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Data Science

Exploring a Genetic Algorithm Approach to Determine Optimal Technical Indicator Parameters for Algorithmic Trading in the Forex Market

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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Data Science

Supervised by

Jorge Miguel Ventura Bravo, NOVA Information Management School

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, Novemeber 19, 2025

Evans Akpo Onorieru

DEDICATION

Dedicated to my father, Capt. Johnbull Onorieu, who passed away during the course of my program. In loving memory of your love and support.

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I would like to express my deepest gratitude to my advisor, Prof. Jorge Miguel Bravo, who provided invaluable support, patience, and guidance throughout my master's thesis. His expertise and wealth of knowledge was instrumental in guiding me through this research journey. I am also profoundly grateful to the faculty and staff of the Data Science Program at Nova IMS for fostering a stimulating and conducive learning environment and for providing the necessary learning resources for my research.

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A special and heart felt thanks to my best friend and amazing life-partner, Adeola Adeniji - your presence has been heaven to my soul; words fail to express how wonderful you are to me. I am also deeply grateful to Louis Imosi, a friend turned brother, for his encouragement, support, and the many laughs we shared during the highs and lows of this academic endeavor.

To the King, from whom all knowledge and wisdom flows - thank you God.

ABSTRACT

This thesis investigates the application of Genetic Algorithms (GAs) to optimize technical indicator parameters in algorithmic trading, focusing on the Relative Strength Index (RSI) and Average Directional Index (ADX) within the Forex market. The central motivation is to address the limitations of static calibration methods, which often fail to adapt to the non-stationary and structurally complex nature of financial markets. The GA was implemented in Python using the DEAP framework, with reproducibility ensured through fixed random seeds. Historical EUR/USD daily data from 2009–2019 was used for in-sample optimization, while out-of-sample testing covered 2020–2023. The GA searched over RSI and ADX parameter ranges using tournament selection, blend crossover, and polynomial bounded mutation, with fitness defined by cumulative return and annualized Sharpe ratio. Empirical findings show that the GA converged on RSI(7) and ADX(7), achieving an in-sample cumulative return of 18.73%, outperforming conventional benchmarks. However, out-of-sample testing revealed a negative cumulative return of –20.42% and poor risk-adjusted performance, underscoring the challenge of generalization. Robustness tests produced mixed results: while performance was preserved under randomized data and weekly timeframes, profitability eroded under randomized trade order and across alternative currency pairs. Slippage and rolling-window analyses further highlighted the sensitivity of the strategy to trading frictions and regime shifts. These results affirm the potential of GAs as a heuristic for navigating complex financial optimization problems but also emphasize the need for rigorous validation frameworks and adaptive retraining. Future research should extend this approach by incorporating alternative risk-adjusted objectives, macroeconomic covariates, and multi-objective evolutionary frameworks that balance profitability, risk, interpretability, and regulatory compliance.

RESUMO

Esta tese investiga a aplicação de Algoritmos Genéticos (AGs) para otimizar parâmetros de indicadores técnicos na negociação algorítmica, com foco no Índice de Força Relativa (RSI) e no Índice Direcional Médio (ADX) no mercado Forex. A motivação central é abordar as limitações dos métodos de calibração estática, que muitas vezes não conseguem se adaptar à natureza não estacionária e estruturalmente complexa dos mercados financeiros. O GA foi implementado em Python usando a estrutura DEAP, com reprodutibilidade garantida por meio de sementes aleatórias fixas. Dados históricos diários do EUR/USD de 2009 a 2019 foram usados para otimização dentro da amostra, enquanto os testes fora da amostra cobriram 2020 a 2023. O GA pesquisou intervalos de parâmetros RSI e ADX usando seleção de torneio, cruzamento misto e mutação polinomial limitada, com aptidão definida pelo retorno acumulado e índice de Sharpe anualizado. Os resultados empíricos mostram que o GA convergiu para RSI(7) e ADX(7), alcançando um retorno acumulado na amostra de 18,73%, superando os benchmarks convencionais. No entanto, os testes fora da amostra revelaram um retorno cumulativo negativo de –20,42% e um desempenho ajustado ao risco insatisfatório, ressaltando o desafio da generalização. Os testes de robustez produziram resultados mistos: enquanto o desempenho foi preservado sob dados aleatórios e prazos semanais, a rentabilidade foi prejudicada sob ordens de negociação aleatórias e em pares de moedas alternativos. As análises de slippage e janela móvel destacaram ainda mais a sensibilidade da estratégia às fricções de negociação e mudanças de regime. Estes resultados confirmam o potencial dos GAs como heurística para navegar problemas complexos de otimização financeira, mas também enfatizam a necessidade de estruturas de validação rigorosas e retreinamento adaptativo. Pesquisas futuras devem ampliar esta abordagem, incorporando objetivos alternativos ajustados ao risco, covariáveis macroeconómicas e estruturas evolutivas multiobjetivas que equilibrem rentabilidade, risco, interpretabilidade e conformidade regulatória.

KEYWORDS

Genetic Algorithm (GA); Average Directional Index (ADX); Relative Strength Index (RSI); Out-of-Sample (OOS); In-Sample (IS), Forex (FX)

Sustainable Development Goals (SDG):

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1. INTRODUCTION

Algorithmic trading has become an increasingly dominant field in modern financial markets, enabling both retail traders, investors, institutions to execute trading strategies with speed, precision, and in an automated fashion. These systems are based on quantitative rules that mitigate behavioral biases, and exploit short-lived market inefficiencies (Chaboud et al., 2014).

Some of the technical indicators such as the Moving Averages, Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD) continue to serve as fundamental building blocks for signal generation within these trading strategies. However, a critical and persistent challenge lies in the selection and calibration of the parameters that underlie these indicators. Technical indicators sensitivity to parameter configurations has been widely acknowledged, and the inability to adapt these parameters dynamically to changing market conditions can be challenging, especially when these strategies are deployed in a live ever-evolving financial market (Sullivan et al.,1999). The choice of parameter configuration grossly impacts the performance of a trading strategy, and the failure to dynamically adjust these parameters frequently leads to considerable fragility when strategies are implemented in live, evolving market conditions (Sullivan et al., 1999).

The conventional parameter optimization methods such as grid search or manual calibration often fall short in dynamic market environments characterized by volatility clustering, structural breaks, and liquidity shocks. These static approaches typically identify suitable parameters that perform well on historical data but are ill-suited to generalize under shifting market regimes (Bailey et al., 2016). Given the non-stationary nature of the financial market, overfitting strategies to past patterns often exacerbates poor performance. Seemingly optimal configurations when confronted with unseen data often perform below expectation as well. Parameter settings must evolve alongside changing market dynamics to preserve the profitability, resilience, and risk management capabilities of algorithmic trading systems.

As a result, there is growing academic and industry interest in developing dynamic optimization techniques capable of improving and maintaining trading strategy efficacy over time and across different market conditions. Regulatory bodies and initiatives such as the IOSCO guidelines on the use of AI in trading, Basel III, and the Market Abuse Regulation (MAR) in Europe have emphasized the requirement for algorithmic systems to not only be profitable but also transparent, explainable, and auditable. These regulatory imperatives inform the methodological design of this study. The proposed Genetic Algorithm framework is structured to maintain interpretability throughout its optimization process and integrates validation procedures that are independently reproducible and verifiable. This design ensures alignment with global standards of accountability and model governance, enabling optimization outcomes to be systematically traced, justified, and subjected to rigorous compliance audits.

First formalized by Holland[1] in 1975 as an evolutionary search heuristic, Genetic Algorithms (GAs) inspired by natural selection serves as a promising solution to tackle these trading challenges. Genetic algorithms iteratively refine populations of potential solutions via selection, crossover, and mutation, facilitating comprehensive exploration of intricate, multimodal, and nonlinear search spaces. In contrast to conventional optimization methods that may prematurely converge to local optima, GAs aims to achieve a balance between exploration and exploitation, making them especially effective for problems characterized by rugged, noisy, or non-convex objective functions Goldberg (1989). In algorithmic trading, this refers to the ability to identify indicator parameter configurations that are both lucrative on historical data and resilient throughout varying market conditions.

Early implementations of genetic algorithms in trading techniques revealed their potential of being a promising approach in solving search problems. Utilizing genetic algorithms to identify technical trading rules in the S&P 500 revealed limited yet statistically significant prediction capability Allen & Karjalainen (1999). (Huang et al., 2015) recorded considerable flexibility and enhanced pairs trading using genetic algorithms compared to traditional statistical methods. (Ozturk et al., 2016) effectively utilized genetic algorithms to enhance indicator combinations in Forex trading, resulting in significant profitability during backtesting. However, throughout these investigations, issues related to overfitting, insufficient cross-validation, and susceptibility to market frictions persisted as significant concerns. Subsequent research by (Chen et al., 2008) and (Ko et al., 2023) expanded the applications of genetic algorithms to emerging markets and cryptocurrencies, demonstrating the adaptability of evolutionary methodologies.

A noticeable gap in the existing literature is the limited incorporation of real-world trading constraints into the building and optimization process of trading strategies using GAs. Many GA-based trading systems evaluate candidate solutions solely on generic profitability metrics, not considering critical factors such as transaction costs, slippage, liquidity risk, and execution latency (Bailey et al., 2016; De Prado, 2018). Another is the failure to implement rigorous out-of-sample test, including rolling window validation and walk-forward analysis, has led to concerns that reported performance improvements are artifacts of data mining rather than indicators of genuine strategy robustness.

In addition, most studies optimize trading parameters for a single market or asset class; this approach raises concerns about the applicability of the resulting strategies to other markets or asset classes, further emphasizing that testing on different markets is essential to avoid overfitting to features of a particular historical dataset. Dynamic financial systems demand that optimization methods identify parameter sets that are

[1] https://en.wikipedia.org/wiki/Holland%27s_schema_theorem

resilient across diverse market conditions, not just tailored to a particular one (Bravo & Silva, 2006; Bravo et al.,2018, 2021, 2022, 2025; Simões et al., 2021).

Addressing these limitations, recent research has advocated for hybrid approaches combining GAs with other machine learning techniques, such as reinforcement learning and fuzzy logic systems, to enhance adaptivity and robustness (Bayram et al., 2020). While hybrid models show promise, they often introduce additional complexity and opacity, complicating deployment in regulated financial environments that increasingly require model explainability and auditability.

With the above mentioned, this study directly addresses the research gaps by systematically evaluating whether Genetic Algorithms can uncover technical indicator parameter sets that not only optimize historical trading performance but also generalize effectively across different market environments and maintain robustness under realistic trading conditions. It investigates the extent to which GAs can adapt indicator parameters dynamically in response to market-regime shifts, and whether GA-optimized strategies maintain robustness across multiple Forex assets and varying timeframes. The causal mechanism investigated posits that GAs, through adaptive evolutionary search processes, dynamically align strategy parameters with underlying market structure, thereby improving timing and accuracy, reducing risk of overfitting, and improving risk-adjusted returns relative to traditional static optimization methods.

The contribution of this research is threefold. First, it addresses a critical gap in literature by integrating realistic trading constraints into the evaluation of GA-optimized strategies. Second, it advances methodological best practices by emphasizing dynamic validation techniques that better reflect live trading conditions. Third, it contributes to the broader theoretical discourse on adaptive financial systems by empirically testing the extent to which evolutionary optimization frameworks can succeed in markets characterized by nonstationary, complexity, and endogenous structural evolution (Lo, 2005; Hommes, 2006).

The remainder of this paper is structured as follows. Section 2 reviews the literature on evolutionary optimization methods applied to trading strategy development, emphasizing gaps and emerging trends. Section 3 outlines the methodology, including GA implementation details, fitness function design, and validation frameworks. Section 4 presents empirical results and analysis. Section 5 concludes with a discussion of implications for academic research, trading system design, and financial regulation.

2. LITERATURE REVIEW

Many studies have examined the use of genetic algorithms (GAs) for optimizing trading strategy parameters, especially technical indicator configurations. While most focus on the Forex market and equity, a growing number is extending towards commodities, cryptocurrencies, and futures. Early literature largely explored GAs to optimize parameters of single-indicator strategies such as the Moving Average Convergence Divergence (MACD) or Relative Strength Index (RSI). Using a GA-optimized MACD crossover strategy, (Deac & Iancu, 2023) reported that the optimized strategy outperformed traditional fixed-parameter approaches in equity markets; although, limitations on issues of overfitting and lack of generalization were observed in different market conditions. In a similar vein, (Ozturk et al., 2016) investigated the optimization of rule combinations involving multiple technical indicators within the foreign exchange market. Their results indicated notable profitability within the training data; nonetheless, substantial performance deterioration became evident when evaluated on out-of-sample conditions.

