

Scalper Major: A Computational Solution for Automated Trading in High Volatility Environments

José Jeovane R. Cordeiro^{1,2}, Arlino Henrique M. de Araújo², Guilherme A. Avelino²

¹Federal Institute of Maranhão (IFMA)
Coelho Neto Campus – Olho D’Aguinha Neighborhood
CEP: 65.620-000 – Coelho Neto – MA

²Federal University of Piauí (UFPI)
Minister Petrônio Portella University Campus – Ininga Neighborhood
CEP: 64.049-550 – Teresina – PI

jose.cordeiro@ifma.edu.br, {arlino, gaa}@ufpi.edu.br

Abstract. Research Context: The foreign exchange (Forex) market is the largest and most liquid in the world, characterized by high volatility and continuous operation. In this environment, human decision-making is often compromised by emotional biases and the limited ability to process large amounts of information in real time. **Scientific and/or Practical Problem:** Traditional trading strategies have weaknesses, including delayed signals and a lack of robust risk metrics. Furthermore, many existing studies in the literature focus only on cumulative return, neglecting the risk-return trade-off and practical applicability. **Proposed Solution and/or Analysis:** This work presents Scalper Major, an automated trading system designed to operate consistently in the Forex market. Its modular architecture integrates technical and managerial heuristics, as well as strict risk and capital management mechanisms. **Related IS Theory:** The research is based on the principles of information systems, applied to automated decision-making, aligning technical indicators, computational heuristics, and financial metrics as reliable support tools for investors. **Research Method:** The system was implemented in MQL5 on the MetaTrader 5 platform. The evaluation was conducted through eight-year backtests on four major currency pairs, taking into account commissions, execution delays, and various market scenarios. **Summary of Results:** With an initial capital of \$20,000.00, Scalper Major achieved significant results: a net profit of \$751,533.23, a win rate of 82.54%, and a maximum drawdown of 9.43%. The Sharpe Ratio of 1.63 demonstrates superior risk-return efficiency compared to related studies. **Contributions and Impact to IS area:** The study, in addition to proposing an operational tool, presents a methodological advancement by creating a novel compilation of the main evaluation indicators for automated trading systems.

1. Introduction

Trade among people has existed since ancient civilizations. However, the pillars of the modern foreign exchange market began to consolidate in the 19th century with the emergence of the gold standard system, which the Bretton Woods Agreement later reinforced in 1944 [Bordo 1993]. The idea underlying the gold standard dates back to David Hume in 1752, who argued that international trade should be balanced through the flows of

precious metals [Caffentzis 2001]. The gold standard was in effect until 1914 and was later replaced in 1944 by the Bretton Woods Agreement, which pegged exchange rates to the U.S. dollar. As part of this agreement, institutions such as the International Monetary Fund (IMF) and the World Bank were created to promote global economic stability [Bordo 1993]. However, in 1971, the United States abandoned the convertibility of the dollar to gold, ending the Bretton Woods system and ushering in the era of floating exchange rate regimes, which characterize the modern foreign exchange market [Meltzer 1991].

The foreign exchange market, also known as Forex (Foreign Exchange Market), stands out as the largest and most liquid in the world. Besides this one, there are other markets, such as the stock market (equities), cryptocurrencies, futures, and derivatives, among others. These segments handle billions and even trillions of dollars daily. For example, on August 12, 2025, data from NASDAQ¹ showed that the volume of shares traded on the Composite index was approximately US\$ 372.4 billion. In the cryptocurrency market, data from July 2025 show that the total monthly trading volume was approximately US\$ 1.77 trillion², which represents an average of US\$ 57.1 billion per day. In turn, data published by the CME Group³, one of the world's largest derivatives exchanges, recorded an average daily volume (ADV) of US\$ 1.1 trillion for stock index futures.

Although the values presented above are high, they do not surpass the trading volume of the Forex market. The latest report released by the Bank for International Settlements (BIS)⁴, with data collected in April 2022, shows that the average daily trading volume in Forex was US\$ 7.5 trillion – a figure higher than that of any other market. This significant volume is a direct consequence of the unique characteristics of the foreign exchange market, such as high liquidity and decentralization, which involve the buying and selling of currencies among governments, financial institutions, corporations, and individual investors [El Mahjouby et al. 2024, Olorunsheye and Meenakshi 2024].

The combination of these characteristics, along with its continuous operation – 24 hours a day, 7 days a week – offers significant profit opportunities, particularly for short-term strategies such as scalping and day trading [Zafeiriou and Kalles 2021]. However, although accessible and with potential for gains, this market is influenced by various exogenous factors, including geopolitical events, economic announcements, and natural disasters, which significantly increase volatility and contribute to a volatile environment [Chantona et al. 2020]. Furthermore, due to its noisy, non-stationary, chaotic, and deterministic nature, predicting exchange rates represents a significant challenge for researchers and investors [El Mahjouby et al. 2024, Ismail et al. 2022].

Ismail et al. highlight that in this scenario, human performance is often compromised by emotional biases, such as fear, greed, and impatience, which can lead to significant losses. Furthermore, the speed required to capitalize on opportunities in short-term strategies, such as scalping, exceeds the human capacity to process information and execute orders in a timely manner [Ismail et al. 2022]. To overcome these difficulties, many traders resort to technical indicators. However, Povitukhin and Karmanova

¹<https://www.nasdaqtrader.com/Trader.aspx?id=DailyMarketSummary>

²<https://www.theblock.co/post/365199/crypto-exchange-volume-july>

³<https://br.tradingview.com/cme/>

⁴https://www.bis.org/statistics/rpfx25_announcement.htm

[Povitukhin and Karmanova 2020] point out that these tools are, for the most part, lagging – that is, they react to price movements that have already occurred instead of accurately predicting them. This characteristic often results in the generation of false or delayed signals, leading the trader to make errors and, consequently, suffer financial losses.

To address these challenges, automated trading systems emerge as a promising solution for executing strategies consistently and efficiently, reducing the influence of emotional biases, and optimizing operational performance. However, in a recent survey conducted by these researchers, they found that the Forex market is an underexplored area in the scientific literature on algorithmic trading, despite its significant economic importance. Nevertheless, existing works present significant methodological limitations, such as the lack of risk metrics and the absence of testing in a live environment.

