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Optimization of Algorithmic Trading Strategies and Risk Management

***A. S. Adewuyi, T.O. Aliu, S. F. Olaniran, O. T. Wahab**

Department of Mathematics and Statistics, Faculty of Pure and applied sciences, Kwara State University, Malete, Nigeria

*Corresponding Author: adewuyiadebayo@gmail.com

ABSTRACT In algorithmic trading, computer programs are used to execute trades based on predefined logic, although their success depends critically on the choice of parameters. This study bridges the gap between theoretical models and practical trading by optimizing two technical indicators, Relative Strength Index (RSI) and Exponential Moving Average (EMA), using exhaustive grid search on historical EURUSD and GBPUSD data spanning January 2023 to June 2025. The optimization results show that optimal parameters vary across currency pairs. In addition, the study expands the optimization framework by incorporating position sizing and risk constraints to further bridge the gap between academic models and real-world trading activities. Statistical validation shows that the optimal strategies have significant mean returns ($p < 0.001$), while the confidence intervals of the Sharpe ratios do not include zero. These in-sample significance results are interpreted cautiously because the strategy selection process involved multiple parameter configurations.

KEYWORDS: Optimization; Parameter Optimization; Exhaustive Search; Algorithmic Trading; Financial Market.

I. INTRODUCTION

Algorithmic trading uses computer programs that can execute trades quickly and with a low cost (Addy et al., 2024). Automated systems have dominated global markets since the 1970s (Kissell, 2013; Gomber & Zimmermann, 2018). Technical indicators such as RSI and EMA generate trading signals (Oktaba & Grzywinska Rapca, 2023). However, those indicators are sensitive to the choice of parameters. This study addresses overfitting and practical implementation gaps through systematic optimization. While Genetic Algorithms prove valid for Financial Optimization (Christodoulou-Volos, 2025) existing work ignores pair-specific fragility and rarely couples parameter search with position sizing constraints. This study contributes:

(a). Pair-Specific Optimization: EMA period 30 yields +$995.29 (Sharpe 1.66) on EURUSD but -$1,951.56 on GBPUSD confirming parameters are currency-dependent.

(b). Risk Constraint Integration: Optimization combined with a nominal initial risk of approximately 1% per trade was assumed based on the fixed 0.10-lot position size and 50-pip stop-loss.

(c). Theory-Practice Bridge: Reproducible methodology linking pip value and stop loss to optimization.

This project optimizes RSI and EMA strategies on EURUSD and GBPUSD. Section 2 defines the indicators and performance metrics. Section 3 details optimization and replicability. Section 4 presents results, validation, limitations, and conclusion.

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II. DEFINITION OF TERMS AND MATHEMATICAL FORMULA

A. Moving Average (EMA)

The Moving averages were introduced by (Patrick G. Mulloy, 1994) there are different types of MA and the main objective of moving average is to identify current the trend of a financial instrument based on its previous price levels, for this study we will be using the Exponential Moving Average (EMA). EMA is a widely used technical chart indicator; it responds to a change in price points faster than other moving averages. The Exponential Moving Average (EMA) formula is given by:

$$EMA_t = \beta \, X \, Price_t + (1 - \beta) + \quad EMA_{t-1} \tag{1}$$

Where EMA_t is the current EMA value, $Price_t$ is the current price, EMA_{t-1} is the previous EMA value, β (smoothing factor) is defined as:

$$\beta = \frac{2}{N+1} \tag{2}$$

N is the EMA period (number of bars).

B. Relative Strength Index (RSI)

As introduced by (J. Welles Wilder Jr, 1978), RSI is also a popular technical indicator that measures the strength and weakness of a currency pair by comparing its up movements versus its down movements over a given time period. It is a momentum indicator which means that it's used to determine the speed and strength of price movement. RSI value ranges from 0 to 100 with readings over 70 often considered as overbought and readings below 30 are considered oversold. The Relative Strength Index (RSI) is given by:

$$RSI = 100 - \frac{100}{1+RS} \tag{3}$$

where:

$$RS = \frac{Average\ Gain\ over\ N\ periods}{Average\ Loss\ over\ N\ periods} \tag{4}$$

To compute RSI:

(a). The gain and loss for each period were computed using equation (5) and (6):

$$\text{Gain} = \max\,(0, Close_t - Close_{t-1}) \tag{5}$$

$$\text{Loss} = \max\,(0, Close_{t-1} - Close_t) \tag{6}$$

(b). The average gain and loss were calculated such that:

$$\text{Avg Gain} = \sum \frac{Gain\ over\ N\ periods}{N} \tag{7}$$

$$\text{Avg Loss} = \sum \frac{Losses\ over\ N\ periods}{N} \tag{8}$$

After the first average gain and average loss, we can use these for subsequent calculations:

$$\text{Avg Gain}_t = \frac{\text{Avg Gain}_{t-1} \times (N-1) + \text{Current Gain}}{N} \tag{9}$$

$$\text{Avg Loss}_t = \frac{\text{Avg Loss}_{t-1} \times (N-1) + \text{Current Loss}}{N} \tag{10}$$

Where t is the current period price, $t-1$ is yesterday's period close price, N is the look back period used for RSI calculation (typically 14 periods), $N-1$ is one period less than N, used in the smoothing formula for averaging gains and losses.