Further research studies investigated the dynamic re-calibration of trading rules. (Huang et al., 2015) utilized genetic algorithms for pairs trading, demonstrating that dynamic parameter modification in response to market conditions yielded superior returns relative to fixed thresholds. However, performance decline in rolling periods highlighted the vulnerability of even GA-optimized strategies to regime shifts. Extending this line of work by hybridizing genetic programming and GAs in emerging markets, (Chen et al., 2008) highlighted that hybrid evolutionary models better captured non-linear market dynamics but still struggled with abrupt structural changes. Their empirical results demonstrated that hybrid models more effectively captured the non-linear behaviors characteristic of these markets. However, persistent challenges in adjusting to sudden structural transformations suggest that while parameter flexibility enhances adaptability, it alone does not assure long-term strategy robustness.

In terms of robustness testing, several studies explored the application of GA-optimized strategies across multiple datasets. Studies on evolutionary optimization method showed that although GAs generally enhanced in-sample profitability, most strategies exhibited poor transferability across markets, emphasizing the risk of overfitting parameters to in-sample datasets. Furthermore, technical trading rules were optimized simultaneously for profitability and robustness across US and European indices, and the conclusion was that without multi-objective fitness functions explicitly penalizing overfitting, genetic algorithms tend to converge on fragile solutions, which is consistent with earlier warnings by (Bailey et al., 2016) regarding backtest overfitting.

Similarly, (Ko et al., 2023) found that GA-optimized strategies consistently outperformed fixed-parameter benchmarks during volatile periods, and this was revealed after evaluating evolutionary algorithms, including Non-dominated Sorting Genetic Algorithm II (NSGA-II) in the context of cryptocurrency trading. However, liquidity constraints and high transaction costs significantly reduced real-world effectiveness. Concerns raised by (Driaunys et al., 2014) revealed that after applying GA-driven arbitrage system in natural gas and futures markets, evolving market microstructures demanded continuous adaptation of model to match market environment.

Certain studies emphasized the necessity of online or dynamic evolutionary optimization. Worthy of note is that implementing online genetic programming that periodically re-optimized Forex trading strategies maintained profitability better than static counterparts under structural breaks. These findings correspond with the Adaptive Markets Hypothesis posited by Lo (2005), which indicates that markets develop as adaptive systems necessitating the concurrent evolution of trading models.

The hybrid models combining GAs with machine learning, fuzzy logic, and statistical techniques have also been extensively utilized in the studies of (Bayram et al., 2020). The findings showed that integrating fuzzy rule-based systems with GA optimization resulted in improved robustness to noisy data and smoother performance. Application of fuzzy systems in GA-based portfolio optimization also revealed superior adaptability compared to classical optimization techniques (Ghandar et al., 2009) . However, these gains came at the cost of increased model complexity, which raises concerns about transparency and auditability to regulatory bodies. In the same vein, De Brito & Oliveira (2012) combined GAs with support vector regression (SVR) for financial time series forecasting and achieved even better generalization performance, although a notable drawback was increased complexity in the model which introduced computational overhead, interpretability challenges, and limiting practical deployment despite theoretical advantage.

(X.-Q. , Chen et al., 2023) integrated genetic algorithms with deep learning models in financial trading, exhibiting improved prediction efficacy. As noted in previous research, transparency and complexity continue to be significant issues, particularly in regulated settings that necessitate auditability and explainability. (Sermpinis et al., 2012) integrated genetic algorithms with recurrent neural networks for exchange rate prediction, emphasizing the balance between adaptability and model transparency.

In response to approaches for mitigating shortcomings of genetic algorithm, alternative heuristic methods have been explored to tackle such shortcomings. Marwala (2010) introduced simulated annealing (SA) as a resilient method for evading local optima, while acknowledging that it reduced convergence speed. Engelbrecht (2007) analyzed Particle Swarm Optimization (PSO) while Storn & Price (1997) investigated Differential Evolution (DE), both demonstrating accelerated convergence in specific contexts. Comparative analyses by (X.-Q. , Chen et al., 2023) revealed that although Particle Swarm Optimization (PSO) and Differential Evolution (DE) demonstrated enhanced convergence speed, Genetic Algorithms (GAs) offered greater flexibility in exploring intricate solution landscapes, rendering them especially appropriate for financial trading contexts marked by irregular and noisy fitness surfaces.

Another key factor to consider in trading strategy optimization is the performance indicators employed to assess strategy robustness. Most studies predominantly employed traditional metrics such as maximum drawdown, cumulative returns, Sharpe ratio, and Sortino ratio. However, (Bailey et al., 2016) argued that such metric does not sufficiently reflect tail risk and adaptation to dynamic market environments. Conditional Value at Risk (CVaR), Omega ratio, and recovery ratios have been proposed as more appropriate robustness metrics. Although not many studies have systematically integrated them into GA-based optimization processes. Incorporating such metrics could mitigate the optimism bias associated with conventional backtesting and better reflect real-world strategy resilience. However, limitations of advanced measures such as CVaR and Omega ratio in Forex contexts, includes sensitivity to tail estimation, threshold selection, extreme outliers due to economic events, and non-stationary market conditions. Incorporating these advanced metrics would significantly increase complexity, runtime, and potentially constrain the scope of robustness testing.

Another optimization technique that has gained attention is the use of agent-based models to further provide theoretical support for dynamic strategy adaptation. (Challet et al., 2001) and LeBaron (2001) studies through simulations showed that financial markets are complex adaptive systems where successful strategies inevitably erode over time as market participants learn and adapt. This buttresses that static GA optimization may only provide temporary advantages unless combined with mechanisms for periodic retraining or co-evolution. In an ever changing market, the necessity for heterogeneity and bounded rationality of financial agents reinforces the necessity for flexible, adaptive optimization frameworks capable of surviving different market conditions. Applied genetic reinforcement learning (GRL) in portfolio optimization showed that combining evolutionary search with reinforcement learning techniques exhibited adaptability to varying market conditions and better handling of non-stationary financial environments. Although GRL is a novel area in the optimization space, their success highlights promising directions for future adaptive trading research, particularly in continuously evolving markets.

As observed across the reviewed studies, while majority of research focuses on enhancing profitability, a limited number of studies explicitly consider transaction costs and slippage in GA optimization or algorithmic trading in general. (Chen et al., 2008) and (Ko et al., 2023) recognized the distorting effects of unaccounted expenses, whilst De Prado (2018) rigorously critiqued backtests that do not incorporate realistic execution frictions. A significant restriction remains in the empirical GA optimization literature: attaining robust historical returns without guaranteeing deployable, net-of-cost performance.

As observed in the literature above, GAs is a powerful solution for discovering superior trading parameter configurations. Their effectiveness depends heavily on dynamic adaptability, robust validation procedures, incorporation of real-world frictions, and integration with behavioral and structural theories of market evolution. Static optimization, even if initially successful, runs the risk of becoming obsolete as market conditions evolve. Hence hybrid models, dynamic retraining, integrating adaptive learning, and rigorous robustness testing offer promising pathways to overcoming these limitations.

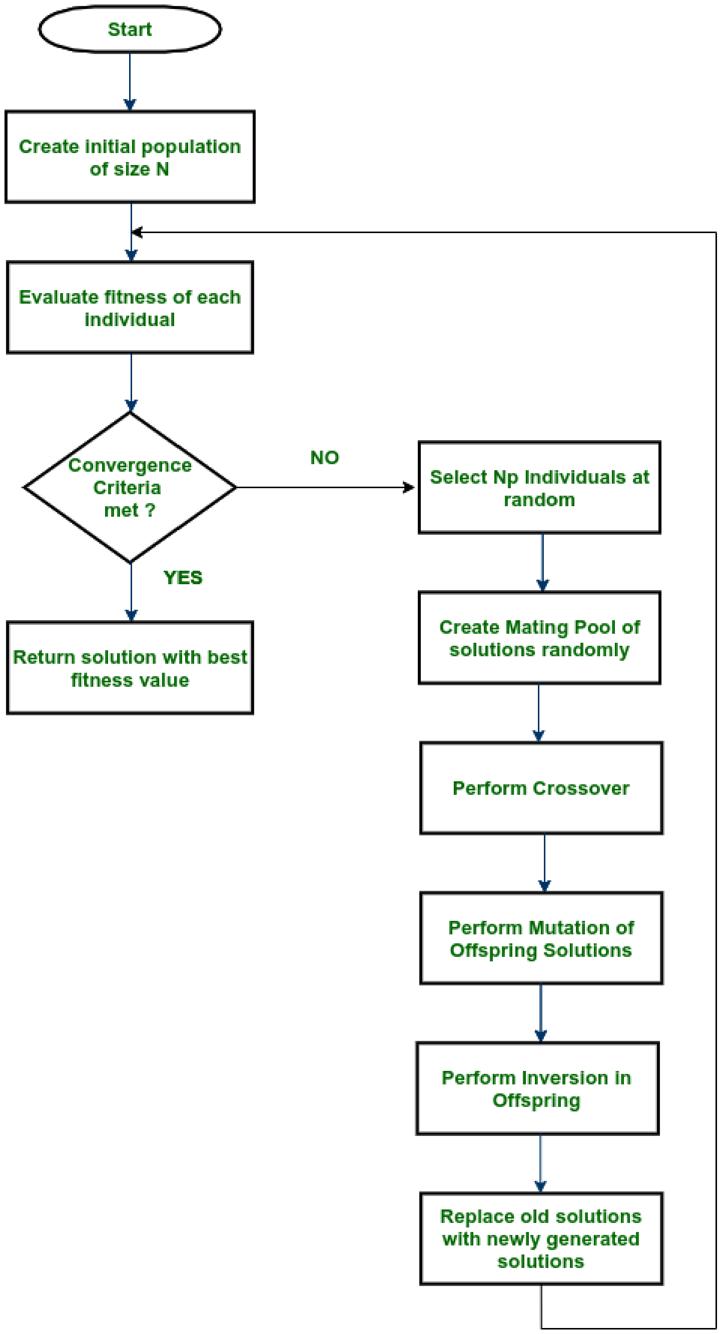
This paper aims to contribute to the emerging literature by systematically evaluating GA-optimized technical indicator parameters across multiple sample sets, with extensive rigorous robustness test, and comparing results against traditional fixed-parameter benchmarks. By doing so, we seek to provide practical insights into the design of resilient and adaptive algorithmic trading strategies grounded in robust empirical evaluation.

3. EMPIRICAL STUDY

Genetic Algorithms (GAs) are a class of stochastic, population-based optimization techniques inspired by the Darwinian principle of natural selection. In this study, GA is utilized to calibrate a technical trading strategy that combines two indicators: Average Directional Index (ADX) and Relative Strength Index (RSI) - for use in algorithmic trading. The primary objective is to identify optimal parameter combinations that jointly maximize historical cumulative return and risk-adjusted performance, as measured by the Sharpe Ratio. Together, these two objectives form a multi-objective fitness function, enabling the GA to balance profitability against volatility and downside risk.

The model is evaluated using daily historical data from four major currency pairs: EUR/USD, GBP/USD, AUD/USD, and NZD/USD. These pairs are characterized by high liquidity and narrow spreads and account for most of the forex volume globally. The dataset spans the period 2009–2023, subdivided into an in-sample period (2009–2019) for training and parameter optimization and an out-of-sample period (2020–2023) for performance validation.

Figure 3-1 Simple Genetic Algorithm Flow, sourced from geeksforgeeks (2021)[2]



GAs operate through the iterative evolution of a population of candidate solutions (individuals), each encoding a set of strategy parameters (genes). The following components define the structure of the GA used:

- Individuals: Parameter sets for the ADX-RSI strategy.
- Genes: Encoded values representing RSI period and ADX period thresholds.

[2] https://www.geeksforgeeks.org/machine-learning/simple-genetic-algorithm-sga/

- Population: A collection of individuals in a generation.
- Fitness Function: Quantifies strategy profitability via cumulative return and Sharpe ratio.