The solution to this problem lies in creating a tool that automates the decision-making process based on objective criteria and specialized heuristics. This tool must also consider essential evaluation metrics, such as Return, Risk, and Risk-Adjusted Return, to ensure a disciplined and systematic execution of trades, even under adverse market conditions. To this end, the present work introduces Scalper Major, an Expert Advisor (EA) developed based on objective technical criteria, strict risk management rules, specialized heuristics, and a modular architecture, which enables automatic operation with minimal human intervention in the Forex market. To achieve this goal, the following specific objectives were established:

- Design a modular architecture composed of specialized components.
- Integrate technical and managerial heuristics to identify trading opportunities.
- Establish a risk and money management model that promotes judicious control of exposure and resource allocation in trades.
- Implement and validate the system in a simulated environment through backtests with real historical data, using appropriate metrics.

The adopted strategy was validated through a backtesting process that covered the period from January 2016 to December 2023. For this simulation, Scalper Major was configured to operate specifically on the currency pairs EUR/USD, GBP/USD, USD/CAD, and USD/CHF. In this stage, an initial capital of \$20,000.00 was used, and the system achieved a total net profit of \$751,533.23. This resulted from a gross profit of \$1,060,523.23 and gross losses of \$308,991.00, which included trades closed with a negative balance and operational costs. In total, 11,571 trades were executed, of which 7,217 (62.37%) were Long (buy) trades and 4,354 (37.63%) were Short (sell) trades. The overall win rate was 82.54%, with an 83.66% rate for Long trades and an 81.42% rate for Short trades.

The main contributions of this work are as follows:

1. Unpublished compilation of the main trading metrics used to evaluate automated trading systems.
2. A set of technical and managerial heuristics aimed at identifying trading opportunities and executing orders efficiently, with strict risk control and money management.
3. A modular architecture composed of specialized components that enable the implementation of the proposed approach.

4. A functional implementation of the proposed architecture and approach, validated through extensive simulations with historical data.

The structure of this work is organized into sections that detail the investigated problem and the proposed solution. Section 2 presents the theoretical background necessary for understanding the study. Section 3 discusses the main related works. Section 4 describes the proposed solution in detail. Section 5 presents the empirical results obtained from the application of the proposed solution in a simulated environment with real historical data. Finally, Section 6 presents the conclusions of the study.

2. Background

This section covers the conceptual and technological foundations necessary to understand this work.

2.1. The Financial Market and the Forex Market

According to Olorunsheye and Meenakshi [Olorunsheye and Meenakshi 2024], the financial market has a significant influence on multiple aspects of society, including the economy, education, business, employment, and public safety. The foreign exchange market, often abbreviated as Forex, is the global marketplace for trading currencies. Unlike centralized stock exchanges, such as the NYSE or B3, the Forex market operates in a decentralized manner on the Over-the-Counter (OTC) model; that is, transactions occur directly between the involved parties, without the intermediation of a central exchange [El Mahjoub et al. 2024]. Forex transactions always occur in pairs; that is, the purchase of one currency simultaneously implies the sale of another.

The exchange rate is determined by the interaction of supply and demand among the parties involved, as well as by the economic conditions of the countries issuing the currencies. A large part of this market's volatility is concentrated in seven currency pairs. These pairs – AUD/USD, EUR/USD, GBP/USD, NZD/USD, USD/CAD, USD/CHF, and USD/JPY – are the most traded and account for more than half of the activity in the Forex market [Weithers 2011]. Weithers [Weithers 2011] highlight that the daily transaction volume in these pairs surpasses that of other financial markets, such as the stock market, which reinforces their central importance to the liquidity and functionality of the Forex market.

2.2. Candlestick Patterns

Candlestick patterns are a fundamental tool in financial technical analysis, originating in Japan in the 18th century, where they were initially used to analyze rice prices. Although there is no consensus on the effectiveness of these patterns, their use is widespread among professionals and investors [Heinz et al. 2021]. The literature presents a large number of *candlestick* patterns, with references varying between 103 and 105 different types [Varghese et al. 2023]. These patterns can be categorized in various ways, with one of the most common being based on the number of candles that compose them.

One noteworthy pattern is the Marubozu, which is identified as a bullish Marubozu when its low price is equal to or close to its opening price, and its high is equal to or close to its closing price. The opposite constitutes a bearish Marubozu. This pattern also has the following characteristics: (a) it indicates strong buying or selling pressure; (b) it

represents a potential trend continuation signal; and (c) it is a clear and easily identifiable visual pattern.

2.3. Technical Indicators

Technical indicators are mathematical and statistical tools derived from historical price and volume data of financial assets, used in technical analysis to predict future price movements [Naranjo et al. 2018]. Naranjo et al. also highlight that technical indicators provide a visual representation of market dynamics, helping investors and analysts identify trends, turning points, and price patterns, and make decisions about the optimal timing for opening or closing positions.

Almeida and Vieira [Almeida and Vieira 2023] point out that, among the most widely used technical indicators in technical analysis, Moving Averages (MA) and the Relative Strength Index (RSI) stand out, among others. The authors also highlight two of the most common and widely used types of moving averages: the Simple Moving Average (SMA) and the Exponential Moving Average (EMA). The SMA is calculated as the arithmetic average of prices (P) over a specific number of periods (n). It is used to identify the general direction of a trend over time by smoothing out short-term fluctuations. The formula for calculating the SMA is given in Equation 1.

$$\text{SMA} = \frac{S_t + S_{t-1} + \dots + S_{t-(n-1)}}{n} \quad (1)$$

In the equation above, S_t represents the current value (e.g., the closing price on day t) and $S_{t-1}, S_{t-2}, \dots, S_{t-(n-1)}$ represent the values from previous periods within the calculation window.

