6CCS3PRJ Final Year
Prediction of Cryptocurrency and Stock Price Using Genetic Algorithm

Final Project Report

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Abstract

Recent years have seen the fervour for cryptocurrencies—most significantly, in relation to their integration with artificial intelligence—rise to its peak, a signal for the change in trading practices. ~~The dissertation~~ discusses the use of genetic algorithms in the optimisation of parameters for seven various trading strategies on cryptocurrency markets, stressing an innovative combination of AI with financial tactics. The main objective of this study is to utilize genetic algorithms to optimize parameters and forecast future prices by integrating various indicators and patterns, such as RSI and candlestick patterns, thereby enhancing profitability. Strong time series approaches are adopted in the analysis, which reflects the 30, 60, and 120 minutes over a range of trading pairs such as BTC/USDT, ETH/USDT, and S&P 500. The result indicates that genetic algorithms can significantly improve the performance of traditional methods, particularly for the usual buy-and-hold strategy, and hence give new insights into the effectiveness of automated trading.

Originality Avowal

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Jae Min An

April 26, 2024

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Chapter 1

Introduction

1.1 Introduction to Financial Market Predictions

The ability to predict financial markets has captured the imagination of economists and traders for centuries. The reason behind that is not only the incredible potential financial rewards, but also the intellectual challenge, as the continuous effort to be right ahead of the market. However, the difficulty of the task is obvious, since financial markets are complex adaptive systems, which are characterised by perpetual change and integration of new information(Evans & Allan, 2015). This view is supported by the Efficient Market Hypothesis, which states that stock prices always incorporate the information that is publicly known, making it virtually impossible to beat the market consistently on a risk-adjusted basis(Ullah & Asghar, 2023). However, many empirical studies show the evidence of market inefficiencies. Market can simply be defined as inefficient, since there are circumstances under which prices do not fully reflect the available information; in these instances knowledgeable investors can outperform the less informed, as documented by the studies(Garcin, 2023). The popularity of technical analysis, a methodology used to predict stock prices through analysing historical data, is an ultimate example of the human persistence to think that the market can be consistently outperformed.

1.2 Technical Analysis in Financial Markets

Financial market predictions rely significantly on technical analysis, which serves as one of the fundamental pillars in this endeavor. It has long been recognized as essential for crafting a comprehensive perspective on market dynamics. Existing since the early days of rice markets of Japan, technique analysis has been popularised by Charles Dow in the late 19th century (Arshanapalli, Lutey, Nelson, & Pollak, 2020). Since then, it has experienced significant transformation. Technical indicators, tools of technical analysis, drew the attention of researchers, which resulted in a vast body of study. While in their study on Foreign Exchange trading it seems that technical analysis indeed can provide an edge over fundamental analysis, their trading results offered no answer to the question of the profitability of using TA. However, according to another investigation the profitability of technical trading rules, such as the simple moving average, has been in decline since the 1970s. Specifically, its profitability in the FX market has dropped from robust in the 1970s to negligible in the 1990s(Gerber, 2016; Nguyen & Yang, 2013).

To further add to this, in the study concerning the Singapore Stock Market*, certain TA indicators remain profitable in trading. For example, simple moving average performs better in trading than the relative strength index(Savchenko, 2023). The studies cited above only develop one side of the discussion: they analyse how good are the signals given by technical indicators.

1.3 Role of Genetic Algorithms in Financial Forecasting

Genetic algorithms are also closely associated with finance, and extensive research has already been conducted in this area. Indeed, genetic algorithms have been widely utilized in financial forecasting. For example, in GAs were used in Reinforcement Learning to create an automated trading system in the FX market. The system was consistently profitable and prevented large drawdowns during times of market volatility(Dey & Kapoor, 2021). Additionally, they have been used in to identify stock market future trends. In this study, GAs are used with Multilayer Perceptron to predict stock market trends. The discriminator is created using LSTM and the generator is too, which the difference is only from performance. This study outperforms other machine learning models in predicting trends of S&P 500(Long, Kampouridis, & Jarchi, 2022).

These preceding applications underscore the adaptability and strength of GAs in optimising trading strategies. The current study aims to build upon this foundation by not only optimising the parameters of various trading strategies but also seeking the most advantageous combination of these strategies. The GA's ability to efficiently traverse complex solution landscapes makes it a powerful tool for this purpose.

This study aims to push the boundaries of traditional financial analysis methods. To the best of the knowledge, there is a novelty in testing the genetic algorithm within the context of optimising the parameters of trading indicators, specifically the Relative Strength Index (RSI), which is a momentum oscillator used to measure the speed and change of price movements, coupled with various candlestick patterns in cryptocurrency markets.

1.4 Cryptocurrency Markets

While cryptocurrencies have only recently crept into mainstream finance, their presence can almost not be felt much less than in the stock markets. The fast-growing and increasingly pervasive acceptance of cryptocurrencies can be termed nothing short of revolutionary in recent years. By April 2024, according to CoinGecko, the cumulative market capitalisation of all cryptocurrencies went wild and reached an incredible $2.47 trillion, which further underlines the huge financial weight that digital assets are carrying. This has been drawing the attention of many retail and institutional investors, creating a very liquid market that is, at the same time, the most volatile in existence.

The present study recognises the unique opportunities the cryptocurrency markets represent. Being volatile by nature and with different market dynamics from traditional financial markets, it provides a rich environment for the testing of robustness and effectiveness of trading strategies. At that, the market is quite volatile per se; it means that inefficiencies and strategies may be potentially likely to present themselves faster and with enough magnitude for genetic algorithms to exploit toward better returns(Ullah & Asghar, 2023).

1.5 Methodology

This study, in order to have an all-round understanding, selected a spectrum of the most influential cryptocurrencies—like, for example, Bitcoin and Ethereum —in addition to the S&P 500 index. Indeed, the strategic choice of these cryptocurrencies, since they were in the top 10 regarding market capitalisation and liquidity, may enable the prospect of them representing the larger market and the testing of models developed within this study. Furthermore, best practise in cross-asset comparison involves the inclusion of the S&P 500, trying to check whether results and strategies drawn from the world of cryptos can be replicated, or at least adapted well, in traditional stock markets.

The study is multi-faceted, with data at intervals of 30, 60, and 120 minutes analysed in an approach to edify the diverse trading behaviours. Such a multidimensional approach helps to catch the insight into a very wide spectrum of trading strategies: intraday to swing trading, therefore providing a holistic view on market dynamics and a potential adaptability of genetic algorithms for different trading styles.

The study methodology of this paper lies in the application of six different strategies and two technical indicators, each one trying to find optimised parameters to predict market movements and define optimal long(buy) and short(sell) points. One of the strengths of the genetic algorithm is based on the possibility of optimising complicated problems by proving its use in other fields, so its potential in the financial domain is one of the aims of the study.

To this point, most of the prior study has evaluated strategies in isolation, rather than evaluating the combined effect of multiple combination in the cryptocurrency market. For that reason, this paper aims to to combine multiple technical indicators and strategies through genetic algorithms for finding out whether some synergistic interaction may lead to a more robust, profitable trading.

1.6 Objectives of the Study

This study seeks to explore the intersection of genetic algorithms (GAs), the technica indicator such as RSI and Williams %R, and candlestick patterns, with the aim of practises cryptocurrency trading strategies.

1. The core objective is to employ technical indicators and candlestick patterns within a genetic algorithm framework to determine the most profitable trading parameters. This approach moves beyond static trading rules, fostering a dynamic methodology that can adeptly respond to fluctuating market conditions.

2. A comprehensive evaluation framework will be utilised, involving an analysis of the Annualised Sharpe Ratio. This analysis will assess the effectiveness of the genetic algorithm-driven strategies through simulated trade scenarios.

3. This study conducts a comparative analysis between trading strategies optimised by genetic algorithms and traditional methods, such as the buy-and-hold approach and standard technical indicator-based strategies. The objective is to ascertain the advantages that genetic algorithm optimisation may offer over conventional techniques.

4. It tests these strategies on two different cryptocurrencies and the S&P 500, aiming to assess the generalisability of the strategies across diverse assets and market conditions. By examining these varied financial instruments, the study seeks to offer insights into

the adaptability and effectiveness of the proposed trading strategies in different market environments.

Chapter 2

Background

This literature review explains why technical analysis can be effective and why the market is of interest. It also describes why genetic algorithms are efficacious in financial markets and delves into technical indicators and candlestick strategies, discussing their effectiveness and the logical reasons for their use. The review comprehensively covers technical trading, candlestick patterns, RSI, and genetic algorithms. It links these elements to financial markets and connects them to the study topic of using genetic algorithms to predict future prices and develop innovative rules for generating profits.

2.1 Introduction to Technical Trading

Technical trading utilises historical market data and statistical indicators to predict future market behaviour. Its primary aim is to identify profitable trading opportunities by analysing price movements, volumes, and other market-related data. This approach contrasts with fundamental analysis, which assesses a company's intrinsic value through economic and financial factors.

The origins of technical trading trace back to the 17th-century Dutch financial markets. However, the concept was substantially developed in the late 19th and early 20th centuries by pioneers such as Charles Dow. Dow's theories laid the groundwork for a variety of technical analysis tools and techniques that are in use today(Arshanapalli, Lutey, Nelson, & Pollak, 2020).

2.1.1 Effectiveness of technical trading

Studies that support the effectiveness of technical trading often emphasize its capability to derive actionable insights from patterns in historical data. For instance, a notable study focusing on the New York Stock Exchange composite index used computational techniques to demonstrate how predictive accuracy improves when traditional technical indicators are combined with advanced algorithms, such as neural networks and genetic algorithms. This research, conducted by Christodoulaki, Kampouridis, and Kanellopoulos in 2022, highlights a synergistic effect where the integration of modern computational methods with established trading tools can significantly enhance the decision-making process in financial markets. Such findings are crucial as they validate the integration of artificial intelligence technologies in the realm of financial analytics, potentially leading to more robust trading strategies that capitalize on both past patterns and predictive modeling.

Comparative studies, such as those conducted by Saraswathi and colleagues in 2022, often reveal that the choice between technical and fundamental analysis hinges on specific market conditions and the investment timeframe. Technical analysis tends to be preferred for short-term trading in volatile markets, where rapid price fluctuations are more likely influenced by trader psychology rather than solid economic fundamentals. This is because technical analysis excels in detecting patterns and trends based on past price movements, making it particularly useful when quick decisions are required.

The relevance of technical analysis extends notably into the cryptocurrency market, characterized by its high volatility and the unpredictable behavior of its participants. The cryptocurrency market, still relatively new and evolving, presents unique challenges that traditional financial markets may not, such as sudden large-scale price movements triggered by speculative trading or regulatory news. In this context, technical trading tools like moving averages and the RSI have proven especially beneficial. The 2019 study titled ”Are Bitcoin returns predictable?: Evidence from technical indicators” specifically points out how these tools can be leveraged effectively. It suggests that certain technical indicators are capable of providing insights that are not just theoretical but practically applicable, helping traders make more informed decisions amidst the market’s inherent uncertainties.

