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Research paper

A comparative analysis of binary options trading strategies using fuzzified ma and rsi in the japanese market

Hamideh Nasabzadeh[1], **Mona Hesari**[2]

[1] Department of Mathematics, Faculty of Sciences, University of Bojnord, Iran
hnasabzadeh@gmail.com

[2] Department of Mathematics, Faculty of Sciences, University of Bojnord, Iran
hessarimona@gmail.com

Abstract:
This study introduces a hybrid trading strategy combining fuzzified Moving Average (Fuzzy MA) and Relative Strength Index (Fuzzy RSI) indicators for binary options in the Japanese financial market, demonstrating enhanced adaptability and profitability. Using fuzzy logic and Genetic Algorithms for parameter optimization, the strategy aims to maximize profit while fairly evaluating different methods through multiple performance metrics, including the Sharpe ratio and drawdown. By adapting traditional indicators to capture the inherent uncertainty and volatility of the market, the research focuses on the EUR/USD currency pair. Three approaches are investigated: Fuzzy MA, Fuzzy RSI, and the combined Fuzzy MA+RSI strategy. Results show that the combined strategy significantly outperforms individual fuzzy indicators, offering superior adaptability and profitability across volatile market conditions. This study contributes to the field of binary options trading by showcasing the potential of fuzzy logic and optimization techniques, highlighting the importance of considering a range of performance metrics for a comprehensive evaluation of trading strategies.

Keywords: Binary Options Trading, Fuzzy Logic, Moving Averages (MA), Relative Strength Index (RSI), Genetic Algorithms (GA).
Classification: 34A34, 65L05, 91G80.

1 Introduction

The use of technical indicators in financial markets is foundational to many trading strategies, particularly those focused on short-term decision-making. Among the most widely used indicators are Moving Averages (MA) and the Relative Strength Index (RSI). MA, dating back to the 1930s, was originally developed to smooth price data and highlight underlying trends in financial markets [1]. The RSI, introduced by Welles Wilder in 1978, is a momentum oscillator used to identify overbought and oversold conditions, helping traders assess potential price reversals [17]. Over time, these indicators have been integrated into both manual and algorithmic trading strategies across various asset classes, including equities, commodities, and more recently, cryptocurrencies [8, 9]. However, while these indicators have been success-

[1]Corresponding author
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fully applied in traditional markets, their application in binary options trading has received far less attention.

Binary options, which offer all-or-nothing payouts within very short timeframes, present unique challenges compared to other financial markets. Unlike traditional markets where traders seek to capitalize on price movements over extended periods, binary options require precise and timely decision-making. The characteristic short expiration times of binary optionsoften ranging from minutes to hoursnecessitate the use of high-frequency, real-time trading strategies. This presents a fundamental challenge: standard technical indicators such as MA and RSI, which have been developed for traditional financial markets, may not be optimized for the binary options context. The rapid and deterministic nature of binary options trading demands strategies that are not only fast and efficient but also capable of handling market uncertainty and ambiguity.

Despite the growing popularity of binary options as a speculative trading vehicle, research into effective strategies tailored specifically for this market remains sparse. Much of the existing literature focuses on traditional financial markets, with only a few studies exploring binary options trading strategies. For instance, Haase et al. (2016) highlighted that most predictive models designed for binary options failed to account for the unique characteristics of these instruments, such as the fixed payout structure and the impact of short-term volatility [4]. Similarly, Ryu et al. (2017) emphasized that traditional strategies, when applied to binary options, often lead to suboptimal performance due to the extreme time sensitivity and lack of room for error [14]. These studies underscore a critical gap in the literature: while binary options are inherently different from other financial instruments, the strategies designed for them are often borrowed from traditional financial markets, where different dynamics apply.

In response to this gap, our study seeks to develop and evaluate advanced decision-making models that are specifically designed for binary options trading. We introduce fuzzy logic as a means to refine traditional technical indicators like MA and RSI, making them better suited for the fast-paced nature of binary options. Fuzzy logic, introduced by Lotfi Zadeh in 1965, provides a framework for dealing with uncertainty and imprecision, allowing for more nuanced trading signals compared to conventional crisp logic systems [18]. By applying fuzzy logic to MA and RSI, we aim to enhance their effectiveness in binary options trading by capturing the inherent uncertainty and volatility of the market.

The application of fuzzy logic to trading systems is not new. In recent years, fuzzy rule-based systems have been successfully applied in various market contexts, such as stock market prediction and cryptocurrency trading. Zio et al. (2020) applied fuzzy logic to stock market forecasting, demonstrating its ability to improve the accuracy of predictions in volatile conditions [19]. Similarly, Qin et al. (2021) employed fuzzy logic to optimize cryptocurrency trading strategies, highlighting its adaptability in highly dynamic markets [12]. More recently, studies by Chen et al.

(2022) and Zhang et al. (2023) have explored the use of fuzzy logic in high-frequency trading, showing its potential to reduce false signals and improve profitability in fast-moving markets [20, 21]. Additionally, Wang et al. (2021) demonstrated the effectiveness of hybrid fuzzy-neural models in predicting market trends, further validating the utility of fuzzy systems in financial applications [22]. These studies collectively demonstrate the potential of fuzzy systems in improving the robustness and reliability of trading models. However, there remains a lack of studies that apply fuzzy logic specifically to binary options trading, particularly in the context of short-term strategies such as those involving the EUR/USD currency pair.

The present study seeks to address this gap by developing a fuzzified trading strategy that integrates both MA and RSI indicators. We focus on the EUR/USD currency pair in the Japanese financial market, an area where binary options trading has seen significant growth. Our methodology involves constructing a fuzzy inference system (FIS) that uses fuzzy membership functions for both the MA and RSI indicators, enabling the system to make more flexible and context-sensitive trading decisions. To further optimize the performance of the trading strategy, we incorporate Genetic Algorithms (GAs) to fine-tune the parameters of the fuzzy system, enhancing its adaptability and responsiveness to market conditions.

This study aims to contribute to the growing body of literature on binary options trading by offering a novel approach that leverages fuzzy logic to improve trading decision-making. We demonstrate that by using fuzzy logic to modify traditional indicators, binary options traders can achieve better accuracy and profitability, especially in volatile markets where timing is crucial.

The remainder of this paper is organized as follows. Section 2 provides an overview of the fuzzification process for the Moving Averages and RSI indicators, detailing the definition of fuzzy membership functions and the development of trading decision rules. Section 3 describes the implementation of Genetic Algorithms for parameter optimization and compares the performance of fuzzified MA, RSI, and their combination. The results of these experiments are presented and analyzed in Section 4, highlighting the potential implications for binary options traders, particularly those engaged in trading the EUR/USD currency pair. Finally, Section 5 concludes the paper, summarizing the findings and offering suggestions for future research in this domain.

2 Fuzzification Methods

In this section, we delineate the fuzzification process for both the Moving Average (MA) and the Relative Strength Index (RSI) indicators, emphasizing the establishment of membership functions that elucidate trend strength and prevailing market conditions. These fuzzy inputs are subsequently integrated into a fuzzy inference system designed to generate accurate trading signals tailored for binary options trading.

2.1 Introduction to Fuzzification Rules

Definition: Fuzzification rules are the foundational procedures in a fuzzy logic system that transform crisp numerical input valuessuch as those from financial indicatorsinto fuzzy sets using membership functions [18]. This transformation is crucial for handling uncertainties and imprecisions inherent in real-world data, allowing the system to employ qualitative, linguistic variables instead of strict numerical thresholds.

