency pair datasets. This conclusion is reached considering the monthly averages of PnL, RoR, and Fitness, wherein MTSGA consistently outperforms its counterparts with the highest scores. Furthermore, MTSGA demonstrates robust performance by maintaining the lowest std(RoR).

Rate of Return (RoR)

The boxplots provide a visual representation of the RoR achieved by different trading strategies across three different currency markets: USD/CAD, EUR/NZD, and AUD/JPY (Figure 5.1). By scrutinizing these plots, we can discern several patterns and draw the subsequent observations.

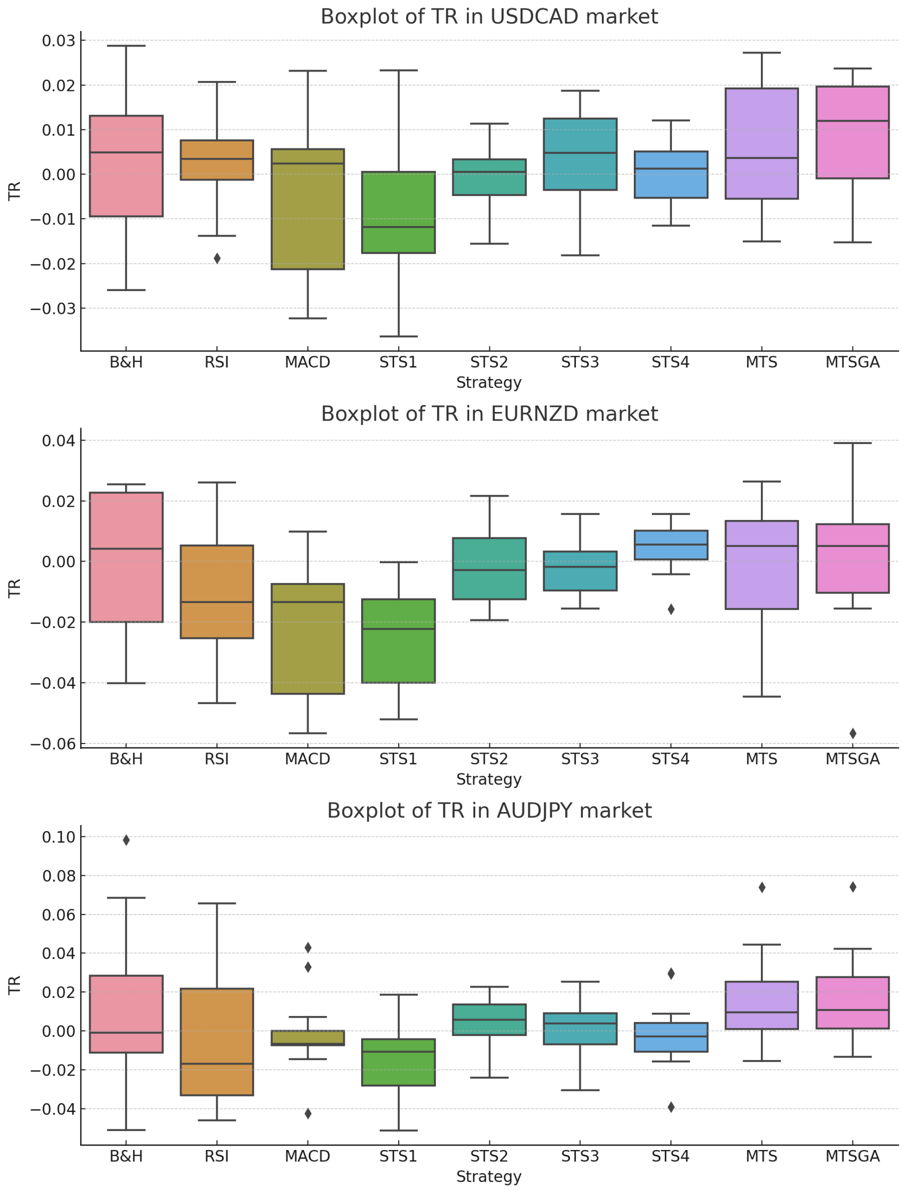

Figure 5.1: Box-plots of RoR by Strategies

MTSGA exhibits promising potential for resilient performance under standard market conditions, as evidenced by its competitive median returns across all examined markets. Particularly in the USD/CAD and EUR/NZD markets, MTSGA's upper quartile performance exceeds that of the majority of other strategies, indicating the possibility of significant returns under favourable market conditions. Although its upper quartile performance in the AUD/JPY market may not excel over all strategies, it still remains comparatively competitive.

Moreover, MTSGA displays a superior performance in its first quartile as compared to other strategies across all markets. This indicates consistent productivity and effective risk management, even during challenging market conditions. The lower whisker of the boxplot reveals that MTSGA experiences fewer severe losses than most other methods in all markets, implying successful downside risk mitigation. Hence, these observations emphasize the fact that MTSGA has a strong an adaptable trading potential owing to its combination of competitive median returns, exceptional upper and lower quartile performance, and resilience during unfavorable situations.

Maximum Drawdown (MDD)

Although MTSGA may exhibit competitive MDD values, it may not always be the best method for managing risk, as seen by its sometimes non-optimal MDD values. However, in comparison to other strategies, MTSGA still presents competitive MDD values. Figure 5.2 shows the boxplots of MDD across various strategies.

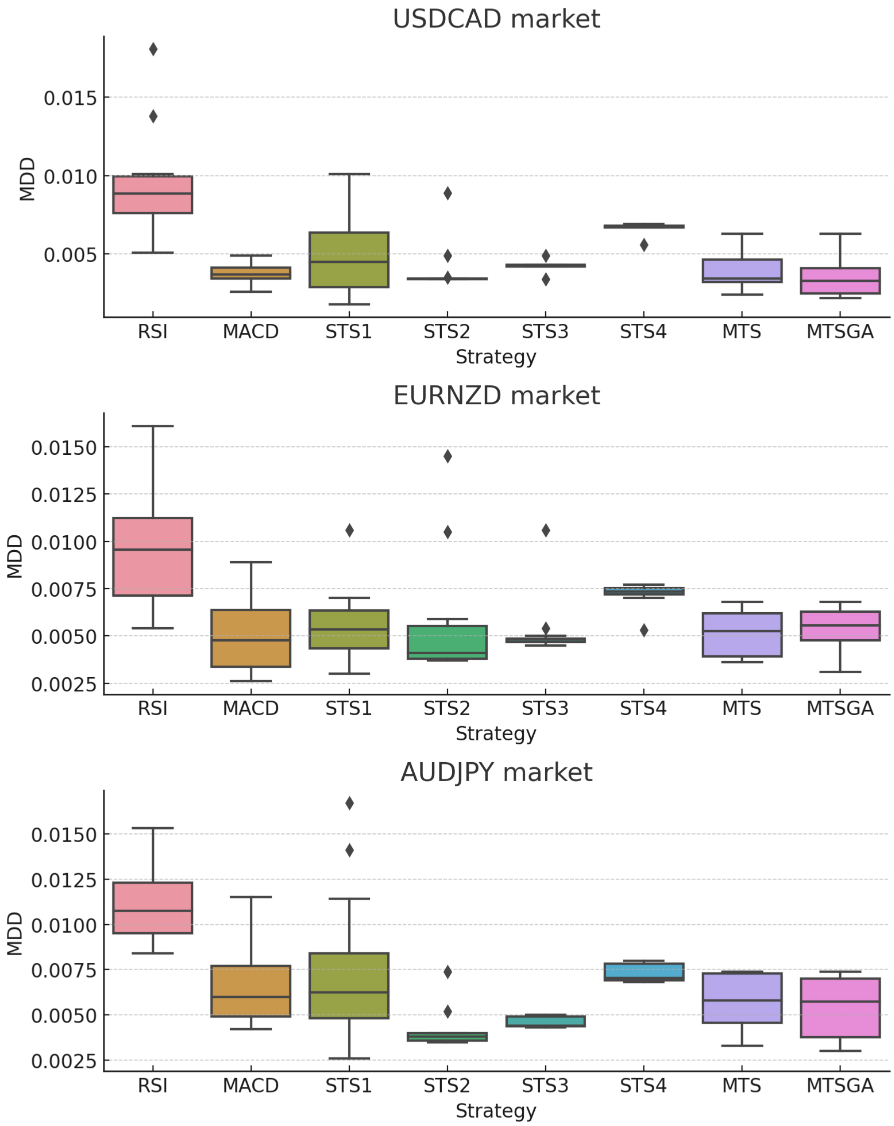

Figure 5.2: Box-plots of MDD by Strategies

This analysis centers on the potential negative consequences associated with MTSGA and comparable trading strategies, except for the B&H strategy. The evaluation yields substantial findings as described below.