Moreover, these insights underscore the dynamic interplay between market behavior and trading strategy effectiveness, emphasizing the need for traders to remain adaptable and responsive to market signals. By utilizing technical analysis, traders in the cryptocurrency markets can better navigate the intricacies of these digital assets, potentially leading to improved trading outcomes based on systematic, data-driven strategies.

2.1.2 Application in Various Markets

Technical trading is well adapted and used in many different market, such as Stock markets, forex markets and cryptocurrencies:

- **Stock Markets:** Candlestick patterns are widely used due to the relative consistency of trading patterns and volume, which often validate the predictive nature of these formations(Gerber, 2016).
- **Forex Markets:**The continuous operation of forex markets offers numerous opportunities for candlestick pattern analysis, with the high liquidity enhancing the reliability of the patterns (Ho, Chan, Pan, & Li, 2021).
- **Cryptocurrencies:** The digital and volatile nature of these markets makes technical analysis especially relevant. Techniques like machine learning and high-dimensional data analysis have been applied to predict price movements effectively in these markets (Saraswathi et al., 2022).

2.1.3 Critiques and Rebuttals

Despite widespread use, technical trading faces criticism, particularly from proponents of the Efficient Market Hypothesis (EMH), which asserts that current stock prices reflect all available information. Critics argue that relying on historical data is fundamentally flawed because past market performance does not necessarily predict future outcomes. However, advancements in computational finance have addressed many of these criticisms. For example, the integration of artificial intelligence and machine learning has introduced a level of objectivity and precision previously unattainable (Hudson & Urquhart, 2022).

2.1.4 Conclusion

Technical trading has proven to be a robust analytical framework capable of adapting to the complexities of modern financial markets. The ongoing development of computational tools and techniques ensures that technical analysis remains relevant, providing traders with valuable insights and a competitive edge in both traditional and emerging markets.

2.2 Candlestick Patterns

Candlestick patterns, pivotal in technical analysis, originate from ancient Japanese commodity trading and are now integral in financial markets worldwide. These patterns, formed from the open, high, low, and close prices of financial assets, provide a visual framework for traders to interpret market sentiment and anticipate future movements. Their extensive application across various markets—including stocks, forex, and cryptocurrencies—highlights their significance in financial strategies(Mamilla, 2019).

2.2.1 The Role of Candlestick Patterns

The importance of candlestick patterns lies in their ability to succinctly capture the market dynamics within a given time frame, providing traders with actionable insights. These patterns can signal everything from continuation in the current trend to imminent reversals, making them indispensable in crafting trading strategies. For example, a ”bullish engulfing” pattern suggests a potential upward movement, while a ”bearish engulfing” pattern may indicate an impending decline, offering traders clues about forthcoming opportunities or risks(Mamilla, 2019).

The effectiveness of candlestick patterns has been validated through several studies(Mamilla, 2019; Kumar & Gupta, 2023), confirming their predictive value across diverse asset classes. In the volatile cryptocurrency market, patterns such as Bullish Engulfing and Bearish Engulfing have been particularly noted for providing reliable signals that precede market movements(Mamilla, 2019).

2.2.2 Critiques and Modern Approaches

Despite their widespread use, candlestick patterns face criticism primarily for their subjective interpretation and the potential for misjudging market signals. Critics argue that historical patterns may not reliably predict future movements, especially in markets influenced by unpredictable external factors(Mamilla, 2019). However, the advent of machine learning and advanced computational methods has begun to address these criticisms by enhancing the objectivity and reliability of pattern recognition. This shift is exemplified by the integration of deep learning networks with candlestick analysis, which improves predictive accuracy beyond traditional methods(Pedrozo et al., 2020).

2.2.3 Conclusion

Candlestick patterns continue to be a fundamental aspect of technical analysis in financial markets, offering insights into market dynamics and potential future directions. The ongoing development of analytical technologies, particularly the integration of genetic algorithms and machine learning, has significantly enhanced the predictive capabilities and utility of candlestick patterns. These advancements not only uphold the historical relevance of candlestick formations but also empower their more effective application in modern trading environments, especially in the rapidly evolving cryptocurrency markets.

2.3 RSI in Market Prediction

One aspect of technical analysis involves the use of technical indicators. Although there are numerous technical indicators available, I have chosen to focus on the Relative Strength Index (RSI) in this review. RSI is widely recognized as one of the most famous and effective technical indicators. I believe that rather than briefly covering many indicators, it is more beneficial to provide a detailed explanation of RSI, which will play a central role in my strategy (Indah & Mahyuni, 2022).

2.3.1 Introduction of RSI

According to Investopedia, RSI is a fundamental tool in technical analysis used to gauge the velocity and magnitude of price movements. By oscillating between zero and 100, RSI identifies overbought or oversold conditions within the market. This analysis is pivotal for traders to discern potential market reversals at thresholds typically set at 70 (overbought) and 30 (oversold). This paper aims to extend the application of RSI by combining it with genetic algorithms and candlestick patterns to forecast cryptocurrency prices, an area marked by high volatility and speculative trading.

2.3.2 Effectiveness of technical trading

RSI is well-known that this indicator performs better when used in conjunction with other indicators rather than on its own. The integration of RSI with other technical indicators or advanced computational methods, such as William %R and LSTM networks, highlights its critical role in technical trading. This combination is particularly important because it enhances the robustness and accuracy of trading signals, which is essential for making informed trading decisions.

For instance, the study by Revo Gilang Firdaus (2021) on Indonesian construction stocks demonstrated the effectiveness of combining RSI with William %R to improve trading signals within specific sectors. This approach's success in a particular sector underlines the adaptability and potential of RSI to be tailored for distinct market conditions. However, its application in sectors like cryptocurrencies, which are known for their high volatility and distinct market dynamics, may require further adaptations. These adaptations are necessary to address the rapid and unpredictable price changes typical of these markets, which differ significantly from more stable sectors like construction stocks.

Moreover, recent studies such as those by Sheetal Phatangare et al. (2023) and Phumudzo Lloyd Seabe et al. (2023) emphasize the integration of RSI with advanced neural network architectures like LSTM, GRU, and Bi-Directional LSTM in forecasting. In conventional stock markets, combining RSI with LSTM networks has shown potential in enhancing forecast accuracy by leveraging historical data to anticipate future price movements. This is particularly valuable because it provides traders with a predictive tool that can adapt to patterns observed in historical data, allowing for more strategic decision-making based on anticipated market movements.

In the volatile realm of cryptocurrencies, the use of RSI alongside such sophisticated neural networks is beneficial for tracking rapid market shifts. This application reflects an innovative approach to handling the intrinsic volatility and unpredictability of cryptocurrency markets. However, the heavy reliance on historical data also poses challenges, such as the potential for model overfitting or underestimating sudden market changes. These issues underscore the importance of continuously refining these models to enhance their predictive power and reliability, ensuring they remain effective in diverse and rapidly changing market conditions.

2.3.3 Challenges and Future Directions

While RSI's robustness is well-documented, its application in cryptocurrency forecasting faces challenges, especially under the unique conditions induced by sudden market movements or global crises(S. Baker et al., 2020). Future research could explore the dynamic recalibration of RSI thresholds or the integration of real-time analytics to enhance responsiveness to market changes. Additionally, combining RSI with candlestick patterns through genetic algorithms could lead to developing more nuanced and adaptive trading strategies.

2.3.4 Conclusion

The application of RSI, when enhanced by genetic algorithms and combined with candlestick patterns, holds significant potential for predicting cryptocurrency prices. This research aims to extend the utility of RSI in high-volatility environments. As financial markets continue to evolve, the adaptation and refinement of traditional indicators like RSI will be crucial for developing sophisticated, effective trading strategies that can withstand both everyday market fluctuations and exceptional economic events.

2.4 Genetic Algorithms in Financial Trading

Introduction

Genetic algorithms (GAs), inspired by natural selection and genetic processes, have become vital tools in the complex domain of financial trading. Known for their robust ability to handle large search spaces and tackle non-linear problems, GAs iterate and evolve populations of solutions through processes such as crossover and mutation, targeting the most effective trading strategies.

2.4.1 Historical Development and Applications

Initially outlined for straightforward optimisation tasks, the versatility of GAs has expanded to more complex applications. Sourabh Katoch and colleagues (2020) highlighted this adaptability across various systems, including big data challenges. Chiho Kim et al. (2021) demonstrated how GAs could optimise parameters in different fields like polymer design, suggesting their applicability in financial models.

2.4.2 Genetic Algorithms in Financial Markets

A seminal foundational work was carried out by Allen, Franklin, and Risto Karjalainen (1999), who optimised trading rules for the S&P 500 using GAs. Although their results were mixed, it was evident that GAs were able to detect trading opportunities that were profitable under some market conditions. Using genetic algorithms for optimisation of the trading rules has been said to enhance the capability of trading systems by automating the generation and testing of highly intricate trading rules. These rules become of essence in the optimisation and search for parameters for the technical trading strategies; it fuses well-established technical indicators with candlestick patterns in an adaptive, robust algorithm for the creation of trading rules.

The integration represents an approach to the inherent volatility and varied conditions in the market with an aim to maximise the returns(Kapoor & Dey, 2011; Tamilchelvi, 2015).

One of the main benefits that have been associated with the use of genetic algorithms is that it is able to search on the structure and the parameters of trading rules simultaneously. This striking shift in methodology from the traditional approach mostly concerns the setting of pre-defined rules with pre-set parameters. It would see to it that the strategies that would be put under selection will have been developed with the help of the empirical evidence drawn from a wide range of combinations of rules in the past; hence, the strategies are more likely to yield positive results(Loh et al., 2022; Fernández, 2019).

There is also considerable literature on the use of genetic algorithms in financial trading with the aim of minimizing risks and maximising returns. The automation that comes with the formulation of trading rules from such algorithms is likely to eliminate human bias and rely more on objective market analysis that is mostly driven by data. For this to be achieved, the rules have to be evaluated under very strict performance measures for a designated training period, followed by a validation phase guaranteeing efficiency on real-market conditions.

Such dynamic functions, under the context of this research, underscore the relevance of genetic algorithms in modern financial markets, which not only assist in seeking profitable trade opportunities but also allow for the development of trade environments with more stability and less erratic behaviour. Further, integrating genetic algorithms within technical indicators and candlestick patterns is an area of wonderful integration, rich in the potential interest it creates, since it results in an extremely sophisticated framework that can conceive trading strategies innovatively and adapt to the dynamic changes in the market(Lee & Sabbaghi, 2019).

2.4.3 Integration with Machine Learning

GAs have been crucial in enhancing machine learning models for market prediction. Research by Ghadeer Saleh and Thushantha Sanju leveraged GAs to fine-tune models like Lasso Regression and XGBOOST, essential for achieving predictive accuracy in fluctuating markets such as cryptocurrencies.Saleh, G., Arabiat, L., & Al-badarneh, A. (2023).This paper focuses on using machine learning models to predict cryptocurrency prices, providing valuable insights for research combining genetic algorithms with technical indicators and candlestick patterns. It compares models like Xgboost, LightGBM, and Bayesian Neural Networks, emphasising the impact of feature engineering on machine learning predictions. Using genetic algorithms to identify optimal combinations of technical indicators and parameters could enhance the accuracy and efficiency of market prediction models, making the insights from this paper beneficial for developing more precise and effective market forecasting tools.