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C. Performance Metrics

The following performance metrics, as calculated by the MetaTrader 5 Strategy Tester, are reported throughout this study:

(a). Net Profit: Total profit or loss in USD after accounting for all trades, commissions, and spread costs.

(b). Drawdown: The maximum peak-to-trough decline in account equity during the testing period, expressed as a percentage of the peak equity. This metric quantifies the worst-case capital erosion experienced by the strategy.

(c). Sharpe Ratio: A risk-adjusted return measure defined as:

$$SharpeRatio = \frac{(R_k - R_f)}{\rho_k} \tag{11}$$

where R_k is the annualized strategy return, R_f is the risk-free rate, and ρ_k is the annualized standard deviation of strategy returns (Reilly & Brown, 2011). In the MetaTrader 5 Strategy Tester, the default risk-free rate is 0%, and the ratio is annualized using a factor of $\sqrt{252}$ based on daily trading data. Higher Sharpe Ratio values indicate better risk-adjusted performance. iv.

(d). Recovery Factor: The ratio of net profit to maximum drawdown, calculated as:

$$RecoveryFactor = \frac{Net\ Profit}{MaximumDrawdown} \tag{12}$$

This metric measures the return generated per unit of risk endured. Values greater than 1 indicate that the strategy has earned more than its worst-case loss.

(e). Expected Payoff: The average profit or loss per trade, calculated as total net profit divided by the total number of trades executed.

(f). Total Trades: The total number of positions opened and closed during the testing period.

III. RESEARCH DESIGN

A quantitative and experimental approach was used for this research to evaluate and optimize algorithmic trading strategies based on technical indicators to determine the optimal strategy parameters by backtesting them on historical data. The optimization framework adopted in this study draws from genetic algorithm (GA) principles, which are based on natural selection of parameters to find optimal configurations that maximize or minimize a selected performance metric (Christodoulou-Volos, 2025).

A. Data Collection

Historical data for GBPUSD and EURUSD for this research were obtained from MetaQuotes, which includes the Open, High, Low, and Close prices on a 1-hour chart timeframe. This timeframe offers a balance between long and short-term trend analysis. The historical period ranges from January 2023 to June 2025.

(a). Open Price: The price at the beginning of the one-hour period.
(b). Close Price: The price at the end of the one-hour period.
(c). High Price: The highest price of an asset within the one-hour period. iv. Low
(d). Price: The lowest price of an asset within the one-hour period.

B. Optimization Techniques

As stated earlier, the optimization framework adopted in this study draws from Genetic Algorithm (GA) principles (Christodoulou-Volos, 2025). However, given the manageable size of the parameter space, an exhaustive grid search was implemented to guarantee identification of the global optimum. This approach eliminates the need for GA hyperparameter specification including population size, number of generations, crossover rate, mutation rate, and selection

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method, thereby enhancing reproducibility. In trading strategy optimization, parameter spaces can be extensive. Optimizing moving averages or stop-loss levels across multiple assets may yield thousands or even millions of potential combinations. To manage computational resources and systematically define the search domain, we employ Start, Step, and Stop parameters:

(a). Start (a_i): The minimum value for the strategy parameter.
(b). Step (s_i): The increment between successive candidate values.
(c). Stop (b_i): The maximum value for the parameter.

When configuring optimization in MetaTrader 5 (MT5), each parameter range is defined by these three values. The number of candidate values for a single parameter i is computed as:

$$N_i = \left[\frac{(b_i - a_i)}{s_i}\right] + 1 \tag{12}$$

This expression enumerates the sequence $a_i, a_i + s_i, a_i + 2s_i, \ldots$ up to the largest value not exceeding b_i. The total number of distinct parameter combinations tested is the product of the per-parameter counts:

$$N_{total} = \prod_{i=1}^{x} N_i = \prod_{i=1}^{x} \left[\frac{(b_i - a_i)}{s_i}\right] + 1 \tag{13}$$

where x denotes the total number of parameters under optimization.