Within the USD/CAD market, MTSGA shows a lower median MDD than other strategies, indicating fewer and less severe drawdowns over the given timeframe. This outcome demonstrates the strategy's proficiency at risk management and resilience to adverse market fluctuations.

In the EUR/NZD market, MTSGA exhibits a lower median MDD compared to other techniques such as MACD, RSI, and STS. This observation indicates that MTSGA is less prone to incurring severe drawdowns. Even though its downside risk may be slightly higher than the MTS strategy, the variability in MDDs for MTSGA shows a lesser extent as compared to MTS strategy. Such an attribute may appeal to investors who prioritize consistent performance and possess low risk tolerance.

Within the AUD/JPY market, MTSGA shows a greater median MDD compared to other strategies such as STS1, STS2, and MTS. Nonetheless, when compared to strategies like STS3, STS4, MACD, and RSI, MTSGA presents more reliable fluctuations in its MDD measurements. This indicates that MTSGA is capable of exercising superior downside risk management.

In summary, MTSGA demonstrates a dependable means of evaluating risk in MDD, outperforming alternative technical strategies adopted across diverse markets. This implies that MTSGA engenders a steady and dependable management of risk.

Win Rate

Upon examination, it is apparent that MTSGA does not display a remarkable win rate. However, when considering the combined performance across diverse measures, it becomes evident that MTSGA demonstrates strong and effective outcomes.

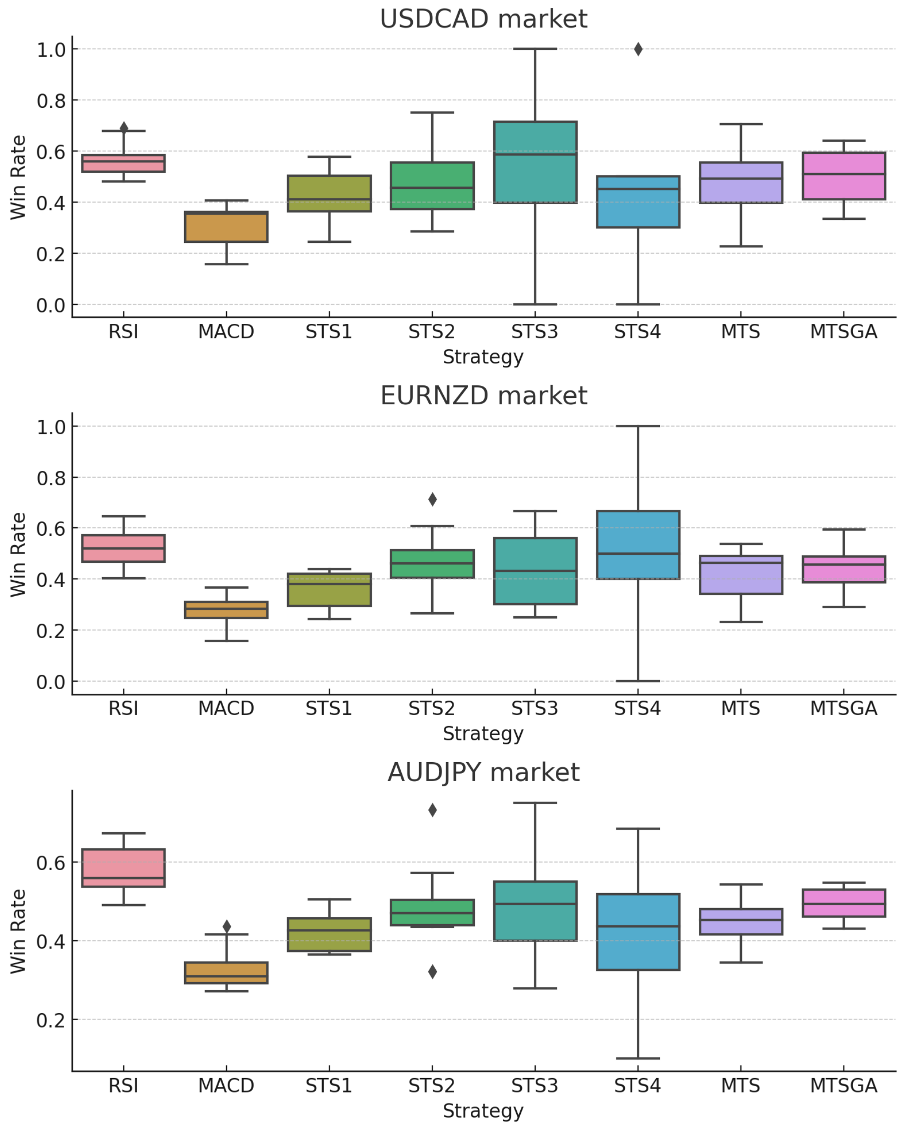

Figure 5.3: Box-plots of Win Rate by Strategies

After analyzing the boxplots above (Figure 5.3), it is clear that there is no significant difference between the median win rate of the MTSGA and that of the other strategies.

Despite the fact that MTSGA does not consistently secure the highest win rate across all three markets, its median win rate remains competitive with other strategies. This suggests that the percentage of profitable trades made by MTSGA is similar to those of other strategies under various market conditions.

In conclusion, the findings underline MTSGA possesses the capability to endure challenging situations in different currency markets. The strategy's propensity for reduced MDD manifests its proficiency in risk management, thereby minimizing the probability of substantial financial setbacks. Ultimately, these findings reinforce the potential effectiveness of MTSGA even under adverse market circumstances.

5.2 Skewness and Kurtosis Analysis

Table 5.4 showcases the examination of skewness and kurtosis indicators for the RoR, MDD, and Win Rate performance metrics of the MTSGA trading methodology across three distinct currency pairs - USD/CAD, EUR/NZD, and AUD/JPY. Skewness is indicative of the degree of asymmetry in a distribution, whereas kurtosis determines the existence of outliers or "tailedness" in a distribution.

Table 5.4: Skewness and Kurtosis of MTSGA

		RoR	MDD	Win Rate
USD/CAD	Skewness	-0.47	0.93	-0.19
	Kurtosis	-1.01	0.09	-1.43
EUR/NZD	Skewness	-0.84	-0.61	-0.02
	Kurtosis	0.96	-0.93	-0.74
AUR/JPY	Skewness	1.02	-0.25	-0.14
	Kurtosis	0.33	-1.45	-1.36

The skewness and kurtosis measures provide insights into the asymmetry and the presence of outliers in a distribution, respectively. A comparison across the three pairs suggests that the performance of the MTSGA strategy varies.

For USD/CAD, the strategy shows a moderate risk-return profile. This is evident from the negative skewness and kurtosis of the RoR metric, suggesting a tendency towards lower returns and a lower likelihood of extreme returns. The MDD metric presents right skewness and near-zero kurtosis, which indicates occasional significant drawdowns and a moderate frequency of extreme drawdowns. The Win Rate metric suggests a reliable performance across varied scenarios.

