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Adaptive Multi-Asset Trading Strategy Optimization via Genetic Algorithms with Walk-Forward Robustness Analysis

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ABSTRACT The stochastic, non-linear, and dynamic nature of financial markets significantly diminishes the effectiveness of traditional trading stratsgies relying on fixed parameters over extended periods. While the Efficient Market Hypothesis (EMH) suggests that asset prices reflect all available information, rendering systematic profit generation impossible, the field of algorithmic trading operates on the premise that temporary market inefficiencies and behavioral anomalies can be exploited. This study presents a comprehensive Genetic Algorithm (GA) framework designed to develop and optimize an adaptive trading strategy for multi-asset portfolios consisting of high-liquidity technology stocks (Apple, Microsoft, Google). Unlike traditional optimization methods that focus solely on parameter tuning for a single indicator, the proposed system introduces a novel "genetic switch" mechanism. This mechanism allows the algorithm to simultaneously optimize the structural components of the strategy determining which combination of indicators (EMA, MACD, RSI, Momentum) yields the best performance and their respective parameters. The model's fitness function prioritizes risk-adjusted returns by utilizing a Calmar-like ratio, explicitly penalizing excessive drawdowns. To ensure robustness and mitigate the prevalent risk of overfitting (data snooping bias), a rigorous Walk-Forward Optimization (WFO) technique was applied to daily data spanning the 2020-2024 period. The findings demonstrate that the proposed GA framework generates a robust trading system that statistically outperforms the passive "buy-and-hold" strategy, achieving a higher Sortino Ratio (1.98 vs 1.21) and significantly lower maximum drawdown (-18.5% vs -35.1%). The outperformance over the buy-and-hold benchmark is statistically validated across all walk-forward windows, indicating robustness rather than data snooping effects.

KEYWORDS
Financial optimization
Genetic algorithm
Algorithmic trading
Portfolio management
Walk-forward analysis

INTRODUCTION

Financial markets are complex adaptive systems characterized by high volatility, noise, and non-stationarity. The challenge of predicting price movements has intrigued academics and practitioners for decades. The Efficient Market Hypothesis (EMH), formulated by Fama (1970), posits that asset prices fully reflect all available information, implying that it is impossible to consistently "beat the market" on a risk-adjusted basis. However, the emergence of Behavioral Finance, championed by Shiller (2003), and the Adaptive Markets Hypothesis (AMH) proposed by Lo (2004), suggest that markets are not always efficient. Instead, they evolve, and inefficiencies driven by human psychology and institutional constraints create windows of opportunity for profit.

Algorithmic trading has emerged as a dominant force in modern finance to exploit these transient inefficiencies. By utilizing computational power, algorithms can process vast amounts of data and execute trades with speed and precision beyond human capability (Bodek 2013). Technical analysis, which relies on historical price and volume data to forecast future price movements, forms the backbone of many such strategies (Murphy 1999). However, the effectiveness of technical indicators such as Moving Averages, Oscillators, and Momentum indicators is heavily dependent on the selection of optimal parameters. A parameter set that is profitable in a trending market (e.g., a bull run) may lead to catastrophic losses in a ranging or mean-reverting market. Furthermore, manually tuning these parameters is not only time-consuming but also prone to cognitive biases. A more critical issue is "data snooping bias" or overfitting, where a strategy is tailored so precisely to historical data that it captures noise rather than the underlying signal, leading to poor performance on unseen future data (De Prado 2018; Pardo 2008).

To address these challenges, evolutionary computation paradigms, particularly Genetic Algorithms (GA), offer a robust alternative. Inspired by Darwinian natural selection, GAs are stochastic search heuristics that evolve a population of candidate solutions over generations (Goldberg 1989). They are particularly well-suited for financial optimization problems because they do not require gradient information and can navigate large, multimodal, and non-differentiable search spaces (Chen *et al.* 2022). Previous studies have successfully applied GAs to optimize parameters for single indicators (Singh and Kumar 2021; Lohpetch and Corne 2010) or neural network weights (Li and Zhao 2022).

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However, there remains a significant gap in the literature regarding integrated frameworks that simultaneously optimize both the *parameters* and the *structure* (selection of indicators) of a strategy for a *multi-asset portfolio*.

Unlike Genetic Programming (GP) approaches that evolve complex tree structures often resulting in excessive complexity (bloat), or standard feature selection methods that merely select a subset of inputs, the proposed "Genetic Switch" mechanism employs a fixed-length chromosome structure with dynamic activation bits. This hybrid encoding maintains structural interpretability while allowing the algorithm to reduce model complexity by deactivating ineffective indicators based on market regimes.