The EMA, unlike the SMA, assigns greater weight to more recent prices, which makes it more sensitive and responsive to market changes. The formula for calculating an EMA is represented in Equation 2. In the following equation, $P(t)$ represents the sequence of observations over time t (e.g., closing price, bandwidth, or displacement), and α (alpha) is the smoothing coefficient, calculated as $2/(N + 1)$, where N is the number of observations considered in the period. Smaller values of N result in a larger α , making the EMA more sensitive to slight variations in the observed samples [Vu et al. 2017].

$$\text{EMA}_x(t) = \alpha \cdot P(t) + (1 - \alpha) \cdot \text{EMA}_x(t - 1) \quad (2)$$

The RSI stands out as one of the most prominent and widely used technical indicators in technical analysis by *traders* and investors [Kulshrestha and Srivastava 2020]. Developed by J. Welles Wilder Jr. [Wilder 1978], the indicator's primary function is to measure the magnitude of recent price changes to evaluate overbought or oversold conditions for a given asset. The RSI has the following capabilities: (a) identifying potential trend reversal points; (b) measuring the strength of the *momentum*; (c) adapting to different time horizons; and (d) having wide acceptance and support in academic studies.

The general formula for calculating the RSI is illustrated in Equation 3. The variable RS (*Relative Strength*) represents the ratio of the average gains to the average losses over a given period n . In this context, n corresponds to the number of time units considered (e.g., days, if the *timeframe* is daily). The resulting value ranges from 0 to 100.

$$RSI(n) = 100 - \left[\frac{100}{1 + RS(n)} \right] \quad (3)$$

Wilder's classic interpretation defines the RSI as follows: (a) "overbought" when the value surpasses 70. This may indicate that the asset is overvalued and due for a bearish reversal, signaling a selling opportunity; and (b) "oversold" when the value falls below 30. This may indicate that the asset is undervalued and about to undergo a bullish reversal, signaling a buying opportunity.

2.4. Negotiation Approaches in the Financial Market

Predicting market trends and financial asset prices poses a constant challenge for investors and researchers. Throughout history, various approaches have been developed with the objective of understanding and profiting in these markets, which can be broadly categorized into traditional methods and, more recently, quantitative methods.

2.4.1. Traditional Negotiation Methods

Traditional trading methods rely heavily on human analysis and judgment, which are often subject to emotions and biases [Ma et al. 2022]. Among the most widely used approaches are fundamental analysis and technical analysis. Patel et al. [Patel et al. 2015] emphasize that fundamental analysis entails a detailed examination of a company's/country's financial and economic situation. In contrast, technical analysis focuses on the retrospective investigation of historical data, including an asset's price fluctuations over time and its associated transaction volume.

2.4.2. Quantitative Trading

Since the 1970s, quantitative trading (QT) has been a topic of interest in both academia and the financial industry [Sun et al. 2023]. QT represents a paradigm shift in how investment decisions are made, using mathematical models, statistical methods, and computational technology to identify investment opportunities and execute trades automatically [Zhang 2023]. QT offers a series of significant advantages compared to traditional trading approaches, which drive its growing adoption in the global financial market. These advantages include: (1) objectivity and discipline, (2) large-scale data processing capability, and (3) reduction of information asymmetry.

2.5. Algorithmic Trading

Also known as automated trading or algo-trading, this technique uses computer programs and algorithms to execute trades in the financial markets [Ansari et al. 2024]. This approach emerged as an alternative to the challenges associated with manual trading and the variability of traditional approaches, aiming to enhance precision and efficiency in financial operations [Ismail et al. 2022]. Such systems utilize computer programs to process large volumes of data and execute trading orders automatically, based on pre-defined algorithms and parameters [Zhang and Khushi 2020]. One of the primary advantages of algorithmic trading is its ability to operate continuously, reacting promptly to market fluctuations, without requiring continuous supervision from a human operator. Algorithmic

trading also offers the following advantages: (1) elimination of human emotions and biases, (2) speed and precision, (3) pattern detection, and (4) greater discipline and consistency.

2.6. Evaluation Metrics

The validation of automated strategies requires the integrated consideration of return, risk, and risk-adjusted metrics, since each group provides a distinct and complementary perspective on the strategy's performance. In this context, return metrics are widely used to measure the profitability and consistency of strategies over time. Risk metrics, in turn, are essential for quantifying maximum losses and measuring risk exposure.

To identify the primary metrics used in the evaluation of automated trading systems, a complementary study was conducted by these researchers [Cordeiro et al. 2025]. In that study, the primary metrics identified were: Annualized Return (AR), Cumulative Return (CR), Maximum Drawdown (MDD), and the Sharpe Ratio. In addition to these metrics, an extensive search in forums and the MQL5 language documentation led to the identification of three secondary metrics to be considered in the evaluation process: Profit Factor (PF), Expected Payoff (EP), and Recovery Factor (RF). Technical details about these metrics are presented in Section 4.4.

3. Related Work

In recent decades, a growing number of studies have focused on investigating computational techniques for modeling and automating trading strategies. The approaches explored range from classic techniques, such as Machine Learning (ML) and Artificial Neural Networks (ANN), to more sophisticated methods, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Reinforcement Learning (RL), and Deep Reinforcement Learning (DRL).

In their research on the development of profitable trading strategies, Povitukhin and Karmanova [Povitukhin and Karmanova 2020] proposed a methodology that integrates technical analysis indicators with ML algorithms, applied to the foreign exchange market. The work is based on the premise that traditional trading systems, which rely exclusively on technical indicators, often yield unsatisfactory financial results due to the inherent lag of these indicators, which cannot keep up with real-time price movements. To overcome this limitation, the authors frame day trading as a classification problem to predict "buy" or "sell" signals at the beginning of each day. The study's central approach is based on the use of supervised learning, in which the authors introduce the concept of a "teacher". This "teacher" corresponds to an idealized model designed to generate stable, low-noise trading signals. One of the study's most relevant insights is its critique of accuracy as the sole metric for evaluating a trading system's effectiveness. The authors argue that the accurate measure of success is profitability, calculated in pips, because even if a system has high accuracy in predicting signals, it may still not be profitable due to the magnitude of the price movements.