On the other hand, the performance of the strategy on EUR/NZD is characterized by a higher risk profile and lower drawdowns. The left skewness and positive kurtosis of the RoR metric indicate a higher probability of extreme outcomes and lower returns. The MDD metric's negative skewness and kurtosis suggest a lower risk of substantial drawdowns. A consistent performance is indicated by the Win Rate metric.

In the case of AUD/JPY, the strategy demonstrates promising returns with lower drawdowns. This is evidenced by the rightward skewness and positive kurtosis of the RoR metric, which indicate favourable prospects for generating profits. The leftward skewness and negative kurtosis of the MDD metric suggest infrequent high drawdowns, thereby highlighting an appealing risk-reward ratio. The Win Rate metric implies a steady win rate.

In summary, these findings can assist investors in aligning their risk-return preferences across different currency pairs when employing the MTSGA strategy.

5.3 Hypothesis Testing

The objective is to evaluate the performance of MTSGA by means of hypothesis testing and juxtapose it against other approaches. This inquiry carries significant importance in confirming the effectiveness of MTSGA as well as its superiority over other options.

In order to scrutinize and evaluate disparities among groups, ANOVA shall be employed based on average comparison. Nevertheless, it is crucial to adhere to certain prerequisites for the suitability of ANOVA. These preconditions are as follows:

1. **Sampling Independence:** Accurate results are ensured by statistical tests that presume the independence of sampling, thereby preventing biased outcomes arising from sample correlation.

2. **Normality:** For ANOVA to be conducted accurately, it is of utmost importance that the normality assumption is valid. For this to hold true, the samples collected from each group must conform to a Gaussian distribution. The Shapiro-Wilk test serves as an effective tool in testing the validity of this assumption. ([67], [68]) It generates a p-value that aids in determining if our sample satisfies the normality requirement. In case the p-value falls below the predetermined alpha level, we can reject the null hypothesis related to normality with confidence.

3. **Homogeneity of Variances:** In statistical analysis, it is assumed that variances are homogeneous. To confirm this assumption, Levine's test will be employed. In the event that the p-value falls below the alpha level, the null hypothesis pertaining to equal variances would be disproved.

Provided that the verification process is successful, we will thoroughly scrutinize both the RoR and MDD for every currency pair.

The ANOVA analysis can be preceded with the Shapiro-Wilk and Levine's tests to verify pertinent assumptions. Once significant dissimilarities in group means are established, performing Tukey's HSD post-hoc test becomes necessary to recognize the varying groups.

In cases where the assumptions of ANOVA are not satisfied, non-parametric alternatives such as Kruskal-Wallis and Mann-Whitney U tests are employed. These methods have demonstrated resistance to breaches of the assumptions.

A level of significance of 0.05 is employed in all the examinations conducted.

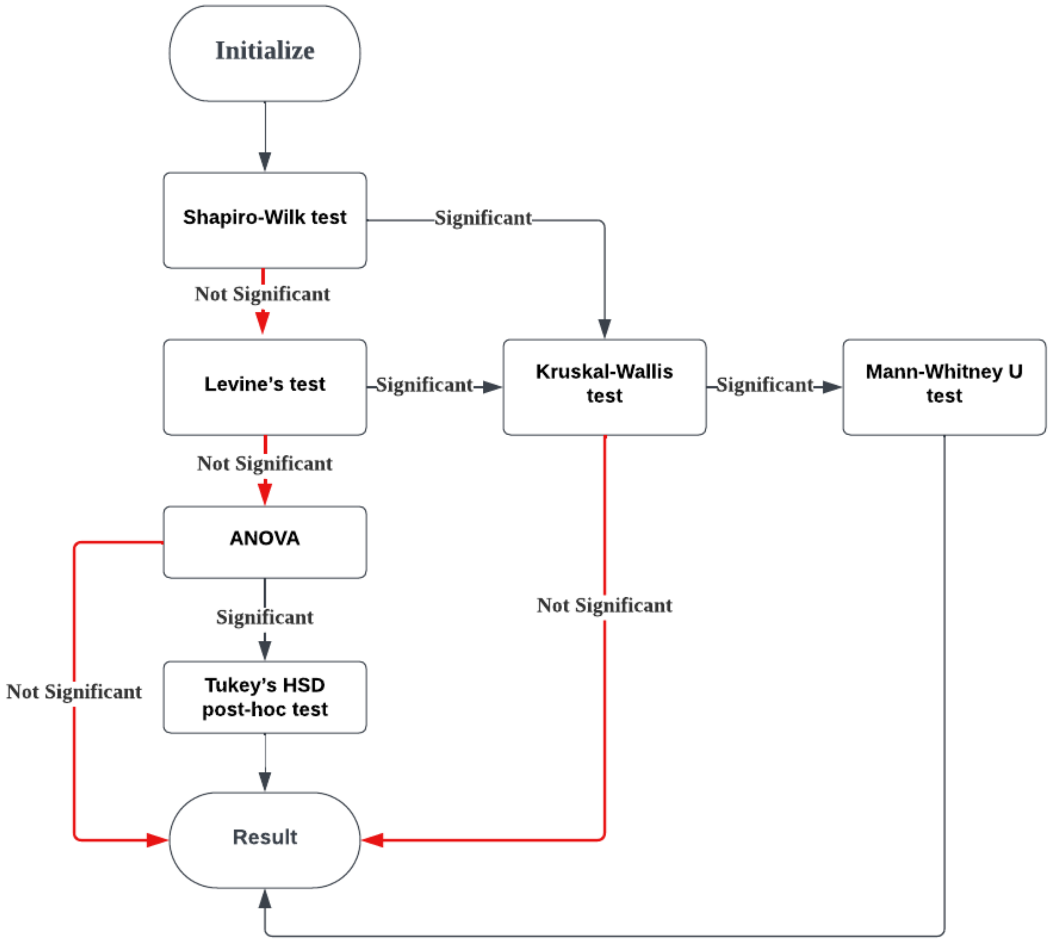

Figure 5.4: Hypothesis Testing Flow Chart

5.3.1 USD/CAD Market

In the following segment, we shall explore an in-depth analysis of the USD/CAD market. Our evaluation of trading strategies within this market will be based on two primary benchmarks: RoR and MDD.

RoR

Table 5.5 presents the p-values resulting from the Shapiro-Wilk test for the normality of RoR distributions across the different strategies. These p-values provide a quantitative measure to assess the adherence of each strategy's RoR to a normal distribution.

Table 5.5: Shapiro-Wilk test for USD/CAD RoR

	B&H	RSI	MACD	STS1	STS2	STS3	STS4	MTS	MTSGA
p-value	0.856	0.830	0.291	0.816	0.858	0.726	0.744	0.489	0.386

Based on the results of the Shapiro-Wilk test, it appears that the null hypothesis of normality for the RoR values of each strategy cannot be rejected at a significance level of 0.05, as all p-values exceed this threshold.

Table 5.6 presents the p-values resulting from the Levene's Test for USD/CAD RoR Homogeneity of Variances.

Table 5.6: Levene's test for USD/CAD RoR

	Levene's Test
p-value	0.07568

Based on the results of Levene's test, where the p-value is greater than 0.05, it is reasonable to uphold the null hypothesis that assumes similar variances between strategy RoR values at a significance level of 0.05.

ANOVA can be applied to examine RoR at this point considering that the presumptions are met. The results are presented in Table 5.7.

Table 5.7: One-way ANOVA test for USD/CAD RoR

	ANOVA Result
statistic	1.79241
p-value	0.08742

The analysis results from Table 5.7 show a test statistic of approximately 1.79 and a corresponding p-value of about 0.08 as a result of the One-Way ANOVA test.