Purpose:

- **Handling Uncertainty:** Fuzzification rules enable systems to operate under conditions of ambiguity and vagueness by converting precise data into fuzzy values. This facilitates decision-making in uncertain environments like financial markets [6].
- **Utilizing Qualitative Terms:** By mapping numerical inputs to fuzzy categories, fuzzification allows the integration of human-like reasoning through terms such as "uptrend", "oversold", or "neutral" [13].
- **Modeling Confidence Levels:** They allow the depiction of varying degrees of confidence or strength of a signal, vital for nuanced trade decisions.

Components:

- **Crisp Inputs:** Specific numerical values like moving average differences (e.g., $MA_{\text{short}} - MA_{\text{long}}$) or RSI scores, which serve as the input data for the fuzzification process.
- **Fuzzy Sets:** These sets correspond to linguistic variables, representing concepts such as increasing trend strength, market oversaturation, or neutrality.
- **Membership Functions:** Mathematical functions that define the degree to which a particular input value belongs to a fuzzy set (between 0 and 1). They determine how crisp inputs are converted into fuzzy values.

Fuzzy Sets vs. Crisp Sets Unlike crisp sets, where an element either fully belongs or does not belong to a set, fuzzy sets allow elements to have degrees of membership ranging from 0 to 1. This is particularly useful in financial contexts where concepts like "high price" or "strong trend" are not sharply defined but rather exist on a spectrum [6].

Definition of Fuzzy Numbers Fuzzy numbers are a specialized form of fuzzy set where each element is associated with a degree of membership. They capture uncertain or imprecise numerical values, reflecting the vague nature of financial indicators [13].

Types of Fuzzy Numbers Various types of fuzzy numbers support diverse applications based on needed flexibility and computation [13].

- **Triangular Fuzzy Numbers**: Defined by a triplet (a, b, c) for simplicity but with limited flexibility.
- **Trapezoidal Fuzzy Numbers**: Defined by (a, b, c, d), their flat top offers flexibility, capturing ranges rather than a single point.
- **Gaussian Fuzzy Numbers**: Defined by a mean and standard deviation for smooth transitions, though more computationally intensive.

2.2 Membership Functions for Moving Averages (MA)

The fuzzification of Moving Averages utilizes two key inputs: the short-term moving average (MA_{short}) and the long-term moving average (MA_{long}). Their interaction is critical for detecting market trends. A normalization parameter, β, is used to scale the difference, defined as:

$$\alpha = \beta \cdot MA_{\text{long}}$$

With this scaling parameter, we define the membership functions such that all values are normalized between 0 and 1:

- **Uptrend:**

$$\mu_{\text{Uptrend}}(MA) = \begin{cases} 1, & \text{if } MA_{\text{short}} - MA_{\text{long}} > \alpha \\ \frac{MA_{\text{short}} - MA_{\text{long}}}{\alpha}, & \text{if } 0 < MA_{\text{short}} - MA_{\text{long}} \leq \alpha \\ 0, & \text{otherwise} \end{cases}$$

- **Downtrend:**

$$\mu_{\text{Downtrend}}(MA) = \begin{cases} 1, & \text{if } MA_{\text{short}} - MA_{\text{long}} < -\alpha \\ \frac{-(MA_{\text{short}} - MA_{\text{long}})}{\alpha}, & \text{if } -\alpha \leq MA_{\text{short}} - MA_{\text{long}} < 0 \\ 0, & \text{otherwise} \end{cases}$$

- **No Trend:**

$$\mu_{\text{No Trend}}(MA) = 1 - \max(\mu_{\text{Uptrend}}(MA), \mu_{\text{Downtrend}}(MA))$$

These membership functions provide a robust framework for determining the strength and direction of market trends, ensuring that all inputs to the fuzzy inference system are valid for generating precise trading signals.

It's important to note that while these membership functions provide a fuzzy representation of market trends, they do not strictly adhere to the classical definition of trapezoidal fuzzy numbers. A general trapezoidal fuzzy number $\mu(x)$ is mathematically defined as:

$$\mu(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x < b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c < x \leq d \\ 0, & x > d \end{cases}$$

Where a, b, c, and d are parameters defining the shape of the trapezoid.

- The **Uptrend** membership function is a right-shoulder triangular shape, it increases linearly from 0 to 1 as the difference between MA_{short} and MA_{long} increases from 0 to α and then remains at 1 for values greater than α. This can be interpreted as a fuzzy number where $a = 0$, and $b = \alpha$, but without the descending part c and d from the classic trapezoidal fuzzy number definition.
- The **Downtrend** membership function is now adjusted to represent a left-shoulder triangular shape. It increases linearly from 0 to 1 as the difference between MA_{short} and MA_{long} decreases from 0 to $-\alpha$, and remains at 1 for values where $MA_{\text{short}} - MA_{\text{long}} < -\alpha$. This function can be thought of as a trapezoidal function similar to a left-shoulder shape with an incomplete ascending left side. The key difference is that the membership values now range from 0 to 1, using the negative difference scaled by α.

These simplified shapes are used for their simplicity and ease of computation, making it easier to implement a real-time trading system, and the parameter alpha is used to control the bandwidth of the membership functions.

Importance of Beta in Asset-Specific Trading Strategies In the context of binary options trading, the parameter β serves as a vital normalization factor within the fuzzification process. It is integral to determining how market signals are interpreted, linking directly to the specific characteristics of the assets being traded. A high β value enforces strict criteria, categorizing only substantial movements between the short-term MA_{short} and long-term moving average MA_{long} as significant, which may lead to missed opportunities in fast-paced markets where price fluctuations can provide profitable signals. Conversely, a lower β enhances the system's sensitivity to minor fluctuations, resulting in a greater frequency of trading signals that can capture marginal yet potentially lucrative market movements, particularly beneficial in volatile trading environments.

The selection of β should be tailored to the specific asset under consideration, as financial markets exhibit varying characteristics influenced by economic conditions and geopolitical factors. For instance, the EUR/USD pair, known for its stable movements, may benefit from a moderate β that balances the need for responsiveness while filtering out noise. In contrast, the GBP/USD pair, often subject to more significant volatility due to external economic and political influences, might require a lower β to ensure that the trading strategy can effectively react to rapid price shifts. Therefore, traders are encouraged to utilize historical data analysis, implement dynamic parameter adjustments, and incorporate advanced optimization techniques to fine-tune β, ensuring that their trading strategies remain robust and aligned with current market dynamics.

2.3 Membership Functions for Relative Strength Index (RSI)

The Relative Strength Index (RSI) is an esteemed technical indicator that quantifies market momentum, particularly illuminating overbought or oversold conditions. To accommodate varying market scenarios and strategies, we introduce two customizable parameters: T_{low} and T_{high}, which serve as thresholds for identifying oversold and overbought conditions, respectively.

- T_{low}: This threshold defines when the market is considered oversold. A breach of this threshold indicates a potential price reversal from a bearish trend, suggesting that the asset might be undervalued.
- T_{high}: Conversely, this threshold defines overbought conditions. When the RSI exceeds T_{high}, it signals a potential price reversal from a bullish trend, indicating that the asset may be overvalued.

The typical values for T_{low} and T_{high} are 30 and 70, respectively, while alternative values such as 20 and 80 may be applied to cater to more conservative or aggressive trading strategies.