Despite the pertinent critique of the isolated use of accuracy, the success metric adopted by the authors is, in itself, incomplete, as it disregards a fundamental factor: risk. The study bases its evaluation solely on Cumulative Return (CR). This approach is inadequate, as it completely ignores risk. A strategy can show a high cumulative return but

with unacceptable risk (massive drawdowns), making it unfeasible in practice. Although the authors critique the isolated use of accuracy and argue for profitability as a more suitable measure of success, they do not measure the risk associated with that profitability.

Luangluewut and Thiennviboon [Luangluewut and Thiennviboon 2023] present a distinct approach to trend prediction in the Forex market, proposing the conversion of price time series into images for processing by a CNN. The experimental results demonstrated the model's high effectiveness, as it achieved an accuracy of 93% in predicting trends on the test set. In addition to the predictive evaluation, the authors conducted trading simulations with a simple algorithm to investigate the practical applicability of the model as a trend indicator. In the scenarios tested, the proposed model achieved returns between 6% and 422% higher than those achieved with traditional technical indicators. This demonstrates the promising potential of treating time series as images for trend prediction in the Forex market. However, similar to the study by Povitukhin and Karmanova [Povitukhin and Karmanova 2020], the strategy's evaluation is based solely on cumulative return. This approach is inadequate, as it completely ignores risk.

In a complementary approach, Chinprasatsak et al. [Chinprasatsak et al. 2020] focused on predicting the daily high and low prices in the foreign exchange market, specifically for the EUR/USD pair. To achieve this, they compared various artificial neural network architectures, including traditional models and the variants they proposed. A central contribution of the work is the evaluation of the forecasting models not through standard error metrics, but through a trading simulation system that measures investment effectiveness in terms of "Total Return" and "Drawdown". The main innovation of the proposed models by the authors lies in the use of Empirical Mode Decomposition (EMD). This process separates the original time series into multiple simpler components, known as Intrinsic Mode Functions (IMFs). The network's output consisted of two numbers: the forecast for the current day's high and low prices. The results of the trading simulation demonstrated that the proposed models significantly outperformed the baseline models. Finally, the authors concluded that EMD's ability to extract relevant information from the signal significantly improved the performance of the neural networks.

Expanding on the application of artificial intelligence in the financial market, Chantona et al. [Chantona et al. 2020] address a fundamental limitation of Reinforcement Learning (RL) models applied to trading. The authors argue that most trading systems existing up to 2020, based on RL, exclusively used historical technical data (such as prices and indicators) as the state input for the decision-making agent. To overcome this gap, the authors propose a hybrid model that enables the trading agent to process and understand both technical and fundamental data in the form of news headlines. The proposal is based on the use of DRL techniques, specifically the Deep Recurrent Q-Network (DRQN) architecture, combined with Recurrent Convolutional Neural Networks (RCNN), Word2Vec, and Long Short-Term Memory (LSTM). Performance was measured using financial metrics, including Net Profit, Annualized Return, the Sharpe Ratio, the Ulcer Performance Index, and Maximal Drawdown. The results demonstrated that the proposed model, which combines technical and fundamental data (named Mix Data), outperformed those that used only technical data.

In an approach focused on the complete automation of the trading process, Ismail et al. [Ismail et al. 2022] developed an automated system to predict movements in the

foreign exchange market. The main objective of the work was to eliminate the human emotional factor that often leads manual traders to significant losses. To achieve this, the authors propose a strategy that combines Technical Analysis (TA) indicators and an ANN to create a system that operates independently on the MetaTrader 4 (MT4) platform. The performance of the optimized EA was validated through a five-year backtest simulation (from 2017 to 2022). The simulation demonstrated that the system was able to generate profit consistently, turning an initial balance of 10 dollars into 185.43 dollars, which proves the viability of the proposed approach. The study concludes that the adoption of ANN-based strategies, when combined with carefully selected technical indicators, can provide significant advantages in predicting market trends and automating trading strategies.

Taken together, the works by Chinprasatsak et al. [Chinprasatsak et al. 2020] and Chantona et al. [Chantona et al. 2020] represent an advancement in their analyses by incorporating Maximum Drawdown (MDD) alongside return metrics. However, the evaluation remains incomplete, as the absence of risk-adjusted metrics, such as the Sharpe Ratio, limits the assessment of the quality of these returns. Thus, it is not possible to determine whether the profits resulted from an efficient strategy or simply from exposure to excessive risk. The work by [Ismail et al. 2022] also presents a similar limitation, focusing only on return metrics (AR and CR), despite its objective being to create a profitable EA.

Addressing the complexity of ML models, the research by Aloud [Aloud 2020] investigates the role of feature selection in the development of a financial trading system. To achieve this, the author proposed a methodology for a multi-agent Deep Artificial Neural Network (D-ANN) system, in which multiple input features – such as technical analysis indicators, intraday seasonality, and fundamental analysis – act as individual agents, each providing a trading recommendation: buy, sell, or hold. The central innovation of the study lies in how the recommendations from these agents are combined. Instead of assigning equal weights to all features, the author uses a Genetic Algorithm (GA) to evolve and optimize the weights of each input.

This process allows the system to learn, over iterations, which agents are more effective and, therefore, should exert greater influence on the final trading decision. The results showed that the D-ANN system outperformed all other strategies, achieving the highest average return and the highest Sharpe Ratio. This study employs a peculiar evaluation approach, relying solely on the Sharpe Ratio. Although it is a powerful metric for evaluating risk-adjusted return, its use in isolation is problematic, as it does not inform the investor about the magnitude of potential losses or operational efficiency (PF). A strategy can exhibit a good Sharpe Ratio but still have an unacceptable drawdown from both a psychological and financial standpoint for an investor.