Selection, crossover, and mutation operators guide the evolutionary process. Tournament selection is applied to retain fitter individuals, while blend crossover promotes genetic mixing. Mutation, implemented with a 20% probability, introduces diversity by randomly altering gene values within defined bounds.

The optimization search space includes:

- RSI period range: 5 to 50
- ADX period range: 5 to 25
  yielding 966 candidate combinations. The dimensionality of this space introduces computational complexity, highlighting the curse of dimensionality in evolutionary optimization.

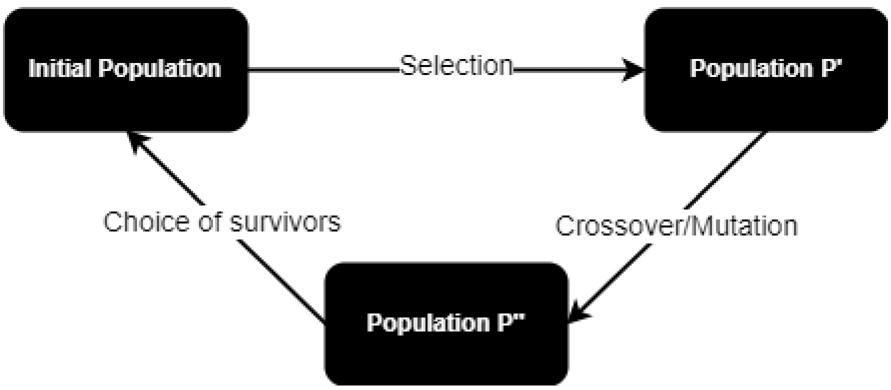
Table 3-1 Comparative analysis of RSI & ADX vs. alternatives

Indicator	Pros	Cons	Alternatives	Paramter Space Justification
RSI (5–50)	- Widely used momentum oscillator - Detects overbought/oversold conditions - Flexible across regimes - Range balances short-term sensitivity (5–10) with longer-term smoothing (30–50) - Strong empirical validation	- False signals in strong trends - Very short periods (<10) noisy - Very long periods (>50) lagging	- Stochastic Oscillator: more sensitive, prone to whipsaws - MACD: trend + momentum but requires multiple parameters - CCI: cyclical detection, less intuitive	Provides interpretable momentum measure with bounded, practical range; avoids complexity of multi-parameter alternatives
ADX (5–25)	- Measures trend strength, complements RSI - Filters trades in strong trends - Range balances responsiveness (5–10) with stability (20–25) - Well-established in literature	- Does not indicate direction - Very short periods unstable - Very long periods lagging	- Moving Average Crossovers: simple but whipsaw-prone - Bollinger Bands: volatility + trend, multiple parameters - ATR: volatility measure, less aligned with trend strength	Adds robustness by quantifying trend strength; simple, interpretable, avoids over-parameterization

Combined RSI + ADX	- Momentum + trend strength synergy - Dual-indicator framework reduces false signals - Parameter ranges wide enough for exploration but bounded to avoid overfitting - Computationally tractable for GA	- Requires careful calibration - Still sensitive to regime shifts	- Other multi-indicator sets (MACD + Bollinger, etc.) expand search space and risk overfitting	Balanced, interpretable, robust; ideal for GA optimization in FX trading

The GA was implemented using the DEAP (Distributed Evolutionary Algorithms in Python) framework, supporting parallel computation to mitigate runtime constraints. DEAP is a novel evolutionary computation framework for rapid prototyping and testing of ideas. It is widely used for genetic algorithm tasks because it offers a flexible, modular architecture that allows researchers to easily customize operators such as selection, crossover, and mutation while providing a rich library of evolutionary tools out of the box. It supports parallel evaluation of individuals, which is essential when fitness functions are computationally expensive, and integrates seamlessly with Python's scientific ecosystem (NumPy, pandas, scikit-learn), making it ideal for quantitative finance applications. DEAP's research-oriented design ensures reproducibility and credibility which makes it well suited for academic research.

Figure 3-2 General architecture of the GA-based strategy optimization process



3.1. Technical Indicators

3.1.1. Average Directional Index (ADX)

The ADX measures the strength of a trend, independent of its direction. It is derived from two directional movement components:

- +DI (positive directional indicator): upward price movement
- –DI (negative directional indicator): downward price movement

Let TR be the True Range, defined as:

$$TR_t = \max(\text{High}_t - \text{Low}_t,\ |\text{High}_t - \text{Close}_{t-1}|,\ |\text{Low}_t - \text{Close}_{t-1}|) \quad (1)$$

Directional movements, +DM and −DM, reflect the strength of price movements in either direction.

The Positive Directional Movement (+DM) measures the difference between the current high and the previous high. It is only considered positive when the current high is greater than the previous high. If not, the value is set to zero:

$$+DM = \text{Current High} - \text{Previous High}, \quad \text{if Current High} > \text{Previous High, else } 0 \quad (1)$$

The Negative Directional Movement (−DM) measures the difference between the previous low and the current low. It is only positive when the current low is lower than the previous low. If not, the value is set to zero:

$$-DM = \text{Previous Low} - \text{Current Low}, \quad \text{if Previous Low} > \text{Current Low, else } 0 \quad (2)$$

The Directional Indicators are normalized measures of the positive and negative directional movements, calculated by dividing the smoothed directional movements by the smoothed True Range.

- Positive Directional Indicator (+DI):

$$+DI = 100 \times \left(\frac{\text{Smoothed } +DM}{\text{Smoothed } TR}\right) \quad (3)$$

- Negative Directional Indicator (-DI):

$$-DI = 100 \times \left(\frac{\text{Smoothed } -DM}{\text{Smoothed } TR}\right) \quad (4)$$

The Exponential Moving Average (EMA) is used to smooth the directional movement indicators and True Range, as well as to calculate the ADX. The formula for EMA is:

$$EMA_t = \alpha \times P_t + (1 - \alpha) \times EMA_{t-1} \quad (5)$$

$Where$:

- (EMA_t) $is\ the\ Exponential\ Moving\ Average\ (EMA)\ at\ time(t),$
- $(P_t) is\ the\ current\ period\ price\ (or\ value),$
- $(\alpha = \frac{2}{n+1})$ $is\ the\ smoothing\ factor, where\ (n)\ is\ the\ number\ of\ periods,$
- (EMA_{t-1}) $is\ the\ EMA\ from\ the\ previous\ period\ (t - 1).$

3.1.2. The Relative Strength Index (RSI) ´

The RSI measures the speed and magnitude of price changes by comparing average gains during "up" periods to average losses during "down" periods.

Thresholds commonly used are:

- RSI < 30: Oversold condition (potential buy signal)
- RSI > 70: Overbought condition (potential sell signal)

Alternative thresholds (e.g., 20/80) can be used for more conservative trading regimes.

The formula for the Relative Strength Index (RSI):

$$RSI = 100 - \frac{100}{1+RS} \quad (6)$$

$Where$:

$$RS = \frac{\text{Average Gain}}{\text{Average Loss}}$$

- Average Gain = The average of all the positive price changes over a specified period.
- Average Loss = The average of all the negative price changes over the same period.

3.2. Trading Strategy Design

The combined RSI-ADX strategy uses both momentum and trend strength filters to generate signals:

- Buy Signal: RSI < 30 and ADX > 25
- Sell Signal: RSI > 70 and ADX > 25

This dual-indicator approach ensures that trades are placed only in strong trending markets with a confirmed directional bias.

Each individual in the GA population is evaluated via a fitness function based on the strategy's cumulative return and Sharpe Ratio:

Fitness Score = (Cumulative Return, Sharpe Ratio)

An out-of-sample test (2020–2023) complements the in-sample training by evaluating generalization to unseen data, mitigating overfitting.

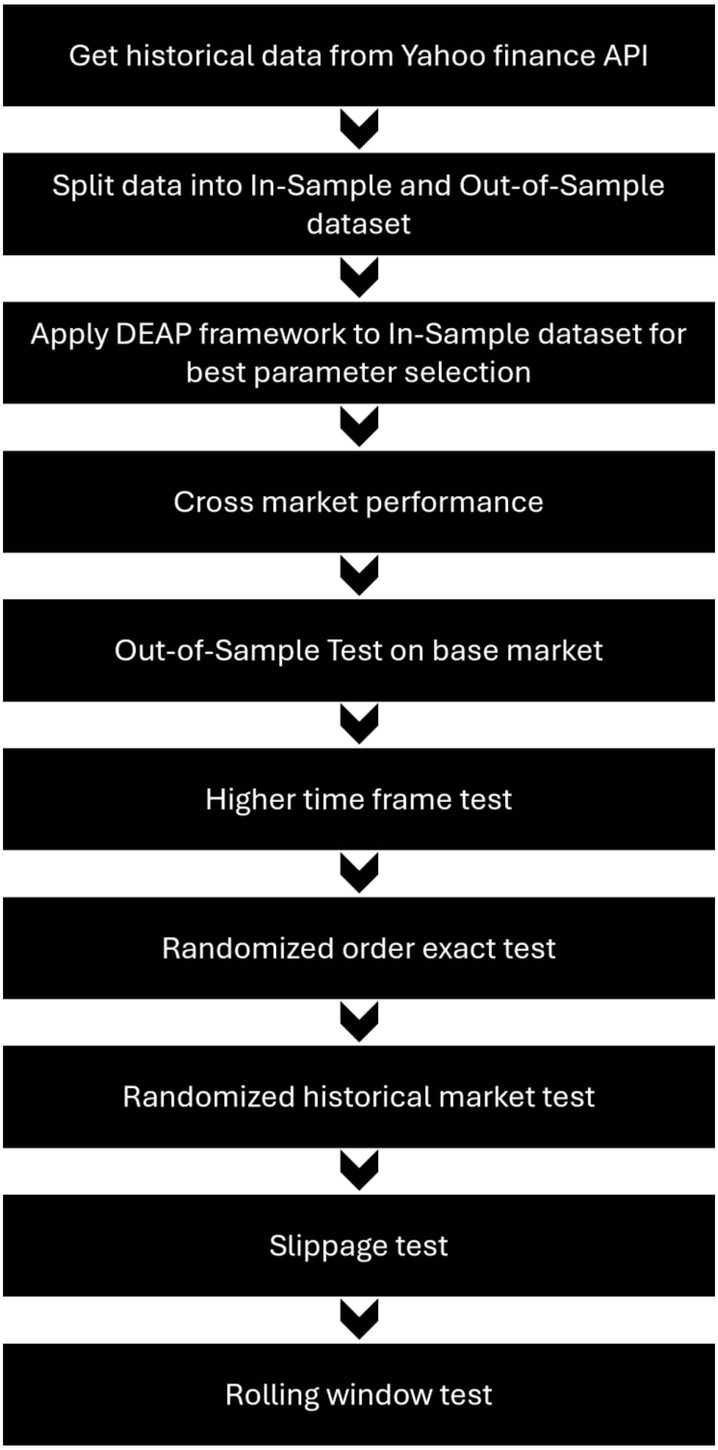
3.3. GA Configuration and Computational Considerations

The configuration parameters for the GA include:

- Population size: 50
- Number of generations: 40 (empirically limited to avoid overfitting)
- Mutation rate: 0.2
- Selection mechanism: Tournament selection
- Crossover mechanism: Blend crossover

The algorithm's stopping criterion is defined by either reaching the maximum number of generations or observing fitness convergence. The DEAP framework's built-in support for multiprocessing significantly reduces runtime. However, as the number of parameters increases, so does the cost of fitness evaluation, necessitating careful model complexity control.

Figure 3-3 Solution architecture, showing optimization loop, evaluation pipeline, and indicator inputs



To ensure the robustness of the optimized strategy, the following validation techniques are implemented:

1. Out-of-sample backtesting on unseen data (2020–2023).
2. Cross-market testing across different currency pairs.

3. Timeframe sensitivity analysis to assess temporal stability.
4. Randomized order test to evaluate behavior under shuffled price series.
5. Randomized historical test to assess stability under altered historical distributions.
6. Slippage test to mirror live market conditions
7. Rolling window test to evaluate strategy consistency

These procedures contribute to a comprehensive assessment of performance reliability, overfitting risk, and adaptability to different market regimes.

4. RESULTS AND DISCUSSION

In this section, we conduct an analysis of the results obtained in the various robustness tests. The investigation focuses on six key aspects that are critical to understanding the effectiveness, robustness, and adaptability of the proposed approach for identifying optimal trading strategy parameters:

1. optimal parameter identification via evolutionary optimization.
2. cross-market generalization performance.
3. out-of-sample tests.
4. test across different time frames.
5. sensitivity to the sequencing of trades via randomized order test.
6. historical structural robustness using randomized market data.