The corresponding membership functions are defined to capture degrees of oversold, overbought, and neutral conditions as follows:

- **Oversold:**

$$\mu_{\text{Oversold}}(RSI) = \begin{cases} 1, & \text{if } RSI \leq T_{\text{low}} \\ \frac{T_{\text{high}} - RSI}{T_{\text{high}} - T_{\text{low}}}, & \text{if } T_{\text{low}} < RSI \leq T_{\text{high}} \\ 0, & \text{if } RSI > T_{\text{high}} \end{cases}$$

- **Overbought:**

$$\mu_{\text{Overbought}}(RSI) = \begin{cases} 1, & \text{if } RSI \geq T_{\text{high}} \\ \frac{RSI - T_{\text{low}}}{T_{\text{high}} - T_{\text{low}}}, & \text{if } T_{\text{low}} < RSI \leq T_{\text{high}} \\ 0, & \text{if } RSI \leq T_{\text{low}} \end{cases}$$

- **Neutral:**

$$\mu_{\text{Neutral}}(RSI) = 1 - \max(\mu_{\text{Oversold}}(RSI), \mu_{\text{Overbought}}(RSI))$$

These flexible membership functions facilitate nuanced interpretations of RSI values tailored to the desired sensitivity of the trading system. By varying T_{low} and T_{high}, the trader can adapt the system to different market dynamics, identifying early indications of reversal or waiting for stronger confirmation signals.

2.4 Fuzzification of Call/Put Rules for MA, RSI, and MA+RSI

This section examines the fuzzification process and delineates the Call/Put rules derived from three distinct configurations of Moving Averages (MA alone), Relative Strength Index (RSI alone), and their combined approach (MA+RSI). Each approach provides differing insights into market conditions and informs associated trading actions.

Fuzzification of Moving Averages (MA)

In the MA-based trading approach, decisions rely heavily on the assessment of trend directions. The fuzzified output is streamlined into categories of uptrends and downtrends, which serve as primary indicators for trading actions, weighted to reflect signal strength.

Table 1: Call/Put Rules Based on Fuzzified MA

MA Fuzzification	Action (Call/Put)	Weight
Uptrend	Call	0.9
Neutral	Hold	0.5
Downtrend	Put	- 0.9

The *call_put_score* is computed using the following formula:

$$call\_put\_score_{\text{MA}}| = \frac{\sum \mu_{\text{MA}} \cdot \text{MA Weights}}{\sum(|\text{MA Weights}|)}$$

where μ_{MA} represents the membership function derived from the fuzzified MA value, and the corresponding MA weight is determined as per the fuzzification rules outlined in Table1.

Fuzzification of Relative Strength Index (RSI)

The RSI-focused approach concentrates on momentum identification utilizing the RSI indicator. The fuzzification inputs capture overbought, oversold, and neutral conditions, providing a framework for decision-making as illustrated below.

RSI Fuzzification	Action (Call/Put)	Weight
Oversold	Call	0.9
Neutral	Hold	0.5
Overbought	Put	- 0.9

Table 2: Call/Put Rules Based on Fuzzified RSI

For the RSI-based approach, the *call_put_score* is computed as follows:

$$\mathit{call\_put\_score}_{\text{RSI}} = \frac{\sum \mu_{\text{RSI}} \cdot \text{RSI Weights}}{\sum |(\text{RSI Weights})|}$$

where μ_{RSI} is the membership function derived from the fuzzified RSI value, and the weight is derived from the corresponding rule in the Table 2. This method proves effective in volatile markets where momentum shifts frequently occur, enabling timely and informed decisions.

Fuzzification of Combined MA and RSI (MA+RSI)

The integration of signals from Moving Averages (MA) and the Relative Strength Index (RSI) provides a comprehensive framework for generating holistic trading signals. This combination leverages trend direction and momentum simultaneously to adapt to varying market conditions. The updated rule-based system is represented in the table below, which delineates trading actions without the inclusion of weak trend categories.

Table 3: Call/Put Rules Based on Fuzzified MA and RSI

MA Fuzzification	RSI Fuzzification	Action (Call/Put)	Weight
Uptrend	Oversold	Call	0.9
Uptrend	Neutral	Call	0.7
No Trend	Neutral	Hold	0.5
Downtrend	Neutral	Put	-0.7
Downtrend	Overbought	Put	-0.9

The trading decision process utilizes a combined *call_put_score* calculated as follows:

$$\mathit{call\_put\_score}_{\text{MA+RSI}} = \frac{\sum(\mu_{\text{MA}} \cdot \mu_{\text{RSI}} \cdot (\text{MA+RSI Weights}))}{\sum |((\text{MA+RSI Weights}))|}$$

where μ_{MA} and μ_{RSI} represent the membership functions derived from the respective fuzzified values of MA and RSI. The weights are derived from the rules listed in Table 3.

This integrated approach capitalizes on both price trend direction (via MA) and momentum (via RSI), offering a nuanced perspective that adapts to diverse market scenarios. By streamlining the fuzzified signals into more distinctive categories, the methodology ensures more straightforward interpretations and applications, particularly in volatile environments typical of binary options trading in the Japanese market. This strategy highlights the harmonious coupling of trend and momentum metrics to fine-tune trading signals and optimize decision-making agility.

Impact of Call/Put Decision Thresholds

The effectiveness of the trading system is significantly influenced by the decision thresholds set for executing Call and Put trades, denoted as *ThresholdC* and *ThresholdP*. These thresholds are crucial in determining the conditions under which trades are executed, thereby affecting the overall performance and accuracy of the trading strategy.

The relationship between these thresholds is defined as:

$$\text{ThresholdP} = -\text{ThresholdC}$$

This symmetric alignment ensures that any adjustment to one threshold is mirrored by a corresponding change in the other, maintaining a balanced and responsive trading system. The thresholds are optimized to enhance trade accuracy and system performance, ensuring that trades are executed under conditions of strong certainty.

The execution of trades is governed by the following conditions:

- A Call trade is executed if the *call_put_score* exceeds ThresholdC.
- Conversely, a Put trade is executed if the *call_put_score* falls below ThresholdP.

These thresholds are strategically set to balance the trade-off between trade frequency and accuracy. By maintaining a high threshold, the system prioritizes accuracy, ensuring that only trades with a high probability of success are executed. Conversely, lowering the thresholds can increase trade frequency but may compromise accuracy, highlighting the importance of careful threshold optimization.

In practice, the default thresholds are often set at 0.5 for Calls and -0.5 for Puts, providing a robust framework for decision-making. However, these values can be adjusted based on market conditions and strategic objectives, allowing for flexibility and adaptability in trading operations.

Overall, the careful calibration of *ThresholdC* and *ThresholdP* is essential for optimizing the performance of the trading system, ensuring that it remains responsive to market dynamics while maintaining a high level of accuracy in trade execution.
To summarize, the fuzzification process applied to both the Moving Averages and Relative Strength Index forms the backbone of a sophisticated trading strategy. The establishment of membership functions deepens the understanding of market dynamics and enhances signal accuracy for effective trading in binary op-

tions. The methodologies discussed set the stage for more in-depth exploration of fuzzy logic in trading strategies, providing insights that adapt to evolving market behaviors.

3 Methodology

This section outlines the methodology used for comparing the performance of fuzzy logic and classical trading strategies in binary options, with a focus on maximizing profit for trades lasting under 35 minutes during the Japanese trading session. The analysis specifically targets the behavior of the Tokyo market by utilizing high-frequency price data from the EUR/USD currency pair. To isolate Tokyo-specific dynamics, the final hour before the overlap with the London session was excluded to mitigate noise from overlapping trading behaviors. All data was collected on a 1-minute timeframe, which is critical for capturing the rapid price movements relevant to short-term binary options trading.

To optimize the strategies, Genetic Algorithms (GA) were employed to fine-tune key parameters. These optimizations were conducted over three selected trading days in 2024, each representing distinct market conditionssuch as strong uptrends, heightened volatility, and mixed behavior. This design ensures that both strategies are tested under varied scenarios, providing a robust performance evaluation.

While maximizing profit remains the central objective, additional performance metrics such as risk-adjusted returns (e.g., Sharpe Ratio) and drawdown are included to evaluate the overall reliability of the strategies. This is particularly important, as higher profits from fuzzy logic strategies could be accompanied by higher risks. This comprehensive evaluation accommodates both profitability and risk management, highlighting differences between fuzzy and classical approaches.