Optimization Implementation

Given the modest parameter spaces examined in this study, a complete enumeration (exhaustive grid search) was performed. This ensures identification of the global optimum within the defined bounds without the stochastic approximation inherent in GA-based methods. The main objective of the exhaustive grid search optimization was to maximize the net profit of each trading strategy throughout the in-sample time. The optimization aimed to find the parameter configuration that yielded the highest net profit within the defined parameter search space while adhering to the applicable trading and risk limitations. Risk-adjusted metrics, such as the Sharpe ratio and maximum drawdown, were not considered simultaneous optimization goals. Instead, they were employed as secondary performance metrics to assess the optimized strategies' quality, stability, and risk.

Exponential Moving Average (EMA) Strategy Optimization

For the EMA strategy, optimization targeted a single parameter the Exponential Moving Average (EMA) period with the following bounds:

i. Start (a_i)=10
ii. Stop b_i=100
iii. Step s_i=10

$$\textit{Substituting:}\quad N_i = \left[\frac{(100 - 10)}{10}\right] + 1 = N_i = \left[\frac{(90)}{10}\right] + 1 = 9 + 1 = 10$$

The candidate periods tested were: (10,20,30,40,50,60,70,80,90,100).

2-EMA Crossover Strategy Optimization

For the 2-EMA crossover strategy, optimization targeted two parameters: the fast EMA period and the slow EMA period. Both parameters were varied from 10 to 100 in steps of 10, with the constraint that the fast EMA period must be less than the slow EMA period. The number of valid combinations is:

$$N_{2MA} = \left[\frac{[10\ x\ 10] - 10}{2}\right] = 45$$

The 10 duplicate or invalid combinations where fast EMA ≥ slow EMA were excluded.

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Relative Strength Index (RSI) Strategy Optimization

For the RSI strategy, optimization targeted three parameters: RSI period, Overbought (OB) threshold, and Oversold (OS) threshold. The parameter bounds are summarized in table below:

Table 1: Relative Strength Index (RSI) Strategy Optimization

Parameter	Start (ai)	Stop (bi)	Step (si)	Ni	Candidate Values
RSI Period	10	20	2	6	(10,12,14,16,18,20)
Overbought (OB)	60	80	5	5	(60,65,70,75,80)
Oversold (OS)	10	30	5	5	(10,15,20,25,30)

The total number of RSI parameter combinations is:

$$N_{RSI} = 6 \ x\ 5\ x\ 5 = 150$$

Execution

All 10 EMA combinations and 150 RSI combinations were backtested using the Meta Trader 5 Strategy Tester in "Slow Complete Algorithm" mode (complete enumeration). The optimization objective was to maximize net profit.

Justification for Exhaustive Search

Exhaustive grid search was chosen over a stochastic GA for two primary reasons. First, the parameter spaces (10 EMA combinations; 150 RSI combinations) were computationally tractable for complete enumeration. Second, exhaustive search guarantees identification of the global optimum within the predefined bounds, whereas a GA tests only a subset of combinations and may converge prematurely to a local optimum. This approach also enhances reproducibility by documenting the exact parameter combinations tested, eliminating reliance on stochastic initialization or convergence criteria.

D. Risk Management Parameters

To ensure consistency with real-time trading conditions and to control drawdown, A fixed position size of 0.10 standard lot was used for every trade on both EURUSD and GBPUSD backtests. With an initial account capital of $5,000, each trade was assigned a 50-pip stop-loss and a 50-pip take-profit. Under the modelling assumption of approximately $1 per pip for a 0.10-lot position this represents approximately 1% of the initial account capital:

$$Risk\ Amount = Account\ Size \times \frac{Risk\ Percentage}{100} = 5000 \times 0.01 = \$50 \tag{14}$$

For a standard trading configuration with a 0.10 lot position size and an average pip value of $1 per pip, the corresponding stop-loss level is calculated as:

$$Stop\ Loss = \frac{Risk\ Amount}{Pip\ Value} = \frac{50}{1} = 50\ pips \tag{15}$$

Thus, with a $5,000 account a 0.10 lot position corresponds to a stop-loss distance of 50 pips. These parameters remain constant across all optimization runs and strategy tests, ensuring comparability of results. The 1% value therefore represents the nominal initial risk per trade, rather than a dynamically maintained 1% risk constraint.

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E. Replicability and Data Availability

In backtesting, spread refers to the difference between bid and ask prices at the time of trade execution. Slippage refers to the difference between the expected price of a trade and the price at which the trade is actually executed. Both are accounted for in the MetaTrader 5 Strategy Tester using historical broker data and a user-defined slippage tolerance.
To ensure reproducibility, the following parameters were used throughout all backtests:
(a). Data Source: MetaQuotes via MetaTrader 5 platform.
(b). Timeframe: 1-hour chart.
(c). Period: January 2023 to June 2025.
(d). Account: $5,000 with 1% risk per trade.
(e). Position Sizing: 0.10 lots (pip value $1, stop-loss 50 pips).
(f). Spread: Historical bid-ask spreads from MetaQuotes server applied to all trades.
(g). Slippage: Default slippage tolerance of 2 pips used for order execution.
(h). Commission: Fixed cost per trade at $0.60.
(i). Optimization: Exhaustive grid search ("Slow Complete Algorithm" mode).