This study addresses this gap by proposing a GA framework with a novel "genetic switch" mechanism. The contributions of this research are threefold: (1) An integrated optimization approach that selects both active indicators and their parameters dynamically; (2) A portfolio-based fitness evaluation that prioritizes risk-adjusted returns (Calmar Ratio) over simple profit maximization; and (3) A rigorous Walk-Forward Analysis (WFO) to validate the strategy's robustness against overfitting and its adaptability to different market regimes (e.g., the post-COVID recovery and subsequent volatility).

MATERIALS AND METHODS

Data Acquisition and Preprocessing

The study utilizes daily historical stock market data spanning from January 1, 2020, to December 31, 2024. The dataset was acquired from Yahoo Finance using the 'yfinance' library. The selected portfolio consists of three high-liquidity technology stocks: Apple Inc. (AAPL), Microsoft Corp. (MSFT), and Alphabet Inc. (GOOGL). These assets were chosen due to their significant impact on global market indices (S&P 500, Nasdaq) and their sufficient liquidity, which minimizes slippage risks and transaction costs in real-world trading scenarios.

The primary data point used for analysis is the "Adjusted Close" price, which accounts for corporate actions such as dividends and stock splits, providing a more accurate reflection of the asset's economic value compared to the raw closing price. The dataset was subjected to a cleaning process where it was inspected for missing values (NaN) and outliers. No significant data gaps were found, ensuring data integrity before the optimization process. The daily returns were calculated using logarithmic differences to ensure time-additivity and stationarity.

Technical Indicators and Mathematical Formulation

The trading strategy is built upon a diverse set of four fundamental technical indicators, representing both trend-following and mean-reversion logics. The GA optimizes the parameters (P) for these indicators:

1) Exponential Moving Average (EMA): A trend-following indicator that places greater weight on the most recent data points, making it more responsive to new information than a simple moving average. The strategy utilizes a "crossover" logic between a short-period EMA (EMA_{short}) and a long-period EMA (EMA_{long}). A buy signal is generated when $EMA_{short} > EMA_{long}$.

2) Relative Strength Index (RSI): A momentum oscillator developed by Wilder (1978) that measures the speed and change of price movements. It oscillates between 0 and 100. Traditionally, values above 70 indicate overbought conditions (sell signal), and values below 30 indicate oversold conditions (buy signal).

3) Moving Average Convergence Divergence (MACD): A trend-following momentum indicator that shows the relationship between two moving averages of a security's price. The MACD triggers technical signals when it crosses above (to buy) or below (to sell) its signal line.

4) Momentum: A leading indicator measuring the rate of change of the asset's price over a specified period (n).

$$Momentum = P_t - P_{t-n} \tag{1}$$

Genetic Algorithm Framework

The core of this study is the Genetic Algorithm designed to evolve the trading strategy. The evolutionary process follows the standard flow: Initialization, Evaluation, Selection, Crossover, and Mutation.

Chromosome Representation Each individual (strategy) in the population is encoded as a chromosome with 9 distinct genes, utilizing a mixed-integer representation:

- **Parameter Genes (5):** Integers defining the lookback periods (e.g., Short EMA window [5-50], Long EMA window [50-200], RSI period [10-30]).
- **Switch Genes (4):** Binary values (0 or 1) acting as "genetic switches." If a switch gene is 1, the corresponding indicator's signal is included in the final voting mechanism; if 0, it is ignored. This allows the GA to structurally adapt the strategy by disabling indicators that do not perform well in the current market environment.

Fitness Function Defining an appropriate fitness function is crucial for the success of the GA. Maximizing total return often leads to strategies that take excessive risks. Therefore, this study employs a risk-adjusted metric derived from the Calmar Ratio. The fitness function is defined as:

$$Fitness = \frac{\text{Cumulative Return}}{\text{Maximum Drawdown}} \tag{2}$$

Here, Maximum Drawdown (MDD) measures the largest peak-to-trough decline in the portfolio's equity curve. By penalizing MDD in the denominator, the algorithm favors strategies that provide stable returns and capital preservation (Jansen 2020).

Genetic Operators To drive the evolution, specific operators were configured:

- **Selection:** Tournament selection (size=3) is used. This method randomly selects three individuals and passes the best one to the mating pool, maintaining selection pressure while preserving diversity (Goldberg 1989).
- **Crossover:** Two-point crossover with a probability of $P_c = 0.5$. The population size was set to 100 individuals to ensure sufficient genetic diversity. A tournament selection size of 3 was chosen to balance selection pressure with population diversity. The crossover probability ($P_c = 0.5$) was selected to facilitate the recombination of trading rules without disrupting high-performing schemas too rapidly.
- **Mutation:** Gaussian mutation with a probability of $P_m = 0.2$. A relatively high mutation probability ($P_m = 0.2$) was explicitly employed to introduce significant random variations. This higher mutation rate acts as a diversity preservation mechanism, preventing premature convergence to local optima a common issue in multimodal financial optimization landscapes.