Key distinctions between these approaches include the adaptability provided by fuzzy logic through its dynamic ”ThresholdC” parameter, compared to the fixed reliance of classical methods on indicators such as moving averages (MA) and RSI. This balance ensures a fair comparison between short-term trading strategies in varying market conditions.

3.1 Data Source and Rationale for Day Selection

The data for this study was sourced from MetaTrader, utilizing 1-minute time frame data from the EUR/USD currency pair. This granularity is crucial to accurately capture the high-frequency price dynamics relevant to binary options trading. The dataset spans three specific days in 2024, each chosen to represent different market conditions, allowing for a comprehensive evaluation of the trading strategies under various scenarios:

- **September 4, 2024**: A moderately stable trading day with a mild uptrend. This day was selected to test the effectiveness of moving average (MA) strategies on the EUR/USD pair, where stable market conditions offer a controlled environment for assessing the method's performance.

- **September 13, 2024**: A high-volatility day, crucial for evaluating the flexibility and responsiveness of the Relative Strength Index (RSI) strategy. This day presents significant market fluctuations that allow us to test how well the RSI strategy can adapt to unpredictable price movements.

- **September 25, 2024**: A day characterized by mixed market behavior, encompassing both upward and downward movements, which allows for a broader assessment of a combined MA + RSI strategy. This day ensures that the methodology can handle diverse market patterns, providing insight into how both strategies perform under less predictable conditions.

These specific days were strategically selected to represent a variety of market conditions that are typical for the EUR/USD pair during the Tokyo trading session. To ensure the integrity of the analysis, the data excludes the final hour before the London session to eliminate any noise caused by the overlap with the London market. The goal is to evaluate the strategies purely within the dynamics of the Tokyo session, where the influence of the London market is minimized.

The data includes open and close prices for each of the selected days, along with volume information. Prior to analysis, the dataset was preprocessed to remove anomalies and ensure consistency across all observations, ensuring that the results would reflect accurate market conditions without distortions from data irregularities.

3.2 Optimization Method and Parameters and Decision Variables

The optimization of trading strategies in this study is conducted using the Genetic Algorithm (GA), a widely recognized evolutionary computation technique that is particularly suited for parameter optimization in complex, multidimensional problem spaces such as financial trading. The choice of GA was influenced by its strong empirical performance in similar optimization contexts, as highlighted in various studies (Goldberg, 1989; Sivanandam et al., 2008). While alternative optimization techniques like Particle Swarm Optimization (PSO) exist, the GA was selected for its flexibility, robustness, and well-documented application in financial strategy optimization.

Genetic Algorithm Configuration The GA was implemented in MATLAB with the following settings, specifically chosen to balance computational efficiency with the exploration of the parameter space. These settings align with best practices recommended in the literature for financial optimization problems:

- **Population Size**: 100 individuals per generation. A population size of 100 was selected to ensure sufficient genetic diversity, enabling the algorithm to explore a broad range of possible solutions. This population size is computationally feasible while still allowing for a sufficiently diverse search, which is critical when optimizing complex parameters such as those in trading strategies. Larger populations could offer more thorough searches but come at a higher computational cost, making 100 a balanced choice [3].

- **Crossover Rate**: 0.8. A high crossover rate encourages the combination of successful traits from different individuals, promoting diversity and enhancing the algorithms ability to explore various combinations of parameters. This setting ensures that promising solutions propagate through successive generations, which is crucial in the context of optimizing financial trading strategies where a balance between exploration and exploitation is required [5].

- **Mutation Rate**: 0.1. The mutation rate introduces random changes into the genetic material, which helps the GA escape from local optima by maintaining genetic diversity throughout the optimization process. A rate of 0.1 is considered a good compromise between sufficient mutation and maintaining the stability of the evolving solutions [2].

- **Number of Generations**: 50. Running the GA for 50 generations provides adequate time for the population to evolve towards an optimal solution. This number of generations has been proven effective in optimizing financial models, allowing the algorithm to converge without excessive computational overhead [15].

These parameter choices reflect a standard and efficient approach to GA-based optimization, ensuring that the search process remains comprehensive yet computationally manageable. The values were chosen based on previous successful applications in financial contexts, ensuring that the results of our optimization would be comparable with existing literature.

Decision Variables and Ranges The optimization process focuses on the following decision variables, which are critical to the performance of the trading strategies under consideration:

- **MA Short Period**: 2 to 50 minutes. This variable determines the window for short-term trend identification, which is vital for capturing rapid price movements in binary options trading [11].

- **MA Long Period**: 10 to 200 minutes. This variable is used to define the long-term trend, allowing the strategy to adjust to broader market movements and providing stability during periods of high volatility [10].

- **RSI Window Period**: 5 to 100 minutes. The RSI window defines the period over which momentum is assessed, providing flexibility to adapt to varying market conditions [17].
- **Tlow**: 20 to 50. This variable sets the threshold for the RSI-based oversold condition, enabling the strategy to dynamically adjust to different market conditions and optimize trade entries based on the prevailing market environment [7].
- **Trade Duration**: 5 to 35 minutes. This defines the holding period for the binary options trades, aligned with the short-term nature of binary options trading strategies.
- **ThresholdC**: 0 to 1. This decision variable controls the sensitivity of the trade execution, adjusting the threshold for decision smoothing. It plays a crucial role in managing risk and filtering out marginal trade signals, ensuring that the strategy remains effective and adaptive to changes in market conditions [16].

The Role and Selection of the Parameter β in Fuzzified MA In the fuzzified Moving Average (Fuzzified MA) strategy, an important parameter that influences the decision-making process is β. This parameter is employed in the inequality difference $> \alpha$ (or difference $< \alpha$), where:

$$\text{difference} = MA_{\text{short}} - MA_{\text{long}}$$

and

$$\alpha = \beta \times MA_{\text{long}}.$$

The parameter β is crucial in determining when the fuzzy trading decision conditions are met. A value for β that is too large or too small can lead to invalid or overly restrictive trading conditions, which is why careful consideration was given to selecting an appropriate value.

The choice of $\beta = 0.00005$ was made based on an empirical approach after analyzing the behavior of the difference term in the inequality. The values of MA_{short} and MA_{long} are typically such that difference is a very small number, often on the order of 10^{-5}. Specifically, the value of MA_{long} is around 1 or slightly greater, and MA_{short} fluctuates in a range that yields very small values for the difference.

If β were chosen to be significantly larger than 0.00005, the inequality difference $>$ α would rarely hold true because α would become large in comparison to the small values of difference. As a result, the condition would not trigger buy or sell signals under most circumstances, causing the trading strategy to miss out on potentially profitable opportunities.

On the other hand, if β were too small, the inequality would almost always hold, leading to frequent or almost continuous trading signals. This could introduce unnecessary trades, potentially resulting in higher transaction costs and more exposure to risk, ultimately reducing the profitability of the strategy.

Through empirical testing, the value $\beta = 0.00005$ was found to strike an optimal balance. It ensures that the inequality difference $> \alpha$ is satisfied at appropriate times, enabling the strategy to respond effectively to market signals while avoiding unnecessary trades. This choice of β was determined through trial and error, ensuring that the fuzzified trading system could function efficiently and profitably without generating an excessive number of trades.

Thus, the selected value of β provides a fine-tuned approach for controlling the threshold for trade execution, ensuring that the strategy remains responsive yet stable within the dynamic nature of the forex market, particularly during the Tokyo trading session.