2.4.4 Future Trends in Genetic Algorithms

As computational power and data availability grow, the synergy of GAs with modern machine learning and data analysis techniques is expected to boost their effectiveness significantly. This evolution will likely make GAs indispensable in developing adaptive, efficient, and personalised trading strategies that can navigate the complexities of the global financial markets.*

2.4.5 Significant Contributions and Case Studies

Innovative applications of GAs, such as those by Myoung Hoon Ha, Sangyeop Lee, and Byung-Ro Moon (2016), have pushed beyond traditional pattern recognition methods to uncover complex and profitable chart patterns. Hyejung Chung and Kyung-shik Shin (2018) have shown how GAs can enhance the performance of LSTM models for stock market prediction, affirming the value of GAs in refining financial technologies.

2.4.6 Overcoming Challenges

Despite their potential, GAs face challenges like high computational demands and the risk of overfitting, where models excel on historical data but perform poorly on unseen data. Implementing cross-validation techniques is essential to ensure the robustness and applicability of the developed trading strategies in real-world scenarios.Addressing the computational intensity and overfitting risks is crucial for maximising the efficiency of GAs. Robust model validation and continuous improvements are necessary to extend their use across more varied financial contexts.

2.4.7 Conclusion

Genetic algorithms have emerged as transformative tools in the realm of financial trading strategy optimisation. Their ability to iteratively evolve solutions makes them particularly well-suited to the dynamic and complex nature of financial markets. With the ongoing integration of GAs with advanced machine learning techniques, there is substantial potential for revolutionising financial trading strategies.

2.5 Conclusion

Several previous studies have supported the advantages of combining these methodologies. For example, one study into the optimisation of technical indicators with GAs has found that a far more accurate and profitable trading strategy could be obtained. In addition, practical examples prove that machine learning models such as LSTM with RSI and candlestick data were useful in recognising complex patterns within the highly volatile crypto market(Phatangare, 2023).

In this study, it combines the synergistic effect of Genetic Algorithms (GAs), RSI, and Candlestick Patterns for enhancing the effectiveness of trading strategies in the cryptocurrency marketplace. Genetic algorithms are notoriously powerful in terms of their ability to optimise a vast array of complex systems, while RSI is a very strong tool in checking momentum within the market; also, candlestick patterns offer great details in visual terms of showing market sentiment and the possibility of reversals.

Most existing literature in the domain of trading strategies is based on traditional stock markets. Very limited research has been conducted in terms of studies on cryptocurrency trading. In this regard, the novel approach not only takes care of the intrinsic volatilities and unpredictabilities of the markets but further tries to take advantage of the peculiar dynamics of the markets to develop very effective trading strategies. In this sense, the research stands clearly distinguished from past works that have focused on combining advanced technical indicators and genetic algorithms towards cryptocurrencies.

Chapter 3

Methodology

This section describes the methodologies underpinning the indicators and candlestick patterns, as well as the datasets, parameters, and evaluation methods.

Methodology Overview

The methodology consists of these two phases: testing and validation. Following this, we utilise genetic algorithms to identify the optimal parameters and strategy combinations for each dataset. Once these parameters are optimised, we proceed to test them on a different dataset to evaluate their performance, specifically examining profitability and the Sharpe ratio to confirm the effectiveness of the optimised parameters. Finally, we implement the hold strategy on the test or out-of-sample dataset to further assess its robustness in realistic market conditions.

3.1 Genetic Algorithm

Genetic Algorithms are utilised not only to deduce the optimal parameters for technical indicators, which serve as features within the dataset, but also to identify the most effective combinations of these strategies. This dual approach involves adjusting individual indicator settings to maximise predictive accuracy and profitability, while simultaneously experimenting with various strategic combinations to determine the optimal synergy among them. This method ensures a comprehensive optimisation that enhances both individual and collective strategy performance.

3.1.1 Concept of GA

Genetic algorithms operate over a population of putative solutions and apply the principle of survival of the fittest in order to produce generations of increasingly better approximations to a solution. At every generation these algorithms select a few individuals from the current population that are the fittest in terms of the problem space and breed them using operators borrowed from natural genetics to create a new set of approximations. This leads to the evolution of populations of individuals more adapted to the environment than the individuals from which they are created, thus solving the problem.

3.1.2 Algorithm Phases

The GA methodology advances through defined stages

Initialisation

At the Initialisation of the algorithm in creating a population of individuals, there exist strings, most of them being chromosomes, whereby each string is a possible solution to a problem. These strings are normally binary but may also represent another form of encoding, according to problem details.

Fitness assessment

The fitness function is applied for every individual within the population. It is a measure of how good the individual solves the problem and its fitness or suitability in the environment. Better solutions are represented by a bigger value of fitness.

Selection

The selection of the fittest individuals that will form offspring. Most often implemented using a roulette-wheel selection, in which the probability of selection is determined by fitness, but also may be implemented through tournament selection, in which the best individual from a randomly chosen subset of the population is selected, or rank-based selection.

Crossover

Some individuals are paired and crossover is applied to get offspring. Crossover is a genetic operator used to recombine the genetic information of two parents to generate new offspring. It is similar to reproduction and biological crossover.

Mutation

After crossover, mutation may occur. It is this step that introduces variability in the offspring chromosomes. It usually flips some bits in binary encoding or introduces small changes in other encoding schemes.

Replacement

The new offspring generated will replace some or all of the older population. Though there are many ways to do this, in general there are two sorts of replacement strategies: removing the worst-performing individuals and more sophisticated methods, like the use of elitism, which preserves the best individuals.

Termination

This selection, recombination, and replacement process iterates until one of the stopping criteria is met. Stopping criteria may be a maximum number of generations, the achievement of some acceptable level of fitness, or criteria of a more problem-specific nature.

3.2 Technical Indicators

The RSI and the Williams %R are a type of momentum indicators which try to capture the rate of change, which is typically used to show the rate of change in prices. Typically, the momentum indicators give us a sense of direction for where the price is heading. We used each indicator on its own as baseline models. Each indicator outputs a signal based on a given rule and then we act upon that signal by taking a trading position. Furthermore, we also combined and tested all indicators together as a single strategy.

RSI

The Relative Strength Index (RSI) is a well-known momentum indicator in the field of technical analysis that compares the magnitude of recent gains to recent losses to determine overbought and oversold conditions in the price of an asset. It is particularly useful for identifying whether the current market condition is overbought, suggesting a potential decline, or oversold, suggesting a potential rise. Typically, an RSI above 70 is considered overbought, whereas an RSI below 30 is considered oversold.

Calculation of RSI The formula for RSI is:

$$\mathrm{RSI} = \frac{\mathrm{RS}}{1+\mathrm{RS}} \times 100 = \frac{A_U}{A_U + A_D} \times 100$$
$$\mathrm{RS} = \frac{A_U}{A_D}$$
$$A_U = \text{Average gain over N periods}$$
$$A_D = \text{Average loss over N periods}$$

1. Calculate U and D for each period.

$$U = \max(\text{Current close} - \text{Previous close}, 0)$$
$$D = \max(\text{Previous close} - \text{Current close}, 0)$$

2. Calculate the average of U and D over N periods to find A_U and A_D.

$$A_U = \frac{U_1 + U_2 + \ldots + U_N}{N} = \mathrm{SMA}(U, N)$$
$$A_D = \frac{D_1 + D_2 + \ldots + D_N}{N} = \mathrm{SMA}(D, N)$$

Note: SMA stands for Simple Moving Average.

Calculation of U and D: U (Up) represents the average of the gains over a specific period, while D (Down) represents the average of the losses over the same period. The exponential moving averages of U and D are computed to determine AU (Average Up) and AD (Average Down). Initially, AU and AD are calculated using the simple moving average of U and D over the first N days. N typically defaults to 14 days.

Interpretation and Analysis

Interpretation The RSI provides a measure of the strength of price momentum by comparing the relative extent of recent gains to losses. A higher RSI, close to 100, suggests that the market has experienced almost exclusively gains over the selected period, indicating strong upward momentum. Conversely, an RSI close to 0 suggests strong downward momentum.

Overbought/Oversold Conditions Overbought: An RSI level above 70 suggests that the asset is overbought, and a reversal might be imminent as traders potentially look to capture profits from the recent price increase. Oversold: An RSI level below 30 suggests that the asset is oversold, and a reversal to the upside might soon occur. RSI thresholds can be adapted based on market conditions and investment objectives, but the typical boundaries are set at 70 for overbought and 30 for oversold, as originally defined by J. Welles Wilder, the creator of the RSI. Overbought/Oversold Conditions

Limitations While RSI is excellent for identifying potential peaks and troughs in market prices, it can be misleading during strong trending periods. For instance, in a strong uptrend, the RSI can remain in the overbought territory for an extended period, continually suggesting a reversal that does not occur as the upward momentum persists.

Strategic Use in Trading RSI can be an effective tool when used in conjunction with other indicators and analysis techniques. It should not be used in isolation due to its sensitivity to sudden price movements and its potential to give false signals during continuous strong trends or sideways markets. Adjusting the RSI sensitivity and combining it with other technical, fundamental, or sentiment analysis tools can enhance its reliability and effectiveness in market prediction.

In conclusion, the RSI is a versatile tool that, when used correctly and with other market analysis techniques, can provide valuable insights into market conditions and help traders make informed decisions based on underlying price momentum trends.

Williams %R

The Williams %R, also known as the Williams Percent Range, is a type of momentum indicator in the field of technical analysis. It oscillates between 0 and -100, providing insights into the overbought or oversold conditions of an asset by calculating how close the current close is to the high and low range over a specified period.

Calculation Method The formula for the Williams %R is:

$$\%R = \frac{H_N - C}{H_N - L_N} \times (-100)$$

where:

$$C = \text{Current close}$$

$$H_N = \text{Highest high over N periods}$$

$$L_N = \text{Lowest low over N periods}$$

Interpretation he closer the Williams %R value is to -100, the stronger the selling pressure, and conversely, the closer to 0, the stronger the buying pressure.

Similar to the Stochastic Fast indicator, the Williams %R measures where the closing price is in relation to the high-low range over a recent period. A value near 0 indicates that the closing price is near the high of the range, and if the price is at a new high, the Williams %R value will be 0. Williams considered a value between 0 and -20 as indicating an overbought market condition.

On the flip side, a value near -100 indicates that the closing price is near the low of the range. If the price is at a new low, the Williams %R value will be -100. Williams considered a value between -80 and -100 as indicating an oversold market condition.

Limitations Due to its sensitivity, the indicator can frequently generate false signals. For example, even if the Williams %R value falls below -80, suggesting an oversold condition, the price may continue to decline instead of rebounding. Therefore, caution should be exercised when interpreting signals from the Williams %R due to its high sensitivity to price movements. It's recommended to use this indicator in conjunction with other analysis tools to confirm trading signals and avoid potential false positives.