Table 1 compares the analyzed studies based on the metrics defined in Section 2.6 and discussed in detail in Section 4.4. The column headings for the table are: Annualized Return (AR), Cumulative Return (CR), Maximum Drawdown (MDD), Profit Factor (PF), Expected Payoff (EP), and Recovery Factor (RF). The purpose of this comparison, in addition to contextualizing the 'Proposed Solution,' is to identify the performance metrics used to evaluate each of the approaches documented in the literature. This initial survey is essential for conducting a subsequent comparative analysis to assess the effectiveness

and robustness of the proposed solution against others.

| Work/Metrics | AR | CR | MDD | Sharpe | PF | EP | RF |
|-------------------------------------|-----|-----|-----|--------|----|----|----|
| [Povitukhin and Karmanova 2020] | No | Yes | No | No | No | No | No |
| [Chinprasatsak et al. 2020] | Yes | Yes | Yes | No | No | No | No |
| [Chantona et al. 2020] | Yes | Yes | Yes | Yes | No | No | No |
| [Aloud 2020] | No | No | No | Yes | No | No | No |
| [Ismail et al. 2022] | Yes | Yes | No | No | No | No | No |
| [Luangluewut and Thiennviboon 2023] | No | Yes | No | No | No | No | No |

Table 1. Comparison between the Works

As can be observed in Table 1, the works discussed in this section present significant methodological gaps by neglecting one or more essential evaluation metrics, which limits the validity and robustness of their automated trading strategies. In contrast, Scalper Major, by employing an evaluation framework that provides a balanced integration of return, risk, and risk-adjusted metrics, offers a much more complete and reliable analysis of its performance.

4. Proposed Solution

Having established the theoretical foundation, the related works, and the relevance of the problem, this section is dedicated to detailing the proposed solution and the criteria for its evaluation. First, the architecture of the proposed system is described, detailing its design and operation. Next, the adopted strategies for managing new trades when the market moves against already open positions and for scaling the lot size are presented. Finally, a systematic survey of the most commonly used financial evaluation metrics in the literature is presented, which not only guides the analysis of the results of this study but also establishes itself as a reference for future research in the area.

4.1. Scalper Major Architecture

Scalper Major is an automated trading system developed to operate in the Forex market, implementing short-term strategies with minimal human intervention. It was implemented using the MQL5 programming language, which is native to the MetaTrader 5 platform. The system's operation is based on a set of rules derived from technical criteria (the signal processor), combined with a strict risk and money management system, as outlined in the architecture presented in Figure 1.

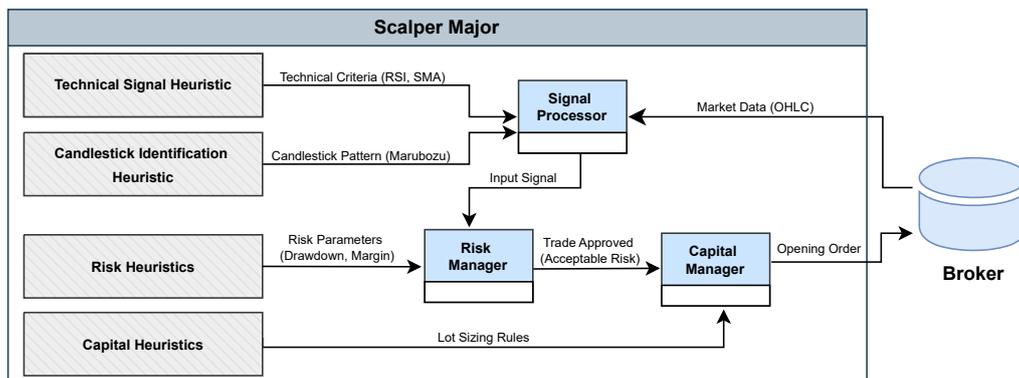


Figure 1. Scalper Major Architecture.

4.1.1. Signal Processor

The operational flow of Scalper Major begins with the receipt of market data (OHLC – open, high, low, close) provided by the broker. This data is directed to the Signal Processor (SP), the first component in the decision-making process. The SP evaluates the feasibility of a new trade using two main heuristics, analyzed at the beginning of each new hour based on the newly closed H1 (1-hour) candle: the Technical Signals Heuristic and the Candlestick Identification Heuristic, which are detailed below.

- **Technical Signals Heuristic:** This heuristic uses a combination of two indicators, the details of which are presented in Section 2.3: the RSI and the SMA. During the testing phase, it was found that the best buy signals were generated when the RSI was below 30, while the best sell signals occurred when it was above 70. Furthermore, it is required that the closing price of the candlestick be at a significant distance from the 20-period Simple Moving Average (SMA-20): below it for buy trades and above it for sell trades. Similar to the 30 and 70 levels for the RSI, the SMA-20 was selected because it yielded the best results in the tests performed. A sharp distance of the price from this average reinforces the hypothesis of an excessive extension of the downward or upward movement, increasing the probability of a correction.
- **Candlestick Identification Heuristic:** This heuristic focuses on recognizing the Marubozu pattern, the characteristics of which are detailed in Section 2.2. During the testing phase, the combination of this pattern with the RSI was found to be a robust confirmation for trade entries. A sell signal is generated when a bullish Marubozu occurs with the RSI in an overbought condition (above 70), indicating a likely exhaustion of the uptrend. On the other hand, a buy signal is generated when a bearish Marubozu is identified with the RSI in an oversold condition (below 30). Figure 2 presents an example of a sell trade executed on the EURUSD asset. It is observed that the RSI of the candle prior to the sell trade is above 70. Furthermore, it is noted that this same candle closed at a considerable distance from the SMA-20 (the white line below the candlesticks). These two conditions, combined with the bullish Marubozu, resulted in a successful sell trade.



Figure 2. Example of a sell trade.

4.1.2. Risk Manager

Once both of the SP's heuristics indicate a trading opportunity, the Risk Manager (RM) is triggered. This component acts as a safety filter, applying the Risk Heuristic to evaluate the strategy's sustainability and protect the capital from excessive losses. Its primary function is to ensure that risk exposure remains within predefined and acceptable limits. This heuristic considers data such as the available free margin and implements a maximum loss (drawdown) control at two levels: individual (per asset) and global. A new trade on a specific asset is blocked if the open trades show a negative float greater than 10%. Additionally, the system ceases to open any new trades if the overall account drawdown (the sum of all floating losses) exceeds 25%. These 10% and 25% limits were set empirically during the testing phase, aiming to strike an optimal balance between allowing the strategy to operate without excessive restrictions while rigorously protecting capital. It is essential to note that the Risk Manager's decision takes precedence over that of the Signal Processor; that is, even if the entry conditions are perfectly met, the operation will be canceled if the Risk Heuristic indicates an exposure that exceeds the defined safety parameters.