The ANOVA test assumes that the RoR means of all strategies are not significantly different under the null hypothesis. If the p-value from this test exceeds 0.05, there isn't enough evidence to reject the null hypothesis.

After performing the ANOVA test, it can be concluded that there is not enough statistical evidence at a 0.05 level of significance to confirm the existence of a significant difference in RoR among two or more strategies.

MDD

We move on to the USD/CAD market's MDD.

The p-values obtained from the Shapiro-Wilk test for normality of MDD distributions across various strategies are shown in Table 5.8. These values measure how well each strategy's MDD conforms to a normal distribution.

Table 5.8: Shapiro-Wilk test for USD/CAD MDD

	B&H	RSI	MACD	STS1	STS2	STS3	STS4	MTS	MTSGA
p-value	0.600	0.043	0.841	0.230	6.700	0.001	1.654	0.268	0.153

Most strategies have p-values higher than 0.05 in the Shapiro-Wilk test, indicating that we cannot reject the null hypothesis of normality for their MDD values at a significance level of 0.05. On the other hand, RSI and STS3 have p-values less than 0.05, indicating that we reject the null hypothesis of normality for these strategies.

The p-values that arose from performing Levene's Test for Homogeneity of Variances for USD/CAD MDD are shown in Table 5.9.

Table 5.9: Levene's test for USD/CAD MDD

	Levene's Test
p-value	3.91583×10^{-10}

The null hypothesis, which assumes that the variances between strategy MDD values are equal, can be rejected at a significance level of 0.05 based on the Levene's test result with a p-value below 0.05.

ANOVA is unsuitable for analyzing MDD values because of the violation of the assumptions of normality and homogeneity of variances. Consequently, we resort to the Kruskal-Wallis test, which is a non-parametric substitute. Table 5.10 exhibits the results obtained from the Kruskal-Wallis test.

Table 5.10: Kruskal-Wallis test for USD/CAD MDD

	Kruskal-Wallis Result
statistic	70.27185
p-value	5.06×10^{-12}

In the Kruskal-Wallis analysis, a test statistic of roughly 70.27 and a p-value of 4.33×10^{-12} were observed. Since the p-value is significantly below 0.05, indicating a significant difference in MDD distributions across at least two strategies, the null hypothesis is rejected.

The comparison of two distinct samples is done through pairwise Mann-Whitney U tests. The outcomes of these tests to determine the different MDD for specific strategies are shown in Table 5.11.

Table 5.11: Mann-Whitney U test for USD/CAD MDD

Group 1	Group 2	Statistic	p-value
B&H	MTSGA	144.0	0.00131
STS4	MTSGA	143.0	0.00141
RSI	MTSGA	143.0	0.00168
STS2	MTSGA	93.5	1.00000
STS3	MTSGA	108.0	1.00000
MACD	MTSGA	94.0	1.00000
STS1	MTSGA	91.0	1.00000
MTS	MTSGA	88.0	1.00000

None of the pairs that include MTSGA strategy, except for B&H, STS4, and RSI, show any significant statistical differences in MDD after adjusting for multiple testing at a significance level of 0.05.

The outcomes indicate that there are notable variations in MDD among certain tactics as per the Mann-Whitney U tests. The MTSGA approach, specifically, has a significantly distinct MDD from B&H, STS4, and RSI approaches.

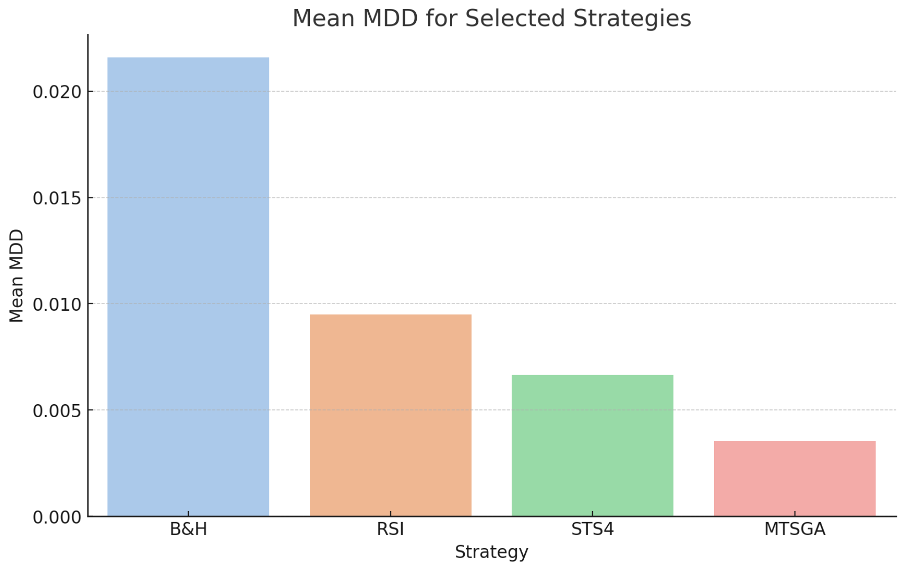

Figure 5.5: MDD bar plot for USD/CAD market

The mean MDD values for B&H, STS4, RSI, and MTSGA were graphed in Figure 5.5. MTSGA had the smallest MDD out of the four strategies analyzed. Additionally, based on the results of the prior Mann-Whitney U test, it can be concluded that

MTSGA has a significantly lower MDD than B&H, STS4, and RSI methods.

5.3.2 EUR/NZD Market

We shall now shift our focus to the EUR/NZD market and proceed with the identical analysis as that of the preceding section.

RoR

Likewise, the Shapiro-Wilk Test is performed as a means of evaluating the conformity of distributions to normality.

Table 5.12: Shapiro-Wilk test for EUR/NZD RoR

	B&H	RSI	MACD	STS1	STS2	STS3	STS4	MTS	MTSGA
p-value	0.083	0.992	0.255	0.338	0.633	0.954	0.339	0.282	0.382

The RoR values of all strategies in Table 5.12 do not significantly deviate from a normal distribution at a 95% confidence level. This is evident as the p-values for each strategy are greater than 0.05, indicating that the null hypothesis regarding normality cannot be dismissed.

Levene's Test is then performed to examine if the variances among the various strategies are consistent.

Table 5.13 displays the p-values obtained from Levene's Test used to evaluate the uniformity of variances in RoR values within the EUR/NZD market.

Table 5.13: Levene's test for EUR/NZD RoR

	Levene's Test
p-value	0.07805

At a significance level of 0.05, the Levene's test p-value for the RoR values of each strategy indicates that the null hypothesis of equal variances is valid. Therefore, there is no justification for rejecting this null hypothesis.

Considering that the presumptions are valid at a level of importance of 0.05, it is appropriate to carry out an ANOVA investigation for the RoR values. A One-Way

ANOVA was executed, and the results are illustrated in Table 5.14.

Table 5.14: One-way ANOVA test for EUR/NZD RoR

	ANOVA Result
statistic	3.83761
p-value	0.00057

Based on the ANOVA test results, where the p-value is below 0.05, we can conclude that there exists a significant variance in the mean RoR of at least two strategies and therefore reject the null hypothesis.

A subsequent analysis is carried out to determine the distinct RoRs of various strategies, employing Tukey's HSD test. The findings are presented in Table 5.15.