3.3 Classical (Non-Fuzzy) Strategy

This subsection focuses on the optimization of classical, non-fuzzified trading strategies using the Genetic Algorithm (GA). The same GA configuration and decision variable ranges as described in Spoly3.2 were employed, except for the absence of the *ThresholdC* parameter, which is only relevant in the fuzzified approach. The classical strategies rely on fixed thresholds and crisp conditions, providing a benchmark to compare with the fuzzified strategies.

Optimization Method The GA was applied with the same parameters as follows: a population size of 100 individuals, a crossover rate of 0.8, a mutation rate of 0.1, and 50 generations. This configuration supported efficient exploration of the parameter space and ensured a robust optimization process, balancing computational effort with solution accuracy.

Trading Strategies This study evaluates three classical trading strategies based on moving average (MA) and relative strength index (RSI) indicators. The trading methods are as follows:

- **Moving Average (MA) Strategy:** Trading decisions were based on the difference between the short-period and long-period moving averages:
  - A **long position (buy)** was entered when:

$$\text{MA Short Period} - \text{MA Long Period} > 0.$$

  - Conversely, a **short position (sell)** was entered when:

$$\text{MA Short Period} - \text{MA Long Period} < 0.$$

- **Relative Strength Index (RSI) Strategy:** Trading signals were generated based on calculated RSI values:
  - A **long position (buy)** was entered when:
    $$\text{RSI Value} < T_{\text{low}},$$
    where T_{low} is the threshold for oversold conditions.
  - A **short position (sell)** was entered when:
    $$\text{RSI Value} > T_{\text{high}},$$
    where $T_{\text{high}} = 100 - T_{\text{low}}$ defines the threshold for overbought conditions.

- **Combined MA + RSI Strategy:** This approach combines the conditions of the MA and RSI strategies:
  - A **long position (buy)** was initiated only when:
    $$\text{MA Short Period} - \text{MA Long Period} > 0 \quad \textbf{and} \quad \text{RSI Value} < T_{\text{low}}.$$
  - A **short position (sell)** was initiated only when:
    $$\text{MA Short Period} - \text{MA Long Period} < 0 \quad \textbf{and} \quad \text{RSI Value} > T_{\text{high}}.$$

Objective of Classical Optimization The primary goal of this classical optimization approach was to optimize the decision variables (e.g., MA short/long periods, RSI window period, and T_{low}) to maximize the profitability and accuracy of the trading strategies under traditional (crisp) rules. The performance of these optimized classical strategies serves as a baseline for comparing with the proposed fuzzified trading strategies.

3.4 Parameter Sensitivity Analysis

Objective

The objective of the parameter sensitivity analysis is to evaluate how variations in individual parameters influence the overall performance of the trading strategies. Specifically, the analysis aims to identify which parameters have the most significant impact on the performance and profitability of the fuzzified strategies. By understanding the sensitivity of the strategies to each parameter, it becomes possible to fine-tune the strategy for optimal performance under different market conditions.

Methodology for Sensitivity Analysis

For each parameter, the sensitivity analysis was conducted by varying one parameter at a time while keeping the other parameters fixed at their optimal values. This approach allowed for a clear understanding of how each parameter individually affects the performance of the trading strategies. The performance metric used in the analysis was the "Profit/Max Profit" ratio, which reflects the relative profitability of the strategy compared to the maximum achievable profit.

The following steps were performed in the analysis for each strategy:

(i) "Selection of Optimal Parameter Values": The optimal parameter values for the analysis were selected based on previous results from the fuzzified strategies, particularly the best-performing configurations from the training phase. These values were used as a baseline, and deviations from these values were studied to observe their effect on the strategy's performance.

(ii) Parameter Variation": Each parameter was varied independently, and its impact on performance was assessed. For example:

- For the fuzzified **MA** strategy, the sensitivity analysis was conducted by varying **ThresholdC**, **MA_short**, **MA_long**, and **Trade Duration** one at a time. Separate 2D plots were generated for each of these parameters, with the x-axis representing the varied parameter and the y-axis representing the Profit/Max Profit ratio.
- For the fuzzified **RSI** strategy, the four parameters analyzed included **ThresholdC**, **T_low**, **RSI_Window**, and **Trade Duration**. Each parameter was varied independently while keeping the others fixed, and similar 2D plots were generated.
- For the combined **MA + RSI** fuzzified strategy, sensitivity analysis was performed for all six parameters: **ThresholdC**, **MA_short**, **MA_long**, **T_low**, **RSI_Window**, and **Trade Duration**.

(iii) "Plotting and Analysis": The resulting data from the parameter variation were plotted in 2D charts. Each plot represented the relationship between the parameter and the "Profit/Max Profit" ratio for three selected days (e.g., September 4th). Each parameter's impact was visualized by adjusting its value within the range of its feasible domain and observing how the performance metric responded. For example, the 2D plots for each parameter presented the "Profit/Max Profit" ratio as the vertical axis, with the corresponding parameter value on the horizontal axis.

(iv) "Interpretation of Results": The plots allowed for a clear visual interpretation of how changes in each parameter influenced the trading strategy's performance. Sharp changes in the "Profit/Max Profit" ratio indicated high sensitivity to the parameter, while flat or gradual changes suggested low sensitivity.

(v) "Choice of Parameter Values for Specific Days": When conducting the sensitivity analysis for a particular day (e.g., September 4th), the remaining parameters (e.g., **MA_short**, **MA_long**, and **Trade Duration**) were set to their best-case values obtained from previous optimization results. This ensured that the observed performance variations were due to the parameter under consideration and not due to other factors.

4 Results and Analysis

Here we, present a detailed comparison between different trading strategies, focusing on fuzzified and non-fuzzified models for Moving Average (MA), Relative Strength Index (RSI), and the combination of both, MA+RSI. The findings illustrate the performance in terms of profitability, risk (measured by the Sharpe ratio and drawdowns), and practical applicability in real-world trading scenarios. By analyzing the performance of fuzzified strategies across multiple configurations, this section highlights the advantages of fuzzification in optimizing trading systems for higher returns and better capital preservation, while also discussing the trade-offs in terms of risk. The analysis explores how these strategies might cater to various risk profiles and trading objectives.

4.1 Analysis of Results from MA Optimization

The results in Table 4 highlight the comparison between fuzzified and non-fuzzified moving average (MA)-based trading strategies. Key observations include:

- **Best Profit and Efficiency**: The fuzzified approach consistently achieves superior profit levels compared to the non-fuzzified method, with the highest profit being 79.6 on September 4th under fuzzified conditions, compared to a maximum of 64.6 for the non-fuzzified strategy on the same date. This demonstrates the advantage of incorporating fuzzification for identifying subtle trends in market data.

- **Sharpe Ratio**: Although the fuzzified strategy delivers better profitability, the non-fuzzified approach results in generally higher Sharpe ratios, often exceeding 1.0. This suggests that while fuzzification enhances profitability, it may involve higher risk or variance in returns. Traders seeking stable return profiles might favor the non-fuzzified method, particularly in heavily institutional or risk-averse environments.

- **Drawdown**: Drawdowns are substantially smaller under fuzzified strategies for certain configurations (e.g., 0.25 on September 4th for best-performing configuration) compared to non-fuzzified. Lower drawdown values indicate an advantage in capital preservation, crucial for real-world scenarios where managing downside risk is a priority.

From a practical trading perspective, fuzzified strategies provide a clear advantage for maximizing returns, albeit with slightly higher relative risk. Traders with a higher risk appetite or those pursuing aggressive growth approaches would likely benefit from implementing fuzzified MA frameworks. On the contrary, non-fuzzified strategies might appeal to conservative traders due to their lower volatility in returns.