The workflow is fully reproducible using any MT5 installation with identical historical data and settings. Transaction costs were included to during the test to provide a more accurate assessment of strategy performance. Historical spreads, 2-pip slippage, and a $0.60 charge per transaction were used consistently across all evaluated strategies and parameter settings. These costs were factored into the reported trading outcomes, ensuring that the resulting profitability reflects the execution cost assumptions.

IV. RESULTS AND DISCUSSION

This section presents the performance of each strategy based on historical backtesting. The GA identified the parameter configuration with the highest net profit, after which Sharpe ratio and drawdown were examined to assess the risk-adjusted characteristics of the resulting strategy.

A. Raw Backtesting Results (Unoptimized)

The results from the unoptimized backtesting show comparative performance between the selected strategies on both EURUSD and GBPUSD pairs without optimization. The EMA strategy (20-period) was unstable, showing small profits on EURUSD but losses on GBPUSD with weak risk-to-reward ratios. The RSI strategy performed strongest on EURUSD, achieving profits with low drawdown, but failed on GBPUSD, indicating pair dependency.

Table 1: Unoptimized Strategy Results

Strategy	Symbol	Net Profit ($)	Drawdown ($)	Sharpe Ratio	Trades
EMA (20 Period)	EURUSD GBPUSD	157.13 -715.24	1165.28 1169.06	0.25 -0.82	687 814
RSI	EURUSD GBPUSD	955.19 - 22.84	609.46 1,205.02	0.89 -0.02	306 346

B. Optimized EMA Strategy Results

Core Optimization Problem: We define a trading system S based on an Exponential Moving Average (EMA) with period n. The goal is to find the value of n that maximizes a performance metric $P(n)$ over historical data. Optimization problem

$$n^* = \arg \max_{n \in [N\text{min}, N\text{max}]} P(n)$$

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Price Data $P = [p_1, p_2, p_3, \ldots, p_T]$

where p_t is the price at time t.

EMA Calculation

Smoothing multiplier:

$$\beta = \frac{2}{n+1}$$

EMA formula: $EMA_t(n) = (p_t \times \beta) + (EMA_{t-1}(n) \times (1-\beta))$

Sample dataset: To illustrate how optimization results were obtained for larger EMA periods, we first demonstrate the mathematical computation for smaller periods ($n = 2,3$).

Trading Signal Generation

$$s_t = \begin{cases} 1 & \text{(Long/Buy)} \quad \text{if } p_t > EMA_t(n) \\ 0 & \text{(Neutral/Flat)} \quad \text{if } p_t \leq EMA_t(n) \end{cases}$$

Returns Calculation:

$$\text{Strategy returns:} \quad R_t(n) = s_{t-1} \times r_t$$

Performance Metric

$$P(n) = \sum_{t=2}^{T} R_t(n)$$

The optimal EMA period n^* is the one that maximizes $P(n)$:

$$n^* = \underset{n}{\operatorname{argmax}} P(n)$$

Input Data

Day (t)	1	2	3	4	5
Price (p_t)	10	12	11	13	14

Log Returns Calculation

$$r_2 = \ln(12) - \ln(10) \approx 0.1823$$

$$r_3 = \ln(11) - \ln(12) \approx -0.0870$$

$$r_4 = \ln(13) - \ln(11) \approx 0.1671$$

$$r_5 = \ln(14) - \ln(13) \approx 0.0741$$

Case 1: Testing Period $n = 2$

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EMA Calculation

$$\textbf{Calculate Multiplier:} \quad \beta = \frac{2}{2+1} = \frac{2}{3} \approx 0.6667$$

$$\textbf{Initialize EMA:} \quad EMA_2 = \frac{10+12}{2} = 11$$

Calculate Subsequent EMAs:

$$EMA_3 = (p_3 \times \beta) + (EMA_2 \times (1-\beta))$$

$$EMA_3 = (11 \times 0.6667) + (11 \times 0.3333) = 7.3337 + 3.6663 = 11$$

$$EMA_4 = (13 \times 0.6667) + (11 \times 0.3333) = 8.6671 + 3.6663 = 12.3334$$

$$EMA_5 = (14 \times 0.6667) + (12.3334 \times 0.3333) = 9.3338 + 4.1110 = 13.4448$$