Table 5.15: Post-hoc Analysis for EUR/NZD RoR

Group 1	**Group 2**	**mean diff**	**p-adj**	**lower**	**upper**	**reject**
MTSGA	RSI	0.0118	0.8421	-0.0363	0.0127	False
MTSGA	STS1	0.0264	0.0250	-0.0509	-0.0019	True
MTSGA	STS2	0.0029	1.0000	-0.0274	0.0216	False
MTSGA	STS3	0.0027	1.0000	-0.0272	0.0218	False
STS4	MTSGA	0.0041	0.9998	-0.0204	0.0286	False
MTSGA	B&H	0.0012	1.0000	-0.0234	0.0257	False
MTSGA	MACD	0.0230	0.0829	-0.0015	0.0476	False
MTSGA	MTS	0.0024	1.0000	-0.0222	0.0269	False

Table 5.15 reveals a notable variation in the average RoR between the MTSGA and STS1 approaches. To be specific, the MTSGA approach outperforms the STS1 method with respect to its mean RoR.

MDD

Subsequently, our attention is directed towards the MDD in the EUR/NZD market. The Shapiro-Wilk test and Levene's test are carried out and the outcomes are exhibited in tables - Table 5.16 and 5.17.

Table 5.16: Shapiro-Wilk test for EUR/NZD MDD

	B&H	RSI	MACD	STS1	STS2	STS3	STS4	MTS	MTSGA
p-value	0.046	0.567	0.235	0.137	0.000	6.307	0.000	0.151	0.159

The outcomes of the Shapiro-Wilk test indicate that for the majority of strategies, the p-values surpass 0.05, indicating that we cannot refute the null hypothesis of normality for their MDD values at a 0.05 significance level. Nevertheless, three strategies - B&H, STS2 and STS4 - exhibit p-values below 0.05, thereby leading to rejection of the null hypothesis of normality for them.

Table 5.17: Levene's test for EUR/NZD MDD

	Levene's Test
p-value	1.97088

At a significance level of 0.05, the null hypothesis pertaining to the equality of variances for RoR values between different strategies is upheld as the p-value resulting from Levene's test exceeds 0.05. Thus, it cannot be justified to reject this null hypothesis.

Due to the breach of the assumption of normality, ANOVA cannot be utilized for analyzing MDD values. Henceforth, we turn to the Kruskal-Wallis test, which is a non-parametric alternative. The outcome of the Kruskal-Wallis test is presented in Table 5.18.

Table 5.18: Kruskal-Wallis test for USD/CAD MDD

	Kruskal-Walli Result
statistic	58.36509
p-value	9.74×10^{-10}

A p-value of less than 0.05 indicates sufficient evidence to reject the null hypothesis and conclude that there is a significant difference in the distribution of MDD among at least two strategies. This allows us to use the Mann-Whitney U test to determine which strategies are specifically affected. The table presenting these results can be found in Table 5.19.

Table 5.19: Mann-Whitney U test for EUR/NZD MDD

Group 1	Group 2	Statistic	p-value
B&H	MTSGA	144.0	0.00131
STS4	MTSGA	136.5	0.00777
RSI	MTSGA	132.0	0.02126
STS3	MTSGA	47.0	1.00000
STS2	MTSGA	57.0	1.00000
MACD	MTSGA	61.0	1.00000
STS1	MTSGA	67.0	1.00000
MTS	MTSGA	65.0	1.00000

According to the results obtained from the Mann-Whitney U tests, there are notable discrepancies in MDD across various methodologies. The MTSGA is particularly noteworthy as it exhibits a significantly different MDD when compared to the B&H, STS4, and RSI approaches.

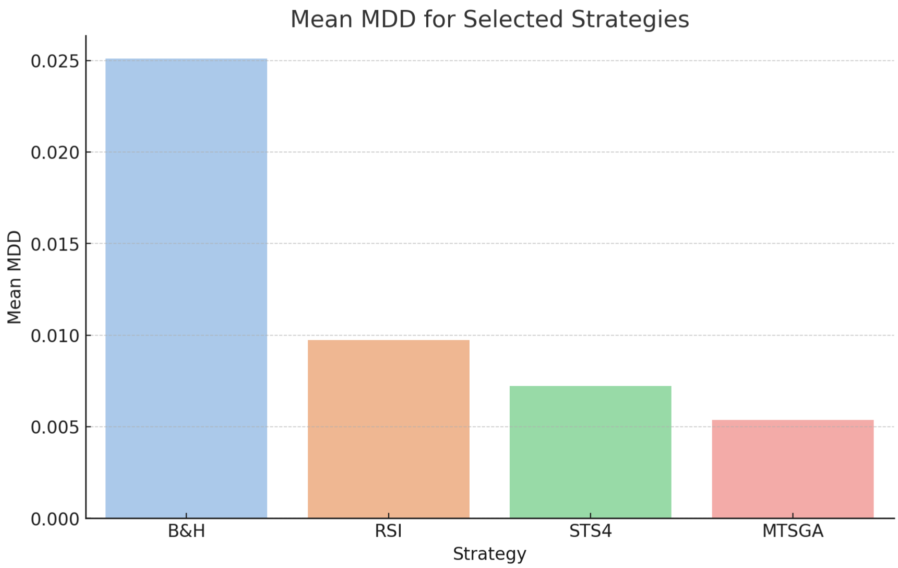

Figure 5.6: MDD bar plot for EUR/NZD market

The MDD mean values for B&H, STS4, RSI, and MTSGA were computed and presented graphically in Figure 5.6. Notably, among the four strategies considered, MTSGA had the smallest MDD. Furthermore, taking into account the outcome of the Mann-Whitney U test conducted earlier, it can be inferred that MTSGA demonstrates a considerably lower MDD as compared to B&H, STS4, and RSI techniques.

5.3.3 AUD/JPY Market

Finally, we shall undertake a similar examination on the market for AUD/JPY.

RoR

We commence with the Shapiro-Wilk test as done previously.

Table 5.20: Shapiro-Wilk test for AUD/JPY RoR

	B&H	RSI	MACD	STS1	STS2	STS3	STS4	MTS	MTSGA
p-value	0.450	0.223	0.047	0.723	0.152	0.918	0.417	0.262	0.203

As indicated in Table 5.20, the statistical significance tests illustrate that the MACD analysis displays p-values lower than the threshold of 0.05. This suggests that we have sufficient evidence to reject the null hypothesis of normality for these methodologies.

Table 5.21: Levene's test for AUD/JPY RoR

	Levene's Test
p-value	0.09227

According to the information displayed in Table 5.21, the p-value exceeds 0.05, thus leading us to accept the null hypothesis.

As the assumption of normality has been violated, we resort to utilizing the Kruskal-Wallis test as a non-parametric option. The results obtained from this particular test are displayed in Table 5.22.

Table 5.22: Kruskal-Wallis test for AUD/JPY RoR

	Kruskal-Wallis Result
statistic	15.05986
p-value	0.05799

In Table 5.22, it can be observed that the p-value exceeds 0.05, which implies that the null hypothesis cannot be rejected at a significance level of 0.05. As a result, there are no notable disparities between the MDD of diverse trading techniques for the AUD/JPY currency pair.

MDD

The data presented in Table 5.23 indicates that the p-values of STS2, STS3, and STS4 are below 0.05. Hence, it is imperative to reject the null hypothesis of Shapiro-Wilk test. Additionally, Table 5.24 illustrates that there exists a p-value less than 0.05. Therefore, one must conclude that the null hypothesis of Levene's test cannot be sustained.

Table 5.23: Shapiro-Wilk test for AUDJPY MDD

	B&H	RSI	MACD	STS1	STS2	STS3	STS4	MTS	MTSGA
p-value	0.996	0.580	0.136	0.073	0.000	0.005	0.012	0.158	0.125

Table 5.24: Levene's test for AUD/JPY MDD

	Levene's Test
p-value	1.49×10^{-14}

The Kruskal-Wallis test should be employed as a result of the violation of the underlying assumptions. The presentation of findings can be observed in Table 5.25.