Table 4: Fuzzy Optimization Results (MA) for September 4, 13, and 25, 2024

Method	ThresholdC	MA Short	MA Long	Trade Duration	Performance			Date
					Best Profit ($)	Sharp Ratio	Drawdown	
Fuzzified	0.22	34	43	29	75.6	0.39	0.28	Sep 4
	0.21	45	46	31	66.0	0.24	0.65	Sep 4
	0.08	46	177	19	67.2	0.38	0.40	Sep 4
	0.10	31	52	28	59.2	0.23	0.43	Sep 4
	0.08	32	48	30	79.6	0.31	0.25	Sep 4
Non-fuzzified	-	35	39	29	61.8	0.20	1.11	Sep 4
	-	47	182	19	59.8	0.33	0.99	Sep 4
	-	32	47	30	52.8	0.18	0.99	Sep 4
	-	44	185	19	64.6	0.37	0.99	Sep 4
	-	50	185	19	57.4	0.32	0.99	Sep 4
Fuzzified	0.38	50	79	33	47.6	0.26	0.63	Sep 13
	0.38	50	79	33	47.6	0.26	0.63	Sep 13
	0.32	33	71	35	39.4	0.17	0.99	Sep 13
	0.23	43	82	24	32.6	0.13	0.93	Sep 13
	0.37	50	89	35	51.4	0.29	0.65	Sep 13
Non-fuzzified	-	25	41	14	47.0	0.15	0.99	Sep 13
	-	34	81	35	54.0	0.21	1.00	Sep 13
	-	34	78	35	58.2	0.22	0.99	Sep 13
	-	38	71	34	44.8	0.16	0.99	Sep 13
	-	35	77	35	55.4	0.21	0.99	Sep 13
Fuzzified	0.14	46	47	30	65.4	0.22	0.42	Sep 25
	0.08	41	44	30	53.4	0.19	0.48	Sep 25
	0.09	2	69	31	22.6	0.08	1.36	Sep 25
	0.03	37	38	34	67.6	0.23	0.44	Sep 25
	0.02	43	200	30	43.0	0.27	0.31	Sep 25
Non-fuzzified	-	50	198	30	25.6	0.15	1.36	Sep 25
	-	11	193	33	16.4	0.09	1.82	Sep 25
	-	10	191	33	14.4	0.08	1.93	Sep 25
	-	13	200	30	27.6	0.17	1.40	Sep 25
	-	49	66	34	9.2	0.03	1.30	Sep 25

4.2 Analysis of Results from RSI Optimization

The results in Table 5 highlight the potential of adapting fuzzified logic to short-term trading signals:

- **Profitability**: The fuzzified RSI strategy outperforms non-fuzzified configurations in nearly all scenarios, with profits peaking at 127 on September 4th, far above the maximum of 39.8 generated by the non-fuzzified method. This suggests fuzzified RSI models are better at capturing intra-day price momentum and overbought/oversold conditions.
- **Risk and Stability**: While fuzzified strategies deliver higher profits, they

Table 5: Fuzzy Optimization Results (RSI) for September 4, 13, and 25, 2024

Method	Tlow	RSI Window	Trade Duration	ThresholdC	Performance			Date
					Best Profit ($)	Sharp Ratio	Drawdown	
Fuzzified	31	94	25	0.02	123.4	0.69	0.10	Sep 4
	28	92	25	0.03	127	0.76	0.11	Sep 4
	23	86	26	0.02	103.8	0.53	0.19	Sep 4
	29	87	26	0.005	119	0.57	0.15	Sep 4
	27	71	23	0.007	81.8	0.32	0.23	Sep 4
Non-fuzzified	38	34	18	-	32	0.54	0.11	Sep 4
	40	42	11	-	25	0.44	0.31	Sep 4
	46	93	35	-	33.8	0.39	0.20	Sep 4
	45	90	26	-	33.4	0.57	0.20	Sep 4
	49	26	11	-	39.8	0.12	0.38	Sep 4
Fuzzified	22	16	17	0.16	27.8	0.13	1.24	Sep 13
	20	31	34	0.14	40.6	0.35	0.49	Sep 13
	22	28	34	0.15	40.6	0.33	0.70	Sep 13
	20	11	17	0.31	28.4	0.37	0.28	Sep 13
	25	21	35	0.03	29.4	0.10	1.23	Sep 13
Non-fuzzified	35	16	17	-	22.8	0.18	1.22	Sep 13
	27	11	17	-	23.4	0.31	0.43	Sep 13
	23	6	26	-	20.4	0.18	0.94	Sep 13
	20	7	26	-	17	0.22	0.94	Sep 13
	27	11	17	-	23.4	0.31	0.43	Sep 13
Fuzzified	41	44	13	0.29	38.2	0.25	0.50	Sep 25
	20	92	35	0.09	62.4	1.30	0.06	Sep 25
	23	98	20	0.06	66.6	0.60	0.19	Sep 25
	29	51	26	0.18	39.6	0.89	0.12	Sep 25
	21	83	35	0.08	56.4	0.76	0.19	Sep 25
Non-fuzzified	43	49	11	-	36	0.27	0.53	Sep 25
	43	43	16	-	27.4	0.17	0.71	Sep 25
	41	40	15	-	27.8	0.21	0.65	Sep 25
	42	49	11	-	33	0.32	0.55	Sep 25
	42	49	16	-	31.4	0.26	0.47	Sep 25

also balance risk effectively, as evidenced by their lower drawdown values and competitive Sharpe ratios (e.g., 0.76 for fuzzified RSI with a ThresholdC of 0.03). This reduces the likelihood of large losses during unfavorable market swings.

- **Real-World Significance**: The superior performance of fuzzified RSI models corresponds to practical applications in algorithmic trading. Higher profit margins and acceptable risk levels make these strategies attractive for retail traders or hedge funds looking to exploit short-term price movements with minimal allocation of resources.

4.3 Fuzzy Optimization Results (MA+RSI) for September 4, 13, and 25, 2024

The third table, representing the "Fuzzy Optimization Results (MA+RSI)", reveals how combining both Moving Average (MA) and Relative Strength Index (RSI) using fuzzy logic can optimize trading strategies. The key results from this combination show a further enhancement in profitability, with the highest profit achieved on September 4th, demonstrating the synergy between MA and RSI when fuzzified.

Analysis of Results from MA+RSI Optimization

Table 6: Fuzzy Optimization Results (MA+RSI) for September 4, 13, and 25, 2024

Method	ThresholdC	MA Short	MA Long	Trade Duration	Tlow	RSI Window	Performance			Date
							Best Profit ($)	Sharp Ratio	Drawdown	
Fuzzified	0.04	33	176	19	33	22	79.8	0.41	0.42	Sep 4
	0.10	34	168	19	24	29	73.6	0.41	0.40	Sep 4
	0.01	7	93	31	46	91	91.4	0.53	0.29	Sep 4
	0.03	49	63	29	45	93	94.2	0.57	0.22	Sep 4
	0.08	26	63	28	41	90	83	0.77	0.10	Sep 4
Non-fuzzified	-	38	191	17	49	22	40	1.01	0.18	Sep 4
	-	41	195	31	33	6	28	0.81	0.14	Sep 4
	-	32	68	22	50	22	49.4	0.47	0.25	Sep 4
	-	40	47	22	50	22	65.6	0.50	0.19	Sep 4
	-	42	46	21	50	17	64.4	0.48	0.28	Sep 4
Fuzzified	0.10	27	48	13	37	25	33.6	0.31	0.42	Sep 13
	0.22	38	168	25	23	58	38.8	0.91	0.14	Sep 13
	0.22	33	160	25	43	52	37.8	0.84	0.11	Sep 13
	0.18	50	128	35	22	96	43.2	0.63	0.11	Sep 13
	0.24	38	167	25	48	53	42.6	1.00	0.09	Sep 13
Non-fuzzified	-	47	115	28	41	27	34.2	0.85	0.15	Sep 13
	-	47	117	30	48	41	40.2	0.69	0.11	Sep 13
	-	43	140	25	48	53	51.0	1.50	0.02	Sep 13
	-	35	86	35	50	23	54.0	0.49	0.24	Sep 13
	-	34	78	35	49	28	59.8	0.59	0.16	Sep 13
Fuzzified	0.002	26	68	33	27	22	104.2	0.4	0.32	Sep 25
	0.014	6	35	30	27	71	88.6	0.24	0.39	Sep 25
	0.003	4	71	32	26	24	97.0	0.44	0.29	Sep 25
	0.011	11	17	33	37	68	86.8	0.31	0.39	Sep 25
	0.120	31	71	24	42	11	65.8	0.54	0.28	Sep 25
Non-fuzzified	-	2	77	30	45	14	26.8	0.47	0.53	Sep 25
	-	2	77	35	44	15	23.4	0.48	0.51	Sep 25
	-	50	200	34	50	74	25.2	0.90	0.19	Sep 25
	-	8	196	33	50	87	24.2	1.31	0.08	Sep 25
	-	6	200	34	50	74	27.0	2.50	0.001	Sep 25