Trading Signals Strategy

t	p_t	EMA_t	Condition	Signal s_t
3	11	11.0000	$11 \leq 11$	0
4	13	12.0000	$13 > 12$	1
5	14	13.0000	$14 > 13$	1

$$R_4 = s_3 \times r_4 = 0 \times 0.1671 = 0$$

$$R_5 = s_4 \times r_5 = 1 \times 0.0741 = 0.0741$$

Total Profit

$$P(2) = -0.0870+0+0.0741 = -0.0129$$

Case 2: Testing Period *n* = 3

EMA Calculation

$$\beta = \frac{2}{3+1} = 0.5$$

$$EMA_3 = \frac{10+12+11}{3} = 11$$

$$EMA_4 = (13 \times 0.5) + (11 \times 0.5) = 12$$

$$EMA_5 = (14 \times 0.5) + (12 \times 0.5) = 13$$

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Trading Signals

t	p_t	EMA_t	Condition	Signal s_t
3	11	11.0000	$11 \leq 11$	0
4	13	12.0000	$13 > 12$	1
5	14	13.0000	$14 > 13$	1

$$R_4 = s_3 \times r_4 = 0 \times 0.1671 = 0$$

$$R_5 = s_4 \times r_5 = 1 \times 0.0741 = 0.0741$$

Total Profit

$$P(3) = 0 + 0.0741 = 0.0741$$

Period n	$P(n)$	Result
2	-0.0129	Loss
3	**0.0741**	**Profit**

Optimal Parameter

$$n^* = \underset{n \in \{2,3\}}{\arg\max}\, P(n) = 3$$

Calculation was extended to bigger EMA periods with risk constraints then optimized by varying the EMA period from 10 to 100 in steps of 10 for both EURUSD and GBPUSD.

Table 2: Optimized Results EMA Strategy (EURUSD)

EMA Period	Net Profit ($)	Total Trades	Expected Payoff	Drawdown (%)	Recovery Factor	Sharpe Ratio
10	-1595.11	846	-1.89	36.66	-0.84	-2.23
20	157.13	687	0.23	18.95	0.14	0.25
30	995.29	560	1.78	6.93	2.40	1.66
40	336.36	496	0.68	14.12	0.42	0.60
50	11.21	464	0.02	20.26	0.01	0.02
60	-178.44	418	-0.43	15.08	-0.22	-0.37
70	-139.79	391	-0.36	15.57	-0.17	-0.28

80	-460.80	354	-1.30	13.20	-0.68	-1.10
90	-619.74	349	-1.78	15.96	-0.76	-1.45
100	-458.85	320	-1.43	13.45	-0.66	-1.07

Table 3: Optimized Results EMA Strategy (GBPUSD)

EMA Period	Net Profit ($)	Total Trades	Expected Payoff	Drawdown (%)	Recovery Factor	Sharpe Ratio
10	-1332.36	1055	-1.26	35.22	-0.67	-1.48
20	-988.00	838	-1.18	23.57	-0.82	-1.13
30	-1951.56	741	-2.63	42.05	-0.89	-2.37
40	-1349.44	644	-2.10	35.09	-0.71	-1.90
50	-311.52	571	-0.55	17.42	-0.32	-0.45
60	-1672.96	544	-3.08	41.19	-0.76	-2.50
70	-1147.40	524	-2.196	31.03	-0.69	-1.77
80	-483.68	466	-1.04	20.40	-0.44	-0.80
90	-916.46	449	-2.04	23.08	-0.78	-1.53
100	-599.72	427	-1.40	19.66	-0.60	-1.05

EURUSD Findings: The best EMA period was 30. It achieved profits of $995.29 with a low drawdown of 6.93%, with highest Sharpe ratio of 1.66. This shows a strong risk-return at that setting. Periods above 50 showed reduced profitability and increased drawdown, suggesting over smoothing.

GBPUSD Findings: Unlike EURUSD, none of the EMA periods tested for GBPUSD produced a profitable outcome. The least negative result was obtained at period 50, with a drawdown of 17.42% and loss of -$311.52.

Other periods resulted in higher losses and drawdowns, especially at shorter EMA periods like 30 and 60.