4.1. OPTIMAL PARAMETER SELECTION VIA GENETIC ALGORITHM

The parameter search space comprised RSI and ADX lookback periods, with the objective function of maximizing cumulative return over the in-sample period (2009–2019). The genetic algorithm (GA), using tournament selection, blend crossover, and mutation, converged on an optimal configuration of RSI = 7 and ADX = 7.

This parameter combination outperformed baseline configuration (RSI =14 and ADX =14), generating a cumulative return of 18.73% over the in-sample period, relative to substantially lower benchmarks under default indicator settings.

Figure 4-1 EUR/USD Cumulative Return Comparison: RSI(7), ADX(7) vs RSI(14), ADX(14) (2009–2019)

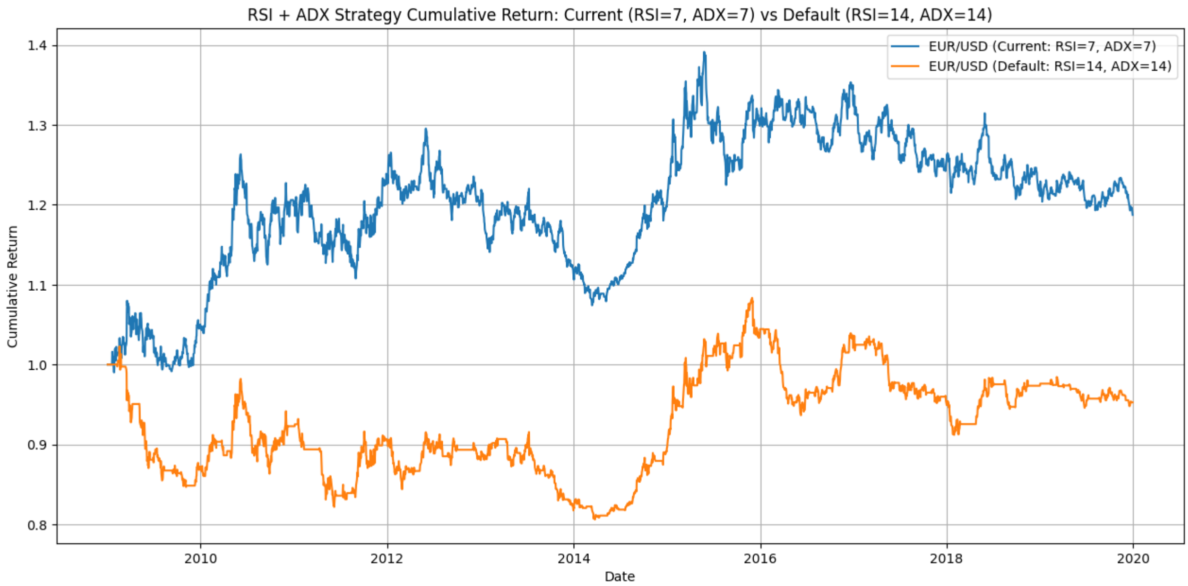


Table 4-1 Sample of Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on EUR/USD (2009–2019)

==== STRATEGY SUMMARY for EUR/USD (Current: RSI=7, ADX=7) ====
Total Profit (sum of trade returns): 0.5361
Cumulative Return: 18.73%
# of Trades: 108
Winning %: 61.11%
Losing %: 38.89%
Profit Factor: 4.44
Sharpe Ratio: 0.21
Max Drawdown: -0.1709
Max Drawdown %: 17.09%
Average Trade: 0.0050
Gross Profit: 0.6920
Gross Loss: -0.1558
Largest Win: 0.0609
Largest Loss: -0.0132
Expectancy: 0.0050
=========================
Paired Trades for EUR/USD (Default: RSI=7, ADX=7):

#	Type	Entry Date	Entry Price	Exit Date	Exit Price	Return
0	Sell	1/19/2009	1.309397	2/6/2009	1.292708	0.012911
1	Sell	2/9/2009	1.295908	2/10/2009	1.291406	0.003486
2	Sell	3/27/2009	1.329204	4/15/2009	1.322594	0.004998
3	Sell	4/17/2009	1.304495	4/28/2009	1.313094	-0.006549
4	Sell	6/3/2009	1.414968	6/12/2009	1.400109	0.010612
...	...	...	...	...	...	...
103	Sell	4/8/2019	1.121957	4/11/2019	1.12765	-0.005049
104	Buy	5/7/2019	1.120185	5/8/2019	1.119107	-0.000962
105	Sell	7/2/2019	1.128745	7/22/2019	1.121831	0.006163
106	Sell	7/23/2019	1.120611	7/29/2019	1.113214	0.006645
107	Sell	12/19/2019	1.111593	12/26/2019	1.109545	0.001845

Table 4-2 Performance Metrics and Trade Outcomes for RSI(14) + ADX(14) Strategy on EUR/USD (2009–2019)

--- EUR/USD (Default Strategy: RSI=14, ADX=14) ---

==== STRATEGY SUMMARY for EUR/USD (Default: RSI=14, ADX=14) ====
Total Profit (sum of trade returns): 0.7073
Cumulative Return: -4.73%
# of Trades: 106
Winning %: 70.75%
Losing %: 29.25%
Profit Factor: 5.22
Sharpe Ratio: -0.02
Max Drawdown: -0.2119
Max Drawdown %: 21.19%
Average Trade: 0.0067
Gross Profit: 0.8750
Gross Loss: -0.1677
Largest Win: 0.0683
Largest Loss: -0.0200
Expectancy: 0.0067
=========================

Paired Trades for EUR/USD (Default: RSI=14, ADX=14):

#	Type	Entry Date	Entry Price	Exit Date	Exit Price	Return
0	Sell	2/6/2009	1.292708	2/13/2009	1.286604	0.004744
1	Sell	2/16/2009	1.279902	2/24/2009	1.287399	-0.00582
2	Sell	3/27/2009	1.329204	4/9/2009	1.315997	0.010036
3	Sell	6/5/2009	1.397194	6/17/2009	1.393806	0.002431
4	Sell	6/29/2009	1.408609	7/8/2009	1.387906	0.014917
...	...	...	...	...	...	...
101	Sell	7/5/2019	1.128579	7/11/2019	1.125885	0.002393
102	Sell	8/19/2019	1.109385	9/10/2019	1.104838	0.004116
103	Sell	11/5/2019	1.112855	11/21/2019	1.107886	0.004485
104	Sell	11/28/2019	1.100485	12/3/2019	1.107911	-0.0067
105	Sell	12/16/2019	1.112446	12/24/2019	1.109385	

The comparative evaluation of the current specification (RSI=7, ADX=7) against the default configuration (RSI=14, ADX=14) demonstrates the sensitivity of cumulative returns and risk-adjusted performance to indicator calibration. The shorter-period RSI coupled with a narrow ADX window produced more frequent trading signals, yielding a higher number of trades and capturing short-term reversals with higher frequency. This specification generated positive cumulative returns and a higher profit factor, suggesting that the magnitude of gains outweighed losses. However, the Sharpe Ratio remained modest, reflecting limited excess return per unit of risk, and drawdowns.

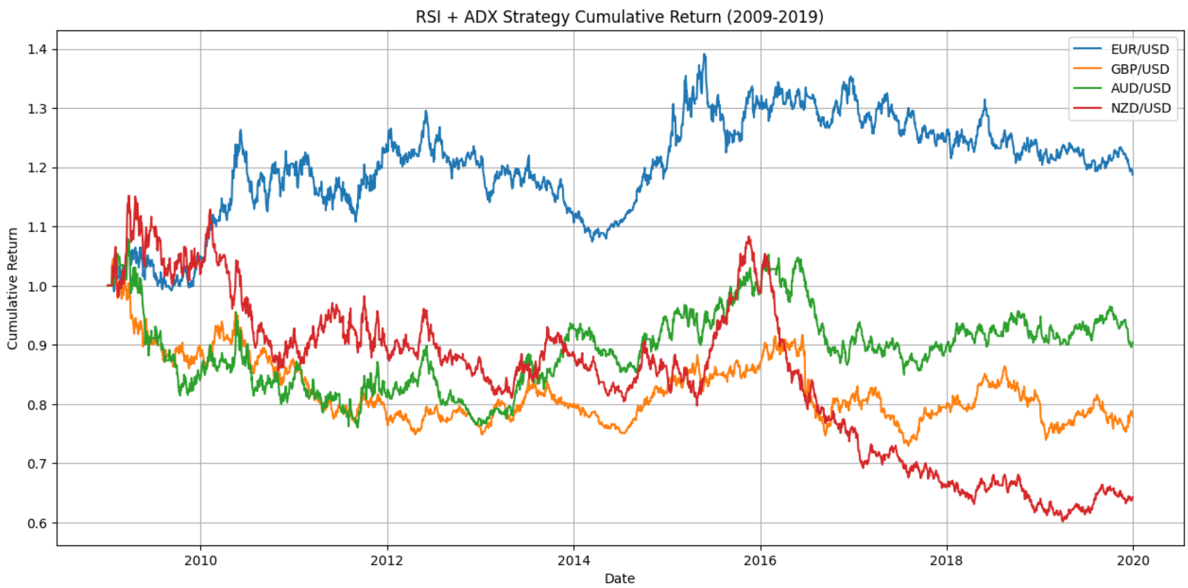
On the other hand, the default configuration produced smoother but fewer signals, resulting in lower trade frequency and diminished responsiveness to short-term volatility. The cumulative return profile was weaker, and drawdowns were more pronounced, underscoring the trade-off between signal stability and adaptability.

This finding confirms that heuristic evolutionary methods can identify robust parameter sets in noisy financial data, especially when coupled with conservative fitness functions.

4.2. CROSS-MARKET GENERALIZATION PERFORMANCE

To assess the robustness of the optimized strategy, the parameter configuration was applied to four major currency pairs—EUR/USD, GBP/USD, AUD/USD, and NZD/USD—over the in-sample period (2009–2019). This step tests the transferability of the strategy across market regimes and macroeconomic conditions.

Figure 4-2 Cumulative Returns of RSI + ADX Strategy Across Major Currency Pairs (2009–2019)



4.2.1. EURUSD

The performance of the EUR/USD trading strategy is evaluated across several key metrics including profitability, drawdown, risk-adjusted returns, and trade efficiency characteristics. These metrics collectively inform the robustness and practical viability of the strategy under consideration.

Table 4-3 presents the summary statistics for the EUR/USD strategy. The strategy yielded a total profit of 0.5361 over 108 trades, corresponding to a final cumulative return of 18.73%. The trade distribution was unevenly split between winners and losers (Winning % = 61.11%), suggesting an asymmetric payoff structure. The strategy achieved a profit factor of 4.44, indicating that gains from winning trades outweighed losses from losing trades. This is further supported by the gross profit (0.6920) exceeding the gross loss (-0.1558), and a positive expectancy of 0.0050 per trade.

Risk-adjusted performance, as measured by the Sharpe Ratio (0.21), was modest, reflecting limited excess return per unit of risk. The maximum drawdown of -0.1709 (17.09%) highlights the potential downside exposure, which may be considered substantial relative to the average trade return (0.0050). Notably, the largest single trade gain (0.0609) exceeded the largest loss (-0.0132), reinforcing the asymmetric reward profile.

The strategy's performance characteristics suggest a moderate level of profitability with controlled but non-negligible risk. The equal win/loss ratio, coupled with a positive profit factor and expectancy, implies that the strategy is profitable.