Table 5.25: Kruskal-Wallis test for AUD/JPY MDD

	Kruskal-Wallis Result
statistic	69.93742
p-value	5.06×10^{-12}

The Kruskal-Wallis test for MDD values across different strategies returns a test statistic of approximately 69.94 and a p-value of approximately 5.0610^{-12}.

Given that the p-value is markedly lower than 0.1, it can be inferred that there exists a noteworthy statistical dissimilarity in the prevalence of MDD across two or more strategies.

To determine the different approaches used for varying MDD, we performed pairwise Mann-Whitney U tests.

Table 5.26: Mann-Whitney U test for AUD/JPY MDD

Group 1	Group 2	Statistic	p-value
B&H	MTSGA	144.0	0.00131
RSI	MTSGA	144.0	0.00131
STS4	MTSGA	117.0	0.36223
STS3	MTSGA	48.0	1.00000
STS2	MTSGA	44.5	1.00000
MACD	MTSGA	90.0	1.00000
STS1	MTSGA	84.0	1.00000
MTS	MTSGA	77.5	1.00000

As per the results obtained from the Mann-Whitney U tests, it is evident that the MTSGA exhibits a markedly different MDD in comparison to the B&H and RSI techniques.

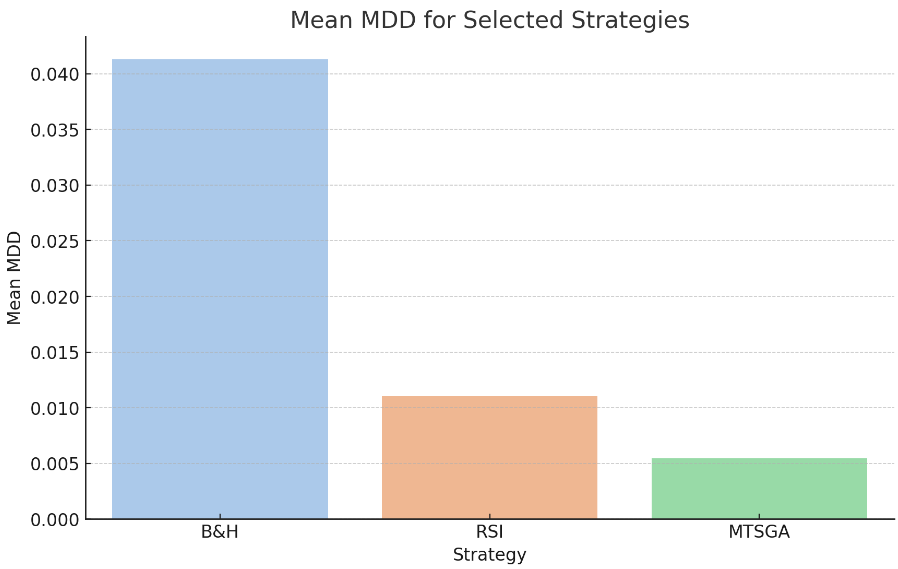

Figure 5.7: MDD bar plot for AUD/JPY market

The average values of MDD for B&H, RSI and MTSGA were calculated and displayed in Figure 5.7. It is worth noting that out of these three strategies, MTSGA exhibited the least MDD. Moreover, considering the results of the previously conducted Mann-Whitney U test, it can be concluded that MTSGA showcases a significantly lower MDD than both B&H and RSI.

5.3.4 Discussion

Regarding the assessment of investment strategies, a statistical examination offers an all-encompassing perspective on the performance of the MTSGA technique relative to other methodologies utilized in the markets for USD/CAD, EUR/NZD, and AUD/JPY. Table 5.27 offers a succinct comparative analysis of the RoR and MDD across these three distinct currency markets, employing multiple strategic methodologies.

Table 5.27: Performance Analysis of Trading Strategies Across Currency Markets

	RoR	**MDD**
USD/CAD	No significant difference	MTSGA lower than B&H, STS4, RSI
EUR/NZD	MTSGA superior to STS1	MTSGA lower than B&H, STS4, RSI
AUD/JPY	No significant difference	MTSGA lower than B&H, RSI

The analysis conducted on the USD/CAD, EUR/NZD, and AUD/JPY markets revealed that there was no notable difference in the RoR across various strategies employed in the USD/CAD and AUD/JPY markets. This implies that all the strategies used were equally efficient in generating returns. However, for the EUR/NZD market, it was observed that the MTSGA strategy outperformed STS1 with a higher RoR, indicating its relative effectiveness in this particular market.

According to the analysis, the MTSGA approach exhibits a consistent trend of lower MDD when compared to B&H and RSI in all markets. As a result, it seems to present minimal risk of facing significant losses. This implies that MTSGA could potentially serve as a secure investment strategy for individuals who prefer caution when dealing with risks.

It is imperative to acknowledge that despite its potential benefits, MTSGA does not consistently surpass other strategies in regards to significant performance and risk measures in the examined markets. There exist various areas for MTSGA's enhancement, hence potential investors must exercise sufficient caution before implementing this strategy.

Chapter 6

Legal, Social, Ethical and Professional Issues

The British Computer Society's Code of Conduct and Code of Good Practice was followed thoroughly during the course of this project [69]. To maintain ethical integrity and honesty, all third-party materials used in the project, such as code libraries, were acknowledged.

Regarding the public interest principle, the development of more effective algorithmic trading strategies can support financial decision-making. However, the potentially complex social and ethical impacts of this work were not thoroughly analyzed in this project. Further examination of the public interest implications would be a valuable area for future research.

In terms of professional competence and integrity, I developed and implemented trading strategies to the best of my abilities. I made sure to give proper credit for any external sources used.

With respect to the duty to the profession, this project contributes to knowledge sharing in the computational finance field that may benefit other researchers. I aimed to maintain professional standards in this project through ethical conduct, knowledge sharing, and respect in all collaborations.

We are dedicated to ethical and professional conduct, as well as making positive contributions to computational finance. These values will continue to shape all future work, ensuring high standards in both technical and ethical aspects.

Chapter 7

Conclusion

In conclusion, the experimental investigation of the integration of Genetic Algorithms (GAs) and Directional Change strategies, referred to as MTSGA, in Forex trading did not yield the anticipated results. Although this methodology possessed theoretical potential, practical findings did not confirm its effectiveness. The hypothesis testing revealed that MTSGA did not significantly improve trading outcomes, suggesting a potential gap between the theoretical assumptions and the actual implementation of this approach in navigating the intricacies of the Forex market.

One possible explanation for this discrepancy lies in the size of the training set used in the study. The decision to limit the training set to one month of data, driven by the need for computational efficiency, might have inadvertently led to underfitting. This suggests that the model may have been too simplistic to capture the full complexity of market behavior and effectively generalize to new data. As a result, the model's learning from the training data could have been inadequate, adversely affecting its performance on unseen data.

Other potential factors contributing to the failure of the hypothesis test could include model mis-specification, inadequate representation of market factors, and issues related to data quality and execution. It's also important to consider the impact of the sample size on the sensitivity of the hypothesis test, as a smaller sample size may limit the ability to detect or represent reliably traits of the target population.

Despite the unanticipated findings, this study provides valuable insights into the challenges of developing effective algorithmic trading strategies. It highlights the crucial role of the size and representativeness of the training data in model performance, emphasizing the trade-off between computational efficiency and model effectiveness. This understanding can inform future research in refining the MTSGA approach and exploring other advanced algorithmic trading strategies.

Future work

Future research endeavors could consider fortifying the Genetic Algorithm (GA) to strengthen the effectiveness of the chosen strategy. One potential direction is the utilization of a more adaptable and flexible GA-Support Vector Machine (GA-SVM) model. The superior predictive accuracy of GA-SVM in forecasting market trends, as emphasized by [70], makes it a promising option for improving predictive precision. In addition, several improvements can be made to DC strategies, including the incorporation of Machine Learning algorithms, such as Support Vector Regression (SVR), to achieve more precise predictions regarding the duration of OS. To address the possibility that OS may not exist, classification algorithms can also be used, according to [1].