C. Optimized RSI Strategy Results

For the RSI-based trading strategy, the primary optimization objective was to maximize net profit, while risk measures were subsequently used to evaluate the resulting optimized strategies. The RSI is defined mathematically as:

$$RSI_t = 100 - \frac{100}{1 + RS_t}$$

Step 1: Signal Generation

For each period t:

$$Signal_t = \begin{cases} 1, & \text{if } RSI_t < 25 \text{ (Buy)} \\ -1, & \text{if } RSI_t > 70 \text{ (Sell)} \\ 0, & \text{otherwise} \end{cases}$$

Step 2: Profit Calculation per Trade

Assuming entry at price P_{entry} and exit at P_{exit}:

$$Profit_i = \begin{cases} P_{exit} - P_{entry}, & \text{for Buy trades} \\ P_{entry} - P_{exit}, & \text{for Sell trades} \end{cases}$$

The total profit across N trades is calculated as:

$$Z(n, ob, os) = \sum_{i=1}^{N} Profit_i$$

The optimal RSI configuration (n^*, ob^*, os^*) is the combination of parameters that maximizes total profit:

$$(n^*, ob^*, os^*) = \arg \max_{(n, ob, os)} Z(n, ob, os)$$

Strategy Return: We define log returns as $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$ and trading returns based on the previous signal as $R_t = s_{t-1} \times r_t$, where $s_t = 1$ (Buy), $s_t = -1$ (Sell), and $s_t = 0$ (Neutral).

Total strategy performance for a given period n is: $P(n) = \sum_t R_t$

Sample data set (RSI period $n = 2$) Price Data:

Day (t)	1	2	3	4	5	6
Price (P_t)	10	11	12	11	10	9

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Step 1: Calculate Gains/Losses

$$\Delta P_2 = 11-10 = +1$$
$$\Delta P_3 = 12-11 = +1$$
$$\Delta P_4 = 11-12 = -1$$
$$\Delta P_5 = 10-11 = -1$$
$$\Delta P_6 = 9-10 = -1$$

Step 2: Calculate RSI for each $t \geq n+1$

For $t = 3$:

Average Gain $= \frac{1+1}{2} = 1$, *Average* Loss = 0, $RSI_3 = 100$

For $t = 4$:

$$\text{Average Gain} = \frac{1+0}{2} = 0.5, \text{ Average Loss} = \frac{0+1}{2} = 0.5$$

$$RS_4 = 1 \quad \Rightarrow \quad RSI_4 = 100 - \frac{100}{1+1} = 50$$

For $t = 5$:

$$\text{Average Gain} = \frac{0+0}{2} = 0, \qquad \text{Average Loss} = \frac{1+1}{2} = 1 \; RS_5 = 0 \Rightarrow RSI_5 = 0$$

For $t = 6$:

$$\text{Average Gain} = 0, \; \text{Average Loss} = 1 \Rightarrow RSI_6 = 0$$

Step 3: Generate Signals

$$\text{Using rules:} \begin{cases} RSI_t < 25 & \Rightarrow \text{Buy } (s_t = 1) \\ RSI_t > 70 & \Rightarrow \text{Sell } (s_t = -1) \\ \text{otherwise} & \Rightarrow \text{No Signal } (s_t = 0) \end{cases}$$

t	$\mathbf{RSI}_t$	**Signal** (s_t)
3	100	-1 (Sell)
4	50	0
5	0	1 (Buy)
6	0	1 (Buy)

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Step 4: Compute Log Returns and Strategy Returns

t	$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$	$st{-}1$	$R_t = s_t{-}1 \times r_t$
2	0.0953	–	–
3	0.0870	–	–
4	−0.0870	−1	+0.0870
5	−0.0953	0	0
6	−0.1053	1	−0.1053

Step 5: Total Profit for RSI (2)

$$P(2) = 0.0870+0-0.1053 = -0.0183$$

For a larger data set, all RSI parameters were tested and optimization was conducted across 150 parameter combinations to identify settings that maximize net profit.

Table 4: Top 10 Optimized RSI Strategy Results on EURUSD

Profit ($)	Total Trades	Drawdown %	Sharpe Ratio	RSI Period	Overbought	Oversold
1243.98	223	9.26	1.57	18	70	30
1230.32	263	8.90	1.27	16	70	30
1205.84	176	7.89	1.93	20	70	30
1127.30	425	10.91	0.89	10	65	25
1000.12	150	7.03	1.68	16	80	30
962.47	167	8.92	1.71	18	70	25
955.19	306	10.60	0.89	14	70	30
916.85	357	10.55	0.81	10	65	20
738.85	195	9.56	1.08	16	70	25
709.85	354	8.86	0.64	12	65	25

Table 5: Top 10 Optimized RSI Strategy Results on GBPUSD

Profit ($)	Total Trades	Drawdown %	Sharpe Ratio	RSI Period	Overbought	Oversold
1312.62	132	8.47	3.52	16	75	25
1297.36	523	14.02	0.86	10	70	30
1222.08	265	7.56	1.54	12	80	30
1030.50	82	5.61	4.53	16	80	25
1023.14	64	5.42	6.56	14	80	20
990.36	114	7.13	3.50	14	80	25
931.02	339	12.28	1.37	10	80	30
909.52	108	10.07	3.03	12	80	20
806.12	90	6.71	2.97	16	75	20
745.30	360	14.26	0.69	10	70	20

RSI Optimization Findings: For EURUSD, the best setups combined RSI periods of 16, 18 and 20 with Overbought=70 and Oversold=30. These combinations consistently yielded profits above $1,200, drawdowns between 7% and 10%, and Sharpe ratios above 1.25, indicating balanced risk and return. For GBPUSD, the best settings occurred with RSI periods of 12, 14, and 16, with higher Overbought thresholds (75-80) and Oversold thresholds (20-25). The top-performing configuration (RSI 16/75/25) achieved a profit of $1,312.62 with a Sharpe ratio of 3.52.