Table 4-3 Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on EUR/USD (2009–2019)

==== STRATEGY SUMMARY for EUR/USD (Current: RSI=7, ADX=7) ====
Total Profit (sum of trade returns): 0.5361
Cumulative Return: 18.73%
# of Trades: 108
Winning %: 61.11%
Losing %: 38.89%
Profit Factor: 4.44
Sharpe Ratio: 0.21
Max Drawdown: -0.1709
Max Drawdown %: 17.09%
Average Trade: 0.0050
Gross Profit: 0.6920
Gross Loss: -0.1558
Largest Win: 0.0609
Largest Loss: -0.0132
Expectancy: 0.0050
=========================

Trades for EUR/USD:

Date	Trade Type	Price	RSI	ADX
1/1/2009	Exit	1.399894	NaN	NaN
1/19/2009	Sell	1.309397	16.498279	59.146214
2/6/2009	Exit	1.292708	37.350283	22.497266
2/9/2009	Sell	1.295908	51.48652	26.192256
2/10/2009	Exit	1.291406	55.887666	21.494681
...	...	...	...	...
12/16/2019	Sell	1.112446	58.037329	54.341327
12/18/2019	Buy	1.115138	71.441441	54.532456
12/19/2019	Sell	1.111593	60.393193	48.579577
12/26/2019	Exit	1.109545	33.904524	22.350752
12/27/2019	Sell	1.110112	29.099165	35.275888

4.2.2. GBPUSD

Table 4-4 presents the results of the GBP/USD strategy. The strategy generated a total 93 trades culminating in a final cumulative return of -22.07%. The winning percentage (51.61%) slightly exceeded the losing percentage (48.39%), suggesting a marginal edge in trade selection. The profit factor of 2.51 indicates that the strategy's gross profit (0.4617) was 151.3% higher than its gross loss (-0.1838), supporting the presence of a positive reward-to-risk ratio.

The Sharpe Ratio of -0.20 reflects an underperforming return per unit of risk. This is further evidenced by the maximum drawdown of -0.3023 (30.23%), which represents the largest peak-to-trough decline in equity. The average trade return (0.0030) and expectancy (0.0030) suggest consistent but modest gains per trade, with the largest win (0.0376) significantly smaller than the largest loss (-0.0212), indicating occasional downside spikes. Overall, the GBP/USD strategy demonstrates negative returns.

Table 4-4 Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on GBP/USD (2009–2019)

```
==== STRATEGY SUMMARY for GBP/USD ====
Total Profit (sum of trade returns): 0.2779
Final Cumulative Return: -22.07%
# of Trades: 93
Winning %: 51.61%
Losing %: 48.39%
Profit Factor: 2.51
Sharpe Ratio: -0.20
Max Drawdown: -0.3023
Max Drawdown %: 30.23%
Average Trade: 0.0030
Gross Profit: 0.4617
Gross Loss: -0.1838
Largest Win: 0.0376
Largest Loss: -0.0212
Expectancy: 0.0030
==========================
```

Trades for GBP/USD:

Date	Trade Type	Price	RSI	ADX
1/1/2009	Exit	1.4741	NaN	NaN
1/19/2009	Sell	1.442544	17.56881	43.80032
1/29/2009	Buy	1.427898	83.49425	28.05414
2/2/2009	Exit	1.421202	63.49751	22.53708
2/5/2009	Sell	1.463208	69.41555	29.08545
...	...	...	...	...
11/25/2019	Sell	1.285347	49.91539	31.9563
12/2/2019	Exit	1.291289	47.04086	21.27252
12/3/2019	Sell	1.294063	53.98235	29.92115
12/4/2019	Buy	1.299782	78.74759	42.36418
12/17/2019	Sell	1.327246	59.72457	58.70028

4.2.3. AUD/USD

The AUD/USD trading strategy was assessed over a ten-year period from January 1, 2009, to December 31, 2019, using a comprehensive set of performance indicators. These metrics provide insight into the strategy's profitability, risk exposure, and trade execution efficiency.

Error! Reference source not found. Table 4-5 presents the results of the AUD/USD strategy. The strategy executed 91 trades, yielding a total profit of 0.5658. Despite a winning percentage of 61.54%, the final cumulative return was negative (-9.57%), suggesting that the magnitude of losses outweighed gains over the evaluation period.

The Sharpe Ratio of -0.03 reflects a negative risk-adjusted return, implying that the strategy underperformed relative to a risk-free benchmark. The maximum drawdown of -0.2951 (29.51%) highlights substantial downside exposure, which may be considered excessive given the average trade return of 0.0062 and expectancy of 0.0062.

Table 4-5 Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on AUD/USD (2009–2019)

==== STRATEGY SUMMARY for AUD/USD ====
Total Profit (sum of trade returns): 0.5658
Final Cumulative Return: -9.57%
# of Trades: 91
Winning %: 61.54%
Losing %: 38.46%
Profit Factor: 4.56
Sharpe Ratio: -0.03
Max Drawdown: -0.2951
Max Drawdown %: 29.51%
Average Trade: 0.0062
Gross Profit: 0.7246
Gross Loss: -0.1588
Largest Win: 0.0778
Largest Loss: -0.0149
Expectancy: 0.0062
=========================

Trades for AUD/USD:

Date	Trade Type	Price	RSI	ADX
1/1/2009	Exit	0.70502	NaN	NaN
1/19/2009	Sell	0.667379	10.995333	43.070574
2/5/2009	Exit	0.651763	40.800551	24.50779
2/6/2009	Sell	0.675721	55.670735	32.599629
2/12/2009	Exit	0.656814	56.019114	22.711645
...	...	...	...	...
12/9/2019	Buy	0.683532	81.041864	60.790828
12/11/2019	Sell	0.68114	68.254924	47.06046
12/13/2019	Buy	0.692713	74.590982	57.291432
12/16/2019	Sell	0.687479	55.971737	61.478604
12/25/2019	Buy	0.692185	73.979276	58.1664

4.2.4. NZD/USD

The total profit across all trades was 0.5156, yet the final cumulative return was negative (-35.73%), indicating that the strategy failed to generate sustainable growth over time. The winning percentage (53.47%) was fairly close to the losing percentage (46.53%), suggesting a balanced hit rate but insufficient edge in trade outcomes.

The profit factor of 3.03 implies that profits significantly exceeded losses. However, the Sharpe Ratio of -0.28, which denotes a negative risk-adjusted return and signals underperformance relative to a risk-free benchmark. The maximum drawdown of -0.4778 (47.78%) reveals significant downside exposure, which may be considered excessive given the modest average trade return of 0.0051 and expectancy of 0.0051.

Gross profit (0.7699) exceeded gross loss (-0.2543), but the largest win (0.1452) was only significantly greater than the largest loss (-0.0176), indicating asymmetry in trade outcomes. This lack of skew may have contributed to the strategy's inability to recover from drawdowns and generate consistent returns.

Table 4-6 Performance Metrics and Trade Outcomes for RSI(50) + ADX(7) Strategy on NZD/USD (2009–2019)

==== STRATEGY SUMMARY for NZD/USD ====
Total Profit (sum of trade returns): 0.5156
Final Cumulative Return: -35.73%
# of Trades: 101
Winning %: 53.47%
Losing %: 46.53%
Profit Factor: 3.03
Sharpe Ratio: -0.28
Max Drawdown: -0.4778
Max Drawdown %: 47.78%
Average Trade: 0.0051
Gross Profit: 0.7699
Gross Loss: -0.2543
Largest Win: 0.1452
Largest Loss: -0.0176
Expectancy: 0.0051
=========================

Trades for NZD/USD:

Date	Trade Type	Price	RSI	ADX
1/1/2009	Exit	0.584215	NaN	NaN
1/19/2009	Sell	0.537403	7.276175	62.07203
2/9/2009	Buy	0.534702	74.97774	53.63941
2/10/2009	Sell	0.52521	66.97537	47.6967
2/11/2009	Buy	0.524907	75.05484	43.23966
...	...	...	...	...
11/20/2019	Buy	0.643141	71.32235	47.37822
11/21/2019	Sell	0.6411	60.49331	44.77264
12/3/2019	Buy	0.649878	88.33009	56.78518
12/16/2019	Sell	0.65927	65.3287	68.85864
12/25/2019	Buy	0.6643	72.99689	51.5003

Overall, the NZD/USD strategy demonstrates an excellent profit factor but suffers from poor cumulative performance and excessive drawdowns.

Trading strategies based on technical indicators occupy a central role in shaping the capacity of algorithmic systems to generate consistent returns across heterogeneous market environments, in securing profitability under varying volatility regimes, and in protecting portfolios from excessive drawdowns. In the RSI–ADX framework, in which signals are closely linked to momentum oscillations and directional strength measures, following a compulsory threshold principle, the calibration of indicator periods determines the level of profitability that strategies can achieve when deployed across different currency pairs. Everything else constant, the more liquid and structurally stable the market, and the more continuous the alignment between momentum reversals and trend strength, the higher the cumulative returns and the lower the drawdown exposure will be. Over the last decade, several waves of empirical testing designed to ensure the long-term sustainability of trading strategies in the face of major regime shifts (volatility clustering, liquidity shocks, commodity price cycles) have brought and will continue to bring major changes in the conditions under which algorithmic systems operate. Although these strategies may have contributed to addressing the profitability problem in highly liquid pairs such as EUR/USD, it is crucial to assess their effect in terms of robustness, since structural or regime-specific fragility challenges will likely emerge in pairs with higher volatility and thinner liquidity.

Increasingly, trading systems experience single or multiple interruptions to their profitability trajectories at some point in time. These events have a long-term scarring effect on future performance possibilities, particularly in pairs such as GBP/USD and NZD/USD, and thus permanently affect the cumulative return profile and the sustainability of the strategy. Previous literature has investigated the economic (and financial) implications of regime dependency extensively, particularly the negative and persistent effect of volatility shocks on the generalizability of technical trading rules. The present results confirm this pattern: while EUR/USD demonstrates resilience and profitability, the strategy fails to generalize across GBP/USD and NZD/USD, where drawdowns are excessive and cumulative returns remain negative despite respectable win rates and profit factors. This divergence underscores the necessity of cross-market validation, rolling recalibration, and adaptive optimization frameworks, since static indicator thresholds are insufficient to secure robustness across diverse trading environments.

Table 4-7 Summary of RSI(7) + ADX(7) Strategy Performance Across Forex Pairs (2009–2019)

Pair	Trades	Total Profit	Cumulative Return	Winning %	Profit Factor	Sharpe Ratio	Max Drawdown	Max Drawdown %	Avg Trade	Gross Profit	Gross Loss	Largest Win	Largest Loss	Expectancy
EUR/USD	108	0.5361	**18.73%**	61.11%	4.44	0.21	-0.1709	17.09%	0.005	0.692	-0.1558	0.0609	-0.0132	0.005
GBP/USD	93	0.2779	**-22.07%**	51.61%	2.51	-0.2	-0.3023	30.23%	0.003	0.4617	-0.1838	0.0376	-0.0212	0.003
AUD/USD	91	0.5658	**-9.57%**	61.54%	4.56	-0.03	-0.2951	29.51%	0.0062	0.7246	-0.1588	0.0778	-0.0149	0.0062
NZD/USD	101	0.5156	**-35.73%**	53.47%	3.03	-0.28	-0.4778	47.78%	0.0051	0.7699	-0.2543	0.1452	-0.0176	0.0051

4.3. OUT-OF-SAMPLE TEST ON BASE MARKET

The Out-of-Sample (OOS) test is a crucial robustness test in quantitative finance for validating trading strategies. It involves evaluating a strategy's performance on data that was not used during the development or optimization phase. The Out-of-sample validation was conducted on EUR/USD for 2020–2023 using the fixed GA-optimized parameters. This analysis examines whether the observed in-sample gains generalize to unseen data, a critical criterion for model robustness and deployment viability.

The trading strategy was evaluated using daily price data retrieved via the yfinance library. A total of 39 trades were executed, with performance metrics offering insight into profitability, risk exposure, and trade efficiency.

The strategy yielded a total profit of 0.0626, with a cumulative return of -20.42%. This negative return suggests that the strategy could not generate net gains over the evaluation period. The winning percentage of 38.46% is significantly below the losing percentage of 61.54%, indicating a poor performance in trade selection.

A profit factor of 1.79 reflects strong profitability relative to losses, suggesting that gains were nearly two times larger than losses on average. The largest win (0.0512) also exceeded the largest loss (-0.0099), reinforcing the strategy's favorable reward-to-risk profile.

The Sharpe Ratio of -0.07, however, indicates negative risk-adjusted performance. The maximum drawdown of -0.2946 (29.46%) reveals noticeable downside exposure, which may not be acceptable depending on the investor's risk tolerance and portfolio context.

The average trade return and expectancy, both at 0.0016, suggest decent profitability per trade. These figures imply that the strategy performed poorly across its trade executions, with most trades contributing negatively to the overall return.