4.1.3. Capital Manager

After the operation is validated and approved by the RM, control is transferred to the Capital Manager (CM), the last component in the flow before the execution of a new trade (position). The CM's primary responsibility is to size the lot for new trades, a fundamental step in capital management. To achieve this, the CM employs the Capital Heuristic to determine the optimal lot size. The lot size is automatically adjusted based on the risk parameters defined in the EA and the total capital available in the account. This mechanism ensures that the exposure level adapts to the growth or decline of the account equity, promoting the scalability of returns in favorable scenarios and, crucially, capital preservation during periods of loss, thereby avoiding disproportionate risk exposures. Unlike the Risk Heuristic, which acts as a veto mechanism, the Capital Heuristic does not block the trade. Finally, once the lot size is defined, the CM sends the request to open the new position to the broker, completing the automated cycle. The joint application of these criteria, from signal identification to capital sizing, allowed the implemented strategy to achieve promising results in tests using historical data, as demonstrated and discussed in Section 5.

4.2. Trading and Recovery Strategy

However, if the market moves against the initial position, the EA activates a recovery mechanism that combines the grid and martingale strategies. The grid strategy consists of opening new positions at predefined price intervals as the market moves against the original position. The martingale strategy, in turn, involves increasing the lot size of the subsequent trade. Nevertheless, its isolated use is high-risk. To circumvent this danger, Scalper Major adopts a hybrid and innovative approach. Before applying the martingale, the system opens two consecutive positions with the same lot size, then doubles the lot size. For example, the lot sequence would follow the pattern 0.01, 0.01, 0.02, 0.02, 0.04, 0.04, and so on, until the maximum number of openable positions is reached.

Furthermore, a new order in the grid is opened only if the SP identifies a new valid entry signal, according to the criteria already detailed. This prevents the indiscriminate opening of positions that occurs in pure martingale systems. Additionally, to limit risk exposure, a maximum of 14 simultaneously open trades has been set per asset for each direction (14 buy and 14 sell). When the grid and martingale system are active, the profit target is met when the total profit of the winning positions reaches a value three times greater than the accumulated loss of the losing positions, ensuring a favorable risk-return ratio for the recovery. We emphasize that the parameters mentioned in this section are not derived from curve fitting but rather are defined as operational safety constraints.

4.3. Lot Sizing Model with Progressive Rebalancing

The logic for the dynamic calculation of the lot size is formalized through a series of equations presented below. These equations adjust the trading volume based exclusively on the account's accumulated historical profit, P_h .

4.3.1. Rebalancing Factor Calculation (Q_b)

Equation 4, presented below, indicates the number of times that the historical profit (P_h) has surpassed the rebalancing threshold R . The factor Q_b is an integer that represents the number of rebalancing events.

$$Q_b = \begin{cases} \left\lfloor \frac{P_h}{R} \right\rfloor, & \text{se } R > 0 \\ 0, & \text{se } R \leq 0 \end{cases} \quad (4)$$

4.3.2. Adjustment of Reference Capital Base (B'_x)

The initial reference base capital, B_x , which represents the amount of profit required to justify each increment of the base lot, is adjusted based on the factor Q_b . For each rebalancing event, a constant $C = 1000$ is added to the base capital, making the criterion for a lot increase stricter. Equation 5 shows how this criterion is calculated.

$$B'_x = B_x + (C \cdot Q_b) \quad (5)$$

4.3.3. Calculation of Final Lot Size (L)

Finally, the final lot size to be returned by the variable L is calculated, as represented in Equation 6. The equation determines how many multiples of the adjusted base capital (B'_x) are contained within the historical profit (P_h). This result is then multiplied by the base lot size corresponding to B_x , L_{base} (e.g., 0.01). The use of the floor function ($\lfloor \cdot \rfloor$) ensures that the lot is only incremented after the profit has fully covered the new threshold.

$$L = \begin{cases} L_{base} \cdot \left\lfloor \frac{P_h}{B'_x} \right\rfloor, & \text{se } P_h \geq B'_x \\ 0, & \text{se } P_h < B'_x \end{cases} \quad (6)$$

The principle of Scalper Major's lot scaling method is based on the premise that the trading volume should be a function directly proportional to the accumulated profit. This non-linear scaling approach, triggered by the rebalancing threshold R , makes the system progressively more conservative: as profits increase, the capital requirement for the next lot increment also grows. From a risk management perspective, this methodology aims to mitigate the impact of large drawdowns that can occur after periods of significant profit.

4.4. Financial Assessment Metrics

Next, each metric used for evaluating the strategy's performance will be detailed. It is crucial to highlight that the consolidation of these metrics is the result of an extensive and complex survey conducted in the specialized literature.

- **Annualized Return (AR):** Represents the compound growth rate of an investment over one year. It is an essential metric for evaluating the long-term performance of a strategy, allowing direct comparisons across different periods and asset classes, even when referring to distinct investment horizons [Huang et al. 2024].
- **Cumulative Return (CR):** Represents the percentage change in capital from the beginning of the investment to the present moment [Huang et al. 2024]. This metric is widely used to measure the total profitability of an investment or trading strategy over a specific time horizon [Li et al. 2024]. A high cumulative return may indicate significant growth of the invested capital, but it does not necessarily reflect the stability of the gains.
- **Maximum Drawdown (MDD):** Measures the maximum observed loss from the peak value of an investment or strategy to its lowest point before a recovery [Shahsafi and Naderkhani 2024]. It is also often interpreted as the maximum exposure to risk or the most significant possible capital loss [Olorunsheye and Meenakshi 2024]. This metric is essential for assessing the risk associated with a trading or investment strategy [Rahimpour et al. 2024], as it reveals the magnitude of losses during adverse market periods. Strategies with a high MDD may be considered riskier, as they require significant recovery to return to their previous level.
- **Sharpe Ratio:** Evaluates the risk-adjusted return of an investment or trading strategy [Rahimpour et al. 2024]. It helps investors interpret risk-adjusted performance [Li et al. 2019] by measuring the excess return obtained per unit of risk taken and is widely used to assess the effectiveness of trading strategies. Values greater than 1 indicate a more favorable risk-return relationship for the strategy [Carta et al. 2021], which is why traders extensively use it to evaluate the efficiency of trading systems [Blažiūnas and Raudys 2019].
- **Profit Factor (PF):** According to the MQL5 documentation⁵, the PF can be understood as the ratio of gross profit to gross loss, where a value of 1 indicates that the sum of profits is equivalent to the sum of losses. Huang and Martin [Huang and Martin 2019] explains that the PF, which can be understood as the annualized rate of return per unit of risk, is a crucial metric for evaluating the performance of leveraged trading strategies.