EMA Period Combination

To assess the benefit of combining strategies, a 2-EMA crossover strategy was optimized for both EURUSD and GBPUSD by varying fast and slow EMA periods.

Table 6: Top 3 2-EMA Optimization Results for EURUSD

Profit/Loss ($)	Drawdown %	Sharpe Ratio	Total Trades	Cost ($)	EMA 1	EMA 2
1227.40	8.26	1.65	404	40.40	20	40
1148.67	9.06	1.502	411	41.10	10	30
1080.78	10.31	1.45	359	35.90	10	40

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Table 7: Top 3 2-EMA Optimization Results for GBPUSD

Profit/Loss ($)	Drawdown %	Sharpe Ratio	Total Trades	Cost ($)	EMA1	EMA 2
1232.10	13.49	1.58	378	37.80	20	40
695.44	14.24	0.81	492	49.20	20	30
598.36	11.16	0.76	404	40.40	30	40

The best setup on EURUSD produced a profit of $1,227.40 (24.5% return) with a drawdown of 8.26% and a Sharpe ratio of 1.65, indicating strong and balanced performance. On GBPUSD, the best setup yielded $1,232.10 (24.6% return) with a drawdown of 13.49% and a lower Sharpe ratio of 1.58. Within the tested sample, the two EMA strategies produced higher profitability with comparatively favorable risk adjusted performance.

D. Out of Sample Validation

An independent out of sample dataset was introduced in order to evaluate the robustness of the optimized trading methods and lower the danger of over-fitting. For parameter optimization and the initial in-sample analysis, the original dataset spanning January 2023 to June 2025 was kept. For out-of-sample validation, a different dataset spanning July 2025 to July 2026 was used solely. The new out of sample dataset was subjected to the same optimal parameters that were found during the initial optimization phase. Using observations from July 2025 to July 2026, no parameter optimization or modification was carried out. The same performance metrics and trading conditions used in the initial analysis were used to assess the out of sample performance.

Table 8: Out of Sample Performance of the Optimized Trading Strategies (July 2025–July 2026)

Currency Pair	Strategy	Parameter	Net Profit ($)	Drawdown %	Sharpe Ratio	Total Trades
EURUSD	EMA	30	232.81	5.14	1.00	210
EURUSD	RSI	18/70/30	103.53	7.87	0.34	74
EURUSD	2-EMA	10/30	369.98	4.91	1.34	148

Table 9: Out-of-Sample Performance of the Optimized Trading Strategies for GBPUSD (July 2025–July 2026)

Currency Pair	Strategy	Parameter	Net Profit ($)	Drawdown %	Sharpe Ratio	Total Trades
GBPUSD	EMA	10	-417.48	12.87	-1.11	426

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GBPUSD	RSI	16/75/25	207.30	3.39	1.17	43
GBPUSD	2-EMA	20/40	429.98	6.25	1.22	160

The out of sample results demonstrate that the improved strategies generally maintained their performance when applied to the independent July 2025 to July 2026 dataset.

E. Statistical Validation

To assess whether observed performance represents genuine strategy effectiveness rather than data fitting noise, approximate statistical significance tests were computed from the available backtest metrics. A one sample ttest was used to determine the strategy returns' statistical significance. Nevertheless, the reported p-values are dependent on the selection procedure and do not take multiple testing or data-snooping effects into account because the optimum methods were chosen from a variety of parameter combinations. As a result, rather than providing conclusive proof of better strategy performance, the statistical significance results are considered as informative in-sample evidence.

Mean Return Significance

The t-statistic for mean trade return was approximated as

$$t = \frac{\bar{r}\ x\ \sqrt{T}}{\rho}$$

where $\bar{r}$ is expected payoff, T is total trades, and $\rho = \frac{\bar{r}}{Sharpe}$. Under the null hypothesis of zero mean return, this follows a t-distribution with $T-1$ degrees of freedom.