3.2.1 Candlestick Patterns

Hammer Candlestick Patterns

The Hammer candlestick pattern is identified by the following conditions:

1. The lower shadow is at least twice the length of the body:

   $L \geq 2B$

2. There is little or no upper shadow:

   $U \approx 0$

where:

- $B = |\text{Open} - \text{Close}|$ represents the absolute value of the body.
- $L = \text{Low} - \min(\text{Open}, \text{Close})$ is the length of the lower shadow.
- $U = \max(\text{Open}, \text{Close}) - \text{High}$ is the length of the upper shadow.

The Hammer pattern typically appears during a downtrend and suggests a potential reversal or support level. The small or absent upper shadow and the long lower shadow indicate that selling pressure was initially strong but subsequently overpowered by buying pressure by the end of the period.

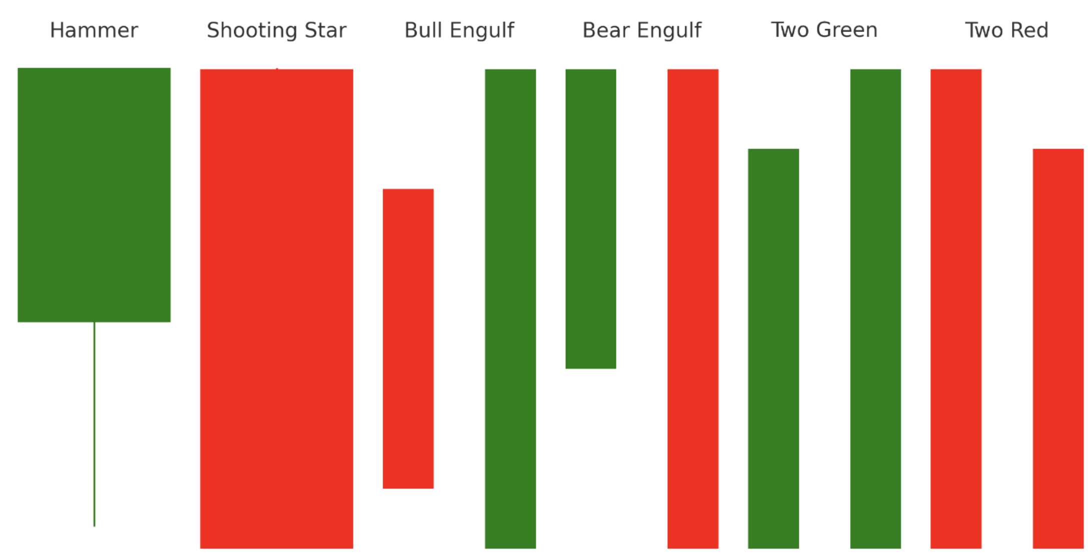

Figure 3.1: Six candle patterns

Shooting Star Candlestick Pattern

The Shooting Star candlestick pattern is identified by the following conditions:

1.The upper shadow is at least twice the length of the body:

$U \geq 2B$

2.There is little or no lower shadow:

$L \approx 0$

where:

- $B = |\text{Open} - \text{Close}|$ represents the absolute value of the body.
- $U = \text{High} - \max(\text{Open}, \text{Close})$ is the length of the upper shadow.
- $L = \min(\text{Open}, \text{Close}) - \text{Low}$ is the length of the lower shadow.

The Shooting Star pattern typically appears during an uptrend and suggests a potential reversal or resistance level. The long upper shadow and the small or absent lower shadow indicate that buying pressure was initially strong but subsequently overcome by selling pressure by the end of the period.

Bullish Engulfing Candlestick Pattern

The Bullish Engulfing candlestick pattern is identified by the following conditions:

1.The first candle is a small black body that indicates a decline:

$\text{Open}_1 > \text{Close}_1$

2.The second candle is a large white body that completely engulfs the body of the first candle:

$\text{Open}_2 < \text{Close}_1 \quad \text{and} \quad \text{Close}_2 > \text{Open}_1$

where:

- $\text{Open}_1, \text{Close}_1$ represent the opening and closing prices of the first candle, respectively.
- $\text{Open}_2, \text{Close}_2$ represent the opening and closing prices of the second candle, respectively.

The Bullish Engulfing pattern typically appears during a downtrend and suggests a potential reversal or upward momentum. The pattern indicates strong buying pressure that overcomes prior selling pressure.

Bearish Engulfing Candlestick Pattern

The Bearish Engulfing candlestick pattern is identified by the following conditions:

1.The first candle is a small white body that indicates an advance:

$\text{Open}_1 < \text{Close}_1$

2.The second candle is a large black body that completely engulfs the body of the first candle:

$\text{Open}_2 > \text{Close}_1 \quad \text{and} \quad \text{Close}_2 < \text{Open}_1$

where:

- $\text{Open}_1, \text{Close}_1$ represent the opening and closing prices of the first candle, respectively.
- $\text{Open}_2, \text{Close}_2$ represent the opening and closing prices of the second candle, respectively.

The Bearish Engulfing pattern typically appears during an uptrend and suggests a potential reversal or downward momentum. The pattern indicates strong selling pressure that overcomes prior buying pressure.

Consecutive Two Green Bars

The pattern of consecutive two green bars is identified by the following conditions for two consecutive candles:

1.The first candle is green, indicating a price increase:

$\text{Close}_1 > \text{Open}_1$

2.The second candle is also green, indicating a further price increase:

$\text{Close}_2 > \text{Open}_2$

3.The second candle opens at or above the closing price of the first candle:

$\text{Open}_2 \geq \text{Close}_1$

where:

- $\text{Open}_1, \text{Close}_1$ represent the opening and closing prices of the first candle, respectively.
- $\text{Open}_2, \text{Close}_2$ represent the opening and closing prices of the second candle, respectively.

This pattern typically indicates continuing buyer dominance and is a bullish signal, especially when occurring in a downtrend as it may suggest a potential reversal.

Consecutive Two Red Bars

The pattern of consecutive two red bars is identified by the following conditions for two consecutive candles:

1. The first candle is red, indicating a price decrease:

   $\text{Close}_1 < \text{Open}_1$

2. The second candle is also red, indicating a further price decrease:

   $\text{Close}_2 < \text{Open}_2$

3. The second candle opens at or below the closing price of the first candle:

   $\text{Open}_2 \leq \text{Close}_1$

where:

- $\text{Open}_1, \text{Close}_1$ represent the opening and closing prices of the first candle, respectively.
- $\text{Open}_2, \text{Close}_2$ represent the opening and closing prices of the second candle, respectively.

This pattern typically indicates continuing seller dominance and is a bearish signal, especially when occurring in an uptrend as it may suggest a potential reversal to a downtrend.

3.3 Data processing

The cornerstone of any robust algorithmic trading framework is high-quality data. To ensure this, we have implemented a meticulous pre-processing protocol through a Python script named ‘prepare.py‘. This script is crucial for transforming raw market data into a structured CSV file that is more conducive to analysis and trading algorithm deployment.

Data Preparation Details:

Time Conversion

The script converts the timestamp of each data entry to a Unix-style format, represented in milliseconds, to maintain precision and consistency.

3.3.1 Market Data

Each entry in the prepared dataset, referred to as ‘all-feature-data‘, inherently includes the basic market attributes: Open, High, Low, Close, and Volume.

- **Open:** The price at the start of the candlestick, indicating the first trading price of the period.
- **High:** The highest price reached during the candlestick's formation.
- **Low:** The lowest price during the time period.
- **Volume:** The total quantity of the asset traded during the candlestick's formation.

date	Open	High	Low	Close	volume
1400506200000	1876.66	1886.0	1872.42	1885.08	2664250000
1400592600000	1884.88	1884.88	1868.14	1872.83	3007700000
1400679000000	1873.34	1888.8	1873.34	1888.03	2777140000
1400765400000	1888.19	1896.33	1885.39	1892.49	2759800000
1400851800000	1893.32	1901.26	1893.32	1900.53	2396280000
1401197400000	1902.01	1912.28	1902.01	1911.91	2911020000
1401283800000	1911.77	1914.46	1907.3	1909.78	2976450000

Figure 3.2: Example of dataset in CSV format

3.3.2 Feature

While the 'prepare.py' script sets up the foundational data structure, it is also designed to accommodate the addition of various technical indicators as features if needed, such as RSI values or Williams %R.

However, instead of statically embedding features like RSI or Williams %R into the dataset, we opt to calculate these indicators on-the-fly during each iteration of the genetic algorithm. This approach allows the GA to modify the parameters of these indicators dynamically, tailoring them to maximise trading strategy efficacy.

By not pre-embedding these features into the data, the framework retains the flexibility to adjust indicator parameters dynamically based on the genetic algorithm's evolving solutions. This method ensures that the trading strategies are always optimised based on the most current and algorithmically refined settings, leading to potentially higher accuracy and profitability in trading outcomes.

3.4 Fitness Evaluation

The Sharpe Ratio

The Sharpe ratio, introduced by economist William F. Sharpe in 1966, is a financial metric used to measure the performance of an investment relative to a risk-free asset, adjusted for its risk. The formula for the Sharpe ratio is given by:

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}$$

where:

- R_p is the return of the portfolio,
- R_f is the risk-free rate,
- σ_p is the standard deviation of the portfolio's excess return.

Key Takeaways

- **Risk-Adjusted Performance:** It measures how much excess return is received for the extra volatility endured when holding a riskier asset.
- **Excess Returns:** These are the returns an investment earns over the risk-free rate.
- **Use Cases:** It is commonly used to evaluate stocks, mutual funds, and hedge funds.
- **Evaluation Metric:** It assesses both historical performance and forecasts future performance using expected returns and volatility.

Calculation Process

1. Compute the excess returns over the risk-free rate for the time period under consideration.
2. Determine the volatility by calculating the standard deviation of the excess returns.
3. Calculate the Sharpe ratio by dividing the excess returns by the volatility:

$$\text{Sharpe Ratio} = \frac{\text{Average Excess Returns}}{\text{Volatility}}$$

Utility and Limitations

- **Predictive Value:** Provides a snapshot of how returns have compared to the risks taken, though historical data may not guarantee future performance.
- **Limitations:** Assumes returns are normally distributed, which can be misleading for assets with non-normal distributions.

Practical Example

Consider a portfolio with:

- an average annual return of 15%,
- a risk-free rate of 3%,
- a standard deviation of returns at 10%.

The Sharpe ratio would be calculated as:

$$\text{Sharpe Ratio} = \frac{0.15 - 0.03}{0.10} = 1.2$$

This indicates that the investment returns 1.2 units of excess return per unit of risk, which is considered relatively favourable.

Chapter 4

Implementation

Our trading simulation supports strategies for both long and short positions. A long position is taking a purchase position on a financial asset, say stocks or commodities, and expecting the prices to rise, being able to sell at an increased price and make profit. On the other hand, a short position borrows and sells assets at their current market value with the expectation of repurchasing them at a future date at a price lower than the one that the sale was conducted at, to profit from the difference in value.