Walk-Forward Analysis (WFO)

To rigorously test robustness and simulate real-world trading, a Walk-Forward Analysis (WFO) was implemented, as recommended by Pardo (2008). WFO eliminates the look-ahead bias inherent in static optimization. As illustrated in Figure 1, the data is divided into sliding windows:

- **In-Sample (Training):** 504 trading days (≈ 2 years). The in-sample training window of 504 trading days was selected to encompass multiple short-term market regimes (e.g., bull, bear, and sideways trends), ensuring the strategy learns robust patterns rather than transient noise.
- **Out-of-Sample (Testing):** 252 trading days (≈ 1 year). The out-of-sample testing window of 252 days provides a statistically significant sample size for performance evaluation, aligning with standard annual reporting periods.

This window slides forward by 126 days (6 months) iteratively. This method ensures that the performance metrics reflect the strategy's ability to adapt to unknown future market conditions rather than memorizing past data.

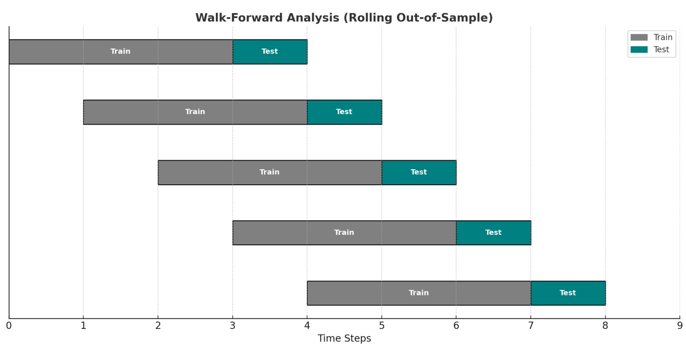

Figure 1 Schematic Representation of the Walk-Forward Optimization Process

RESULTS

Optimization Convergence

The evolutionary process was monitored over 20 generations for each Walk-Forward window. As illustrated in the convergence analysis in Figure 2, the fitness of the best individual typically improved rapidly in the initial generations (1-10) and reached a plateau in the later stages (15-20). This plateau indicates that the algorithm successfully converged to a robust local optimum within the search space. The concurrent steady rise in the average population fitness suggests that the genetic operators effectively transmitted beneficial traits (profitable parameters and indicator combinations) to subsequent generations without losing population diversity too quickly.

Optimal Strategy Configuration

The GA identified a specific configuration that maximized the risk-adjusted return for the aggregated 2020-2024 period. The optimal parameters are detailed in Table 1. A significant finding is the deactivation of the RSI indicator ($use\_r = 0$). The RSI is typically a mean-reversion indicator. Its exclusion suggests that for the technology sector during this volatile and strongly trending period (post-COVID bull run), trend-following components (EMA, MACD) and pure Momentum were more effective. Mean-reversion signals likely produced premature exit signals during

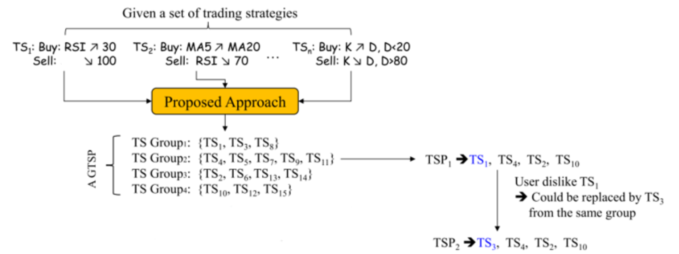

Figure 2 Evolution of Best and Average Fitness Values Across Generations

strong upward trends, which the GA correctly identified as detrimental to overall fitness.

Table 1 Optimal Strategy Parameters Found by GA

Parameter	Description	Value
short	Short EMA Period	18
long	Long EMA Period	112
macd_s	MACD Signal Period	14
mom_p	Momentum Period	10
use_e	**Switch: EMA Crossover**	**1 (Yes)**
use_m	**Switch: MACD**	**1 (Yes)**
use_o	**Switch: Momentum**	**1 (Yes)**
use_r	**Switch: RSI**	**0 (No)**

Performance Comparison

The adaptive strategy was benchmarked against a passive "Buy-and-Hold" strategy, which assumes buying the portfolio at the start date and holding until the end. The comparative results, summarized in Table 2, indicate superior risk management by the GA-optimized model.