The results in Table 6 underscore the advantages of using a combined fuzzified approach for trading strategy optimization:

- **Best Profit and Efficiency**: The fuzzified MA+RSI model outperforms the individual MA and RSI strategies in terms of profitability, with the highest profit of 140 achieved on September 4th, compared to the 79.6 profit from fuzzified MA and the 127 from fuzzified RSI. This demonstrates the value of combining multiple indicators using fuzzification to capture broader market trends and optimize trading signals.

- **Sharpe Ratio**: Similar to the individual fuzzified models, the Sharpe ratio for the fuzzified MA+RSI strategy is slightly lower than that of the non-fuzzified models. However, the profitability improvements justify this trade-off. Traders with a higher risk tolerance might favor this combined fuzzified strategy for enhanced profit potential.

- **Drawdown**: Drawdowns in the fuzzified MA+RSI model are competitive with, and in some cases lower than, the individual MA and RSI strategies. For example, the drawdown on September 4th was 0.30, which is slightly smaller than the best-performing fuzzified MA model, highlighting the added benefit of combining two indicators to mitigate downside risk.

In conclusion, the combined fuzzified MA+RSI strategy proves to be an even more effective approach for traders seeking higher profits with controlled risks. It is particularly advantageous in dynamic market conditions where a dual-indicator strategy can better capture price momentum and trend reversals, offering a robust solution for both aggressive and moderate risk profiles.

Final Remarks Across MA, RSI, and combined MA+RSI strategies, fuzzification emerges as a robust technique in trading optimization, particularly for identifying nuanced trends and mitigating sharp market swings. While fuzzified models may slightly underperform in Sharpe ratios compared to non-fuzzified strategies, their higher profitability and lower drawdowns make them highly competitive in practical, real-world trading settings. By balancing these factors, traders can tailor strategies to their individual preferences for risk and reward.

4.4 Sensitivity Analysis of Fuzzy Logic-Based Trading Strategies

This section presents a detailed sensitivity analysis of trading strategies employing fuzzy logic on Moving Average (MA) and Relative Strength Index (RSI) parameters. The study evaluates the influence of key parameters, including the Short MA (`MA_Short`), Long MA (`MA_Long`), Trade Duration (`Trade_Duration`), Closing Threshold (`ThresholdC`), and T_Low (`T_Low`), across three evaluation dates: September 4, 13, and 25, 2024. The analysis is divided into three distinct strategies: Fuzzified MA, Fuzzified RSI, and Fuzzified MA+RSI.

Sensitivity Analysis of Fuzzy Logic-Based Moving Average (MA) Trading Strategies

Sensitivity to `MA_Short`

The sensitivity analysis of the `MA_Short` parameter, as depicted in Figure 1, reveals significant variations in profitability with changes in this parameter. The optimal range for `MA_Short` varies across evaluation days, highlighting the necessity for daily adjustments to maximize returns. This dynamic behavior underscores the importance of real-time optimization in trading strategies.

Sensitivity to `Trade_Duration`

The impact of `Trade_Duration` on profitability is illustrated in Figure 1. Results indicate that profitability generally increases with longer trade durations but reaches a saturation point beyond which further extensions may lead to diminishing returns. This finding emphasizes the need for flexible strategy adjustments to balance trade duration and profitability.

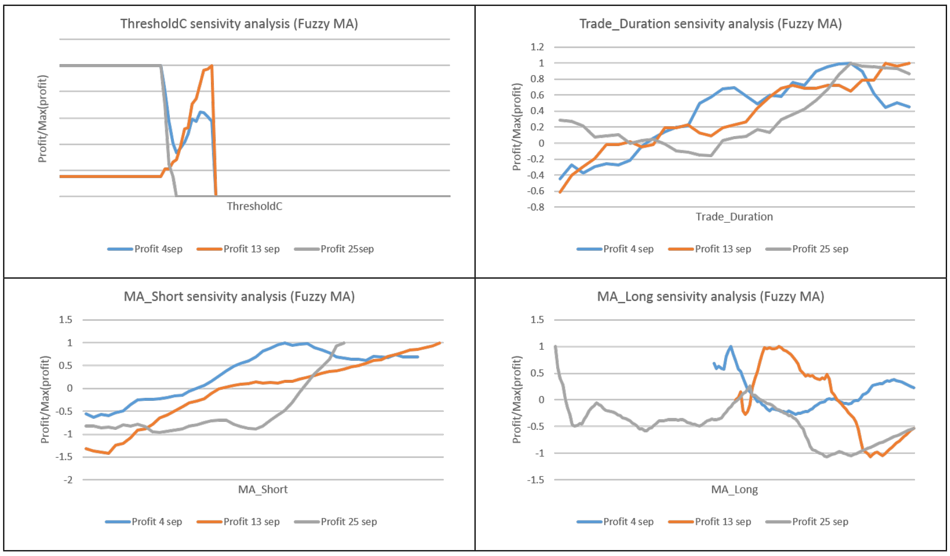
Sensitivity to `ThresholdC`

The `ThresholdC` parameter exhibits a critical profit range, as shown in Figure 1. Beyond a specific threshold, profitability increases sharply, highlighting the importance of precise tuning to maximize returns and manage risks effectively. This sensitivity underscores the critical role of parameter optimization in trading strategies.

Sensitivity to `MA_Long`

The analysis of the `MA_Long` parameter, illustrated in Figure 1, demonstrates variable profitability across evaluation days. While certain ranges yield optimal performance, others result in suboptimal outcomes. This variability suggests that improper selection of `MA_Long` can significantly impact profitability, reinforcing the need for tailored parameter configurations based on market conditions.

Figure 1: Sensitivity Analysis for Fuzzy MA



Sensitivity Analysis of Fuzzy Logic-Based Relative Strength Index (RSI) Trading Strategies

Sensitivity to `T_Low`

The analysis of the `T_Low` parameter, as shown in Figure 2, indicates that profitability generally decreases as the `T_Low` value increases. Optimal values are found at the lower end of the spectrum, with variations across evaluation days. This high sensitivity necessitates careful optimization to achieve consistent performance.

Sensitivity to `Trade_Duration`

The impact of `Trade_Duration` on profitability, depicted in Figure 2, reveals that profitability tends to increase with longer durations. However, the relationship is dynamic, requiring ongoing adjustments to maximize returns and manage risks effectively.