4.1 Position

$$P = \begin{cases} 1 & \text{if it anticipates an upward movement} \\ -1 & \text{if it anticipates a downward movement} \\ 0 & \text{if it decides to hold or sit} \end{cases}$$

Long trades are predicated on upward price movement, while short trades—those that bet on downward price movement—by nature are seen to be riskier and can have unlimited losses in the event that the price movement takes a different direction contrary to the trader's expectations. There is also an option to remain indifferent, known as a hold or sit, meaning there is no commitment of trading actions at that moment. We define the long position as the number 1, the short position as -1, and the neutral hold/sit position as 0 in this paper.

4.2 Transaction Cost

For each trade, we apply a transaction cost of 0.05%, to make the trading environment more realistic and avoid the possible overfit of the trading algorithm. Overfitting happens when the model becomes too complex and explains the noise in the data set rather than capturing the underlying pattern. In the absence of transaction costs, one is too easily led to overtrade. The algorithm would exploit minor fluctuations, which in the real world would be counteracted by the fees on the trades themselves. In actual trading, however, one faces such costs, which inherently bounds the profitable trades possible.

We do this because our 0.05% fee is based on real trading fees of the Upbit exchange, and, as such, our simulation is updated and reflects actual current market conditions as of 1 April 2024. This is relevant to keep the test for the trading strategies consistent and thus a consistent test, making the simulation honest.

The simulation of trading, in its process, is uniform and develops in three major steps.

4.3 Trading Simulator Procedure

The trading simulator is designed to rigorously evaluate various trading strategies under conditions that closely resemble actual market scenarios. For our simulations, we use backtesting.py. The process consists of the following sequential steps:

4.3.1 Feature Generation

- We begin by generating predictive indicators from historical market data, a process called Feature Generation. This utilises technical analysis tools such as the Relative Strength Index (RSI) and Williams %R to identify patterns that could predict future market movements.

4.3.2 Position Determination

- Next is Position Determination. Based on the generated indicators, the simulator decides the trading position to take: long (+1), short (-1), or neutral (0). This decision is driven by a set of algorithmic rules that convert data insights into actionable trading signals.

4.3.3 Signal Processing and Execution

- The third step is Signal Processing and Execution. Once a trading decision is reached, the simulator executes the trade according to the strategy's guidelines. It manages trade entries and exits to align with the signals while ensuring no contradictory trades are made.

4.3.4 Transaction Cost Application

- Following this, we apply a Transaction Cost. To simulate a real trading environment, the simulator deducts a fixed transaction fee of 0.05% from each trade, mirroring the costs typically encountered on a trading platform. By the sharpe ratio, the next generation is computed in a genetic algorithm.

4.3.5 Profit and Loss Calculation

- Performance Evaluation is then conducted. The simulator assesses the strategy's effectiveness after accounting for transaction costs. It calculates the net profit or loss for each trade by considering both the price changes and the fees, accumulating these results over the entire simulation period.

```
Start                     2023-11-08 20:30:00
End                       2024-04-19 20:00:00
Duration                    162 days 23:30:00
Exposure Time [%]                   67.870968
Equity Final [$]                19980798.1422
Equity Peak [$]                 19981094.2422
Return [%]                           0.000967
Buy & Hold Return [%]               13.294787
Return (Ann.) [%]                    0.002175
Volatility (Ann.) [%]                0.002391
Sharpe Ratio                         0.909782
Sortino Ratio                        1.382254
Calmar Ratio                         1.451126
Max. Drawdown [%]                   -0.001499
Avg. Drawdown [%]                   -0.000162
Max. Drawdown Duration       22 days 01:00:00
Avg. Drawdown Duration        2 days 19:09:00
# Trades                                    1
Win Rate [%]                            100.0
Best Trade [%]                        4.04567
Worst Trade [%]                       4.04567
Avg. Trade [%]                        4.04567
Max. Trade Duration         107 days 23:30:00
Avg. Trade Duration         107 days 23:30:00
Profit Factor                             NaN
Expectancy [%]                        4.04567
SQN                                       NaN
_strategy                 JMstrategy(input...
_equity_curve                             ...
_trades                        Size  EntryBa...
dtype: object
```

Figure 4.1: Enter Caption

4.4 Example, Encoding, Combination

BTC/USDT 120 mins Strategy Performance	
Component	**Details**
Encoding	[14, 77, 38, 0.7539, 20, -10, -75, 1, 0, 0, 1, 1, 0, 0, 1]
Rule	Hammer & Bear Engulf & Two Green & Simple Will
Sharpe Ratio	4.9886

Figure 4.2: Enter Caption

The parameters in the list represent the following values respectively:

1. RSI Length: 14 days
2. RSI Overbought Threshold: 77
3. RSI Oversold Threshold: 38
4. Fibonacci Level: 0.7539
5. Williams %R Length: 20 days
6. Williams %R Overbought: -10
7. Williams %R Oversold: -75
8. Hammer Candlestick Pattern: Present (1)
9. Shooting Star Candlestick Pattern: Not present (0)
10. Shooting Star Candlestick Pattern: Not present (0)
11. Bullish Engulfing Pattern: Present (1)
12. Bearish Engulfing Pattern: Present (1)
13. Two Consecutive Green Candles: Present (1)
14. Two Consecutive Red Candles: Not present (0)
15. RSI Active: Yes (1)
16. Williams %R Active: Yes (1)

From these parameters, it's evident that the trading strategy utilises RSI for identifying overbought and oversold conditions, and incorporates various candlestick patterns such as hammer, bearish engulfing, and consecutive green candles. Additionally, the Williams %R indicator is used, suggesting a comprehensive approach to gauge market sentiment and potential price movements.

4.4.1 Example of Signal Processing with RSI

Setting Thresholds

- Overbought threshold: RSI > 77
- Oversold threshold: RSI < 38

Generating Signals

Long Position Signal: A long position signal is generated when several conditions converge: the RSI crosses below the oversold threshold of 38, suggesting the asset may be undervalued, in conjunction with the appearance of a Hammer candlestick pattern and two consecutive green bars. This combination indicates a strong potential for a price increase, as it represents a reversal from a downward trend to potential upward momentum.

Short Position Signal: A short position signal occurs when the RSI crosses above the overbought threshold of 77, indicating the asset may be overvalued, and this is accompanied by a Bearish Engulfing candlestick pattern. This setup suggests that after a period of price increase, a reversal is likely, where prices could potentially decrease as selling pressure overtakes buying momentum.

Executing Trades

If you are already in a 'short' position when a 'long' signal occurs, you would exit the short position and potentially enter a long position. Conversely, if the current position is not 'short' and an RSI-based 'short' signal is generated, you would take a short position. If you are in a 'long' position and a 'short' signal occurs, you would exit the long position and may enter into a short position. Calculating Profit and Loss: Each trade's profit or loss is calculated by considering the entry and exit points, adjusted for transaction costs. The cumulative profit or loss is tracked across all trades to evaluate the strategy's overall performance. Let's illustrate with an example:

The current RSI reading is 28, which is below the oversold threshold. Your current position is 'short' because you anticipated a price drop. Now, the RSI signals that the asset is oversold, so you decide to exit your 'short' position. When you change positions, the transaction cost of

0.1% is applied. If the asset's price goes up after you take the long position, you will make a profit (minus the transaction costs). Conversely, if the price falls, you'll incur a loss.

Chapter 5

Legal, Social, Ethical and Professional Issues

5.1 Ethical Concerns

The use of genetic algorithms in predicting financial markets, such as cryptocurrency and stock prices, raises significant ethical concerns. The primary concern is the potential for misuse of predictive models. If used irresponsibly, these models could manipulate market prices or advantage certain investors over others, leading to unfair trading practices. Therefore, it is crucial to develop and utilize these algorithms with a commitment to fairness and transparency.

Predictive modeling in financial markets must also consider the impact on economic stability. Rapid, algorithm-driven trades can contribute to market volatility, potentially harming unassuming investors and the broader economic landscape. Ethical considerations must include the welfare of all market participants, ensuring that the technology does not exacerbate economic inequalities.

Another ethical aspect involves data privacy. The models rely on vast amounts of data, some of which may be sensitive. It is essential to handle this data responsibly, ensuring compliance with data protection regulations and respecting the privacy rights of individuals and institutions whose data might be analyzed.

5.2 Professional Issues

Professionally, this project aligns with several best practices and codes of conduct in computational finance and data science. Adhering to these standards is vital to maintain integrity and public trust in the use of algorithms for financial predictions:

- Transparency: Clearly document and disclose the methodologies used in the algorithms to ensure that stakeholders understand how predictions are generated.
- Accountability: Take responsibility for the outcomes of the predictions, including potential errors or mispredictions. Regular audits and updates to the models should be implemented to enhance their accuracy and reliability.
- Fairness: Ensure that the algorithms do not create or perpetuate bias against any group or individual. This includes regular checks for biases in data collection, model training, and outcome interpretation.

By addressing these ethical and professional issues, the project aims to develop a robust predictive tool that enhances understanding and decision-making in financial markets without compromising ethical standards or professional integrity.

Chapter 6

Evaluation

In this chapter, we will discuss the results. First, we will calculate the Sharpe ratio using only one strategy. This is to compare the difference when using optimised parameters obtained through a genetic algorithm, which we will calculate second. The second result we will explore is optimising parameters using a genetic algorithm. We will determine the Sharpe ratio of the optimised parameters, identify the best parameters for each data set, and examine actual trades conducted. We will also compare its effectiveness against a hold strategy. The third aspect will involve applying the optimised parameters to different data sets. By doing so, we can determine if this algorithm can be profitable in real trading and whether it has avoided overfitting.

6.1 Single Strategy

In this study, we initially test each strategy independently using the default parameters for RSI and Williams %R, alongside other indicators. This initial testing serves as a baseline to assess the effectiveness of these strategies in their conventional form. Subsequently, we apply genetic algorithms to optimise these parameters and compare the outcomes. This approach allows us to evaluate whether the use of genetic algorithms can enhance the performance of trading strategies beyond their standard parameter settings. Each strategy is rigorously tested across the dataset which is segmented into distinct subsets specifically designed for this comparative analysis, ensuring a thorough evaluation of both the baseline and optimised strategies.

The results obtained when evaluating the use of single strategies individually on the sample dataset. This involved using only one strategy at a time, for example, using only RSI or only William %R.

BTC/USDT									
Time	**RSI**	**W %R**	**Combined RSI & W %R**	**Hammer**	**Shooting**	**Bull engulf**	**Bear engulf**	**Two Green**	**Two Red**
30 min	-1.3088	-10.984	-2.6155	0.8723	-0.354477	0.86806	-1.3569	0.763702	0.277485
60 min	-2.16222	-7.414976	-4.1868	2.28644	-2.284679	2.47342	-2.138667	2.153512	-2.135091
120 min	-1.97760	-4.2065	-1.98027	2.81897	-2.85828	2.841859	-2.690816	1.898512	-2.8602

Table 6.1: Performance summary for BTC/USDT across various strategies

’Time’ on the table is the unit of time given to the data, with one candle representing a period of thirty minutes. For example, a 4-hour period would have 8 candles of 30 minutes, 4 candles of 60 minutes, and 2 candles of 120 minutes.