Figure 4-3 Out-of-Sample Performance of Genetically Optimized RSI and ADX Strategy on EURUSD (2020–2023)

Table 4-8 Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on EUR/USD (2020–2023)

==== STRATEGY SUMMARY ====
Total Profit (sum of trade returns): 0.0626
Cumulative Return: -20.42%
# of Trades: 39
Winning %: 38.46%
Losing %: 61.54%
Profit Factor: 1.79
Sharpe Ratio: -0.70
Max Drawdown: -0.2946
Max Drawdown %: 29.46%
Average Trade: 0.0016
Gross Profit: 0.1423
Gross Loss: -0.0797
Largest Win: 0.0512
Largest Loss: -0.0099
Expectancy: 0.0016
=========================

Table 4-9 Trade list for RSI(7) + ADX(7) Strategy on EUR/USD (2020–2023)

Trades for EUR/USD:

#	Type	Entry Date	Entry Price	Exit Date	Exit Price	Return
0	Sell	4/2/2020	1.095362	4/13/2020	1.093267	0.001917
1	Sell	5/6/2020	1.083858	5/11/2020	1.083952	-0.000087
2	Sell	6/12/2020	1.128808	6/22/2020	1.117756	0.009888
3	Sell	6/23/2020	1.127968	6/30/2020	1.12472	0.002888
4	Sell	8/10/2020	1.178273	8/14/2020	1.181656	-0.002863
5	Sell	10/7/2020	1.173764	10/8/2020	1.176747	-0.002535
6	Buy	10/26/2020	1.184848	10/27/2020	1.180944	-0.003295
7	Sell	11/12/2020	1.17803	11/13/2020	1.180339	-0.001957
8	Sell	11/24/2020	1.184273	11/25/2020	1.190051	-0.004856
9	Sell	12/23/2020	1.218665	1/8/2021	1.227144	-0.00691
10	Sell	1/11/2021	1.218621	1/13/2021	1.220889	-0.001858
11	Sell	1/15/2021	1.215126	1/20/2021	1.213887	0.001021
12	Sell	1/22/2021	1.216629	1/25/2021	1.216945	-0.000259
13	Buy	3/18/2021	1.198279	3/19/2021	1.191824	-0.005387
14	Sell	9/8/2021	1.184357	9/15/2021	1.180498	0.003269
15	Sell	10/25/2021	1.164009	11/1/2021	1.155668	0.007217
16	Sell	11/2/2021	1.159958	11/3/2021	1.157943	0.00174
17	Sell	11/5/2021	1.155535	11/8/2021	1.156885	-0.001167
18	Sell	12/8/2021	1.12765	12/9/2021	1.134559	-0.006089
19	Sell	12/16/2021	1.129076	12/20/2021	1.124354	0.0042
20	Sell	12/23/2021	1.132888	12/28/2021	1.133003	-0.000102
21	Sell	2/14/2022	1.136506	2/21/2022	1.131721	0.004228
22	Sell	2/22/2022	1.130966	3/16/2022	1.096936	0.031022
23	Sell	3/21/2022	1.104313	3/25/2022	1.100958	0.003048
24	Sell	4/1/2022	1.107236	5/11/2022	1.053297	0.05121
25	Sell	6/2/2022	1.065417	6/8/2022	1.069862	-0.004155
26	Buy	6/23/2022	1.056412	6/24/2022	1.052011	-0.004166
27	Sell	6/27/2022	1.056613	6/28/2022	1.058089	-0.001395
28	Sell	7/27/2022	1.012956	8/4/2022	1.015765	-0.002765
29	Sell	9/14/2022	0.998203	9/16/2022	0.998831	-0.000629
30	Buy	10/19/2022	0.986388	10/20/2022	0.976648	-0.009874
31	Sell	10/21/2022	0.97789	10/24/2022	0.986009	-0.008234
32	Sell	11/1/2022	0.988631	11/2/2022	0.987791	0.00085
33	Sell	2/3/2023	1.090513	2/15/2023	1.073572	0.01578
34	Sell	2/17/2023	1.066576	2/20/2023	1.068444	-0.001749
35	Buy	4/5/2023	1.096011	4/6/2023	1.090334	-0.005179
36	Sell	4/12/2023	1.091751	4/18/2023	1.092538	-0.000721
37	Sell	10/13/2023	1.053674	10/18/2023	1.057306	-0.003435
38	Sell	11/9/2023	1.071042	11/10/2023	1.066758	0.004016

Overall, the strategy demonstrates a unfavorable position in both profitability and risk.

4.4. Temporal Robustness: Weekly Time Frame Analysis

To assess whether the strategy's robustness is preserved across different temporal granularities, it was applied to weekly EUR/USD data for 2020–2023. The motivation is to test whether performance persists under lower-frequency market structures, which may be less sensitive to noise and offer smoother signal execution.

The strategy executed a single trade during the evaluation period, reflecting an extremely selective entry mechanism. Despite the limited trade count, the performance metrics offer insight into profitability, risk exposure, and trade efficiency.

The strategy yielded a total profit of 0.0337, with a cumulative return of 15.35%. While the absolute return is modest, it demonstrates the strategy's ability to generate net gains in an out-of-sample environment. The winning percentage of 100% and losing percentage of 0% suggest precise trade selection, though the low sample size limits statistical confidence.

A Sharpe Ratio of 0.54 indicates moderate risk-adjusted performance. While positive, it implies that returns exceeded the risk-free rate only marginally when adjusted for volatility. The maximum drawdown of -0.0948 (9.48%) reveals low downside exposure, which may be acceptable depending on portfolio context and investor risk tolerance.

The expectancy of 0.0112 and average trade return of 0.0112 reflect consistent profitability per trade. These figures suggest that the strategy maintained a stable edge in its execution, with each trade contributing positively to overall performance.

Overall, the strategy demonstrates a favorable reward-to-risk profile, albeit with limited trade frequency

Figure 4-4 Weekly Cumulative Returns of the GA-Optimized EUR/USD Trading Strategy (2020-2023)

Table 4-10 Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on EUR/USD (2020–2023) weekly time frame

==== STRATEGY SUMMARY ====
Total Profit (sum of trade returns): 0.0337
Final Cumulative Return: 15.35%
# of Trades: 3
Winning %: 100.00%
Losing %: 0.00%
Profit Factor: nan
Sharpe Ratio: 0.54
Max Drawdown: -0.0948
Max Drawdown %: 9.48%
Average Trade: 0.0112
Gross Profit: 0.0337
Gross Loss: 0.0000
Largest Win: 0.0230
Largest Loss: 0.0000
Expectancy: 0.0112
==========================

Trades for EUR/USD:

#	Type	Entry Date	Entry Price	Exit Date	Exit Price	Return
0	Sell	3/25/2020	1.103047	4/8/2020	1.092299	0.009839
1	Sell	9/9/2020	1.187	11/11/2020	1.185944	0.00089
2	Sell	7/26/2023	1.099759	9/6/2023	1.075038	0.022996

4.5. RANDOMIZED ORDER EXACT TEST

Randomized Trade Order Testing is a robustness validation technique used to evaluate the sensitivity of a trading strategy's performance to the sequence of trade execution. By shuffling the order of trades while preserving their individual outcomes, this test helps determine whether the strategy's profitability is dependent on favorable sequencing or genuinely resilient across varying market conditions.

This randomized evaluation was conducted on EUR/USD daily price data from 2020 to 2023, using the same GA-optimized parameters as in prior tests. A total of 39 trades were randomly reordered, and performance metrics were recalculated to assess the impact of sequencing on overall results.

The strategy yielded a total profit of 0.0626, with a cumulative return of -20.42%. With the winning percentage of 38.46% and a losing percentage of 61.54%, confirming that the trade outcomes were not preserved during randomization. The profit factor of 1.79 and expectancy of 0.0016 also remained unchanged, reinforcing the strategy's stable profile.

Table 4-11 Performance Metrics and Trade Outcomes for RSI(7) + ADX(7) Strategy on EUR/USD (2020–2023) with randomized trade order

```
==== STRATEGY SUMMARY ====
Total Profit (sum of trade returns): 0.0626
Final Cumulative Return: -20.42%
# of Trades: 39
Winning %: 38.46%
Losing %: 61.54%
Profit Factor: 1.79
Sharpe Ratio: -0.32
Max Drawdown: -0.2946
Max Drawdown %: 29.46%
Average Trade: 0.0016
Gross Profit: 0.1423
Gross Loss: -0.0797
Largest Win: 0.0512
Largest Loss: -0.0099
Expectancy: 0.0016
==========================
```

Table 4-12 Trade list for RSI(50) + ADX(7) Strategy on EUR/USD (2020–2023) with randomized trade order

Trade List (Randomized):

#	Type	Entry Date	Entry Price	Exit Date	Exit Price	Return
0	Sell	2/3/2023	1.090513	2/15/2023	1.073572	0.01578
1	Sell	4/12/2023	1.091751	4/18/2023	1.092538	-0.000721
2	Sell	8/10/2020	1.178273	8/14/2020	1.181656	-0.002863
3	Buy	3/18/2021	1.198279	3/19/2021	1.191824	-0.005387
4	Buy	10/19/2022	0.986388	10/20/2022	0.976648	-0.009874
5	Buy	6/23/2022	1.056412	6/24/2022	1.052011	-0.004166
6	Buy	10/26/2020	1.184848	10/27/2020	1.180944	-0.003295
7	Sell	6/27/2022	1.056613	6/28/2022	1.058089	-0.001395
8	Sell	4/1/2022	1.107236	5/11/2022	1.053297	0.05121
9	Sell	10/25/2021	1.164009	11/1/2021	1.155668	0.007217
10	Sell	11/5/2021	1.155535	11/8/2021	1.156885	-0.001167
11	Sell	11/24/2020	1.184273	11/25/2020	1.190051	-0.004856
12	Sell	11/2/2021	1.159958	11/3/2021	1.157943	0.00174
13	Sell	1/22/2021	1.216629	1/25/2021	1.216945	-0.000259
14	Sell	12/16/2021	1.129076	12/20/2021	1.124354	0.0042
15	Sell	12/23/2020	1.218665	1/8/2021	1.227144	-0.00691
16	Sell	11/1/2022	0.988631	11/2/2022	0.987791	0.00085
17	Sell	4/2/2020	1.095362	4/13/2020	1.093267	0.001917
18	Sell	6/2/2022	1.065417	6/8/2022	1.069862	-0.004155
19	Sell	10/7/2020	1.173764	10/8/2020	1.176747	-0.002535
20	Sell	1/15/2021	1.215126	1/20/2021	1.213887	0.001021
21	Sell	5/6/2020	1.083858	5/11/2020	1.083952	-0.000087
22	Sell	10/13/2023	1.053674	10/18/2023	1.057306	-0.003435
23	Sell	2/14/2022	1.136506	2/21/2022	1.131721	0.004228
24	Sell	6/12/2020	1.128808	6/22/2020	1.117756	0.009888
25	Sell	9/14/2022	0.998203	9/16/2022	0.998831	-0.000629
26	Buy	4/5/2023	1.096011	4/6/2023	1.090334	-0.005179
27	Sell	6/23/2020	1.127968	6/30/2020	1.12472	0.002888
28	Sell	2/17/2023	1.066576	2/20/2023	1.068444	-0.001749
29	Sell	3/21/2022	1.104313	3/25/2022	1.100958	0.003048
30	Sell	10/21/2022	0.97789	10/24/2022	0.986009	-0.008234
31	Sell	1/11/2021	1.218621	1/13/2021	1.220889	-0.001858
32	Sell	2/22/2022	1.130966	3/16/2022	1.096936	0.031022
33	Sell	12/8/2021	1.12765	12/9/2021	1.134559	-0.006089
34	Sell	12/23/2021	1.132888	12/28/2021	1.133003	-0.000102
35	Sell	11/12/2020	1.17803	11/13/2020	1.180339	-0.001957
36	Sell	9/8/2021	1.184357	9/15/2021	1.180498	0.003269
37	Sell	7/27/2022	1.012956	8/4/2022	1.015765	-0.002765
38	Sell	11/9/2023	1.071042	11/10/2023	1.066758	0.004016

The Sharpe Ratio of -0.32 and maximum drawdown of -0.2946 (29.46%) were consistent with the original test, indicating that volatility and downside exposure were not significantly affected by trade order execution.