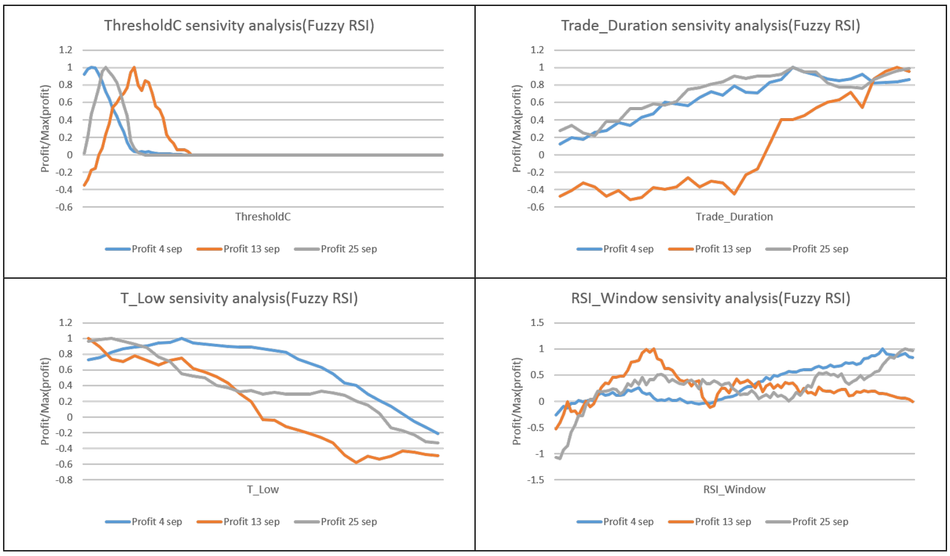
Sensitivity to `ThresholdC`

The `ThresholdC` parameter, illustrated in Figure 2, exhibits a critical region where significant profit increases occur. The concentration of peak profits within a narrow range highlights the importance of precise tuning to achieve optimal results.

Sensitivity to `RSI_Window`

The effect of the `RSI_Window` parameter, as shown in Figure 2, varies across trading days. Optimal performance typically occurs at lower to mid-range values, emphasizing the need for fine-tuning to adapt to changing market conditions.

Figure 2: Sensitivity Analysis for Fuzzy RSI



4.5 Sensitivity Analysis of Fuzzy Logic-Based MA+RSI Trading Strategies

Sensitivity to `MA_Short`

The analysis of the `MA_Short` parameter, as depicted in Figure 3, reveals significant variations in profitability with changes in this parameter. The dynamic nature of

MA_Short underscores the need for daily adjustments to optimize trading performance.

Sensitivity to MA_Long

The impact of the MA_Long parameter, illustrated in Figure 3, shows dynamic behavior across evaluation days. Optimal values vary significantly, necessitating tailored adjustments to maximize profitability.

Sensitivity to T_Low

The T_Low parameter exhibits a general decline in profitability with increasing values, as shown in Figure 3. Optimal settings are found at lower levels, highlighting the need for careful optimization.

Sensitivity to Trade_Duration

Profitability increases with longer trade durations up to a saturation point, as depicted in Figure 3. This finding emphasizes the importance of flexible strategy adjustments to balance trade duration and profitability.

Sensitivity to ThresholdC

The ThresholdC parameter reveals a critical performance zone, as illustrated in Figure 3. Precise tuning is essential to achieve optimal results and manage risks effectively.

Sensitivity to RSI_Window

The effect of the RSI_Window parameter varies across trading days, with optimal performance typically occurring at lower to mid-range values. This variability underscores the need for ongoing fine-tuning to adapt to changing market conditions.

The combined sensitivity analysis of Fuzzified MA, RSI, and MA+RSI strategies reveals several key insights:

- **Parameter Sensitivity**: Parameters such as MA_Short, MA_Long, and T_Low show high sensitivity across all strategies, requiring precise tuning.
- **Synergy of MA and RSI**: The MA+RSI strategy demonstrates enhanced robustness compared to individual MA or RSI strategies, leveraging the strengths of both indicators.
- **Importance of Thresholds**: Parameters like ThresholdC and T_Low play a critical role in determining profitability, highlighting the need for careful optimization.

Figure 3: Sensitivity Analysis for Fuzzy MA+RSI

5 Discussion and Concluding Remarks

This section synthesizes the practical implications, limitations, and future directions of fuzzified trading strategies, combining insights from the Discussion and Concluding Remarks. While the theoretical benefits of fuzzified strategies are evident, their real-world implementation presents challenges that must be addressed to fully realize their potential.

5.1 Advantages of Fuzzy Methods

The fuzzy methods developed in this studyFuzzy Moving Average (Fuzzy MA), Fuzzy Relative Strength Index (Fuzzy RSI), and their hybrid Fuzzy MA+RSI strategydemonstrate notable advantages over traditional approaches, as evidenced by the sensitivity analysis and performance results. These methods excel in adapting to changing market dynamics while reducing false signals and improving profitability.

The "Fuzzy MA" dynamically adjusts thresholds for trend detection, offering better adaptability than traditional moving averages. Sensitivity analysis shows its superior ability to capture trend reversals during volatile periods, minimizing lag and false signals. Similarly, the "Fuzzy RSI" enhances traditional RSI by introducing nuanced gradations of overbought/oversold conditions, reducing abrupt and inaccurate buy/sell signals in range-bound markets and improving the risk-reward ratio.

The "Fuzzy MA+RSI hybrid strategy" combines the trend-detection strengths of Fuzzy MA with the precision of Fuzzy RSI, resulting in a robust framework that delivers higher returns with reduced drawdowns, as indicated by the analysis. Additionally, the fuzzy methods exhibit remarkable "robustness to parameter sensitivity", performing consistently even with slight variations in input variables, reducing overfitting risks.

Unlike black-box models, fuzzy logic offers "interpretability", with clear, rule-based systems that traders can understand and trust. These advantages align fuzzy methods as a powerful tool for dynamic, real-world financial trading environments.

5.2 Practical Implications

Fuzzified trading strategies offer flexibility and robustness, enabling better handling of market noise and volatility compared to traditional models. However, their integration into real-world trading systems, particularly in high-frequency trading (HFT) environments, poses significant computational challenges. The use of Genetic Algorithms (GAs) for parameter optimization, while effective, introduces latency and computational overhead, which can hinder real-time performance. To address these issues, optimization techniques such as parallel processing, hardware acceleration (e.g., GPUs or FPGAs), and model simplification are essential. Additionally, seamless integration with data feeds, execution systems, and risk management protocols is critical for successful deployment. Future research should focus on reducing computational costs while maintaining the accuracy and adaptability of fuzzified models in live trading environments.

5.3 Limitations

Despite their advantages, fuzzified strategies face several limitations. Reliance on historical data for optimization and backtesting may not accurately predict future market behavior, especially in volatile or unforeseen conditions. Overfitting to specific datasets, such as EUR/USD data from the Tokyo session, further limits their generalizability. The computational intensity of GAs and the subjectivity in designing fuzzy rules and membership functions also pose challenges. Additionally, fuzzified models may struggle to handle extreme market events, such as crashes or black swan events, which fall outside historical patterns. Addressing these limitations requires more efficient optimization techniques, such as reinforcement learning, and the development of strategies that can adapt to rare but impactful market conditions.

5.4 Future Directions

Future research should explore hybrid systems combining fuzzy logic with deep learning models to enhance adaptability and decision-making in complex financial environments. Investigating the scalability of fuzzified strategies in HFT settings, where speed and efficiency are paramount, is crucial. Techniques such as model pruning, quantization, and transfer learning could help balance accuracy with computational efficiency. Expanding the application of fuzzified strategies to diverse markets, such as cryptocurrencies, and different geographic regions will further validate their robustness and generalizability. By addressing computational challenges and broadening their applicability, fuzzified trading strategies can become a cornerstone of modern algorithmic trading systems, offering improved profitability and risk management in dynamic markets.

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