⁵MQL5 Documentation: <https://www.mql5.com/pt/docs>

- **Expected Payoff (EP):** The MQL5 documentation defines EP as a statistical indicator that represents the average profit or loss per trade. For Qin and Li [Qin and Li 2011], EP is a practical tool for evaluating and comparing trading strategies in scenarios of uncertainty, offering a way to quantify expected outcomes even when historical data is scarce or inadequate.
- **Recovery Factor (RF):** According to the MQL5 documentation, the RF is an indicator that reflects the strategy's risk level, representing the amount the system is willing to risk to obtain a profit. Nasution et al. [Nasution et al. 2024] points out that values above 1 indicate that the EA has good recovery capability, while values below 0.3 reveal that the EA has difficulty overcoming the Drawdown.

In comparison with related works in the literature, the proposed solution addresses recurring limitations in previous approaches, including the lack of risk-related indicators and the lack of transparency in money management. By integrating a realistic empirical evaluation with a comprehensive set of metrics, Scalper Major represents an advancement in the state of the art of automated trading, making a significant contribution to the development of computational tools that support decision-making in the financial market.

5. Results and Discussions

This section presents the results achieved by Scalper Major in a controlled (simulated) environment. Scalper Major was developed using Quantitative Trading techniques (detailed in Section 2.4.2) and was configured to operate specifically on the currency pairs EUR/USD, GBP/USD, USD/CAD, and USD/CHF. The selection of these assets was based on the results obtained from tests conducted on 24 currency pairs, with an average duration of 8 hours per asset. During the evaluation process, the metrics discussed in Section 4.4 were taken into consideration.

The EA's backtesting period corresponds to the interval between January 2016 and December 2023. This period was methodologically chosen to subject the proposed strategy to various market conditions. The inclusion of these distinct scenarios aims to validate the strategy's robustness and generalization capability, evaluating its performance not only in favorable market conditions but also during periods of stress and systemic market uncertainty. These events include: (1) the Brexit referendum and the US presidential elections of 2016 and 2020, (2) the global COVID-19 health crisis, which catalyzed one of the fastest bear markets in history, (3) the start of the war in Ukraine, with consequent stress on commodity markets, and (4) the subsequent abrupt transition from an environment of expansionary monetary policy to a restrictive cycle of quantitative tightening to combat global inflation.

To better approximate the results to real market conditions, the following factors were considered: (a) a commission rate of 7 dollars per lot, (b) an exemption from the swap fee (although it is common for some brokers to charge it), and (c) an execution delay of 50 ms. In the simulation process, an initial capital of \$20,000.00 was used, and the system achieved a total net profit of \$751,533.23, resulting from a gross profit of \$1,060,523.23 and gross losses of \$308,991.00, which include trades closed with a negative balance and commissions. In total, 11,571 trades were executed, of which 7,217 were long (buy) trades and 4,354 were short (sell) trades. The overall win rate was 82.54%, with an 83.66% rate for long trades and an 81.42% rate for short trades.

Figure 3 presents the grouped distribution of the trades made in each month of the analyzed years. A relatively uniform distribution is observed, with values varying approximately between 800 and 950 entries. The month of March stands out, with the highest number of entries, overtaking the 900 mark, while April recorded the lowest quantity, showing a slight decrease compared to the other months. Figure 4 presents the monthly distribution of profits and losses throughout the analyzed period, enabling a more detailed analysis of seasonality and financial performance patterns. It is observed that profits, represented by the blue bars, consistently exceed losses, indicated by the red bars, in all analyzed months. The months of May, June, and July stand out as those with the highest profitability, with an absolute peak recorded in June, when profits surpassed \$130,000.00. On the other hand, the months of February and December recorded the lowest profit.

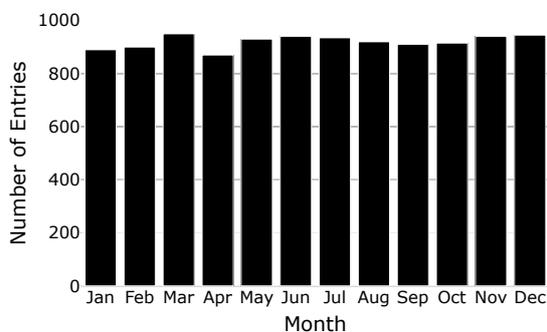


Figure 3. Negotiations per Month.

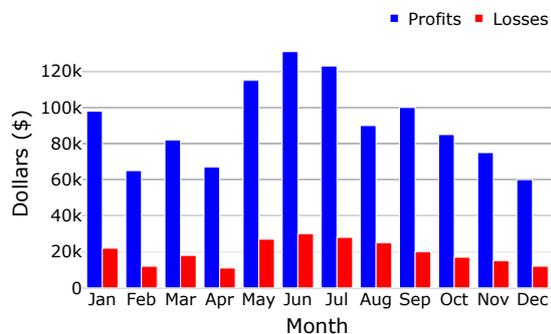


Figure 4. Profits and Losses.

Figure 5 presents the risk graph, in which the blue line represents the account's growth, and the green line represents the drawdown. The graph also demonstrates robust and consistent growth over time, underscoring the effectiveness of the strategy. A notable point in the trading history occurred in July 2023, when the system experienced its most significant drawdown, reaching a value of 9.43%. The curve also shows that, immediately after this setback, the system not only reversed the losses but also quickly resumed its upward trajectory, continuing to generate new profits, which attests to the soundness and recovery capability of the employed strategy.