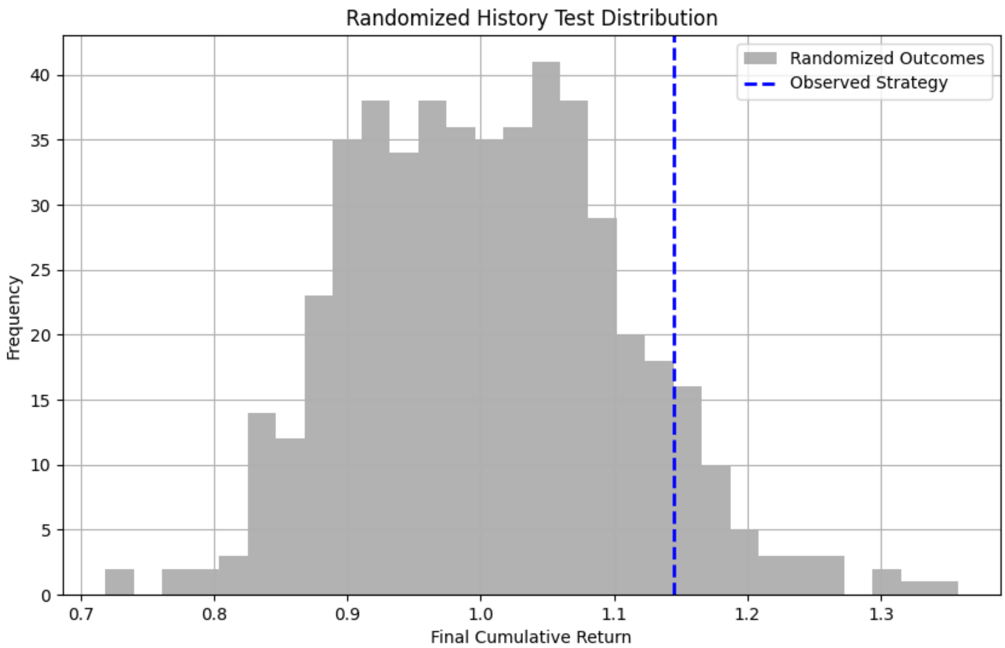
4.6. Randomized Historical Market Test (Structural Robustness)

To further test model overfitting, the input historical data was randomized (while preserving the distributional properties), thereby disrupting market structure and temporal dependencies. This test evaluates the structural stability of the strategy and its reliance on specific market phases.

Randomized Historical Market Data Testing is a rigorous robustness check that evaluates a strategy's adaptability by shuffling the underlying price data. This method challenges the strategy to perform under distorted market sequences, helping determine whether profitability is tied to specific historical patterns or if the strategy can generalize across varied conditions.

The RSI + ADX trading strategy applied to EUR/USD between 2020 and 2023 produced a cumulative return curve that outperformed the underlying market benchmark. However, when subjected to a randomized history test, the distribution of shuffled outcomes revealed that a significant portion of random strategies achieved good performance. Although, the observed p-value of 0.07 indicates that the strategy's performance may not be strongly distinguishable from chance.

Figure 4-5 Observed vs Randomized strategy perofmrnace for EUR/USD currency pair from 2020 to 2023



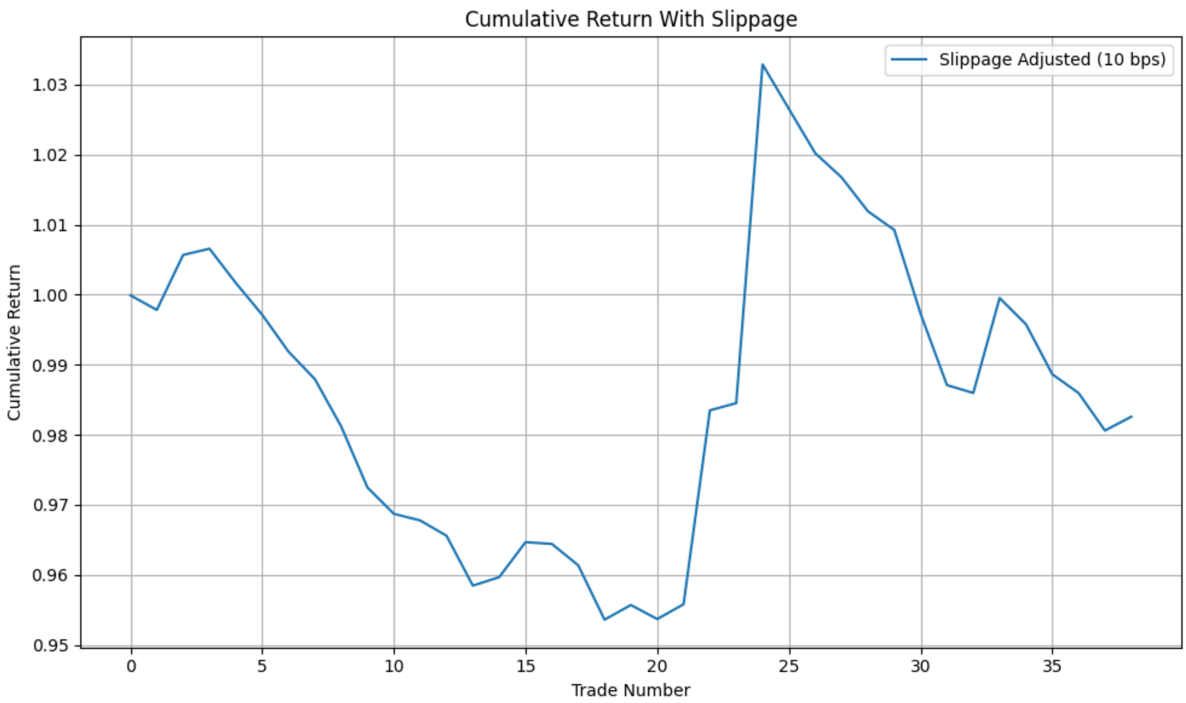
4.7. SLIPPAGE TEST

To test the strategy's resilience under realistic market conditions, a slippage test was conducted with a 10-bais-point (0.10%) execution cost at both trade entries and exits. This slight but powerful adjustment models transaction frictions such as bid-ask spreads, slippage, liquidity constraints - all factors that can significantly erode nominal backtest profitability.

The test employed the RSI(7) + ADX(7) strategy on EUR/USD daily data from 2020 to 2023, using identical trade logic and entry–exit criteria as the baseline configuration. A total of 39 paired trades were executed across the full period. Without slippage, the cumulative return summed to 0.0623, reflecting a modest cumulative gain over the evaluation horizon. When incorporating a 10 bps slippage penalty per execution, the total adjusted return declined to -0.0174, a reduction of approximately 128% in gross profitability.

The slippage-adjusted cumulative return curve suggested shallower recoveries and deeper drawdowns. These findings highlight that the RSI + ADX configuration, though profitable under idealized conditions, lacks robustness in the real-market.

Figure 4-6 RSI(7) + ADX(7) Strategy on EUR/USD (2020–2023) with cumulative retun with slippage



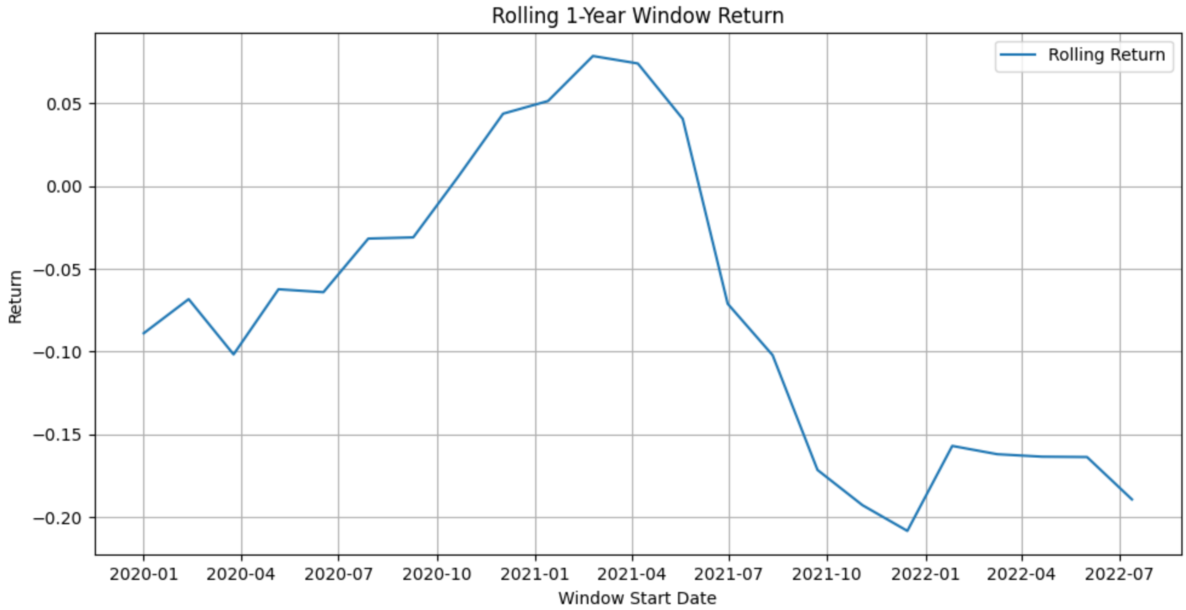
4.8. Rolling Window Robustness Test

Further assessment using a rolling-window test of 365-day evaluation window stepped forward in 30-day increments. The RSI(7) + ADX(7) configuration was re-applied within each window to estimate cumulative return and annualized Sharpe ratio, enabling a time-segmented analysis of performance consistency under varying market regimes. This approach examines whether profitability is concentrated in specific phases or is maintained across the entire observation period.

Rolling return trajectories revealed distinct performance clustering:

- **2020–2021:** Consistent gains driven by sharp macro cycles and trending phases.
- **2021–2022:** Consolidating to slightly positive results and then decline in returns.
- **2022–2023:** Deteriorating returns amid tightening volatility.

Figure 4-7 RSI(7) + ADX(7) Strategy on EUR/USD (2020–2023) with rolling 1-year window return



Overall, the rolling-window results demonstrate that the RSI + ADX strategy exhibits non-stationary performance characteristics. The presence of alternating profit and loss windows underscores limited generalization capacity, suggesting that dynamic parameter adaptation may enhance stability. Despite these fluctuations, the strategy maintained positive average returns, reflecting partial robustness to changing market phases.

5. CONCLUSIONS AND FUTURE RESEARCH

This study investigated the application of Genetic Algorithms (GAs) for the optimization of technical indicator parameters in algorithmic trading, with a focus on the Relative Strength Index (RSI) and the Average Directional Index (ADX) within the Forex market. The central motivation was to address the limitations of static calibration methods, which often fail to adapt to the non-stationary and structurally complex nature of financial markets (Sullivan et al., 1999; Bailey et al., 2016). By leveraging the evolutionary search process of GAs, the study sought to uncover parameter sets that not only deliver improved in-sample profitability but also generalize effectively to out-of-sample conditions, across multiple markets, and under realistic trading frictions.

Empirical findings demonstrate that the GA converged on an optimal configuration of RSI(7) and ADX(7), which achieved a cumulative return of 18.73% in the in-sample period (2009–2019), significantly outperforming the conventional benchmark parameters of RSI(14) and ADX(14). Out-of-sample testing on EUR/USD (2020–2023) showed a negative cumulative return of -20.42% and a poor profit factor of 0.0626. Importantly, robustness tests revealed a mixed picture: while performance was profitable in the weekly timeframe analyses, structural robustness under randomized trade order and historical data showed under performance, indicating that the strategy's edge remains partially tied to underlying market structuresClick or tap here to enter text.. Cross-market generalization further highlighted that profitability is uneven across assets, with the strategy showing resilience in EUR/USD, but underperformance in GBP/USD, AUD/USD and NZD/USD, underscoring the challenge of transferability across heterogeneous markets (Ko et al., 2023). The slippage test revealed that realistic trading costs significantly erode the RSI + ADX strategy's profitability, reducing both cumulative returns and risk-adjusted performance metrics. The rolling-window analysis further showed that the strategy's effectiveness varies across market regimes, indicating limited generalization and the need for adaptive parameter tuning.