Table 10: Statistical Significance of Optimal Strategies

Strategy	Pair	Trades	Expected Payoff ($)	Sharpe Ratio	t-statistic	p-value
EMA 30	EURUSD	560	1.78	1.66	39.3	<0.001
RSI 20/70/30	EURUSD	176	6.85	1.93	25.6	<0.001
RSI 16/75/25	GBPUSD	132	9.94	3.52	40.5	<0.001
2 EMA 20/40	EURUSD	404	3.04	1.65	33.2	<0.001
2 EMA 20/40	GBPUSD	378	3.26	1.58	30.8	<0.001

The optimized technique produced a statistically significant mean return ($p < 0.001$) using the conventional t-test. However, this finding should be viewed with caution because the technique was chosen after a thorough evaluation of numerous parameter configurations. The provided p-value does not account for the ensuing data snooping and selection bias, therefore it should not be construed as conclusive evidence of superior performance.

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Sharpe Ratio Confidence Intervals

Using first order asymptotic standard error approximation based on $\frac{1}{\sqrt{T}}$ scaling, 95% confidence intervals for Sharpe ratios were constructed as $SR \pm 1.96\ x\ SE$.

Table 11: Sharpe Ratio 95% Confidence Intervals

Strategy	Pair	Sharpe Ratio	Trades	Standard Error	95% Confidence Intervals
EMA 30	EURUSD	1.66	560	0.042	[1.58,1.74]
RSI 20/70/30	EURUSD	1.93	176	0.075	[1.78, 2.08]
RSI 16/75/25	GBPUSD	3.52	132	0.087	[3.35, 3.69]
2 EMA 20/40	EURUSD	1.65	404	0.050	[1.55, 1.75]
2 EMA 20/40	GBPUSD	1.58	378	0.051	[1.48, 1.68]

All 95% confidence intervals lie entirely above zero, confirming that risk-adjusted performance is statistically significant at conventional levels.

Data Snooping Consideration

The optimization procedures tested 10 parameter combinations for the EMA strategy and 150 combinations for the RSI strategy. Multiple testing inflates the probability of identifying spuriously high performance due to selection bias (White, 2000; Harvey & Liu, 2015).

Caveats

These approximations assume that returns are normally distributed and independent, assumptions that are often violated in financial data. Rigorous validation using bootstrap resampling of trade-by-trade returns and formal data snooping correction is recommended for future work. Nevertheless, the results provide preliminary evidence that observed performance is unlikely attributable entirely to random chance. To further evaluate the optimized strategy's robustness and generalizability, an independent out of sample dataset that was not included during parameter optimization was used. Out of sample results provide a more comprehensive assessment of whether observed performance extends beyond the data used to develop strategies.

F. Limitations and Future Research

This study has some limitations that warrant acknowledgment. The same historical window (January 2023-June 2025) was used for both optimization and evaluation. Consequently, reported results represent in-sample performance and may reflect overfitting to this specific period. Future research should use walk-forward optimization with distinct training and testing windows to assess out-of-sample robustness. Second, only two currency pairs (EURUSD, GBPUSD) on a single timeframe (1-hour) were examined, limiting generalizability to other instruments and timeframes. Third, the framework assumes static optimal parameters, while market regimes change over time. In future work, it is possible to use regime switching models

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or machine learning methods to allow parameters to be updated dynamically. Fourth, the statistical validation of the results in Section 4.4 relies on asymptotic approximations which assume normally distributed and independent returns. Robust validation based on bootstrap resampling of trade-by-trade returns and no formal data-snooping correction (e.g. Deflated Sharpe Ratio) was undertaken. Future research needs to include these robust methods to increase confidence in the results. Despite having these limitations, the pair-specific optimization framework and risk constraint integration presented herein provide a foundation for more robust algorithmic trading research.

CONCLUSION

This study examined the optimization of algorithmic trading strategies using exhaustive grid search on EURUSD and GBPUSD. There are three main findings. Firstly, for pair-specific optimization: a 30 EMA period did well on EURUSD (+$995.29, Sharpe ratio 1.66) but poorly on GBPUSD (-$1,951.56) showing optimal parameters are currency-dependent. Second, the results indicate that, within the tested sample, combining two moving averages produced more balanced risk-adjusted returns than single EMA strategies. Third, a fixed 0.10-lot position size corresponds to approximately 1% nominal risk at the initial $5,000 account balance, assuming a $1 pip value and a 50-pip stop-loss links theoretical optimization to real trading. Approximate statistical validation confirmed that optimal strategies exhibit statistically significant mean returns ($p < 0.001$) and Sharpe ratio confidence intervals which do not include zero. While results are in-sample and require cautious interpretation regarding out-of-sample generalizability, the framework demonstrates the importance of pair-specific parameter selection and provides a replicable foundation for future research incorporating walk forward validation, bootstrap resampling, and dynamic parameter adaptation.

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