The RSI (Relative Strength Index) setting is at the standard length of 14. The value of RSI reaching over 70 signals overbuying, while the value under 30 signals overselling. For example, sending a long signal or even advising on a long position once the RSI drops into the oversold zone.

W%R (Williams Percent Range) is calculated in default settings. The Youden ”Combined RSI & W%” trading rule will be valid when conditions of RSI and W%R both are satisfied at the same time.

Just as the ’Hammer’ strategy, this is also taken in one instance when a hammer pattern is coincident with one of the RSI or W%R conditions. Similarly, the ’Shooting’ strategy is meant for a shooting star pattern with either of the RSI or W%R conditions being met.

$$
\text{position} = \begin{cases} \text{Long}(1), & \text{if (RSI is oversold)} \\ & \text{or (William's \%R is oversold)} \\ & \text{or (Hammer pattern AND (RSI oversold OR William's \%R oversold))} \\ & \text{or (Bull Engulfing pattern AND (RSI oversold OR William's \%R oversold))} \\ & \text{or (Two consecutive green bars AND (RSI oversold OR William's \%R oversold))}, \\ \text{Short}(-1), & \text{if (RSI is overbought)} \\ & \text{or (William's \%R is overbought)} \\ & \text{or (Shooting Star pattern AND (RSI overbought OR William's \%R overbought))} \\ & \text{or (Bear Engulfing pattern AND (RSI overbought OR William's \%R overbought))} \\ & \text{or (Two consecutive red bars AND (RSI overbought OR William's \%R overbought))}, \\ \text{Sit}(0), & \text{otherwise} \end{cases} \tag{6.1}
$$

The definition of trading signals involves

- Long: As with the short, the condition comes in if any of the following is true: RSI or W%R, individual or both combined with the hammer pattern; bull engulfing pattern; or two consecutive green bars, both combined with either RSI or W%R.

- Short: Enter a short position when one of the following conditions is true: RSI or W%R forming a shooting star, bear engulfing pattern, or two consecutive red bars, all combined with the following.

ETH/USDT									
Time	**RSI**	**W %R**	**Combined RSI & W %R**	**Hammer**	**Shooting**	**Bull engulf**	**Bear engulf**	**Two Green**	**Two Red**
30 min	-2.77171	-9.8992	-2.57162	-2.66479	2.54075	-1.3154	2.37011	-1.8440	2.35244
60 min	-0.81693	-8.2360	-3.1874251	1.47589	-1.10138	-1.5464	-1.51850	-0.98872	-1.38628
120 min	-1.5292	-4.887076	-2.04617	-1.19595	-1.49740	-0.31440	-1.20559	0.99732	-1.52928

Table 6.2: Performance summary for ETH/USDT across various strategies

After testing with default parameters(테이블 넘버), an interesting observation was made about Bitcoin. Bitcoin is highly volatile, which can lead to abrupt price fluctuations. This volatility presents both high risks and opportunities within trading strategies. Strategies utilising the RSI and William %R indicators generally showed negative results. Interestingly, strategies integrated with specific market conditions, such as the 'hammer', 'bull', and 'green' scenarios, demonstrated positive outcomes. Given that a Sharpe ratio exceeding 2.0 is typically considered very good, these findings suggest that implementing certain strategies during specific technical patterns or market conditions could potentially lead to better results.

Ethereum, like Bitcoin, exhibits high volatility but can be further influenced by specific development events or platform upgrades. This implies greater unpredictability, suggesting that fundamental analysis becomes more crucial during actual trading. Strategies that solely utilised the RSI and William %R indicators consistently yielded negative results. Overall, default settings did not perform well. Notably, using 30-minute data, strategies that recognised short conditions like the Shooting Star pattern, Bear Engulf pattern, and Two Consecutive Red Bar patterns showed positive outcomes.

The S&P 500 exhibits significantly lower volatility compared to cryptocurrencies, offering a more stable growth expectation. Generally, it achieved values close to zero, suggesting a stark contrast to the volatile nature of cryptocurrencies. Strategies using RSI and William %R indicators alone mostly yielded negative results. However, positive outcomes were observed in strategies combined with 'hammer' and 'bull' conditions, indicating that technical analysis can be effective in traditional markets as well. Considering the Sharpe ratios range from the 1s to the 2s, typically, ratios in the 1s are considered acceptable or good, while those in the 2s are rated as very good.

Cryptocurrencies, due to their high volatility, show that strategies combined with technical patterns or specific conditions can significantly impact performance, particularly when aligned with positive patterns. Traditional stock markets, with their relatively low volatility and stable growth patterns, demonstrate that while technical analysis can be effective under certain conditions, a Buy & Hold strategy is generally more viable. Yet, it was observed that default parameter settings were not profitable.

The success of strategies can vary based on assets, time intervals, market conditions, and more. It is important to note not only the Sharpe ratio but also the time dimension. Traders focusing on 30-minute candles tend to trade more frequently compared to those using 4-hour candles, often trading around 20 times more per week.

This provides insight into the characteristics of each time interval and which strategies might be effective or should be avoided. It was noted that longer candles, like the 120-minute candles showed higher averages. This suggests that longer timeframes may enhance the effectiveness of technical indicators, indicating that they are more suited for capturing larger trends rather than small fluctuations. Therefore, 하나만 사용하는 technical analysis and indicators are likely more suitable for swing trading than day trading.

6.2 Combined Strategies

In this section, the study leverages genetic algorithms to identify optimised parameter values for each dataset. The tables provide detailed insights, including the name of the dataset, gene encoding, the strategic rules applied, and the achieved Sharpe ratios. This data represents the best-performing genes produced by the genetic algorithms for BTC, ETH, and S&P 500, analysed across intervals of 30, 60, and 120 minutes. To mitigate the risk of overfitting, parameters were carefully constrained.

Figures 7.1 through 7.9 illustrate backtesting trades based on the data from Tables 7.4, 7.5, and 7.6.

A key focus of these optimised rules is to assess their performance relative to a standard buy & hold strategy. For the 120-minute candles of BTC and S&P 500, the buy & hold strategy marginally outperformed, achieving returns of 166.76% and 34% respectively, compared to 143.89% and 19.74% with optimised parameters. Nevertheless, the optimised strategies demonstrated superior performance across all other datasets when compared to the hold approach.

In the realm of cryptocurrencies, strategies like the Two Green, Shooting, and Will patterns were predominantly utilised, alongside a range of other pattern strategies. These strategies generally yielded better results with optimised parameters compared to those employing a single, unoptimised strategy. Notably, executing buy/sell decisions when multiple patterns coincide proved to be a stable and profitable strategy. This emphasises that a combination of technical analysis, indicators, and patterns can significantly enhance profit generation.

However, when unrestricted genetic algorithms were used to determine the best genes while maximising the Sharpe ratio, some trades occurred only once or twice. This phenomenon was particularly notable in the S&P 500. Although technical analysis aligns well with cryptocurrencies, it led to a low trading frequency in traditional stock markets, even with restricted parameter ranges. This suggests potential overfitting and indicates that the tested strategies may not be effective universally across different market types.

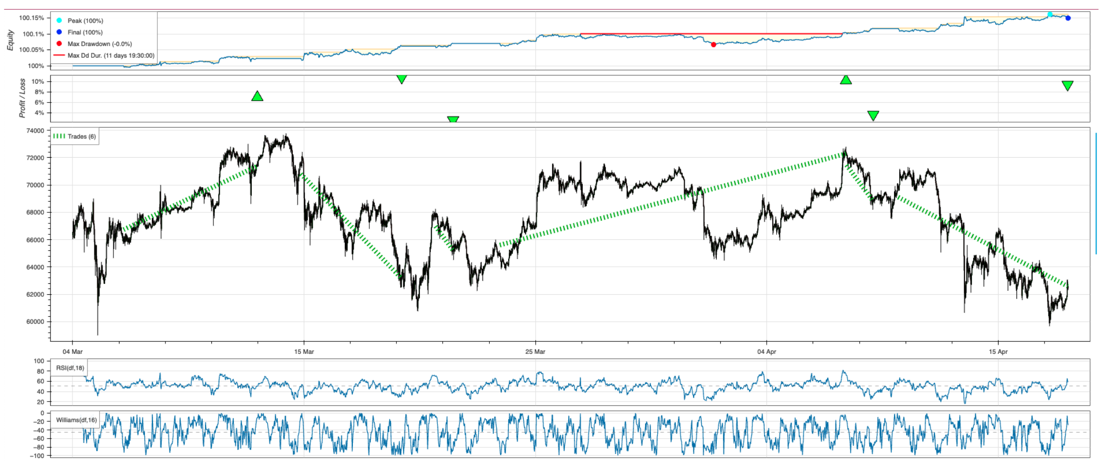

Figure 6.1: BTC/USDT, 30

Understanding the figures: a line indicates a position has been taken; the start of the line represents the entry point, and the end signifies the exit. Red lines denote losing trades, and green lines represent profitable trades. Additionally, RSI indicators and William %R can be seen. Green triangles mark the entry and exit points of trades.

6.3 Application

In this section, the research investigates whether optimised parameter values are applicable and effective across different datasets, with the objective of determining their adaptability and consistency in generating profits. Consider a scenario where a specific parameter set, optimisd for BTC on 60-minute candles dataset, achieves a high Sharpe ratio. However, it's uncertain whether these parameters will consistently translate into actual profits. There is a potential risk of overfitting or the parameters might not perform well with different datasets. Consequently, this section is dedicated to conducting experiments to rigorously test these parameters under various conditions.

Optimised parameter

	120	60	30
BTC	3* 47.962581= 143.887743	6*8.776946 = 52.661676	6*7.233906 = 43.403436
ETH	5*15.142355 = 75.711775	6*9.091629 = 54.549774	8*2.562729 = 20.501832
S&P 500	1*19.741894 = 19.741894	1*19.420461 = 19.420461	2*10.571271 = 21.142542

Buy & HOLD

	120	60	30
BTC	166.760342	49.922407	-6.187017
ETH	69.999721	34.097733	-22.451258
S&P 500	34.022616	17.60344	13.294787

Figure 6.2: The table above shows the returns using optimized parameters, and below are the returns from a buy-and-hold strategy

The findings are summarised as follows:

In the BTC Data, The parameters were effective across all 120-minute intervals and also showed effectiveness in 60-minute candles, except for those specifically optimised for 30 minutes. Only parameters designed for 30-minute intervals were effective at that specific timeframe, indicating that parameters optimised for larger time frames could be applied to smaller ones. Interestingly, these parameters also proved effective in S%P 500 dataset which represents stock markets.

For ETH, parameters for 120-minute candles were effective across all tested intervals. The 60-minute parameters performed well universally, while those for 30-minute intervals showed limited success. This suggests that for cryptocurrencies, using parameters optimised for larger candles might be preferable, as they are broadly applicable.