Moreover, the parameters of the GA and the application of the Directional Change strategies could undergo refinement to optimize the model's performance. Such refinements could contribute to a more robust model that can better navigate the complexities of the Forex market.

Furthermore, the integration of extra technical strategies could provide a more comprehensive capture of market features. This could further enhance the proposed methodology by ensuring a complete portrayal of market dynamics, ultimately leading to better trading outcomes.

Despite the lack of empirical support for the proposed GA-Directional Change approach in this study, the exploration of these techniques within the context of Forex trading continues to be a promising research avenue. By incorporating the lessons learned from this study, future investigations can continue to advance the field towards more effective and robust algorithmic trading strategies.

Bibliography

[1] A. Adegboye, M. Kampouridis, and F. Otero, “Algorithmic trading with directional changes,” 2022. [Online]. Available: https://repository.essex.ac.uk/33750/1/s10462-022-10307-0.pdf

[2] M. Kampouridis, T. Melissourgos, and O. Salman, “Optimization of trading strategies using a genetic algorithm under the directional changes paradigm with multiple thresholds,” *IEEE Congress on Evolutionary Computation (CEC)*, 2023.

[3] J. McCall, “Genetic algorithms for modelling and optimisation,” *Elsevier B.V.*, 2005.

[4] M. Kampouridis and F. E. Otero, “Evolving trading strategies using directional changes,” *Expert Systems With Applications*, vol. 73, pp. 145–160, 2017.

[5] Y. Yadav, “How algorithmic trading undermines efficiency in capital markets,” *68 Vanderbilt Law Review 1607*, 2015. [Online]. Available: https://scholarship.law.vanderbilt.edu/vlr/vol68/iss6/3

[6] Bank for International Settlements, “Fx execution algorithms and market functioning,” *Report submitted by a Study Group established by the Markets*, 2020. [Online]. Available: https://www.bis.org/publ/mktc13.pdf

[7] T. Ketmanee, “Algorithmic trading and retail traders’ struggles on the forex trading platform,” *Journal of Mekong Societies*, vol. 19, no. 1, pp. 23–44, 2023.

[8] D. Simon., “volutionary optimization algorithms,” *John Wiley Sons*, 2013.

[9] M. E. Aloud, “Profitability of directional change based trading strategies: The case of saudi stock market,” *International Journal of Economics*

and Financial Issues, vol. 6, no. 1, pp. 87–95, 2016. [Online]. Available: http://www.econjournals.com

[10] Bank for International Settlements, "Triennial central bank survey: Otc foreign exchange turnover in april 2022," 2022.

[11] J. James, I. Marsh, and L. Sarno, Eds., *Handbook of Exchange Rates.* West Sussex, UK: Wiley, 2012.

[12] R. Çay, M. Dacorogna, U. A. Muller, O. Pictet, and R. Olsen, *An Introduction to High-Frequency Finance.* Elsevier Science & Technology, 2001.

[13] E. Li, J.; Tsang, "mproving technical analysis predictions: An application of genetic programming," *Application of Genetic Programming. In Proceedings of the Twelfth International FLAIRS Conference, Orlando, FL, USA*, 1999.

[14] A. W. H. Sullivan, R.; Timmermann, "Data-snooping, technical trading rule performance, and the bootstrap," *J. Financ.*, 1999.

[15] Y. Yen, S.M.F.; Hsu, "Profitability of technical analysis in financial and commodity futures markets—a reality check," *Decis. Support Syst*, 2010.

[16] J. J. Murphy, "Technical analysis of the financial markets: A comprehensive guide to trading methods and applications," *New York Institute of Finace*, 1999.

[17] J. W. Wilder, "New concepts in technical trading systems," *Winston-Salem, North Carolina: Hunter Publishing Company*, 1978.

[18] Y. Chen, "Backtesting performance with a simple trading strategy using market orders," 2016, https://www.math.fsu.edu/~ychen/research/backtesting.pdf.

[19] I. Aldridge, *High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems*, 2nd ed. Hoboken, NJ: John Wiley & Sons, May 2013.

[20] M. Popov and R. Madlener, "Fcn working paper no. 5/2014 backtesting and evaluation of different trading schemes for the portfolio management of natural gas," May 2014. [Online]. Available: https://www.fcn.eonerc.rwth-aachen.de/global/show_document.asp?id=aaaaaaaaaajdxtf

[21] P. J. Brockwell and R. A. Davis, *Time Series: Theory and Methods*, 2nd ed., ser. Springer Series in Statistics. New York, NY: Springer,

1991, springer Science+Business Media New York 1991. [Online]. Available: https://doi.org/10.1007/978-1-4419-0320-4

[22] E. Tsang, "Why is directional change good for tick-to-tick data?" YouTube video, October 2020. [Online]. Available: https://youtu.be/E3bR3fXLak0

[23] D. M. Guillaume, M. M. Dacorogna, R. R. Davé, U. A. Müller, R. B. Olsen, and O. V. Pictet, "From the bird's eye to the microscope: A survey of new stylized facts of the intra-daily foreign exchange markets," *Finance and stochastics*, vol. 1, no. 2, pp. 95–129, 1997.

[24] E. Tsang, "Definitions of directional change events," Centre for Computational Finance and Economic Agents (CCFEA), University of Essex, Essex, UK, Working Paper WP050-10, December 2010.

[25] V. Petrov, A. Golub, and R. B. Olsen, "Agent-based model in directional-change intrinsic time," *Available at SSRN 3240456*, 2018.

[26] Y.-K. Lin, "Directional change framework for target transformtation in time series forecasting," 2022.

[27] E. P. K. Tsang and J. Chen, *Detecting Regime Change in Computational Finance: Data Science, Machine Learning and Algorithmic Tradin.* Chapman Hall;, 2020.

[28] J. B. Glattfelder, A. Dupuis, and R. B. Olsen, "Patterns in high-frequency fx data: discovery of 12 empirical scaling laws," *Quantitative Finance*, vol. 11, no. 4, pp. 599–614, 2011.

[29] R. M. H. Funtado, "A prediction based model for forex markets combining genetic algorithms and neural networks," 2018.

[30] M. Aloud, M. Fasli, E. Tsang, A. Dupuis, and R. Olsen, "Stylized facts of the fx market transactions data: An empirical study," *Journal of Finance and Investment Analysis*, vol. 2, no. 4, pp. 145–183, 2013.

[31] E. P. Tsang, R. Tao, and S. Ma, "Profiling financial market dynamics under directional changes," *Quantitative finance*, vol. 1164887, 2015. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/14697688.2016

[32] E. P. Tsang, R. Tao, A. Serguieva, and S. Ma, "Profiling high-frequency equity

price movements in directional changes," *Quantitative finance*, vol. 17, no. 2, pp. 217–225, 2017.

[33] M. Aloud, E. Tsang, R. Olsen, and A. Dupuis, "A directional-change event approach for studying financial time series," *Economics*, vol. 6, no. 1, 2012.

[34] J. B. Glattfelder and A. Golub, "Bridging the gap: Decoding the intrinsic nature of time in market data," *arXiv preprint arXiv:2204.02682*, 2022.

[35] A. Kablan and W. L. Ng, "Intraday high-frequency fx trading with adaptive neuro-fuzzy inference systems," *International Journal of Financial Markets and Derivatives*, vol. 1, no. 1, pp. 68–87, 2011. [Online]. Available: https://doi.org/10.1504/IJFMD.2011.038529

[36] N. Alkhamees and M. Fasli, "A directional change based trading strategy with dynamic thresholds," in *2017 International Conference on Data Science and Advanced Analytics*. IEEE, 2017, pp. 1–7.