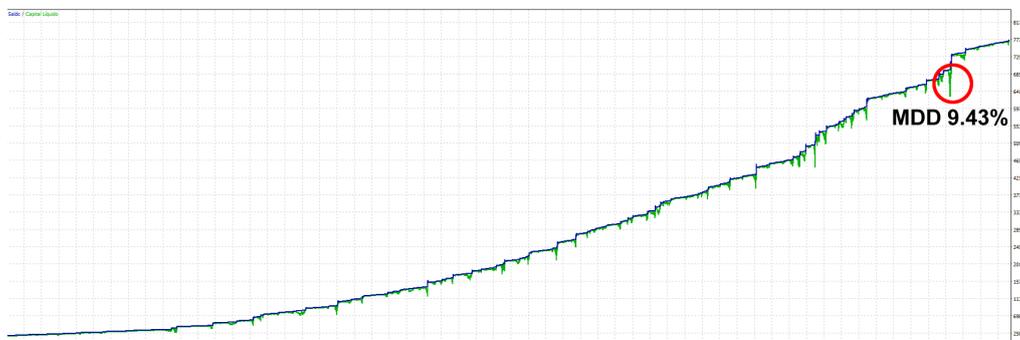


Figure 5. Risk and Robustness.

Table 2 presents an analysis of Scalper Major's performance in comparison to the works presented in Section 3, using the metrics made available in the respective studies.

The data presented demonstrate that the results of Scalper Major are notably superior across most of the analyzed metrics. The most significant indicator is the Cumulative Return (CR), which reached \$751,533.23 from an initial deposit of \$20,000.00. This superiority is also reflected in the risk-adjusted return metric. The Sharpe Ratio of 1.63 is the highest among the studies that reported it. This suggests that the strategy was more efficient at generating returns for each unit of risk assumed.

Additionally, its win rate of 82.82% is among the highest, highlighting its robust operational consistency. Although the work of Ismail et al. [Ismail et al. 2022] presents a higher Annual Return (AR) (79.32) than Scalper Major (57.87), the study does not report the Maximum Drawdown (MDD) of its strategy. The absence of the MDD seriously compromises the validity of the presented results, as a high return may have been achieved at the cost of a very high and potentially unacceptable risk for an investor. Scalper Major, on the other hand, presents an MDD of 9.43%, offering complete transparency about its risk. Although not listed in Table 2, other relevant data include: the Profit Factor of 3.43, the Expected Payoff of 64.95, and the Recovery Factor of 11.47.

| Work/Metrics | Deposit (\$) | CR (\$) | AR (%) | MDD (%) | Sharpe | Accuracy (%) |
|------------------------------|------------------|-------------------|--------------|-------------|-------------|--------------|
| Scalper Major | 20.000,00 | 751.533,23 | 57,87 | 9,43 | 1,63 | 82,82 |
| Povitukhin and Karmanova | - | 1.171,15 | - | - | - | 70,0 |
| Chinprasatsak et al. | 10.000,00 | 2.925,00 | 9,75 | 7,72 | - | - |
| Chantona et al. | 21.200,00 | 71.182,62 | 11,64 | 3,67 | 1,26 | - |
| Aloud | - | - | - | - | 0,42 | 68,5 |
| Ismail et al. | 10,00 | 175,43 | 79,32 | - | - | 79,7 |
| Luangluewut and Thiennviboon | - | 76.713,37 | - | - | - | 93,0 |

Table 2. Scalper Major vs Other Works

Other important data worth highlighting are as follows: (a) the best trade resulted in a profit of \$15,948.80, while the worst trade generated a loss of -\$1,890.00; (b) the maximum number of consecutive wins was 7, while the maximum for consecutive losses was 2; and (c) the most significant loss from a losing streak was -\$8,587.32, while the most significant profit from a winning streak was \$27,165.33. In general, the risk was adequately managed, and the system maintained a high level of consistency, even in the face of chaotic events. Additional data not presented in this article can be accessed through the report available at the following link: <https://zenodo.org/records/16983868>. At the same link, the EA is available, along with the instructions on how to replicate the results.

The results discussed in this section highlight the robustness and consistency of Scalper Major in a simulated environment, demonstrating significant performance in both profitability and risk control. The financial metrics presented indicate the system's efficiency in capturing market opportunities while simultaneously mitigating losses. These findings, although promising, will be further explored in future analyses, with a focus on validation in *live* environments and on the evaluation of aspects related to adaptation to different market conditions.

6. Conclusion

This work presents Scalper Major, an automated trading system (Expert Advisor) designed to operate efficiently and consistently in the Forex market, an environment known

for its high volatility and complexity. The proposed solution stands out for its robust, modular architecture, which cohesively integrates technical and managerial heuristics to identify opportunities with strict risk and capital control. The main contributions of this research are multifaceted and represent a significant advancement in the field of algorithmic trading. First, the work provides an unpublished compilation of the main evaluation metrics used in the literature for trading systems, serving as a benchmark for future research. Second, it develops a set of specialized heuristics for identifying opportunities and executing orders, combined with strict risk control and money management. Finally, it presents a functional implementation of the proposed architecture, validated through extensive simulations with historical data.

The results obtained and consolidated in Table 2 demonstrate the notable superiority of Scalper Major in comparison to other solutions in the literature. The strategy's robustness was validated through an extensive backtesting period, spanning from January 2016 to December 2023, which included high-impact events and various market regimes, such as the COVID-19 crisis and the war in Ukraine. This validation under adverse conditions demonstrates the system's generalization capability and soundness, reinforcing the results presented and consolidated in Table 2, which show the notable superiority of the proposed solution compared to others in the literature. In summary, Scalper Major not only proves to be a profitable and risk-managed tool in a simulated environment but also contributes significantly to the state of the art by establishing a new standard of methodological rigor and transparency in the evaluation of automated trading systems. The promising results pave the way for future research, including validation in a live environment and adaptation to different market conditions.

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