For the S%P 500, parameters optimised for 120-minute intervals aligned well across similar durations in the stock market. Those for 60-minute intervals were effective across both cryptocurrencies and stocks, particularly those optimised for 120 minutes. A notable observation was that parameters optimised for 30-minute candles in the S&P 500 were effective and even applicable to cryptocurrencies.

Strategically, parameters for 120-minute intervals appear to be robust across various asset classes. Parameters for 60-minute candles can be effectively applied to 120-minute intervals but are generally less suitable for smaller intervals in cryptocurrencies. Utilising S&P 500's 30-minute parameters, which are broadly applicable to both stocks and cryptocurrencies, emerges as an optimal strategy for versatile application across asset classes and timeframes.

For cryptocurrencies such as BTC and ETH, the optimised parameters show distinct advantages. In BTC, the 120-minute and 60-minute optimised parameters consistently performed well, surpassing basic holding strategies in most scenarios except when directly compared to hold returns over similar intervals. For ETH, the effectiveness is even more pronounced, with both 120-minute and 60-minute parameters demonstrating adaptability and robust profit generation across all tested intervals. The 30-minute parameters, however, did not show much success, underscoring the importance of choosing the right time frame for optimisation in volatile markets like cryptocurrencies.

Optimal usage of these parameters suggests that for holding strategies, particularly in 120-minute intervals, simply holding might yield profits comparable to using optimised parameters, presenting a less risky alternative. Conversely, for 60 and 30-minute candles, employing unoptimised parameters substantially increases risk, which underscores the benefits of using tested and optimised parameters. The best practise involves combining multiple signals using S&P's 30-minute, and 60-minute parameters alongside 120-minute strategies to maximise potential returns.

The results in stock markets, particularly with the S&P 500, are compelling. optimised parameters that were effective in cryptocurrency markets were also applicable here, indicating a high degree of adaptability. Specifically, the 120-minute parameters adapted seamlessly across similar stock market durations, providing consistently positive results that generally matched or exceeded the returns from a standard hold strategy. This crossover success highlights the potential of using crypto-optimised parameters in more traditional financial markets, providing a strategic advantage.

This comprehensive analysis confirms that while the adaptability of parameters varies across different markets and timeframes, certain strategies, especially those tested for S&P 500, have a broad application and can significantly enhance profitability.

[h]