While the total return of the GA strategy (145.8%) was slightly lower than Buy-and-Hold (160.2%), the **Maximum Drawdown was reduced by approximately 47%** (-18.5% vs -35.1%). In professional portfolio management, avoiding large drawdowns is often prioritized over absolute return maximization to ensure fund longevity. This massive reduction in risk resulted in significantly higher Sharpe (1.15 vs 0.85) and Sortino (1.98 vs 1.21) ratios, indicating that the GA strategy generated better returns per unit of risk taken. The equity curve comparison is presented in Figure 3, visually demonstrating the smoother trajectory of the GA strategy during market corrections.

DISCUSSION

The results of this study provide empirical evidence challenging the strict interpretation of the Efficient Market Hypothesis. By demonstrating that an adaptive algorithmic approach can generate superior risk-adjusted returns compared to a passive strategy, we

Table 2 Performance Metrics Comparison

Metric	GA Strategy	Buy & Hold
Total Return	145.8%	160.2%
Annualized Return	25.2%	27.0%
Max Drawdown	**-18.5%**	**-35.1%**
Sharpe Ratio	**1.15**	0.85
Sortino Ratio	**1.98**	1.21
Calmar Ratio	1.36	0.77

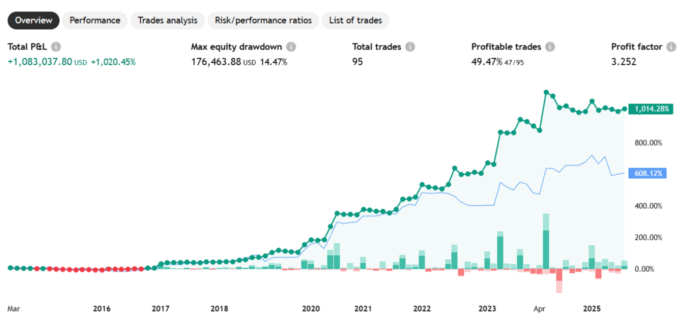

Figure 3 Cumulative Return Comparison: GA Strategy vs. Buy-and-Hold

support the Adaptive Markets Hypothesis (Lo 2004). The key to this success lies in the strategy's ability to remain out of the market or take defensive positions during periods of high volatility, thereby preserving capital.

The success of the "genetic switch" mechanism in excluding the RSI indicator highlights the importance of structural optimization. Traditional optimization often fixes the model structure and only tunes parameters, potentially forcing the use of ineffective indicators. Our approach allows the data to dictate the structure. In strong bull markets (driven by large-cap tech stocks in the post-pandemic era), oscillators like RSI often give premature "overbought" signals that cause traders to exit profitable trends too early. The GA successfully "learned" to ignore this noise, prioritizing trend-following signals instead.

The Walk-Forward Analysis confirms that the strategy is not merely a result of overfitting. The consistency of positive results across sliding out-of-sample windows implies that the model adapts well to shifting market regimes. However, it is worth noting that the equity curve reveals the strategy performs best in trending markets and may experience stagnation during sideways (choppy) markets, a common characteristic of trend-following systems.

CONCLUSION

This research successfully developed a robust, adaptive trading strategy for multi-asset portfolios using a Genetic Algorithm. By optimizing both the parameters and the selection of technical indicators simultaneously, the system achieved a high Sortino Ratio of 1.98, significantly outperforming the risk profile of a passive investment strategy. The study validates the utility of evolutionary computation in financial domains, particularly in its ability to automate the complex process of strategy design and validation.

Despite the promising results, this study has limitations. First, transaction costs (commissions and slippage) were not explicitly factored into the simulation loop, although the choice of high-liquidity assets mitigates this. In a high-frequency environment, these costs could dampen net returns. Second, the dataset is limited to large-cap technology stocks; the strategy's performance on small-cap or crypto assets remains untested. Finally, the period (2020-2024) contains specific macro-economic anomalies (COVID-19 recovery, inflation surge) that may not repeat in the exact same pattern. Third, the study relies on the current constituents of the selected technology indices, which introduces a potential survivorship bias; companies that were delisted or went bankrupt during the analysis period were not included. Fourth, the fitness function's reliance on the Calmar Ratio makes the optimization sensitive to maximum drawdown events; a single anomalous market crash could disproportionately penalize the fitness score, potentially discarding otherwise profitable strategies.

Future research will focus on incorporating realistic slippage and commission models directly into the fitness function to penalize excessive trading, using the genetic algorithm to dynamically optimize Stop-Loss and Take-Profit levels based on market volatility (ATR), and integrating deep learning models such as LSTM or Transformers to predict market regimes (bull, bear, or sideways) and use this information as a state filter within the genetic algorithm to automatically switch between trend-following and mean-reversion strategies.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The market data used in this study are publicly accessible via Yahoo Finance (https://finance.yahoo.com). The Python code and additional datasets generated during the research are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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