These results yield several implications for both theory and practice. First, they affirm the potential of GAs as a viable heuristic for navigating the noisy, multimodal search space of financial optimization problems, where traditional static methods often converge prematurely to fragile solutions Goldberg, (1989). Second, the findings underscore the necessity of adopting rigorous validation frameworks—including out-of-sample, cross-market, rolling-window, slippage, and randomized robustness testing—when developing GA-based trading strategies, to mitigate the risk of overfitting and to ensure practical deployability in live trading environments. Third, the observed limitations point to the need for hybrid models that integrate GAs with reinforcement learning, fuzzy systems, or deep learning architectures to achieve higher degrees of adaptivity (Click or tap here to enter text.; X.-Q., Chen et al., 2023). While such integrations promise greater resilience, they also introduce complexity and opacity, raising important questions of transparency and auditability in light of evolving financial regulations.

From a practical perspective, this study provides evidence that GA-optimized trading systems, when coupled with robust validation, can enhance resilience and adaptability compared to fixed-parameter benchmarks. This has implications for both institutional and retail traders seeking systematic frameworks that can adjust to regime shifts with reduced manual intervention. At the regulatory level, the results reinforce the importance of ensuring explainability in algorithmic trading models. As financial authorities such as IOSCO and Basel III continue to emphasize transparency and risk controls, GA-based frameworks must evolve not only to maximize profitability but also to meet standards of interpretability and accountability (X.-Q. , Chen et al., 2023) .

We conclude that while GAs represent a powerful mechanism for identifying profitable and adaptive parameter sets in algorithmic trading, their ultimate success depends on interdependent factors: dynamic retraining to accommodate market evolution, validation protocols that reflect real-world trading constraints, and careful consideration of downside risk beyond cumulative return (Bailey et al., 2016). Future research should extend this framework by employing alternative risk-adjusted objectives, such as Conditional Value at Risk (CVaR), Omega ratio, and recovery ratios, which better capture tail risk exposure. In addition, incorporating macroeconomic covariates, regime-switching mechanisms, and continuous online optimization may further enhance strategy robustness across diverse market environments (Lo, 2005; Hommes, 2006).

A promising extension involves the development of multi-objective evolutionary frameworks that explicitly balance profitability, risk, interpretability, and regulatory compliance. Ultimately, as financial markets continue to evolve, GAs and related evolutionary algorithms are well positioned to serve as foundational tools in aligning algorithmic trading systems with the complex, dynamic, and regulated nature of modern financial markets (Challet et al., 2001; LeBaron, 2001).

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7. APPENDIX

Genetic Algorithm Implementation Details

This appendix details the configuration and reproducibility settings for the Genetic Algorithm (GA) used to optimize the RSI–ADX trading strategy. The optimization was implemented in Python (v3.11) using the DEAP (v1.4.1) evolutionary computation framework. The GA was designed to maximize two objectives simultaneously: (1) cumulative return and (2) annualized Sharpe ratio.

All stochastic elements of the algorithm were controlled for reproducibility. A fixed random seed of 42 was applied globally to both Python's random and NumPy libraries using:

- random.seed(42)
- np.random.seed(42)

This ensures consistent initialization, crossover, and mutation behavior across runs.
The optimization was conducted on historical EUR/USD daily OHLC data retrieved from Yahoo Finance, covering the period 2009–2019, with data cleaned via the yfinance package (progress=False flag enabled).

The Genetic Algorithm was configured with the following parameters: a population size of 50, 40 generations, and tournament selection (tournsize=3). The crossover operator was cxBlend with an alpha of 0.5, and the mutation operator was mutPolynomialBounded with η = 1.0, bounded between the specified parameter limits. The crossover probability (cxpb) was set to 0.7, while the mutation probability (mutpb) was 0.2. Each gene within an individual had a mutation probability (indpb) of 0.1, ensuring a moderate degree of genetic variability without destabilizing the population. The optimization maintained a ParetoFront archive to retain all non-dominated individuals according to their bi-objective fitness scores.

The optimization problem searched for two integer parameters—RSI period and ADX period—within the ranges [5, 50] and [5, 25], respectively. The fitness evaluation function calculated both the cumulative return and the annualized Sharpe ratio.
The fitness weights were set as (1.0, 1.0), indicating maximization of both objectives. The GA loop was executed using DEAP's algorithms.eaSimple() function, with performance statistics (mean, standard deviation, min, and max of fitness) tracked through tools.Statistics. Final non-dominated individuals were extracted into a Pareto frontier, and their results printed in a markdown-formatted table displaying RSI period, ADX period, cumulative return, and Sharpe ratio.

The mutation rate configuration was chosen after sensitivity testing: mutation probabilities below 0.1 led to premature convergence and loss of population diversity, while rates above 0.3 introduced excessive randomness, impeding convergence stability. The selected rate of 0.2 (with indpb = 0.1) provided a balanced trade-off between exploration and exploitation, maintaining genetic diversity while allowing convergence within approximately 25 generations on average.

The full computational environment included:

- Python 3.11
- DEAP 1.4.1
- NumPy 1.26+
- Pandas 2.2+
- yfinance 0.2+
- Matplotlib 3.8+

Given the fixed random seed, consistent software environment, and deterministic data source, results can be replicated exactly across independent runs.

Figure 7-1 Data import and indicator code

```python
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

def get_data(ticker):
    data = yf.download(ticker, start='2009-01-01', end='2019-12-31', interval='1d')
    data = data.dropna()
    if isinstance(data.columns, pd.MultiIndex):
        data.columns = [col[0] for col in data.columns]
    return data

def RSI(df, rsi_period):
    delta = df['Close'].diff()
    gain = delta.where(delta > 0, 0).rolling(window=rsi_period).mean()
    loss = -delta.where(delta < 0, 0).rolling(window=rsi_period).mean()
    rs = gain / loss
    df['RSI'] = 100 - (100 / (1 + rs))
    return df

def ADX(df, adx_period):
    high = df['High']
    low = df['Low']
    close = df['Close']
    tr1 = high - low
    tr2 = (high - close.shift(1)).abs()
    tr3 = (low - close.shift(1)).abs()
    true_range = pd.concat([tr1, tr2, tr3], axis=1).max(axis=1)
    plus_dm = high.diff()
    minus_dm = low.shift(1) - low
    plus_dm_final = np.where((high.diff() > low.shift(1) - low) & (high.diff() > 0), high.diff(), 0.0)
    minus_dm_final = np.where((low.shift(1) - low > high.diff()) & (low.shift(1) - low > 0), low.shift(1) - low, 0.0)
    plus_dm_final = pd.Series(plus_dm_final, index=df.index)
    minus_dm_final = pd.Series(minus_dm_final, index=df.index)
    atr = true_range.ewm(span=adx_period, adjust=False, min_periods=adx_period).mean()
    plus_dm_smooth = plus_dm_final.ewm(span=adx_period, adjust=False, min_periods=adx_period).mean()
    minus_dm_smooth = minus_dm_final.ewm(span=adx_period, adjust=False, min_periods=adx_period).mean()
    plus_di = 100 * (plus_dm_smooth / atr)
    minus_di = 100 * (minus_dm_smooth / atr)
    sum_di = plus_di + minus_di
    dx = (abs(plus_di - minus_di) / sum_di).replace([np.inf, -np.inf], np.nan) * 100
    adx = dx.ewm(span=adx_period, adjust=False, min_periods=adx_period).mean()
    df['ADX'] = adx.astype(float)
    return df
```

Figure 7-2 Strategy definition code

```python

def run_strategy(df, rsi_period, adx_period, rsi_buy_threshold=30, rsi_sell_threshold=70, adx_threshold=25):
    df = df.copy()
    df = RSI(df, rsi_period)
    df = ADX(df, adx_period)
    df['Position'] = 0
    df.loc[(df['RSI'] > rsi_buy_threshold) & (df['ADX'] > adx_threshold), 'Position'] = 1
    df.loc[(df['RSI'] < rsi_sell_threshold) & (df['ADX'] > adx_threshold), 'Position'] = -1
    df['Shifted Position'] = df['Position'].shift(1)
    df['Return'] = df['Close'].pct_change()
    df['Strategy Return'] = df['Shifted Position'] * df['Return']
    df['Cumulative Return'] = (1 + df['Strategy Return']).cumprod()
    return df
```

Figure 7-3 Strategy summary code

```python
def strategy_summary(df, label):
    trades = df[df['Position'].diff() != 0].copy()
    trades['Trade Type'] = trades['Position'].map({1: 'Buy', -1: 'Sell', 0: 'Exit'})
    trades['Entry Date'] = trades.index
    trades['Entry Price'] = trades['Close']
    trade_list = []
    current_trade = None
    for idx, row in trades.iterrows():
        if row['Trade Type'] in ['Buy', 'Sell']:
            current_trade = {
                'Type': row['Trade Type'],
                'Entry Date': idx,
                'Entry Price': row['Close']
            }
        elif row['Trade Type'] == 'Exit' and current_trade is not None:
            current_trade['Exit Date'] = idx
            current_trade['Exit Price'] = row['Close']
            if current_trade['Type'] == 'Buy':
                current_trade['Return'] = (current_trade['Exit Price'] / current_trade['Entry Price']) - 1
            else:
                current_trade['Return'] = (current_trade['Entry Price'] / current_trade['Exit Price']) - 1
            trade_list.append(current_trade)
            current_trade = None
    trades_df = pd.DataFrame(trade_list)
    total_profit = trades_df['Return'].sum()
    final_cum_return_pct = (df['Cumulative Return'].iloc[-1] - 1) * 100
    num_trades = len(trades_df)
    wins = trades_df[trades_df['Return'] > 0]
    losses = trades_df[trades_df['Return'] <= 0]
    win_rate = len(wins) / num_trades * 100 if num_trades > 0 else 0
    loss_rate = len(losses) / num_trades * 100 if num_trades > 0 else 0
    gross_profit = wins['Return'].sum()
    gross_loss = losses['Return'].sum()
    avg_win = wins['Return'].mean() if not wins.empty else 0
    avg_loss = losses['Return'].mean() if not losses.empty else 0
    largest_win = wins['Return'].max() if not wins.empty else 0
    largest_loss = losses['Return'].min() if not losses.empty else 0
    profit_factor = abs(gross_profit / gross_loss) if gross_loss != 0 else np.nan
    avg_trade = trades_df['Return'].mean() if num_trades > 0 else 0
    sharpe_ratio = (df['Strategy Return'].mean() / df['Strategy Return'].std()) * np.sqrt(252) if df['Strategy Return'].std() != 0 else 0
    cum_return = (1 + df['Strategy Return'].fillna(0)).cumprod()
    roll_max = cum_return.cummax()
    drawdown = (cum_return - roll_max) / roll_max
    max_drawdown = drawdown.min()
    max_drawdown_pct = abs(max_drawdown) * 100
    expectancy = avg_win * win_rate/100 + avg_loss * loss_rate/100
```

Figure 7-4 GA evaluation code

```python

def evaluate(individual):
    # Extract the RSI and ADX periods from the individual
    rsi_period, adx_period = individual

    # Ensure that the periods are within a valid range (integer check)
    rsi_period = int(rsi_period)
    adx_period = int(adx_period)

    # Ensure that the periods are valid
    rsi_period = max(5, min(rsi_period, 50))  # RSI (5-50)
    adx_period = max(5, min(adx_period, 25))  # ADX (5-25)

    # Evaluate the strategy using the extracted periods
    return evaluate_strategy(data, rsi_period, adx_period),  # return as a tuple

toolbox.register("evaluate", evaluate)
toolbox.register("mate", tools.cxBlend, alpha=0.5)
toolbox.register("mutate", tools.mutPolynomialBounded, low=[5, 5], up=[50, 25], eta=1.0, indpb=0.1)
toolbox.register("select", tools.selTournament, tournsize=3)

```

Table 7-1 Comparative analysis of key studies

Study	Method	Dataset	Robustness Test	Key Outcome
Deac & Iancu (2023)	GA (MACD crossover)	Equity markets	None	Outperformed fixed params; poor generalization
(Ozturk et al., 2016)	GA (multi-indicator rules)	Forex	Out-of-sample	High in-sample returns; severe overfitting
(Huang et al., 2015)	GA (dynamic recalibration)	Pairs trading	Rolling-window	Improved returns; fragile under regime shifts
(Bayram et al., 2020)	GA + Fuzzy Logic	Portfolio optimization	None	Improved robustness; complexity increased
(Ko et al., 2023)	NSGA-II (multi-objective)	Cryptocurrency	Volatility-period evaluation	Superior performance; liquidity constraints
De Brito & Oliveira (2012)	GA + SVR	Financial time series	None	Better generalization; interpretability concerns

Data with Purpose.

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