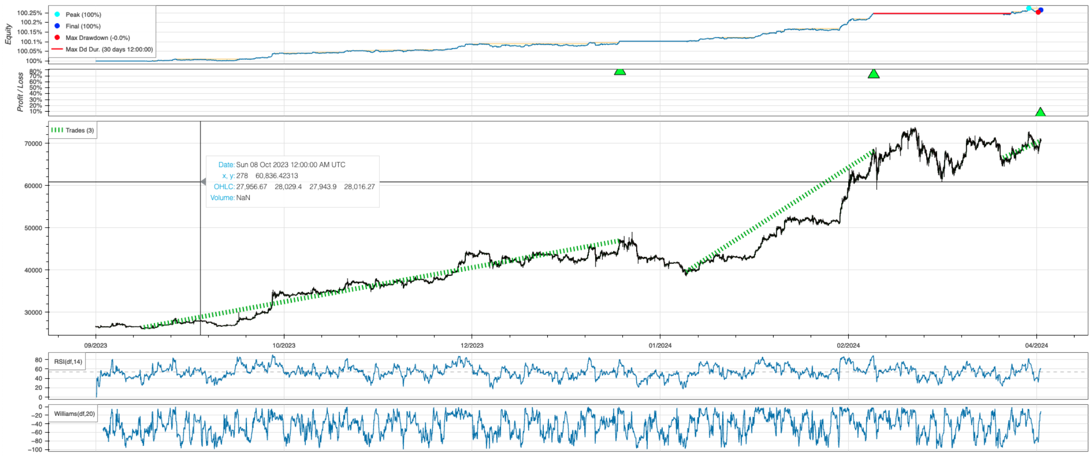

Figure 6.3: BTC/USDT, 120

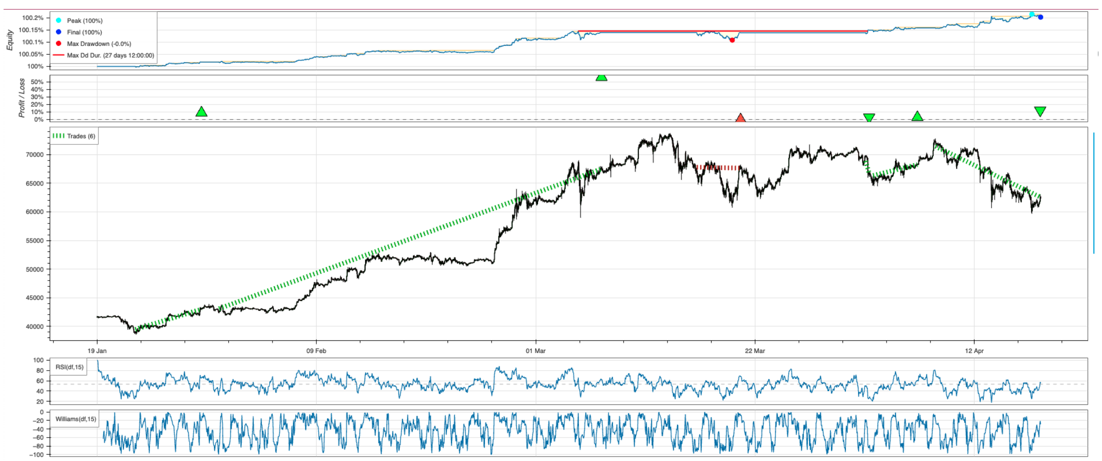

Figure 6.4: BTC/USDT, 60

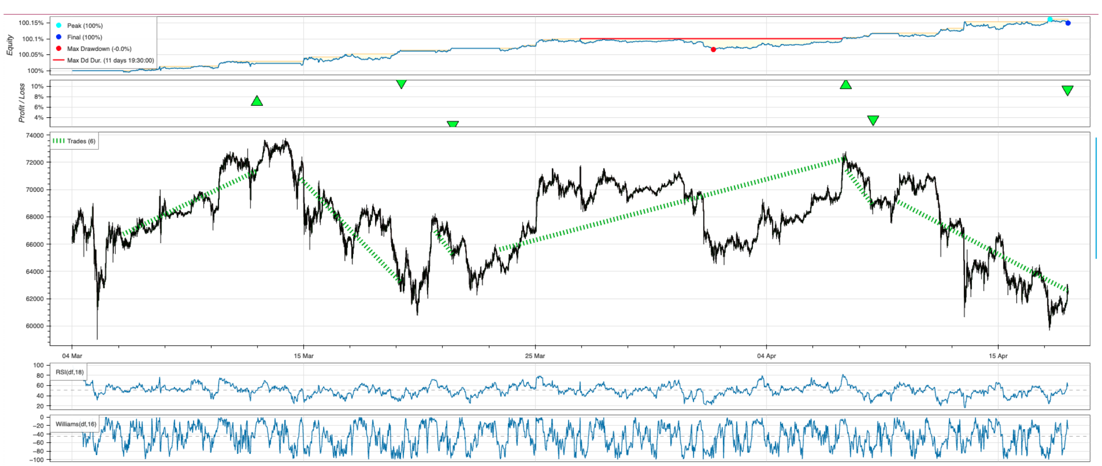

Figure 6.5: BTC/USDT, 30

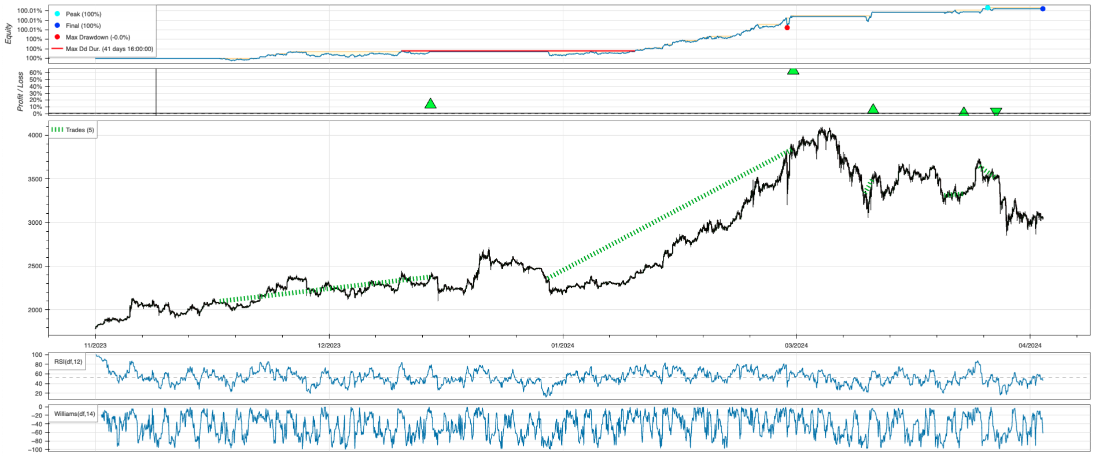

Figure 6.6: ETH/USDT 120

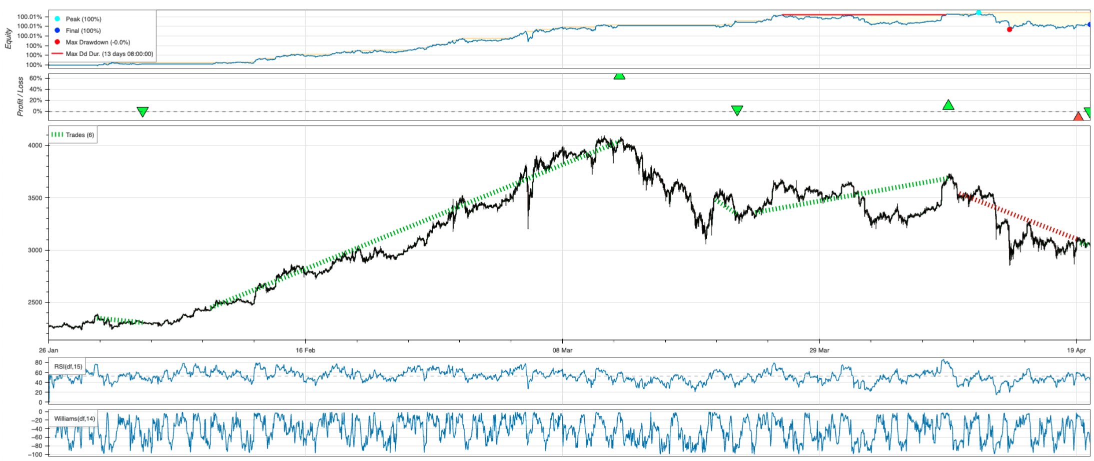

Figure 6.7: ETH/USDT, 60

Figure 6.8: ETH/USDT, 30

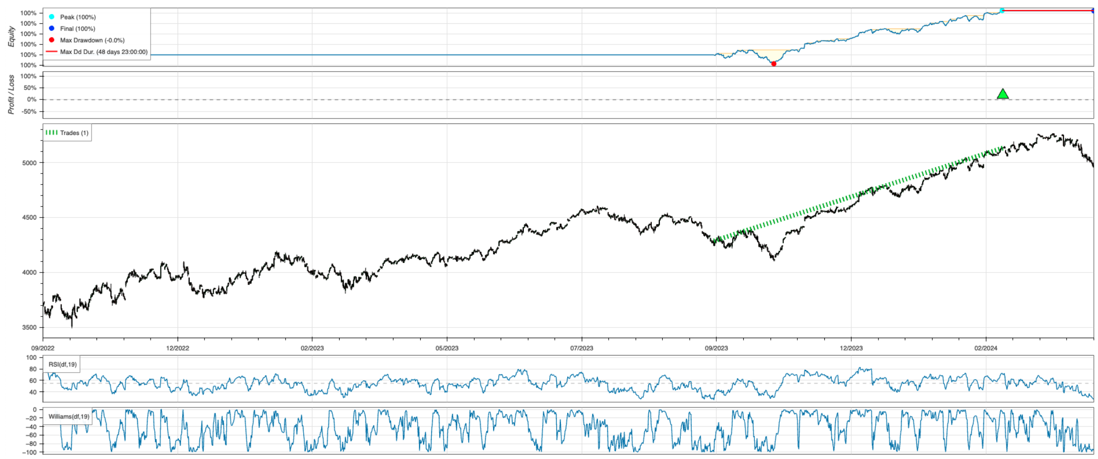

Figure 6.9: S%P 500, 120

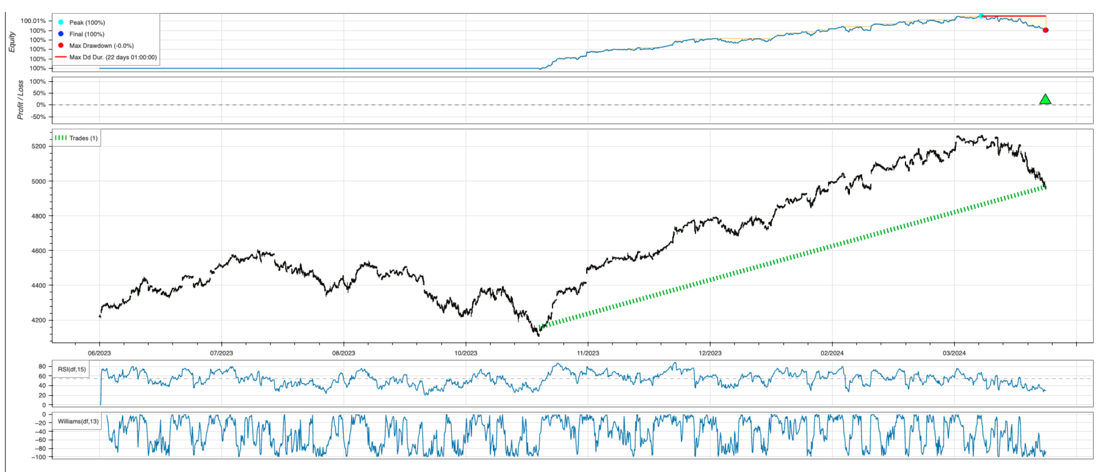

Figure 6.10: S%P 500, 60

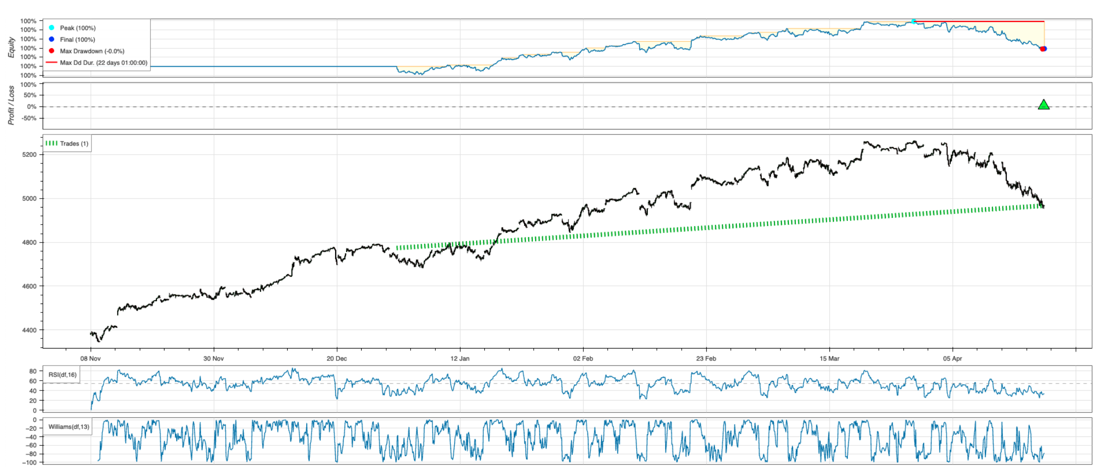

Figure 6.11: S%P 500, 30

Table 6.3: Performance summary for BTC/USDT across various strategies and timeframes

BTC/USDT 120 mins Strategy Performance	
Component	**Details**
Encoding	[14, 77, 38, 0.7539, 20, -10, -75, 1, 0, 0, 1, 1, 0, 0, 1]
Rule	Hammer & Bear Engulf & Two Green & Simple Will
Sharpe Ratio	4.9886

BTC/USDT 60 mins Strategy Performance	
Component	**Details**
Encoding	[15. 69. 35. 1. 15. -25. -77. 0. 1. 1. 1. 0. 0. 0. 0.]
Rule	Shooting & Bull Engulf & Bear Engulf
Sharpe Ratio	5.08799

BTC/USDT 30 mins Strategy Performance	
Component	**Details**
Encoding	[18, 60, 32, 0.6418, 16, -19, -77, 0, 1, 0, 0, 0.3811, 1, 0, 1]
Rule	Shooting & Two Green & Two Red & Simple Will
Sharpe Ratio	6.4830

Table 6.4: Performance summary for S&P 500 across various strategies and timeframes

S&P 500 120 mins Strategy Performance	
Component	**Details**
Encoding	[19. 67. 26. 0.57841492 19. -14. -82. 0. 1. 0. 1. 0. 0. 1. 1.]
Rule	Shooting & Bear Engulf & Simple RSI & Simple Will
Sharpe Ratio	1.8843

S&P 500 60 mins Strategy Performance	
Component	**Details**
Encoding	[15. 60. 38. 0.35538712 13. -23. -85. 1. 1 0. 1 1 1 1 0.]
Rule	Hammer &Shooting & Bear Engulf &Two green & Two red & Simple RSI
Sharpe Ratio	2.27015

S&P 500 30 mins Strategy Performance	
Component	**Details**
Encoding	[16. 70. 30. 0.39689154 13. -26. -82. 1. 0. 0. 1. 0. 1. 1. 1.]
Rule	Hammer & Bear Engulf & Two Red & Simple RSI & Simple Will
Sharpe Ratio	1.68592

S&P 500									
Time	**RSI**	**W %R**	**Combined RSI & W %R**	**Hammer**	**Shooting**	**Bull engulf**	**Bear engulf**	**Two Green**	**Two Red**
30 min	-4.72960	-15.2119	-4.9812	2.38187	-1.21176	2.4338	-2.2386	0.89740	-2.2490
60 min	-3.7337	-8.7753	-3.7337	1.38516	0.38230	1.248979	-1.4013	1.172720	-1.5627
120 min	-0.3268	-3.0159	-0.5544	1.3885	-1.26269	1.36816	-1.27651	1.38925	-1.4108

Table 6.5: Performance summary for S&P 500 across various strategies

Table 6.6: Performance summary for ETH/USDT across various strategies and timeframes

ETH/USDT 120 mins Strategy Performance	
Component	**Details**
Encoding	[12, 75, 23, 0.6079475775798355, 14.0, -16.0, -74, 0, 1, 0, 1, 1, 0.0, 0, 1]
Rule	Shooting & Bull Engulf & Bear Engulf & Two Green & Simple Will
Sharpe Ratio	4.06317
ETH/USDT 60 mins Strategy Performance	
Component	**Details**
Encoding	[15, 67, 37, 0, 14, -13, -75, 0, 0.0, 0.0, 0.0, 1, 1, 0.0, 1]
Rule	Two Green & Two Red & Simple Will
Sharpe Ratio	4.21098
ETH/USDT 30 mins Strategy Performance	
Component	**Details**
Encoding	[14. 67. 24. 1. 19. -11. -76. 1. 1. 0. 1. 1. 0. 0. 0.]
Rule	Hammer & Shooting & Bear Engulf & Two Green & Two Red
Sharpe Ratio	5.14007

Chapter 7

Conclusion and Future Work

7.1 Conclusion

This study has demonstrated the potential of using genetic algorithms for optimizing trading strategies in both cryptocurrency and stock markets. By comparing the performance of single strategies against optimized parameters, it was evident that genetic algorithms can significantly enhance the Sharpe ratio, thereby increasing the profitability and effectiveness of trading strategies.

This findings revealed that optimized parameters generally outperformed traditional single-strategy approaches, particularly in volatile markets such as cryptocurrencies. The application of these parameters across different datasets confirmed their robustness and adaptability, showing promising results in both simulated and real trading environments. Moreover, the comparative analysis with the hold strategy highlighted the potential of optimized trading algorithms to capture profitable opportunities that a passive strategy might miss.

The research also underscored the importance of considering market volatility and the specific characteristics of each dataset when applying optimized parameters. The adaptability of these parameters across various markets and conditions suggests that they are not only effective but also versatile tools for enhancing trading performance.

7.2 Future Work

Despite the encouraging results, there are several areas where future research could expand upon this work:

1. Algorithm Improvements: Further refinement of the genetic algorithms could enhance their efficiency and effectiveness. Incorporating more advanced genetic operations or exploring hybrid approaches combining genetic algorithms with other optimization techniques could yield better optimization outcomes.

2. Wider Range of Financial Instruments: Expanding the research to include a broader array of financial instruments, such as options, futures, and bonds, could provide deeper insights into the applicability of optimized parameters across different financial markets.

3. Real-Time Trading Implementation: Implementing the optimized strategies in a real-time trading environment would provide valuable data on their performance under live market conditions. This would also help in identifying potential practical challenges and refining the strategies accordingly.

4. Machine Learning Integration: Integrating machine learning models to predict market trends alongside the genetic algorithm could enhance the predictive power and accuracy of the trading strategies. This could involve developing predictive models that work in tandem with the optimization process to adjust strategies based on anticipated market movements.

5. Comprehensive Risk Management Framework: Developing a more comprehensive risk management framework to accompany the optimized strategies would be crucial, especially in highly volatile markets. This could include strategies for minimizing potential losses and systematically managing the investment portfolio.

6. Cross-Market Analysis: Further studies could explore the cross-market effects and how global economic changes affect the performance of optimized trading strategies. This would be particularly pertinent in a globally interconnected market environment.

By addressing these areas, future research can continue to advance the field of financial trading optimization, offering traders and investors more sophisticated tools to enhance their decision-making and profitability in a range of market conditions.

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