[37] A. Bakhach, E. Tsang, and V. Chinthalapati, "Tsfdc: A trading strategy based on forecasting directional change," *Intelligent Systems in Accounting, Finance and Management*, vol. 25, 07 2017.

[38] M. Aloud and N. Alkhamees, "Intelligent algorithmic trading strategy using reinforcement learning and directional change," *IEEE Access*, vol. 9, pp. 89 039–89 047, 2021.

[39] A. Bakhach, E. P. K. Tsang, and H. Jalalian, "Forecasting directional changes in the fx markets," in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, 2016, pp. 1–8.

[40] A. Adegboye, M. Kampouridis, and C. G. Johnson, "Regression genetic programming for estimating trend end in foreign exchange market," in *2017 IEEE Symposium Series on Computational Intelligence (SSCI) Proceedings*. IEEE, 2018.

[41] A. Golub, G. Chliamovitch, A. Dupuis, and B. Chopard, "Multi-scale representation of high frequency market liquidity," *Algorithmic Finance*, vol. 5, no. 1-2, pp. 3–19, 2016.

[42] V. Petrov, A. Golub, and R. Olsen, "Instantaneous volatility seasonality of

high-frequency markets in directional-change intrinsic time," *Journal of Risk and Financial Management*, vol. 12, no. 2, p. 54, 2019.

[43] E. Mayerhofer, "Three essays on stopping," *Risks*, vol. 7, no. 4, p. 105, 2019.

[44] V. Petrov, A. Golub, and R. B. Olsen, "Intrinsic time directional-change methodology in higher dimensions," *Available at SSRN 3440628*, 2019.

[45] J. Palsma and A. Adegboye, "Optimising directional changes trading strategies with different algorithms," in *2019 IEEE Congress on Evolutionary Computation (CEC)*, 2019, pp. 3333–3340.

[46] OECD, "Artificial intelligence, machine learning and big data in finance: Opportunities, challenges, and implications for policy makers," 2021. [Online]. Available: https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf

[47] M. Chen and W. Zhou, *I. MACHINE LEARNING AND DATA SCIENCE APPLICATIONS IN INVESTMENTS*. CFA Institute Research Foundation, 2023.

[48] A. Azzutti, W.-G. Ringe, and H. S. Stiehl, "Machine learning, market manipulation and collusion on capital markets: Why the "black box" matters," *European Banking Institute Working Paper Series 2021 - no. 84, University of Pennsylvania Journal of International Law, Vol. 43, No. 1, 2021*, 2022. [Online]. Available: https://ssrn.com/abstract=3788872

[49] N. Ehrentreich, "Technical trading in the santa fe institute artificial stock market revisited," *Journal of Economic Behavior Organization*, 2006.

[50] A. Bigiotti and A. Navarra, *Optimizing Automated Trading Systems*, 01 2019, pp. 254–261.

[51] D. Snow, "Machine learning in asset management—part 1: Portfolio construction—trading strategies," *The Journal of Financial Data Science Winter 2020*, 2020.

[52] J. Wu, X. Chen, H. Zhang, L.-D. Xiong, H. Lei, and S. Deng, "Hyperparameter optimization for machine learning models based on bayesian optimization," *Journal of Electronic Science and Technology*, vol. 17, pp. 26–40, 2019.

[53] J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," vol. 13, no. null, 2012.

[54] Z. Zhi-Hua, "Applications of data mining in e-business and finance: Introduction," *Appl. Data Min. E-Bus. Financ.*, 2008.

[55] L. Z. C. Ni, J.; Cao, "Evolutionary optimization of trading strategies," *In Applications of Data Mining in E-Business and Finance; IOS Press: Amsterdam, The Netherlands*, 2008.

[56] S. Mani, "Financial forecasting using genetic algorithms," *Applied Artificial Intelligence, 10, 543–566*, 1996.

[57] . M. B.-R. Kwon, Y.-K., "A hybrid neurogenetic approach for stock forecasting," *IEEE Transactions on Neural Networks, 18(3), 851–864. doi:10.1109/TNN.2007.891629*, 2007.

[58] P. K. . X.-F. Evans, C., "Utilizing artificial neural networks and genetic algorithms to build an algo-trading model for intra-day foreign exchange speculation," *Mathematical and Computer Modelling, 58(6), 1249–1266*, 2013.

[59] . O. F. E. B. Kampouridis, M., "Heuristic procedures for improving the predictability of a genetic programming financial forecasting algorithm." *Soft Computing, 1–16*, 2015.

[60] P. K. Xinpeng Long, Michael Kampouridis, "Genetic programming for combining directional changes indicators in international stock markets," *Parallel Problem Solving from Nature – PPSN XVII, 2022, Volume 13399 ISBN : 978-3-031-14720-3*, 2022.

[61] A. Bakhach, "Developing trading strategies under the directional changes framework with application in the fx market," 2018.

[62] D. M. Pictet, O.V., "Using genetic algorithms for robust optimization in financial applications," *Neural Netw. World 5(4), 573–587*, 1995.

[63] J. C. Dempster, M.A.H., "A real-time adaptive trading system using genetic programming," *Quant. Finance 1(4), 397–413*, 2001.

[64] D. T. Hryshko, A., "System for foreign exchange trading using genetic algorithms and reinforcement learning," *Int. J. Syst. Sci. 35(13), 763–774*, 2004.

[65] O. M. Brabazon, A., "Evolving technical trading rules for spot foreign-exchange markets using grammatical evolution," *Comput. Manag. Sci. 1(3), 311–327*, 2004.

[66] HistData.com, "Free forex historical data," Data set. [Online]. Available: https://www.histdata.com

[67] S. Shapiro and M. Wilk, "The shapiro-wilk and related tests for normality," 1965.

[68] N. M. Razali and Y. B. Wah, "Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests," *Journal of Statistical Modeling and Analytics Vol.2 No.I, 21-33*, 2011. [Online]. Available: https://www.nrc.gov/docs/ML1714/ML17143A100.pdf

[69] British Computer Society, "BCS Code of Conduct," 2023, [Online; accessed 30-July-2023]. [Online]. Available: https://www.bcs.org/membership/become-a-member/bcs-code-of-conduct/

[70] L. j. Liang bang long and Y. Guanghui, "Research on stock price prediction model based on ga optimized svm parameters," 2016. [Online]. Available: http://article.nadiapub.com/IJSIA/vol10_no7/24.pdf

Appendix A

Parameter Extraction Post Genetic Algorithm Application

In this chapter, the outcomes of the Multi-Threshold Strategy Optimized with Genetic Algorithm (MTSGA) are presented after undergoing the Genetic Algorithm (GA) as displayed in Table A.1. The primary focus herein is the numerical parameters derived for various currency pairs through this computational process. Table 1 showcases the outcomes for each pair, namely CAD/USD, EUR/NZD, and AUD/JPY. Each of the columns represents a distinct parameter (a, b_1, b_2, w_1, w_2, w_3, and w_4) derived post-application of GA.

These parameters offer valuable insights into the behavior and trends of these currency pairs when subjected to the GA. They form a essential part of the analytical findings of this dissertation, offering concrete evidence that reinforces the theoretical and empirical discussions presented in the primary content of the project.

Table A.1: The outcomes for MTSGA after applied GA

	a	b_1	b_2	w_1	w_2	w_3	w_4
CAD/USD	0.29	0.59	0.73	0.68	0.14	0.83	0.56

	a	b_1	b_2	w_1	w_2	w_3	w_4
EUR/NZD	0.29	0.46	0.71	0.29	0.41	0.12	0.94

	a	b_1	b_2	w_1	w_2	w_3	w_4
AUD/JPY	0.3	0.6	0.75	0.75	0.96	0.14	0.78